Evolutionary Economics and Social Complexity Science 28

Yuji Aruka *Editor*

Digital Designs for Money, Markets, and Social Dilemmas

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Volume 28

The Japan Association for Evolutionary Economics (JAFEE) always has adhered to its original aim of taking an explicit "integrated" approach. This path has been followed steadfastly since the Association's establishment in 1997 and, as well, since the inauguration of our international journal in 2004. We have deployed an agenda encompassing a contemporary array of subjects including but not limited to: foundations of institutional and evolutionary economics, criticism of mainstream views in the social sciences, knowledge and learning in socio-economic life, development and innovation of technologies, transformation of industrial organizations and economic systems, experimental studies in economics, agent-based modeling of socio-economic systems, evolution of the governance structure of firms and other organizations, comparison of dynamically changing institutions of the world, and policy proposals in the transformational process of economic life. In short, our starting point is an "integrative science" of evolutionary and institutional views. Furthermore, we always endeavor to stay abreast of newly established methods such as agent-based modeling, socio/econo-physics, and network analysis as part of our integrative links. More fundamentally, "evolution" in social science is interpreted as an essential key word, i.e., an integrative and /or communicative link to understand and re-domain various preceding dichotomies in the sciences: ontological or epistemological, subjective or objective, homogeneous or heterogeneous, natural or artificial, selfish or altruistic, individualistic or collective, rational or irrational, axiomatic or psychological-based, causal nexus or cyclic networked, optimal or adaptive, micro- or macroscopic, deterministic or stochastic, historical or theoretical, mathematical or computational, experimental or empirical, agent-based or socio/econo-physical, institutional or evolutionary, regional or global, and so on. The conventional meanings adhering to various traditional dichotomies may be more or less obsolete, to be replaced with more current ones vis-à-vis contemporary academic trends. Thus we are strongly encouraged to integrate some of the conventional dichotomies. These attempts are not limited to the field of economic sciences, including management sciences, but also include social science in general. In that way, understanding the social profiles of complex science may then be within our reach. In the meantime, contemporary society appears to be evolving into a newly emerging phase, chiefly characterized by an information and communication technology (ICT) mode of production and a service network system replacing the earlier established factory system with a new one that is suited to actual observations. In the face of these changes we are urgently compelled to explore a set of new properties for a new socio/economic system by implementing new ideas. We thus are keen to look for "integrated principles" common to the above-mentioned dichotomies throughout our serial compilation of publications. We are also encouraged to create a new, broader spectrum for establishing a specific method positively integrated in our own original way.

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Editor

Digital Designs for Money, Markets, and Social Dilemmas

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Preface

This book project was proposed in 2021 during the era when we have rushed into facing a harsh reality. We are still in the midst of a period of exploration. However, one thing is for certain. We have to face the oncoming new socioeconomic system accompanied by big changes in our style of communication, whether money or information. We just try to organize our insights toward our new thought. Fortunately, many excellent scholars have joined into this book project. The book is titled *Digital Designs for Money, Markets, and Social Dilemmas*. The book contains six parts: Evolution of money and thinking complexities in the AI era; Goods market and the future of labor market; Computational social approaches to social dilemmas, smart city, cryptographics; Artificial market experiments; The randomness and high frequencies in financial data; Other trading strategy issues and the effects of AI usage. These issues may be indispensable subjects in our age. Study these subjects and have a step forward to the future society!

Kyoto, Japan
January 2022

Yuji Aruka

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Chapter 1
A Step Forward to the Future Society

Yuji Aruka

Abstract An innovative feature of this book is its econocentric structure, focusing on digital designs. From the outset, econocentrism is linked with monetary exchange as the core engine of capitalism. Needless to say, monetary exchange and its ledger system will undergo significant innovations soon, synchronizing with the new stage of communication style backed by pervasiveness of quantum computing. In fact, the new coronavirus pandemic has changed lifestyles worldwide, which are unlikely ever to return to their original form. This great transformation will change the nature of the socio-economic system itself, which will be centered on digital designs. At present, money is starting to undergo a major revolution. Many books dealing with digital designs and innovations have been published, but few if any of them focus on monetary and analytical methods in the way that this present volume does. Dealing with the new attributes brought about by this great change will be beyond the scope of traditional economics. Digital tools, such as blockchain, cryptocurrency, and crypt assets as well as distributive ledger systems, require new modes of analysis. First, the evolution of money and complex thinking necessary for understanding that change must be analyzed. Furthermore, the way that goods markets are mutually coordinated and the future of the labor market must be understood, points that are emphasized in the first section of the book. Second, other computational approaches to social dilemmas, crypt graphics, and the supply chain are introduced in the latter part. To facilitate understanding of the core engine of market capitalism, the detailed settlement mechanism in terms of an AI market experiment is also presented.

Keywords Changes of the style of production · Landscape of exchange systems · AI market experiments · Transductive reasoning · Horizontal visibility graph · Network structure of time series

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1.1 A View on the Current Situation Beyond the Older Economics

We are facing a harsh reality. First, the superstars like Vanguard and BlackRock (extraordinary asset management corporations) have now dominated nearly the world. These corporations directly or indirectly dominated almost 80% of international capitals worldwide. In this century, we cannot miss corporations that operate above the governments. More interestingly, these financial institutes are not regulated by the banking acts. A traditional macro/financial model, whether orthodox or heretical, no longer holds. Second, the reasoning method is also changing. Previously, we believed the reasoning must be achieved from induction to deduction by way of approximation function. We did not believe in an alternative scientific method. However, it may be the new normal to believe in transduction, which is represented by machine learning. In this context, we will also be forced to change our style of communication, whether money or information.

1.1.1 The Harsh Reality and Its Dominance of the Fast Track Path to the Future

Given such a reality, where the free market mechanism has broken down, evolutionary economics needs some game changing ideas. Even Nobel laureates no longer provide us with future insights. Creative Destruction, which is a very famous term of Schumpeter, the pioneer of evolutionary economics, literally is under way in the world. Sometimes this word is replaced with the Great Reset. However, we still have no idea of what the coming system is after the destruction. We have not established any measure on the coming society.

The new coronavirus pandemic has changed lifestyles worldwide, which are unlikely ever to return to their original form. This great transformation will change the nature of the socio-economic system itself and will be centered on digital designs. This direction may suggest agendas which the United Nations (UN) and the World Economic Forum(WEF) proposed around the Sustainable Development Goals (SDGs).[1] In fact, such a fast track to progress will be a dominant factor to determine the future path. However, the human history is not necessarily uniquely established in advance. We may thus avoid identifying the future track with the established acts in this book.

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[1] In the scheme of WEF, "we are stepping into the era of the Internet of Bodies from Things" by collecting our physical data via a range of devices that can be implanted, swallowed, or worn. https://www.weforum.org/agenda/2020/06/internet-of-bodies-covid19-recovery-governance-health-data/.

1.1.1.1 Econocentrism Containing Monetary Exchange

At present, money is beginning to undergo a major revolution. Many books dealing with digital designs and innovations have been published, but few if any of them focus on monetary and analytical methods in the way that this present volume does. Taking into account the new advancement of the monetary exchange, our book will be called econocentric.[2]

1.1.2 The Limits of Older Economics

Dealing with the new attributes brought about by this great change will be beyond the scope of traditional economics. Digital tools, such as blockchain, cryptocurrency, and crypt assets as well as distributive ledger systems, require new modes of analysis. First, the evolution of money and complex thinking necessary for understanding that change must be analyzed. Furthermore, the way that goods markets are mutually coordinated and the future of the labor market must be understood, points that are emphasized in the first section of the book. Second, in the latter part, other computational approaches to social dilemmas, cryptographics, and the supply chain are introduced in the latter part. To facilitate understanding of the core engine of market capitalism, the detailed settlement mechanism in terms of an AI market experiment is presented.

To date, traditional economics have chosen to argue “market in general,” as symbolized by general equilibrium theory, which was originally established in 1870s. In reality, unfortunately, there is no longer a held “generality” by any means, as Leon Walras first expected. To depict the modern market, it may be not only inappropriate but also boldly far-reaching for us to discuss the market in general.

It is difficult for the classical coverage of the economic reasoning to analyze the contemporary system, which we imagine. However, we temporarily illustrate how classical economics approaches the modern macroeconomic system, according to Schefold (2021). Schefold assessed the Cambridge/Keynesian economics inheriting from classical economics in the following manner:

> Piketty shows that larger fortunes tend to be associated with higher rates of return on financial investments, and in this modern reality is different (Piketty 2014), but we cannot analyze here how the rich get richer. . . . I only want to stress that the Cambridge economists could not easily leave the narrow framework of steady state analysis, because

[2] The definition of econocentrism seems not necessarily uniquely established in *Oxford Dictionary*, for example. Usually, econocentrism simply means the use of the principle of supply and demand at least loosely when we formalize “the value of intangible assets like human emotional development or environmental sustainability, and the monolithic implied trustworthiness of market dynamics.” The usage does not imply the strict use of the principle of supply and demand. Cited from Urban Dictionary: https://www.urbandictionary.com/define.php?term=econocentrism. In our context, the econocentrism may rather focus on the use of the principle of monetary exchange.

> it was associated with the constant capital-output ratio, but they had no theory for its determination. (Schefold 2021, 13)

Here the steady state analysis is connected with the assumption of a constant capital-output ratio. The idea of Joan Robinson, Keynse's best disciple, regarded that there were few reswitchings of the choice of techniques happening excepting around the corner points, in the event that there were held a constant capital-output ratio almost everywhere. So the dynamics of macroeconomics will be concentrated on the field of investment, in particular, behaviors of investors.[3]

> [O]nce a production function is given, Keynesian analysis is inherently more flexible, not in the sense of agnosticism, but by emphasizing forces that matter in the real world, principally the behavior of investors. ... The investment climate can be assessed. Neo-Fisherians believe that moderate rises of interest rates and prices might go together, involving rational expectations. With a constant capital-output ratio, the effect of a small and slow rise of the interest rate similarly seems precarious, but possible for a Keynesian, in what Joan Robinson called a state of tranquility that is not disturbed by a process of substitution Schefold (2021).

Fortunately, we recently acquired two major technological advancements. One is AI, in general; the other is Bitcoin or cryptocurrency, in particular. The latter is a byproduct in association with blockchain technology. But the impact of either Bitcoin or Ethereum is enormous in theory and in practice. In particular, Ethereum is more interesting in the sense that it also provides with **smart contract**. This has the potential power to innovate the economic system, quite possibly, the social system.

1.1.2.1 A Note on Quantum Financial System (QFS)

Finally, we need to take note of the new advent of quantum financial system (QFS). As IMF noted in Fall 2021, "Quantum computers could crack the cryptography that underpins financial stability."[4] QFS could be also an alternative to Bitcoin and so on. Quantum bit may be superior to 0, 1 bit. However, the current crypto money will still stay in the power of decentralization and community consensus.

1.1.2.2 How the Contemporary System Differs Much from the Image of Classical Economics

We are instead interested in how the contemporary system differs substantially from the image of classical economics. Fortunately, we recently acquired two major technological advancements. One is AI, in general; the other is Bitcoin or cryptocurrency, in particular. The latter is a byproduct in association with blockchain

[3] Schefold then assumed that confidence returns, as the pandemic peters out, so that the option to raise interest rates again presents itself (Schefold 2021, 16).

[4] https://www.imf.org/external/pubs/ft/fandd/2021/09/quantum-computings-possibilitiesand-perils-deodoro.htm.

technology. But the impact of either Bitcoin or Ethereum is enormous in theory and in practice. In particular, Ethereum is more interesting in the sense that it also provides with **smart contract**. This has the potential power to innovate the economic system, quite possibly, the social system.[5]

1.1.3 Some Instances of Using Blockchain

It is noted that blockchain is not simply a mining technology for crypt-currencies. Blockchain also is used a censor technology, e.g., in order to retrieve a defective lot in a factory system of the manufacturing industry.

1.1.3.1 Currency Exchange

Among them, we note the IBM blockchain applied to the currency exchange, which provides the financial institutions with a better opportunity by way of a world wire network (API): either are transformed into “a stable coin” as the digital asset, which can achieve a simultaneous exchange between the two. Here messaging, clearing, and settlement for the desired exchange will be integrated by blockchain technology without falsifying bookkeeping. The latter usage may be classified into a hybrid application of blockchain in a sense that blockchain is incorporated as a sub-system of the currency exchange. **IBM Blockchain** is an instance to deliver value around the world. See https://www.ibm.com/blockchain.

1.1.3.2 A Simple Auction Design on the Ethereum Platform

In 1993, Nick Szabo described about how users could input data or value then regain it from the transfer system as if it were a digital vending machine. **Ethereum** shares the same function as Bitcoin in a sense that **the network** can transfer value from one to another. Different from Bitcoin, Ethereum provides each node with additional information account, which could function as the distributive ledger for each, while Bitcoin only transfers the value of currency (Fig. 1.1).

[5] Aruka (2022) focuses on the settlement mechanism of the Bitcoin Exchange, discussing its uniqueness and commonality as compared with the stock exchange. We then introduce our new idea of digit length frequency distribution when we are interested in fully random iterated cellular automata (FRICA). Finally, we apply the length distribution to the price time series generated by the U-Mart acceleration experiment tool and examine the neutralizing effects by the change of the market transaction strategy composition, which may suggest some possible criteria whether the market may be rigged or not.

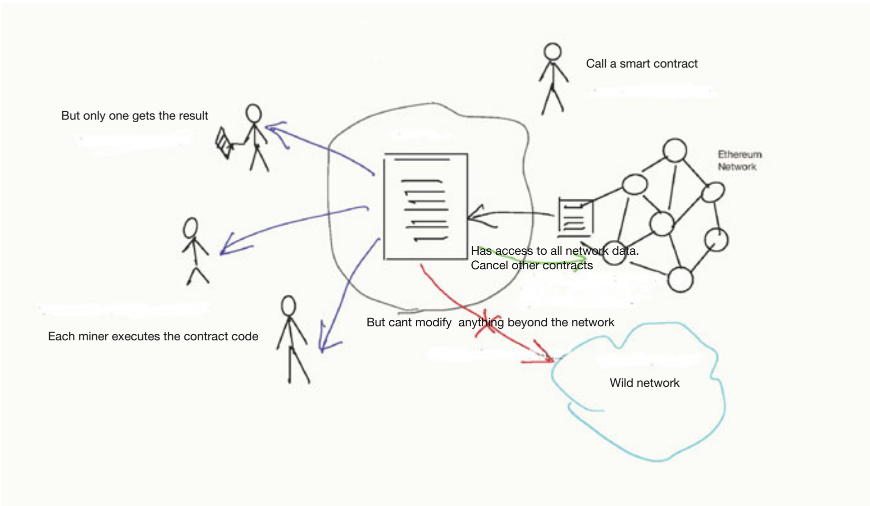

Fig. 1.1 Smart contracts on the Ethereum platform. Cited from https://vas3k.com/blog/ethereum/ but the chart was originally produced

1.1.3.3 Turing Completeness and Smart Contract

Ethereum is called a system written in Turing complete language. As a Turing complete system means a system in which a program can be written that will find an answer, Ethereum, if it is, allows to program **autonomous agents**. The contract will be called **smart contract**.[6]

The features of smart contract are summed up as follows.

– Smart contracts are fulfilled with multisignature accounts, which imply that "funds are spent only when a required percentage of people agree."
– Smart contracts can manage agreements between users, say, if one buys insurance from the other.
– Smart contracts provide utility to other contracts (similar to how a software library works).
– Smart contracts can store information about an application, such as domain registration information or membership records.

[6] The items described below are cited from https://www.coindesk.com/information/ethereum-smart-contracts-work.

1.2 Some Fundamental Changes of the Style of Production and the Landscape of the Socio-Economic System

The economics of production of the last century depend on capital and labor. In the nineteenth Century, the factors of production were land and labor. Land has been replaced with capital as the capitalistic production develops. This suggests that production style is not always fixed. To our understanding, the style is now transitioning, when a universal tool making machine actually appears. Siemens has already provided this kind of entity.[7]

Almost every input will be invisible excepting program codes. In this entity, substitution between factor inputs will not matter in view of cost comparison. In other words, this entity will no longer guarantee the idea of a continuous substitution between physical factor inputs. Thus, this kind of the entity will not only drastically reduce the time of production and the related cost of labor input but also make invalid the traditional idea of a choice of techniques. Now, the economic distributive principle will not be guaranteed by a so-called production function analysis; thus, we must prepare a new analysis of production, although we are faced with too many corrective tasks to establish it along the traditional grounds. In this chapter, we rather just refer to some fundamental problems of traditional production analysis.

1.2.1 The Short-Run Production Function and Its Aggregation Form

Hildenbrand's production function study was published in Hildenbrand (1981) but did not see the light of day until Dosi et al. (2016) drew attention to it. As is well known, the law of returns is assumed a priori in the traditional production function. However, Hildenbrand (1981) drew a short-run production function using the example of the Norwegian tanker industry in 1967 (377 vessels with a load capacity of over 15,000 tons). The tankers were of various types, 57 were turbine-driven and 320 were motor-driven, and their production dates ranged from 1950 to 1966. The output of the tanker industry is tonnes per day times miles transported. Following tradition, only two inputs are considered: fuel and labor. Referring to the work of Johansen and Eide, the production function for the Norwegian tanker industry is shown in the upper panel of Figure 3 of Hildenbrand (1981, 1100). As shown in his figure, the techniques used in the industry may represent some combinatorial compositions. A simple understanding on firms' technology will contradict reality. In fact, the industrial technology is based on a wide range of

[7] See **Siemens' website** page titled: Automation systems for all requirements https://new.siemens.com/global/en/products/automation/systems.html.

unequal productivities reflecting a complex technology. Thus the real isoquant of the industry will not compose a typical isoquant on the material(capital)-labor plane.

According to Hildenbrand (1981), this idea differs from the traditional production function. We define the projection of Y on the input space $\Re^l_+$:

$$D = \{V \in \Re^l_+ | (V, X) \in Y \texttt{ for some } X \in \Re_+\}$$

It then holds **the traditional production function**:

$$F(V) = \max\{X \in \Re_+ | (V, X) \in Y\}$$

The operator max in the above has excluded the possibilities of "certain institutional barriers to factor mobility in aggregating the individual production sets" (Hildenbrand 1981, 1097).

In general, the *ex post* technology of a production unit is a vector is a production activity a that produces, during the current period, a_{l+1} units of output by means of $(a_1, \ldots, a_l)$ units of input. **The size of the firm** is the length of vector a, i.e., a multi-dimensional extension of the usual measure of firm size (Fig. 1.2).

1.2.2 An Alternative Production Set of Zonotope-Basis

Given $Y = (a_1, \ldots, a_l)$, a set of generators for n, the zonotope Y is the convex hull of all vectors of the form a; that is, (Y) is the Minkowski sum of all segments $[0, a_i]$, where $a \in Y$, i.e., $\sum_{a_i \in Y} a_i$. Also $Z(Y)$ is the shadow of the r-dimensional cube $[0, 1]^r$ via the projection in $\Re$:

$$Vol(Y) =: \sum_{1 \le i_1 \le i_2 \cdots \le i_l \le N} |\Delta i_1, \ldots, i_l|$$

Here $|\Delta i_1, \ldots, i_l|$ is the module of the determinant. This kind of discussion will suggest a new growth/innovation theory of production. It is noted that $Vol(Y)$ measures the volume of a rugby ball. The idea of **Volume** is defined by Dosi et al. (2016). The absolute measure is the Gini volume of the zonotope, which could be regarded as a generalization of the well-known Gini index. Let $Vol(P_Y)$ be the volume of the parallel top P_Y of diagonal $d_Y = \sum_{n=1}^N a_n$, that is, the maximal volume we can get when the industry production activity $\sum_{n=1}^N a_n$, that is fixed. It then holds the Gini volume:

$$Vol(Y)_G = \frac{Vol(Y)}{Vol(P_Y)}$$

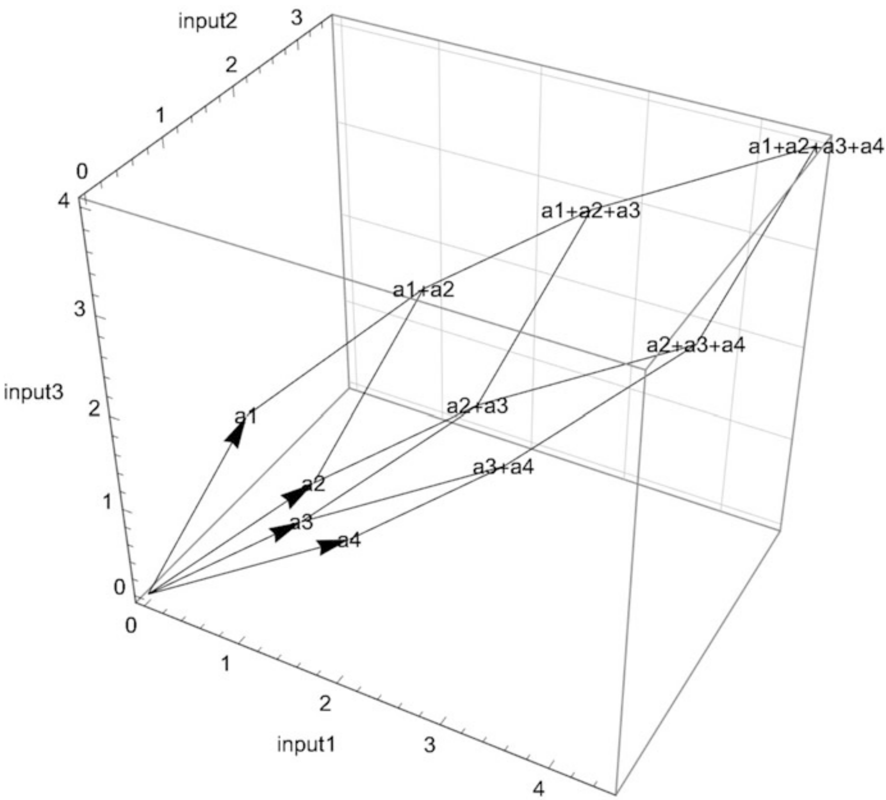

Fig. 1.2 Hildenbrand's short-run production set and its three-dimensional zonotope. The author depicted this figure by Mathematica

Thus we can empirically measure the productivity growth by the change of inequality. It also is noted that the idea of smaller firm size does not necessarily generate greater growth of the industry.

1.2.3 The Effect of Financial Industry on the Real Economy

The present economic system seems to be keenly examined in terms of several insights of the new coordinates. The advent of financial big bang was too shocking to lose sight of the effectiveness of production economy. However, it is easy to verify that the effect of financial activities is extremely small in view of value added or income creation if we measure its effect by a macroscopic GDP aggregate. As Table 1.1 shows, the contribution to GDP of the financial industry, even altogether with the insurance industry, is merely 3.2%. This ratio is also within 10% even in the USA.

Table 1.1 The input-output table of 13 sector, 2015, Japan at production prices

Industry	Value added (million yen)
Agriculture, forestry, and fishery	11310425
Mining	21116028
Manufacturing	202892254
Construction	3699380
Electricity, gas, and heat supply	20506251
Commerce	32587127
Finance and insurance	17327829
Estate	11884118
Transport and postal services	34909649
Information and communications	28703703
Public administration	1157289
Services	78757323
Activities not elsewhere classified	4728298
Total of intermediate sectors	469579674
Total of gross value added sectors	548238714

Readers will be surprised to know how small the income creation capability the financial industry is, despite the extraordinary financial wealth creation. Therefore, in summary, we are forced to recognize the dichotomy of economy between the real economy and the financial economy. Both linkages are really thin.

1.2.4 The Landscape of Exchange Systems

Now we inspect how the market exchange will be constructed. The classical image of market exchange breaks down by reflecting both the rapid change of the market organization and the communication system. For the market organization, as shown by Mirowski (2007), a market is repeatedly either spun off or complemented from the underlying market, forming a highly complicated layered system in the evolution of market. On the other hand, as a rapid change of the communication system locally and globally, a series of new exchange mechanisms has appeared. These may be an essential concept for understanding the modern market system and the contemporary societal system. Incidentally, non-symbolic methods may reflect fast thinking, while symbolic methods may reflect slow thinking, as Kahneman (2011) pointed out.

> Among financial technologies, HFT is a striking factor. The operation speed is on the order of microseconds, preventing much working from being performed by human intelligence. In fact, the average processing speed of Bitcoin is about 10 min, leading us to excessively depend on computing ability such as "proof of work." ….. [On the other hand, the] horizontal axis shows the type of processing, from less symbolic to more symbolic. Symbolic processing implies the so-called programming based one. Through the recent rapid progress of pattern recognitions due to machine and deep learning, non-symbolic

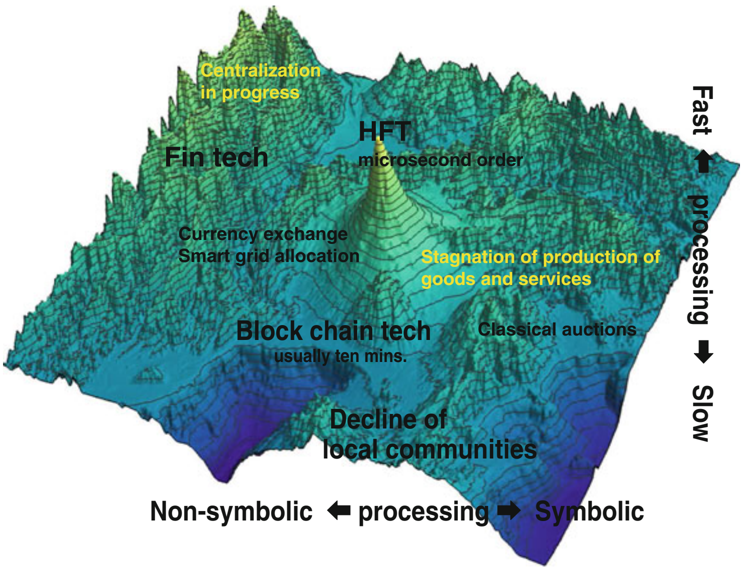

Fig. 1.3 The landscape of exchange systems. Source: cited from Fig.1 of Aruka et al. (2020a)

> processing will begin a new stage of AI work to replace previous human works (Aruka et al. 2020a, 380).

Through the recent rapid progress of pattern recognitions due to machine and deep learning, non-symbolic processing will begin a new stage of AI work to replace previous human works. Thus we can depict Fig. 1.3.

Thus, we depict the rough profile of AI usage of the modern society as Fig. 1.3. It should be noted that our society currently relies on AI in this way of multilayered ways.

1.2.4.1 The Hyper-Speed Domain: Relaxed Static Stability

This observation may call us "the relaxed static stability." Depending on the idea of "fail safe," structural stability has been important in designing planes and ships up to now. On the contrary, a modern stealth fighter like Lockheed F35 is designed by the idea of relaxing "static stability." It is well known that bicycles behave much more quickly than tricycles and attempt to restore its instability by resort to their countermotion. The countermotion will be controlled by computational powers. Thus, we expect that some nonlinear effect is implemented behind the financial flash crashes, always accompanying a countervailing power (Fig. 1.4).[8]

[8] See Arthur (2009, 73).

Fig. 1.4 Lockheed Martin F-35 lightning II. Source: cited from Wikipedia. https://en.wikipedia.org/wiki/Lockheed_Martin_F-35_Lightning_II

1.2.4.2 The Slow Speed Domain: Distributive System of P2P Exchange Network

In contrast with the hyper-speed domain, it matters "the slow speed" to employ blockchain technology. Here the word "slow" may be interpreted as "nonhyper-speed" or "non-microsecond." In view of a certain scaling, blockchain may be enough speedy excepting the mining speed of Bitcoin. In this sense, it is easy to identify the crypt-currency using blockchain technology with a slow speed technology. More interestingly, there currently exists a worldwide nodes network at the basis of **P2P transaction**. It is interesting to see a global bitcoin node distribution which is always accessed from the homepage https://bitnodes.earn.com/nodes/live-map/.

1.2.4.3 The Difference Between the Traditional Transaction and the P2P Transaction

Even HFT transaction requires an "auctioneer." Although the "auctioneer" is a computer server, even HFTs usually assume a centralized system of both double auction and batch auction on the restrictive administration of two rules: time priority and price priority. Thus, no trade holds without matching coordination or the continued announcement of the matching results. However, the size of information generated in the HFT transaction rapidly increases due to the faster speed of settlement.

1.2.4.4 P2P Transactions Also Generate a Rapid Growth of Information

P2P transaction on the basis of blockchain mining. As the number of transaction node increases, a geometrically rapid growth of transaction information is generated due to its network properties. A practical application of P2P transaction may be feasible just when the grand infrastructure for mining is arranged at any rate (Fig. 1.5).

1.2.5 Transductive/Symbolic Reasoning

It was noted in the earlier section that symbolic/non-symbolic coordinates will be a key coordinate to identify the parts of the socio-economic landscape. We will then examine this reasoning. Brownlee (2017) compactly illustrates transductive learning as follows:

Transduce To transduce means to convert something into another form, i.e., to convert (something, such as energy or a message) into another form essentially sense organs transduces physical energy into a nervous signal. *Merriam-Webster Dictionary* (online), 2017

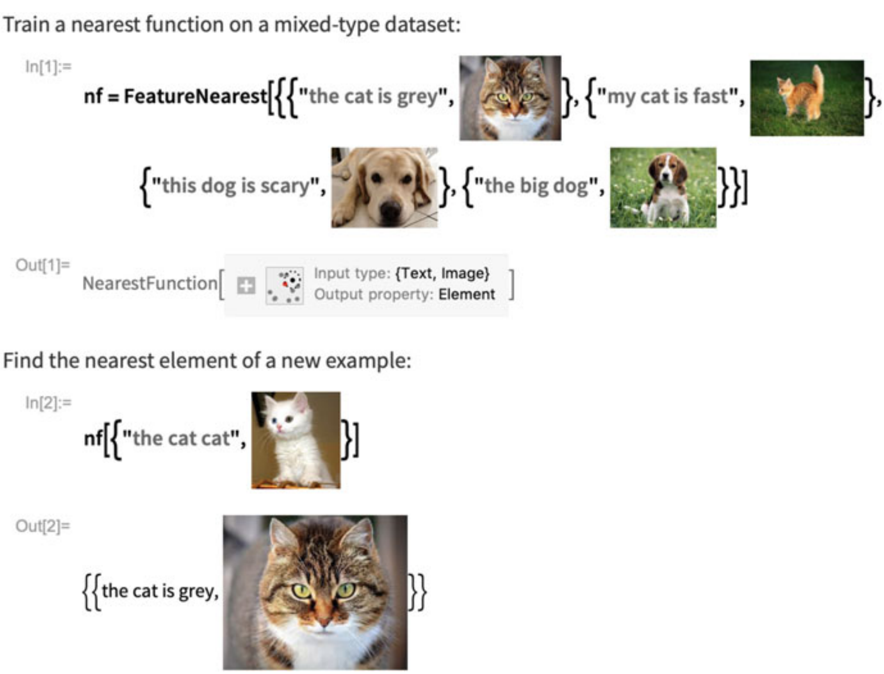

Fig. 1.5 A symbolic processing. Source: Made from mathematica

Transducer in engineering It is a popular term from the field of electronics and signal processing, where a transducer is a general name for components or modules converting sounds to energy or vice versa. *Digital Signal Processing Demystified* Broesch (1997).[9]

Transduction in biology The action or process of transducing; especially : the transfer of genetic material from one microorganism to another by a viral agent (such as a bacteriophage) . *Merriam-Webster Dictionary* (online), 2017

1.2.5.1 Transductive Learning

It is an interesting framing of supervised learning where the classical problem of "approximating a mapping function from data and using it to make a prediction" is seen as more difficult than is required. Instead, specific predictions are made directly from the real samples from the domain. No function approximation is required.

> The model of estimating the value of a function at a given point of interest describes a new concept of inference: moving from the particular to the particular. We call this type of inference **transductive inference**. Note that this concept of inference appears when one would like to obtain the best result from a restricted amount of information (Vapnik 1998, 169)

1.2.5.2 Example of *k*-NN Classification

The test sample (green dot) should be classified either to blue squares or to red triangles. If $k = 3$ (solid line circle) it is assigned to the red triangles because there are 2 triangles and only 1 square inside the inner circle. If $k = 5$ (dashed line circle) it is assigned to the blue squares (3 squares vs. 2 triangles inside the outer circle). Cited from Wikipedia https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm. The right figure of Fig. 1.6 is an extended version of the left figure. The center point should be estimated whether blue or red.

1.2.6 Science and Ethics

Until now, prediction has inevitably been associated with the following problems, as Klaus Mainzer, professor emeritus at the Technical University of Munich and philosopher of science, has pointed out. In his book Mainzer (2007), Mainzer discusses the "prediction problem" in terms of the Joseph effect (persistence) and

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[9] All signal processing begins with an input transducer. The input transducer takes the input signal and converts it to an electrical signal. In signal processing applications, the transducer can take many forms. A common example of an input transducer is a microphone.

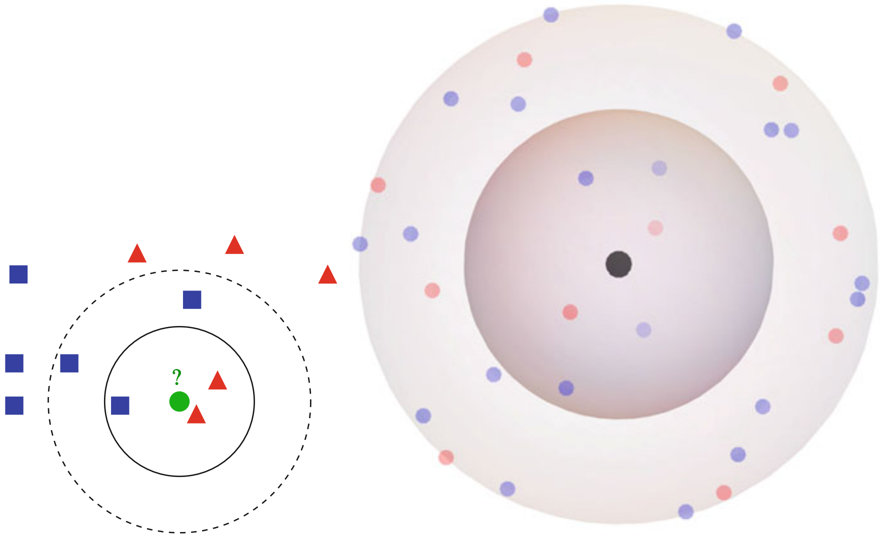

Fig. 1.6 K-nearest neighbors algorithm and its generalization. The right figure is a three dimensional extension of the left figure. The left figure is cited from Wikipedia article's figure https://en.wikipedia.org/wiki/K-nearest_neighbors_algorithm#/media/File:KnnClassification.svg

the Noah effect (discontinuity). According to Mainzer (2007), we discussed science and ethics.[10]

> We have a particular type of self-fulfilling prophecy like the Oedipus effect. According to this effect interpreted by Robert K. Merton, a true prophetic statement—a prophecy declared as truth when it is not—may sufficiently influence people, either through fear or logical confusion, so that their reactions ultimately fulfill the false prophecy. This implies that the collective macrostate of social various orders (order parameter) can be averaged over its parts. We apply this self-fulfilling rhetoric to our rational expectation hypothesis. This hypothesis might be self-fulfilling either through fear or logical confusion, of course. But this prophecy must be faced with some logical failure. It could be verified in the framework of complex dynamics that this hypothesis only referred to a unilateral direction of the whole dynamics in which direction a single rational individual had to contribute to the rational macrostate of economy. Moreover, we need the other aspect of the full feedback: "Its order parameters strongly influence the individuals of the society by orientating (enslaving) their activities and by activating or deactivating their attitudes and capabilities" (Mainzer 2007, p. 395). This is just the slaving principle as a whole elucidated as synergetics by Haken (1977) and Weidlich (2000, 2007). These dynamics are thus encompassed by critical values, outside of which the system falls into an unstable situation. So to be fulfilled, the prophecy might be circumvented.

Consideration in this dimension will contain some ethics by judging whether the effect of Joseph(persistence) or Noah(discontinuity) should be placed.

[10] This part summarizes Aruka (2009, 311).

However, what we are now convinced of is that the advent of the quantum computer age will fundamentally change the system of information communication, including monetary exchange. At that time, the traditional analysis of induction-deduction will be replaced by an analysis based on transduction (machine-learning inference), which will make it possible to make predictions that traditional analysis has missed, and this will make traditional predictions themselves obsolete. MIT is already working intensively on new predictions (time machines?) based on this understanding. However, the basis of the Great Reset will still be a revolution in computing power and the associated revolution in communication.

To be sure, we are faced with this kind of prediction difficulties. In a near future, however, a new science should get over them in the era of galactic space development by humans, if extraterrenial factors were taken into account. Thus we will explore the networks structure of the time series, i.e., something causal.

Although we attempt to grip only a slight indication, in the following, we will cast a new light on the time series prediction in view of visibility graph. This will suggest a new inferential procedure as a means to obtain something causal to connect the time series with a network structure.[11]

1.3 The Time Series in View of Horizontal Visibility Graph

1.3.1 The Visibility Graph

Firstly we define **the visibility graph**.

> By definition, in **the visibility graph**, each node indicates a sample that is connected to another node if visibility between the two exists.

The operation to connect the segments is then explained in the following manner.

– According to **the rule of visibility graph** in between the highest node and the second highest node, we can connect each other of the values. In other words, two vertices(nodes) are connected by an edge if the corresponding events in the time series are larger than all the events between them.
– Thus a time series will be transformed into a visibility graph as follows. The bars represent the values of the time series. Suppose the initial node is the starting node. Choose the values consecutively until a higher value than the initial value is found. Then, specify the higher value as the end node.

[11] We already learned that something causal will sometimes cause chaotic behaviors if a nonlinear relationship is given. However, something causal must be necessarily condition for an exact prediction.

– Otherwise, no lower value than the initial value, the next value after the first will be chosen as the end node. Replace the end node with the initial one and repeat the same procedure. The batch of the procedure will be regarded as a cycle.
– Due to Kaurov (2013) in Wolfram demonstration project, we focus on the starting node of each batch to connect them to form **a graph-theoretic shortest path algorithm**.

A *horizontal* time evolution is thus constructed in view of visibility graph as follows:[12]

1.3.1.1 The Shortest Path

This study develops both of the time evolution of CA and the network formation in view of HVG. According to Kaurov (2013), we call this development **an evolution of a finite elementary cellular automaton (ECA)**. This can be done in a few different ways. We can consider every step of an ECA evolution to be a binary number and calculate its decimal form by counting digits from **left** to right or in reverse. **The shortest path** consists of each starting node of each cycle in view of network formation. We may then measure a difference between each event and each node of the shortest path with realized matching. In his smart demonstration, Kaurov has shown **a graph-theoretic shortest path algorithm** by connecting the starting nodes of each cycle in view the HVG. This path is depicted in *yellow* colors on his HVG network (Fig. 1.7).

1.3.1.2 Fully Random, Rule-Based Iterated Cellular Automata (FRICA)

In our recent studies like Aruka et al. (2019, 2020b), we focus on the horizontal evolution of our time series generated by the **FRICA**. Rule 110 proves itself to reproduce such structures. Much more interestingly, Wolfram's research group has also discovered these from the behaviors of Fully Random, Rule-based Iterated Cellular Automata (**FRICA**) with multiple rules. FRICA is employed to access *how damaging* the inclusion of a given rule is to the universal behavior of rule 110, for instance. Thus, we can then detect some critical conditions that may make a certain local structure collapse by changing a selection of the rules. This new observation may bring us a new perspective, at least, a useful hint, on how to measure the market performances.

We apply the ideas of shortest path algorithms to the FRICA to get Fig. 1.8.

[12] More details are discussed in Wolfram Community titled Kaurov's "Visibility Graphs: Dualism of Time Series and Networks"https://community.wolfram.com/groups/-/m/t/33771.

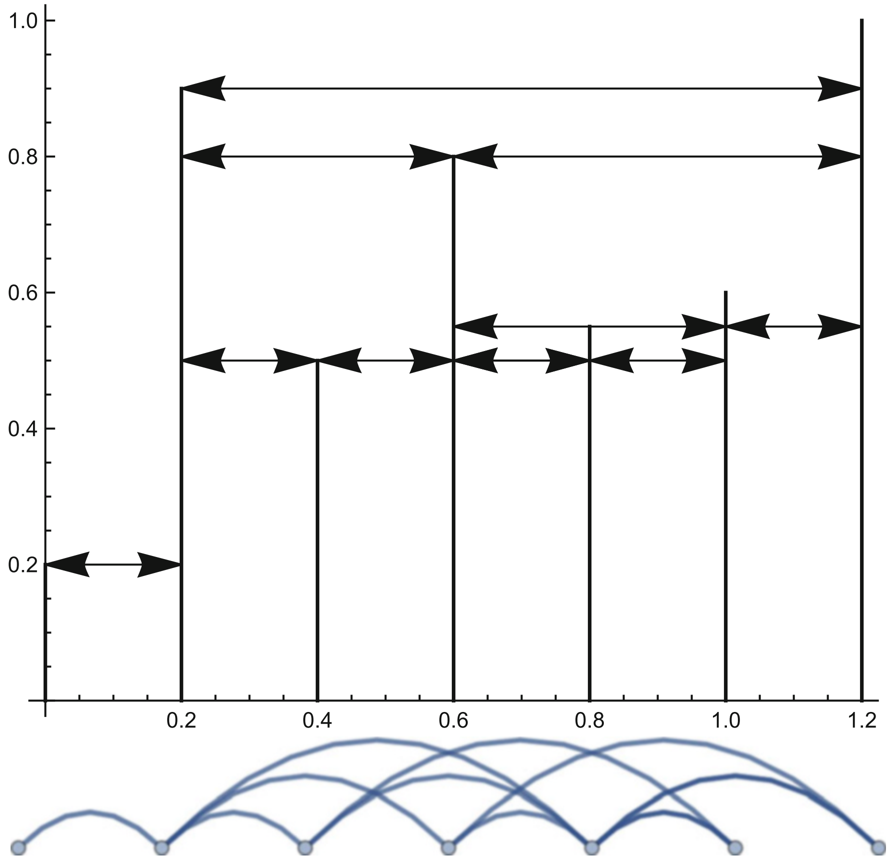

Fig. 1.7 A simple illustration of HVG and its network. Source: These diagrams were depicted by referring to ABC Lacasa et al. (2008). By definition, in **the visibility graph**, each node indicates a sample that is connected to another node if visibility between the two exists.

1.3.2 Exponential Distributions Reflecting Events Recurring "at Random in Time"

Next, we look on some application of the horizontal visibility graph. Lacasa et al. (2008) have given the exponential distribution derived from the HVG. They then dealt with the cases where "*the algorithm captures the random nature of the series, and the particular shape of the degree distribution of the visibility graph is related*

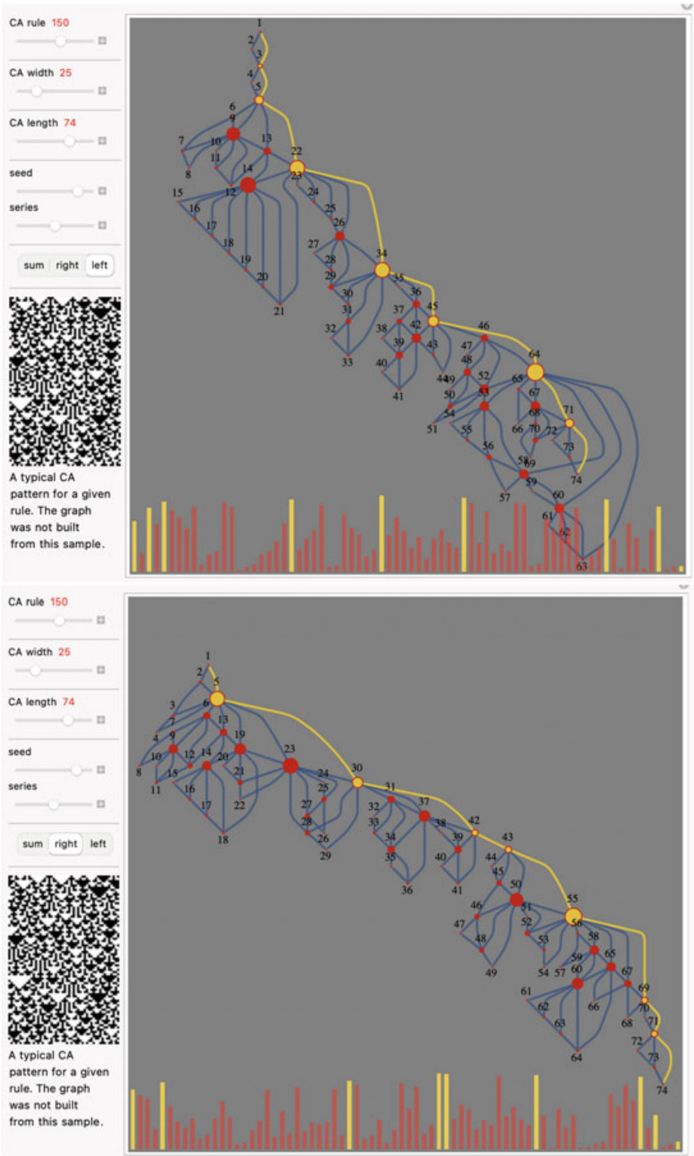

Fig. 1.8 The HVG and its graph-theoretic shortest path algorithm in the left/right sided case of the FRICA (rules 150, 25 and 74). These figures are simulated by the use of Kaurov (2013)

to the particular random process."[13] It is thus seen that exponential distributions have a close link to events recurring "at random in time."

[13] In their Fig. 3 of Lacasa et al. (2008), the "first 250 values of $R(t)$, where R is a random series of 106 data values extracted from $U[0, 1]$." On the other hand, the "degree distribution $P(k)$ of

It is then interesting to know the logical links of other distributions. **Mathematica** briefly gives a good illustration of the history of exponential distribution.

> Historically, the exponential distribution has been used most widely to describe events recurring "at random in time," i.e., in circumstances in which the future lifetime of an individual has the same distribution regardless of its present state. The use of the exponential distribution has increased significantly over the last 75 years, due in part to considerable research within the field of order statistics beginning in the early to mid-1950s. Since then, the exponential distribution has been used to model various phenomena over intervals of approximately constant rate, e.g., the number of phone calls placed in a specific time interval each day. In stochastic processes, the exponential distribution describes the lengths of interarrival times in homogeneous Poisson processes. The exponential distribution is also used in credit risk modeling, queueing theory, reliability theory, physics, and hydrology.[14]

Mathematica also gives the logical links between exponential distribution and other distributions. This figure must be helpful to know the internal relationships between them. Usually in econophysics, we like to see a particular link between power law distribution and exponential distribution. But it is also important to observe the other distributions through the exponential distribution.

We refer to the relationships between the exponential distribution and the other well-known distributions in our field.[15]

Power Distribution Power distribution is a transformation of an exponential distribution; exponential distribution can be obtained from power distribution,

Pareto Distribution Pareto distribution is a transformation of exponential distribution; transformation of a Pareto distribution yields an exponential distribution.

LogisticDistribution Logistic distribution is a transformation from exponential distribution; logistic distribution is a transformation from exponential distribution.

Poisson The parametric mixture of Poisson distribution and exponential distribution follows geometric distribution.

1.3.3 Contriving a Simple Market to be Manipulated

Now we narrow down the manipulation in the market exchange. When we employ a virtual market simulator like U-Mart, it will be an easy work whether the market could be manipulated. We commonly implement a so-called technical analytical agent in the U-Mart. In recent years, we have already discovered a special agent set, i.e., **Nakajima-Mori agent configuration**, to always realize any given real price movement.

1.3.3.1 The Minimal Nakajima-Mori Agent Set in the U-Mart Futures Price Formation

In the U-Mart experiment, the default standard set of strategies is fixed in the way of Table 1.2. As the bodies of each strategy are simultaneously increased, the possibility to match current orders to settle them may be much bigger. It is

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the visibility graph associated with $R(t)$ (plotted in semilog). Although the beginning of the curve

Table 1.2 The default composition

Agent strategy	No. agents
TrendStragey	2
AntiTrendStragey	2
Random	3
*S*Random	3
SRsiStrategy	2
RsiStrategy	2
MovingAverageStrategy	2
*S*MovingAverageStrategy	2
SFSpreadStrategy	2
DayTradeStrategy	2
MarketRandomStrategy	2

noted that the representative strategies of traditional technical analytical agents are employed.[16]

On the other hand, the minimal Nakajima-Mori agent set is driven by many simulations of the U-Mart acceleration experiment in the following way.[17]

1.3.4 Characterizing the Even Matching in the Market Transaction

In the narrative of double auction, as the transaction continues much longer, the market may sometimes fall into a state of steadiness as a result of even matching forces from both directions of rising and declining. This state of the market is called "even matching."

As the rising rate declines after the consensus breaks down, we will then catch up again with a sell-off opportunity. The figure illustrates this matching process in the case of rising trend. The right edge of the triangle is the point where the market can move either up or down. Thus, a triangle will be formed just before a breaking out of the price series. The red circle of the figure indicates a breakout point to buy when the price will rapidly increase. The breakout point will also break down if the

approaches the result of a Poisson process, and *the tail is clearly exponential*. This behavior is due to data with large values (rare events), which are the hubs."

[14] This part is cited from Mathematica index. https://reference.wolfram.com/language/ref/ExponentialDistribution.html.

[15] The detailed relationships of not only the mentioned distribution but also the other distributions are found in Mathematica's reference https://reference.wolfram.com/language/ref/ExponentialDistribution.html.

[16] See the details of the strategies employed in the U-Mart system for Chap. 11 written by Professor Nakajima.

[17] See the details for Aruka et al. (2019, 2020b).

Table 1.3 The minimal composition

Agent strategy	mini bodies
Random	1
AntiTrend	1
DayTrade	1
MovingAverage	3
Rsi	1
Trend	2
SRandom	6
SFSpread	5
SMovingAverage	4
SRsi	3

price no longer rises. This, then, means the end of an even matching process (Table 1.3).

1.3.4.1 Triangle Formation in the Market Transaction

Interestingly, in view of visibility graph, the initial point of the triangle formation may be regarded as the start of a segment to be connected as **the shortest path**. Thus **the breakdown point** also means the end of the same segment of the shortest path. The triangle of the figure just corresponds to a segment of the shortest path of the price time series.[18]

1.3.4.2 A Breaking Point on the Shortest Path

In other words, the shortest path of our price time series will be interpreted with a whole path connecting each new segment after each, each time the consensus breaks down and the price is wandering about.

At the state where the triangle is kept shaped longer, there may be accumulated orders that were ordered earlier. These previous orders will contribute to the market price either much lower or above a newly assigned order. As a result, the market price will be **pegged** down to a bottom or a ceiling. The event will often occur in **the narrative of double auction** (Fig. 1.9).

The mentioned event will be reproduced as a jumped futures price if we employ the price time series generated by the Nikkei225 spot time prices daily based (Fig. 1.10).[19]

[18] Dr. Yoshihiro Nakajima, my collaborator, contributed to this interpretation. The author is thankful for his wise advice.

[19] The Nikkei225 data partly employed to a part of the period from 1965 to 2021 fitted to the experimental tool period range.

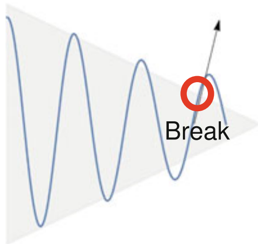

Fig. 1.9 Triangle formation in the case of an ascending price trend

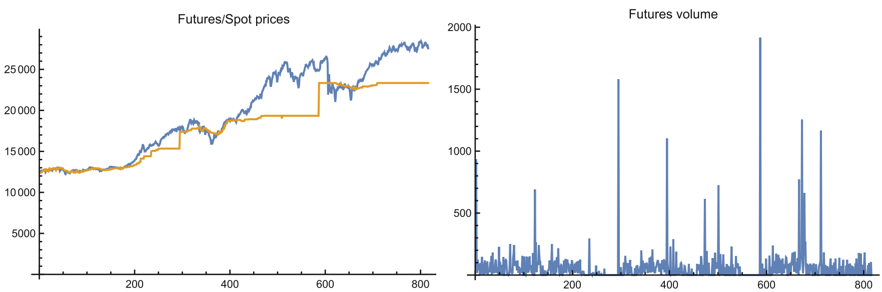

Fig. 1.10 Nikkei225 spot prices case

1.3.4.3 The Shortest Path of Nikkei225

Finally, we depict the shortest path of this case and its network structure. The latter shows the set of strategies playing the key role in settling down the futures market exchange on the shortest path (Figs. 1.11 and 1.12).

1.4 The Construction of This Book Project

In the conclusion of this chapter, we briefly look the construction of this book project titled: *Digital designs for money, market, and social dilemmas*

In advance, we planned three unique selling points (USPs) of your book.

- Understand how the new society will be designed by focusing on the evolution of money and thinking complexities in the AI era.
- Learn how the settlement mechanisms of futures market as one of the core engines of market capitalism can work in AI market experiments.
- Study what kind of computational social analyses we need to simulate social dilemmas, cryptographics, and supply chain.

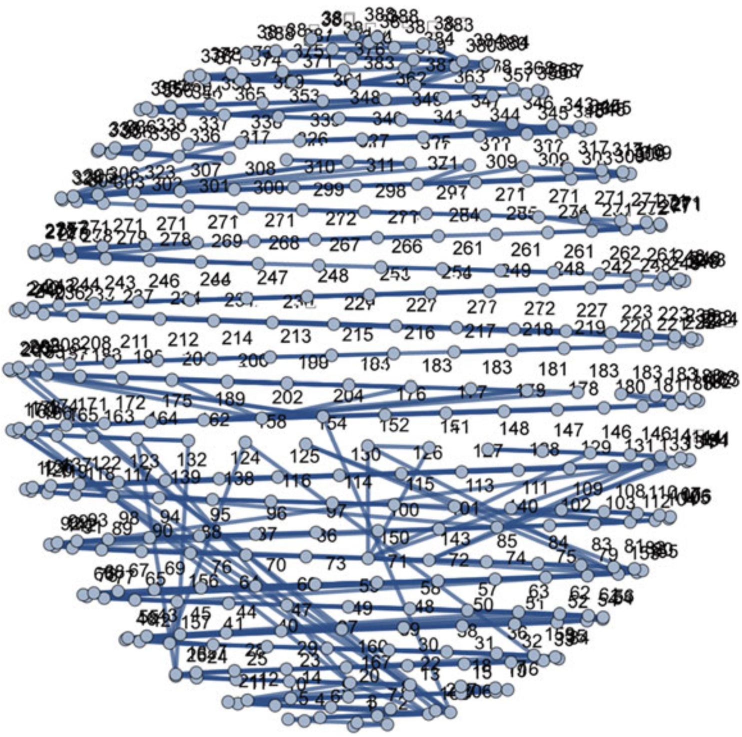

Fig. 1.11 The shortest path derived from the Nikkei225 spot time series

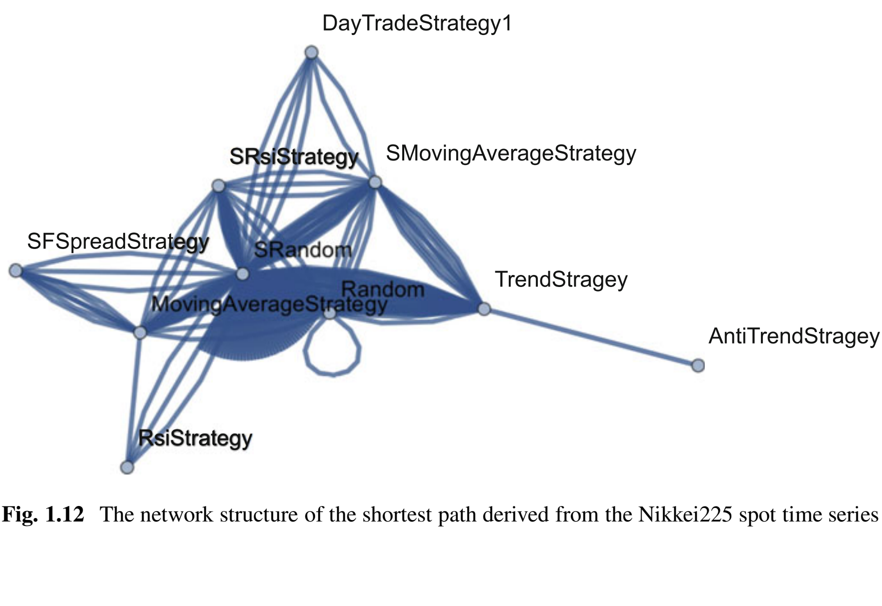

Fig. 1.12 The network structure of the shortest path derived from the Nikkei225 spot time series

1.4.1 *The Composition of Chapters Briefly Looked*

1.4.1.1 The Evolution of Money and Thinking Complexities in the AI Era

At the beginning of this chapter, we noted that traditional economics kept the principles of the barter economy. It does not matter whether money is considered good and bad. It is merely regarded as neutral. Neither do the negative aspects of banking in money creation matter. Therefore, we are forced to observe the qualities of the kinds of money in the face of the large technology innovation, such as high frequency transactions and blockchain.[20]

In the Part 1 of this book project, we address **the evolution of money and thinking complexities in the AI era**. Prof. Makoto Nishibe,[21] the author of Chapter 2, is the organizer of "Senshu University Digital-Community Currency Consortium Laboratory" (abbreviated into "Good Money Lab" (goodmoneylab.org/) to manage an industry-academia-government-private consortium. In this movement, he aims to make the natural environment and the economy and society more harmonized and sustainable. Mr. Yoshikazu Takasaki, who is a member of Good Money Lab, the author of Chapter 3, is the chairman of the board of **Doreming**, "a company based in Fukuoka City, Japan has developed a smart-phone payroll system that allows direct payment at nearby stores for take-home pay after deducting taxes and social insurance using attendance management information" (Cited from Chapter 2). Chapter 3 placed as the appendix part of Chapter 2 just as the "About us" of Doreming. The readers will know for what purpose and how the corporation is working in details. In our book project, first, it is believed that the most important matters in economics must be the evolution of money and thinking complexities in the AI era. Thus this matter constructs the first part of this book project.

1.4.1.2 The Detailed Composition of Chapters

We have collected 19 papers which includes a practical report. The composition of chapters is classified into 6 parts as a whole.

Part 1 Evolution of money and thinking complexities in the AI era
Part 2 Goods market and the future of labor market

[20] Money creation and banking, in particular, after going off the gold standard, is accompanied with grave problems, as Frederick Soddy, Nobel laureate in chemistry in 1921. He was very interested in economics. He is called the pioneer of ecological economics. He described the following metaphor of banking: "Whether or not the old lady who overdrew her account and sent the banker a cheque for the amount is an invention, there is not the slightest doubt about this being the normal, natural, and regular method of the Old Lady of Threadneedle Street." (Soddy 1934, 91–92).

[21] He was formerly the president of the Japan Association for Evolutionary Economics http://jafee.org. He is also distinguished as evolutionary monetary economist domestically as well as internationally.

Part 3 Computational social approaches to social dilemmas, smart city, cryptographics
Part 4 Artificial market experiments
Part 5 The randomness and high frequencies in financial data
Part 6 Other trading strategy issues and the effects of AI usage

For convenience of the readers, we mention all the contents of the chapters as a table.

We already summarized the first part. In the following, we introduce the other parts and their associated chapters following the first part.

In the second part, we prepare the two chapters on **goods market and the future of labor market**. Chapter 4 is titled: Model structure of agent-based artificial economic system responsible for or reproducing fundamental economic behavior of goods market. The author of this chapter is Professor Shigeaki Ogibayashi, who has expertise to social computer science, in particular, agent-based modeling of the macro economy and the other social dilemmas. As he wrote at the beginning of his chapter, he believes that agent-based modeling can elucidate the causal mechanism of social phenomena by his bottom-up method to detect minimal indispensable factors. His insights were developed from his practical engineering experience at the largest steel company in Japan. Chapter 4 provides us with a pocket-sized simulation of heterogenous interactive agents of the domestic economy. Chapter 5 prepares for the labor market. Chapter 5 prepares the new look on the labor market undergoing rapid change due to the implementation of AI and ICT. Here, Professor Junko Furukawa provided us a set of careful observations on the effects of AI and ICT into labor market. The advent of Siemens' universal machine was introduced in Chap. 1. The historical stream of automation is irreversible by the strong trend to save labor on capital side. Chapter 5 will supplement the observations of macroeconomic modeling.

In the third part, we will deal with **the computational social approaches to social dilemmas, smart city, cryptographics**. Needless to say, as the book title suggests, these matters are the main subject. The author of Chap. 6 is Professor Jun Tanimoto, who has expertise to sociophysics around the social dilemmas, gives us an excellent presentation of the "Mathematical framework to quantify social dilemmas." He has many contributions of internationally famous journals in his field. His academic coverage ranges between human, environmental, and social systems to declare them successfully explicit on the simulation space. Chapter 7 is titled: "Agent-based simulation for service and social systems and large-scale social simulation framework." The author of this chapter is Dr. Hideyuki Mizuta, IBM computer scientist, who works, in particular, with large-scale simulation. He is not only familiar with the so-called super computers but is also trained by the IBM tradition of service science. These backgrounds will provide us with a good insight into the subject. Quite interestingly, XASDI is compactly illustrated. According to him, XASD is a large-scale agent-based social simulation framework with enormous number (millions) of agents to represent citizens in cities or countries. By this tool, we must not forget a large-scale effect in social simulation. Chapter 8 is

	Digital designs for money, market, and social dilemmas	Yuji Aruka (ed.)
Chapter 1	A step forward to the future society	Yuji Aruka
Part 1	Evolution of money and thinking complexities in the AI era	
Chapter 2	'Good Money Drives Out Bad' among Diversifying e-moneys: Cryptocurrency, Stablecoin, and Digital-Community Currency	Makoto Nishibe
Chapter 3	[A practical case study] About us of Doreming	Yoshikazu Takasaki
Part 2	Goods market and the future of labor market	
Chapter 4	Model structure of agent-based artificial economic system responsible for reproducing fundamental economic behavior of goods market	Shigeaki Ogibayashi
Chapter 5	AI and the future of the labor market: The advent of a new paradigm?	Junko Furukawa
Part 3	Computational social approaches to social dilemmas, smart city, cryptographics	
Chapter 6	Mathematical framework to quantify social dilemmas	Jun Tanimoto
Chapter 7	Agent-based simulation for service and social systems and large-scale social simulation framework	Hideyuki Mizuta
Chapter 8	Characterization of XRP crypto-asset transactions from networks scientific approach	Yuichi Ikeda
Part 4	Artificial market experiments	
Chapter 9	The emergence of markets and artificial market experiments	Kazuhisa Taniguchi
Chapter 10	Trading agents for artificial futures markets	Hajime Kita
Chapter 11	Default agent set for artificial futures market simulation	Yoshihiro Nakajima Naoki Mori
Chapter 12	Programmed trading agents and market microstructure in an artificial market	Takashi Yamada
Chapter 13	Artificial intelligence (AI) for financial markets: a good AI for designing better financial markets and a bad AI for manipulating market	Takanobu Mizuta
Part 5	The randomness and high frequencies in the financial data	
Chapter 14	Possible relationship of the randomness and the stock performance	Mieko Tanaka and Yumihiko Ikura
Chapter 15	Random matrix theory (RMT) application on financial data	Takuya Kaneko and Masato Hisakado
Chapter 16	How does the entropy function explain the distribution of high frequency data?	Hiroyuki Moriya
Part 6	Other trading strategy issues and the effects of AI usage	
Chapter 17	The Emergence of Periodic Properties of Ordering Strategies under Disruption in the Beer Game	Hiroshi Sato
Chapter 18	Network of investment-oriented social media	Masachika Sueki
Chapter 19	Student Learning in the age of AI	Yoshifumi Kono

titled: “Characterization of XRP crypto-asset transactions from networks scientific approach.” The author is Professor Yuichi Ikeda, who is an internationally active econophysicist. He is also an expert in network analysis. In this chapter, he dealt with XRP, a cryptocurrency, which is issued by Ripple Inc. Compared with the international remittance, the speed of remittance is faster than the traditional one.[22] Professor Ikeda analyzed the network science characteristics of XRP’s transaction network and discuss the relationship between network topology and XRP price. This will be a useful contribution in this field.[23]

In the fourth part, we address **the issues of artificial market experiments**. During over the last 20 years, the editor of this book project and his colleagues are committed to the U-Mart project.[24] Chapter 9 is titled: “The emergence of markets and artificial market experiments.” The author is Dr. Kazuhisa Taniguchi, who is evolutionary economist. He gives a philosophical consideration on the emergence of exchange and the market itself in the human history. He also refers to his educational experience around the U-Mart experiment. Chapter 10 is titled: “Trading agents for artificial futures markets.” The author is Professor Hajime Kita, who is a computer scientist familiar with both computational architectural design and social science. He designed the grand architecture of the U-Mart system and the hybrid experiment of machine and human agents. His smart idea in the U-Mart design has really given a long life to the U-Mart system, even in the era of HFT. Chapter 11 is titled: “Default agent set for artificial futures market simulation.” The author is Professor Yoshihiro Nakajima, who comes from economics and holds PhD in complexity science and previously joined a big security company when he was young. In this chapter, he carefully illustrated the standard agent strategy set of the U-Mart system and their performances. Chapter 12 is titled: “Programmed trading agents and market microstructure in an artificial market.” The author is Professor Takashi Yamada, who is an internationally unique scholar being committed to the fields of algorithmic programming and experimental game theory. In this book project, he dealt with the U-Mart experiment in view of programmed trading agents different from the U-Mart default technical agents. He also has given the empirical analysis of human agent experiment and driven the relations between the evolution of their trading strategy and the characteristics of order book. Chapter 13, the final chapter of this part, is titled: “Artificial intelligence (AI) for financial markets: a good AI for designing better financial markets and a bad AI for manipulating market.” The author is Dr. Takanobu Mizuta, who has expertise to agent-based simulation, in particular, on the

[22] In Sect. 1.2 of the present chapter, we noted that the high frequency transactions are too fast to compare with blockchain transactions in the landscape of socio-economic system.

[23] It is also noted that XRP is issued by a private corporation. Nevertheless, Bitcoins and Ethereum are exceptionally administrated by noncommercial entities, although the exchange of Bitcoins is often organized by private companies.

[24] The U-Mart system is an artificial intelligent futures transaction system with a long-run lifetime that was initiated by Japanese computer scientists in 1998 (See Aruka (2015), 111–112 and Shiozawa et al. 2008).

AI market design for finance.[25] As he is joining to a capital hedge fund, he has an acute interest in finding a paradoxical result that machine learning will rig the market. We already saw Professor Nishibe's stand point on money, that is, not good or bad. It always matters how to make the AI operate.

In the fifth part, we address **the randomness and high frequencies in the financial data**. Needless to say, the idea of randomness has dominated even social science since the astronomer and sociologist Lambert Adolf Jacob Quételet, who, in 1835, for the first time, challenged others to think of the "average person" as well as statistics.[26] It matters in the random matrix theory (RMT), due to the use of matrix, the eigenvalue distribution. Thus it is very important to judge randomness among the principal components of a system by the principal component analysis (PCA) if we construct any matrix system for empirical verification. In particular, it becomes important to measure the randomness of large-sized numerical data in order to make the analysis much more efficient. Chapter 14 is titled: "Possible relationship of the randomness and the stock performance." The author is Dr. Mieko Tanaka, who is also an internationally acting computer scientist and physicist originally trained in the USA. She is interested only in RMT and also in studying whether computers can generate pseudogenuine randomness. In this chapter, several interesting propositions are driven from RMT test by measuring performance of TOPIX data: first, "the higher randomness of minute wise profits of individual stock indicates the better performance compared to other stocks of lower randomness" during some different data and places, and second, "Sudden decrease of randomness predicts future decline of stock index." Chapter 15 is titled: "Random matrix theory (RMT) application on financial data." The author is Professor Takuya Kaneko, who is an internationally acting econophysicist. In this chapter, the authors employed a middle-scaled data of cryptocurrencies, foreign exchange rates, and financial commodities and applied RMT to them. It is interesting to find that cryptocurrencies have closer distribution to the theoretical shape of RMT. In this part, we also deal with the issue around "high frequency transactions." Chapter 16 is titled: "How does the entropy function explain the distribution of high frequency data?" The author is Mr. Hiroyuki Moriya, who is a professional currency trader. He has developed a thoughtful idea about the concept of entropy. Here, he is studying the financial data by another idea different from the last two chapters. He introduced the two elementary concepts of transaction data: the minimum price increment and the sum of squared price increments. In the theoretical context of the late professor Masanao Aoki, UCLA, thus, he empirically tested his assumption that the majority of economic agents trade with this minimum price increment and the related matters by the use of HFT data of Nikkei 225. Here it is noted that he also focused on the exponential decay of distribution.

[25] Here, he did not use the U-Mart system but his own designed system in the similar spirit of the U-Mart. It is noted that the futures market is dealt with in the U-Mart system.

[26] Mainzer (2007, 48).

In the Part 6, we address **other trading strategy issues and the effects of AI usage**. Chapter 17 is titled: “The Emergence of Periodic Properties of Ordering Strategies under Disruption in the Beer Game.” The author is Professor Hiroshi Sato, who is not only internationally acting computer scientist with socio-economic insight but also well known as the architect of the first version of the U-Mart system.[27] In this chapter, he adopted the beer game which many business schools prefer as the teaching material to learn the supply chain. He updated the original game in terms of genetic algorithm to replace humans with the evolving AI agents. In this game, factories and wholesalers are stock sensitive, and distributors and retailers are flow sensitive. Two kinds of change may occur. A disruption of the supply chain occurs somewhere, and other reactions occur, such as the extension of the length of the supply chain. He then confirms that the sensitivity of each sector tends to be the same. Chapter 18 is titled “Network of investment-oriented social media.” The author is Professor Masachika Sueki, who is financial economist and is an expert in network analysis on investors. He is specifically interested in selecting one of the investor strategies, i.e., how individual investors can reduce their disadvantage to collect information compared with institutional investors. It then matters how to utilize the Investment-oriented social media. In this chapter, he employs Minna-no-kabushiki, a Japanese investment-oriented social media platform, to analyze the links between investors and their link creations. According to his result, there does not seem to be detected the attractiveness of high-performance investors forming the subnetworks; in contrast, several subnetworks attract investors. Chapter 19 is titled: “Student Learning in the age of AI.” The author is Professor Yoshifumi Kono, who is evolutionary economist. In the U-Mart experiment mentioned above in this book project, the collaboration of human and machine agents is one of the main features of the experiment, and the analysis of its learning effects is also important. In Chap. 12, such an effect is analyzed in algorithmic programming. On the other hand, Chap. 19 is a different attempt to analyze the effect of AI usage by human in terms of a traditional cost-benefit framework. Interestingly, he focused on the behavior of cost saving thought to measure the leaning performance of his students under his original experimental design.

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[27] The present U-Mart version is ver. 4.

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Part I
Evolution of Money and Thinking Complexities in the AI Era

Chapter 2
"Good Money Drives Out Bad" Among Diversifying e-Moneys: Cryptocurrency, Stablecoin, and Digital Community Currency

Makoto Nishibe

Abstract The present chapter depicts the modern outlook of evolution of money in the twenty-first century as the ongoing process of diversifying such private e-moneys as cryptocurrency, stablecoin, and digital community currency and then gives an answer to the central question for understanding modern money under the myth of "one nation, one money," which is the enigma of what fiat central bank notes are. Differently from MMT, they are neither material money nor credit money, but purely informational "ideational money" or "symbolic money" regardless its present status as "debt" on the balance sheet of BOJ. Crucially, such real nature of modern money is shared by all the aforementioned private moneys. This chapter further explains, as Hayek clarified in his "Denationalization of Money," the conditions for evolutionary principle of choice in currency in terms of different "quality" with a non-fixed rate expressed as "good money drives out bad," contrary to famous Gresham's law only regarding different "quantity" only in a fixed rate expressed as "bad money drives out good."

Keywords Evolution · Diversity · Denationalization of money · Gresham's law · Bad money · Good money · Choice in money · Community currencies · Digital community currencies · Cryptocurrencies · MMT

2.1 Introduction

First, we will introduce the status quo of Japan's cashless society, which is lagging the rest of the world, and the challenges that lie ahead. Sweden is said to be a perfect model of a cashless economy since almost all payments are conducted without

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cash. In East Asia, China and South Korea are well known as advanced cashless economies, where electronic payment systems and digital coins are widely accepted.

In Japan, many QR code mobile payment systems managed by big private companies such as PayPay, Rakuten Pay, Line Pay, au Pay, merpay, and others have finally appeared since 2018. They are now in fierce competition for customers, in which Origami Pay, which had developed their business in advance, was acquired by merpay, latecomer. The current leading system is PayPay with most users, about 25 million as of February 2020. All systems are roughly the same in use: a buyer scans the QR code of a seller with the built-in camera of a smartphone, input the amount, and pay.[1]

Besides, there is a wide range of digital coins which are all based on the fixed exchange rate system of "1 coin = 1 yen," from national stablecoins that cover the entire domestic market, such as Mizuho Bank's J-coin pay and MUFG's Coin to community-based digital community currencies, such as Kintetsu Harukas Coin, Kintetsu Shimakaze Coin, Sarubobo Coin, Aqua Coin, and BayStars Coin. The movement to go cashless is thus spreading to the local level.

In our vision of the future of cashless economies, however, we cannot ignore digital community currency (DCC) and cryptocurrency that have evolved from grassroots tradition of money in the last decades although those are not regarded as e-money in cashless society campaign by the Japanese government at present. Such non-national private currencies as cryptocurrencies and community currencies have been rapidly growing and widely diversifying in the deindustrialized global capitalism since 1980s. Cryptocurrencies still keep on gaining their presence with high volatility and high growth rate regardless frequent formation and collapse of bubble.

The central question for understanding and envisioning modern money in the twenty-first century is the enigma of what fiat central bank notes that exist at the core of the modern myth "one nation, one money" are and what they are worth. To dispel the myth and solve the enigma, we should reconsider the real nature of modern legal tender as inconvertible central banknotes under the floating rate system operating since 1973. Although the Bank of Japan's balance sheet still shows outstanding banknotes as liabilities, fiat central banknotes are not material money, nor are they credit money with repayment obligations like convertibles. They are purely informational money, completely independent of physical use values and debt–credit relationships. In other words, they should be regarded as a third type of money called "ideational money" or "symbolic money." This characteristic is shared not only by modern national currencies but also by increasingly diverse private currencies, including cryptocurrencies and community currencies. If we rethink Bank of Japan notes as equity securities or utility tokens and conduct a thought experiment on what might happen if they are listed as net capital on the

[1] At most convenient stores and supermarkets in Japan, the seller scans the barcode of a smartphone of the buyer with the built-in scanner of cash registers for automatic settlement.

balance sheet, we can begin to see the possibilities of a future in which currencies are diversified.

How such new "currencies" survive through users' choice in money and what the criteria of such decision are crucial points to be considered. In such diversity of money where it is possible to seek the kinds of money to be desired, we must realize the true meaning of Hayek's principle of choice in currency in terms of "quality," which is "good money drives out bad," instead of the Gresham's law only regarding "quantity," which is "bad money drives out good." For the principle of "choice in currency" to function well, (1) different denominations for distinction of money in quality and (2) the non-fixed exchange rates are necessary. Since cryptocurrencies met these conditions, the principle of choice in money began to work. They satisfied the forementioned two conditions for users' choice in money to begin to work and simultaneously took the test for good money through users' search for it. However, cryptocurrencies failed to pass the criteria of "a stable value of money" that Hayek attached importance to for good money.

For cryptocurrencies and other digital money to become "good money," it is at least indispensable to have "a stable value of money" that enables for currency to be more accepted and smoothly circulating. Whether a community-based or local consumer market can be formed, and workers' salaries can be paid by it are also other important factors for good money. In this respect, DCC with the connotation of local area and community could be a strong candidate for good money. Two DCCs in Japan, Sarubobo coin, and Aqua coin are now challenging toward realization of good money. Finally, we will introduce Good Money Lab, an industry-academia-government-private consortium to foster DCCs as good money.

2.2 From Cashless Economies to Evolution and Diversity of Modern Money

2.2.1 Backward Cashless Economies in Japan

We are currently approaching the so-called cashless economies where electronic representations of money replace such traditional currency as coin or banknote, and the transfer of digital information facilitates instant transactions. The term "cashless" refers to the settlement of transactions without cash. Specifically, it refers to the use of bank account transfers, automatic payments, credit cards, debit cards, and electronic money to purchase goods and services and to pay for public transportation. The degree of use of cashless payments is higher in metropolitan areas and among younger people. Cashless payments are also more likely to be chosen for high-value payments.

In other countries, the use of cashless payments is already progressing along with the rapid growth in the use of smartphones. In Sweden, the most developed country, the cashless rate is a whopping 98%. This is because credit and debit cards can be used almost everywhere, including in small stores, and also because of the widespread use of Swish, a digital currency that uses smartphones.

In 2012, the National Bank of Sweden and six major banks jointly developed Swish, which is based on a payment authentication system called “Bank ID” that links a national ID to a bank account. As of the end of October 2017, there were 5.97 million Swish users, which is about 60% of the population. About 14 billion kronor (about 180 billion yen) is spent annually on Swish, of which about 90% is used for personal remittances, 7% is used in stores, and 4% is used for e-commerce. It seems to be used mainly as a means of money transfer between individuals. This may sound like an extreme science fiction story, but in Sweden, many young people are using microchips implanted in the skin of their hands.

In contrast, the cashless rate in Japan is still low, at 18% in 2015 and 20% in 2016. In Japan, the use of e-money has long been widespread in railroads, convenience stores, and supermarkets. However, Japan lags far behind neighboring South Korea (89%, 2015), China (60%, 2015), and the United Kingdom (50%, 2015) in the ratio of cashless transactions. In Korea, in response to the 1997 Asian currency crisis, the government launched an aggressive program to promote the use of credit cards. As a result, the credit card usage rate is 57%, which is extremely high compared to 16% in Japan.

In China, the smartphone payment system using QR codes (Quick Response matrix barcodes) developed by Denso, a Japanese Toyota-affiliated parts manufacturer, has been widely used, partly because of the deep-rooted distrust of the yuan. Alibaba’s Alipay, China’s version of Amazon, and Tencent’s WeChat Pay, China’s largest SNS company, are the two major systems, with 500 million and 1 billion users, respectively, but Alipay accounts for 70% of the total settlement value. Alipay is widely used by large stores and public services, small stores, street vendors, Mobike and ofo bicycle sharing, and Uber cab dispatch service.

In Kenya, Africa, there are still quite a few poor people who do not have bank accounts, so it has been difficult for migrants to send money to their families. However, since most of them had cell phones, Vodafone’s SMS-based small payment system, M-Pesa, was developed and spread.

2.2.2 Japanese Government’s Policy to Promote Cashless Payment and Rapidly Diversifying QR Code Mobile Payment Systems

The cashless society in Japan took off when the “Strategy for the Rebirth of Japan,” approved by the Cabinet in 2015, included the “spread of cashless payments” as a guideline for the Tokyo Olympics scheduled to be held in 2020. In the “Future Investment Strategy 2017—Reforms for Society 5.0” approved by the Cabinet on June 9, 2017, the government stated its policy of “aiming to double the ratio of cashless payments to around 40% over the next 10 years.” Furthermore, when the

Osaka Expo was decided to be held in the fall of 2018, the target of 40% was moved up to 2025.

Incidentally, the term "Society 5.0" refers to the fifth new society in human history that is expected to arrive in the future, following (1) hunting society, (2) agrarian society, (3) industrial society, and (4) information society. It can be called a value-creating society. In this new society, new values and services will be created one after another, and these values and services will bring affluence to the citizens who are the subjects of the society. In particular, innovations such as IoT, big data, artificial intelligence (AI), robotics, and the sharing economy are expected to trigger the fourth industrial revolution and solve various social issues by incorporating them into all industries and people's lives. ICT (Information and Communication Technology) has been utilizing the data already available on the Internet (virtual data), but the technologies of the Fourth Industrial Revolution will deal with the real data outside the Internet. The key to competitiveness will be to utilize real data in the fields of medical care, automated driving, factory equipment, agriculture, and construction, as well as to accumulate real data on the history of business transactions in the market, and to coordinate software and hardware, as well as software and the field. These are all "coordinating technologies" in which Japan has an advantage.

In 2018, Japan has made progress in creating an environment that is expected to contribute to the shift to cashless transactions, with the enactment of the revised Banking Act and the revised Installment Sales Act. The Ministry of Health, Labor and Welfare (MHLW) is working to allow salary payments in digital coins in fiscal 2020.

Various types of interpersonal remittances using smartphones and QR code payment systems have also emerged. In recent years, new mobile payment services have emerged in Japan, such as PayPay, Rakuten Pay, D-payment, and au Pay, which allow prepaid, debit, and credit card payments from bank accounts, Line Pay and Kyash, which allow members to divide and send money to each other, and PayPal, which allows international payments and remittances. For merchants, there are Square, AirPAY, and STORES Terminal (formerly Coiney), which provide terminals for credit card, IC card e-money, and QR code payments. In addition, J-Coin Pay from Mizuho Bank, one of the megabanks, and Yucho Pay from Japan Post Bank have been introduced, and the movement toward cashless transactions has been accelerating rapidly.

Mobile payments offer various advantages to both consumers and businesses/shops compared to existing payment methods. For consumers, the ability to make almost all payments with a single smartphone increases convenience by eliminating the need to carry cash, many credit cards, and loyalty cards and speeds up the settlement process. In addition, they will be able to enjoy economic benefits such as earning shopping points and coupon discounts.

On the other hand, for businesses and merchants, payment is simple, requiring only a printed QR code or a mobile terminal, eliminating the need for initial investment and rental costs for credit cards, debit cards, and electronic money readers. This will reduce the burden of fees compared to credit cards and save the cost and time of handling cash. In view of society as a whole, digital money can be an infrastructure that contributes to stimulating consumption, such as by increasing inbound tourists from China, Korea, Taiwan, and other countries. Digital money will also make it possible to capture the entire transaction history, thus eradicating the underground economy associated with crime and tax evasion and facilitating tax collection. It also paves the way for the analysis of consumer behavior through big data to be used for marketing and as macro data to be used for policy purposes to understand economic trends.

What are the reasons for the lack of progress in going cashless in Japan? It is often said that it is the security, the high level of trust in cash, and the development of POS. In a country like Japan, where the cash system is strong and bank accounts and credit cards are already institutionalized, people's transaction settlement practices are fixed and not easily changed. This makes it difficult for mobile payments to spread rapidly. Therefore, there is a need for measures to go cashless that will simultaneously change such 'outer institutions' as social laws and regulations as well as such "inner institutions" as people's practices and awareness. In the wake of the consumption tax hike, a 2% exemption for cashless transactions was temporarily implemented, but this alone is not enough to change people's practices.

In many countries around the world, person-to-person remittances and their application to mobile QR code payments are contributing to a cashless society, as we saw earlier with Swish in Sweden, m-pesa in Kenya, and Alipay and WeChat Pay in China. In contrast, in Japan, the cashless policy, which can be said to be under the jurisdiction of the Ministry of Economy, Trade and Industry (METI), is notable for its focus on the spread of traditional credit card payments. We need to break away from this stove-piped administration and implement cross-ministry measures to promote the spread of mobile remittance and payment systems, especially the unification and standardization of QR code payments, and the establishment of new payment infrastructure and governance institutions.

2.2.3 The Rise of Utilization Rate of Cashless Payment Under the Spread of New Coronavirus and the Deregulations for Mobile Payroll System

In the wake of the recent spread of the new coronavirus, there seems to be an increase in the use of cashless transactions, especially QR code and contactless smartphone payments. According to a survey conducted by MMD Research Institute on April 22, 2020, among 5530 men and women aged 18–69 years who use smartphones, the top payment methods were cash (88.4%), credit cards (68.7%), and QR code smartphone payments (40.3%), with consumer behavior trending downward in the last 3 months, according to the report. In addition, more than 20% of respondents said that the new coronavirus caused a change in their payment methods ("Slightly changed" 12.9%, "Changed" 7.3%). Among them, 73.6% of respondents answered that they have decreased their use of cash, followed by 28.5% of respondents who answered that they have increased their use of transportation e-money, while 78.9% of respondents answered that they have increased their use of QR code smartphone payment, followed by 65.3% of respondents who answered that they have increased their use of contactless smartphone payment (https://mmdlabo.jp/investigation/detail_1860.html).

So far, we have considered the spread of cashless only in terms of consumer payments. In contrast, we need to think about cashless from the income perspective of producers as well. First, if companies and stores go cashless and workers can receive their salaries in e-money (digital coins), they will be able to spend their money without having to withdraw cash from their bank accounts at ATMs. This should lead to rapid progress. However, the 70-year-old Labor Standards Law, which stipulates that all wages must be paid in cash, stands as a barrier to this.

In March 2018, at a meeting to discuss national strategic special zones, Tokyo Governor Yuriko Koike proposed allowing the use of a "payroll system" that enables foreign workers who cannot open bank accounts to receive their salaries without cash.

Yoshikazu Takasaki, chairman of the board of Doreming, a company based in Fukuoka City, Japan, has developed a smartphone payroll system that allows direct payment at nearby stores for take-home pay after deducting taxes and social insurance using attendance management information and has been operating it in Vietnam, where most workers do not have bank accounts. In June of the same year, Mr. Takasaki called for deregulation under the Labor Standards Law to allow this system to be used in Japan.

In response, the Ministry of Health, Labor and Welfare (MHLW) reviewed its regulations on wage payment and moved to allow payment by digital money. This will increase convenience for companies, workers, and consumers alike and reduce the cost of handling cash, if the cashless system is promoted, not only for payment of consumption but also for receiving wages. The smooth circulation of digital money among businesses and individuals could lead to the widespread use of private currencies that can circulate in multiple times.

In fact, Sarubobo Coin of Takayama and Hida Cities in Gifu Prefecture and Aqua Coin of Kisarazu City in Chiba Prefecture have already begun trials in which employees of the city, chamber of commerce and industry, and financial institutions receive part of their salaries and bonuses in these local coins. This seems to be the catalyst for the spread and smooth circulation of these DCCs.

2.2.4 Evolution and Diversity of Modern Private Moneys: Cryptocurrencies and Digital Community Currencies With/Without Public/Private Blockchains

In 2002, when the European Union (EU) launched the euro as the legal tender for a single regional currency of Europe and its expansion of circulation areas was initially observed, many people predicted that a single global currency would eventually emerge and then it could be used anywhere on the globe. However, the European debt crisis began in 2008, following the subprime crisis in the USA, with the collapse of Iceland's banking system, and it spread primarily to Portugal, Ireland, Italy, Greece, and Spain in 2009. When PIIGS, which is a derisive acronym of those countries as the weakest economies in the eurozone, triggered the sovereign debt crisis, and the financial crises in Greece and Cyprus worsened, there arose intense fears that the euro would eventually collapse. Furthermore, with Britain's decision of departure from the EU and the birth of the Trump administration in the USA, a shift to inward-looking policies, such as protecting domestic industries and curbing immigration, made clear the shift from socioeconomic globalization to nationalization and localization.

In 2009, when Bitcoin appeared in a tiny online community on the Internet, it was barely known to anyone. Only in the past several years, such cryptocurrencies as not only Bitcoin but altcoins including Litecoin, Ethereum, and derivative tokens have rapidly spread all over the world, expanded its scale, and increased its number. The innovation of new money became active worldwide. Thus, expectations for cryptocurrencies have soared. However, we have witnessed in the recent repetitive bubble bursts of cryptocurrencies that their exchange values were quite volatile to the extent that they can no longer be called "currency" or "money" for usual transactions. Cryptocurrencies seem to have become speculative financial instruments that fluctuate in value, which made difficult to use it as the means of exchange to trade goods and services. Since then, global monetary authorities finally began to use the term "crypto-assets" rather than "cryptocurrencies" to express such properties of them as "speculative" financial commodities.[2]

Since the 1980s, community currencies had already spread around the world. However, there were defects with community currencies, such as limited distribution areas and users and difficulty in sustaining operations.[3] To overcome such problems, the "Digital community currencies (DCCs)" have emerged in various forms in Japan and overseas. DCCs fuses superior digital technologies of cryptocurrencies such as blockchains, mining, and smartphones' QR code scanning with the dual value purposes in community currencies s such as "stimulation of a local economy"

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[2] See Nishibe (2016) for the full account on money in general and modern money including Bitcoin.

[3] For more details on the theoretical implication, the present states of community currencies, refer to Nishibe (2012, 2020, 2021).

and "revitalization of socio-cultural community." DCCs are various social or community-oriented digital coins for promoting local consumption and social investments in the same spirit of community currencies. They have already been implemented or are currently planned not only in Japan but also in the world. It can be seen as a new movement to create a currency that is useful for corporate activities and people's lives by stabilizing the value of money and limiting circulation to local and community areas.

In Japan, as we have just seen above, megabanks, regional banks, local credit unions, railway companies, and local governments have begun to experiment or conduct national, regional, and local "stable coins" pegged to the yen (1 coin = 1 yen) within specific circulation areas of customers or local community. In the cashless economy envisaged in the future, multiple currencies will coexist in multilayered circulation areas at different geographical levels, such as national, regional, and local.

Noteworthily, those coins on a large scale in terms of numbers of users and circulation areas on the national and regional level implement Distributive Ledger Technology (DLT) or blockchain developed for cryptocurrencies, but those coins on a small scale on local levels do not. Furthermore, the DLT adopted by those on the national and regional level is a private blockchain that is different from Bitcoin's public blockchain.

In the case of public blockchains, anyone has access to all transaction records without permission and can participate in their operations by becoming a node called "miner." The presumed developer of Bitcoin, Satoshi Nakamoto, ingeniously incorporated the idea of "Proof of Work" with appropriate design of economic incentives for a cluster of computers as "miners" who must contribute tremendous computational work for successfully completing "blocks" as pages of a ledger or record book by using a cryptographic Hash function to reach a consensus over time-stamped transactions. Openness, decentralization, and democracy are the unique characters of such public blockchains as in Bitcoin and altcoins.

Such properties of public blockchains enable cryptocurrencies to be self-managed by distributed networks of "miners" without any centralized authority and to become self-sustained independent money. These characteristics do not conform to conventional concepts of security and reliability of networks based on closed and centralized systems in financial institutions such as banks. This is why the digital coins on the national and regional levels managed by banks and private companies cannot adopt public blockchains. However, it might be possible for DCCs by nature to adopt DLT of public blockchains because the organization of DCCs should be open, decentralized, and democratic. Moreover, public blockchains must be quite useful for managing DCCs because they can make the system secure, reduce administrative works, and log all transactions so that the alleged defects of community currencies can be considerably overcome.

On the other hand, access to the database of private blockchains is only allowed for the users and nodes with permission by a manager. Then, they are closed, centralized, and dominated networks exclusively managed by a particular group of people or organizations. Consequently, to develop and maintain private blockchains is costly because they need to create their own inhouse network of servers without any cooperation from miners on the Internet. Such high costs must have prevented those coins on the local level from adopting private blockchains. The coins on the regional and local levels can be identified as DCCs since they form communities of participants and use the Internet, smartphones, and QR codes. They do not necessarily have to implement DLT, whether it is a public blockchain or a private blockchain. However, public blockchains seem to be compatible with and useful for existing community currencies as mentioned above.

In the twenty-first century, non-national currencies such as complementary community currencies, DCCs, and cryptocurrencies are expanding in terms of volumes and kinds. Thus, the widespread use of such non-statutory money other than those issued by national central banks has increased the diversity of currencies. These are the observable facts nobody can deny. Nevertheless, we are unconsciously accustomed to the idea that money is created and controlled solely by the state. However, the history of a monopolistic national currency is not so long as we think. It is just over 170 years since Bank Charter Act 1844 commonly known as Peel's Bank Act, which had made Bank of England legitimate as the UK's central bank. The idea has been powerful because it is tied up with the centrality implied in such fiscal and monetary policies executed by the state and the central bank. We must release ourselves from such stereotype to seek a new way of adequately understanding the diversity and evolution of modern monetary systems and find a new bottom-up approach for evolutionary theory and policy with a diversity of money, different from conventional top-down approaches found in micro theory without money as well as a macro policy with single money.[4]

Besides, we cannot merely be satisfied with describing such ongoing events of the plurality of money. We should be concerned with explaining how money diversifies and maintains itself; in other words, monetary systems dynamically change with its diversity kept. To the end, we need to consider how participants or users select from many alternatives of currencies so that some of them can only survive in the evolution of money. It is also necessary to focus on diverse monetary and social exchange systems, such as schemes that contribute to economic diversity, social cohesion, democratic participation, and environmental sustainability, as in community currencies and cryptocurrencies.[5]

[4] On plurality and diversity of money, see Gomez (2018), and on the diversity of community currencies, see Nishibe (2018).

[5] We have constructed the theoretical model of institutional ecosystems to explain and describe the evolutionary dynamics of currently observed diversified money (Hashimoto and Nishibe 2017). In the model, an institution such as money is a game constrained by given game rules, and a variety of institutions such as diversified money constitute a complex institutional ecosystem subject to a meta-rules composed by players' value consciousness as criteria to evaluate multi-games. Refer to the article if interested in such theoretical aspects of this topic.

2.3 Commonality Between Cryptocurrency and Fiat Legal Tender as Modern Money: Purely Informational "Ideational Money" or "Symbolic Money"

2.3.1 Violent Price Movements of Bitcoin and Altcoins

The prices of Bitcoin, the leading cryptocurrency, and other Altcoins seem to be unstoppable. In 2017, Bitcoin price has risen more than 20-fold in less than a year, which is rarely seen in such a large annual rate of increase, even in the most volatile marketable stocks.

In December 2017, Bitcoin hit its then-highest, ¥2.2 million (=$19 thousand), its market capitalization reached ¥34 trillion (=$296 billion). At the time, Toyota was Japan's largest stock company by market capitalization at ¥22.8 trillion, and NTT was the second largest at ¥12.2 trillion. In terms of market capitalization, Bitcoin was almost equivalent to the combined market capitalization of Toyota and NTT. People were amazed at the breakthrough, but it did not take long for the bubble to burst.

Since then, the price of Bitcoin has continued to decline, falling below ¥0.37 million (=$3.2 thousand) in December 2018, a drop to one-sixth in a year from its summit. Thus, the Bitcoin bubble burst with a bang, but its price has gradually recovered, and it finally surpassed its previous highest in December 2020, and it has recorded the highest again at ¥7.6 million (=$6.7 thousand) in October 2021, and the price stay around its highest level (Fig. 2.1). The price has risen less than fourfold in 2020 and it has so far twofold in 2021 (up until October).

Truly, the price volatility of Bitcoin is very high, but this is true not only for Bitcoin but for all cryptocurrencies. Many altcoins have shown greater volatility than Bitcoin: in 2017, the price of Ether, the then-second largest by market capitalization, reached 100 times its value, and that of Ripple, the then-fourth

Fig. 2.1 The formation and collapse of the Bitcoin bubble (Source: coinmarketcap.com)

largest, reached a whopping 200 times its value. And within 2018, of the 27 major cryptocurrencies (coins and tokens) with a market cap of more than $1 billion, 23 had fallen by 20% or more and 6 had crashed by 40% or more only in 24 h.

2.3.2 Amazing Growth in Bitcoin's Long-Term Value

Whether or not such violent rallies and crashes can be called "abnormal" depends on what you consider "normal." Certainly, compared to financial instruments such as stocks and bonds, the volatility is many times, in some cases dozens of times, higher. Stocks have income gains in the form of dividends and bonds have income in the form of interest, and in that sense, they are tied to the real economy. On the other hand, virtual currencies have no such income gains, so their theoretical fundamental value as an asset is zero.

From here, we cannot immediately conclude that the fact that the market price of Bitcoin is positive, even though there should be no real price for Bitcoin, means that the market price is all a bubble and should eventually disappear as an illusion. This is because the fundamental price of legal tender as an asset is also zero, because if you deposit the legal tender yen in a bank, you will earn interest, but if you just hold the cash as a wardrobe deposit, you will not earn anything. Legal tender, which has no real theoretical price, is trading at a respectable positive price in the foreign exchange market. In a somewhat roundabout way, we could even say that legal tender today is like "stocks" issued by the central bank of each country, received by the people, and circulated without interest or dividends. So, if we are talking about a bubble, it is not only about Bitcoin. It can even be said about legal tender.

Let's calm down a bit and take a longer-term look at the change in the value of Bitcoin, which was famously used by programmer Laszlo Hanyecz to pay 10,000 Bitcoins for two Papa John's pizzas on May 22, 2010. Since then, May 22 has been known as Bitcoin Pizza Day. At the time, one bitcoin was about $0.0041, so 10,000 bitcoins were about $41 as of August 7, 2020, one bitcoin is about $11,854, so 10,000 bitcoins are equivalent to $118.54 million. That's a staggering 2.89 million times in 10 years. This rate of increase is astounding, and it is as if something was created out of nothing. However, when compounded, the rate is 442.7% per year. In other words, if a price increase of 4.427 times in 1 year continues for 10 years, the price will increase 2.89 million times. As you can see, Bitcoin has risen and fallen many times, and the volatility is very high, but over the course of 10 years, it has not only continued to exist, but has increased its value against the legal tender dollar by 2.89 million times. Even those who believe in legal tender, but not Bitcoin, should be aware that this is a fact.

It is also true that Bitcoin, which continues to increase in value relative to legal tender, has become the driving force behind the growth of altcoins and tokens, which have expanded their base to thousands. In this sense, Bitcoin is the killer currency that gave birth to the digital coins.

2.3.3 *Facebook's Stablecoin Libra or Diem: Glocal Digital Community Currency Beyond National Borders*

In the last decade, private currencies such as community currencies and cryptocurrencies have come to coexist with legal tender as national currencies, and their presence is rapidly increasing.

In June 2019, Facebook, the world's largest social networking provider with 2.4 billion members, launched a plan of new digital coin called "Libra," a digital currency initiative backed by a basket of currencies consisting of a weighted average of several legal tender currencies. The currency basket was said to be the US dollar (50%), the euro (18%), the Japanese yen (14%), the British pound (11%), and the Singapore dollar (7%).

Libra was usually characterized as a blockchain-based cryptocurrency or staple coin that enables a simple, global payment system and financial infrastructure. However, another way of looking at it is to think of Libra as a massive glocal (global and local) digital community currency that will empower billions of members by unlocking their expertise, skills, and potential. Moreover, Facebook's community is larger than any single nation, its circulation area is not only beyond national borders and would be potentially the largest in the world. Besides, its value is expected to be more stable than other national currencies as it is pegged to a basket of national currencies.

In response to this somewhat shocking news, financial authorities, policy makers, and lawmakers in Europe and the United States expressed concern and opposition to the idea, saying that if Libra were to replace the reserve currency, the US dollar, it could destabilize the global financial order and lead to tax evasion and money laundering. As a result, the original plan was put on hold for a long time, but on December 1, it was reported that the Libra would be renamed "Diem," which means "day" in Latin, and may be launched as a unique stablecoin backed by the US dollar on a one-to-one basis. At this moment it is said Diem may be launched within 2021. Anyway, in order to properly determine what Libra or Diem is, we need to reconsider the nature of the legal tender as national currency that is now dominant in the world.

2.3.4 *Dematerialization of Money: "Dematerialization of Monetary Substance" and "Demonetization of Monetary Media"*

The digitalization of money and the shift to cashless transactions, which are currently underway, became possible only on the premise of the dematerialization of money, which was made possible by the emergence and spread of fiat money. This is because the value embodied in fiat money has been completely separated from the physical use value of the specie (gold coin or bullion) used to secure it.

By switching from traditional physical value representation media composed of materials such as ink, paper, and printing presses, which are used for printing fiat money, to other physical value representation media composed of hardware such as computers, smart phones, smart cards, as well as software such as operating systems and applications, in addition to infrastructure such as power plants, power lines, optical fibers, radio towers, and artificial satellites, we can replace all the analog information of money with digital information. This has enabled smoother, more efficient, remote, global, and automatic monetary transactions even without human intervention.

The current "dematerialization of money" means the dilution of things as substance that embody and represent value, rather than things as media that express and transmit value. In other words, the "dematerialization of money" means the "dematerialization of monetary substance" and not necessarily the "dematerialization of monetary media." In the ongoing digitalization of money and cashless society, out of the genuine money consisting of "cash" and "deposits," we are trying to reduce the tangible things expressing analog information called "cash" as much as possible by substituting the digital information of "value" of electronic money and digital coins (cashless society) and integrate as much genuine money as possible into intangible figures of digital information called "deposits."

In this case, we notice that there are important intangible industrial products such as electricity, electromagnetic waves, light, and sound as well as many tangible industrial products such as electric wires, optical fibers, computers, and smartphones, the latter of which we can only see and touch, and that those intangible and tangible industrial products for enabling digital monetary media have rather increased in volumes. In other words, we can see that the "dematerialization of monetary substance" has currently progressed, but the "dematerialization of monetary media" has not progressed much.

In the white paper by Satoshi Nakamoto, Bitcoin was intended to be a "P2P digital cash system" that would use blockchain (Distributed Ledger Technology) to completely digitize "cash" through distributed ledger and distributed issuance. The core idea has been forgotten, and Mr. Craig, who I assume to be considered as one of Satoshi Nakamoto, is trying to reinstate it. The idea of Central Bank Digital Currencies (CBDCs), which would allow the state and central bank to turn cash into digital cash while maintaining the traditional central bank centralized issuance, is being promoted mainly in China and is one step closer to reality. CBDCs can be either wholesale, which is used only for settlement among financial institutions and businesses without changing the existing coexistence of analog "central bank notes (cash)" and digital "current accounts (deposits)" in the existing central bank currency, or general-purpose, which changes the existing structure of cash and deposits by completely digitizing cash and is used by all entities, including citizens. In any case, if we can completely eliminate analog central bank notes, we will be able to settle funds more efficiently, but even in that case, we will need to answer the fundamental question of whether Bank of Japan notes as "cash" are certificates of obligation or something else.

2.3.5 A Tree Diagram of Money with Four Stages: Primitive Money, Material and Credit Money, Cash and Deposit Money, and Various Non-national Moneys

Central banknotes have a long history as the legal tender of the nation-state and have a solid institutional foundation, so their value may appear to be unassailable. However, if you think about it, it has only been about 270 years since Peel's Bank Act of 1844, which practically established the monopoly of the Bank of England, the first central bank in history to issue notes. In terms of human history, that is just a blink of an eye, and it is an event that could change at any time. We are not trying to say that the value of Bitcoin is much more stable or solid than legal tender. If we look at the evolution of money from a very long-term perspective of thousands of years, both legal tender with its 270 years of history, and Bitcoin with its only 10 years of history, are not that different in terms of the length of time they have been around. In addition, they both share the common characteristics of modern money.

The value of modern currencies, such as fiat legal tender, cryptocurrencies, and community currencies, is not supported by intrinsic value such as the use value of the physical goods that make up the currencies, nor by the credit (debt) guaranteed by the currencies, nor by expected future earnings such as interest and dividends. In other words, modern money is neither material money (commodity money) nor credit money, and it is not securities such as bonds and stocks that pay interests and dividends, either. Then, what exactly are these modern currencies?

According to the theory of the origin of material money, it emerges spontaneously as a means of exchange to mediate indirect exchange because direct exchange (barter) becomes more difficult as the number of goods increases. This leads to another assertion that thus emerging material money such as gold coin or bullion is the principal money, and credit money is derived as an IOU that proves the credit-debt relationship of material money. In contrast, the theory of the origin of credit money argues that the credit settlement system is the money because the ledger, which is a record of transactions written by numbers and letters, plays the role of money even if there is no physical object as in material money in the first place. In other words, credit money can be established on its own without the existence of real entity such as use value of material money if there was some acknowledged ledger form using written language. According to this view, money is not a thing as a means of exchange, but a transferable credit or debt. It is a transaction clearing system consisting of three basic elements: (1) a unit of value, (2) an accounting system, and (3) transferability.

Perhaps because cryptocurrencies like Bitcoin and Ethereum use a distributed ledger technology called Blockchain, the latter idea is growing in power. Thus, credit money is now becoming to be believed to be not necessarily a derived representation of material money nor emerged in capitalist economy but to have already existed in the ancient world. In medieval Europe, wooden-made split tally sticks were widely used, in which the creditor and debtor recorded their debt information, which was then split in two and kept by both parties as a certificate. Single tallies, in which debt information was recorded on animal bones, can be traced back to the Paleolithic period. This type of credit money was used not only by private merchants and artisans, but also between them and the official state. Thus, it has become increasingly clear that credit money has a history as long as that of material money.

As a result, the view that the essence of money is not material money but credit money, and that modern money is an IOU that circulates on the basis of credit relationships, has gradually gained strength. Randall Wray, one of the founders of Modern Monetary Theory (MMT), developed a theory of money whose origin is credit money. It combines nominalism, which holds that money is merely a unit of nominal value, and chartalism, which holds that money is created as a means of direct economic activity of the state, such as fiscal spending, with its compulsory right to collect taxes. In Wray's view, modern central banknotes do not represent real value as in the case of material money but are negotiable instruments of indebtedness (IOUs) that represent a unit of account and are issued on the basis of the state's ability to collect taxes. Whether this view of MMT is correct or not will be discussed later.

Here the problem is if it is appropriate to ask which expresses the essence of money, material money, or credit money, and which is the historically prior origin? For the question itself may be wrong. The reason why we think that the money that forms the market economy is *either* material money *or* credit money is because we unconsciously assume that money has developed on a straight path in history. This is probably because the modern money that we daily get used to under the current "one nation, one money" system is only one type of national currency. However, if the evolution of money branches into multi-track rather than just single-track, and if the ways of monetary exchange have been always diverse in history, it should not be possible to explain the actual history using only a single theory or position (Fig. 2.2).

The tree diagram depicts the evolution of money in four stages: (1) the emergence of primitive money as a medium for gift-giving and reciprocity in primitive communities; (2) the parallel development and growth of "material money" represented by gold, and "credit money" represented by IOUs (I Owe You), as media for equivalent exchange in the market economy since ancient times; and (3) the coexistence of two currencies, cash currency and deposit currency, with the core of central banknotes integrating material money and credit money in the period of establishment of capitalism; and (4) the ongoing diversification of private currencies, such as cryptocurrencies, corporate currencies, gift certificate/tokens, and community currencies.

The salient feature of such primitive money is that it was used to realize ritual and customary bilateral gift-giving and return within a certain community, or multilateral reciprocal relation as a chain of gift-giving among three or more parties. In addition, primitive money contained both economic and commercial purposes as well as social and cultural purposes, the latter often being more important. When money emerged from primitive money in the community used for reciprocity as

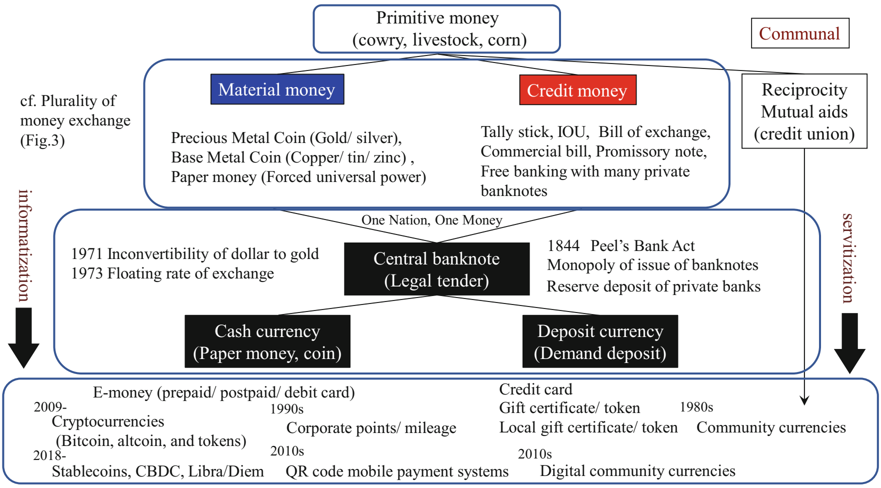

Fig. 2.2 A tree diagram of money (prepared by the author)

well as redistribution eventually to provide the principle of equivalent exchange in the market, it branched into two types of money, material money and credit money, and evolved in parallel while influencing each other. In the history of mankind, primitive money, which is internal money and special-purpose money for community reciprocity and redistribution, has been the forerunner, and material money and credit money, which are external money and all-purpose money for the development of market economies outside and among communities, have continued to expand in parallel (Polanyi 1957).

2.3.6 *Plurality of Monetary Exchanges in History and the Evolution of Money Through Self-Organization, Replication, Variation, and Selection*

From a global historical perspective, it is known that there were a variety of ways of monetary exchange, not a single way (Kuroda 2020). In Fig. 2.3, the horizontal axis indicates whether transactions are anonymous or nominal (named), and the vertical axis indicates whether they are interregional or local. According to these two axes, monetary exchange can be classified into four different areas. First, let us look at the first quadrant, which is anonymous and interregional. In the international marketplace, where traders who are strangers to each other engage in high-value transactions, they are paid in precious metals (gold and silver coins), which are material money. Next, in the second quadrant, which is both nominal and local, remote trade could be conducted using bills of exchange, which is a credit currency mediated by a trustworthy third party, because it is possible to trust a partner with

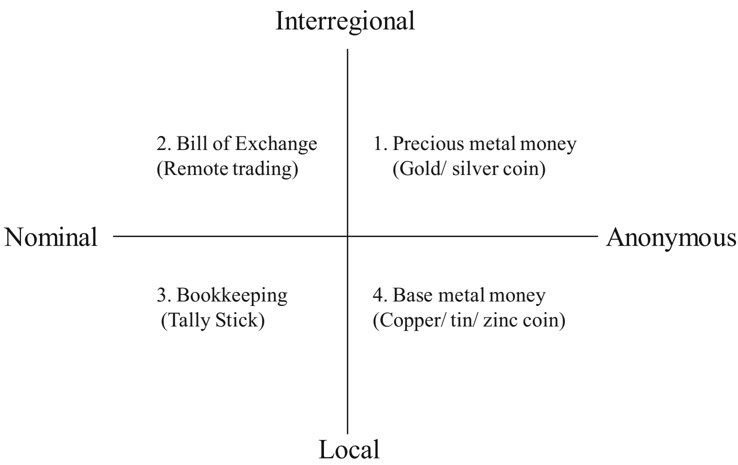

Fig. 2.3 Plurality of monetary exchanges (source: Kuroda (2003, 2020) amended by the author)

whom one has had a long-term face-to-face business relationship. Furthermore, the third quadrant, which is manifestly nominal and localized, corresponds to the case where consumers shop at neighborhood stores or artisan workshops. Since small transactions were carried out by acquaintances who knew each other, bookkeeping transactions were carried out using credit money such as tallies to describe credit–debt relations. Finally, the fourth quadrant, which is anonymous and localized, refers to transactions in non-permanent markets such as regular markets and bazaars around cities. In small transactions between strangers at fish and vegetable markets, where the buyers and sellers were strangers, payment was made with base metal currency, which is material money.

In this way, material money is used in anonymous business relationships and credit money is used in nominal (named) business relationships, and the specific form of money is determined according to whether the transaction is interregional or local. However, from the nineteenth century onward, with the development of capitalist market economies and the establishment of central banks, the "one nation, one money" system was established, and the diversity of monetary exchange was lost, and material money with physical use value became cash money and credit money in commercial banks became deposit money. As a result, the plurality of monetary exchanges was lost. The diversity of currencies, which had once disappeared, is now emerging again as the diversity of non-national, private currencies, taking the form of e-money.

Money, like language, was not originally invented or deliberately created by anyone, but was naturally created through the repeated interaction of people. In addition, the rules differ slightly from region to region, and as the rules change little by little over the long period, the system that is accepted by the people of each region and era is inherited, and the system that is not is discontinued and no longer used. Money is thus self-organized, propagated, and spread, and new types and characteristics are created through innovations in which people intentionally change the rules regarding new materials, technologies, and the scope of distribution. Those that adapt well to the sometimes rapidly changing environment survive, and those that do not perish. In other words, the evolution of money is a dynamic and complex phenomenon that consists of four different processes: (1) self-organization (emergence), (2) replication (propagation and diffusion), (3) variation (innovation as artificial mutation), and (4) selection (survival and extinction).[6]

2.3.7 Reconsidering the Nature of Legal Tender as National Currency

Let us now reconsider the controversial issue of central banknotes, which make up the bulk of legal tender and underpin the national monetary system at large. What exactly is a central banknote? Is it a liability or an asset? Why do they circulate from person to person? Let us take Japan's central bank, the Bank of Japan as an example.

If Bank of Japan notes are held by all economic entities other than the Bank of Japan, including the Japanese government, private financial institutions, corporations, and citizens, they are recorded as "cash" in the assets section of their balance sheets. However, in the Bank of Japan's own balance sheet, the balance of outstanding Bank of Japan notes (the total amount of Bank of Japan notes held by all entities other than the Bank of Japan at a given point in time) is recorded as "banknotes issued" in the liabilities section of the balance sheet. Bank of Japan's "current accounts" in the same liabilities section are deposits made with the Bank of Japan by all private financial institutions.

When the Bank of Japan engages in "buying operations" to purchase previously issued bonds from financial institutions, it transfers the proceeds to the BOJ current accounts of the counterpart financial institutions, thereby increasing the BOJ current accounts. The Bank of Japan issues Bank of Japan notes and supplies them to the market when private financial institutions withdraw Bank of Japan notes as cash from the Bank of Japan current account. When this happens, the number of Bank of Japan notes issued increases, and the Bank of Japan current account decreases by the same amount. Conversely, if financial institutions do not need cash, they will deposit it in the Bank of Japan's current account, which will reduce the amount of banknotes issued and increase the Bank of Japan's current account by the same amount. This return is called the "reflux" of Bank of Japan notes. On the other hand, "cash" is recorded in the assets section of the balance sheet. This portion is recorded as "cash" because it is issued when the Mint, an independent administrative

[6] For more information on the basic concepts and framework of evolutionary economics, refer to the following literature and papers: Aruka (2015), Dopfer and Potts (2008, 2009), and Nishibe (2006, 2012).

agency, manufactures coins on behalf of the government and delivers them to the Bank of Japan. In other words, "cash" does not refer to Bank of Japan notes but to the supplementary currency issued by the government and held by the Bank of Japan, different from daily usage of the term "cash."

Thus, central banknotes issued by the central bank are certificates of indebtedness and represent liabilities of the Bank of Japan to other entities, and only government money (supplementary currency as coin) held by the Bank of Japan itself is considered to be an asset as "cash." According to the Bank of Japan's financial statements as of March 31, 2020, total assets were 604,484.6 billion yen, total liabilities were 599,937.2 billion yen, and net assets were 4547.3 billion yen. The balance of banknotes issued by the Bank of Japan is 109,616.5 billion yen. At present, cash as asset accounts for only 0.19% of banknotes issued as a liability.

Here, the following points should be noted. If the government manufactures 200 billion yen in coins at a cost of 40 billion yen and delivers them to the Bank of Japan, 200 billion yen in "cash" will be recorded in the assets section of the Bank of Japan, but no liabilities will be incurred by the government. Therefore, the difference between the two, 160 billion yen, becomes revenue. This gain on money issuance is called seigniorage. In the Middle Ages, seigniorage referred to the privileges of feudal lords, and especially to the profits from the issuance of gold and silver coins. If seigniorage occurs in coins, does it also occur in Bank of Japan notes? It is tempting to think that if 100 trillion yen of Bank of Japan notes are printed and issued at a cost of 20 trillion yen, the difference of 80 trillion yen would be seigniorage, but the general view is that seigniorage does not occur because Bank of Japan notes are recorded as liabilities, not assets. We will discuss whether this is true or not later.

The Bank of Japan used to issue convertible banknotes that had to be exchanged on demand for the nation's standard currency, specie (gold or silver coin). A convertible banknote is a check of deposit of specie, a certificate of debt obligation guaranteeing that the bank will hand the specie over to the person who brings it to the bank. Under the gold standard and/or silver standard, specie is a coin that contains a certain amount of precious metal based on par value and whose real value does not differ from its marked face value, i.e., gold/silver coin or bullion. In Japan, the New Currency Ordinance of 1871 set the gold parity at "1 yen = 1.5 g of pure gold," but the Coinage Law of 1897 halved the gold parity to "1 yen = 0.75 g of pure gold."

When the Bank of Japan issued convertible banknotes, it entered the gold or silver bullion or coins for specie reserve as assets on its balance sheet and the banknotes issued as liabilities. The Bank of Japan convertible notes were negotiable certificates of obligation (IOUs) and were credit money. However, since Nixon's cancelation of direct convertibility of US dollar into gold in 1971 and the transition to a floating exchange rate system in 1973, all national currencies, including the US dollar, are no longer guaranteed to be convertible to gold. The central banks of each country now issue inconvertible banknotes that are not guaranteed to be convertible into specie. That is fiat money, legal tender, or cash, and there is no longer specie. The exchange rates that fluctuate daily in the foreign exchange market merely indicate relative exchange ratios between national currencies, and do not represent any absolute real value. From a postmodern philosophical point of view, modern money is just information that displays only "differences."

However, the Bank of Japan kept on making an entry of the balance of central banknotes issued as "banknotes issued" in the liabilities section of its balance sheet, just as it did when it issued convertible banknotes. Included in the assets section are not gold or silver coins or bullion for specie reserve, but government bonds, loans, Exchange Traded Funds (ETFs), Real Estate Investment Trusts (REITs), and stocks paid with BOJ banknotes and current deposits.

According to the latest financial statements for FY2019 (as of March 31, 2020) shown in Fig. 2.4, Japanese government bonds (JGBs, Japanese government securities in Fig. 2.4) account for the largest portion of total assets at 485,918.1 billion yen, followed by loans and bills discounted at 54,328.6 billion yen, ETFs at 29,718.9 billion yen, foreign currency assets at 25,966.2 billion yen, equities at 727.7 billion yen, REITs at 575.3 billion yen, gold bullion: 441.3 billion yen cash: 205.1 billion yen, etc. It should be noted that JGBs, ETFs, and REITs have grown significantly. On the other hand, in the liabilities section, banknotes issued, and deposit increased up to 109,616.5 billion yen and 447,076.2 billion yen, respectively, while government deposits decreased to 12,633.8 billion yen, which is probably due to an increase in extraordinary spending for corona countermeasures.

ETFs and REITs, which are assets other than JGB, have been rapidly growing among assets since 2010, when the Bank of Japan began buying them to help the Japanese economy escape the crisis and promote stable growth after the Subprime financial crisis. They are not stocks of specific industries or companies, or specific buildings or land, but rather indices that represent the weighted average of the market value of Japanese stocks and Japanese real estate listed and traded on the stock market, so the Bank of Japan is, so to speak, an anonymous holder of real estate and stocks for all of Japan. If you closely look into the ETFs owned by the Bank of Japan and add up the shares that make up the ETFs, you will find that there are more than 200 companies in which the Bank of Japan owns 5% or more of the shares, and about 50 companies in which it owns 10% or more. The Bank of Japan not only influences the stock market, but also has a great deal of influence over these private companies as an indirect major shareholder, although it is the asset management companies that exercise the voting rights.

Why is the balance of central banknotes issued listed as a liability on the balance sheet? In the Bank of Japan's view, this is because the stability of the value of Bank of Japan notes is due to the Bank's appropriate monetary policy, which makes them "like" certificates of obligation. It is also claimed that such a dealing of central banknotes issued is the same as major central banks of foreign countries. However, we do not understand the logic behind the Bank of Japan notes' "debt-like" status.[7] For, whether inconvertible central banknotes are debt instruments or not is irrelevant to the appropriateness of the BOJ's monetary policy and public confidence in the BOJ. Since fiat money has no obligation to be redeemed in the first place, the

[7] https://www.boj.or.jp/announcements/education/oshiete/outline/a23.htm/.

Item	yen
ASSETS	
Gold	441,253,409,037
Cash	205,061,074,044
Japanese government securities	485,918,129,988,422
Commercial paper	2,551,889,033,716
Corporate bonds	3,220,825,190,968
Pecuniary trusts (stocks held as trust property)	727,714,519,973
Pecuniary trusts (index-linked exchange-traded funds held as trust property)	29,718,938,645,617
Pecuniary trusts (Japan real estate investment trusts held as trust property)	575,305,889,680
Loans and bills discounted	54,328,648,000,000
Electronic loans	54,328,648,000,000
Foreign currency assets	25,966,256,288,216
Foreign currency deposits	1,732,262,396,986
Foreign currency securities	2,355,224,668,143
Foreign currency mutual funds	60,613,713,087
Foreign currency loans	21,818,155,510,000
Deposits with agents	23,994,220,003
Other assets	590,051,545,382
Bills and checks in process of collection Capital subscription to the Deposit Insurance Corporation, and the	6,356,685
Agricultural and Fishery Cooperative Savings Insurance Corporation	225,000,000
Capital subscription to an international financial institution	15,278,374,364
Withdrawn cash to be returned to the government	38,707,429,941
Refund on accrued tax	52,621,989,719
Accrued interest receivable	470,183,576,216
Others	13,028,818,457
Tangible fixed assets	216,444,108,401
Buildings	105,726,690,246
Land	84,124,182,999
Lease assets	7,598,665,055
Construction in progress	7,458,248,538
Other tangible fixed assets	11,536,321,563
Intangible fixed assets	129,890,768
Utility rights	129,890,768
Total assets	**604,484,641,804,227**

LIABILITIES	
Banknotes	109,616,575,483,650
Deposits (excluding those of the government)	447,076,239,363,367
Current deposits	395,256,035,035,254
Other deposits	51,820,204,328,113
Deposits of the government	12,633,850,593,434
Treasury deposit	150,001,026,112
Domestic designated deposit	12,239,860,364,524
Other government deposits	243,989,202,798
Payables under repurchase agreements	24,116,347,566,200
Other liabilities	84,086,119,657
Remittances payable	14,760,764,172
Taxes payable	28,031,000,000
Lease liabilities	7,988,759,130
Others	33,305,596,355
Provision for retirement benefits	203,316,793,791
Provision for possible losses on bonds transactions	4,799,292,993,013
Provision for possible losses on foreign exchange transactions	1,407,536,000,000
Total liabilities	**599,937,244,913,112**
NET ASSETS	
Capital	100,000,000
Legal reserve	3,252,007,626,093
Special reserve	13,196,452
Net income	1,295,276,068,570
Total net assets	**4,547,396,891,115**
Total liabilities and net assets	**604,484,641,804,227**

Fig. 2.4 Balance sheet of Bank of Japan (March 31, 2020). Source: Financial Statements for the 135th Fiscal Year/Fiscal 2019 (https://www.boj.or.jp/en/about/account/zai2005a.pdf)

question of debt repayment does not arise whatever happens. If this is the case, then there should be no need to correlate the amount of banknotes issued that are recorded in the liabilities section of the BOJ's balance sheet, with the amount of government bonds, stocks, and real estate purchased with banknotes that are recorded in the assets section.

If the plunge in JGBs, stocks, and real estate were somehow attributable to the Bank of Japan's monetary policy failures rather than to exogenous natural disasters or the global financial crisis, the Bank of Japan would be held accountable and would lose the confidence of the public, corporations, and investors. In such an event, if the outstanding Bank of Japan notes would remain as liabilities, the Bank would be at risk of becoming insolvent as its liabilities exceeded its assets as the value of its assets declined. However, in the case of the central bank, even though it becomes insolvent, the government would certainly provide capital injections and other bailouts, so it is unlikely that the bank will go bankrupt anytime soon.

Such risks, even if they are the result of monetary policy failures and a loss of confidence, are independent of the fact that Bank of Japan notes are certificates of obligation. Rather, by maintaining such an interpretation, the risk of insolvency has seemingly increased. What the BOJ is doing now to support the private sector in the fight against the new coronary infection is unlimited purchases of JGBs and increased purchases of CP, corporate bonds, etc. Accordingly, the BOJ's issuance of banknotes and its balance sheet are expanding further. Therefore, the insistence that identification of Bank of Japan notes as debt certificates can work as a break against excessive issuance causing hyperinflation may be incorrect.

There is no small possibility that the Bank of Japan's ultra-easy monetary policy stance will create significant risks in the future. What would be more consistent with such monetary policy would be to gracefully recognize "banknotes in issue" as capital and record them in net assets. If the government changes this conventional practice retained from the age of convertible banknotes and declares that it will change the items listed in its financial statements from now on, the banknotes it issues, which account for nearly 20% of liabilities, will disappear in an instant, and its net assets will increase by that amount, which should prevent it from falling into insolvency even if the value of its assets, including JGBs, is severely damaged.

2.3.8 Bank of Japan Notes Are Not "Certificates of Obligation" but "Equity Securities"

First, we must deeply consider what exactly is a "debt" without obligation to repay. Modern fiat central banknotes are not issued as negotiable certificates of debt obligation to be redeemed in specie when it is refunded to the central bank after circulating among economic agents other than themselves as asset "cash," as was the case with earlier convertible banknotes. Therefore, we must admit that it is no longer credit money. Of course, it is also not material money that retains its intrinsic use value. Then, what exactly is a “debt” that does not have to be repaid? In fact, the expression “debt” without obligation to repay is a literal contradiction. There is no such thing as a debt without an obligation to repay it. What it simply means is a situation where there is no more debt and no more repayment.

The Bank of Japan was established with a capital of 100 million yen, but it has now issued more than 100 trillion yen in Bank of Japan notes, a million times that amount, which continue to circulate as fiat money with no obligation to repay. To understand this curious reality, we only need to reconceptualize Bank of Japan notes not as certificates of debt obligation or IOUs but as equity securities, a means of raising funds on a massive scale. The modern central banknote is conceivable as an equity security issued by the central bank in the name of “cash.” We thus reinterpret it as a quasi-security or utility coupon without voting rights nor dividends, not as IOUs.

ICO (Initial Coin Offering) is a popular way to raise funds by “presale” of new tokens to investors in exchange for contributions in-kind of such cryptocurrency as Bitcoin or Ether before they are listed on an exchange. There are two types of tokens issued through ICO: security tokens that come with revenue sharing rights, and utility tokens that are a means of payment like service vouchers or gift certificates. Since Bank of Japan notes do not hold any rights for interest or revenue, they provide such services of “money” as payment and purchasing power to buy anything. So, it can be considered as a utility token. In recent years, financial regulators around the world have been trying to regulate crypto-asset tokens by regarding them as the latter. But what if the central bank notes can be also regarded as utility tokens? It surprisingly resembles the way in which fiat central banknotes are issued as equity for financial institutions’ contribution in kind of government bonds as we have just seen even if it has no risk of rip-off as in ICO.

Then, what changes if we understand fiat central banknotes as securities of contribution? First, it changes the meaning of central banknotes as money: fiat central banknotes are neither material money nor credit money, but a third kind of money: ideational or symbolic money, in other words, utility token. By recognizing this, it can be clarified that modern money, including national currency as well as non-national private currency such as cryptocurrency and community currency, shares such unique characteristics that were not present in earlier material money and credit money.

Second, in the balance sheet, capital is distinguished from liabilities and is entered as net assets in the same credits of a balance sheet. If the Bank of Japan reinterprets “banknotes issued” as capital, then “banknotes issued” will disappear from liabilities and be recorded as net assets, eliminating almost all fears of insolvency even if the value of current holdings such as government bonds, real estate, and stocks were to collapse significantly.

It is self-evident from the outset that the principle of self-responsibility does not apply to central banks which are certain to be bailed out by the government even if they become insolvent. Rather, it may be more appropriate to clarify beforehand in principle that central banks are capitalized by the banknotes they issue because they play a public role in finance, and therefore the risk of their failure becomes extremely small compared to that of private entities. When Japan's bubble economy collapsed and the USA fell into a financial crisis after the Lehman Shock, the government broke the universal principle of self-responsibility by bailing out major financial institutions with capital injections using taxpayers' money as a stopgap measure. However, if such an event took place to central banks, it would be much better to fundamentally solve the problem by changing the monetary and financial principles rather than executing ad hoc bail-out with public funds.

If we assume that a financial institution receives Bank of Japan notes as equity securities, how can we understand trading in JGBs for "cash"? The financial institution would be seen as making contributions in-kind of the JGBs, rather than monetary contributions, and receiving the Bank of Japan notes as capital contribution securities. In other words, it is not a sale of a commodity for money, but an investment in kind in the form of JGBs for the delivery of investment securities. In such a case, the entities contributed in-kind are not goods and services, but rather securities such as government bonds, corporate bonds, CPs, bills, corporate bonds, ETFs, and REITs, which are exchanged mainly by the Bank of Japan and financial institutions as assets. Since modern capitalism has reached the ultimate stage of free investment, then considering central bank notes as equity securities is not particularly strange, as it places the principle of investment at its core. If the Bank of Japan were to actually record "banknotes issued" as capital rather than liabilities on its balance sheet and make such information widely available, the perceptions and actions of the government, financial institutions, corporations, and the public would not remain the same, but would change dramatically.

First, how would the government view it? The government's budget deficit has been increasing, with the outstanding amount of government bonds issued at the end of FY2019 (end of March 2020) reaching a record high of 997.9 trillion yen, and the outstanding amount of long-term debt for the national and local governments combined standing at 1125 trillion yen or 197% of GDP. The Bank of Japan's JGB holdings at the end of the same period were also 486 trillion yen, so almost half of all JGBs held by the Bank. If Bank of Japan notes are recorded in net assets as capital instead of liabilities, the risk of the Bank of Japan becoming insolvent would be significantly reduced, and it would be able to hold even more government bonds even if long-term interest rates were to rise sharply, and government bond prices were to plummet accordingly. The central bank's underwriting of new government bonds is currently prohibited by Article 5 of the Fiscal Law. But the situation is that the nation eventually contributes new government bonds in kind and provides capital to the central bank, in exchange for receiving "legal tender" as security of investment from the Bank of Japan. Eventually, they would exchange of debt certificates as JGBs and equity securities as Bank of Japan notes. Then the central bank should not be specifically prohibited from doing so, since the risk is ultimately borne by the government as the investor.

This may sound similar to MMT's argument that unlimited issuance of government bonds is possible. MMT sees the government and the central bank as a single integrated entity and argues that no matter how much government bonds are issued, there will be no problem because the central bank can finance all of them, because fiat central bank notes are guaranteed to be valid by the state's authority to levy taxes. This arises from the incorrect notion of money that modern fiat central bank notes are a form of credit money based on "chartalism." It is completely different from our claim that modern money is no longer material money nor credit money, but ideational or symbolic money. We consider that MMT concept of modern money is outdated and its policy implication is mistaken.

The relationship between the central bank and financial institutions has long been thought of as a one-way hierarchical relationship, with the central bank assisting and bailing out financial institutions and supervising and regulating them, as seen in the "bank of banks," the "lender of last resort," and the reserve deposit system. If, however, Bank of Japan notes are explicitly stated to be equity securities for capital contributions by private financial institutions to the Bank of Japan, then the opposite effect of financial institutions jointly supporting and assisting the central bank is clarified, and this would create a more interactive and equal relationship between the two. If financial institutions are investors in the Bank of Japan, there will be risks associated with investments in kind rather than trading in money. However, even if the value of assets such as government bonds, stocks, and real estate were to be severely damaged, the risk of the Bank of Japan becoming insolvent would be significantly reduced, which would simultaneously reduce the risk to financial institutions of investing in the Bank of Japan.

Financial institutions that hold current accounts with the Bank of Japan would not only view the cash, Bank of Japan notes as certificates of contribution in the Bank, but would also view their current accounts as the same securities they receive on withdrawal of their deposits. For the Bank of Japan, the current account is a liability, but the Bank of Japan only have to repay the financial institutions for the securities for their investment under the name of "legal tender." So, theoretically, issuing an unlimited number of such securities will not cause the Bank of Japan to become unable to repay its debts. Although the author does not agree with it, the unlimited supply of monetary base, which the Bank of Japan has already implemented as QQE (Quantitative-Qualitative Easing), should be more consistent with this logic. This is also true of MTT.

However, this is subject to the condition that there is no possibility of the other party refusing to accept the note due to the side effect of hyperinflation. Even though Article 46, Paragraph 2 of the Bank of Japan Act stipulates that "banknotes issued by the Bank of Japan shall be accepted without restriction as legal tender," it does not necessarily mean that the other party can be "forced" to accept the banknotes because physical commodities of necessary use value such as rice and eggs become material money with a much higher purchasing power in such a hyperinflationary situation, as was seen in Germany after the defeat of WWI. It is not always possible to force the other party to accept paper money.

The value of modern money is spontaneously formed and automatically maintained by the inertia and conventions from the past and the expectations and anticipations for the future that people unconsciously or consciously rely on in their daily receipts. In other words, the value of modern money is formed and grown by self-fulfilling notions. In this sense, the modern money since the 1970s is neither material money nor credit money, but rather purely informational money that should be called "ideational money" or "symbolic money."

If individuals and companies recognize that cash and deposits are also risk involving investment securities, the traditional monetary mindset that holding money is secure and that money has no risk will change.[8] We will be forced to realize that we are investors who choose portfolios of various assets on our own initiative and responsibility, while constantly being aware of such risks, and the nature of free investment capitalism will be strengthened.[9] However, "investment" is not just quantitative "speculation" aimed at increasing the volume of one type of national currency. As private currencies other than legal tender become more diverse, individuals and companies will begin to consider their main objective more comprehensively and eventually aim at not only quantitative expansion by selecting multiple currencies to match their values and styles while taking various risks into consideration, but also qualitative improvement of their possibilities and world in the future by utilizing these currencies.

2.4 What Is Good Money? Hayek's Principle of Choice in Currency in Terms of "Quality" Realize That "Good Money Drives Out Bad"

2.4.1 Gresham's Law

In this era of diversification and evolution of money, we can no longer see money as given, ready-made, and top-down. We should regard it as being bottom-up created and selected by users. Therefore, in the creation and selection of money, the question of what kind of money becomes "good money" is crucial. It is not just convenient, efficient, and stable. What exactly is "good money"? It is the most fundamental question. The answer is not something anyone can give, but something we have to find by ourselves.

Let us first check "Gresham's law" that is one of the famous monetary principles in economics claiming that "bad money drives out good."[10] The nineteenth-century

[8] The "liquidity preference" that Keynes introduced in his The General Theory (Keynes 1936) assumes that the interest rate of money is zero compared to positive interest rate of bonds, but the reason why he assumes so is because the risk of holding money is zero unless there is no accelerating inflation. This may have reflected the normal monetary attitudes of the British rather than the Germans, who experienced hyperinflation after World War I.

[9] In my view, it is "free investment" rather than "free trade" that characterizes modern global capitalism. For more on this, see Nishibe (2020).

[10] The full survey article on history of precedents and transition of theoretical meanings of Gresham's law is found in Verde (2008). The author explained three refinements of Gresham's law in history, but he mentioned Akerlof's discussion on the lemon's market of the asymmetric information, but he does not mention the theoretical implication of Gresham's law for diversifying

Scottish money and credit theorist Henry Dunning McLeod had given the name after the sixteenth century Tudor Treasury Secretary Sir Thomas Gresham. However, there are many precedents for the law since the Ancient Greek era (Mundell 1998; Selgin 1996, 2003). Nicolaus Copernicus, who is famous for advancing the theory of heliocentric system, is one of such precedents who accurately acknowledge the law (Ziffer 1957).[11] Accordingly, this law is currently sometimes called "Gresham–Copernicus' law."

The meaning of this law is as follows. Let us assume that there are two gold coins (silver coins make no difference). The face value of a gold coin is the denomination of the unit of measure, e.g., Pound, and the real value of a gold coin is its content of gold. When the real value of one gold coin is lower than the face value of the other due to debasement, including the issuing body's mixture of base metals and users' clipping or scraping, which one will you use to pay first? Assuming users behave selfishly, they are supposed to use "bad money" with low content of gold first and try to keep "good money" with a high content of gold. Then bad money will be circulated, and good money will be hoarded. Thus, Gresham's law originally meant "Gresham's law of coinage" in the case of the debasement of minting coins. In general, in the case of any material money (commodity money) in which the material has an intrinsic value, good money with the small difference between the face value and real value will be preserved as an appropriate asset, and, as a result, bad money will gradually prevail in the market.

However, if we expand its substantial meaning of the law to bimetallism where both gold and silver are adopted as a standard of value with the fixed exchange rate, the relatively lower evaluated one will circulate among users. Gresham's law is also valid for the case where gold coins with the same unit of denomination (e.g., yen) and convertible paper money that can be converted into gold coins coexist. For people would tend to keep on hand the gold coins with higher real value and try to use the convertible paper money with lower real value first. Furthermore, even in the case of inconvertible paper currency, Gresham's law still holds. If there are two inconvertible paper currencies with different inflation rates due to the difference in the amount of currency issued, bad money with a low real value caused by high inflation rate drives out good money with a low inflation rate.

Gresham's law tells us that it is a very convenient law for minters and issuers of money. If the issuer reduces the gold content of gold coins and reduces the casting cost, the difference between the face value and the commodity value can be obtained as Seigniorage (profit from minting) while bad money continues to circulate. Besides, as a result, if the real value of money decreases and the inflationary trend progresses, inflation has the actual effect of substantially reducing the nation's fiscal

modern money including community currencies and cryptocurrencies as well as modern monetary policies.

[11] Copernicus's *Monete cudende ratio (On the Coinage of Money)* is his third version of his treatise on money and coinage written in Latin in 1526 (). Nicholas Oresme's *On the origin, Mature, La, and Alteration of Money* is found more than century earlier works (Mundell 1998).

deficit. Because of these dual benefits, the government tends to mint and issue bad money that incessantly causes inflation. And if there is no legitimate choice for users but to use a coin bearing the king's seal, such bad money will be forced to circulate within the nation, which will be a big nuisance for users.

Next, let us apply this to the present day. Today, neither standard money such as gold or silver coins nor convertible paper money is in circulation. Inconvertible banknotes issued by the central bank and subsidiary coins minted by the Mint Bureau of the Ministry of Finance are legally designated as legal tender. The production cost of a 500 yen coin is only about 20 yen at most. Then, the seigniorage for the central bank on minting a 500 yen subsidiary coin would be 480 yen. Its real value is only 4%, negligibly small compared to a gold coin. Similarly, the production cost of a 10,000 yen note is only about 10 yen at most. Its real value is now only 0.1%. Then, we would like to say that the seigniorage for the central bank on issuing a 10,000 yen central banknote would be 9990 yen. But be careful. It is a controversial point. As we have just seen above, in the current institutional setting of accounting, the central banknotes are not regarded as asset but liability on its own balance sheet. So, they say it cannot be seigniorage. But, as we discussed earlier, if the central banknotes are to be shifted from liabilities to capital in net assets, we may say once again that 9990 yen is the seigniorage. Inconvertible legal tender potentially become a real "bad money."

From some time after WWII in Japan, the yen could be exchanged for dollars at a fixed rate of "1 dollar = 360 yen," and dollars could be exchanged for gold at a rate of "1 ounce of gold = 35 dollars." Therefore, we could say that the yen was indirectly convertible into gold. However, President Nixon stopped the conversion of dollars to gold in 1971 due to the shortage of gold reserves, and all developed countries shifted to floating exchange rates in 1973. Since then, the legal currencies of each country have lost their anchor based on the value of physical commodities such as precious metals and commodity baskets. The floating exchange rate system merely indicates the relative exchange rate between legal currencies and does not show the absolute value as in the gold standard system. Therefore, it often fluctuates greatly depending on the speculation of investors in the foreign exchange market.

In the Asian currency crisis in 1997, investors who expected the asset bubble to end flowed out of the country from Asian countries such as Malaysia, Thailand, and Korea. As a result, in these countries, the real economy fell into a recession by the collapse of currency and assets, and people's living conditions deteriorated rapidly. Modern money is not only a means of circulation and a measure of value for buying and selling goods but also a store of value and liquidity as a shelter from volatility for investment. In the case of FX (foreign exchange margin trading), money itself is the subject of speculation to make profits from trading. Thus, modern money suffers not only quantitative deterioration due to a tendential decline of real value but also qualitative deterioration due to large value fluctuation accompanied by the nullification of real value.

The Bank of Japan, under its Abenomics policy, has continued QQE, or an unlimited supply of cash currency with negative interest rates, in an attempt to achieve an inflation target of 2%. The weaker yen improved the performance of exporting companies and boosted stock prices. However, inflation has not occurred as expected because banks do not increase their lending to supply deposit money to the market. This situation occurs because banks consider that they do not have borrowers considering the risks involved. The government's inflation targeting policy aims to improve the economy by raising nominal prices through an increase in money stock despite the lack of favorable investment opportunities. It assumes the extreme assumption that people's expectations of inflation based on the illusion of money will continue. In reality, the rise in wages has been slow, and households whose real purchasing power has declined have tightened their purse strings. The Bank of Japan governor, Kuroda, has now stopped short of mentioning a deadline for achieving a 2% inflation rate and seemingly has given up on that goal. Centralized issuance of cash by the central bank under the national managed currency system has made such unsound economic policies possible.

Modern legal tender as an inconvertible currency is bad money not only in the quantitative sense that its real value is tremendously smaller than its face value in contrast to gold coins, but also in the qualitative sense that it has become an object of the speculation as a financial asset like a stock and a derivative commodity so that it shows an extraordinarily high degree of capital function and that it also serves an instrument of current arbitrary and risky monetary policy by central banks. We could say here was the culmination of evil. In such a pathological situation of the modern money system, it was significantly expected that Bitcoin, which differed from the centralized issuing legal tender, would potentially become a new original currency based on the decentralized issuing by utilizing blockchain or DLT. However, once cryptocurrencies began to be exchanged with legal tender on the exchanges, Bitcoin and other cryptocurrencies rapidly became speculative. They rose in prices sharply, especially in 2017, as their public recognition of names increased, but made a sudden plunge in 2018. The price fluctuation was tremendously huge, compared with legal tenders such as the dollar and euro. It seemed that cryptocurrencies had become financial instruments with high risks and high returns, just like FX with quite high leverage by a factor of 10, rather than "money" that transacts goods and services. Disappointingly, cryptocurrencies have become indeed "bad money."

2.4.2 Hayek's Denationalization of Money and the Principle of "Choice in Currency"

The Austrian School economist Hayek, in his book *The Denationalization of Money* (Hayek 1976b), stated that a desirable currency can be found as a "good money" only when multiple currencies of different quality mutually compete. For that purpose, the principle of "choice in currency" for "Good money drives out bad" should work instead of Gresham's law stating, "Bad money drives out good." If only monopoly currencies and their simulacrums exist, that is, currencies can be differentiated only by the quantity of real value, amount of issue, and interest rate when they have the same face value or the fixed exchange rate, the Gresham's law will come into effect.

For example, in Scotland and Hong Kong, several private banknotes with the same standard of measure circulate alongside the legal tender, which is the central banknote. Private banknotes are different from legal tender, but they use the same name and unit of measure, i.e., "pound sterling" or "Hong Kong dollar." This creates the possibility that such private banknotes will be refused by some stores, but in most cases, they will be circulated as having the same value as central banknotes. Thus, they will be substitutive currencies of legal tender. In this case, legal tender and substitutive currency are apparently different currencies, but they can be used as money with the same name and unit of measure.

Even if the central bank properly adjusts the amount of legal tender issued so as not to impair its real value, i.e., so as not to cause inflation, if private banks, which issue private substitutive currency with the same name and unit of measure, issue too much of it, the supply of such substitutive currency will increase, its real value will decline, and inflation will occur. In this way, the legal tender with the same real value as before will be hoarded as "good money" because people will try to use the "bad money" that has the same nominal value but has a lower real value first. In other words, even if legal tender and substitutive currencies are outwardly distinguished, if the exchange ratio between them remains fixed at one to one, the substitutive bad currencies will drive out the legal tender good currency. This is the result of what Gresham's law works.

In order for a competitive relationship between multiple currencies of different quality to be established, a situation must be created in which this Gresham's law does not hold, and Hayek's principle of "choice in currency," "good money drives out the bad" must come into play (Hayek 1976a). This is the case when multiple currencies of different quality enter a competitive relationship of "monopolistic competition." The following two conditions are necessary for it: (1) multiple currencies should have different denominations (names) of the unit of measure, the types of reserve assets and reserve instruments so that they can be distinguished not only in such quantities but also in qualities such as users' trust on the stability of value of money, and (2) the exchange rates between currencies must not be fixed entirely, but they must be somewhat changeable reflecting users' evaluation of the differences in quality.

In a capitalist economy, as a result of such monopolistic competition, the principle of commodity selection, "good commodity drive out bad commodity," is at work. This is the merit and strength of the capitalist market economy. Monopolistic competition, which is applied to heterogeneous goods and services with slightly different quality and design, rather than perfect competition, which is applied to completely homogeneous and perfectly substitutive goods and services, is the reality of competition in a market economy. Monopolistic competition is by no means an exceptional situation, but represents a universal situation. The principle of commodity selection brought about by such monopolistic competition is the outstanding characteristic of a market economy, which does not exist in a planned economy. In other words, markets are better appreciated because they make goods not only cheaper, but also better, not because they realize efficient allocation of scarce resources.

Monopolistic competition thus generally refers to an oligopolistic situation in which there are incompletely substitutive commodities supplied by heterogenous firms, and they differ in quality and design, even though they form a market for roughly the same kind of commodities, and in which both price and non-price competition among firms occur simultaneously. Hayek tried to apply the concept of monopolistic competition that is usually used in terms of commodity differentiation to the differentiation of money. He thought that money differentiation through monopolistic competition bring about "better money" that have better quality of money. The principle of "good money drives out bad money" is a principle that begins to operate only when the issuer of money innovates its currency service to enable competition in quality. The "denationalization of money," as Hayek called it, was a dynamic process in which multiple private currencies of differentiating quality would create this complex and intricate process of "monopolistic competition" or, in other words, "rivalry." It does not mean perfect competition that is a condition for Pareto efficiency of resource allocation as in neoclassical microeconomics. It is important to note that other economists' criticisms of these ideas of Hayek often do not fully understand this point.

The principle of choice in currency does not work under the current situation where currencies are monopolized by the state and legal tender is dominant. This is because the "one nation, one money" institution of modern money must be changed for it to be applicable. However, if multiple currencies of the same quality are issued freely, as is the case in Scotland and Hong Kong as free banking theorists insist, the Gresham Law, which states that "bad money drives out good money," will come into play.

Since cryptocurrencies obviously met these two conditions, the principle of choice in money began to function. The next problem was whether cryptocurrencies could pass the test of users' choice in money in search for good money. Hayek defined the currency with "a stable value of money" to mitigate uncertainty as "good money" (Hayek 1976b, Chap. 13). The prices of the current cryptocurrencies to legal tenders are so volatile that they are by no means good money from the viewpoint of Hayek. However, it is not clear whether the condition of good money should be based only on the stability of currency value. If the result of the selection made through inter-currency competition is seen as "good money," the criteria should be continuously discovered and innovated through evolution. For cryptocurrencies to escape from the present state in which they seem just objects of speculation and to become "good money" usable in actual transactions, the stability of currency value with the formation of consumer goods market for them is at least indispensable.

Currency stability usually means that hyperinflation, causing a sharp decline in value of money, never take place. But Bitcoin is programmed to continually increase its scarcity and value over time by mimicking the "mining" of gold with limited reserves. In that sense, speculation in bitcoin is inevitable. Still, the critical issue of unstable currency value arises because cryptocurrencies have been in sale for legal tender at real-time floating rates on hundreds of exchanges all over the world. The floating exchange rate system similar to FX quickly enabled speculation aiming at a trading margin by using value fluctuation. In fact, without this factor, bitcoin would not have been as globally popular as currently. However, it is the very factor which prevents bitcoin from becoming good money.

Currently, bitcoin is only available for a small portion of all merchandizes, and altcoin and tokens have to be converted into bitcoin to use them for purchase of goods and services. Even at shops where bitcoin is available, users have to pay by converting the list price in legal tender into bitcoin. If you expect the price of bitcoin to go up, you better to hold it than to pay it for taking appreciation profit. On the contrary, if the price is expected to drop, it will be better to use it than to keep it, but the seller may refuse to accept it. Because of violent price fluctuation of bitcoin, such speculation depending on expectation is always easy to occur, and the factor of speculative investment always mixes in the consumption. It is mainly international hedge funds, investment banks, and corporate and individual speculators who buy and sell these cryptocurrencies globally. Since cryptocurrencies are convenient tools for foreign remittance, illegal transactions such as money laundering, tax evasion, and drug dealings are inevitably involved. It is a world far from the vast majority of ordinary people.

2.4.3 The Precondition of Good Money: Ordinary People in an Actual Socioeconomy

To reconsider what criteria of good money are, we should return to the right image of the human nature of ordinary people who daily use good money in an actual socioeconomy. It must be the real precondition for the criteria of good money.

We live by consuming the basic goods and services necessary for food, clothing, and housing with the income obtained by working and decide the lifestyle based on our sense of values, and carry out hobbies and activities depending on our interests, and acquire knowledge and information. Because of emotional and psychological biases, we cannot make the best choice. Nor can all options be known in advance. Not only is there a limit to rationality, but there is also a limit to ability in all aspects such as information gathering, decision-making, and action-taking.

Therefore, the place that ordinary people buy consumer goods by money is not a vast global market but a common local market which spreads in the vicinity of one's own life. In addition to blood relation, regional ties, and neighborhoods, the communities as the active fields of life, labor, and hobby as well as the community as the sharing field of language, value, and interest are considerably related to the local market. A human being is not a rational fool who can make globally optimum decisions all the time, which is actually the image of rational agents assumed in orthodox economics. Instead, it is a decent but emotional animal that judges based on the bounded knowledge and information that are framed by its own value and interests in the local region, and lives belonging to various communities. Thus, we should consider that good money is the money that ordinary people need to live their daily lives.

There is an inevitable impression that cryptocurrencies have become far from ordinary people because only speculative capital functions have become independent. To convert such cryptocurrency into good money that enriches people's lives, a strategy to positively introduce such multilayered sets of territorial locality and virtual community will be effective. Here we need to learn from the present situations of DCCs that are in practice in local communities, seeking a good hint for criteria of good money.

In order for such DCCs to become a good currency, it is essential to create a market for consumer goods. In addition, it is important for merchants to use it to pay for purchases and wages. As a result, if the circulation of the currency can cover not only the market for consumer goods but also the market for production goods and investment goods, the local economy will be revitalized through local production for local consumption. To achieve this, DCCs need to form a new local currency market that fuses two seemingly incompatible areas: the "volunteer" area, such as mutual help and sharing within the community, and the "business" area, such as shopping in shopping malls and business-to-business transactions. To do this, we need the support of the local government, but we also need to bring together the various groups, organizations, and citizens who are currently scattered and disparate, such as local governments, economic organizations, shopping malls, schools, welfare councils, and hospitals, to reestablish the community itself.

In Japan, DCCs are spreading in local communities, such as Sarubo Coin in Hida Takayama City and Aqua Coin in Kisarazu City. The question is whether or not they will be able to create a local virtual local currency market rooted in the local community and achieve regional development. That is the issue for the future. Let us take a look at some of the concrete developments.

2.4.4 Can Japanese DCCs Such as Sarubobo Coin and Aqua Coin Become Good Money?

Here let us see more details of the activities of Sarubobo coin and Aqua coin as the representatives of DCCs.

2.4.4.1 Sarubobo Coin

Sarubobo coin is a DCC issued by the Hida Credit Union. The full-scale operation started in December 2017. The aim is to revitalize the economy of the Hida-Takayama region, Gifu Prefecture. Since Hida-Takayama district is very popular inbound tourist place with old streets and villages of traditional wooden buildings, international visitors as well as local residents and domestic tourists are expected to use the application for Sarubobo Coin.

To increase the number of shops that can use the service, the shop has adopted a system in which customers can use the service only by placing a paper with a unique QR code. On the customer side, the QR code is quicky read by a smartphone app for Sarubobo coin, and the payment is made by inputting the price of the product.

Users can not only spend at merchants but also send money between users, so they can pay as a thank you for volunteering or mutual aid. Merchants can also use them to make payments to other merchants. Sarubobo Coins are thus expected to encourage internal circulation of DCC for “local production for local consumption,” where local products can be purchased at local stores, and to revitalize local industries by circulating within the region as much as possible while circulating from place to place, instead of immediately flowing out like the legal tender, yen.

This can also be seen as a fintech solution for regional development. Sarubobo Coin uses a system called “MoneyEasy” provided by Finovalley, a subsidiary of IRIDGE, a software vendor located in Tokyo. Although it does not use a blockchain like cryptocurrency, it ensures the security of a financial institution and significantly reduces the investment cost of the system.

As of December 2019, the number of participating stores was approximately 1200 that represents 16 ~ 17% of all targeted stores, the Sarubobo Coin app has about 10,000 users. Of these, about 9000 are local users, accounting for 12–13% of the total number of users, excluding the elderly and children, with a total recharge amount of over 1 billion yen.

Hida City and Hida Credit Union concluded the “Agreement on information distribution using Sarubobo Coin App in times of disaster” to further promote the use of electronic local currency in administration. In October 2018, the Hida City government introduced a model for e-payment system in which the municipal health and tax sections of the city can pay fees at various counters with Sarubobo coin. Using the Sarubobo Coin app, users can scan a QR code placed at the counter of each section and pay fees such as a copy of a residence certificate, a certificate of seal impression, and a tax payment certificate. As it stands, users in both cities are still limited, but it is expected to increase.[12]

The current challenge is to promote the use of Sarubobo coin further and to encourage the use of Sarubobo coin in transactions between many companies. For Sarubobo coin to circulate the local economy, materials and goods purchased by stores must also be paid in Sarubobo Coin. Since April 2018, companies have been able to pay each other for a 0.5% fee. However, the use of the system is still limited to about 15 million yen (Morikawa 2020).

[12] The total number of cases in which the Hida City Office paid its handling fees was 417 between April and November 2019. It is 16, 7650 yen. The proportion of processed cases was 6.55% at the tax office. During the period from April 1 to December 10, a total of 136 Sarubobo coin payments were made using a statement of payment, amounting to 278, 2081 yen (Morikawa 2020).

2.4.4.2 Aqua Coin

Aqua Coin is a DCC that can be used on smartphone applications in Kisarazu City, Chiba, to revitalize the local economy in terms of finance and economics, but also to form local communities in terms of social welfare by strengthening ties and promoting mutual aid, under the City banner of organic city and sustainability. "Aqua Coin" is named after "the Aqua Line" that is a four-lane highway across Tokyo Bay connecting Kawasaki City, Kanagawa Prefecture with Kisarazu City in Chiba Prefecture.

Kimitsu Credit Union, Kisarazu City, and the Kisarazu Chamber of Commerce and Industry have entered into a tripartite cooperation agreement to introduce Aqua Coin. Users can easily pay by reading the QR code installed in the member stores. Member stores can easily and immediately introduce the system by installing only a QR code, reducing the initial installation cost. Coins deposited as sales proceeds can be used not only to be cashed into bank accounts but also to be paid (remittance) to other member stores, thus activating the circulation of money within the region.

Aqua Coin aims to revitalize the local economy by increasing consumption activities in local communities such as shopping malls, promoting the circulation of funds within the community, and attracting consumption from outside the community by inbound tourists. In addition, the city will provide points in the form of Aqua Coins for volunteer activities to promote mutual aid within the community, thereby revitalizing the local community as well.

As of August 2020, there were 10,000 app installs and more than 500 member shops. Total consumption reached 260 million yen in March 2020. The merchant exchange fee is 1.5–1.8%, and the remittance fee is 0.5%, but it is free for a limited time (December 2, 2019, to September 30, 2020).

There are two ways to use. To use cashless payment by charging cash, use "Aqua Pay." The usage limit is 100,000 yen, and the coin is valid for 1 year. The user installs the special application on their smartphone, charges Aqua Coins at a rate of "1 yen = 1 coin," and then scans the QR code installed at the merchant store to make a cashless payment. Cash can be charged at Kimitsu Credit Union counters and automatic charging machines, or by purchasing a prepaid card from vending machines installed at tourist information centers, etc., reading the QR code on the back of the card, and entering the charge code. The prepaid card can be given as a gift to others, making it a tool for introducing and promoting the Aqua Coin. You can also earn Aqua points when charging and through various campaigns. Aqua Coins expire at the end of the current month 1 year after the date of last use, and the Aqua Points awarded expire at the end of the current month 1 year after the date of award.

If you have an account at Kimitsu Credit Union, you can use "Aqua Bank." The usage limit is 2,000,000 yen, and the coins are valid for 3 years. Once you install the special application, you can charge and use the coins immediately from your deposit account. Aqua Bank's exclusive features include a money transfer function for sharing the bill that enables money transfer between individual users, as well as Aqua Coin Denki. Aqua Coin Denki is a new electricity plan launched on February

3, 2020, through a partnership between Kimitsu Credit Union, Finovalley (software vendor of application for Aqua Pay and Aqua Bank), and eNetwork Systems (ENS: a company that develops OEM sales platforms for electricity) that allows users to pay for their electricity bills with Aqua Coins. Not only can users receive up to 9% of their electricity bills in Aqua Points, but ENS will also donate 0.5% of sales to Kisarazu City, making it a mechanism for citizens to support urban development.

Aqua Coin has unique features not found in other mobile payments due to the collaboration between the local government and the private sector. For example, the Kisarazu City Government Point System called “Razu Points,” which was implemented in April 2019, can be used in conjunction with Aqua Coin. Razu Points are awarded for participating in volunteer activities and community events and are distributed as paper cards, with 100 points per card. At the 2019 Kisarazu Market Festival, 100 Razu Points were given to each participant of the food education seminar, and those who answered questionnaires and made other efforts to raise disaster prevention awareness also received points. Razu Points were also given to those who made efforts to improve disaster prevention awareness by answering questionnaires. As health improvement program for citizen, 5 points are given to those who walk more than 8000 steps per day and 10 points are given to those who walk more than 8000 steps per day more than for 10 days per month, by using smartphone pedometer function.

In addition, from June 12, 2019, Aqua Coin can be used to pay fees for issuing certificates at the City Hall counter to improve citizen services and reduce the workload at the counter. From November 2019, employees of Kimitsu Credit Union, Kisarazu City, and Kisarazu Chamber of Commerce and Industry began to voluntarily receive part of their salaries in Aqua Coins so that the circulation of DCC are expected to be activated.

In this way, if “Razu Points” earned through non-commercial transactions such as volunteer work, community activities, health activities, and dietary education are circulated in shopping malls, supermarkets, convenience stores, and other commercial transactions as Aqua Points, and if Aqua Points received as part of salaries are used within the region, not only will the currency stay within the region and not flow out, but it will also increase the velocity of circulation within the region, which is expected to have the effect of stimulating the economy.

2.5 Conclusion

Such DCCs as Sarubobo Coin and Aqua Coin are pegged to yen for a stable value of money as one of the conditions for good money. For them to get closer to good money, the formation of the consumer goods market is indispensable. The utilization of purchasing payment and wage payment by the member retailers is essential as well. Sarubobo Coin and Kisarazu Coin are proceeding in the direction since they stated to let workers of local government, local institutions, chamber of commerce receive those coins as part of their monthly salary and bonus. If the currency circulation can cover not only the market of consumer goods but also the market of production goods, investment goods, and labor, the local economy will be able to be revitalized through DCC circulations within the local area based on the input–output relation of "local production for local consumption."

For this purpose, it is necessary for DCCs to form a relatively independent market seeking for "local production for local consumption" in which the volunteer domain such as mutual help and share in the community and the business domain such as shopping in the shopping street and transactions between enterprises, which are mutually incompatible at first glance like oil and water, are fused. The activities of non-profit organizations are indispensable, and the cooperation of local shopping districts, chambers of commerce and industry, and social welfare councils is required. Above all, sustained support from local governments, rather than temporary, will be effective.

Aqua Coin has a unique institution, Razu Points, for vitalizing local economy as well as local community initiated by Kisarazu City government, which evaluates non-commercial transactions such as volunteer works, spontaneous activities, and mutual aid in Razu points and motivate participants to use the Razu points thus earned for commercial transactions in local shops. This can surely help to form local consumer goods market as well as "local production for local consumption."

It will be a future challenge whether or not DCC markets rooted in local communities can be created so that local revitalization can be achieved. As we have just seen, Sarubobo coin in Hida-Takayama, Gifu, and Aqua coin in Kisarazu, Chiba are already in the process of creating DCC markets for "local production for local consumption" in their local areas. These are all bottom-up monetary innovations that aim to create a new kind of DCC by combining the good principles of community currencies with the high technology of cryptocurrencies.

In 2019, we established "Senshu University Digital-Community Currency Consortium Laboratory," whose abbreviation is "Good Money Lab" (goodmoney-lab.org/), as an industry-academia-government-private consortium to foster DCCs as good money that can improve people's living environment, increase their happiness in terms of QOL, and make the natural environment and the economy and society more harmonized and sustainable. We pursue the ideal way of money in which the principle of choice in currency as "Good money drives out bad" works well, not the Gresham's law "Bad money drives out good."

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Chapter 3
Practical Case Study About US: Doreming—Establishing the Practice of the Measures to Create a New Paradigm of "Revenue Share Finance"

Yoshikazu Takasaki

Abstract Doreming Japan Co., Ltd. is a Japanese corporation to provide a new style of "Revenue Share Finance" by the use of its own mobile wallet as digital money in order to help the poor worldwide. The corporation is now internationally permitted to be occupied to Level 39 in London, where excellent companies from all over the world join. The ultimate purpose is to help the poor and to realize share finance fairly for all the population suffering from the poverty. We demonstrate this system will also contribute the public function to an automatic tax collection system for transaction tax and consumption tax at the time of settlement.

Keywords Revenue share finance · MySalary (application name) · Mobile wallet · Digital money

3.1 A Short History of Doreming

In 2015, Doreming Japan Co., Ltd. was incorporated in Fukuoka Japan, for the purpose of raising income of people and increasing the middle-income group with the aim of helping the poor and those who do not have a bank account in Japan. In 2016, after we learned that two billion adults do not have bank accounts in the world, we founded Doreming Ltd. in London to help financial refugees in developing countries. We are incubated as the first Japanese company to Level 39, where excellent companies from all over the world join, and we have started the financial refugee relief business in the world. We were invited for the World Bank Annual Meetings, the Innovate Finance Global Summit, and the Future Investment

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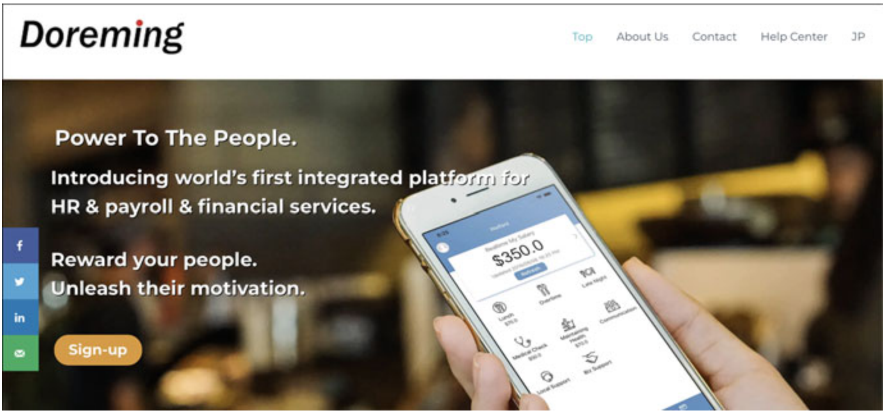

Fig. 3.1 The top page of Doreming website: https://www.doreming.com

Initiative in Saudi Arabia. For details, have a look on Doreming's website. Figure 3.1 shows its entrance.

Our strengths are the following:

1. Offer "MySalary"[1] that allows employees to receive their take-home wages at any time they need because our system calculates their wages in real time.
2. "MySalary" helps to run payroll with fair evaluation such as providing allowance for working during busy hours and working for dirty, dangerous and difficult jobs, as well as providing a premium allowance based on the amount of work and performance.
3. "MySalary" allows employees to top up the amount of take-home wages directly to their Mobile Wallet as Digital Money.
4. Income tax, local tax, pension, and social insurance can be automatically collected at the time of receiving wages, which can be expected to reduce an employer's clerical work, government tax collection cost, and unpaid tax collection cost.
5. Provide "Revenue Share Finance" that automatically distributes sales to related parties at a predetermined rate the moment sales are deposited or settled with Digital Money and also be used for an automatic tax collection system for transaction tax and consumption tax at the time of settlement.

In the following, we illustrate these advantages one by one. Needless to say, "digital" money of our style plays a key role. By developing this kind of new money, thus, we aim at "Revenue Share Finance." Figure 3.2 summarizes our activity.

[1] "MySalary" is the name of application.

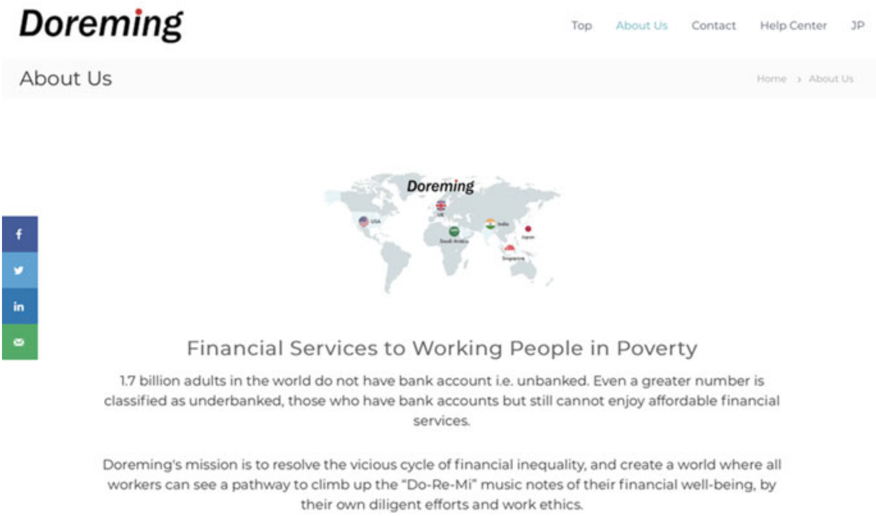

Fig. 3.2 Financial service to working people in poverty. Cited from "About Us" of Doreming website: https://www.doreming.com/about-us/

3.2 Help the Poor by Giving Them Real-Time Access to Their Wages Through "MySalary"

3.2.1 Summary of the Current Situation

I thought about the reason why it seems normal to pay the workers on that day they worked; however, wage payments are deferred. Good reason is that since employers did not have money to pay their employees immediately, they asked their employees to wait and wrote a loan book with an attendance sheet as a wages payable. Evil reason is that since employers give their employees a job, they have the power to defer wage payments and they could earn interest on the deferred amounts of wages. There was a time when a bad person bought a child from a poor family, forced the child to work, and took a cut from money the child earned. If you pay your employees in cash every day, you might be worried that cash can be stolen in your office safe. Because of that, you have decided to pay it later with a lump sum. However, there are many people who have a hard time living and need money. About one-third of the Japanese working population, 21 million, are non-regular workers with an average annual income of 1.75 million yen. As compared with regular workers with an average annual income of 4.36 million yen, the income gap is more than double. We are proposing employers who are borrowing salaries to stop deferred payments and introduce a system that allows employers to pay their employees whenever they need. The 2008 Lehman shock quickly led to a crisis of a number of companies. Non-regular workers were kicked out from dormitories.

Some of them could not pay rent as they were dismissed, sheltered in an internet cafe, which we called “internet cafe refugees,” and it was a big social problem back then. Factoring companies pay a part of their salary before the payday and take high commissions from those who are in trouble. Imagine when you are in trouble with those who afflict and create further problems, you cannot do that terrible thing.

Many non-regular worker and single-parent families tend to give up sending their children to private schools due to high tuition. Instead, they send their children to public high schools after graduating from compulsory junior high school. The educational background gap is created because there are some children who cannot go to college after high school due to the income gap of the family. In the United States, under the slave acts, foreign workers who do not have a bank account are suffering from borrowing money from loan sharks due to deferred wage payments. They sued their employers because if employers did not defer wage payments, they would not need to use and suffer from predatory loans. A prepaid payroll card has been introduced for those who do not have a bank account in the United States. It is troublesome and worried about theft for employers to give salaries in cash. Since many workers live in unsafe places, payroll cards are safer than cash, and it spreads. In Japan, despite the large number of people who do not have bank accounts, it is ignored. Many companies reject paying salaries in cash to people who do not have a bank account because it is risky. Some people have trouble opening a bank account such as for those who have failed in business and their accounts removed, for those who do not want to reveal their address due to divorce or runaway, and foreign trainees. In addition, the number of business owners who went bankrupt during the Covid-19 pandemic and cannot have a bank account may increase rapidly. Japan also needs to introduce a payroll card soon.

3.2.2 Measures to Help the Poor

If you are an employer who has a feeling of gratitude to employees as “thank you for working,” we want you to stop deferring wage payments especially for non-regular workers and low-income people. We want developing countries to switch from a “deferred payroll system” to an “real-time payroll system” and amend the law to reduce disparities, suicides, and criminals.

3.2.3 Practice of the Measures to Help the Poor

In 2008, in order to reduce poverty and disparity in Japan, we developed a cloud system that allows you to transfer your take-home wages to your bank account at any time, called “MySalary.” In 2018, at the government-sponsored National Strategic Special Zones Advisory Council in Japan, we proposed to Prime Minister Abe, Finance Minister Aso, Chief Cabinet Secretary Suga, etc. that the ban on digital wage payments using a payroll card should be lifted. Even though the Cabinet official decided it in the fall 2018, it was postponed due to the opposition of the major labor unions. However, we are working to rescue workers who are in trouble of having a bank account as soon as possible. We have launched our services in Vietnam, India, Saudi Arabia, and the United Kingdom.

3.3 Accelerate to Go Cashless with "MySalary" to Create a Safe and Secure Society

3.3.1 Summary of the Current Situation

In the 1990s, merchants began to store cash sales and change in their stores in Japan because banks closed night safes. In consequence, thieves and robberies at restaurants, retail stores and service industries have surged throughout Japan. I was struck by the Great Hanshin Earthquake on January 17, 1995, in Japan. When I returned home from the evacuation center and cleaned up, I noticed that the commemorative coins and stamps were stolen. In Nagata Ward, Kobe, wealthy people lost a large amount of cash by fires, and they became a family in relief. On March 11, 2011, during the Great East Japan Earthquake, many houses were washed away by tsunami, and money under the mattress was gone. In the countryside of Japan, there are no banks or ATMs nearby, so many people have cash for their living. They are worried that cash will disappear due to thieves or disasters. Farmers in developing countries also said that they go to the town to sell their harvest, take cash back, and bury it under the floor of their houses to hide it. However, they are worried that it could disappear due to thieves or disasters. Japan needs to rely on foreign workers due to the aging population and lack of human resources. In Japanese houses, coins are dropped under the bed, money is offered to the Buddha, and coins are there when you open a drawer. What would happen if you send a foreign care helper to such a house? If she picks up the dropped coins and brings her home, she will become a criminal. Japan would be a country that conducts sting operations and creates criminals. For many foreigners who work at a convenience store, supermarket, and restaurant, the relationship of trust between them and their managers declines every time there is a cash balance error that does not match the cash balance at the time of checkout. To eliminate such cases, we should reduce cash. If it accelerates to go cashless, accounting work will be greatly reduced and productivity will be improved, which is full of merits. In 2016, the United Nations told us that the US distributed cash from a helicopter to Iraqi people, but it was not sure if the money reached people who really needed it. So, we were asked to cooperate to develop a system that can send money to people who are in need via mobile phone. In 2017, we were asked for help by a bank in a developing country who we met at the Asia Development Bank event. They wanted to lend money to local farmers, but because there were no banks or ATMs, they could not lend. Also, because cash transportation and collection were costly, they thought that they could lend farmers with mobile money as farmers had a mobile phone. In 2018, even at the United Nations in Kenya, it was not sure whether the relief money was distributed to right persons at refugee camps, so we were asked for help to send it directly to mobile phones with Mobile Money "M-PESA."

3.3.2 Measures to Accelerate to Go Cashless

With digital money, it can recover money lost due to a disaster if it is linked with a ledger management system that records the balance. It is even more secure if you are in a mobile wallet that is connected to a telecommunication line. Since the biometric authentication system of the mobile phone can identify the person, it also has the effect of preventing identity theft.

If salary is paid in cash, cashless will be slowed, so it is effective to implement a digital wage payment to expand cashless payment. Customize our payroll system which tracks who, when and how much paid to distribute relief money to refugee camps and for those who are in trouble.

In addition, digital money could prevent fraud and intermediate exploitation because it can manage the shops, businesses, and periods that can be used.

3.3.3 Practice of the Measures to Accelerate to Go Cashless

From 2018, we support English, Chinese, Vietnamese, Swahili, Hindi, and Karnataka and support the labor laws of Vietnam, India, Saudi Arabia, and the United Kingdom. You can top up your take-home wages with Mobile Money at any time. We will continue supporting the countries with requests. We added the function, which can top up the amount of take-home wages to Prepaid Wallet and Payroll Card.

3.4 Support the Acceleration of the Spread of Digital Money with "MySalary"

3.4.1 Summary of the Current Situation

In Japan, many stores want to stop cash payments and go cashless because it is time consuming and costly to prepare changes, make mistakes in checkout, deposit sales to the bank, and carry the risk of thieves. We visited Kenya to see M-PESA, and we were accompanied by young people born and raised in Kibera, which is the largest slum in Africa. Kibera slum was a very unsanitary city with poor security, no water and sewage, and the houses were shabby. Shops in slums can hardly use cash. There is a sticker called “M-PESA” for mobile money payment. According to the young man who guided us, shops do not accept cash because they can be targeted by thieves. Of the 10 major Japanese retailers, 4 of them have an operating profit of greater than 3%, yet the transaction fee of a small Japanese business is also greater than 3%. There is no way they can afford to pay for it. This causes delay in cashless transactions. In rapidly growing populations of Asia and Africa, two-thirds of the world’s adults do not have a bank account because there are only banks in the city. In addition, it is difficult for the poor to have a bank account because of a system that automatically deducts the fee when the bank has a balance of less than a certain amount called the account maintenance fee. Instead, Mobile Prepaid, which deposits cash first, has been rapidly adopted. In Kenya, which is the most advanced country on mobile prepaid, people receive wages in cash and top up the cash to their mobile phones to change it to Mobile Money. Low-income people hesitate to use it because the top-up cost is high as agents push their costs of rent, labor, and cash transportation to consumers. Top-up fees and transaction fees are a burden and cause of restraining the expansion of cashless society. The world’s first banknote is said to be Jiaozi issued in the Song dynasty of China. From a grain deposit receipt to convertible banknotes that can be exchanged for gold and silver, and after the Great Depression in 1929, the gold standard was abolished and a monetary system managed by the Central Banks of each country was adopted. Recently, more Central Banks plan to move to digital money because banknotes incur huge costs such as printing, management, cash transportation, safe, rent, cash security, counterfeit bill detector, ATM, labor cost, and potential virus infection. Saudi Arabia has announced that it will be able to reduce costs by one trillion yen annually, and it has been officially announced that China and India will also shift to digital money. This is because when Digital Money becomes widespread, it will reduce thieves, fraud, tax evasion, and terrorist funds, resulting in a safer society.

3.4.2 Measures to Support the Acceleration of the Spread

We would like to refer to Europe in order to reduce transaction fees in Japan to about 1%. In Europe, the interchange fee for debit card is 0.2% and the credit card is 0.3% by law, so even if you include the cost of the operation support company, the settlement fee is about 1%. A news article says that the People’s Bank of China would make fees zero when sending money or paying with digital yuan. If the remittance and transaction fees become zero, donations and social tipping will become more active, which will be effective in revitalizing the economy. We hope that the case will have a positive impact on other countries. In Japan, the GDP is about 500 trillion yen, salary income is about 250 trillion yen, and the salary is used for rent, utilities, and consumption.

Assuming that all expenses are settled with digital money, and even 1% will have a market size of 2.5 trillion yen. Reduce cash payments in Kenya and developing countries, pay with Mobile Money, and top up directly to your Mobile Payments Wallet to significantly reduce your fees. We will reduce fees and support the expansion of cashless payments.

3.4.3 Practice of the Measures to Accelerate to Go Cashless

Added a function that allows people who do not have a bank account to transfer or top up wages directly from a company's bank account to an employee's wallet with Digital Money, following the wage transfer service from a company's bank account to an employee's bank account. The remittance system works with systems that use highly secure technology.

3.5 Support the Government's Securing of Financial Resources Through Automatic Tax Collection or Automatic Borrowing with "Revenue Share Finance"

3.5.1 Summary of the Current Situation

In Japan, the calculation of income tax, local tax, social insurance premium, pension, and employment insurance premium is complicated and full of exceptions, which puts a great deal of cost on an employer. It may have been complicated to increase employment, but with the aging population and declining birthrate, the labor shortage is serious. We think that it should be simplified to improve productivity. In addition, because employers who collect taxes under the withholding tax system pay taxes, there are cases where employers go bankrupt without paying taxes. There are many reports of "disappearing pensions" where the pension was deducted from the salary, but it was not paid. We found out when we received a statement at the time of receiving the pension. We think that taxes should be automatically collected at the time of paying salary, so that taxpayers can see the tax payment history. In Japan, people who pay the consumption tax are consumers. However, merchants and businesses keep the consumption tax and pay after deducting the consumption tax with purchases. This work alone is overwhelming because an employer is burdened with a great deal of cost. There are many people who have been dismissed, reduced working hours, and their income because of the Covid-19 pandemic. However, there is no way to speedily rescue those who are in serious trouble. The current situation is that applications are paper based, and government officials have to spend a great deal of time and effort investigating. If you go to a restaurant or accommodation facility in a developing country and try to make a payment with a card, you may be asked to pay by cash instead by saying that the POS is currently not working. In case of cash sales, clerks may cooperate and steal the cash, so owners want to reduce cash payments. On the other hand, there is a case that some owners request cash settlement because they do not want to pay the vat. There was a country that demonetized high-value banknotes due to a rapid increase in the number of business owners who pay a part of cash in real estate transactions where larger amounts of money evades consumption and corporation tax. In Asia and Africa, the population is rapidly increasing, and the number of people going out from the countryside to the city is increasing rapidly. The number of street sleepers is also increasing, and the slums are getting bigger and bigger.

3.5.2 Measures to Support the Government's Securing of Financial Resources

In Japan, the complicated calculation formula of salary-related tax can be made simple and easy to understand, and the moment salary is paid, the tax is automatically collected and recalculated on an annual income basis at the time of final tax return. By automating confiscation and refunds, the government can reduce tax collection costs and fraud to create a fair society. If the consumption tax paid at the time of settlement is automatically collected, the tax collection cost and fraud will be reduced. If 80% of the salary income of 250 trillion yen is used for consumption, 200 trillion yen × consumption tax = approx. 20 trillion yen can be automatically collected. If it is a settlement tax that collects tax for each settlement, assuming that GDP of 500 trillion yen will collect 20 trillion yen, the amount of tax collection will be equivalent to 4% of GDP. We are proposing to create a "Financial Data Storage Warehouse" for relief that can be quickly provided to those who are in need. Work diligently, lend a part of the earned money to the government and pay taxes, store history data in the data warehouse, so that the government will be able to support you in the event of an unexpected situation such as an earthquake, flood, storm, fire, virus, etc. Employers could not predict this Covid-19 pandemic. For such a case, if there is an environment where you can immediately check information such as the number of working days, working hours, working place, name of employer or business, take-home amount of wages, income tax, local tax, pension, social insurance premium, employment insurance premium, current address, dependents, and resident number, the government official can also check it immediately. You can also look up sales information immediately. We would like to create a safe and secure "Financial Data Storage Warehouse" that has been certified by the government. With few developing countries paying more than 5% of their population, the governments of developing countries are short of financial resources. As a countermeasure, instead of tax, the government can borrow a part of salary from people; let us say 5%, and the government returns it after 13 months, so that the working population × average monthly income × 5% × 12 months can be borrowed. If the financial resource is allocated to invest in infrastructure construction projects such as water and sewage, electricity, telecommunications, garbage disposal, roads, and housing, this can create jobs for people in slums and reduce poverty.

3.5.3 Practice of the Measures to Support the Government's Securing of Financial Resources

We were invited for a meeting with central banks of 50 countries in Abu Dhabi in 2018 and proposed that the prime ministers or presidents of developing countries borrow 5% of their citizen's wages to create financial resources and invest in infrastructure to reduce unemployment. We exchanged business cards with all 50 countries. Twenty-five countries told us to come and gave us mobile numbers. In 2019, we visited 12 countries and exchanged information.

In 2021, many developing countries suffered serious financial difficulties because of the Covid-19 pandemic. The government of developing countries where the number of unemployed has increased rapidly is encouraging the use of Mobile Money. We are proposing to secure financial resources, increase employment through infrastructure construction, and provide relief to the unemployed through a system that can automatically collect settlement tax or consumption tax at the time of settlement. In 2021, solid Japanese companies were forced to close and made significant losses due to earthquakes, floods, storms, fires, viruses, etc. Because such an unexpected event can occur, we encourage employers who value employees to store their work, salary, and sales data. Management and operating costs will be covered by using the information stored in this storage to make money. Since the cost and profit are also Digital Money, the information can be opened without hiding. We have decided to create an organization that operates and manages a reliable "Financial Data Storage Warehouse" without fraud or diversion.

We will also provide developing countries with "Financial Data Storage Warehouses" that make full use of the latest cyber security technology.

3.6 Provide a Society with Dreams and Hopes to the Poor Through "Revenue Share Finance"

3.6.1 Summary of the Current Situation

In Japan, the founders who made the manufacturing industry a large scale came up with ideas to solve problems that are occurring around them and succeeded in delivering their products and services. Of course, this is the first time to do it, so while there is no track record or funds, there was a time that a banker negotiated with his or her branch manager when a banker saw the business potential and behaviors that founders were trying to get it done by trial and error, sweating, and desperately trying to accomplish it. I also had the experience of receiving a loan from a bank branch manager when opening a hamburger shop in Hyogo 10 years after I worked as a cook in Osaka. Bankers at that time became the driving force behind Japan's economic growth, with the birth of many large manufacturing companies with their judgements. However, many banks today do not lend to people who have no track record. The government created the Credit Guarantee Association and the Japan Finance Corporation because banks do not want to take risks, and banks end up just connecting to them. I feel that the society becomes dreamless and hopeless because even motivated young people cannot start a business without money.

Japanese banks do not lend to people who have no property, no collateral, or no track record. Japanese investors only get dividends from net income, so they do not invest in people who do not want to go public. The reason is that many small- and medium-sized enterprises in Japan do not want to pay taxes. If they make a profit, they often buy luxury cars, luxury homes and offices and entertainment, so they do not pay dividends. Listed companies in Japan tend to hesitate to invest in the long-term future or in giving back to the society because their best interest is to secure short-term profits. They would ask "How much does it make to propose a new business?"

One of the reasons why this is the case is that shareholders complain if the profits are reduced by investing for the future. It seems that many shareholders do not fall in love with the company or business they invest in, but they want to make profits by selling at a higher price. Many Japanese venture capital firms buy shares low and sell them high to make profits.

I think that is the best interest for asset managers. However, in the US market, if a company has a vision and potential, rather than chasing short-term profits, it is often the case that the stock price would not fall even if it is not profitable in the short run. We hope that Japan will follow the same.

3.6.2 Measures to Provide a Society with Dreams and Hopes

To secure short-term profits, many listed companies do not invest or quit investing for the long-term or for social causes which we think hinders improvement of the social environment and economic growth. Pollutions in developing countries also show the consequence of seeking short-term profits despite the potential risk of litigation in the future. Regarding the current situation of air and water pollution, we propose a system that can extend the period of debt repayment based on the scoring for the level of social impact. With digital money, you can distribute revenue to your business partners, investors, and employees the moment sales are made. In the case of cash, it cannot be distributed unless everyone stays in the same place.

If you attempt to distribute revenue with the current bank transfer system, it will not be possible unless a large amount of transactions can be processed. There is a possibility with a "Revenue Share Finance" system that can distribute revenue at a predetermined rate at the moment of settlement. When starting a business, land, property, and equipment costs are the most costly.

However, if the bank or financial institution owns those costly assets and approves you to use the assets with a Revenue Share Finance scheme, a part of the sales will be deposited to them at a predetermined rate at the moment when sales are made. We are proposing banks to change from an era of earning interest rates to an era of earning revenue. With this business model, you will be profitable for as long as your business continues. Poor people also have an opportunity to start a business if they have technologies and ideas. We want to provide young people with an equal opportunity to start a business regardless of income level.

3.6.3 Practice of the Measures to Provide a Society with Dreams and Hopes

Digital money makes it possible to distribute revenue to business partners, investors, and employees at the moment of settlement (Revenue Share Finance). There are no bounced or unpaid payments that can happen with deferred payment. The surplus money can be used for equipment acquisition, property acquisition, and borrowing and can be automatically collected as the owner at the moment of settlement. Even if you deposit money in a bank, you not just earn little interest, but also you are not protected when your bank goes bankrupt as you can only get the compensation amount. Instead of deposit, lend it to young people who are motivated and have skills and abilities, yet they cannot afford to rent factories, stores, or machinery. Leave finance, legal, and accounting to specialists. By concentrating on your business and your customers, your sales will increase. The moment your customer makes payment, revenue will be distributed and sent to applicable beneficiaries immediately. Revenue Share Finance is a financial service that can be provided only with digital money. We would like to provide it to young people in developing countries.

Part II
Goods Market and the Future of Labor Market

Chapter 4
Model Structure of Agent-Based Artificial Economic System Responsible for Reproducing Fundamental Economic Behavior of Goods Market

Shigeaki Ogibayashi

Abstract Agent-based modeling (ABM) features its capability not only to deal with the heterogeneity of agents but also to elucidate the causal mechanism of social phenomena. The latter can be done by clarifying the model structure required to reproduce the phenomenon through systematic computer experiments. This article presents some examples of such studies that uncovered the causal mechanism of the goods market's fundamental economic behaviors, including price equilibrium, business cycles, the effect of tax cuts in both income and corporate taxes. The condition of the validity of ABM and the causal mechanism of business cycles are also discussed.

Keywords Agent-based model · Model structure · Fundamental economic behavior · Price equilibrium · Supply chain · Business cycles · Tax reduction · Causal mechanism · Validity

4.1 Introduction

Many social problems depend on government policy. In democratic societies, government policy should essentially aim to allow people of all levels to lead spiritually and materially rich and safe lives. Economic policy should be determined to effectively promote the economy, taking into account various aspects of problems such as the growth rate of , inflation rate, unemployment rate, as well as wealth inequality. However, this is not the case in reality. Most countries have various social problems, including remarkable wealth inequality between rich and poor and the issue of social welfare, which appear to be becoming increasingly serious. Japanese

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economy fails to increase GDP for more than 30 years, being unable to overcome the deflation, despite of remarkable monetary easing policy. Why is it so difficult to overcome the problem?

Underlying these problems is the fact that the true causal mechanisms of various phenomena in society are not well understood and shared among people, and the policy-making process is likely to be designed for those who have vested interests or powers. To realize a truly democratic society, it is therefore desirable to correctly understand the causal mechanisms underlying the emergence of social and economic phenomena, based on which social and economic policy by the government is scientifically backed.

In both natural and social systems, there exists a cause and causal mechanism for the occurrence of each phenomenon. In the fields of natural science and engineering, hypotheses and equation-based models concerning these causal mechanisms have been proposed based on observation of the behavior of various phenomena, which are verified by a series of controlled experiments. Thus, natural science and engineering comprise accumulated knowledge and data on the causal mechanisms of various phenomena. The background that various hypotheses have been proved by experiments, owing to which the causal mechanism of each phenomenon has been clarified, is that natural phenomena behavior is universal and unchanged over time and space. For example, an apple falls down due to the gravity, and the speed of the falling apple obeys the Newton's law of motion. This causal relationship is verified by experiments and valid all over the world without depending on the historical time. The same is true for various laws of nature. Because of this principle, hypotheses concerning causal mechanisms could be proved true or not by researchers worldwide without depending on time and space in the field of natural science.

Conversely, in the fields of social science and economics, various phenomena are caused by decision-makers' behaviors and their interactions, which change with time and place and depend on the heterogeneity of individual's intentions. In principle, it is therefore impossible to conduct controlled experiments such as those for natural phenomena in the social world. This implies that a traditional equation-based model approach is in principle insufficient to clarify the causal mechanism of social phenomena, because equation-based model is essentially based on the assumption on the causal mechanism of the phenomenon, which cannot be validated due to the impossibility of controlled experiment. Furthermore, the causal mechanisms between the causes and effects related to social phenomena are too complicated to be represented in the form of equation-based model, because the human behavior that causes changes in the state of society depends on the state of society itself, and the manner of dependence varies across individuals. Therefore, there is a limit to expressing such mechanisms with a simple set of equations in the case of social phenomena.

On the contrary, agent-based modeling (ABM) could be a powerful approach for elucidating the causal mechanisms of social phenomena, because it is a bottom-up type modeling method where only behavioral rules of individual decision-makers called agents are assumed without any assumptions relating to aggregate variables and causal mechanism. ABM is a modeling method where an artificial society is constructed on a computer, assuming the actions of multiple decision-makers. Then, a macro phenomenon emerges as a result of agents' actions and interactions. The causal mechanism of each phenomenon that emerges in the artificial society on a computer could be the same in the real world, because each of the aggregate phenomena is caused due to the agents' actions and their interaction, the principle of which is the same as in the real world. For this reason, if the assumed input conditions only include individual behaviors of decision-makers, without including aggregate factors, (i.e., if the model is entirely bottom-up), it is, in principle, possible to build a model so that the causal relationship emergent in the artificial society could be same as that in the actual system. The validity of the model is evaluated by the extent how close the model reproduces every feature of the macro phenomenon in question in the real world.

The history of ABM dates back to John von Neumann's "theory of self-reproducing automata" (von Neumann 1966). Cellular automata devised based on this theory are considered to provide the roots of ABM. One of the earliest models is Thomas Schelling's ethnic segregation model (Shelling 1969). Subsequently, "Growing Artificial Societies" written by Epstein and Axtell (1996), "Simulation for the Social Scientist" by Troitzsch Gilbert and Troitzsch (2005), and "Agent-Based Models" by Gilbert (2008) were published. Gilbert (2008) proposed the idea that a model can be roughly classified into abstract, middle range, and facsimile models in terms of the degree of precision, meaning that the first step of building an agent-based model is the abstract model followed by the middle range and facsimile models. Moreover, criticisms regarding the validity of ABM have been reported, including the argument that ABM cannot specify the necessary conditions for reproducing a specific macro phenomenon because of its inherent functional complexity (Marks 2007).

Based on the background of this history, many researchers seem to consider that although ABM is effective in offering hints on the emergent mechanisms of phenomena in the real world, it is not sufficiently reliable for elucidating the causal mechanisms to replace the traditional approach of economics. Thus, ABM has received little recognition as a promising methodology worth being used to decide public policies. Moreover, the potential of ABM for elucidating the social phenomenon stated above has not been well recognized in the literature except for one paper entitled, "Economy needs agent-based modeling" by Farmer and Foley (2009).

However, as many modelers have probably experienced, ABM emerges different macro phenomena with different input conditions that are assumed. For example, suppose the emerged phenomenon in ABM under a particular set of behavioral rules differs from that in the real world in its feature. In that case, modelers might change the input conditions until the model reproduces the features of a macro phenomenon in question. It is also noted that not all factors of the input condition change the characteristics of the macro phenomenon that is the output, even at a qualitative level. Among the factors for a specific input condition, the set of factors that are indispensable for the emergence of the macro phenomenon is considered the cause of the macro phenomenon in question; therefore, there is a causal relationship between the input condition that consists of a set of indispensable factors and the macro phenomenon. The input condition comprises agents' types, behavioral rules, and attribute variables. Because combining these factors can provide a model structure simulating a real system, let us refer to the input condition as a model structure below.

Suppose we perform a series of computer experiments that systematically change the model structure until the model reproduces every feature of the macro phenomenon in question. Then, by conducting this procedure, we can elucidate the model structure indispensable for reproducing the characteristics of a macro phenomenon observed in the real world. In such a model, the causal relationship between the model structure and the macro phenomenon in the model can represent the causal relationship in the real world. Next, by considering why factors in the model structure clarified by computer experiments are indispensable, it is possible to gain a better understanding of the causal mechanism of that phenomenon.

The author has found that there are indispensable model structures for reproducing various socio-economic phenomena. Considering why the model structure was indispensable confirmed that the extracted causal mechanism was reasonable.

This chapter describes the model structure of an agent-based artificial economic system responsible for reproducing fundamental macroeconomic phenomena. Those phenomena include price equilibrium, supply chain, business cycles, positive effects of a tax cut for income, and corporate taxes, which are research examples for elucidating the causal mechanism of fundamental macroeconomic behaviors.

Among these phenomena, the positive effects of a tax cut for income tax and corporate tax are the phenomena whose indispensable factors for the reproduction in ABM are the most systematically elucidated, followed by the business cycles.

4.2 The Model

The details of the model are described in the form of ODD protocol shown in the Appendix. The outline of the model, the action sequence, and behavioral rules of agents are shown below.

4.2.1 Outline of the Model

The agent-based model of the artificial economic system in the present study includes consumers, producers, a bank, and a government as autonomous decision-making agents. The type of agents and their behavioral rules are shown in Table 4.1, which are changed depending on the experimental levels. Consumers are divided into three types of agents: workers as the base type, executives who are included or

Table 4.1 Outline of agents and their behavioral rules

Agent	Type	Output to be supplied	Product type to purchase	Outline of behavioral rules
Consumer	Worker	The labor force for firms	Consumer goods	Consumers work and obtain the wage from the producer, bank or government, pay tax, and purchase consumer goods. A part of the income will be deposited in the bank account as per the Keynesian consumption function. Buying consumer goods is performed according to the utility which each consumer uniquely holds. Consumers transact in the stock market, aiming to increase their assets when the model includes the stock market
	Executive	Management for firms		
	Public workers	The labor force for government		
Enterprise				Enterprises employ consumers, get profits from operating activities, and pay wages and tax
Producer				Producers supply and sell products in the goods market
	Retailer	Consumption goods	Consumer goods	Retailers and raw material makers decide both the quantity and price of each class of product to be produced based on the number of goods in stock. If necessary, they invest in equipment based on the demand to expand production capacity
	Raw material maker	Material goods	Materials, equipment Consumer goods Equipment	
	Equipment maker	Equipment	–	
Bank	Bank	The fund for producers' investment	–	The bank keeps the surplus money of other agents in their respective bank accounts and lends money to firms for investment
Government	Government	Redistribution of wealth	Consumer goods	The government collects tax from other agents, pays wages to public workers, and spends the remaining money on public expenditure

not in the model in the analysis of the effect of corporate tax reduction and public workers when the government is taken into account in the study of the effect of tax reduction. Producers are divided into three types of agents, i.e., retailers, raw-material makers, and an equipment maker, as shown in Table 4.1. Markets are also divided into three types: a goods market as the base type, which includes the markets for consumer goods and material goods, a stock market when it is taken into account in the analysis of business cycles, and a labor market when it is taken into account in the study of the effect of tax reduction.

Each agent is heterogeneous in its state variables including initial value of bank deposits as well as in the other parameters included in their behavioral rules.

4.2.2 Sequence of Actions

The set of activities of each agent constitutes period-based units, where one period is assumed to correspond to 1 month in the real system. During each period, agents act according to the sequence of eight steps. At the end of the series of actions in each period, a GDP value is calculated based on an input-output table obtained by summing each agent's account data. The eight steps dictating the agents' actions are as follows:

1. Agents pay any unpaid tax from the previous period. After paying taxes, agents create a budget plan for consumption, paying wages, or public spending.
2. Raw-material makers decide on the quantity and price of products to be produced, produce several types of raw materials, and supply these to the material goods market.
3. Retailers decide on the quantity and price of products to be produced, purchase raw materials in the material goods market, produce several types of consumer goods, and supply these products to the consumer goods market.
4. Consumers, retailers, raw-material makers, and the government purchase products in the consumer goods market.
5. Each firm pays wages to employees and executive compensation to the executives while the government pays salaries to public workers.
6. Retailers and raw-material makers consider expanding production capacity based on total sales in the previous periods, and, if necessary, they decide to invest to increase production capacity by buying new equipment from the equipment maker. When the labor market is taken into account in the model, employing a new worker is another alternative for them to expand production capacity, which is to be chosen depending on the financial merit.
7. When the model includes a stock market, consumers buy or sell stocks aiming to increase their financial assets.
8. Each agent settles its accounts using the double-entry bookkeeping method. They calculate their income and profit for the current term and then determine the amount of tax to be paid based on these figures.

4.2.3 *Outline of Agent's Decision-Making Rules*

4.2.3.1 Behavioral Rules of Consumers

Consumers create a budget for consumption $E_b{}^t$. This budget is calculated by adding after-tax income $I^t(1 - r_{i\_\mathrm{tax}})$, which represents the Keynesian consumption function (Keynes 1936), to the money withdrawn from the deposit described as their bank deposit D^t multiplied by a withdrawal ratio r_{wd} at each fiscal period t. The formula for the budget is shown in Eq. (4.1). Here, r_{i_tax} is the income tax rate, a is the consumer's autonomous consumption, and b is the marginal propensity to consume as per the Keynesian consumption function. The withdrawal ratio r_{wd} is selected randomly for each agent during each period.

$$E_b{}^t = a + bI^t\left(1 - r_{i_{\mathrm{tax}}}\right) + r_{\mathrm{wd}}{}^t D^t \tag{4.1}$$

When purchasing products in the consumer market, consumers select goods based on their utility and affordability (as determined by the utility function for each class of products and the agent's budget constraint, respectively). Moreover, when a stock market is included in the model as an experimental level to analyze the reproducibility of business cycles, consumers buy or sell stocks aiming to increase their financial assets. The details of the consumers' action rules in the stock market are described in the author's previous study (Takashima et al. 2014).

4.2.3.2 Behavioral Rules of Producers

The retailers and raw-material makers both decide the quantity and price of their product at the beginning of each period. The price of each product is increased or decreased depending on the number of goods they held in stock at the end of previous period. The quantity to be produced is decided in such a way that the probability of being out of stock must be less than 5%; this is estimated based on total sales from the last ten periods.

The production capacity Y is defined by the Cobb–Douglas function (as shown in Eq. (4.2)), where K is the number of units of capital equipment, L is the number of employees, and α is assumed to be 0.25. Besides, A is a bounded proportionality constant representing the total factor productivity that is randomly assigned being assumed to be unique to each producer i.

$$Y_i\,(K, L) = A_i K^{\alpha} L^{1-\alpha} \tag{4.2}$$

Retailers and raw-material makers initially have one unit of equipment and a specified number of employees. They will invest to increase their production capacity by buying an equipment from the equipment maker when their products produced at maximum production capacity continued to be sold out at each period during a specified number of periods. When the model includes the labor market as an experimental level, they have two choices for performing investment: buying a piece of equipment from the equipment maker or employing a new worker from the labor market, depending on the financial merit.

When investing in equipment, they may finance the funds by either borrowing from the bank, issuing new shares in the stock market, using their internal funds, or using some combination thereof. The funds financed by the bank are repaid with interest in equal-sized payments each period for a constant number of consecutive periods. An upper limit of the number of loans is placed on total investment so that, during the repayment period, additional financing will be limited. The equipment makers produce equipment following the requirements from retailers and raw-material makers as long as it is within their production capacity. In the present study, the price of the equipment is assumed constant. The details of the decision-making rules for investment and financing were described in the author's previous study (Takashima et al. 2014; Takashima 2014; Ogibayashi and Takashima 2019), as well as the ODD protocol described in the Appendix.

One executive and several workers are initially assigned to each of the producer agents. The producers pay wages to workers and wages plus executive compensation to the executive in each period. The executive compensation comprises a salary, a bonus, and long-term incentives. Wages comprise a fixed salary and a bonus, which are randomly assigned to each employee between a lower and an upper limit. The bonus is assumed to be paid only when the producer's profit is positive.

4.2.3.3 Behavioral Rules of the Bank

The bank lends money in the form of long-term loans to producers (in line with their demands for investment), charging a 3% interest rate. The bank also lends money to producers in the form of short-term loans so that they may meet their requirements when their working capital to pay fixed wages and or purchase raw materials becomes sufficiently depleted. In the present study, the bank is initially given a massive quantity of funds so that there is no limitation on lending to producers, except in the case where the firm applying for a loan has already borrowed funds being during the repayment period, and the number of loans has already reached the upper limit. This limitation of borrowing especially restricts the investment when the upper limit of the number of loans is assumed to be one, which is two in the case of the base model.

4.2.3.4 Behavioral Rules of Government

The government collects corporate and income taxes, pays wages to public employees, and uses the surplus funds for public expenditure, as dictated by their expenditure policy. Public employees' salaries are calculated in each fiscal period so that they are equal to the average income of private employees.

Government expenditure is assumed to consist of market purchasing and firm subsidy. Market purchasing is an extreme form of efficient public expenditure in which the government directly purchases goods at the market price with the same behavioral rules as the consumers. In the case of public investment, this policy corresponds to the government placing job orders with firms at the market price in an entirely competitive situation. The subsidy for firms is an extreme form of inefficient public expenditure in which the government distributes funds to producers, without any limitations on their use. In this case, most of the funds distributed could be transferred to the bank account without being used in the market. This policy corresponds to the government placing job orders at a value far above the market price or paying money for jobs that have no economic value.

The ratio of the expenditure for the subsidy for firms to the total spending is defined as the inefficiency of government expenditure.

4.3 Simulation Conditions

4.3.1 Simulation Conditions for Reproducing Price Equilibrium

The type of agents included in the model are consumers and retailers. The income of each consumer is randomly assigned as a constant value defined at the start of simulation to evaluate whether the price of each class of products tends to become a constant value after the multiple periods. Their behavioral rules are essentially same as described in Sects. 4.2.3.1 and 4.2.3.2. Namely, the consumers buy the products supplied by retailers every period to maximize the individual's utility within the limit of disposable income. The disposable income is assumed constant at the beginning of every period. The weights of utility for each class of product are randomly assigned to each agent and the exponent of the number of products for the utility is assumed -2. If the products of same class are available in the market with a different prices, the consumers buy the products of lowest price. Thus, the consumer's buying strategy is low-price oriented.

Each retailer increases or decreases the price and the number of products depending on the number of stocks at the end of the previous period. More precisely, the producer increases the price if the number of stocks equals zero and decreases it if that number exceeds zero and the price is lower than the average price in the market. Thus, the producer's adjustment of production and pricing for each class of product is stock-control oriented. Moreover, the quantity to be produced is decided in such a way that the probability of being out of stock must be less than 5%; this is estimated based on total sales from the last ten periods.

The case where the decision-making of price change does not depend on the average price in the market is also analyzed as an experimental level and the increasing and decreasing rates are also experimentally changed.

The case where the production quantity is changed with a constant increasing or decreasing rate is also analyzed as an experimental level.

4.3.2 Simulation Conditions for Reproducing the Effect of Supply Chain

In this case, a raw-material maker is added as additional type of producer who produces raw material products for retailers. Therefore, the retailers buy raw-material products from the raw material market and produce the products for consumers and supply them to the retail market. The production capacities of retailers and raw-material maker are randomly assigned to each producer, and their upper and lower limits are changed experimentally. Each consumer is randomly assigned to each retailer or raw-material maker as a worker and the wage for each consumer is paid by the retailer or the raw-material maker, i.e., the employer. The wage is paid to each of the worker which is decided every period depending on the total sales, and the total sales of retailers is the sum of the money paid by consumers for buying the products in the retailer market.

Thus, the consumer's income varies every period and the funds circulate among retailers, raw-material makers, and consumers.

4.3.3 Simulation Conditions for Reproducing Business Cycles

In this case, an equipment maker and a bank are added as additional types of agents. The behavioral rules of the equipment maker and the bank are described as in Sects. 4.2.3.2 and 4.2.3.3. The behavioral rules of investment and financing are added as producers' decision-making processes. Each agent settles the account each period using double-entry book keeping. By summing up those account data, the input-output table and GDP values are calculated at the end of each period in the similar manner in the real world. The factors regarding investment in equipment and the means of financing said equipment are changed as input conditions to find the necessary model structure for reproducing periodic change in GDP (i.e., a business cycle).

The changes in consumers' wages and the amount of money spent on investing in equipment are also analyzed. The criteria of the producers' decision-making on investment as experimental levels include the case based on demand, the case without investment, the case with random investment at a fixed interval, and the criterion based on internal rate of return as shown in Table 4.2. In the case based on internal rate of return, the producers decide to invest when the internal rate of return is expected to be greater than the interest rate which is assumed to be constant. This criterion on investment corresponds to the case of decision-making

Table 4.2 Simulation conditions for the analyses of business cycles

			Basic model	Analysis of investment rules	Analysis of financing rules	Analysis of MEC model
Action rule	Producer	Decision-making rule of equipment investment	Based on demand	No investment/random	Based on demand	Based on an internal rate of return
		Rule of financing	Bank financing and internal funds	Bank financing	Using internal funds/issuance of stock	Using internal funds
		Rule of executive compensation	Without	Without		
		Deletion of equipment	Without	Without		With
		Price of equipment	Fixed	Fixed		Variable
		Upper limit on the number of loans	Limited (one)	Limited (one)		Unlimited
	Consumer	Rule of withdrawal deposit	With	With		
	Government	Taxation	Without	Without		
Market		Goods market	With	With		
		Stock market	Without	Without	Without/with	Without
		Labor market	Without	Without		

based on the marginal efficiency of capital (MFC) proposed by Keynes (Keynes 1936). Here, the internal rate of return is calculated using the expected value of the investment's marginal productivity, the price of the product, and the operating ratio of the equipment. The life of the equipment is assumed to be 60, and the price of the equipment is assumed to be $EP^{t+1} = EP^{t}(1 + 0.1\,(O^{t}/Y))$, where EP^{t} is the price of the equipment in period t, O^{t} is the number of equipment orders received in period t, and Y is the production capacity of the equipment maker (Takashima and Ogibayashi 2014). The means of financing the funds for buying one unit of equipment as experimental levels include the case with bank financing, the case with internal funds, the case with the issuance of stock and the combination of them. In the base model, funds for investment are assumed to be financed from the bank in half and internal funds in half.

Thus, the factors relating to the model structure changed in this case are decision-making rules on investment and financing rules for investment, the number of experimental levels of which are four in the former and three in the latter, respectively.

The simulation conditions for the analysis of business cycles are summarized in Table 4.2.

4.3.4 Simulation Conditions for Reproducing the Effect of Income Tax Reduction

A government and executives are added to the base model as additional types of agents and consumers are divided into the public and private workers and executives. Paying tax is added to the base model as additional behavioral rules for consumers who pay income tax and for firms who pay corporate tax. Paying executive compensation is also added as an additional behavioral rule for firms. The firms' decision-making on investment is assumed to be based on demand, and the necessary funds are assumed to be financed from the bank in half and internal funds in half. The upper limit of the number of loans is assumed as two. The behavioral rules of government are also added to the base model which are characterized by the inefficiency of government expenditure as defined in Sect. 4.2.3.4. The inefficiency of government expenditure is changed between 0 and 100% with 10% intervals.

The parameter values which are changed to analyze their influences on GDP are the following. First, the income tax rate is varied between 10% and 30% with a 5% interval, and the executive compensation is changed from 0 to 0.5. The withdrawal ratio is varied between 0 and the maximum value, which is assumed to be 0.2, or 0.5 or 0.8. Changing the withdrawal ratio corresponds to altering the marginal propensity to consume as given in Eq. (4.1).

4.3.5 Simulation Conditions for Reproducing the Effect of Corporate Tax Reduction

The base model is the same as in Sect. 4.3.4. Paying executive compensation for firms is changed as being included or not as an experimental level. The upper limit of the number of loans is also changed from one to three as an experimental level to clarify the influence of the mitigation of credit rationing on the positive effect of corporate tax reduction on GDP. The inefficiency of government expenditure is changed between 0 and 100% with 10% intervals.

In this study, the influence of the inclusion of a labor market is also analyzed as one of the experimental levels, because it is well known that corporate tax reduction results in reducing unemployment in the real system (Sakuma et al. 2011) which could contribute the emergence of the positive influence of corporate tax reduction. In the model taking into account the existence of labor market, it is additionally assumed that the firm can decide either to invest in equipment or to employ a new worker depending on the financial merit when it needs to expand the production capacity. In the latter case, the firm puts a help-wanted advertisement in the labor market to employ a new worker. On the other hand, if a firm goes bankrupt, the workers in the firm become out of work, applying for a new job in the labor market, while getting unemployment benefits from the government. The details of the behavioral rules of producers when there is a labor market are described in the author's previous study (Ogibayashi and Takashima 2014).

The parameter values changed to analyze the influence of the factors mentioned above on GDP are the following. For the analysis of corporate tax reduction, the corporate tax rate is varied between 10% and 30% with a 5% interval, the income tax rate is assumed to be 20%, executive compensation is changed as 0.75, 0.85, and 0.95, and the withdrawal ratio is changed between 0 and 0.5. In addition, the inefficiency of government expenditure is varied between 0% and 100%, with a 10% interval for both analyses.

Thus, the factors relating to the model structure changed in this experiment are:

- The inefficiency of government expenditure
- The inclusion of executive compensation
- The use of internal funds for investment
- The upper limit of the number of loans (i.e., mitigation of credit rationing)
- The inclusion of the labor market

The simulation conditions for the analysis of income tax and corporate tax reductions are summarized in Table 4.3.

The factors represented by the yellow area shown in Table 4.3 are systematically changed in the simulation to elucidate their effect on the tendency of the emergence of the positive influence of the reductions in income tax rate and corporate tax rate on GDP.

Table 4.3 Simulation conditions for the analysis of income tax and corporate tax reductions

		Influence of income tax		Influence of corporate tax	
		Inefficiency of government expenditure	Rule of agents	Inefficiency of government expenditure	Rule of agents
Agent	Consumer	150			
	Retailer	30			
	Raw material maker	6			
	Equipment maker	1			
	Bank	1			
	Government	1			
Rules of producers	Rule for investment	Based on demand			
	Rule for financing	Loan and internal funds	Loan/loan and internal funds	Loan and internal funds	Loan/loan and internal funds
	Rule of executive compensation	With	With/without	With	With/without
	The upper limit on the number of loans	Limited (one)	Limited (one)/limited (three)	Limited (one)	Limited (one)/limited (three)
Rules of consumers	The rule of withdrawal deposit	With	With/without	With	With/without
Rules of government	Inefficiency of government expenditure	0~100% (10% interval)	30%	0~100% (10% interval)	30%
	Income tax rate	10%, 20%, 30%	10%, 20%, 30%	Fixed 20%	Fixed 20%
	Corporate tax rate	Fixed 20%	Fixed 20%	10%, 20%, 30%	10%, 20%, 30%
Market	Goods market	With			
	Stock market	Without			
	Labor market	Without	With/without	Without	With/without

4.4 Simulation Results

4.4.1 *The Necessary Model Structure for Reproducing Price Equilibrium*

Under the condition where the consumers buy products of cheaper and more preferable ones from the viewpoint of utility within the limit of disposable income and the producers increase or decrease the number to produce and the price of products depending on the number of unsold products at each period, the average price, and the number of products supplied tend to become a constant value without depending on their initial values when consumer's income is assumed constant as shown in Figs. 4.1 and 4.2 (Takashima 2014). Under this condition, the number of products supplied tends to become the number of bought products, and the price changes to become a constant value accordingly as shown in Fig. 4.3 (Ogibayashi and Takashima 2010).

Namely, in addition to the heterogeneity in the agents' behaviors and attribute variables, the consumer's low-price oriented buying strategies and producer's stock-control oriented strategies of adjusting the number to produce and the price of the products are the indispensable factors in the model structure to reproduce the equilibrium of the price and production quantity.

The ways of adjusting the number and the price of products to produce at each time step affect the time required to become the equilibrium state and the variation of the number of stocks. However, they are not indispensable factors of price equilibrium because they do not affect whether the price and production quantity become an equilibrium state or not. Likewise, the average-price-dependent decision-

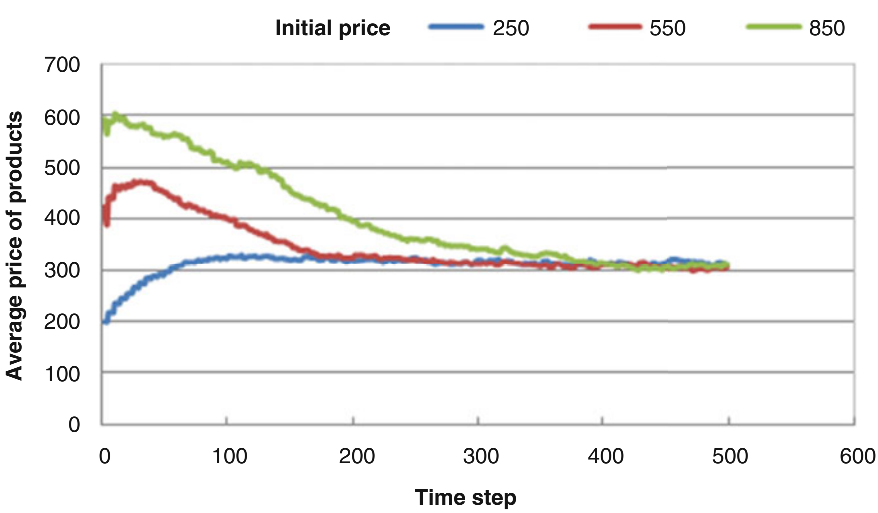

Fig. 4.1 The change in the price during the time step, reaching the equilibrium state

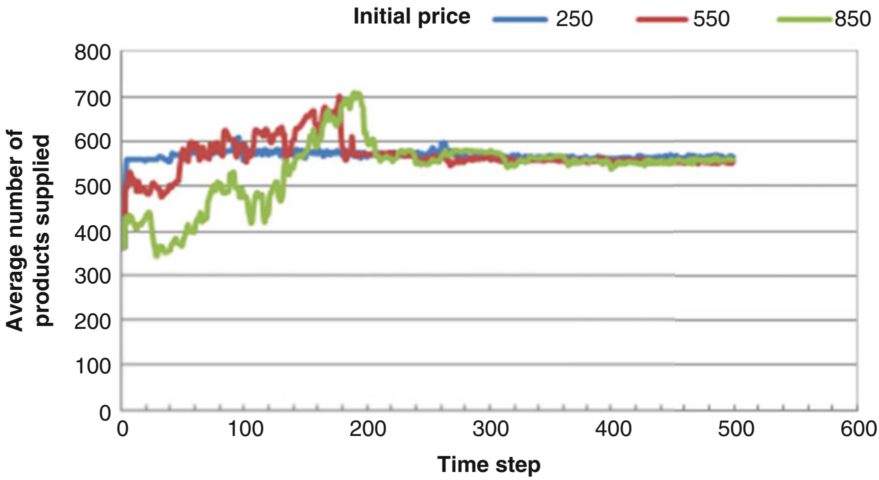

Fig. 4.2 The change in the number of products supplied to the market during the time step, reaching the equilibrium state

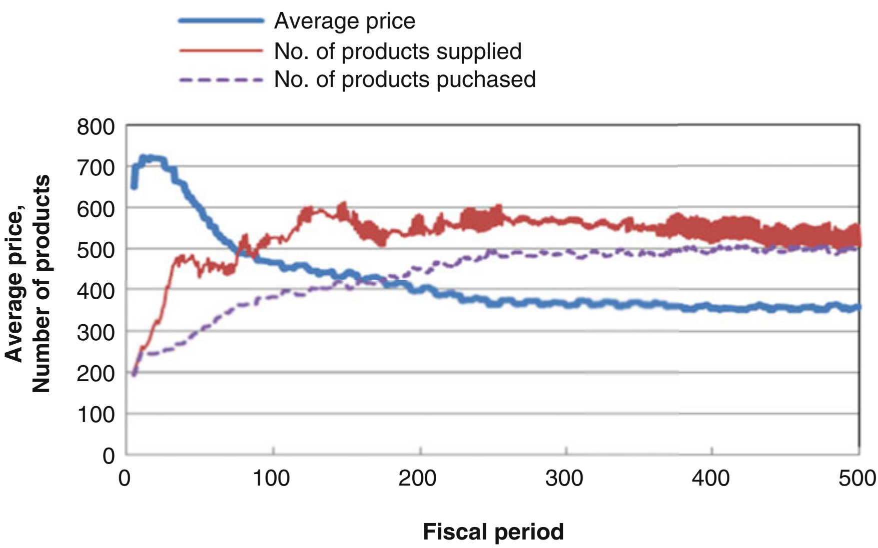

Fig. 4.3 The change in the average price of products and the numbers of those supplied and purchased, showing those values tend to become an equilibrium state

making of the price change influences the variation of the number of stocks of each agent at each time step. However, it is also not an indispensable factor because it does not affect the attainment of price equilibrium.

In this model, the price of products is not unique because each producer decides the price and supplies the products independently. Because of the low-price-oriented

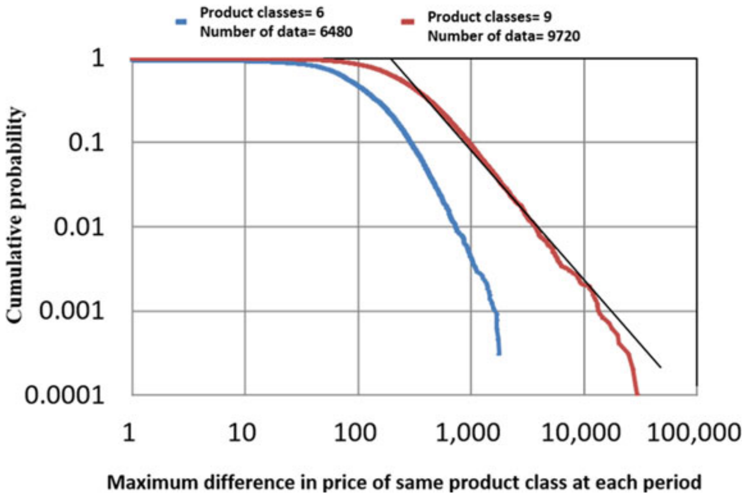

Fig. 4.4 Cumulative probability in the maximum difference in price of same product class at each period, showing the price difference at each period obeys power law distribution

buying strategy of consumers, cheaper products sell out preferentially, and the more expensive products remain unsold in the market at each period. As shown in Fig. 4.4, the maximum difference in the price of products purchased at each period obeys power-law distribution. Figure 4.4 is depicted based on the data presented in the reference (Takashima 2014). The fact that the maximum difference in the price follows power-law distribution suggests that the artificial system of the present model is a complex one.

4.4.2 Necessary Model Structure for Reproducing the Effect of Supply Chain

The feature of the effect of supply chain is that production amount and the price of products of producers of one type depends on the production capacity of producers of another type who supply the raw material to the producer of first type.

Under the simulation conditions described in Sect. 4.3.2, this feature of supply chain is well reproduced by the model as shown in Figs. 4.5 and 4.6. Namely, as shown in Figs. 4.5 and 4.6, the number of products supplied by retailers is dependent on the production capacity of raw-material makers, and the average price of retailers' products increases with a decrease in the production capacity of raw-material makers.

In Figs. 4.5 and 4.6, the set of numbers for the production capacity of raw-material makers such as 20–40, 30–60, 40–80, and 50–100 represent the lower and

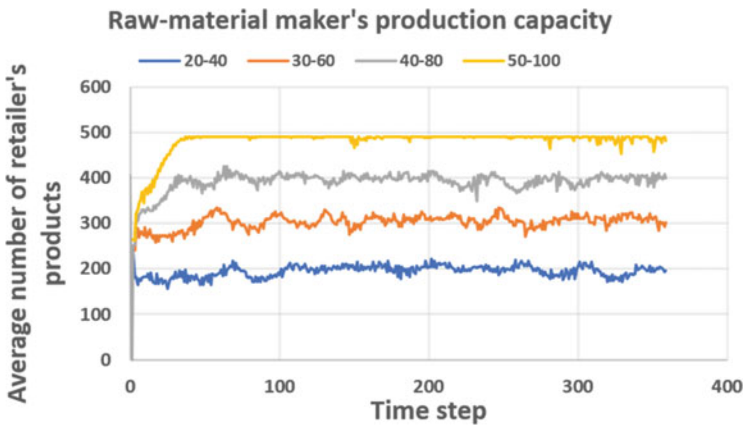

Fig. 4.5 The change in the number of retailer's products with time, showing the effect of supply chain in the number of products in the market

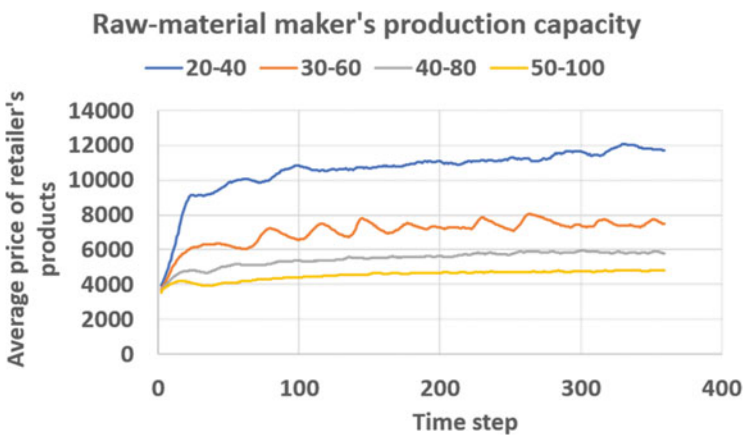

Fig. 4.6 The change in the price of retailer's products with time, showing the effect of supply chain in the price of products in the market

upper limit of the production capacity, between which the production capacity is randomly assigned to each agent.

Note that the difference between this model and the model described for price equilibrium is that this model includes raw-material makers as an additional class of producers and that funds circulate among agents. Namely, as for the fund circulation, the producers pay the wages based on the sales at each step, which becomes the consumers' income. The behavioral rules of consumers and producers are the same as those of the model described for price equilibrium. However, each worker's wage is assumed to be the total sales of the employer per capita for simplicity.

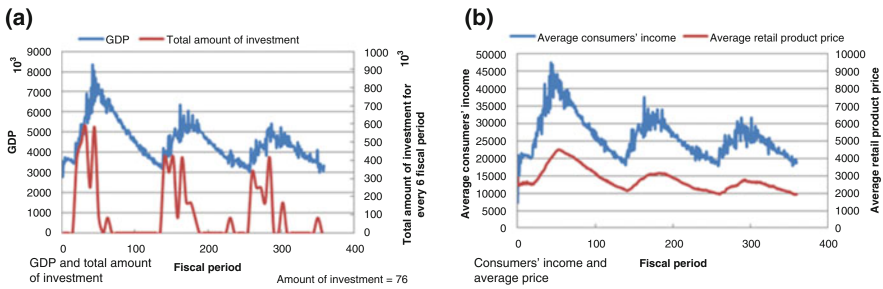

Fig. 4.7 Change in GDP and total amount of investment (**a**) and average consumer income and average consumer price over time (**b**) under the conditions of the base model (bank financing and investment decision-making on the basis of demand)

Thus, in the case of the funds' circulation model, the effect of a supply chain is automatically reproduced without changing the essential behavioral rules of consumers and producers employed in the price-equilibrium model.

4.4.3 The Necessary Model Structure for Reproducing Business Cycles

Figure 4.7a, b (Ogibayashi and Takashima 2019; Takashima and Ogibayashi 2014), and Fig. 4.8 (Ogibayashi and Takashima 2019) show the simulated results under the base model condition, in which it is assumed that investment decision-making is conducted based on demand, and the necessary funds for investment are financed from the bank with fixed repayment periods in half and internal funds in half. Here, it is confirmed that the inclusion of internal funds in addition to the bank financing is not essential because similar results are obtained in the case with bank financing only. Figures 4.7a and 4.8b show that the cyclical changes in GDP, which incorporate the synchronized movements in the average price of consumption goods and average consumer income, are reproduced showing the emergence of business cycles. Moreover, the level of aggregate funds for investment is high during the period of a booming economy where GDP is increasing (see Fig. 4.7a).

As shown in Fig. 4.8 (Ogibayashi and Takashima 2019), an increase in investment also results in an increase in the level of workers' wages at equipment makers during the same period of a booming economy, which induces the following increase in the level of workers' salaries at retailers.

From these results, the business cycle mechanism reproduced by the base model is as follows. In the beginning periods of the booming stage, some firms with strong sales decide to invest in equipment, causing an increase in the wage levels of workers at equipment makers, which induces an increase in demand, wages, and other firms' investment at the aggregate level. After the majority of producers have made their

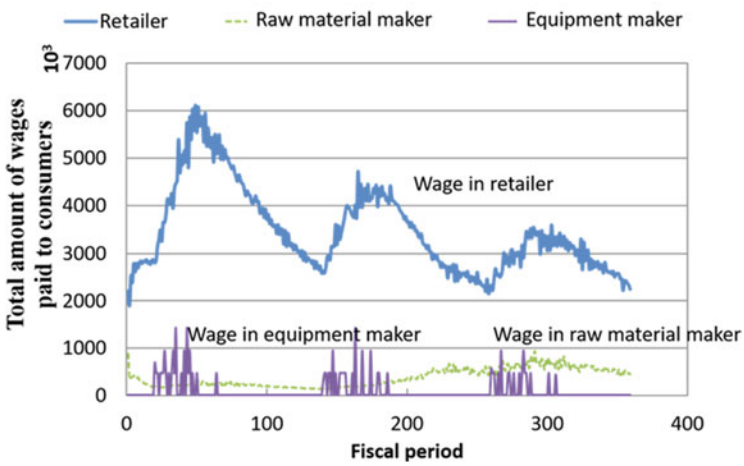

Fig. 4.8 Change over time in consumer's wage over time under the condition of the base model (bank financing and investment decision-making on the basis of demand)

investments, the total amount of repayment per period becomes more significant than the total amount of borrowing because of credit rationing. This flow of funds from the market to the bank induces a decrease in total sales, workers' wages, and investments, thus resulting in a recession. The details of the behaviors of this flow of funds were described in the author's research article previously (Ogibayashi and Takashima 2019, 2010; Takashima and Ogibayashi 2014).

When we assume that producers either do not invest (i.e., there is no debt) or conduct investment randomly, with no regard to total sales, there is no periodic change in GDP, as shown in Fig. 4.9 (Ogibayashi and Takashima 2019). Therefore, we can conclude that the model must incorporate endogenous decision-making about capital investment based on demand to reproduce business cycles.

Moreover, the model must incorporate a certain level of synchronization in investment among agents because business cycles do not emerge when the investment is randomly conducted in time, as shown in Fig. 4.9. However, this synchronization in investment is automatically established in the case of demand-based decision-making for investment, as shown in Fig. 4.8.

Financing from the bank (i.e., loans) is another responsible factor for reproducing business cycles. As shown in Fig. 4.9, when investment is financed by issuing new shares in the stock market without borrowing from the bank, periodic changes in GDP (i.e., business cycles) do not emerge. The business cycles do not appear in the case of financing by the issuance of stock only because the funds financed by the issuance of stock are not required to pay back, and there is almost no specific restriction for conducting additional investment concerning funding. This result indicates that bank financing for investment where repayment is incorporated is indispensable for reproducing business cycles.

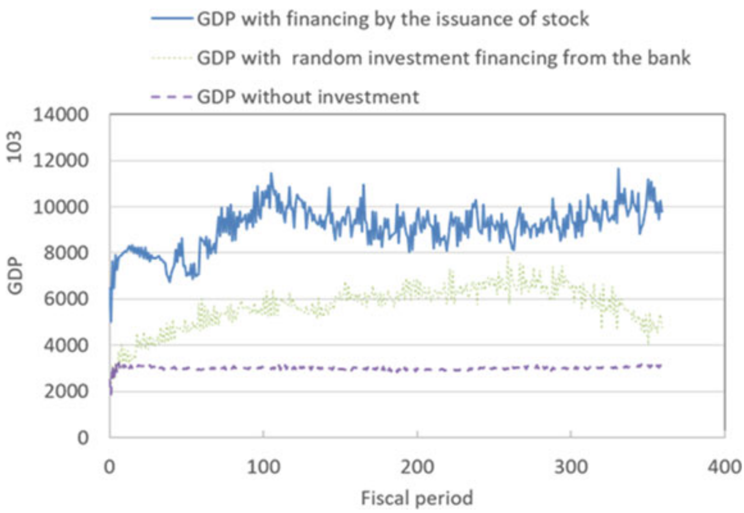

Fig. 4.9 Changes in GDP over time in the cases without investment, with random investment financed from the bank, and with demand-based investment financed by the issuance of stock

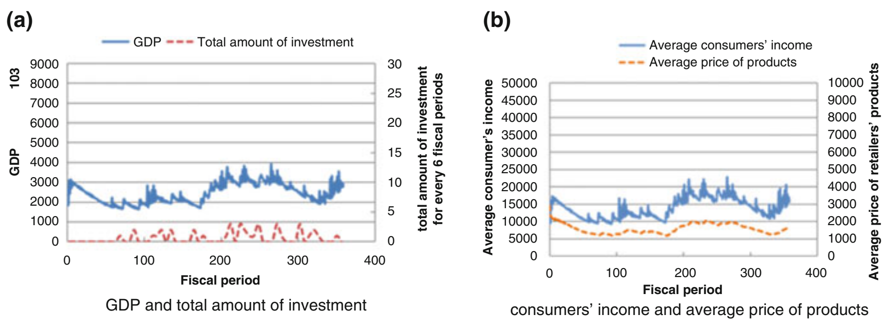

Fig. 4.10 Changes over time in GDP and the total amount of investment (**a**) and average consumers' income and the average price of retailers' products (**b**) in the case with demand-based investment financed only by internal funds

When only internal funds finance the investment, GDP shows slight cyclical variations, as shown in Fig. 4.10a (Ogibayashi and Takashima 2019). Moreover, this variation in GDP incorporates cyclical fluctuations in the average price of products (i.e., consumer price) and consumers' income, as shown in Fig. 4.10b (Ogibayashi and Takashima 2019). This result indicates that the variation in GDP shows a kind of business cycle caused by the requirement for the time interval for firms to raise funds for additional investment. However, financing by internal funds is not a major cause of business cycles because of the following facts, as shown in Fig. 4.10b, c. First, the amplitudes of the variations in GDP and consumers' income and the average price of products are very small. Next, the period correspondence between GDP and the amount of investment is not clear compared to those with bank financing.

These results indicates that the indispensable factors for reproducing business cycles would be bank financing where repayment is incorporated, demand-based investment decision-making, and a certain level of synchronization among agents in investment. Here, the model must also include indispensable factors in the model structure for reproducing price equilibrium. Those factors are consumers' low price-oriented buying strategy and producers' stock-control-oriented adjustment strategy of the price and number of products, as well as the heterogeneity of agents' behavioral rules and attribute variables.

On the other hand, Keynes proposed that the marginal efficiency of capital (MEC) is the primary determinant of the business cycle (Keynes 1936). This, in turn, implies that the internal rate of return is the essential factor underlying business cycles. Following this reasoning, an additional experiment was conducted in which producers decide to invest when the internal rate of return is expected to be greater than the current interest rate and the funds for investment are assumed to be financed by internal funds only (i.e., without bank financing). Calculated chronological change in GDP and average price of products indicates that the cyclical variations, namely business cycles, do not emerge under this experimental condition, as shown in Fig. 4.11 (Ogibayashi and Takashima 2019). Not that the price of equipment as well as internal rate of return also does not show cyclical variations, as shown in Fig. 4.12 (Ogibayashi and Takashima 2019). The primary reason for this is that there is little to no change in the aggregate capacity of supply. Decreases in production capacity suffered by some producers due to the scrapping of equipment are balanced out by the surpluses of others. As such, without bank financing, variation in production capacity due to the scrapping of or investment in equipment cannot, by itself, influence the price of the retail product or the expected

Fig. 4.11 Changes over time in GDP and the average price of products in the case with financing by internal funds only, where investment is judged based on the internal rate of return

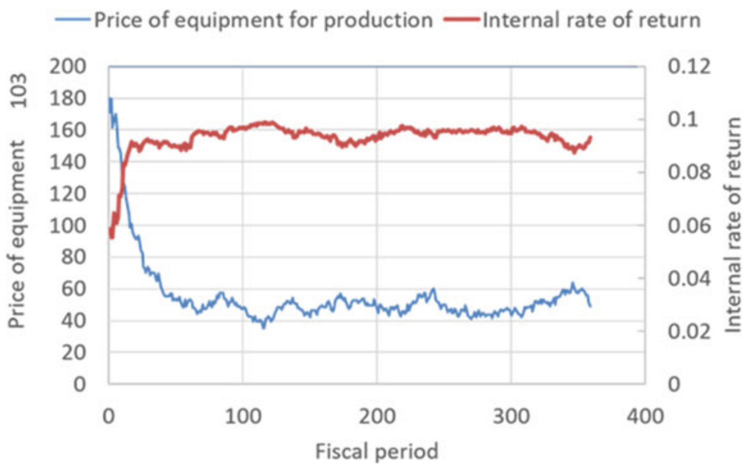

Fig. 4.12 Changes in the price of equipment and internal rate of return over time

return. Therefore, marginal efficiency of capital is not considered a major factor for generating business cycles when there is any degree of surplus in the aggregate production capacity.

Thus, the marginal efficiency of capital proposed by Keynes is not an indispensable factor for reproducing business cycles.

Therefore, as mentioned above, we can conclude that the indispensable factors for reproducing business cycles would be:

- Demand-based decision-making for investment
- Bank financing where repayment is incorporated
  (i.e., credit creation with some restriction)

Now, by considering the reason why these factors are indispensable for reproducing business cycles, we can get better understanding of the causal mechanism of the emergence of business cycles, which is considered as follows.

The bank financing for investment (i.e., credit creation) increases the funds circulating in the market, which increases someone's income and promotes the economy. In contrast, the repayment of funds forces the funds circulating in the market to flow back to the bank, which decreases the circulating funds, decreasing someone's income and deteriorating the economy. Thus, although investment could promote economy by increasing the productivity, the essential mechanism of the business cycles is the flow of funds between the bank and the market.

Note that the model structure required to reproduce business cycles mentioned above is enough to reproduce the positive correlation between GDP growth rate and the increasing rate of consumer price. As can be seen in Fig. 4.7a, b, cyclical changes in GDP incorporate the synchronized movements in the average price of consumer goods as well as the average consumer income. Figure 4.13a (Ogibayashi and

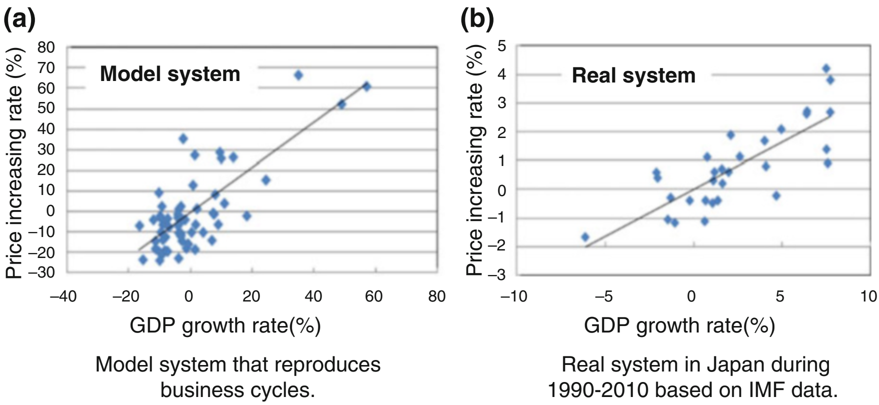

Fig. 4.13 Relationship between increasing rate of average price and GDP growth rate in the model system and the real system in Japan based on IMF data during 1990–2010. (**a**) Model system that reproduces business cycles. (**b**) Real system in Japan during 1990–2010 based on IMF data

Takashima 2013) shows the relationship between GDP growth rate and increasing rate of the average consumer price obtained in the calculation.

On the other hand, chronological data of GDP and consumer prices in G7 countries are available in IMF world economic outlook database (IMF 2010). Figure 4.13b shows the relationship between annual growth rate of GDP and increasing rate of consumer price in Japan during 1980−2010.

Note that the positive relationship between GDP growth rate and the increasing rate of consumer price obtained in the model is very similar with that of real data.

In general, the correlation between two factors observed in the real world does not always represent the real causal relationship, because of the possibility of spurious correlation. Even in the case of the correlation between the factor A and B, both of which is caused by the third factor C, it is almost impossible in the real world to elucidate what is the factor C that is the cause of A and B, because controlled experiment is almost impossible in the real world. However, in the case of ABM where we can conduct controlled experiment, it is possible to find out the causal factor. In the case of Fig. 4.7a, the causal factors of GDP growth and price-increasing rate is the flow of funds between the bank and the market, based on the mechanism mentioned above.

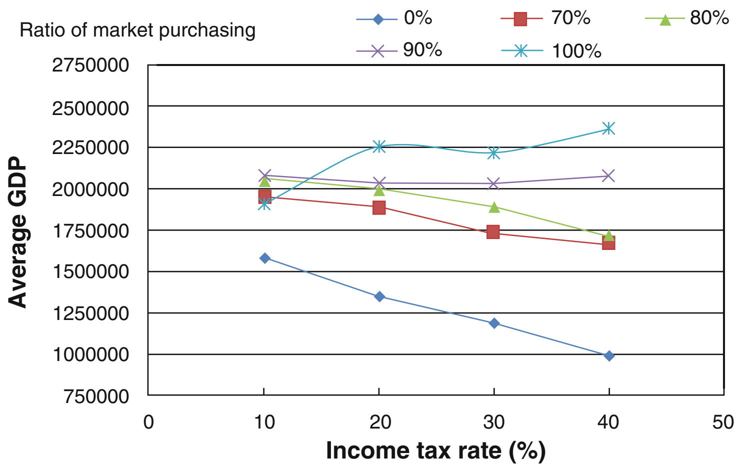

Fig. 4.14 Influence of the inefficiency of government expenditure on the relationship between GDP and income tax rate

4.4.4 The Necessary Model Structure for Reproducing the Positive Influence of an Income Tax Reduction on GDP

The influence of the income tax rate on GDP is analyzed for various ratio of market purchasing or the inefficiency of public expenditure. As the inefficiency of public expenditure is defined as the ratio of firm subsidy to the total public spending as explained in Sect. 4.2.3.4, the ratio of market purchasing is defined as one minus the inefficiency of public expenditure. The calculated relationship between the income tax rate and GDP is shown in Fig. 4.14 (Ogibayashi and Takashima 2013) for various market-purchasing ratios. Note that the negative correlation between the income tax rate and GDP is only reproduced when the market-purchasing ratio is less than 80%, i.e., the inefficiency is more than 20%. The critical market–purchasing ratio at which the correlation changes from positive to negative decreases with a decrease in the substantial marginal rate of consumption of consumers, which is dependent on the withdrawal ratio on bank deposits, decreases. Namely, the negative correlation between the income tax rate and GDP is more likely to occur when the market–purchasing ratio is small enough compared to the substantial marginal rate of consumption of consumers.

Thus, the indispensable factor to reproduce positive effect of income tax reduction is that the government expenditure includes any type of inefficient public spending.

From this result, the causal mechanism of positive effect of the tax cut in income tax is that the tax cut decreases the share of the funds of government and increases that of the consumer, thereby increases the funds spent in the market.

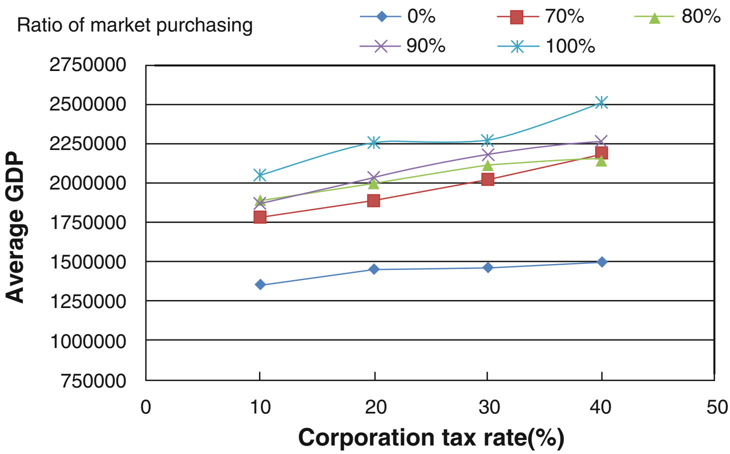

Fig. 4.15 Influence of the inefficiency of government expenditure on the relationship between GDP and corporate tax rate

4.4.5 Model Structure Necessary for Reproducing the Positive Influence of Corporate Tax Reduction on GDP

The influence of the corporate tax rate on GDP is also analyzed for various market purchasing ratios or public expenditure inefficiencies. In the case of corporate tax rate, the correlation between the corporate tax rate and GDP shows consistently positive for the market purchasing ratio from 0% to 100% as shown in Fig. 4.15 (Ogibayashi and Takashima 2013). This result implies that some additional factors are required in the model to reproduce the positive effect of corporate tax reduction.

The reason for the positive correlation shown in Fig. 4.15 is that some additional factors that are not taken into consideration in the base model decreases the efficiency of public expenditure and increases the efficiency of consumers' expenditure. The candidate of such factors might be the executive compensation, firms' investment, financing for investment including relevant restriction of credit creation, and labor market.

These include executive compensation, the use of internal funds for investment, and an increase in the upper limit of the number of loans (i.e., mitigation of credit rationing), and the effect of labor market.

Therefore, the effects of these factors are analyzed by changing the factors one by one.

Figure 4.16a, b (Ogibayashi and Takashima 2019) show the effect of executive compensation, the use of internal funds for investment, and bank financing on the relationship between corporate tax rate and GDP. Here, the upper limit of the number of loans is assumed to be 3, and the inefficiency of government expenditure is assumed to be 0.3. Figure 4.16 shows that the negative relationship between corporate tax and GDP occurs only when executive compensation, the use of internal

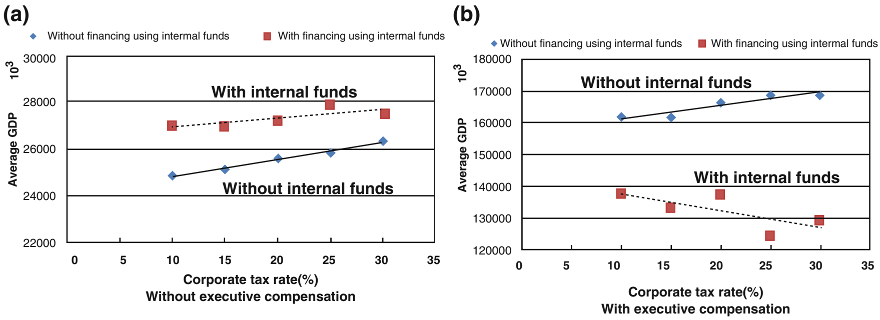

Fig. 4.16 Influence of the inclusion of internal funds rule and executive compensation rule on the relationship between the GDP and corporate tax rate, where assumed inefficiency of government expenditure is 0.3, and the upper limit of the number of loans is 3. (**a**) Without executive compensation. (**b**) Without executive compensation

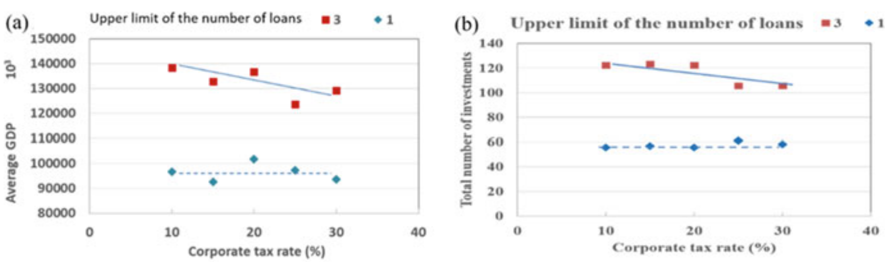

Fig. 4.17 Influence of the upper limit of the number of loans on the relationships between corporate tax rate and GDP (**a**) and total number of investment (**b**)

funds for investment, and the inefficiency of government expenditures are included in the model. An increase in the upper limit of the number of loans (i.e., mitigation of credit rationing) is another necessary condition to reproduce the positive effect of tax reduction.

Figure 4.17 (Ogibayashi and Takashima 2019) shows the influence of the upper limit of the number of loans on the relationships between corporate tax rate and GDP (see Fig. 4.17a) and the number of investments (see Fig. 4.17b) when both executive compensation and financing using internal funds are included in the model, and the inefficiency of government expenditure is assumed to be 0.3.

Note that both the average GDP and the number of investments both show negative correlation with the corporate tax rate only when the upper limit of the number of loans is large enough (i.e., the mitigation of credit rationing is applied). Thus, the mitigation of credit rationing is also one of the indispensable factors to reproduce the effect of corporate tax reduction.

In this study, the influence of the labor market is also analyzed. However, as shown in Fig. 4.18, the negative correlation between GDP and corporate tax rate is consistently reproduced regardless of the existence of labor market if the four factors

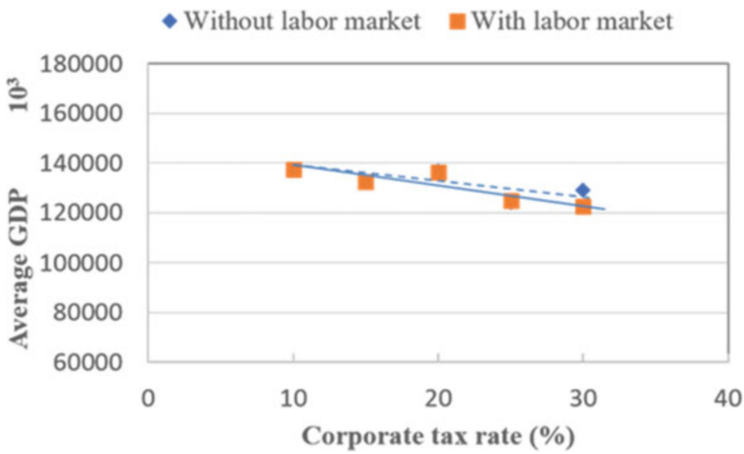

Fig. 4.18 Influence of the labor market on the relationship between corporate tax rate and GDP, under the condition that includes all four factors, namely, government inefficiency, executive compensation, the use of internal funds, and the mitigation of credit rationing (i.e., the upper limit of the number of loans is assumed to be 3)

mentioned above are included in the mode. Namely, the positive effect of corporate tax reduction is reproduced without depending on the inclusion of the labor market, if the four factors mentioned above are already included in the model. Thus, the inclusion of the labor market is not a required condition for reproducing the positive influence of corporate tax reduction, indicating that the unemployment rate which could vary due to the tax cut is not the causal factor for the positive influence of tax reduction.

In sum, it is concluded that four factors—the inefficiency of government expenditure, executive compensation, the use of internal funds for investment, and an increase in the upper limit of the number of loans (i.e., mitigation of credit rationing)—must be included in the model to reproduce the negative correlation between the corporate tax rate and GDP. If any one of these factors is not included, the positive effect of corporate tax reduction cannot be reproduced. In other words, among the 16 possible combinations that include or exclude each of these four factors, only one case in which all four factors are included successfully reproduced the positive effect of corporate tax reduction. Although we considered, before the experiment, that unemployment levels could affect the influence of tax reduction, the results show that the negative correlation between GDP and the corporate tax rate is consistently reproduced regardless of the existence of the labor market if the four factors mentioned above are included in the model, as shown in Fig. 4.18 (Ogibayashi and Takashima 2019), indicating that the inclusion of the labor market in the model is not an indispensable condition for reproducing the negative correlation.

Now, let us consider the reason why these four factors are necessary to reproduce the positive influence of corporate tax reduction. It is noted that two of the four factors, namely the use of internal funds for investment and the mitigation of credit rationing are the factors that promote a firm's investment, which makes the firm's surplus money increased by the corporate tax reduction consumed in the market without being deposited in the bank. Executive compensation is another factor that promotes the firm's surplus money flowing out to the market. Funds that flow out from the bank to the market increase someone's income, increasing consumption, thus increasing GDP. The substantial marginal propensity to consume by the private sector is the ratio of the funds flowing out to the market (e.g., in the form of firms' investments as well as executives' consumptions) to the total amount of firms' surplus funds increased by the tax reduction.

The efficiency of government expenditure, on the other hand, is considered to be a substantial marginal propensity to consume by the public sector.

Therefore, the positive effect of corporate tax reduction is realized when the substantial marginal propensity to consume by the private sector (including both firms and consumers) is greater than that of the public sector. In addition, the four factors mentioned above are collectively required to reproduce the positive effect of corporate tax reduction, because the marginal propensity to consume in the private sector could be larger than that in the public sector only when all of four factors exist in both the model system and the real system.

These findings suggest the followings:

First, the corporate tax reduction increases GDP only when the government's effective marginal propensity to consume (expressed by the degree of efficiency [i.e., one-inefficiency] of government expenditure) is smaller than that of the aggregate private sector. Namely, corporate tax reductions increase GDP when producers' surplus money (increased by the tax reduction) can be spent effectively in the market, in the form of firms' investment and/or consumption by executives and workers. Conversely, the corporate tax reduction does not promote economy, if the firms are reluctant to invest to expand production capacity or to increase productivity.

Second, the inefficiency of government expenditure weakens the economy. In the model, the degree of inefficiency is defined as the ratio of firm subsidies to the total amount of public expenditure. In the actual system, the inefficiencies might be caused by many factors of wasteful expenditure, such as public orders with higher-than-market prices, subsidies to firms in the industry, or rent-seeking behavior (Tollison and Congleton 1995).

4.5 Discussions

4.5.1 The Validity of the Model in ABM

As described in the introduction, ABM has so far received little recognition as a promising methodology that is reliable to use for deciding public policy. Namely, many researchers seem to consider that although ABM is effective in offering hints on the emergent mechanism of phenomena in the real world, it is not sufficiently reliable for elucidating the causal mechanism to replace the traditional approach of economics.

However, as many modelers have probably experienced, ABM emerges different macro phenomenon if the input condition of the model assumed is different. If the emerged phenomenon in ABM under a certain set of behavioral rules differs from that in the real world in its feature, modelers might change the input conditions until the model reproduces the features of a macro phenomenon in question. Namely, it is quite reasonable to consider that there must be a causal relationship between the input conditions of the model and the emergence of macrophenomenon if the model is entirely bottom-up where any aggregate variables and their relationships are not assumed.

Based on this idea, this chapter describes some examples that revealed the indispensable model structure to reproduce the macrophenomenon in question. The results of this study indicate that the necessary conditions exist for reproducing price equilibrium, the effect of supply chain, positive relationship between GDP growth rate and the increasing rate of consumer price, business cycles, and the positive effect of the reductions of income tax rate and corporate tax rate. Here, the necessary conditions are the sets of factors that characterize the model structure, which can be elucidated by running a series of computer experiments where each of the factors is changed one at a time. These factors are indispensable for the model to reproduce the desired phenomenon, meaning that the phenomenon under concern does not emerge in the artificial society if any one of these indispensable factors is not included in the model.

A typical example is the condition for reproducing the positive effect of corporate tax reduction. As the present research study revealed, four factors are required to reproduce the phenomenon because, among 16 possible combinations involving these four factors, only one case results in the emergence of the phenomenon, namely the case in which all four factors are included in the model.

Moreover, by considering why such factors are required to reproduce each phenomenon, as described, we can gain a better understanding of the causal mechanisms of these social phenomena. The causal mechanisms estimated based on the indispensable factors elucidated by the computer experiments are found to be quite reasonable. The reason for this is discussed below.

A system is a set of interacting objects and is defined as a proper relation on sets (Mesarovâic and Takahara 1989). Social system is an input-output system, where input consists of a set of causal factors and the output is a set of various social phenomena. Because any social phenomenon is considered to emerge from agents' actions and their interactions, the causal factors consist of the type of agents, the behavioral rules of each type of agent and the attribute variables that are included in the behavioral rules. The set of the factors characterizing the agents' actions and their interactions is the system structure, which is defined as a set of categories of agents, their behavioral rules, and relevant attributes variables. Those attribute variables that are responsible for the emergence of macrophenomenon are included in the agent's behavioral rules. The attribute variables contain numerical values. Note that the numerical values of variables are not crucial for the qualitative reproducibility of the social phenomenon, because the emergence of the macro phenomenon is insensitive to the numerical values of the variables as Mark pointed out (Farmer and Foley 2009). Therefore, numerical vales of the attribute variables are only responsible for the quantitative reproduction of the social phenomenon. In contrast, the attribute variables for which numerical values are set to be more than a minimum value that guarantee the minimum level of the heterogeneity are responsible for the qualitative reproduction of the social phenomenon.

Therefore, it is quite reasonable to consider that, for each of the macrophenomenon, there must be a specific model structure that is responsible for the emergence of a particular macrophenomenon. Here, the model structure consists of a set of behavioral rules for each type of agent and the attribute variables.

In the case of an entirely bottom-up agent-based model, the validity of the model is assessed how close the model reproduces every feature of the phenomenon under concern. If the model reproduces the set of the features of the phenomenon, we can conclude that the indispensable factors in the model structure are the causal factors of the phenomenon. Then, by considering why those factors are required to reproduce the phenomenon, we can gain a better understanding of the underlying mechanisms of the social phenomenon.

This chapter describes the examples of this procedure. Based on those examples that elucidate the set of indispensable factors for reproducing the phenomenon and the estimated causal mechanism, above-mentioned principle in ABM is considered valid for various social phenomena.

Note that the model structure that can reproduce the desired macro phenomena could not be unique because there could be multiple causes. However, this does not undermine the validity of the model mentioned above. If different system structures cause the same phenomenon in the model, multiple causes exist even in the real system. Conversely, if we defined the features of the phenomenon in detail, the cause and the phenomenon could be a one-to-one correspondence. In any case, we can better understand the causal mechanisms of the social phenomena by piling up the knowledge on the indispensable system structure for each of the macro phenomena.

4.5.2 The Causal Mechanism of Business Cycles

According to the review presented by Onwumer et al. (2011) (Ormerod and Rosewell 2009), seven economists have so far proposed the causal mechanism of the business cycles, which are Veblen T.B., Marx K., Schumpeter, J.A., Friedman, M.F., Keynes, J.M., Minsky, H.P., Scherman H.J.

Among these economists, only Veblen and Minsky proposed credit creation as the factor responsible for the business cycles (Ormerod and Rosewell 2009). Namely, as the cause of business cycles, Veblen suggested the repetition of the over-expansion of credit and subsequent credit contraction, and Minsky proposed the repetition of borrowing for investment and over-borrowing that collapse in investment. On the other hand, Keynes proposed the changes in the marginal efficiency of capital due to the expectations and price changes as the cause of business cycles (Ormerod and Rosewell 2009).

According to the present research, the essential mechanism of business cycles is the repetition of the borrowing from the bank and repayment to the bank accompanied by investment. The former causes the flow of funds from the bank to the market, thereby promoting the economy. While the latter causes the flow of funds from the market to the bank, thereby deteriorating the economy.

This mechanism is very close to the idea of Veblen and Minsky. But, in contrast, Keynes's idea of the marginal efficiency of capital is not the primary mechanism of the business cycles.

Thus, this result suggests that ABM can evaluate whether economic theories are true or not.

Therefore, ABM could be a promising methodology to elucidate the causal mechanism of various social problems to overcome them. Furthermore, it is expected that ABM could help the government design public policies based on the piled-up knowledge on the causal mechanism of the social issues, which could be a key process to establish a genuinely democratic society.

4.6 Conclusion

The indispensable conditions of the model structure for reproducing price equilibrium, the effect of the supply chain, business cycles, and the positive impact of income tax and corporate tax reductions are analyzed using an agent-based model.

In addition, based on the indispensable factors, the causal mechanisms of these phenomena are estimated, which are found to be quite reasonable.

The results are summarized as follows:

1. The factors indispensable to reproduce price equilibrium are consumers' low-price-oriented buying strategy and producers' stock-control-oriented adjusting strategy of the price and quantity of the products.
2. The factors indispensable to reproduce the business cycles are the bank financing (i.e., credit creation), where repayment is incorporated, producers' demand-based investment decision-making. This model structure also reproduces the positive correlation between GDP growth rate and increasing rate of consumer price.
3. The factors indispensable to reproduce positive effect of income tax is the inefficiency of government expenditure.
4. The factors indispensable to reproduce the positive effect of corporate tax reduction are the inefficiency of government expenditure, executive compensation, internal funds for investment, and an increase in the upper limit of the number of loans (i.e., mitigation of credit creation).

5. Based on these findings, this study proposed causal mechanisms of business cycles and the positive effect of tax reduction. Business cycles emerge due to the repetition of the flow of funds between bank and market. This flow is caused due to borrowing and repayment from and to the bank accompanied by investment. The positive effect of tax reduction emerges when the substantial marginal propensity to consume in the private sector is more significant than that in the public sector.
6. This study proposed new perspectives on the validity of ABM based on these findings, the essence of which is the following. In the case of an entirely bottom-up model in ABM, it is possible to identify the indispensable factors for qualitatively reproducing each macro phenomenon. Here, input factors of the model are expressed by the model structure defined by the agents' categories, behavioral rules, and relevant attributes variables. We can elucidate the necessary factors in the model structure by running a series of systematic computer experiments where the elements are changed one by one, with other factors being kept constant. By considering why such factors are required to reproduce the phenomenon, it is possible to better understand the causal mechanism of the phenomenon.

Acknowledgments The author would like to thank Dr. Kousei Takashima who is the coauthor of most of this research that are cited in the references.

Appendix: Overview, Design Concepts, and Details Protocol

This appendix describes the model in terms of the Overview, Design Concepts, and Details (ODD) protocol by Grim et al. (2006).

Purpose

The purpose of this model is to experimentally elucidate the underline mechanism of the complex macroeconomic phenomena. The model also aims to clarify the conditions under which the model structures reproduce these phenomena in an agent-based artificial economic system where macroeconomic indicators emerge as a result of agents' actions and interactions. In the present study, the purpose of this model focuses on elucidating the model structure to reproduce the positive influence of corporate tax reduction on GDP and to obtain a clearer understanding of the mechanism behind this effect.

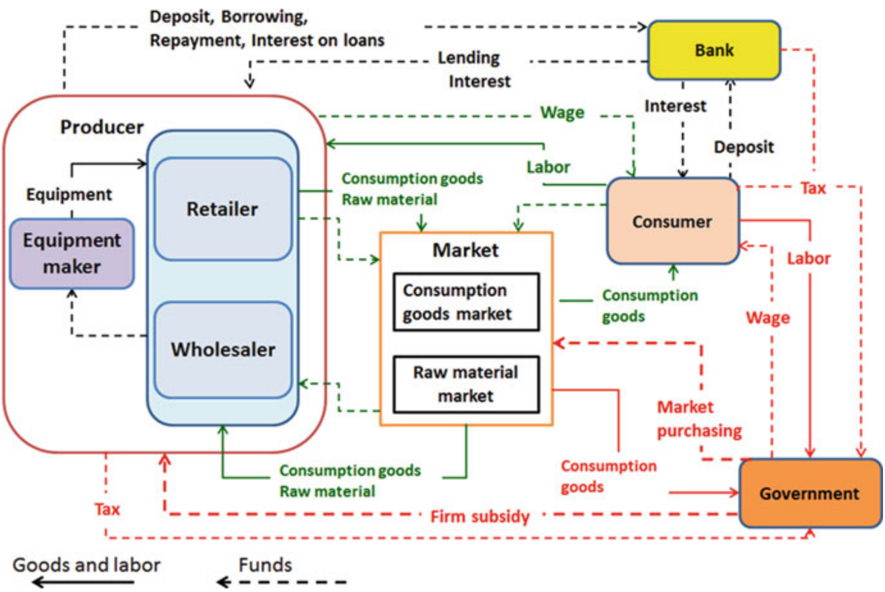

Fig. 4.19 Outline of the entities and their relationships

Entities, State Variables, and Scales

The entities included in this model are agents, goods, and markets, which are the minimum requirements of a macro economy of a nation. Agents include the following: consumers, comprising workers, and executives of private sector firms and public workers; producers, comprising retailers, raw-material makers, and an equipment maker; a bank; and a government. Goods include consumption goods for any agents, raw-material goods for retailers, and equipment as capital goods for retailers and raw-material makers. The market is divided into a consumption goods market and a raw-material goods market. We assume that capital goods transactions take place directly between equipment makers and buyers. Figure 4.19 shows the relationship between these entities, including the flows of goods, labor, and funds among the agents.

The entities included in this model and their characteristics are described in Table 4.4.

State variables are divided into those for agents and those for other entities. Each agent belongs to a different category, according to its behavior, such as agents in general, buyers, enterprises, and producers. State variables for agents are divided into those for an agent's behavioral category and those peculiar to each type of agent. State variables for each behavioral category are described in Table 4.5, and the state variables peculiar to each type of agent are described in Table 4.6. The state variables of other types of entities are described in Table 4.7.

Table 4.4 Entities included in the model and their characteristics

Entities	Descriptions
Agent	Characterized by agent id, agent type, cash it holds, deposit it holds, common behavioral rules as a buyer, a seller, and an enterprise
Consumer	Works for one of other agents, get wages, pay income tax, and purchase consumption goods
Retailer producer	Produces consumption goods, ships them to the market, employs workers, pays wages and corporate tax. It also buys consumption goods
Raw material maker	Produces raw material goods, ships them to the market, employs workers, pays wages and corporate tax. It also buys consumption goods
Equipment maker	Produces equipment based on the orders from retailers and raw material makers, employs workers, pays wages and corporate tax
Government	Collects tax from other agents, employs public workers, pays wages, and supplies subsidies to the firms as public expenditure
Bank	Keeps deposits from consumers and firms, finances funds for investment
Goods	Characterized by 12 types of product classes, price, seller's id, and buyer's id. There are no behavioral rules for goods
Consumption goods	Produced and supplied to the market by retailers, bought by several types of buyers
Raw material goods	Produced and supplied to the market by raw material makers, bought only by retailers. One-to-one correspondence is assumed between raw material goods and consumption goods, representing the smallest supply chain
Equipment	Produced by an equipment maker according to the requirement for investments from retailers and raw material makers
Market	Characterized by a set of goods objects. Goods remained unsold at a time period are recognized by the corresponding seller agents at the beginning of next period as goods in unsold stock
Consumption goods market	Consumption goods are supplied by retailers and bought by buyers, including consumers, retailers, raw material makers, and the government. An event of buying one of the goods is synchronously recognized by a corresponding seller agent, resulting in the payment by a buyer
Raw material goods market	Raw material goods are supplied by raw material makers and bought by only retailers. Transactions are conducted with the same algorithm as in the case of consumption goods

Table 4.5 State variables for agents' behavioral category

		Characteristics of state variable			
Category of entity	State variable	Initial setting	Difference among agents	Change in time step	Description
Agent in general	*Agent id*	Sequential	Different	Invariable	Identification number of agents
	Agent type id	Specified	Same or different	Invariable	Specified number of agent type for consumers, retailers, raw material makers, an equipment maker, a bank and the government
	Cash	At random	Different	Variable	Cash possessed by an agent, which varies each time step
	Deposit	At random	Different	Variable	Deposit possessed by an agent in the bank, which varies each time step
Buyers	*Weight of utility for each product class*	At random	Different	Invariable	The weight of utility for each product class of goods to purchase, initially assigned at random between 0 and 1 for each agent. Non-zero value is assigned for all of the product classes in case of government and for 2 classes in case of other agent types of buyers
	The number of goods purchased	–	Different	Variable	The number of goods purchased for each product class, which is reset at the beginning of each time step
	Exponent in utility function	At random	Different	Invariable	The exponent of the number of goods to purchase in utility function
Enterprises	*Number of employees*	At random or specified	Different	Variable or invariable	The number of agents working in an enterprise including workers and an executive
	Agent_id of an executive	At random	Different	Invariable	The agent id of the consumer specified as an executive
	Agent_id of workers	At random	Different	Variable	The agent id of the consumer specified as a worker

Enterprises (Continued)	*Fixed wages*	At random	Different	Invariable	The amount of fixed wages to be paid to each employee including an executive
	Bonus ratio	Specified	Same	Invariable	The ratio of bonus to be paid for workers with respect to before-tax profit
	Executive compensation ratio	Specified	Same	Invariable	The ratio of executive compensation paid to the executive with respect to after-tax profit. In this study, executive compensation is assumed to be an extra bonus paid to an executive, which is defined as the executive compensation ration multiplied by after-tax profit of the enterprise
Producers	*Product class id*	At random	Different	Variable	The class id of product to produce
	A list of goods in the market	–	Different	Variable	A list of the objects of the producer's supplied goods in the market. At the beginning of each period, it shows a list of unsold stocks in the market. During each period, it increases with an increment number of produced goods and decreases with an increment number of goods sold during the period
	Dismissal flag	–	Different	Variable	The flag number for decision-making of the dismissal of a worker. When the profit is negative or positive at a certain period, the dismissal flag is increased or decreased by 1. When the dismissal flag reaches a critical flag number of dismissal, the producer fires one employee who is selected at random
	Quit-production flag	–	Different	Variable	The flag number for decision-making regarding production stoppage. When the products of a specific class are all remain unsold at a period, the quit-production flag is increased by 1. When it is not, it is decreased by 1. When it reaches a critical flag number to quit production, the producer stops its production

Table 4.6 State variables peculiar to each type of agent

Entity	State variable	Characteristics of state variable			Description
		Initial setting	Difference among agents	Change in time step	
Consumer	*Working place*	At random	Different	Variable	The agent id of the enterprise or government the consumer works for
	Marginal propensity to consume	Specified	Same	Invariable	The proportionality constant of disposable income after tax for the budget for purchasing consumption goods
	Basing consumption	Specified	Same	Invariable	The minimum budget for purchasing consumption goods when withdrawal of deposit is assumed to be zero
	Withdrawal ratio	At random	Different	Variable	The ratio of money withdrawn from the deposit to purchase consumption goods. It is randomly assigned for each agent at every period during the simulation
Retailer and raw material maker	*Purchasing ratio*	Specified	Same	Invariable	Percentage of accumulated profit for buying consumption goods. The budget for consumption is determined as the purchasing ratio multiplied by accumulated profit
	Proportionality constant of production function	At random	Different	Invariable	The proportionality of cobb Douglas's production function, which represents the total factor productivity of each producer
	Investment flag	–	Different	Variable	The flag number for deciding investment. It increases or decreases by one depending on the producer's own unsold stock in the market
	Upper limit of the number of loans	Specified	Same	Invariable	The upper limit for the number of issuance of long-term loans at a time, the funds of which are required for investment and financed by the bank. They cannot invest in equipment when their number of loans has already reached this value

Equipment maker	*Price of equipment*	Specified	–	Invariable	The price of one unit of equipment
	Maximum number of production per each period	Specified	–	Invariable	The upper limit of production per period. When it receives orders more than this value, it does not meet the requirement of producers and rejects the order
Bank	*Repayment period*	Specified	–	Invariable	Repayment period of long-term loan
	Interest rate on loans	Specified	–	Invariable	Lending interest rate on loans for producer's investment
	Interest rate on deposits	Specified	–	Invariable	Interest rate on deposits of producer and consumer
Government	*Income tax rate*	Specified	–	Invariable	Income tax rate levied on consumer's income
	Corporate tax rate	Specified	–	Invariable	Corporate tax rate levied on producer's profits
	Salary for public workers	–	–	Variable	Salary for a worker who works for government, which is determined as the average of wages per capita including bonus in the private sector
	Ratio of market purchasing	Specified	–	Invariable	Ratio of the budget for purchasing goods in the market to the total public expenditure
	Ratio of firm subsidy	Specified	–	Invariable	Ratio of the budget for subsidizing firms with no limitation of its use to the total public expenditure

Table 4.7 State variables of other types of entities

		Characteristics of state variable		
Entity	State variable	Initial setting at creation	Change in time step	Description
Consumption goods	*Product class number*	Specified by the producer	Invariable	The id number of product class determined by the producer
	Price	Specified by the producer	Variable	The price of the product determined by the producer at every period
	Seller's number	Specified by the producer	Invariable	The agent id number of the producer who produced the product
	Buyer's number	Specified by the buyer when being purchased	Invariable	The agent id number of the agent who bought the product. It is determined when it was bought
Material goods	*Product class number*	Specified by the producer	Invariable	The id number of product class determined by the producer
	Price	Specified by the producer	Variable	The price of the product determined by the producer at every period
	Seller's number	Specified by the producer	Invariable	The agent id number of the producer who produced the product
	Buyer's number	Specified by the buyer when being purchased	Invariable	The agent id number of the agent who bought the product. It is determined when it was bought
Market	*A list of consumption goods*	–	Variable	A list of consumption goods currently available in the market
	A list of material goods	–	Variable	A list of material goods currently available in the market

Tables 4.5, 4.6, and 4.7 present the characteristics of the state variables: the initial settings, differences among agents, and how values change with a change in time step. The initial settings are the values assigned to the state variables of the objects when the objects are created. The difference among agents shows whether the values are the same or different among the agents. The change in time step indicates whether the values are time dependent.

Process Overview and Scheduling

The present model consists of three submodels: a fund circulation submodel, a price equilibrium submodel, and an investment submodel. The fund circulation submodel constitutes the fundamental structure of the model in which the latter two submodels are implemented. The model consists of three processes: initialization, where the objects of the entities are created and initialized; the sequence of seven actions performed by agents during each time step; and the calculation of the average GDP and other statistical data of macroeconomic indicators. The seven steps comprise the actions at the beginning of every time step, the production of raw materials, the production of consumption goods, purchasing of consumption goods, payment of wages, actions for investment, and the actions at the end of every time step. The pseudocode that describes this process is given in Fig. 4.20, and the sequential events conducted by each type of entity during each time step are described in Fig. 4.21.

Design Concepts

Basic Principles

The general concept underlying the model design of ABM is that the behavior of an artificial economic system can mimic the real-world behavior if the model structure and the structure of the real systems have a homomorphic relationship. This relationship is considered to be fulfilled when the structural factors of the modeled system are essentially the same as those of the real system with respect to the relevant macroscopic economic phenomenon. Therefore, ABM can be useful in describing the mechanism of a macroeconomic phenomenon by performing controlled experiments in which only one factor of interest varies at a time, while holding other factors constant. In this way, ABM clarifies the structural conditions necessary for the model to reproduce the macroeconomic phenomenon being studied.

```
for period=0 to period bound
  if period=0 then
    Initialize agents, set parameters, set initial conditions.
    Agents do actions in the similar way as period>0 with some exceptions.
  else
    1. Agents pay unpaid tax for the previous period, make a budget plan for expenditures.
    2. Raw material makers decide the amount and price of products.
       They produce raw materials of several types, supply them to the market.
    3. Retailers decide the amount and price of products, purchase raw materials.
       They produce products of several types, supply them to the market.
    4. Agents except for the equipment maker and the bank purchase products in the market.
    5. Retailers and raw material makers judge the necessity of investment on the basis of
       total sales in the previous periods. If necessary, they invest in equipment.
    6. Each firm pays wages and executive compensation for workers and the executive.
       Government pays wages for public workers.
    7. Each agent settles its accounts, calculating income or profit for the current term,
       based on which the amount of tax to be paid is determined.
     If necessary, each retailer dismisses a worker on the basis of profits for previous periods
       or decides to stop production of a certain type of products on the basis of its total sales.
  Calculate GDP and input-output table by summing the accounts data of all agents.
end for
Calculate average GDP for all periods.
```

Fig. 4.20 Pseudocode of the model

	Sequential events of each type of agent during a fiscal period						
	Step 1 Start of processing	**Step 2** Material goods production	**Step 3** Consumption goods purchasing	**Step 4** Consumption goods purchasing	**Step 5** Wage receiving or paying	**Step 6** Investment	**Step 7** End of processing
Consumer	Tax payment, Budget planning			Consumption goods purchasing	Wage receiving		Settlement of accounts
Raw material maker	Tax payment, Budget planning	Production	Sales receiving	Consumption goods purchasing	Wage paying	Investment & financing	Settlement of accounts
Retailer	Tax payment, Budget planning		Material purchasing, production	Sales receiving	Wage paying	Investment & financing	Settlement of accounts
Equipment maker	Tax payment, Budget planning				Wage paying	Equipment production & selling	Settlement of accounts
Bank	Tax payment, Budget planning				Wage paying	Funds lending	Settlement of accounts
Government	Tax collection, Budget planning			Consumption goods purchasing	Wage paying		Settlement of accounts

Fig. 4.21 The sequential events in each time step for each type of entity

Emergence

The modeled artificial systems should include heterogeneous and autonomous agents. Their behavioral rules might be similar, but the values of their state variables should be different. Therefore, the heterogeneous agents behave differently and interact with each other. Macroscopic phenomena emerge from these actions and interactions, which affect the microscopic behavior of the agents, resulting in a micro–macro link in the dynamics of the systems. In this way, artificial economic systems can behave as complex systems.

Adaptation

Retailers and raw-material makers adjust the price and number of products they supply to the market by gauging the demand in the market. To do so, they observe the number of stock items that remain unsold at the end of each time step. These producers also use the market demand to adjust their production capacity and number of employees. In this way, the artificial economic systems in this study possess an internal adaptation mechanism.

Objectives

Consumers and producers hold their own objective functions, such as maximizing utility or profits.

Prediction

Retailers and raw-material makers predict the total sales of their goods based on the sales figures from the ten most recent periods. Based on this prediction, they decide on the amount of production in the next time step so that the probability of goods being out of stock is less than 5%. When they decide to invest in equipment, they first predict the financial benefit of the investment by estimating the increase in profit gained from a one-unit increase of equipment and the subsequent increase in production capacity.

Sensing

Retailers and raw-material makers gauge the market demand by observing the amount of goods still in stock at the end of each time step. They also calculate the optimal number of employees based on the profit of the current term, as well as the potential financial benefit of increasing or decreasing the number of employees and, therefore, their production capacity.

Interaction

The price equilibrium is loosely attained by the interaction between agents' purchasing actions and producers' actions when adjusting their production levels and product prices. In addition, the circulation of funds and the emergence of various macroeconomic indicators, such as GDP, are the result of the actions of agents and their interactions. The investment behavior is also a result of the interaction between buyers and producers.

Stochasticity

Various state variables are randomly defined at the start of the simulation or during the simulation. Typical examples are agents' initial funds, state variables that distinguish agents (e.g., product classes), production capacities, utility weights, and a consumer's workplace. These are defined using random numbers with a uniform distribution.

The order of agents' actions for the same type of agent is also defined by shuffling the set of agent id numbers using a uniform random number at every time step.

Observation

At the end of each time step, each agent settles its account using the double-entry bookkeeping method. An input-output table for the artificial system is defined by summing the calculated data for all agents. The macroeconomic indicators, such as GDP, tax revenue, total funds for each type of agent, total salaries paid by producers, and the total number of investments, are calculated based on the input-output table and other account data of the agents. In addition, statistical data, such as the total number of goods produced or bought during each time step, the average price of products, and the amount of funds circulated between the bank and other types of agents, are also calculated at the end of each time step. The average values of these data for the overall simulation can also be obtained and used for various types of analysis.

Initialization

All state variables of the agents are initialized when the agent objects are created. These initial values are described in Tables 4.8 and 4.9. An agent id is sequentially assigned for each agent, but this number is only used to distinguish agents. Each agent object is initially assigned randomly to one of the types of agents. Public employee's salaries are calculated in each fiscal period so that they are equal to the average income of private employees.

Table 4.8 Initialization of state variables for agent's behavioral category

Category of entity	State variable	Descriptions	Initialization
Agents in general	*Agent id*		Sequentially assigned
	Agent type id		Randomly assigned
	Cash	– Consumer	30,000–50,000
		– Retailer and raw material maker	80,000–160,000
		– Equipment maker	200,000–220,000
		– Bank	96,000,000–104,000,000
		– Government	10,000
	Deposit		0
Buyers	*Weight of utility for each product class*	– Consumer	0–1
		– Producer and government	0
	Exponent in utility function		–2
Enterprises	*Number of employee*	– Retailer	4–5 at random
		– Raw material maker	3
		– Equipment maker	2
		– Bank	1
	Fixed wages		7000–7500
	Bonus ratio		75%
	Executive compensation ratio		95%
Producers	*Product class id*		2 classes are randomly assigned for each agent between 1 and 6 at the start of simulation
	Dismissal flag	Dismissal flag	0
		Critical flag number for dismissal	5
	Quit-production flag	Quit-production flag	0
		Critical flag number to quit production	20

Table 4.9 Initialization of state variables peculiar to each type of agents

Entity	State variable	Descriptions	Initialization
Consumer	*Working place*		Randomly specified
	Marginal propensity to consume		70%
	Basic consumption		3000
	Withdrawal ratio		0–50%
Retailer and raw material maker	*Purchasing ratio*		70%
	Proportionality constant of production function	– Retailer	8–10
		– Raw material maker	50–150
	Investment flag	– Investment flag	0
		– Critical number for investment	20
	Upper limit of the number of loans		3
Equipment maker	*Price of equipment*		500,000
	Limit number of production per each period		4
Bank	*Repayment period*		120
	Interest rate on loans		3%
	Interest rate on deposits		0.50%
Government	*Income tax rate*		20% (standard)
	Corporate tax rate		20% (standard)
	Salary for public workers		Unspecified
	Ratio of market purchasing		60% (standard)
	Ratio of firm subsidy		40% (standard)

Input Data

No data from the real system is used as input data for the simulation.

Submodels

Funds Circulation Submodel

This submodel constitutes the fundamental structure of the model, the outline of which is described in the pseudocode presented in Fig. 4.20. The basic principles of the circulation of funds and additional behavioral rules are presented below.

Basic Principles of Fund Circulation

Consumers work for one of the other agents, receive wages, buy consumption goods produced by retailers, and pay income tax to the government. Retailers produce consumption goods using raw material goods supplied by raw-material makers, where minimum units of supply chain processes are implemented in the model. The behavioral rules for the strategies of consumer purchasing and producers' production are described in the price-equilibrium submodel. Retailers and raw-material makers invest in equipment when doing so will increase their profit. The investment strategies are described in investment submodel.

The government levies income tax and corporation tax, pays wages to public employees, and conducts public expenditure, comprising market purchasing as an extreme case of efficient public spending and firm subsidies as an extreme case of inefficient public spending.

In this way, funds circulate among agents in the artificial economic systems as a result of agents' actions and interactions.

Related Behavioral Rules

1. *Agents' behavioral rules for determining their consumption budget.*

   Every agent, other than the bank, determines a consumption budget at the beginning of each time step. The definitions of the budget are different each type of agent.

   For the consumer agent:

$$E_b^t = a + bI^t + r_{\mathrm{wd}}^t D^t$$

where $E_b{}^t$: Consumer's consumption budget; a: Basic consumption; b: Marginal propensity to consume; I^t: after-tax income; r_{wd}: Withdrawal ratio; D^t: Bank deposit.

For the producer agent: Purchasing ratio multiplied by the amount of internal funds.

For the government agent:

$$E_b^t = E_{\mathrm{all}\_b}^t - \mathrm{wage}_G^t$$

where E_b^t: Total public expenditure budget; $E_{\mathrm{all}\_b}^t$: Total amount of tax revenue; wage_G^t: Total salaries paid to public employees.

The budgets for market purchasing and for firm subsidies are defined as the ratio of the respective amount of public expenditure to the total budget.

2. *Payment of salaries.*

2-1 Salaries paid by enterprises.

Each enterprise agent pays a fixed salary, a bonus, and executive compensation.

The total amount paid as salaries depends on both the before-tax profit and accumulated profit, as given below:

$$E_w^t = \begin{cases} W_f & \text{if} \quad \pi^{t-1} < 0 \\ W_f + W_b^{t-1} & \text{if} \quad \pi^{t-1} > 0 \text{ and AC} < 0 \\ W_f + W_b^{t-1} + \mathrm{EC}^{t-1} & \text{if} \quad \pi^{t-1} > 0 \text{ and AC} > 0 \end{cases}$$

where $E^t{}_w$: Total salary amount; W_f: Fixed salary; W_b: Bonus; EC: Executive compensation; AC: Accumulated profits.

The total amount of salaries paid to workers or to executives is given below.

$$W_C^t = W_f + W_b^{t-1}/\mathrm{ne} \text{ for workers}$$

$$W_C^t = W_f + W_b^{t-1}/\mathrm{ne} + \mathrm{EC}^{t-1} \text{ for executives}$$

where $W^t{}_c$: Total salaries paid to workers or to executives; ne: The number of employees.

2-2 Salaries paid by the government

The government pays fixed salaries to public workers based on the previously determined budget for wages.

3. *Agents' behavioral rules for settling accounts at the end of each time step*

3-1 The rules for consumers

Consumers define the amount of income tax to be paid based on their income and remember this as the amount of unpaid tax:

$$\mathrm{Tax}_i = W_C^t \, r_{i\_\mathrm{tax}}$$

where Tax_i: The amount of income tax; r_{i_tax}: The income tax rate.

A part of consumers' income, including unpaid tax, is kept on hand as cash and deposited in the bank, as given below:

$$\mathrm{deposit} = (1 - b)\left(W_C^t\left(1 - r_{i\_\mathrm{tax}}\right)\right) - a$$

3-2 The rules for producers

Producers define their profit based on total sales and total expenses:

$$\mathrm{Pr}_p^t = S^t - \left(W_f + \sum \mathrm{co}^t + \mathrm{int}^t + \mathrm{dep}^t\right)$$

where Pr_p: The profit before bonus; S: Total sales; $\Sigma\mathrm{co}$: Total expenses for raw materials; int: Interest to be paid; dep: Depreciation expenses.

Producers define the amount to be paid as bonuses to employees based on the profit before bonuses, as given below. They remember this as the amount of unpaid bonuses:

$$W_b^t = \mathrm{Pr}_p^t r_{\mathrm{bonus}}$$

where r_{bonus}: The ratio of bonus.

Based on this value, they define their before-tax profit as given below:

$$\mathrm{Pr}_{a\_\mathrm{tax}}^t = \mathrm{Pr}_p^t \left(1 - r_{\mathrm{bonus}}\right)$$

where $\mathrm{Pr}^t{}_{a\_\mathrm{tax}}$: The before-tax profit.

Then, they calculate the amount of corporation tax to be paid and remember this as the amount of unpaid tax:

$$\mathrm{Tax}_c = \mathrm{Pr}_p^t \left(1 - r_{\mathrm{bonus}}\right) r_{c\_\mathrm{tax}}$$

where Tax_c: The amount of corporation tax; r_{c_tax}: The rate of corporation tax.

Based on this value, they define their after-tax profit and executive compensation, and remember this as unpaid executive compensation:

$$\mathrm{EC}^t = \mathrm{Pr}_p^t \left(1 - r_{\mathrm{bonus}}\right)\left(1 - r_{c\_\mathrm{tax}}\right) r_{\mathrm{exec}}$$

where r_{ecex}: The ratio of executive compensation.

Extracting the executive compensation from their after-tax profit enables producers to define their accumulated profit, as given below:

$$\mathrm{Ac}^t = \mathrm{Ac}^{t-1} + \mathrm{Pr}_p^t \left(1 - r_{\text{bonus}}\right) \left(1 - r_{c\_\text{tax}}\right) \left(1 - r_{\text{ecex}}\right)$$

3-3 The rules for the government.

The government defines the total amount of tax revenue and expenses, and passes the resultant money on to the next period.

4. *Others*

4-1 The rules for dismissal

At the end of each time step, the retailer fires one of its employees if its dismissal flag reaches a critical value. The employee to be fired is selected at random and is assigned to the producer with the largest accumulated profit.

4-2 The rules for stopping production and for bankruptcy

At the end of each time step, the producer stops production of a certain class of product if its flag reaches a critical value. When a producer stops all its product classes, it then goes bankrupt, and a new producer object is created with new initial variables.

Price Equilibrium Submodel

The present model mimics the price equilibrium in the market according to the following two principles.

Lowest-Price-Oriented Purchasing Strategy by Buyers

All buyers purchase consumption goods within the limits of their consumption budget. If there are products within the same product class, but with different prices, they will select the cheapest of them. The consumption goods bought are indexed by buyer's id and are removed from the market and moved to the buyer.

In addition, consumers purchase products to maximize their utility within the limit of their consumption budget.

$$\max u = \sum_i w_i x_i^{\alpha} \ \text{ s.t.} \sum_i p_i^t x_i \le E_b^t$$

where w_i: The weight of utility for each product of class i; x_i: The number of products to purchase; p_i: The price of a product; α: An exponent of x_i.

Stock-Control-Oriented Production Strategy by Sellers

1. The behavioral rules used by producers to determine the price of their products.
   The price of a product is defined according to the number of products in stock and the amount bought in the market.

$$p^t{}_i = \begin{cases} (1+\gamma_i)\, p^{t-1}{}_i & \text{if} \quad s_i^{t-1} = 0 \\ (1-\gamma_d)\, p^{t-1}{}_i & \text{if} \quad s_i^{t-1} > 0 \text{ and } p^{t-1}{}_i < p_{\text{avei}}^{t-1} \end{cases}$$

   where γ_i: The ratio of a price increasing; γ_d: The ratio of a price decreasing; $s^{t-1}{}_i$: The amount of goods in stock at the end of previous period; $p^{t-1}{}_{\text{avei}}$: The average price of goods bought in the market in the previous period.
2. The strategy for amount to be produced (the production plan).
   (a) The number of products to be produced in a given period is defined so that the probability of goods being out of stock is 5%:

$$q_{si}^t = q_{\mu i}^t + 1.65 q_{\sigma i}^t$$

   where $q^t{}_{si}$: Target number of goods in stock; $q^t{}_{\mu i}$: Average sales during the past ten periods; $q^t{}_{\sigma i}$: Sigma of total sales during the past ten periods
   (b) Producers decide on the number of products to produce according to the number of products in stock, adjusting their target as shown below.

$$q^t{}_i = \begin{cases} q_{si}^t\,(1+\varepsilon) & \text{if} \quad s_i^{t-1} = 0 \\ q_{si}^t\,(1-\varepsilon) - s_i^{t-1} & \text{if} \quad s_i^{t-1} > 0 \end{cases}$$
$$\text{If } q^t{}_i > Y_i(K, L) \quad q^t{}_i = Y_i(K, L)$$

   where $q^t{}_i$: The amount of production; ε: The ratio of changing amount of production; $Y_i(K, L) = A_i K^{\alpha} L^{1-\alpha}$: Production capacity; K: The number of units of equipment for production; L: The number of employees; A: A proportionality constant.

Investment Submodel

Producers' Behavioral Rules for Investment Decisions

The retailer or raw-material maker decides to invest when the three conditions listed below are fulfilled. Once the agent decides to invest, it becomes a candidate for investment and is included in the list of candidates owned by an equipment maker.

Conditions for investment:

1. The investment flag number exceeds a critical value for investment.

2. The financial benefit from an increase in one unit of equipment is positive, as given below.

$$\Delta\pi_K = \max_i \left[\left(p_i^t - c_i^t \right) \{ Y_i\,(K+1, L) - Y_i\,(K, L) \} - (r_0 + 1/N)\,F \right] > 0$$

where p_i: The price of goods of product of class i; c: The variable cost per unit product; r_0: The borrowing interest rate; F: The borrowed money required to buy one unit of equipment; N: The repayment period.
3. The accumulated profit at the end of current term is greater than half the necessary funds for investment.

The Behavioral Rules for Equipment Makers

The equipment makers randomly select one of the candidates for investment and sell that agent a unit of equipment. If there is more than one candidate, the equipment maker continues to produce and sell until the number of equipment units reaches the equipment maker's production capacity.

Producers' Behavioral Rules for Financing and Buying Equipment

The selected retailer or raw-material maker purchases one unit of equipment. Before purchasing, the agent finances half the necessary funds using internal funds from accumulated profits and the other half from the bank. After purchasing, the retailer or raw-material maker renews its production capacity by increasing the number of units of equipment by one in the Cobb–Douglas-type equation.

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Chapter 5
AI and the Future of the Labor Market: The Advent of a New Paradigm?

Junko Furukawa

Abstract Information and communication technology (ICT) is changing society as we know it, and artificial intelligence (AI) will replace almost half of the current jobs in the near future. The ICT-based economy has several novel aspects that the industrial economy did not possess: network externalities, monopolies of platforms, provision of zero price services, and ambiguous roles between consumers and producers; ICT's matching ability will cultivate markets in a deeper and more thorough manner than before. While the demand for high-skill labor related to technological progress increases, the skills gap remains wide. How will individuals who are under permanent threat of unemployment or are excluded from the market by AI respond to this situation? In this chapter, I propose a simple thought experiment to consider the impact of AI on the labor market. In this experiment, I examine the following aspects: the social implementation of AI, responses of workers to survive, social cost of unemployment, possibility of disruption, and the advent of a new society accompanied by changes in values. These analyses will help determine how institutional design and economic policy can be harnessed to address the social dilemma arising from technological innovations that raise labor productivity.

Keywords Knowledge-based economy · Artificial intelligence (AI) · Technological unemployment · Skill gap · Network externality · Winner-takes-all · Prosumers · Thorough marketization · Semi-market economy · Gig economy · Reputation · Intuition

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5.1 Impact of Technology on the Economy and Labor

A revolution in scientific thought and technological innovation can occasionally bring about major paradigm shifts. Similar to the transition from geocentrism to heliocentrism, the adoption of fossil fuels during the Industrial Revolution also had a massive impact on society. It gave us the machinery industry, where before the late eighteenth century, we only had agriculture, handicrafts, commerce, and plunder as means to create wealth. The machinery industry and its marketization brought wages and opportunities for social advancement to people who had been languishing at the bottom of the economic ladder for generations and released them from the gloomy *steady state*. The emergence of a middle class created new economic dynamism in which demand stimulated production. Marketization has led to the success of capitalism and the free circulation of accumulated capital around international markets, which frequently results in financial crises, such that it almost resembles a *casino*.[1] As a result of capital accumulation, the marginal productivity of capital has also declined. The increase in inequality in income and assets, as well as the decline of the middle class, will gradually accumulate as factors of political instability.

Nowadays, ICT is once again bringing great changes to the economy and society, with the substitution of labor by AI especially increasing the pressure on the labor market. In this chapter, we discuss the near future of the market and society, focusing on the impact of this ongoing technological innovation.

5.2 Characteristics of the Twenty-First Century Economy

The three revolutionary technologies that are expected to bring about a paradigm shift in the economy and society of the twenty-first century are genetic engineering (G), nanotechnology (N), and robotics (R), which Ray Kurzweil termed GNR. The genome of genetic engineering has the potential to elucidate the fundamental information of life and change the program of life activities, while cloning technology enables the replication of organisms. Nanotechnology can potentially allow us to reconstruct the world at will by enabling manipulation at the molecular level. Robotics (which includes AI) is the creation of non-biological intelligence beyond original human intelligence which can revolutionize human labor (Kurzweil 2005). In this chapter, we will focus on the last of the three.

ICT can process digitized information. As bits of information can be transmitted instantly and over great distances, human communication can easily transcend time and space. In its nascent stages, ICT was thought to be an inexpensive technology

[1] Strange (1986) named the international financial market, which had become so violent that the state institutions lost control of capital, as *casino capitalism*.

that would enable spontaneous communication and bring about a democratic and equal world, but there are multiple unforeseen dimensions of this phenomenon.

We refer to the mode of production in which *information goods* are central to industry as *the knowledge-based economy*. The knowledge-based economy of the early twenty-first century is based on the Internet of Things (IoT). Government agencies, security information networks, companies, factories, machines, stores, distribution systems, water and energy supply systems, airplanes, vehicles, houses, appliances, furniture, human bodies, pets, clothes, plastic bottles, vegetables, and so on are connected via the Internet and computers in every corner of the world.

The characteristics of the *networked knowledge-based economy* differ marginally from those of the industrial economy. Externalities have become increasingly important. The existence of supply-side externalities (or increasing returns) in manufacturing predate the Industrial Revolution, as Adam Smith described. Although economists have widely pointed out this phenomenon, economics has dealt with it as a *market failure*. However, in a knowledge-based economy, demand-side externalities (or network externalities) are pivotal to the economy and can no longer be treated as an exception. Network externality refers to the condition in which the more consumers use the same service or goods, the greater the benefit for each consumer.

Network externality was initially discussed in terms of hardware, such as telephones or DVD players, the utility of which increased with the number of users (Rohlfs 1974). As intangible information goods have started adding more value than tangible goods, network externalities associated with information goods, such as software or platforms, have become significantly important. When your benefit increases if you use the same service as others, then everyone will increasingly flock to the same service, and *a winner-takes-all* scenario, or a monopoly naturally occurs.

Platform enterprises such as Google, Amazon, Facebook, Apple, Alibaba, Tencent, and Baidu form information nodes. They often adopt a strategy of maximizing the number of users by offering free services in order to reach a critical mass, which is the minimum number of users for which network externalities are effective (Furukawa 2014). This is because critical mass is a necessary condition for the natural growth of users to help the company gain a monopoly. However, there is no guarantee that the monopoly of the company will last forever. Once the penetration rate reaches 100%, the network externalities will no longer work. Accordingly, the lifespan of ICT companies is expected to be shorter than that of manufacturing companies.

The knowledge-based economy has several other characteristics (Furukawa 2010). In an industrial economy, consumers and producers are clearly delineated. However, in a knowledge-based economy, consumers can participate in the production process through the two-way exchange of information between consumers and producers via ICT. Consumers who are both consumers and producers are called *prosumers*. Companies are capitalizing on the opportunity to utilize consumers as free laborers. They are already taking root in the form of ATMs at banks, self-checkout at stores, and tablet ordering at restaurants, which provides companies with ideas, product feedback, and helps them save on marketing and advertising costs through word of mouth.

All actions on the Internet are accumulated as digital data at the information nodes. The platform industry constantly collects huge amounts of information, and the accumulated big data is analyzed by data mining and other methods to extract new information, which in turn adds new value.

5.3 Impact of AI on Labor

5.3.1 Decrease in Employment

As algorithms for processing data advance, AI can bring convenience to people and concurrently replace human labor. First, to what extent will AI be able to approach and exceed human capabilities? From a critical standpoint, Searle (1980) defined *strong AI* as a well-programmed computer that is not merely a tool in the study of the mind, but rather a mind of its own that has a robust cognitive state. However, if an AI program solves problems and makes inferences that fall short of human cognitive abilities, it is referred to as *weak AI*. Even if a computer can translate a language into perfect Chinese, it is not the same as a machine that understands the *meaning* of the Chinese message.

In contrast, Kurzweil (2005) predicts that the *singularity,* when AI will gain consciousness and emotions and surpass humans, will occur around 2045.

Experts are divided over whether AI will reach such a stage of singularity. Some say that there is a possibility that it will inevitably happen if AI correctly implements a program optimizing itself. However, others do not believe this will occur because the thinking mechanism is fundamentally different between machines and humans, and consequently, AI can never become equivalent to human intelligence. However, this is not central to the most recent discussion on the extent to which AI will replace current labor. This is because if machine learning and deep learning currently under AI development and the scope of social application are expanded, AI can immediately replace existing labor. In fact, an AI beat a professional chess player in 1988, a shogi pro in 2001, a Go pro in 2005, won 60 games in a row in early 2005, and decided to retire from competition against humans after defeating the world's top Chinese Go pro, Ke Jie, in May of the same year. Since then, AI has continued to evolve in AI-to-AI games, surpassing and eliminating human intellectual labor in some respects.

In his 1930 essay, Keynes predicted that economic problems would be solved within a hundred years due to technological innovation and that humans would not need to work in an age of excess and leisure, but instead maybe work 3 h a day out of habit (Keynes 1930). 2030 is almost upon us.

Since the onset of ICT in earnest, Mortensen and Pissarides (2016), Brynjolfsson and McAfee (2011), and many other experts have highlighted the issue of technological unemployment. Among them, the simulations conducted by Carl Benedict Frey and Michael A. Osborne of Oxford University in three industrialized countries, the USA, the UK, and Japan, are well known because they allow for international comparison (Frey and Osborne 2014, 2017; NRI 2017). They estimated that the percentage of the workforce that can be replaced by AI between 10 and 20 years from now is 47%, 35%, and 49% in the USA, the UK, and Japan, respectively. A similar study in Japan yielded a simulation result of 55% (David 2017). These simulation results thus confirm Keynes's prediction.

Frey and Osborne explored the potential of AI based on whether existing jobs are routine or atypical, and whether they involved recognition or manual labor. Their analysis found that Japanese labor was the most affected by AI in all the three countries. The occupations that are most likely to be replaced by AI (over 50%) are general office work, personnel affairs, and low-skilled labor such as driving, food production, assembly of appliances and electrical equipment, building cleaning, and delivery.

Being well-educated and having a high income do not guarantee job security. It was concluded that jobs that pay far more than average, such as those of CPAs, patent attorneys, judicial scriveners, marine engineers, and programmers can also be replaced by AI.

Fragmented and modularized jobs are appropriate for offshoring. Middle-income countries that depend on offshoring from developed countries for their income will not be immune to having their jobs recaptured by AI in developed countries.

Nonetheless, most economists posit that technological unemployment is not a concern. They are optimistic that technological unemployment is a short-term phenomenon similar to the Industrial Revolution, when the excess agricultural workers moved toward industrial work and the excess industrial workers due to mechanization shifted into new service industries. However, many specialists considering AI and labor problems are concerned that there seems to be no alternative in the post-AI world for people who are engaged in routine and repetitive tasks.

In his analysis of technological unemployment, Martin Ford predicts that the introduction of AI will reduce employment, increase labor productivity, and raise wages. Prices will fall and demand will increase for a while, but in the medium term, this trend will not continue and the majority of current jobs will disappear. The demand for jobs involving advanced cognition and creation will be high, but the skills on the labor supply side will be low, resulting in a mismatch between supply and demand. The unemployment ratio will rise, and inequality will become rampant. For households that fall into the low-income bracket or are unemployed, the tuition and opportunity costs of higher education will not pay for themselves if a job is not guaranteed after college. Reducing their opportunities to learn the advanced knowledge needed for a knowledge-based economy makes their job transition even more difficult (Ford 2009).

Inequality in education will further widen the mismatch of skills between labor supply and demand.[2] As long as education inequality persists, the problem of income and asset inequality cannot be resolved. The polarization of society, which is already serious, will be taken to the extreme, and the unemployed and unskilled labor force will prevail throughout society. An unemployment rate of nearly 50% is not ordinary, and it is not a level that can be dealt with by conventional economics.

5.3.2 AI and Employment Scenarios

In light of this pessimistic landscape, let us add our own consideration to this scenario. Table 5.1 shows the results of the author's thought experiment on the development of AI and future employment. Theoretically, both the progress of AI and the opposite are possible. If AI advances, it will branch off into strong AI and weak AI, as mentioned earlier (Sect. 5.3.1). The assumed scenarios herein are derived from the relationship between the development of AI and employment.[3]

If strong AI is developed and computers with capabilities that surpass those of humans are created, and companies pursue maximizing labor productivity, theoretically all human labor will be replaced by AI and employment will disappear. In reality, AI owners and machine creators would be the only ones working, and they will take care of all social functions. As Keynes dreamed, all humans will be freed from labor as the fruits of technological progress are equally distributed. A kind of paradise will be realized (strong AI+ employment reduction).

However, jobs will still be created in the following cases: (1) when high-skilled labor can be performed by strong AI but for some reason the jobs remain, (2) when wages are so low due to mass unemployment that human labor is less expensive than the cost of AI, (3) when new ultra-low-wage human jobs are created to support or complement AI, and human labor is more desirable and has value for the rich (such as warmth or imperfectness), or (4) where labor is done as a hobby that disregards cost and wages (strong AI+ active employment).

Next, as shown in the third scenario in Table 5.1, in the scenario where weak AI remains in the machine learning phase, the cost of AI is low enough to replace

[2] World Economic Forum (2020) reports a prospect of job creation and replacement by machines in 5 years. It predicts that by 2025, the proportion of humans in labor will decrease from 67% in 2020 to 53%, and 85 million jobs may be replaced by a shift in the division of labor between humans and machines or algorithms, while 97 million new jobs, such as data analysts, big data specialists, digital marketing and strategy specialists, digital transformation specialists, and so on, are expected to emerge. Nevertheless, the increasing ratio of the latter will slow down, and the skill gaps will continue to be wide. Employers will retrain 50% of their employees replaced by AI to relocate them in the companies, even though it is not certain that the investment will pay off. This seems to be typical of employees who are able to remain employed in the short term. Government retraining supports those who are unemployed in 26 advanced and emerging countries.

[3] It should be noted that market and social conditions are influenced by policies, social institutions, and AI program concepts, so there is also more diversity than discussed here.

Table 5.1 AI progress, employment status, and market and social conditions (translated from Furukawa 2020)

Scenario	Employment status	Market and social conditions
Strong AI+ employment reduction	Theoretically all human labor is replaced by AI. All are unemployed, or a handful of employers are taking care of rest of all as a social function	The entire population is completely free from labor, besides a few AI owners and machine creators
Strong AI+ active employment	Theoretically all human labor can be replaced by AI. Still demand for high skilled labor exists, and new jobs are created to take advantage of low-wage labor	Human labor is less expensive than AI. Extremely low-wage labor includes providing services for the rich, and supporting AI. Humans in an all-AI world create new value. Extreme disparity
Weak AI+ employment reduction	Routine labor will be replaced by AI. 50% of jobs will be lost. High-skilled labor and labor which involves cognition or judgment remain employed	Scenario by Frey et al. The cost of AI is low enough to replace human jobs. Skill gaps remain wide. Retraining is effective. The disparity is great
Weak AI+ active employment	Routine labor will be replaced by AI. Less than 50% of jobs will be lost High-skilled or cognitive labor is in employment. Atypical labor is also in employment	AI is replacing human jobs. The cost of AI is higher than wages. All AI development is oriented toward symbiosis with humans. Skill gaps stay high. Retraining is effective. The disparity is considerable
No progress in AI+ domestic employment reduction	Non-AI mechanization, use of low-wage labor abroad (foreign investment, outsourcing), legalization of domestic non-regular employment is continued	Similar to Pre-ICT economy. It is unrealistic that AI development stops
No progress in AI+ active domestic employment	Employment of low-skilled labor continues	Similar to Pre-ICT economy. It is so unrealistic that AI development stops

human jobs, and about 50% of employment disappears. Atypical labor that involves cognition, or complicated judgment is difficult to replace, and creative high-skilled labor is employed. This is close to the situation assumed by Frey and Osborne (weak AI+ employment reduction).

However, the fourth scenario is one with weak AI that maintains over 50% of labor. The analysis by Frey and Osborne shows the upper limit of the theoretical value of machines replacing labor as far as can be inferred from the present; it does not take into account the market mechanism. In the real economy, labor rather than the theoretical value will remain in employment for the moment, because the need for considerable atypical physical labor, especially in small- and medium-sized enterprises (SMEs) will remain. AI cannot be implemented due to the low capital investment capacity and lack of financial resources. If wages are lower than the price of AI, maintaining employment will be less expensive. However, there is a high possibility that such companies will be rendered irrelevant by waves of AI and be eliminated.

In contrast, humans will continue to be employed when the concept of AI development is oriented toward symbiosis between humans and machines in a positive manner. In addition, as in the case of the second scenario in Table 5.1, human employment will continue in the following cases: (1) when high-skilled labor that can be performed by AI remains for some reason, (2) when there is a new demand for ultra-low-wage labor, (3) when AI can be used but human labor is preferred, or (4) when labor is performed for pleasure (weak AI+ active employment).

However, if there is no progress in AI (the economy before the advent of AI), in order to compress labor costs, the economy will focus on substituting non-AI machines as much as possible. Foreign investment and out-sourcing will take advantage of low-wage labor overseas to avoid high domestic wages (no progress in AI+ domestic employment reduction).

In the absence of shifting to AI and the ensuing job reduction, a large portion of low-skilled labor will remain in employment. Non-regular employment and foreign trainees will continue to acquire domestic low-wage jobs (no progress in AI+ active domestic employment). However, under the current situation, it is difficult to stop the development of AI, and it is unrealistic to expect the scenarios shown in rows 5 and 6 of Table 5.1 to continue.

If we consider the market mechanism, the scenarios will most likely be those described in the second to the fourth scenarios in Table 5.1. The degree of unemployment will vary depending on the institutional design, but the common denominator is that the evolution of AI will exert continuous downward pressure on wages, causing them to regain elasticity. The demand for labor arises when wages are lower than machine rentals or when there are tasks that cannot be replaced by machines. What happens then in the market and society?

5.4 Market Changes Brought About by AI

5.4.1 Thorough Marketization

Let us first consider how ICT can bring about market changes. The sharing of information across time and space by ICTs expands and deepens markets. I refer to this impact by ICTs as *thorough marketization.*

For example, ICTs can easily link new goods so that competitors can exist in remote areas. When the goods are commodities, a perfectly competitive market will be realized; a store in the neighborhood and one 300 km away, which used to be too prohibitive to price check, are now just two lines of information on the same screen for the customer. If the prices are the same, the customer can make an indiscriminate choice. If there is even a slight difference in price, the cheaper product is just a click away. Theoretically, *the law of one price* can expand worldwide.

Of course, the same situation occurs in the labor market. The stable labor employed during the era of the industrial economy is first replaced by flexible labor through the institutionalization of a non-regular employment system. Because the massive number of people unemployed due to the shift to AI will be eager to return to the labor market, their contracts will be shortened and their work will be fragmented. This liquidated labor force is sometimes referred to as a *nomad*. Polarization emerges between high-wage, high-skilled nomads, and low-wage, low-skilled nomads. The former move from organization to organization as professionals with their own strong areas of expertise, signing contracts with companies for each project, and the latter are marginalized from regular employment and are stuck with piecemeal jobs.

For both the classes of nomads, ICTs will play a role in connecting workers and employers with each other and bring about encounters that never existed before. In the form of *crowdsourcing,* it is possible to obtain cooperation from an unspecified number of experts on the Internet for free, while at the same time, it is possible to order and receive modularized, simple, low-skill, piecemeal jobs for prices as low as one cent per task. The latter type of work, with its low unit prices and ultra-short contracts, is called *gig work*, and the economy that results from it is called a *gig economy*. As labor moves with the click of a mouse, the bonds between the employer and employee will become short-term and tenuous. This expands the scope of the labor market and the *liquefication* of the labor force, resulting in an increase in the elasticity of wages.

ICT is also the most efficient way to respond to diversification in consumer preferences. For example, digging up a *long tail* is possible only with ICT. Long tail is a term that Anderson (2006) coined from *the long-tail distribution* of statistics, which refers to the long line of the power law curve drawn by taking the sales ranking on the horizontal axis and its frequency on the vertical axis (Fig. 5.1). Thus far, in the market economy, the top 20% of the most popular products generate 80% of the sales and almost 100% of the profits. This is due to the physical limitations of logistics stores. Even in large stores, the sales floor is limited and customers cannot access products that are not displayed in the store. Therefore, in the industrial economy era, the standard model was to develop hit products that would fit into this top 20% category, arouse consumer interest through advertising aimed at the volume zone, and then mass produce them. However, products sell differently on the Internet. For example, 98% of the 10,000 songs that were converted to digital content sold at least one copy in 3 months (Anderson 2006). Long forgotten old hits continue to sell via the Internet. In the case of information goods, the market can be *expanded* to a global scale by the act of downloading, and in the case of tangible goods, by combining them with delivery services. Goods lurking in the tail will also emerge in the market, and the market will *deepen*.

Gig work with ultra-short-term contracts mentioned above also exist in the long tail. Special-skilled but low-demand labor can also enter the labor market through the Internet, and the market will *deepen*. However, whether this form of work with

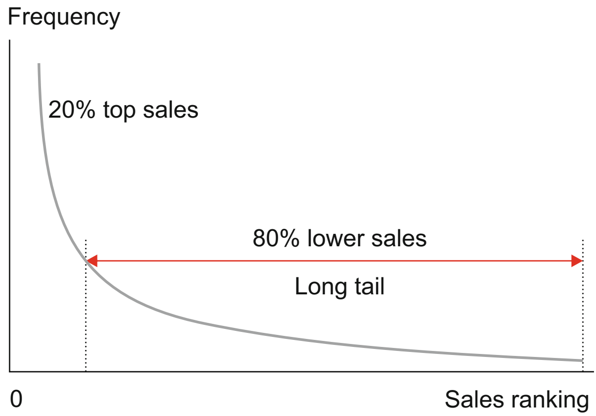

Fig. 5.1 Long tail (translated from Furukawa 2020)

its extremely short, time-limited contracts can satisfy the human need for security remains to be seen, and it is expected to lead to harsh living conditions.

The *deepening* of the market includes a *sharing economy.* Idle personal assets that have been unused and stocked are now being shared and supplied to the market. Airbnb has made a market out of individuals' spare rooms, and Uber has made a market out of individuals' spare time with their cars. In the flea market on the Internet, unwanted household items have been actively recycled and sold since the dawn of the ICT age.

Pursuing the efficiency of durable consumer goods operating in the market will *deepen* the market. In an *idle economy,* cabs that cannot transport passengers can be transformed into logistics providers that receive orders via ICT to deliver goods. Thus, the idle time of durable goods can be marketed to the full extent. Some loss-making bus companies in rural areas in Japan have been able to avoid going out of business by partnering with parcel delivery companies like *Yamato Transport* or Japan Post to transport goods to and from relay points. Another successful company is *RAKSUL*, which offers printing services at unbelievably low prices by diverting work to many printing companies that are unable to obtain steady orders.

New market completion has resulted in the extinction of geographic and physical constraints, and goods that were previously unmarketable are being supplied to the market. This *expansion and deepening* of the market is a phenomenon that can be termed *thorough marketization.* As a result of thorough marketization, prices generally decline as shown in Fig. 5.2. The long tail includes a large number of goods and services whose prices are zero in the market, because the supply of such commodities is almost indefinite by suppliers, which includes amateur producers.

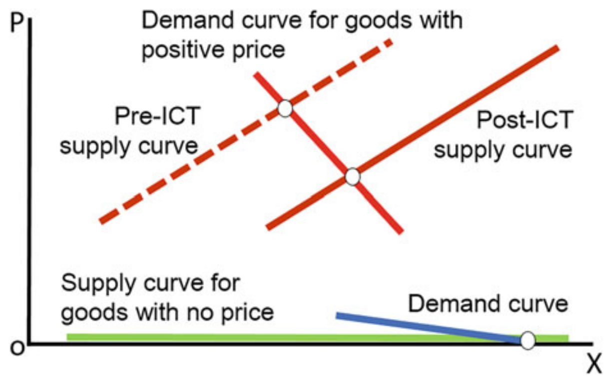

Fig. 5.2 Thorough marketization and price change (translated from Furukawa 2020). *P* price, *X* quantity of supply and demand

5.4.2 What AI-Substituted Workers Choose

An economic society that is constantly under the pressure of unemployment by AI needs high adaptability. Responses to the situation can be diverse but they are all a matter of survival. Most of us will face this situation, and how we respond to it through trial and error will become the basic factors shaping a new society.

Figure 5.3 is a thought experiment showing the responses of workers who are replaced by AI. There are three possible directions for this.

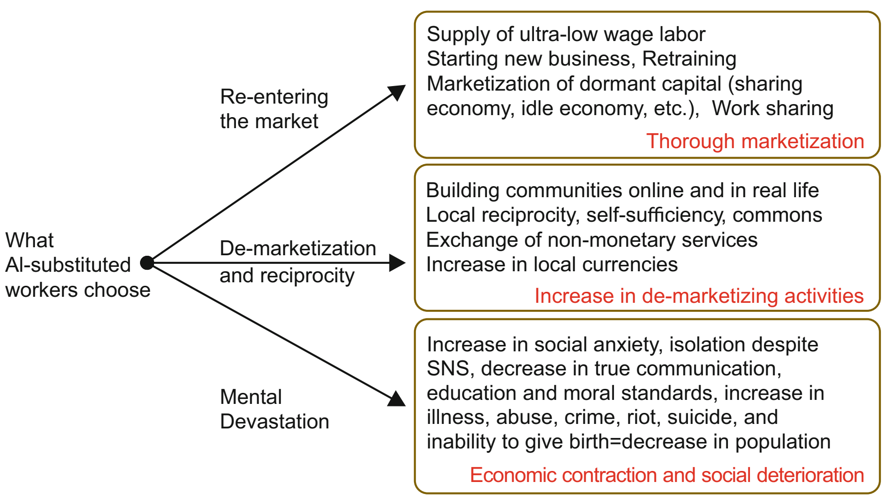

Fig. 5.3 Three responses of workers replaced by AI (translated from Furukawa 2020). There is more than one choice. The choices can be combined. However, this choice also depends on the social system

Re-entering the Labor Market

The first is to remain or re-enter the labor market as a worker. As discussed in Sect. 5.3.2, labor demand and employment are maintained when wages are lower than the cost of AI, even if the task is routine. For tasks involving making decisions and handling complex, non-repetitive situations in which AI is not as effective, humans have a comparative advantage and employment will be retained. For SMEs with limited financial resources, human labor may be less expensive, depending on the price of AI implementation.

If human labor can be retrained and converted to highly skilled workers, they can definitely re-enter the market as high-skilled labor.

The second method to return to the market is via the creation of new jobs, including venture businesses. In the ICT-enriched knowledge-based economy, it is easy to go into business with just an idea. Anyone can sell goods and services privately on the Internet. For more serious startups, angel funds help monetize good ideas. It is also easy to raise funds through microfinancing and crowdfunding, which are relatively new concepts. In the case of microfinancing, a financial institution, such as Grameen Bank, gives a small loan with no collateral required to those most in need. In contrast, crowdfunding is a way to raise money by presenting an entrepreneur's idea to a large number of people via the Internet. This approach helped Orphe bring their LED smart footwear product to the market.

If an idea is tangible, a 3D printer will make it easier to realize. It would enable distributed, tailor-made production in a flexible range of varieties and volumes. One does not need to own a 3D printer. A makerspace is an hourly workshop that is equipped with all the necessary tools to enable creating prototypes and products without raising significant capital.

A variety of new professionals will emerge in the knowledge-based economy: YouTubers, models of human avatars for AI or augmented reality (AR), and Internet gamers in the field of e-sports, where some are already earning high incomes from streaming their matches.[4] There is also a growing trend of prosumers on the Internet where people earn quasi-currency in the form of points as consumers by providing information, answering surveys, posting feedback, and so on, in response to requests from platforms or other companies.

As shown in the second, third, and fourth lines of Table 5.1, when a large pool of surplus workers suffer from ultra-low wages, new tasks may be created. This scenario should not be underestimated. In an all-AI world, *real human hands* create new values such as face-to-face sales services, personal care, nursing care, companionship, and pet walking. These are needs that can be provided by machines

[4] Ishiguro (2021) and Hirano (2021) referred to AI robots in their recent works. The main character in Hirano's *Real Intention* works as a *real avatar*. Real avatars are a new type of occupation where a human agency visits places with AR headsets to deal with the requirements on behalf of the wealthy who cannot or do not want to execute the job by themselves due to aging, living abroad, or other reasons. The labor cost is so low that workers are used to support AI, not be replaced by AI. The cases discussed here are vividly portrayed and described by these novelists.

but cannot be satisfied by AI, and for which direct human services are desirable for those who can afford them. This means that low-wage, labor-intensive services such as butlers and domestic servants, which have been given up due to skyrocketing wages as capitalism developed, may be revived under a new guise. However, for human beings who have experienced democracy and human rights, low-wage labor and class fixation may not be comfortable options. This is due to the shadow cast by the large income and asset disparity in the background.

The third measure to return to market includes the sharing economy, idle economy, and gig work through thorough marketization, as discussed in Sect. 5.4.1. Traditional work-sharing, in which a single person shares a task with several others, is also gaining importance. There are cases in which people actively use work-sharing to maintain their work–life balance in line with their own life plans, and cases in which people are not hired as full-time employees but they reluctantly agree to share the workload nonetheless.

Progress in De-marketization

The second response of AI-substituted workers is *de-marketization.* Workers who are forced out of their regular jobs may seek ways to remain in the labor market. Even if they have jobs, their income generally decreases due to non-regular employment, short-term contracts, gig work, and work sharing. As a defensive measure, they might use their newfound time to rebuild their lives. They may leave the city and move to the countryside where land prices are lower, either alone or with their families, grow the necessary agricultural products in the fields, live a semi-self-sufficient life, and procure necessities and basic services through mutual cooperation and exchange with local residents. Local currency and eco-money would also be useful. Those who are capable may use their talents to *produce* for the market by composing, cartooning, designing, handcrafting, video shooting, and video editing, and so on. It would be relatively easy to set up online stores, which they may do in parallel with non-regular employment or gig work to generate monetary income. For example, items that can only be purchased with money (such as the Internet or smartphone communication costs) will be paid for with monetary income, and people will go to town to shop for special occasions. The prices of daily necessities will fall further due to lower manufacturing costs using AI and 3D printers, the sharing economy, and recycling, which are all forms of thorough marketization (Sect. 5.4.1). Thus, people alienated from the stable labor market of long-term contracts will regain their place in society, quality of life, and human dignity through the formation of non-market mechanisms and social capital. This is the path to a *semi-market economy*, where people live dichotomously, at times immersed in the reciprocal economy and at other times accessing the market as needed, while securing their own economic and mental health.

The revival of family reciprocity between men and women or quasi-family between friends can also be considered a part of the de-marketizing process. For example, according to the latest estimates of mechanization during the Industrial Revolution, the male employment ratio in the industrial sector in England and Wales increased by 10% between 1710 and 1851, while the total employment ratio remained constant at 45% for 150 years. In other words, female labor, which was replaced by labor-saving mechanization in the textile industry, was absorbed into other sewing trades and domestic servitude, as well as into domestic housework and childcare. As the standard of living of workers improved, the quality of domestic services, which could not be obtained in the market, became indispensable, and the male breadwinner model was formed (Saito 2014). However, it is possible that the current low marriage rate, which has some correlation with the increase in the female employment rate, will be reversed and the division of roles and cooperation within the family in different guises will be restored.

Similarly, there is a strong possibility that the sharing economy in the traditional sense will be revived: the sharing of woodlands and other natural areas like commons, the sharing of durable consumer goods such as cars and farming tools, and the sharing of houses and practice of *osusowake*, in which one shares what has been given to them or any surplus with others in local communities. These practices will help save money.

Once the basic infrastructure of life is secured, these workers may begin to create, transmit, and realize themselves. This creation is not always associated with rewards. It is wonderful if it is rewarded, but even if it is not rewarded in terms of money, gaining *reputation* and sympathy from others for being helpful to others and appreciated can be a way of self-realization that is equally as rewarding as money.

Production and consumption behavior via the Internet has become the norm, and the Internet provides global information on the supply of knowledge goods, physical goods, and mutually beneficial services in large quantities. A large number of novel ideas and goods overflowing in the long tail will satisfy people's needs at a low price, which brings a sense of fulfillment to the providers, and may form a larger field of creativity, including ideas that end up being of no consequence.

De-marketing may be conducted positively by seeking to restructure a way of life and values, or out of necessity, to survive unemployment. It is more likely to combine with re-entry into the market. Creativity nurtured outside the market may revitalize the market, and the balance between the natural environment and the market—in other words, *the circular economy*—may begin in earnest here. This kind of movement has already begun on a small scale in rural areas and even in some urban areas.

Mental Devastation

The third response or reaction of those who have been replaced by AI is mental devastation. It is difficult to keep one's spirit strong when one is constantly unemployed, financially impoverished, or fearful of losing one's job. The inability to maintain dignity increases mental anxiety. This effect is exaggerated when one is always immersed in one's smartphone and browsing social networking sites (SNS), which leads to a high possibility of losing confidence and becoming more isolated. Once the psyche is devastated, matters become worse as people lose the ability to communicate in a truly human way, even with superficial contact on the Internet. Illness, abuse, and crime increase, educational and moral standards decline, and addiction increases as people turn to drugs, alcohol, and gambling for a brief respite.

Shorter lives and an increase in suicides will affect the reproduction rate which will eventually contribute to the deterioration of society. This is the astronomical social cost of unemployment.

The above three assumptions are expected to proceed simultaneously in a mixed manner, rather than in any one particular manner. It is natural to assume that this trend will occur long before the unemployment rate reaches 50%, given that the signs of this trend have already been observed among those in the labor market who have been marginalized.

5.4.3 Contraction of the Monetary Economy

The vast majority of the potentially unemployed will be working for lower wages or lower incomes than the middle class of the twentieth century. However, the individuals at the center of the platform industry will gain new economic bases and more influence. The data gathered on such platforms will help them refine their decisions to provide better services. The manufacturing and service sectors (including finance) will push to replace labor with AI to increase labor productivity. The current disparity between the haves and have-nots will widen further as those who can develop new technologies will replace those who cannot.

Declining employment and income will lead to a decline in purchasing power. This means that the *middle class* that supports capitalism through mass consumption will disappear. A large number of consumers without money will be forced to leave the market and satisfy their needs via the long tail or de-marketization methods. While ICTs promote thorough marketization, aggregate demand for a money-based market economy will decline and firms will be unable to continue producing as much as they did during the industrial economy era, causing the monetary economy to shrink. Advertising revenue, which is currently the main source of income for platform enterprises, will be unable to function in the absence of consumers.

An offshoot of the GNR (Sect. 5.2) will be the provision of new services to low-income populations. Simultaneously, markets will be generated for expensive goods and services that the masses will never be able to afford, such as custom-made babies at the genetic level, cloned organs for transplantation from one's own cells, travel to Mars, flying cars, and so on; only a handful of wealthy people will avail of and benefit from these products. This may lead to market segregation.

Now, we have to redefine *the economy.* If the economic framework is viewed as the activities of a broader economy that encompass the market economy, it does not necessarily mean that the economy itself will shrink. This is because it is quite possible to have a shrinking market economy that constitutes a prominent high-price zone within a broader economy that supports the de-market activities of people outside the market. However, if we err in this delicate process, social instability will be inevitable.

5.5 Pathways to a New Society

It would be ideal if society can function with 50% of people unemployed.

As Keynes (1930) predicted, this would mean that humanity is freed from labor. People can enjoy freedom, creativity, and spirituality while enjoying inexpensive goods and services produced by machines. The real question is: How do we deal with the possibility that the fruits of technological progress will not be distributed equally?

5.5.1 Ideal Conversion

It is important to remember that income inequality often produces emotions that can overturn history. The transformation of Chinese dynasties, the collapse of nineteenth-century civilization, Britain's exit from the European Union, the rise of the radical right in Europe, and Trump's supporters in the USA are all swells of popular revulsion and rage generated primarily by inequality. On a planet where the Internet links us all, the theoretical possibility that this sentiment can instantly generate global solidarity cannot be underestimated. It will be much easier for the solidarity of 99% of the have-nots to defeat the wealthy 1% in the future than it was in the age of industrial economy with material limitations. The Jasmine Revolution, Brexit, and the birth of the Trump administration have already proven that social networking sites can influence a shift in the power structure. A variety of policies have been proposed to cope with growing inequality. There have been many proposals for corrective measures, such as more progressive taxation, universal basic income, stricter tax haven regulations, and higher corporate taxes. However, in a world where the winners of the market have *structural power* over institutional decisions for policy frameworks through politics, how can we achieve income redistribution to a level for society to be sustainable?

If the richest 1%, or those in the ICT platform and financial industries realize that their continued monopoly on wealth will one day strangle them, will they be wise enough to cut back on their greed? The contributions of prosumers, the existence of users, and the cash of depositors are now bringing them wealth, and the consumers that the wealthy believe to be their customers are customers with potential liquidity who can leave at the click of a mouse if only an alternative service was available. Accumulated financial capital is fictitious capital that shrinks instantly with the collapse or decline of financial markets.

If, in contrast, the wealthy actively contribute to the correction of inequality, for example by accepting the financial burden of income redistribution such as more progressive taxation or basic income planned by the government, they will certainly gain the respect and *reputation* of the future society. The *reputation* of a company or individual actively participating in this new economy is a stable form of capital that can "lock-in" a large customer base who have regained purchasing power through income redistribution.

In fact, there is a growing trend to invest in companies that consider environmental, social, and governance (ESG) as well as financial statements as factors necessary for long-term corporate prosperity, and to withdraw or disclose capital from companies that do not. This is not to deny that companies should be highly profitable, but that companies should be more socially responsible to reflect society's expectations. This is an example of how the reputation derived from social considerations can become a source of profit, similar to traditional corporate social responsibility (CSR). Therefore, it is easy to imagine companies building their reputations by contributing to the reduction of inequality.

5.5.2 Role of Government

The government's role in social consequences is unexpectedly large. This is because if we make a mistake, we cannot exclude the possibility of the third response of the AI-substituted workers in Sect. 5.4.2, which is an increase in the social cost of unemployment, that is, mental devastation and riots due to the global solidarity of the poor. Governments must prepare in advance measures to reduce the social cost of unemployment given that inequality will inevitably increase.

Measures to address income and asset inequality must be taken seriously. The crisis of the wealthy brought about by the monopoly of wealth is likely to be triggered by a market-based economic crisis and social unrest. It will be essential for governments to play a role in strengthening redistributive functions such as progressive taxation, a higher minimum wage, and universal basic income while actively evaluating the wealthy who are willing to return their wealth to society, as well as to secure financial resources through initiatives such as tax haven regulations and digital taxation.

As for the provision of public goods, in addition to securing financial resources for infrastructure development, there are other alternatives for those living in a de-marketized economy, such as imposing tax payments on the labor force to pay for the burden of the beneficiaries. In particular, compulsory education, vocational education, and adult re-education systems need to be expanded to decrease the skill gaps in the labor market, and to avoid the loss of social overhead capital given that basic education and skills are essential for a knowledge-based economy.

It is also important to establish an orderly transition into a semi-market economy, rather than simply regulating the emergence of new technologies and communities within the existing framework and legal system. It will also be necessary to encourage businesses and job creation in connection with the development of new industries, and to strongly promote local efforts to provide economic and psychological support to those who have suffered from mental devastation and whose social bonds have snapped.

5.5.3 Will There Be a Shift in Values?

The era of the industrial economy two and a half centuries after the Industrial Revolution has been a unique period for mankind. By utilizing natural resources and land at an unprecedented rate, many low-income workers managed to ascend into the middle class. However, the technological innovations that arose from the industrial economy are now working to eliminate a large number of them. Are we now in the phase where the middle class of the industrial economy is returning to its *original position* similar to that of low-income workers before the Industrial Revolution? Be that as it may, we cannot simply sit back and watch history being repeated. Just as fossil fuels significantly changed the values of society from feudalism to capitalism, a paradigm shift in ICTs that involves a change in the mode of production should be accompanied by a new set of values.

Keynes predicted that by the year 2030, when technological innovation has solved basic economic problems, the code of morality would change such that *the love of money is detestable* and that *we shall honor those who can teach us how to pluck the hour and the day virtuously and well, the delightful people who are capable of taking direct enjoyment in things* with *certain principles of religion and traditional virtue* (Keynes 1930). He may have been unaware of the advent of ICT, but he discerned that new technology would change the values of society through economic development.

Whether people are beginning to release their attachment to money varies considerably depending on which strata and aspects of society are observed. The constant threat that might be replaced by AI should also make people consider the unique human capabilities that cannot be replaced by AI. Once technological progress allows us to meet our material needs for survival at a reasonable price, our core values will shift to the *intangible*: reputation, social capital, collaboration, intuition, and creativity. These elements are candidates for a new value standard to replace the standards that formed the basis of the modern paradigm of rationality and capitalism: money, tangible assets, ownership, profit, capital accumulation, competition, and efficiency. Since we have already discussed reputation and social capital, we now consider *intuition* and *creativity*. Reich (2001) identified only *geeks* and *shrinks* as the types of workers who would survive in the knowledge-based economy. Geeks are people who create something out of nothing, while shrinks are people who understand people's motivations and unperceived desires. Shrinks can provide a packaged business model by identifying the nodes that can generate added value. The latter may seem to have been made redundant by the analytical power of big data, but if we look closely at the former, creativity and intuition emerge as a unique human ability that is difficult to replace through AI. In light of the fact that AI at the present stage is not very good at cognitive functions and dealing with complex problems, we focus on the mechanisms of human cognition and the brain (which are yet to be fully understood) and the importance of *intuition*, which our ancestors have studied.

Simon (1990), a scholar in cognitive science, Klein (2013), an authority on cognitive psychology, and Polanyi (1966), who defined tacit knowledge as the source of creativity and the link to higher dimensions, knew that *intuition* exists *now* and transcends thought. It is the presence of knowledge that comes directly from the center of the soul, where thoughts are quenched.

5.6 Conclusion

Over 250 years after the Industrial Revolution, technological innovation has once again transformed markets and society. ICT and AI are expanding and deepening markets, exerting downward pressure on prices and wages. In response to the constant pressure of unemployment induced by AI, people will likely build new lifestyles and discover new values. Their behavior guided by these new values will alter society. If we make a mistake in institutional design, social deterioration is inevitable. However, if we do not misallocate the benefits of technological progress, we may hold the key to the creation of a new society in which each individual can enjoy the richness of life that is not necessarily linked to the accumulation of money, but to the development of potentiality and spirituality. Perhaps the time has come for us to start thinking seriously about the social pathways that will lead us there. The advent of the new paradigm is just around the corner.[5]

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Part III
Computational Social Approaches to Social Dilemmas, Smart City, Cryptographics

Chapter 6
Mathematical Framework to Quantify Social Dilemmas

Jun Tanimoto

Abstract The context of social dilemma is of great interest in evolutionary game theory because of its importance in explaining the evolution of cooperation in biological systems. The dilemma strength parameters have been used to numerically characterize the social dilemma to understand how much dilemma existing in a game. However, these parameters cannot be explicitly determined in general. To understand the presence of social dilemma associated with more general game systems, in this chapter, we introduce a new index, "social efficiency deficit" quantifying the payoff difference between social optimum and Nash equilibrium. Whereas the dilemma strength provides a numerical measure of how much dilemma prevailing in a game, the social efficiency deficit depicts the payoff shortfall at Nash equilibrium compared with social optimum. We deliberately delineate the relationship between these two parameters for several game classes such as pairwise Prisoner's dilemma, Chicken game, etc. Notably, Prisoner's dilemma possesses an inverse relationship between them. Nevertheless, we also explore the consistency of the new parameter presuming the situation if a certain social viscosity (e.g., network reciprocity) is included into a dilemma game. Additionally, the pertinence of social efficiency deficit for revealing the presence of social dilemma in vaccination game and traffic flow analysis is illustrated at the end.

Keywords Evolutionary game · Symmetric two-player & two-strategy game · Social dilemma · Dilemma strength · Social efficiency deficit

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6.1 Symmetric Two-Player and Two-Strategy Games

First, let us examine the foundation of a symmetric two-player and two-strategy (2×2) game, which is the most important archetype among evolutionary games. Two-player and two-strategy (2×2) game has most commonly been accepted as archetypical templates in the field of evolutionary game theory.

Let us suppose an unlimited population. The individuals (hereafter sometimes called "agents") are well-mixed. Two individuals are selected at random and made to play the game. The game uses two discrete strategies: cooperation (C) and defection (D). The pair of players receives payoffs in each of the four combinations of C and D. A symmetrical structure between the two players is assumed. In Fig. 6.1, the payoff of player 1 (the "row" player) is represented by the entries preceding the commas; that of player 2 (the "column" player) is represented by the entries after the commas.The payoff matrix is denoted by $\mathrm{M} = \begin{bmatrix} R & S \\ T & P \end{bmatrix}$. Depending on the relative magnitudes of the matrix elements P, R, S, and T, the game can be divided into four classes; the Trivial game with no dilemma, the Prisoner's Dilemma game (sometimes abbreviated PD), the Chicken game (also known as the Snowdrift or Hawk–Dove game), and the Shag Hunt game (sometimes abbreviated SH). The system denoted by this payoff matrix has four degrees-of-freedom, since the number of variables is 4.

As long as a well-mixed and infinite population allowing the so-called Mean Field Approximation (MFA) is presumed, the dynamics of the abovementioned game can be totally evaluated by replicator equation, which makes us theoretically predict the equilibrium (Nash Equilibrium) of any symmetric 2×2 game.

Here, let us define the gamble-intending dilemma (hereafter referred to as GID, or the Chicken-type dilemma), D_g, and the risk-averting dilemma (hereafter referred to as RAD, or the Stag Hunt (SH)-type dilemma), D_r, respectively[1]:

$$D_g \equiv T - R, \tag{6.1}$$

$$D_r \equiv P - S. \tag{6.2}$$

GID can be described in a word as "greed," while RAD can be described as "fear" in a symmetric 2×2 game.

Referring to D_g and D_r, the four game classes are transparently established as PD, Chicken, SH, and Trivial, as summarized in Table 6.1. More importantly, which class—PD, Chicken, SH, or Trivial—is embedded in a given 2×2 game can be fully evaluated by both the signs of D_g and D_r. In other words, we note whether positive or negative signs for D_g and D_r strictly regulate the game class for any arbitrary 2×2 game.

[1] To learn in detail about GID & RAD and D_g and D_r as well as the replicator dynamics, you should consult: Tanimoto (2021).

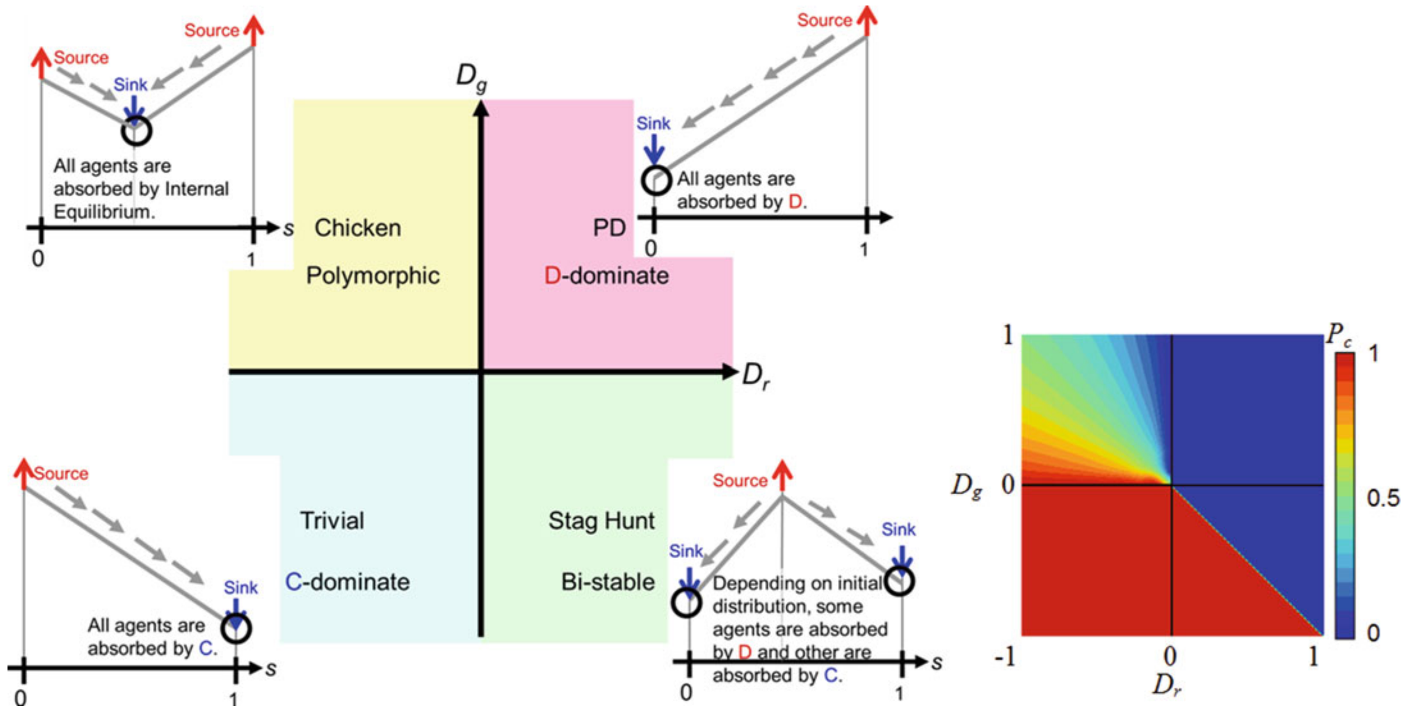

Fig. 6.1 Phase diagram of the dynamics classified by D_g and D_r of a two-by-two game and a summary of the dynamics of each game class (left panel). The right panel shows the cooperation fraction at equilibrium when an infinite and well-mixed population with replicator dynamics is assumed with an initial cooperation fraction, P_c, of 0.5. PD and Trivial are filled out in blue and red, respectively, since D-dominated and C-dominated phases are established. In the Chicken game region, a gradual shift of the cooperation fraction at equilibrium is observed due to the polymorphic phase. In the SH game region, bi-stability shows a twofold phase: either all cooperation or all defection

Table 6.1 Class type in a 2 × 2 game

Game class	Greed; GID? ($D_g > 0$?)	Fear; RAD? ($D_r > 0$?)	Dilemma as a whole?
Prisoner's dilemma; PD	Yes	Yes	Yes
Chicken (snow drift; Hawk–Dove)	Yes	No	Yes
Stag hunt; SH	No	Yes	Yes
Trivial	No	No	No

Here, let us define the cooperation fraction (indicating the fraction of agents taking C strategy in a well-mixed and infinite population) observed at equilibrium, i.e., $t \to \infty$, as $s \in [0, 1]$. And let us name $s = 0$ as all-defectors-state and $s = 1$ as all-cooperators-state. With the replication dynamics, theory teaches us that in PD, all-defectors-state works as sink while all-cooperators-state becomes source. It implies that a PD game always goes to extinction of cooperator irrespective to any initial cooperation fraction, which is called the dynamics of D-dominate. In Chicken, both all-defectors-state and all-cooperators-state work as source, which leads an evolutionary destiny go to another third equilibrium that is called internal equilibrium irrespective to initial cooperation fraction. Because of the internal equilibrium, Chicken is called having a polymorphic equilibrium. In SH, contrasting to Chicken, both all-defectors-state and all-cooperators-state work as sink, which means an evolutionary destiny is bi-stable, i.e., either going to all-defectors-state or all-cooperators-state depending on an initial cooperation fraction. In Trivial class, opposing to PD, all-defectors-state works as source while all-cooperators-state becomes sink. Thus, a Trivial game always goes to extinction of defector irrespective of any initial cooperation fraction, which is called the dynamics of C-dominate.

The above discussion is summarized schematically in Fig. 6.1.

6.2 Social Viscosity

As long as an infinite and well-mixed population is assumed, the theory correctly predicts the dynamics of any symmetric 2 × 2 game, as we have discussed. Going on this fact alone, if one were exposed to the social dilemma modeled by a PD, there would no way for them to cooperate rather than to defect in the long term. In the natural world, however, cooperative behavior is found ubiquitously—not only in human societies, but also among social insects such as ants and bees. This raises the question of what mechanisms must exist in addition to the original situation of an infinite and well-mixed population to promote cooperation among agents?

Therefore, for the last few decades, the puzzle of what can be the "supplementary framework" to solve this dilemma has been subject to heavy research by biologists, physicists, mathematicians, and information scientists. Many studies have taken a simulation approach, respectively, reporting that models introducing a specific new

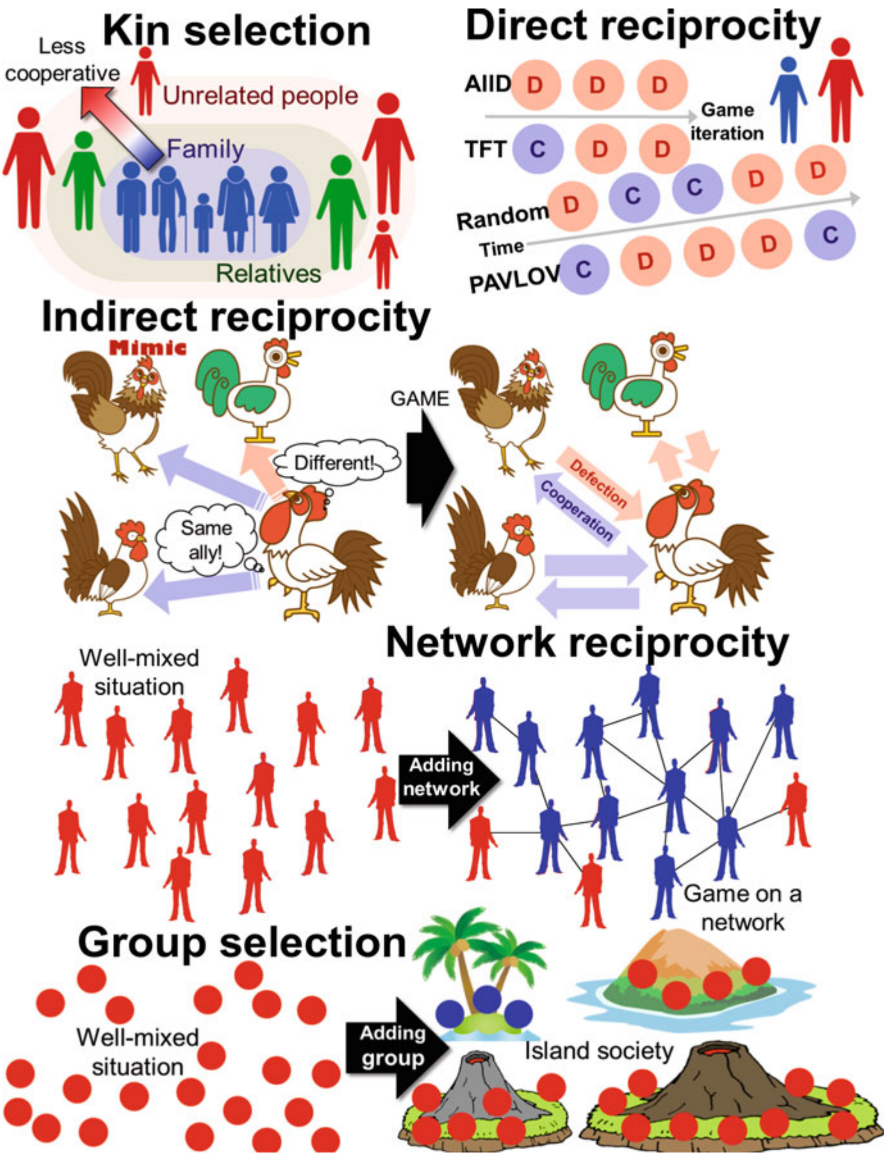

Fig. 6.2 Five basic mechanisms of dilemma resolution and examples of network reciprocity

additional framework somehow enable enhanced cooperation beyond the default presumption of an infinite and well-mixed population. However, they have not directly answered the abovementioned question.

Among these studies, Nowak showed that there are the five fundamental protocols to mitigate or cancel dilemmas,[2] as summarized as in Fig. 6.2. The mechanisms

[2] Nowak (2006).

of these protocols are governed by very ordinary and beautiful mathematical expressions similar to those of kin selection.[3] Nowak refers to these mechanisms as “social viscosity.” Assuming a well-mixed and infinite population, each game is played by a single person whose next encounter is unknown (well-mixed). However, in repeated game battles between a pair of individuals (direct reciprocity) and observing the tag of an opponent (indirect reciprocity), the behavior of an opponent, whether cooperative or defective, can be distinguished. When players play games against only their neighboring players on a certain underlying network, information relating to the strategy is obtained though the network (network reciprocity). If agents are distributed on island societies in which games are played and little inter-island competition might occur, the selection process would work in two layers: among islands and among individuals on an island; this may lead to cooperative agents surviving on some islands (group selection). All of these conditions enable agents to overcome dilemmas and create a cooperative society. These processes essentially reduce the anonymity from that of an infinite and well-mixed population (which exists in a total anonymous state) and authenticates the battle opponents.

6.3 Social Dilemma and Its Mathematical Quantification

We are very much concerned with whether a given game has a “social dilemma” or not. Thus far, we have termed a game without a dilemma as Trivial, in that there is no friction among agents in selecting a dominant strategy. First, we should remind the reader of the stringent mathematical meaning of dilemma: that is, a situation in which the Nash Equilibrium; NE, is not consistent with the socially optimal state. The socially optimal state is the situation in which the average social payoff—that is, the sum of individual payoffs over the population—becomes maximal. This proposition is universal, and can be applied not only to 2×2 games, but also to multi-player and even multi-strategy games.

For a symmetric 2×2 game with a well-mixed and infinite population, dilemmas can be simply classified by whether Chicken-type (D_g) or SH-type (D_r) has positive sign or not as we discussed in Eq. (6.3).

One notable point for discussion is what the socially optimal situation would be. One may guess that the socially optimal state for a PD game as well as a Chicken game is always the all-cooperators state, since every agent enjoys obtaining an R that is greater than P. This is not necessarily correct. If met with $S + T < 2R$, the socially optimal state is certainly an all-cooperators-state; thus, a PD or Chicken game with $S + T < 2R$ requires mutual cooperation to be socially optimal, which is known as the R-reciprocity game. On the other hand, for $S + T > 2R$, mutual cooperation does not realize social optimality. In such a situation, the co-existence of a certain

[3] Hamilton (1963).

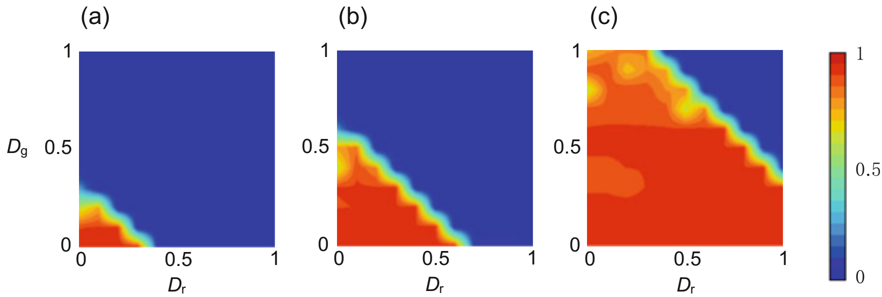

Fig. 6.3 Averaged cooperation fraction D_r–D_g diagrams for (**a**) $R = 1.5$, $P = 1$, (**b**) $R = 1$, $P = 0$, and (**c**) $R = 4$, $P = 2$. Games are played on an 8-neighbor lattice, and the degree of the network is $k = 8$. The population is not infinite but finite; $N = 10^4$ is presumed. In each simulation, an agent plays with their eight immediate neighbors and sums up all payoffs as their accumulated payoff. After the gaming session at each time-step, agents synchronously update their strategy to be either C or D. We adopted Imitation Max (IM) as the strategy-update rule, whereby each agent deterministically copies the best-performing strategy

fractions of cooperators and defectors rather ensures a higher social-average payoff than total cooperation; this is called an *ST* reciprocity game.[4]

Although the respective signs of D_g and D_r suggest whether a dilemma exists, they do not quantify how the social dilemma works. If we add some social viscosity by implementing any reciprocity mechanism in an original game, this fact becomes more tangible. Figure 6.3 displays the MAS result, showing the cooperation fraction in the PD region ($D_g > 0$ and $D_r > 0$) when varying R and P. Returning to Fig. 6.1, the theory based by the formulation of replicator dynamics with a well-mixed and infinite population correctly predicts that the entire PD region is always absorbed by an all-defectors-state (see the red region for PD in the left panel of Fig. 6.1). Being concerned with panel (a), we can evidently confirm that the region with smaller D_g and D_r allows the survival of cooperators, of which the cooperation fraction is quite high (red-triangle region). This is because network reciprocity solves the dilemma situation, letting agents cooperate to obtain mutual cooperation with a payoff of R. Moving to panels (b) and (c), we should note that, with the increase of the difference between R and P (i.e., $R - P$), the red triangle region significantly expands. This fact proves that D_g and D_r fail to appropriately quantify the dilemma strength (Ito and Tanimoto 2018) when a certain mechanism for adding social viscosity is implemented. It would be quantitatively acceptable when we compare two different PD games having same D_g and D_r; say, for example, $\begin{bmatrix} R & S \\ T & P \end{bmatrix} = \begin{bmatrix} 1 & -1 \\ 2 & 0 \end{bmatrix}$ and $\begin{bmatrix} 100 & -1 \\ 101 & 0 \end{bmatrix}$. Those two games have $D_g = D_r = 1$, and thus both belong to the D

[4] Concerning *R* reciprocity and *ST* reciprocity games, you should refer to: Wakiyama and Tanimoto (2011).

& R (donor and recipient) game, a sub-class of PD. Suppose that there is a certain reciprocity mechanism, which implies that an agent has a non-zero possibility of playing with the same opponent more than once. This is possible because the social viscosity added by the reciprocity mechanism breaks the perfectly anonymous situation. If that is the case, cooperation may become a meaningful strategy for the focal player expecting an opponent's cooperation in return. Such a tendency becomes much more significant if there is a huge gap between R and P, since it ensures a sufficiently higher payoff to any cooperator, regardless of whether their opponent cooperates or defects (the payoff difference between 101 and 100 might be negligible as compared with $1 = D_g = D_r$). Now it should be apparent why such a thing takes place and why the set of D_g and D_r is inappropriate as an index of dilemma strength.

A question arising to us is whether an alternative measure can quantify a dilemma strength in the context of a symmetric 2×2 game, even if a reciprocity mechanism is presumed to be implemented.

The answer is "yes," as shown below.

As below, let us introduce the concept of the universal scaling for dilemma strength.

Let us jump directly to the conclusion: the answer lies in the simple idea that both D_g and D_r should be divided by $R - P$ to normalize the influence of the difference. Thus, we define a new set of GID and RAD as $D_g{}'$ and $D_r{}'$, respectively:

$$D'_g \equiv \frac{T - R}{R - P} = \frac{D_g}{R - P}, \tag{6.3}$$

$$D'_r \equiv \frac{P - S}{R - P} = \frac{D_r}{R - P}. \tag{6.4}$$

This definition converts the payoff structure of a game, as represented by M:

$$\mathrm{M} \equiv \left[a_{ij}\right] = \begin{pmatrix} R & P - (R - P)\, D'_r \\ R + (R - P)\, D'_g & P \end{pmatrix}. \tag{6.5}$$

Here, let us rely upon the splendid result of Taylor & Nowak,[5] who successfully deduced that any of the Nowak's five reciprocity mechanisms can be expressed by each transformation applied to an original 2×2 game payoff. This allows us to obtain the equivalent payoff matrix when each of the five reciprocity mechanisms is applied. More importantly, their theory also presumes a well-mixed and infinite population, allowing us to apply the replicator dynamics to quantify an equilibrium. In a word, by slightly altering the equivalent payoff matrix, each of the five reciprocity mechanisms can be evaluated, quantified, and discussed based on the same template of a 2×2 game payoff presuming a well-mixed and infinite population.

[5] Taylor and Nowak (2007).

If you consult with the literature (Tanimoto and Sagara 2007), each of the five reciprocity mechanism is clearly quantified. Here, let us highlight on one of those, the network reciprocity as below.

Network reciprocity relies on two effects: (1) limiting the number of game opponents (diminishing anonymity), leading to increased mutual cooperation; and (2) a local adaptation mechanism whereby a player copies a strategy from a neighbor linked to them through a network. These two effects explain how cooperators survive in a network game of PD, even though players are required to use only the simplest strategy—either cooperation or defection (requiring only 1 bit of memory). The individuals of a population occupy the vertices of a graph; the edges denote who interacts with whom. Each individual interacts with all of their neighbors according to the standard payoff matrix. The payoff for each agent is totaled over all games with their neighbors. An individual's fitness is given by $1 - \omega - \omega F$, where F is the payoff for the individual and ω ($\omega \in [0, 1]$) is the intensity of selection. Here, we consider evolutionary dynamics according to Death-Birth updating (DB),[6] whereby a random individual is chosen in each round to die; then, the neighbors compete for empty sites proportional to their fitness.

A calculation using pair approximation on regular graphs (with each vertex having k edges) leads to a deterministic differential equation that describes how the expected frequency of cooperation (defection) changes over time. This differential equation is actually a standard replicator equation with a modified payoff matrix (i.e., equivalent payoff matrix).[7] This payoff matrix is given by

Network reciprocity

$$\begin{array}{cc} & \begin{array}{cc} C & D \end{array} \\ \begin{array}{c} C \\ D \end{array} & \begin{pmatrix} R & S+H \\ T-H & P \end{pmatrix} \end{array}, \tag{6.6}$$

where H in Eq. (6.6) is defined as follows:

$$H = \frac{(k+1)(R-P) - T + S}{(k+1)(k-2)}. \tag{6.7}$$

Hence, we can revise $D_g{}'$ and $D_r{}'$ to $D_g{}'_{GS}$ and $D_r{}'_{GS}$:

$$D_g{}'_{NR} = \frac{(T-H) - R}{R-P}, \tag{6.8}$$

$$D_r{}'_{NR} = \frac{P - (S+H)}{R-P}. \tag{6.9}$$

[6] Ohtsuki et al. (2006).

[7] Ohtsuki and Nowak (2006).

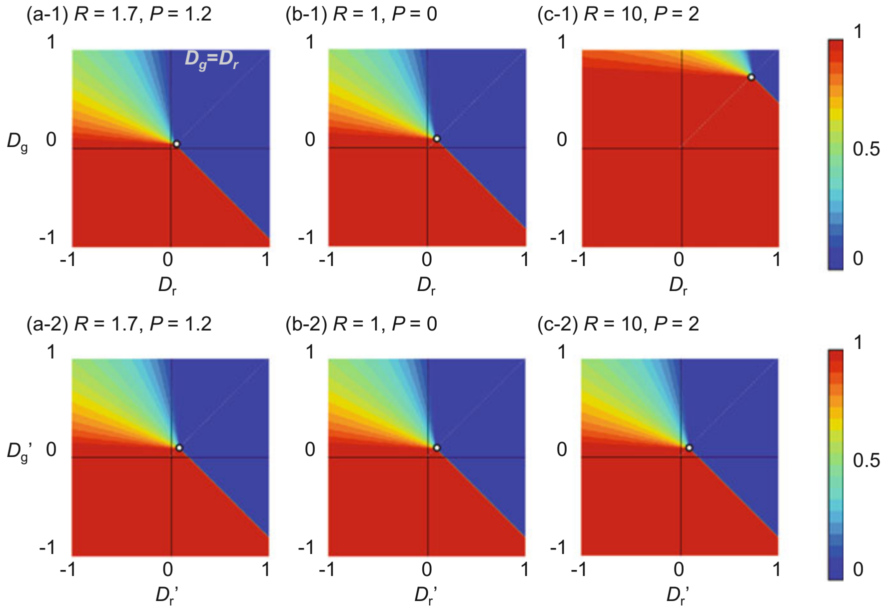

Fig. 6.4 Equilibrium cooperation fraction D_r–D_g (in the upper line) and D_r'–D_g' (in the lower line) diagrams of network reciprocity for (**a**) $R = 1.7$, $P = 1.2$, (**b**) $R = 1$, $P = 0$, and (**c**) $R = 10$, $P = 2$ with the number of neighbors given by $k = 12$

Assuming that $k = 12$, we obtain Fig. 6.4. As in the cases of kin selection and group selection, we are able to confirm that network reciprocity can weaken both Chicken-type and SH-type dilemmas.

The discussion above is based on a theoretical framework using pair approximation on regular graphs. The question of whether the concept of universal scaling for dilemma strength using D_g' and D_r' works well for other cases of various topologies was deliberately explored by Wang and his colleagues,[8] who partially relied upon the multi-agent simulation (MAS) approach varying not only in underlying topology but also in strategy-updating rule. They found that the universal scaling concept given by D_g' and D_r' works reasonably well, even if various strategy-update rules are assumed. In assuming heterogeneous networks like scale-free networks and small-world graphs instead of homogeneous topologies like rings and lattices, the scaling concept malfunctions, because different number of playing games among agents that a heterogeneous networks intrinsically allows significantly affects its evolutionary process. Thus, the underlying topology sometimes becomes more significant than the influence resulting from the game structure.

[8] Wang et al. (2015).

6.4 Concept of a Social Efficiency Deficit

In the previous sub-section, we successfully introduced the idea of "dilemma strength" (hereafter DS) by means of a universal scaling by $D_g{}'$ and $D_r{}'$. One thing to be noted is that DS can be defined only in the case of a 2×2 game. DS cannot be explicitly defined for other cases (i.e., more general social dilemma games such as multi-player games including the PGG), as well as more practical application-oriented games like the vaccination game, which is one of the main topics of concern in the present book, where the time-dependent game structure cannot be given as a static 2×2 payoff matrix or the multiplayer-game payoff function. Although DS is quite powerful, it has the crucial drawback of being inapplicable to other general games.

Needless to say, it is important to examine whether or not a social dilemma works under a certain model-parameter setting. To remedy this accompanying pitfall, in this sub-section, we introduce a new index for explaining the presence of a social dilemma, termed the "social efficiency deficit" (SED) Arefin et al. (2020). In a word, SED indicates how much the payoff could be improved from NE toward a social optimum (SO); that is, SED is accounted for by the difference in payoffs between SO and NE. The term SO signifies the scenario with the maximum socially accumulated payoff of a game. If DS can be treated as a "prognostic" index for whether a social dilemma prevails,[9] SED would be thought as an "ex-post" index, since both the socially optimal payoff and the payoff at NE can always be estimated, regardless of model complexity.[10] Thus, one can predict SED and evaluate whether or not a social dilemma actually works by referring to whether SED is positive or zero.

The dilemma strength refers to a numerical measure of the extent of social viscosity needed to switch from NE to a socially optimal point, while the SED provides information regarding the payoff shortfall at NE compared with SO. Therefore, using δ, we can express SED as

$$\delta = \Pi^{\text{Social Opt.}} - \Pi^{\text{NE}}, \tag{6.10}$$

where $\Pi^{\text{Social Opt.}}$ and Π^{NE} indicate the payoffs at SO and NE, respectively. Referring to the definition of a NE, we should confirm that $\Pi^{\text{Social Opt.}} \geq \Pi^{\text{NE}}$. The absence or presence of a social dilemma corresponds to whether δ is zero or positive. Clearly, if NE coincides with SO, there is no incentive for the game players to try to improve their payoff, which corresponds to a dilemma-free situation. This

[9] This is because for DS, $D_g{}'$ and Dr′ can be identified in advance of actual analysis. Whenever one knows the payoff matrix, DS can be evaluated.

[10] We can reproduce any game model as a form of MAS irrespective of game type, regardless of whether it is two-payer or multi-player, two-strategy or multi-strategy, complex or simple, or realistic or ideal. As long as a MAS model is established, we can explore Nash equilibrium as well as the socially optimal state, at least numerically.

scenario yields no payoff-shortage at NE from SO, which accordingly insists upon the absence of a social dilemma. However, if there is a payoff-gap between NE and SO, then it is still possible to improve the payoff from NE, which demonstrates the existence of a social dilemma. As previously mentioned, the scaling parameters for DS—$D_g{}'$ and $D_r{}'$—were proposed for 2×2 games with a well-defined payoff matrix; however, games having more than two players, more than two strategies, or both are not tractable with the aid of DS parameters, even if the payoff matrix is well-defined. Hence, we can claim that SED is a general parameter for explaining the presence of a social dilemma, regardless of the game structure. Furthermore, if a concrete relationship between DS and SED can be established for a dilemma game, this would allow SED to conjecture not only the existence, but also the extent, of the social dilemma associated with that game. Nonetheless, in the situation where DS cannot be defined explicitly, SED still can illustrate the presence of a social dilemma.

Below, we discuss SED in detail and present its correct definition for several important games.

6.4.1 Donor and Recipient Game

Let us start with the most fundamental and common game: the Prisoner's Dilemma (PD). We have already recognized that a PD requires $T > R > P > S$; thus, it meets with $D'_g = \frac{D_g}{R-P} = \frac{T-R}{R-P} > 0$ and $D'_r = \frac{D_r}{R-P} = \frac{P-S}{R-P} > 0$. Here, let us limit PD to refer to games that need R-reciprocity, not ST-reciprocity; this requires another condition: $S + T > 2R$.

In the following text, we are specifically concerned with the Donor and Recipient (D & R) game, of which the payoff matrix is given by

$$\begin{pmatrix} R\,(= b - c) & -c \\ b & 0 \end{pmatrix} \equiv M_{D\&R}. \tag{6.11}$$

Clearly, $M_{D\,\&\,R}$ has the property $D_g = D_r$. Now, choosing $D_g = D_r \equiv \Delta$, we can easily find $b = R + \Delta$ and $c = \Delta$. D'_g and D'_r can also be rewritten as

$$\begin{cases} D'_g = \frac{\Delta}{R} \\ D'_r = \frac{\Delta}{R} \end{cases}. \tag{6.12}$$

Hence, Eqs. (6.11) and (6.12) establish an inverse relationship between DS and SED—i.e., the higher DS corresponds to the lower SED, and vice versa (see Fig. 6.5). In a game with stronger DS (see panels (a) and (c)), the transition from a defective state D to a cooperative state C requires abundant social viscosity to overcome the dilemma; however, the payoff gain for this state transition is not so significant. By contrast, in a game with lower DS (see panels (b) and (d)), a smaller

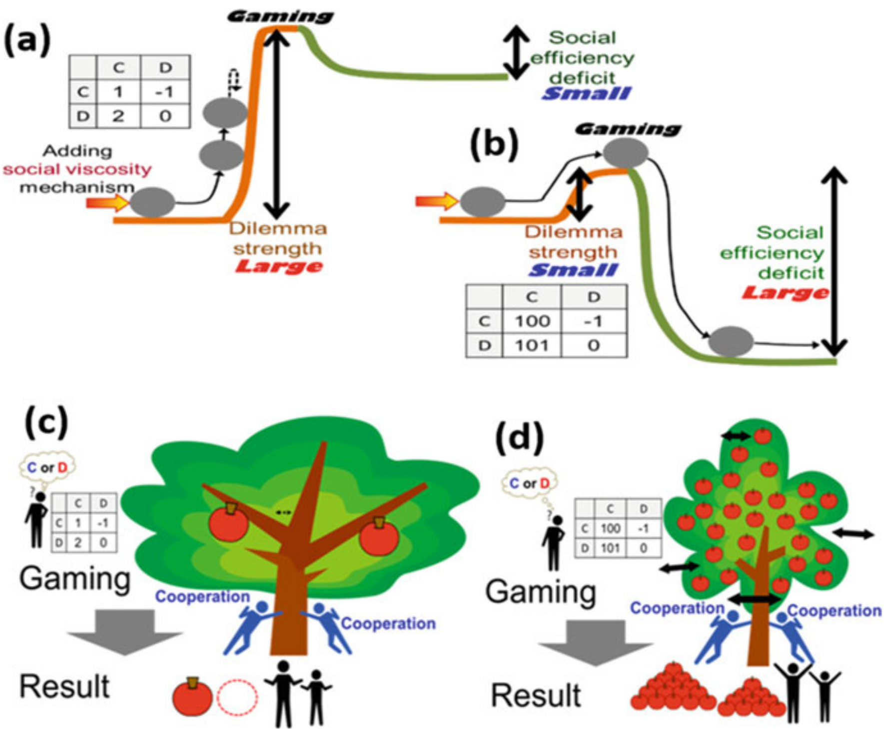

Fig. 6.5 Schematic explanation of (**a**) game with large DS and small SED, and (**b**) game with small DS and large SED observable in a PD game. The game (a) is having a stronger dilemma, consequently, requiring abundant social viscosity to overcome the dilemma but the payoff gain is not worth enough; on the other hand, game (b) is showing the opposite scenario. Games (**c**) and (**d**) are having the same payoff structures as that of (**a**) and (**b**), respectively, but portraying in a different fashion to understand the mechanism. In a PD game with large DS and small SED (**c**), even the dilemma being solved, the fruits brought by cooperation would not be much. Whereas in a game with small DS and large SED (**d**), the dilemma can be easily solved; thus, the fruits brought by cooperation would be much

social viscosity can promote cooperation from defection and yields a higher payoff. This means that a huge payoff shortfall (i.e., higher SED) at NE is observed for the latter game; however, the former game has the opposite scenario. The above discussion can be justified graphically by Fig. 6.6, wherein a DS versus SED graph for a 2×2 D & R game exhibits an inverse relationship with several Δ values. That is, the DS decreases with the increase of δ and vice versa. Additionally, the higher Δ value corresponds to the higher DS, which is quite conceivable.

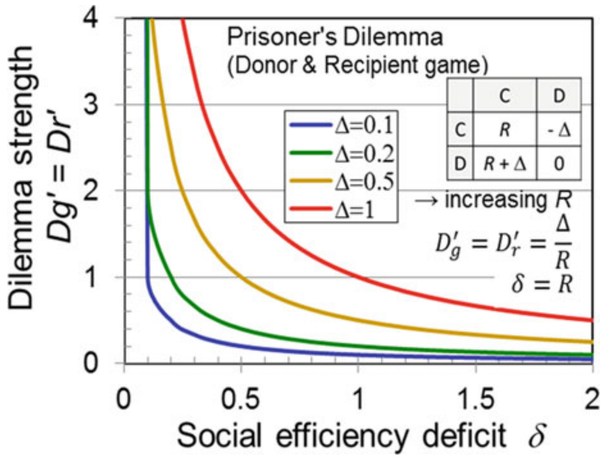

Fig. 6.6 SED vs. DS line graphs showing the inverse relationship between DS (D_g' and D_r') and SED for several Δ values in the case of a 2×2 D & R game. The DS shows a positive correlation with Δ values

6.4.2 PD with the Social Viscosity by Network Reciprocity

Let us explore how adding a mechanism to increase social viscosity to an original game changes the SED. We are concerned with the example of a PD with network reciprocity.

Let us consider the Donor and Recipient game, defined by Eq. (6.11), and apply network reciprocity, quantified by Eqs. (6.8)–(6.10). Equation (6.12) can be replaced by

$$D_{g'NR} = D_{r'NR} = \frac{\Delta}{R} - \frac{kR - 2\Delta}{R\,(k+1)\,(k-2)}. \tag{6.13}$$

Because the D & R game belongs to PD, the SED is $\delta = R - 0 = R$. Here, we obtain the explicit relationship between SED (i.e., δ) and DS ($D_g{}' = D_r{}'$), which is visually shown in Fig. 6.7. With the given values of Δ and k, solving Eq. (6.13) for R allows us to estimate the critical value of SED (let us say; R^*) at which the social dilemma disappears ($D_g{}'_{NR} = D_r{}'_{NR} = 0$),

$$\delta^* = R^* = \frac{\Delta\,((k+1)\,(k-2)+2)}{k}. \tag{6.14}$$

Finally, by increasing δ ($=R$), we examine how DS varies with SED for different degree levels (k) when a social network is introduced in a 2×2 D & R game, as shown in Fig. 6.7. As k increases, the PD with network reciprocity converges toward the default case, i.e., PD without network reciprocity, which is quite likely. If $k = 4$,

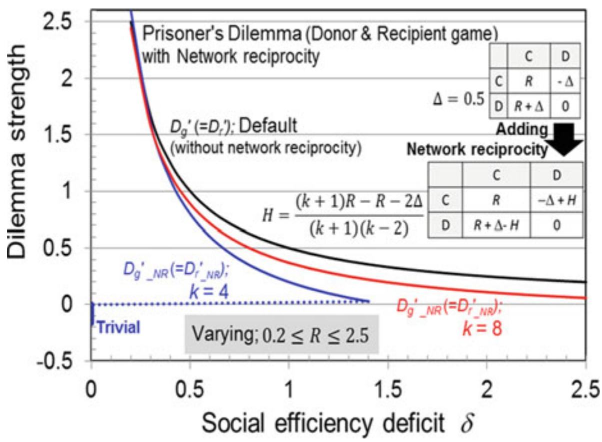

Fig. 6.7 How the relationship between DS (D_g' and D_r') and SED is skewed if network reciprocity is introduced in the case of a 2 × 2 D & R game. At degree level $k = 4$, the dilemma disappears with a little increase in SED and converts to a Trivial game. If we increase the degree level, the game converges to the default PD (without network reciprocity)

the dilemma diminishes at $\delta = 1.5$ (which can be justified using Eq. (6.14)), because the lower the degree level, the higher the possibility of cooperation; thus, PD with network reciprocity becomes a trivial game.

Again, let us confirm that SED works well as an indicator of whether or not a social dilemma exists behind the given game. Zero SED implies a Trivial game with a NE according with the SO.

6.5 Application of Social Efficiency Deficit

In the previous sub-section, we shed light on a 2 × 2 game and PGG that are both standard template models in the evolutionary game. Here, in this sub-section, we touch upon how SED can be applied to a real problem in which a realistic and complex game structure, unlike the static game represented by a simple payoff matrix, is presumed. The main theme of the present book is epidemiology and the vaccination game. Thus, it would be meaningful to discuss how the concept of SED can be used in the vaccination game.

Here, let us briefly explain the structure of the vaccination game with the MFA, in which an individual is exposed to the risk of a seasonal influenza-like communicable disease spreading, and decides either to commit to a pre-emptive vaccination at the beginning of each season (implying cooperation) or not (defection). A vaccination works stochastically to bring perfect immunity (or nothing). An individual's decision whether or not to take a vaccine depends on the relative cost of vaccination C_r ($C_r = C_V/C_I$; $0 \leq C_r \leq 1$; where C_V and C_I are the costs

Table 6.2 Four fractions of individuals with their respective payoffs (values within brackets)

Strategy/state	Healthy	Infected
Vaccinated (V)	HV ($-C_r$)	IV ($-C_r - 1$)
Non-vaccinated (NV)	SFR (0)	FFR (-1)

of vaccination and infection, respectively; without loss of generality, C_I can be set to 1) and vaccine effectiveness e ($0 \le e \le 1$). A cooperator (vaccinator) always obtains perfect immunity for $e = 1$. The spread of the infection obeys the well-known SIR (Susceptible–Infectious–Recovered) dynamics. Namely, in each season, a small initial fraction of infected individuals triggers the spread of the disease into the population with cooperators (vaccinators) and defectors co-existing. SIR dynamics, as formulated by a set of dynamical equations, controls what fraction of individuals are consequently infected before a disease is eradicated. At the end of each epidemic season, the entire population is classified into four fractions of individuals: HV-vaccinated and healthy, IV-vaccinated but infected, SFR-successful free riders (non-vaccinated but healthy), and FFR-failed free riders (non-vaccinated and infected). Table 6.2 summarizes the four classes observed at the end of a season and their respective payoffs. These groups are prone to updating their strategy (committing to vaccinating or not) at the beginning of each season by evaluating their payoffs based on last season's experience following a so-called individual-based risk assessment (IB-RA) rule.

Each season is steered by the local timescale (the days elapsed in a season) in the extent of a disease spreading, final epidemic size (FES), at each season, while repeated season handled by the global time-series lets fraction of vaccinators, called vaccination coverage, time-evolve. We perform a simulation episode until we reach a social equilibrium (Nash equilibrium; NE), at which point we measure the FES, vaccination coverage (VC), and average social payoff (ASP) in the final season. ASP results from the infected cost and the vaccination cost over the entire society. We perform such simulation by varying C_r and e.

6.5.1 Derivation of SED

We calculate the ASP at a social equilibrium (NE) for every combination of C_r and e. We also estimate the ASP at a SO without considering the game approach by taking the maximum ASP for each pair-setting of C_r and e for vaccination coverage (x) ranging from 0 to 1, and then calculate the difference between ASP at SO and NE (as defined in Eq. (6.11)) to derive SED (i.e., δ). Figure 6.8 schematically explains the derivation of SED for a vaccination game. Suppose that $\mathrm{ASP}^{\mathrm{NE}}_{C_{ri},e_j}$ and $\mathrm{ASP}^{\text{Social Opt.}}_{C_{ri},e_j}$ stand for the ASP at NE (panel (a)) and ASP (without game approach) at SO (panel (b)), respectively, for each pair (C_{ri}, e_j). Then, we can define SED at (C_{ri}, e_j) as

$$\delta_{C_{ri},e_j} = \mathrm{ASP}^{\text{Social Opt.}}_{C_{ri},e_j} - \mathrm{ASP}^{\mathrm{NE}}_{C_{ri},e_j}. \tag{6.15}$$

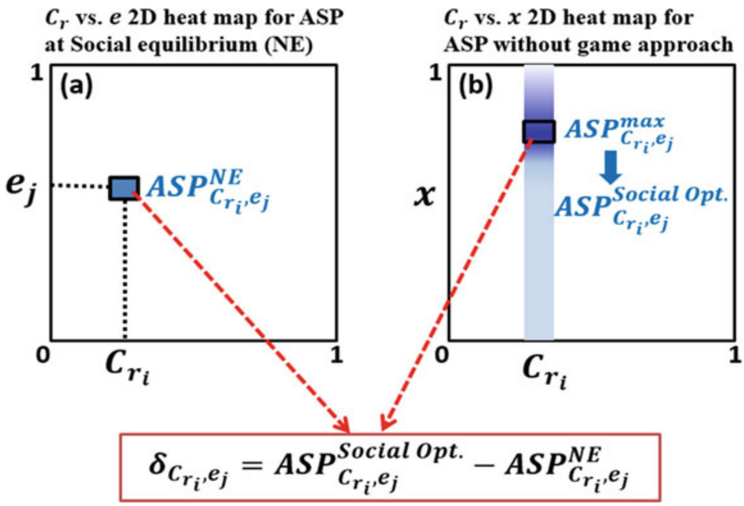

Fig. 6.8 Schematic of the derivation of SED. Panel (**a**) represents the average social payoff (ASP) at NE for a (C_{ri}, e_j) pair, whereas panel (**b**) depicts the ASP (without game approach) for that particular C_{ri} with vaccination coverage x ($0 \le x \le 1$) for each e_j; at this C_{r_i}, the blue region surrounded by the rectangle is assumed to have the maximum ASP, which is called the ASP at social optimum (SO) for the pair (C_{ri}, e_j). Finally, the difference between ASP at SO and ASP at NE yields the SED at (C_{ri}, e_j)

By estimating the SEDs for each pair of (C_{ri}, e_j), we generate a 2D heat map for SED to visualize how SED varies as a function of C_r and e (Fig. 6.9). The triangular region enclosed by blue dashed lines has no SED (consequently no dilemma) because in this case, a lower vaccine effectiveness does not inspire people to vaccinate at all, subsequently leading to a D-dominant trivial state as SO (panel (c)). With the game approach, the counterpart of this triangular region in the VC heat map (panel (b)) also has a D-dominant NE that, in accordance, yields an identical ASP (panels (c) and (d)) to that of observed at SO; that is, the payoff at NE cannot be further improved, and consequently, possesses no social dilemma at all. However, another region enclosed by red dashed lines (panel (a)) (especially for low cost) appears to have no SED. The equivalent region in the VC-phase diagram (panel (b)) displays a C-dominant NE; that is, all people vaccinate, albeit the effectiveness is not very high. Moreover, the ASPs (panels (c) and (d)) associated with this region are almost identical at NE as well as SO, which therefore confers no SED—i.e., no social dilemma is occurring. This implies that the region featuring no SED is C-dominant trivial, which differs from the previous blue triangle region, in which no SED resulted from the D-dominant trivial-game structure.

Meanwhile, the remaining region in panel (a) possesses certain levels of SED that indicate the presence of a social dilemma, whereby we can perceive non-monotonic changes in SED if the vaccination cost is relatively low. These non-monotonic phenomena can be explained using the line graphs in Fig. 6.10 that reveal how

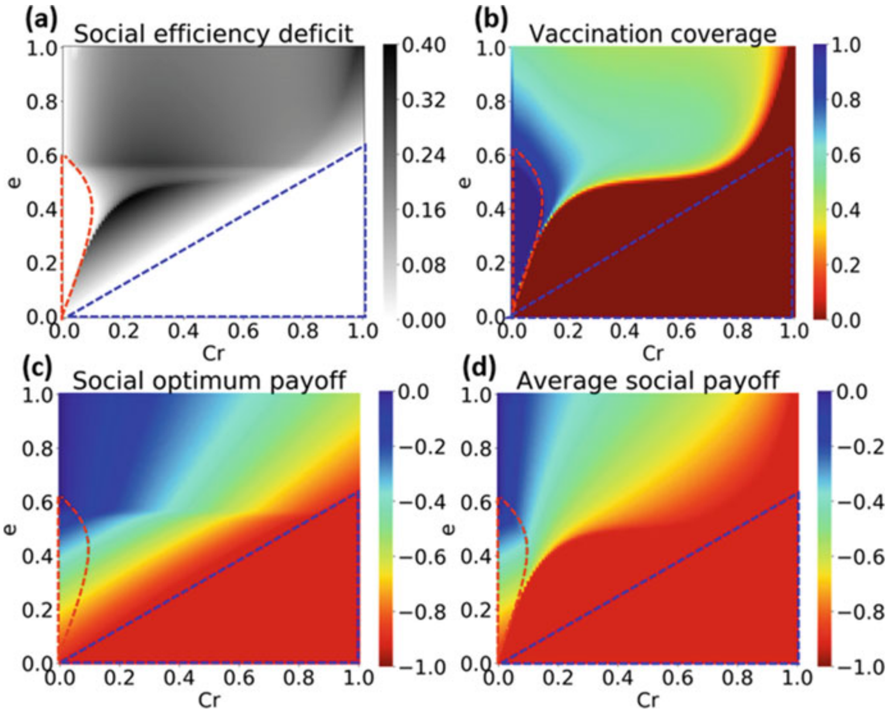

Fig. 6.9 (**a**) C_r versus e 2D heat-map of SED for the vaccination game. The regions enclosed by blue (triangular region) and red dashed lines have no SED, and consequently no social dilemma; (**b**) C_r versus e 2D heat-map of vaccination coverage (VC) at social equilibrium (NE) displaying regions with blue and red dashed lines as D-dominant and C-dominant in NE, respectively; (**c**) C_r versus e 2D heat-map of ASP at social optimum (SO); and (**d**) C_r versus e 2D heat-map of ASP at social equilibrium (NE)

SED, VC, and ASP at SO and NE (with different cost levels) vary as functions of e. Clearly, VC is correlated with C_r and e. With a lower vaccination cost, VC becomes maximal, even with a medium level of effectiveness; however, afterward, it monotonically decreases because the situation with a more effective vaccine might inspire some people to freeride on the so-called herd immunity.[11] These phenomena yield an increasing tendency in ASP with e. By examining the difference between the two payoffs in Fig. 6.10b (below the x-axis), one can easily conceive of the mechanism of the non-monotonic tendency in SED about e (panel a). More specifically, let us consider the case $C_r = 0.1$ (blue-colored line graphs). Here, the highest payoff difference can be observed when e is nearly 0.3. This, in turn, exhibits

[11] With a vaccination coverage above a threshold level, an individual with no vaccination can hardly be infected. Commitment to vaccination from the social majority enables those non-vaccinating individuals to be protected from infection. This is called “herd immunity” and discussed in Chap. 3.

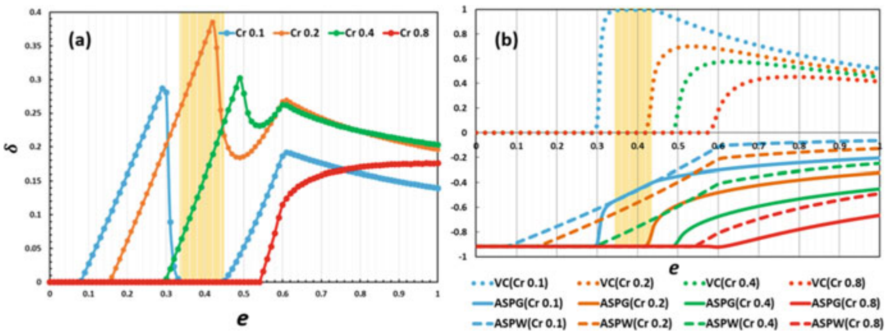

Fig. 6.10 (**a**) e versus δ line graphs showing how SED changes with different cost levels C_r; (**b**) line graphs above the x-axis represent the vaccination coverage (VC) at NE corresponding to several costs, C_r, and line graphs below the x-axis display the corresponding ASPs at NE (solid lines) and SO (dashed lines) when e varies from 0 to 1. ASPG and ASPW stand for ASPs with and without game approaches, respectively. The region filled in light yellow depicts the C-dominant NE (everyone commits to a vaccine) wherein both payoffs merge; this corresponds to the cost $C_r = 0.1$, and consequently there is no SED (no dilemma)

the maximum gap between two ASPs (panel b); in other words, the maximum SED (panel a); afterwards, both payoffs merge (blue solid and dashed lines coincide within the light yellow region in Fig. 6.10b for a certain range of e that accordingly leads to zero SED (no social dilemma). However, another SED peak appears at $e = 0.6$, which can also be justified by observing the payoff difference (blue solid and dashed lines) at $e = 0.6$ from Fig. 6.10b. On the other hand, the situation with an expensive vaccine exhibits no SED (consequently no dilemma) until the vaccine effectiveness reaches a certain level, because no one here intends to take an expensive vaccine that without a satisfactory level of effectiveness.

All discussions above shed clear light on how SED contributes to evolutionary game theory. This enables complex games to be analyzed in terms of whether a social dilemma works behind the model's surface from the mathematical viewpoint, and to elucidate the nature of this dilemma. The concept of DS is certainly a powerful theoretical framework for quantifying a social dilemma. However, it is only applicable to two-player and two-strategy games. SED lacks this drawback because it applies universally to any games, regardless of the number of players and strategies or the complexity. Thus, it is very powerful.

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Chapter 7
Agent-Based Simulation for Service and Social Systems and Large-Scale Social Simulation Framework

Hideyuki Mizuta

Abstract Because of the dynamic and heterogeneous interactions among human beings with their bounded rationality, a service system discussed in Service Science, Management, and Engineering (SSME) is recognized as a complex adaptive system to which quantitative scientific analysis is difficult to apply. In this chapter, we introduce a computational approach for such complex adaptive systems called agent-based simulation. Since the 1990s, agent-based simulation has gained significance as a tool to reproduce complex stock market interactions by modeling human traders as software agents. Recently, agent-based social simulations are utilized to support the decision-making of city planners for various real social issues. For this purpose, we have developed a large-scale social simulation framework "X10-based Agent Simulation on Distributed Infrastructure (XASDI)." In this chapter, we will introduce our earlier work with a small number of agents and then describe the large-scale social simulation framework and its applications.

Keywords Agent-based Simulation · Social simulation · XASDI framework · Service system · SSME

7.1 Introduction

Service systems are complex adaptive systems and also social systems involving human beings. Service systems cannot be represented with convenient sets of mathematical equations mainly because of the complexities and vagaries of human behavior. Therefore, it is quite difficult to evaluate and understand service systems quantitatively with scientific methods. In traditional economic theories, some simplifications such as static equilibrium state, representative agent, and full rationality have been introduced to construct comprehensive and elegant theories

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with feasible solutions, but in the late twentieth century, these assumptions have received increasingly strong criticism that they cannot capture the modern economic crises and dynamic economics of the Internet era. Various approaches from multiple disciplines try to tackle these complex emerging problems (Arthur et al. 1997).

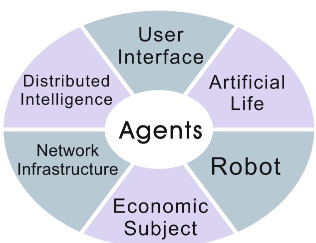
For example, researchers from the fields of physics and computer science are analyzing enormous amounts of data from real-world markets, using statistics to find hidden patterns and new economic principles. This approach is called "EconoPhysics" (Mantegna and Stanley 1999), and it seeks to explore similarities between critical phenomena from physics and market behaviors from economics, such as the now well-known concepts of the long-tail and power-law scaling, phenomena that can be found in many natural and artificial systems.

To understand such systems, we believe agent-based approaches can offer a new set of powerful tools (Mizuta 2016). Since the main method of an agent-based approach is an agent-based simulation (ABS) on computers, researchers using such approaches can model a target service system and its stakeholders with an agent-based model (ABM) and simulate the dynamic behaviors and interactions of the service system with microscopic agents emulated in computers (Namatame et al. 2002).

The word "agent" is used with a variety of meanings for different purposes, such as UI (user interface) agents, email reminder agents, physical agents, or software robots acting as agents to serve people (see Fig. 7.1). In the agent-based approach, each "agent" represents a dynamically interacting economic (or social) entity, thus abstracting the stakeholders from the real world and representing their characteristics of heterogeneity and bounded rationality that traditional economics and social science have difficulty in understanding with models. By using computational agent-based simulations (often written with object-oriented programming languages), such heterogeneous and dynamic interacting agents with bounded rationality can be intuitively implemented as objects with their interactions based on message passing.

Various software technologies such as OOP (Object-Oriented Programming), AI (Artificial Intelligence), and network communications have relationships with ABS. In addition to knowledge of computer software, researchers also need domain knowledge about objective systems such as economics, social science, financial engineering, complex adaptive systems, or behavioral economics. Hence, ABS is a multi-disciplinary science similar to Service Science, Management, and

Fig. 7.1 Various meanings of the word "Agent"



Engineering (SSME), which is the study of service systems and value cocreation phenomena (Spohrer and Maglio 2010).

Agent-based simulation evolved relatively recently as many researchers became able to conveniently use powerful PCs and popular programming languages in the last few decades. In the early period, agents were often designed to reproduce complex adaptive systems and financial markets (Izumi 1998). Then, researchers applied ABS to social behaviors such as norm emergence, game theory situations, learning, and organization.

Currently, agent-based social simulation has begun to be used for more practical and concrete problems such as traffic systems, pedestrian flows, and business operations. To evaluate the complex behavior of interacting enormous entities in a large city, such a social simulation needs to manage millions of agents with various behavior models and preferences. Moreover, the computation power is also required to analyze an enormous combination of possible situations and strategies with repeated simulations (reviews and roadmap are introduced in Noda et al. 2015). Therefore, the distributed parallel execution of large-scale agent-based social simulations on various platform (e.g., post-petascale supercomputers or cloud) is very important.

For this purpose, we have developed a large-scale distributed simulation framework "X10-based Agent Simulation on Distributed Infrastructure (XASDI)" (XASDI 2017) and its applications with the support of JST, CREST. XASDI is available as open-source software at GitHub with tutorial, API documents, sample programs, and a docker file (https://github.com/x10-lang/xasdi). XASDI is a large-scale agent-based social simulation framework with an enormous number (millions) of agents to represent Citizens in cities or countries. It enables highly parallel and distributed simulation with X10 platform (X10 2017) for post-petascale supercomputers.

XASDI software stack contains a core runtime written in X10 language for distributed agents and execution management and Java API bridge to enable application programmer to utilize Java language. By utilizing the XASDI framework, researchers can develop various social simulation applications such as traffic, pedestrian, and evacuation simulations that support decision-making of city planners.

In the balance of this chapter, we introduce our earlier work with a small number of agents and then describe the large-scale social simulation framework and its applications based on the previous papers (Mizuta 2016; Mizuta and Imamichi 2018).

7.2 Market and Auction Simulation

Agent-based simulations (ABSs) reproduce a service system by modeling humans as heterogeneous agents. We introduce several examples from our ABS projects. At first, we applied ABS to understand phenomena in the market system. The stability of prices in asset markets is clearly a central issue in economics. From a system's point of view, markets inevitably entail the feedback of information in the form of price signals, and like all feedback systems may exhibit unstable behavior. Steiglitz and Shapiro (1998) created the price oscillation and bubbles in a simple commodity market model with producer/consumer agents and two types of speculators. In Steiglitz's market model, three types of agents (Regular agent, Value trader, and Trend trader) trade food and gold. Regular agents produce food or gold depending on the price (exchange rate between food and gold) and consume food. Value traders and trend traders are speculators with different strategies.

We considered the stability in this model with various price signals and found that the inversely weighted average of bid price stabilizes the market dramatically (Mizuta et al. 2003). Figure 7.2 shows a screenshot of the simulation where price bubbles appear with heterogeneous agents. The largest window shows two graphs showing the market clearing price and the trade volume. With the simplest market only with regular agents, the market price shows strong oscillation due to inventory cycle (Fig. 7.3). We showed that this price oscillation with producer/consumer agents is stabilized by introducing different price signals (Fig. 7.4). On the basis of the simulation, we also gave analytical results on the simplified dynamical system with different signals.

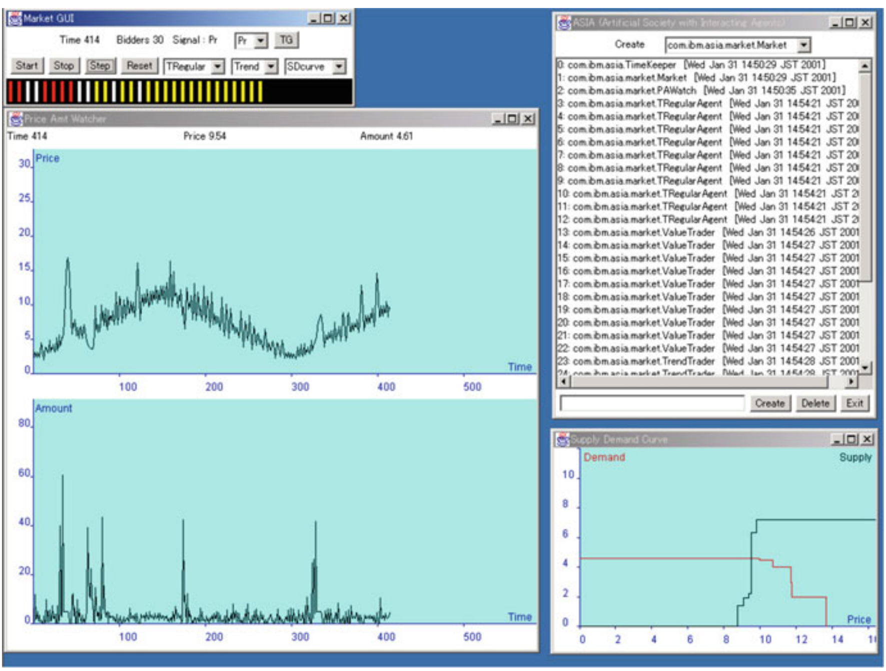


Fig. 7.2 Screenshot of the market simulation

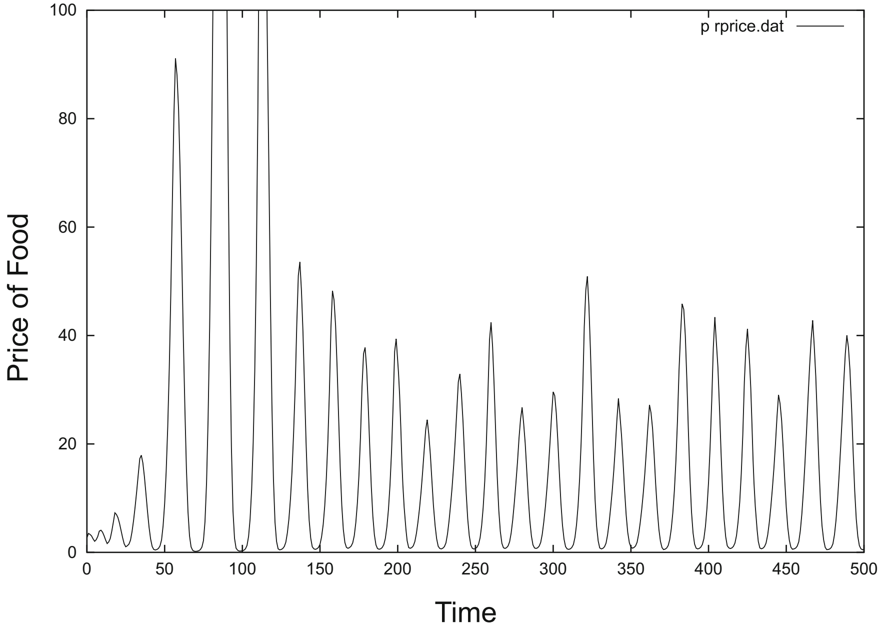


Fig. 7.3 Price vs. trading period with regular agents only

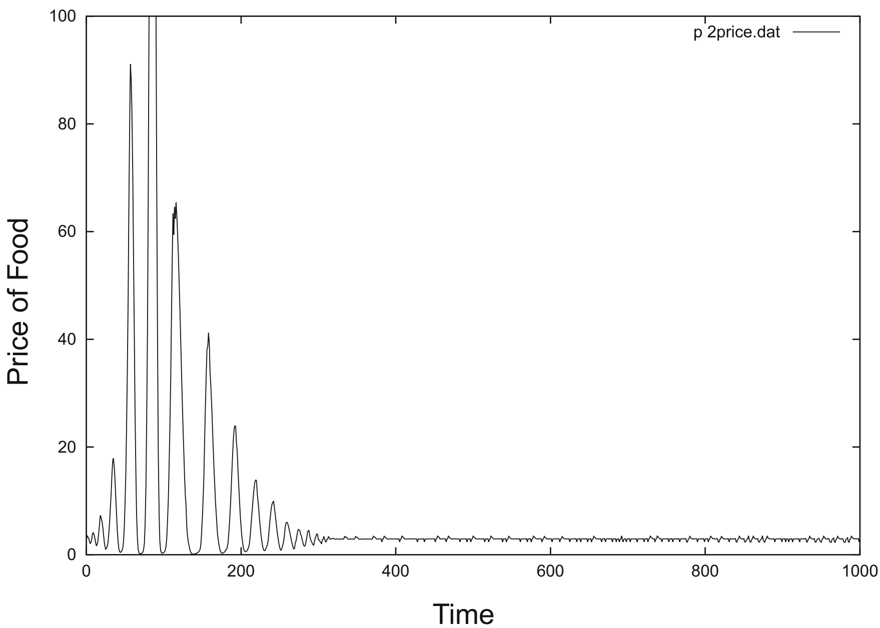


Fig. 7.4 Price vs. period with inversely weighted average bit prices as the signal

Next, we consider a simpler form of market, that is, auctions.

The use of online auctions has grown rapidly since the 90s, and in general, many segments of the economy are becoming granulated at a finer and finer scale. Thus, understanding behavior of auctions, and especially the interaction between the design of auctions, agent behavior, and the resulting allocations of goods and money, has become increasingly important—first not only because we may want to design auctions that are as profitable as possible from the sellers' point of view but also because we may want to bid in auctions or design computer systems that respond well to the loads that auctions generate.

To investigate such dynamic interactions between heterogeneous bidders and also the price formulation through successive auctions, we developed an agent-based simulation of dynamic online auctions (Mizuta and Steiglitz 2000).

In a dynamic auction simulation, we investigated the behavior on popular online auctions with heterogeneous bidder types, e.g., Early Bidders and Snipers. The model considers a single auction involving the sale of one item by one seller to one of many bidders, who submit their bids over time in the interval $[0, T)$ to an auctioneer, who awards the item to the highest bidder at closing time. A bidder can submit more than one bid during the auction. In experiments, the starting bid price is fixed at 1, and the duration of the auction is $T = 500$ time units.

At the beginning of each auction, each bidder determines his first valuation of the item.

At each time period $0 < t < T$, each bidder receives the status of the auction, can update his estimation on a fixed schedule or probabilistic, and can submit bids if the conditions for his strategy are satisfied. In this model, early bidders can bid any time during the auction period, update their valuations continuously, and compete strongly with each other, and snipers wait until the last moments to bid.

An example auction simulated is shown in Fig. 7.5. The graph for the second highest bid price shows price jumps at the last few moments. We also indicate histograms of winning prices by Early Bidders and Snipers in Figs. 7.6 and 7.7. In most cases, Snipers win the item with broadly distributed prices. However, there are small chances for Early Bidders win the item with very low prices or very high prices.

7.3 International Emissions Trading Simulation and Gaming

In a series of works (Mizuta and Yamagata 2001a,b, 2002), we considered agent-based simulations in a computer and gaming experiments with human players for the international CO2 emission trading.

We have been investigating the CO2 emission trading under the Kyoto Protocol. Nation agents correspond to participating countries or regional groups and COP agent is a central auctioneer and manages the international trading. In this model, we created 12 nations' agents; 6 are Annex I countries that are developed countries and assigned reduction targets in the level of emission in 1990, and 6 are Non-Annex

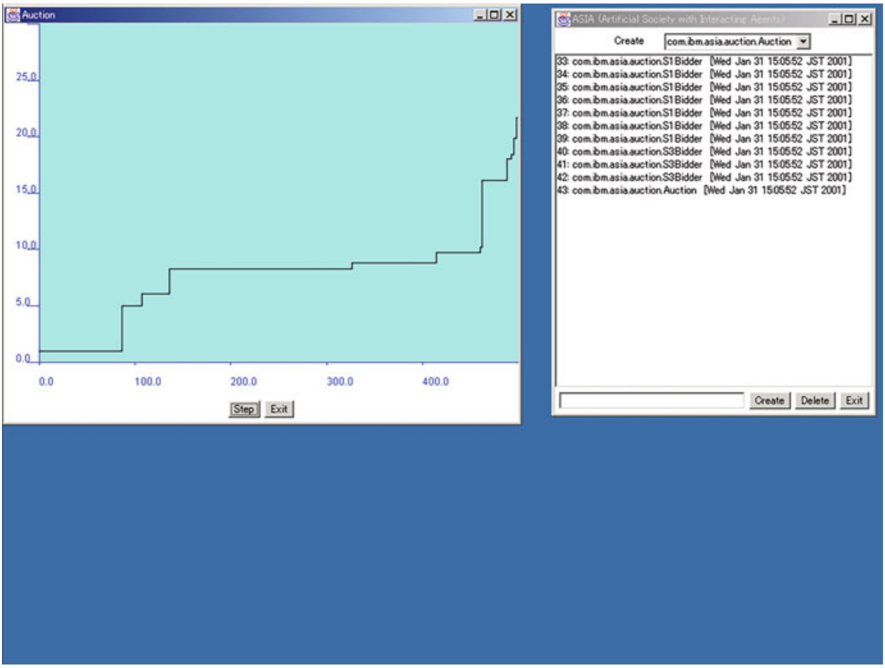


Fig. 7.5 Screenshot of auction simulation

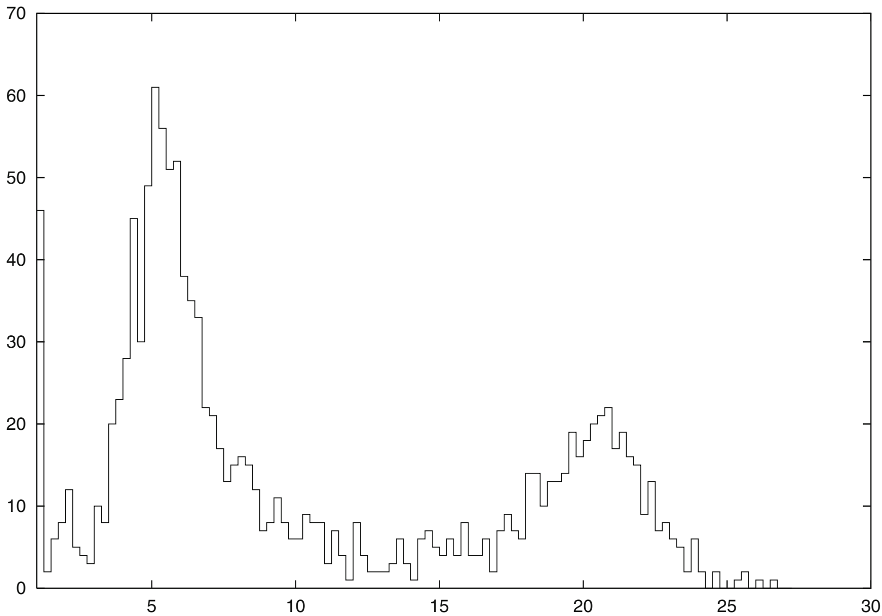


Fig. 7.6 Histogram of winning prices by early bidders

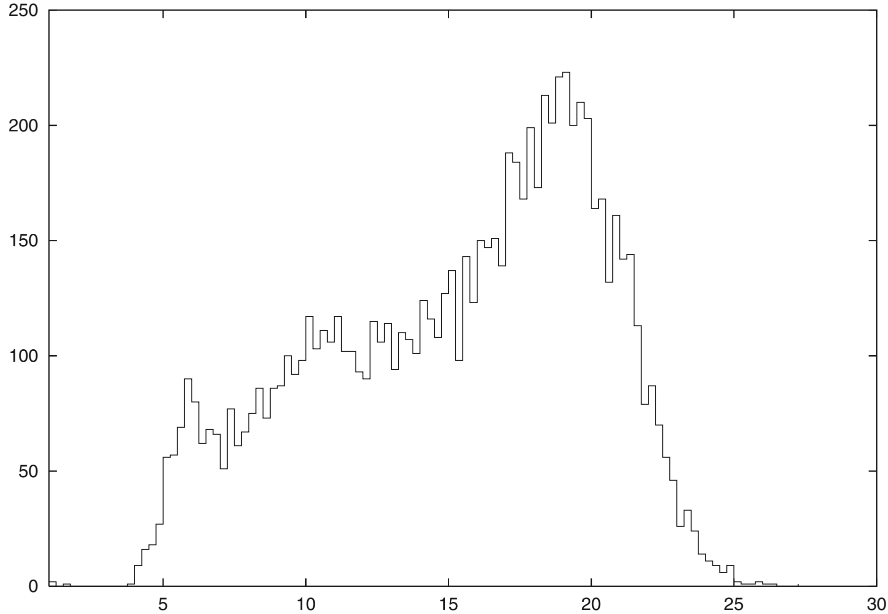


Fig. 7.7 Histogram of winning prices by snipers

I countries that are developing countries and not assigned targets for reduction as in the CERT model (Grütter 2000).

We consider dynamic market development through the first commitment period 2008–2012. In each trading year, the COP agent sends Request for Bid (RFB) messages to all nations which have an asking price. Upon receiving the RFB message, a nation agent examines the asking price and his Marginal Abatement Cost (MAC) to decide the amount of the domestic reduction. Then, he sends back a bid message to the COP agent which says how much he wants to buy or sell at the asked price. After repeating this RFB-BID process, the COP model will find the clearing price where the demand and the supply balance and send the trade message to approve the trades for the year. Thus, the equilibrium price for each year is determined when the MAC functions and the assigned reductions of all of the participants are given.

For the multiple trading periods, we considered a partition of the assigned reduction as a strategy of agents. The dynamics of MAC is given by considering the available technologies for reduction.

As a simple dynamic process for the reduction technology, we adopt reusability and deflation. Once the technology whose cost is lower than the certain price is used, the reusability of the technology will be restricted. On the other hand, the technical innovations and deflation decrease the cost of the technology.

Figure 7.8 shows an example of the simulation views. We can see brief reports on 12 agents and price changes from 2008 to 2012.

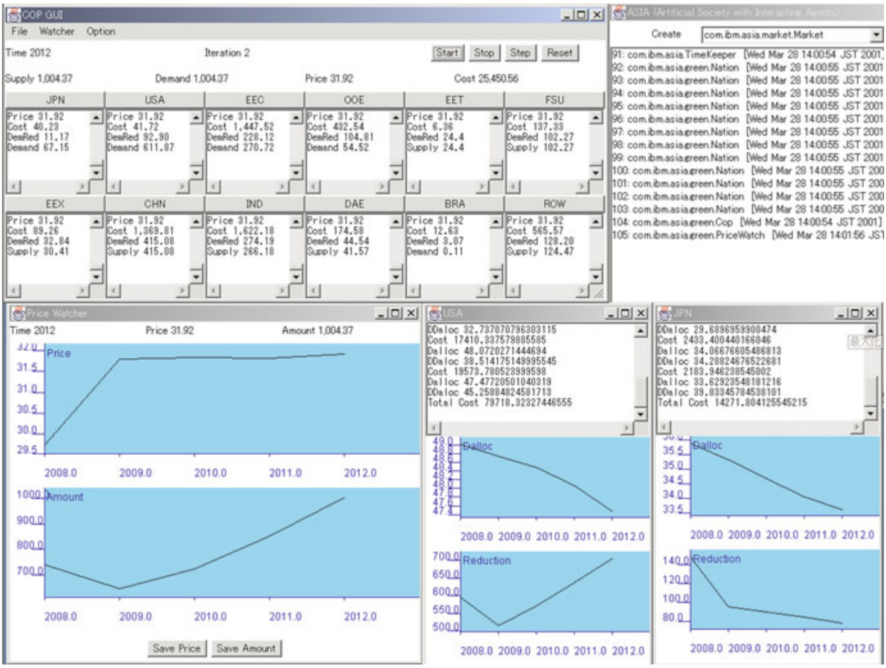


Fig. 7.8 Screenshot of international emissions trading simulation

Gaming simulations with human players in an environment similar to the agents' environment are expected to help us in constructing plausible behavior models and extracting the essential dynamics. We have developed a web application for gaming so that most client PCs with web browsers can easily access it.

In this gaming simulation, players determine the amounts of the domestic reduction of CO2 and the amounts of the excess demand for international emission trading according to the presented price in the RFB at each iteration. Information such as the cost graph, the MAC, the total reduction target, and the trading history is also given.

We show the results of the gaming experiment (Mizuta and Yamagata 2005).

In the experiments, we tried two types of trading model: Walras equilibrium price and double auction (DA). For trading among computational agents, we used Walras trading for one or five trading years to find the equilibrium price and cost-effective strategies. On the other hand, we introduced DA trading for human players since the iterative process of Walras trading is too troublesome for human traders to use and will not converge with dishonest and irrational bids. In an experiment with real human bidders, we tried the Walras trading with students in a preliminary gaming experiment, which did not reach equilibrium. With DA trading, gaming players enjoyed free trading, and sell/buy permits to achieve the target positively.

Table 7.1 Reference and results of gaming experiments

Reference					
Nation	JPN	EEC	OOE	EET	FSU
Cost	47,307	130,852	24,308	−25,351	−84,997
Gaming 04-1					
Nation	JPN	EEC	OOE	EET	FSU
Cost	7783	265,821	12,600	−10,106	−41,655
Perf	84%	−103%	48%	−60%	−51%
Gaming 04-2					
Nation	JPN	EEC	OOE	EET	FSU
Cost	112,143	387,817	30,361	−58,142	−128,823
Perf	−137%	−196%	−25%	129%	52%

The most characteristic behavior emerged in the game was price control by sellers. Sellers (EET: Economies in Transition of Eastern Europe and FSU: Former Soviet Union) were unwilling to sell until the market price became very high, and buyers (JPN, EEC: 15 EU members, OOE: Rest OECD) were forced to pay more than the equilibrium. Even after we changed the assigned countries of the players, this tendency of high price controlled by sellers was sustained and sellers obtained greater revenue than the equilibrium trading of computational agents.

Players and the game controller accessed the online gaming system with their web browsers. The game controller predefined the game's nation parameters and controlled the procession of each game. Each game consists of 5 trading years and one trading year takes about 10 minutes of real time. This web-based gaming system collaborated with the agent-based simulation framework. Hence, we can investigate the behavior of trading using the computational agents with the same factors given to game players.

Two samples of gaming results are shown in Table 7.1. This gaming experiment was held at the University of Tokyo with 10 undergraduate students.

In the experiments (Gaming 04-1 and Gaming 04-2), five countries/areas (JPN, EEC, OOE, EET, and FSU) are assigned to players.

We consider the relative performance of students by comparing their total cost (M$) to achieve the Kyoto targets with the results of the agent-based simulation with Walras equilibrium price.

In Gaming 04-1, JPN showed excellent performance. Investigating the recorded activities in this game, we can see how JPN players achieved such a performance. From the log data, we found that JPN made a large trade with FSU at the early stage. Therefore, JPN need not trade emissions after price rises rapidly and got the high performance. But, FSU and EET studied from the previous game and obtained huge profit by hesitating to trade until the later stage in Gaming 4-2.

Through these gaming experiments, students who did not have previous knowledge quickly studied during the short-term gaming experiments and behaved more effectively. Thus, such a gaming simulation also seems efficient for teaching interaction strategies in complex social systems.

7.4 Agent-Based Simulation Framework XASDI

In this section, we introduce the X10-based Agent Simulation on Distributed Infrastructure (XASDI 2017). This framework is published as an open-source software under the Eclipse Public License (EPL).

XASDI is a large-scale agent-based social simulation framework with an enormous number (millions) of agents to represent Citizens in cities or countries. XASDI enables distributed simulation with the X10 language for post-petascale supercomputers. The X10 programming language (X10 2017) is the APGAS (Asynchronous, Partitioned Global Address Space) language that provides highly parallel and distributed functionalities with Java-like syntax. On the other hand, XASDI provides easy-to-use API with Java that is familiar to application programmer of social simulations and can be developed with powerful IDE functionalities (e.g., Eclipse refactoring and debugger).

XASDI software stack contains a core runtime written in X10 language for distributed agents and execution management and Java API bridge to enable application programmer to utilize Java language (Fig. 7.9). By utilizing XASDI framework, users can easily develop their social simulator with Java on distributed parallel environment without studying X10 language.

The agent in XASDI is referred to as Citizen and Citizen has corresponding CitizenProxy managed in the simulation environment to exchange messages. To manage CitizenProxy, XASDI provides a hierarchical container structure called Place, Region, and World (see Fig. 7.10). CitizenProxies belong to a Place and Places belong to a Region. World can contain several Regions, but usually there is only one Region in the World.

Here, we note the confusing terminology of X10 programming language and this framework. X10 also uses the term "Place"; however, the meaning of the term is different compared with the term of XASDI. The Place of X10 is used to denote the distributed execution environment for multicore or multi-node. To distinguish "Place" of X10 and XASDI, we will use "X10 Place" for Place of X10 and "Place" for Place of XASDI. Only one World instance exists in one X10 Place and manages lists of entities in the World including Region and Citizen. The World can also contain IDs of Citizens in other X10 Places.

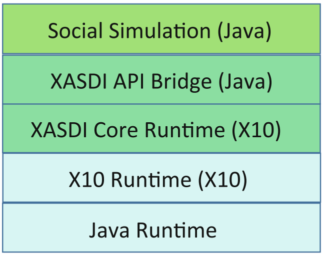


Fig. 7.9 XASDI software stack

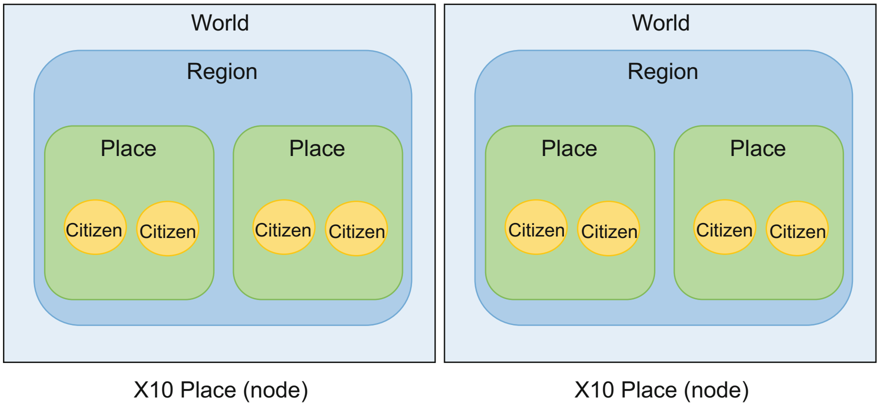


Fig. 7.10 XASDI hierarchical structure to manage agents

Other important classes in XASDI are Message, MessageRepository, and Driver. MessageRepository manages message exchange among CitizenProxy and environment and this class also works as an interface between Java environment and X10 environment to exchange messages in distributed X10 Places. Driver manages execution of the simulation with a corresponding thread. Each Driver is related to Places (and Citizens in the Places) where it has a responsibility for execution.

Finally, XASDI provides a logging mechanism. By preparing log definitions for the application, it can output simulation logs in each X10 Places.

7.5 IBM Mega Traffic Simulator

In this section, we introduce an application of XASDI for the city traffic flow.

We developed a traffic simulator with drivers' behavior models by analyzing the real probe car data that are obtained from GPS equipped on taxies in Tokyo (Osogami et al. 2012, 2013). The agent-based traffic simulator considers each microscopic vehicle as agent, which travels through a given road network with Crosspoints (nodes) and Roads (links). With the XASDI framework, the Vehicle class extends the Citizen class, the Road class extends the Place, and the Crosspoint class extends the Driver class.

Each agent is assigned an origin, a destination, and a departure time as a trip according to an origin-destination (OD) table obtained from population and traffic census survey data. The simulator creates the agent on the origin at the departure time. The agent chooses a route from the origin to the destination, according to a model of the route choice, and travels along that route. In this simulator, heterogeneous agents (vehicles) select a route with their probabilistic preference distribution estimated from probe car data and change their car speed and lane

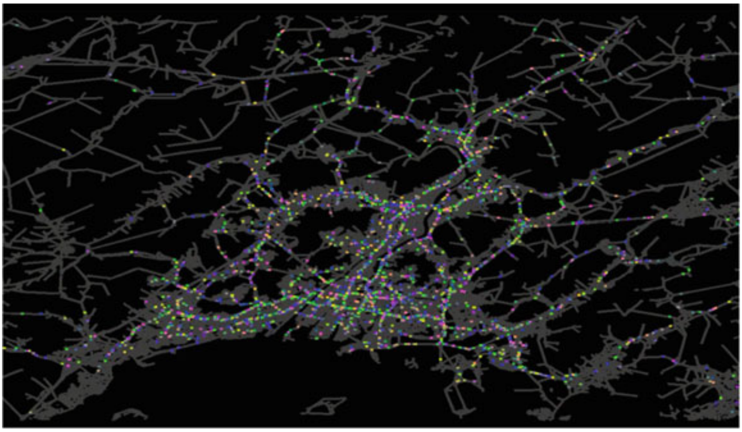


Fig. 7.11 Screenshot of traffic simulation in Hiroshima city

based on the car-following model (Gipps 1981) and Integrated Lane-Changing Model (Toledo et al. 2003) that represent the dynamic interaction with surrounding cars.

At each time step (typically, 1 sec), the microscopic car behavior in roads is controlled by connected Crosspoints, each of which is assigned an individual thread to effectively simulate the fine-grained car movement in and across roads even in a distributed HPC environment. The simulator tracks the location of each agent and records information of vehicles (position and speed), roads (average speed, number of vehicles, CO2 emissions on the road), and trips (travel time and total CO2 emissions of each vehicle) into log files which are used for analysis and visualization. The screenshot of the simulation is shown in Fig. 7.11.

7.6 Pedestrian and Shopping Simulation

In this section, we introduce the pedestrian and shopping simulation for shopping malls and city areas (Mizuta et al. 2016; Mizuta and Imamichi 2018).

By extending XASDI framework, we create Consumer agents (Citizen) that move and shop around the mall. In the mall, there are Zone and Shop (Place) at which a Consumer agent is located.

For the shopping mall simulation, we define Attraction, Move, Shop, and Purchase actions. Each action is related with models possessed by a Consumer agent to allow different behavior for each person. We implemented Attraction, Move, Shop, and Purchase models based on Hui's model (Hui et al. 2009) and combined them with a Walk model.

We consider a three-layer representation of the mall. One map layer is a concrete geospatial representation defined with 3D coordinate data and another is an abstract

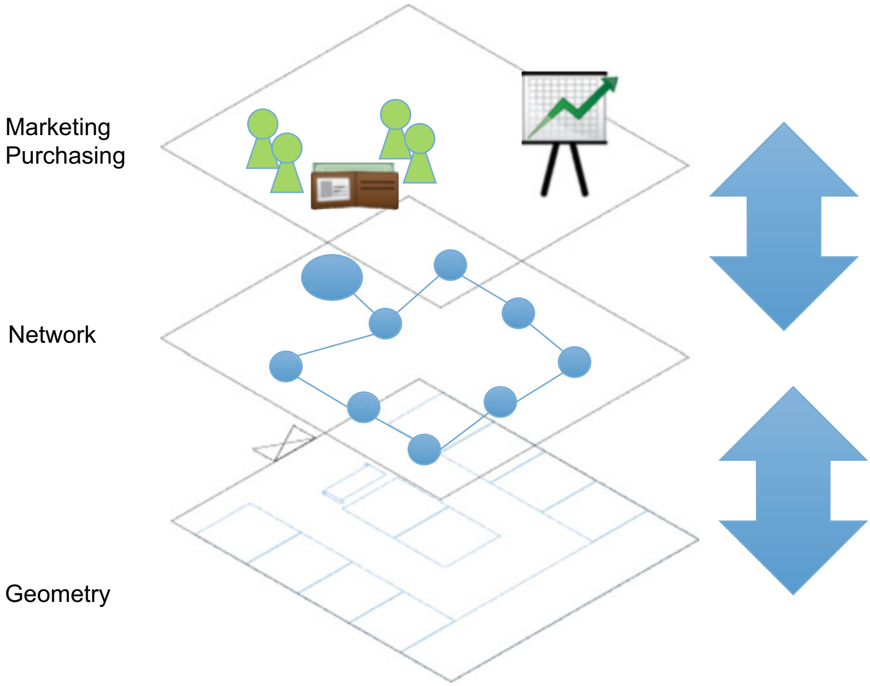


Fig. 7.12 Three-layer structure of shopping mall simulation

network representation defined with nodes and links. Each zone is a node and the adjacency relationship between two zones is a link. On top of these two map layers, we also consider a third economic layer that includes marketing and purchasing activities.

Figure 7.12 shows the three layers of the shopping mall simulation.

For economic activities including destination decision-making in the mall, we use the network representation. For pedestrian activities, we use the geospatial representation. This integration of economic behavior and moving behavior is a key factor of this agent-based simulation.

At the beginning of the simulation, the simulator reads the zone definition file and generates zone objects (including Entrance and Shop) and related GeoZones that represent geospatial locations simultaneously. Consumer agents enter the mall through the Entrance zone at uniform random times during the simulation.

At each time step, agents update their attraction for products and zones, as described later. The attraction is a numeric value associated with each agent (i.e., customer), where the value represents the level of interest of the customer to the zone, or products sold in the zone, at which the agent is located at a given time. Each agent may or may not have a destination. A destination is a zone in the network

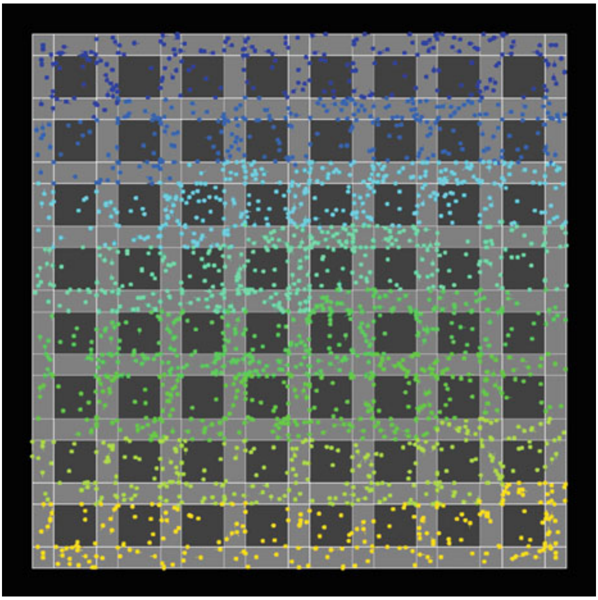


Fig. 7.13 Screenshot of shopping mall simulation

representation. If an agent does not have a destination, it selects a destination with the probability determined on the basis of zone attractions.

If an agent decides to stay in the current zone, or when it reaches the destination, it walks around the current zone using the pedestrian model described in the next section. After the agent decides to make one of the zones its destination, the shortest path on the network is chosen as a trip by Dijkstra's algorithm (Dijkstra 1959), and then the agent walks toward the next zone in the trip.

Figure 7.13 shows the screenshot of the walking consumer in a simple grid mall.

By extending the simulator for shopping mall, we develop a pedestrian simulator in a city. For the shopping mall simulation, we use very simple definition of zone map. Now, we utilize more realistic map definition that can be used for city planning or evacuation.

We extract road network data and building data in Sendai city of Japan from OpenStreetMap (OSM 2017) and convert it to zone map. We choose an area in front of Sendai station for our simulation case.

Figure 7.14 shows the screenshot of the pedestrian simulation in Sendai.

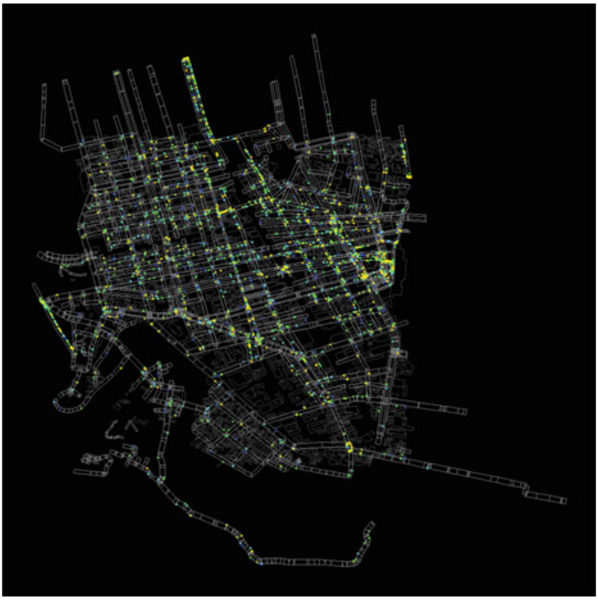


Fig. 7.14 Screenshot of pedestrian simulation in Sendai

7.7 Conclusion

In this chapter, we introduced a computational approach for complex service and social systems called agent-based simulation. Agent-based simulation can become a powerful tool for Service Science, Management, and Engineering (SSME).

In addition, agent-based social simulations are utilized to support the decision-making of city planners for various real social issues, recently. For such a purpose, we developed a large-scale social simulation framework "X10-based Agent Simulation on Distributed Infrastructure (XASDI)." XASDI is available as open-source software at GitHub with tutorial, API documents, and sample programs (https://github.com/x10-lang/xasdi).

We introduced our earlier work with a small number of agents and then describe the details of XASDI framework and its applications. We believe that we can support government and business decision-making through what-if analysis for various scenarios with these simulations.

Acknowledgments The work with XASDI framework and its applications was supported by CREST, JST.

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Chapter 8
Characterization of XRP Crypto-Asset Transactions from Networks Scientific Approach

Yuichi Ikeda

Abstract Decentralized and open information systems based on blockchain technology have received much attention. Blockchain technology can help solve various global issues. For example, international remittances from migrants to their home countries are an important source of funding in emerging economies, and the demand for international remittances is growing. Because of its high transaction speed and low price volatility, the crypto-asset XRP is widely used as a bridge currency for international remittances. In this paper, we reveal the network science characteristics of XRP's transaction network and discuss the relationship between network topology and XRP price. We analyze the entire transaction network by evaluating the various centrality measures and statistically significant triangular motifs.

Keywords Blockchain · Crypto-asset · XRP transaction · Networks analysis · Centrality measures · Triangular motifs

8.1 Introduction

In recent years, decentralized and open information systems based on blockchain technology have attracted much attention. Blockchain technology can be an effective tool to solve various global issues known as the Sustainable Development Goals, SDGs. In this study, we clarify the reality of the financial transaction network of XRP, a crypto-asset based on blockchain technology, from the perspective of network science after providing an overview of blockchain technology and crypto-assets.

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We assess several network science centralities to capture the characteristics of the entire transaction network. Furthermore, we attempt to separate the overall features (signal components) from individual movements (noise components) using machine learning by combining the principal component analysis and the random matrix theory, a method of statistical physics. Extracting the features of the entire transaction network from individual movements is essential for detecting anomalies such as money laundering and fraud. Following this analysis, we identify various triangular motifs and choose one that is statistically significant. We examine the relationship between network topology as captured by statistically significant motifs and the price of XRP.

8.2 Crypto-Asset

8.2.1 Blockchain Technology and the Crypto-Asset Bitcoin

Blockchain is a distributed bookkeeping system in which a certain number of transaction records are managed as a single block, and then as a chain created from the blocks. Figure 8.1 shows a conceptual diagram of a blockchain (Peck 2017). Bitcoin, BTC, goes through a mining process before adding a new transaction record to the blockchain (Nakamoto 2009). Mining is the process of approving a crypto-asset transaction through the efforts of a third party to ensure the transaction's fairness. Proof of Work, PoW, is the approval process, and the person or organization performing the mining is known as a miner. The following steps are taken to record the transaction history. When a new transaction occurs, a hash value (fingerprint) is generated using a Nance (random number). Through trial and error, minors attempt to find the Nance that generates the hash value smaller than the target value. The miner who discovers the Nance that meets the criteria adds the transaction data block

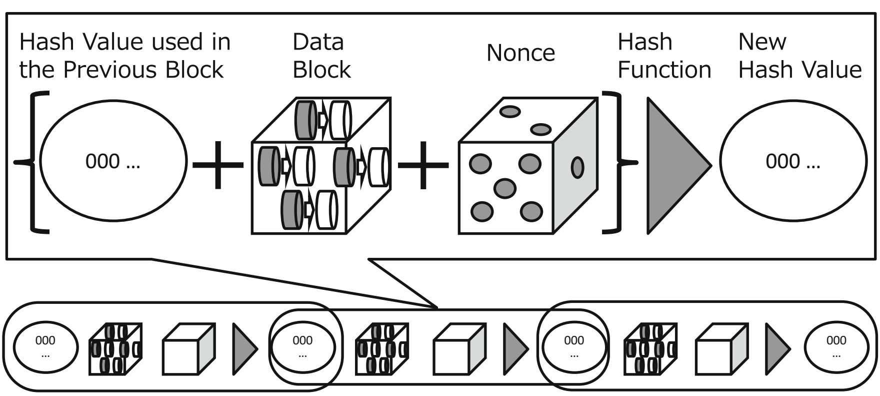

Fig. 8.1 Conceptual diagram of blockchain

to the blockchain and notifies the other miners. The miner will be rewarded if the other miners can confirm the data block and the Nance. Following this procedure, all transaction histories are recorded in the blockchain and approved by an unknown number of people to ensure that transactions are completed correctly. The use of alternatives in crypto-asset BTC is supported by free-participation mining.

In crypto-asset transactions that incorporate the PoW mechanism, anyone can freely participate in mining and receive crypto-asset as a reward for mining. The crypto-asset that is being paid as a reward is brand new. The relationship between supply and demand can easily break down as the amount of currency in circulation changes, and the price can fluctuate wildly, which is considered a disadvantage. In the case of BTC, miners with higher hash rates are more influential in the network because they earn more rewards. Increasing the hash rate necessitates large investments in specialized computers as well as the electricity to power them. Such miners make a significant contribution to keeping BTC active, so it is natural for them to wield considerable power. However, if this trend goes too far, the centralized nature of BTC will become evident.

8.2.2 Using Blockchain Technology to Solve Global Issues

Blockchain can be a fundamental technology to provide solutions to various global issues: international remittance for migrants with low cost, fast, and reliable, digital ID for medical services for refugees, trade-in decarbonized energy, such as renewable energy, nuclear power, and hydrogen, financial inclusion to provide everyone nondiscriminatory financial services, commerce management, such as supply chain and commodity market, economic support for financing and talent matching, etc. (Galen et al. 2019).

Among these issues, the problem of international remittances, including those of immigrants and developing countries, has been attracting particular attention in recent years. International remittances from migrants and others to their home countries are the most important source of funds for developing countries, and the demand for international remittances is growing as economic globalization progresses. In 2018, the global value of international remittances reached $529 billion; except for China, the value of international remittances exceeded the sum of official development assistance, ODA, and foreign direct investment, FDI (Barne and Pirlea 2019). Unlike ODA, which may not reach its intended recipients due to corruption, and FDI, which may not benefit as many people other than the invested industry sectors, international remittances can be sent directly to households in need of funds. As a result, international remittances have emerged as a viable means of raising funds for education, health, employment, and entrepreneurship. Furthermore, international remittances are a consistent source of income for many households. International remittances are considered counter-cyclical because they are directed to households in the destination country that require more money during periods of low economic activity (Frankel et al. 2011).

To use blockchain and crypto-assets for international remittances and other global issues, the price of the crypto-assets must be stable, the amount of energy required for transactions must be appropriate, the cost of the transaction must be low, the speed of the transaction must be high, and the occurrence of anomalies events such as money laundering and fraud must be prevented.

8.2.3 Ripple's Crypto-Asset XRP

XRP, the crypto-asset issued by Ripple Labs. Inc., is managed through the approval process in the transaction system operated using Ripple Transaction Protocol, RTXP, where only transaction records are agreed upon by specific approvers, called validators, can be added. The validators, who play an important role in this process, are chosen from organizations and individuals deemed trustworthy by Ripple. The transaction is recorded to the blockchain if 80% or more of the validators agree to approve it. This is analogous to a special type of majority voting that allows for a quick approval. This approval process is known as Proof of Consensus, or PoC, and it has the advantage of not requiring a large investment or electricity like BTC mining, but it does require a guarantee that Ripple, the operator of RTXP, will not rewrite the ledger at will. Another advantage is that it does not require a large amount of electricity, which corresponds to our society's goal of decarbonization. For this less environmental impact property, XRP is often called "green crypto". The payment system RTXP has been updated from time to time, such as the protocol as of 2014 (Schwartz et al. 2014), the protocol as of 2018 (Chase and MacBrough 2018), and the latest Cobalt protocol (MacBrough 2018).

When the distributed ledger of XRP started to work in 2005, the entire amount of XRP was already issued, and there will be no more. Therefore, the more people who need XRP, the higher the price of XRP will naturally be. If the price of XRP fluctuates significantly before and after a money transfer by a financial institution or an individual, users will find it difficult to use. As a result, as the price of XRP rises, Ripple will normalize it by releasing its XRP holdings into the market. Ripple, however, has taken steps to lock up its XRP holdings so that it cannot freely sell them.

Currently, money transferred overseas via a financial institution has to go through a correspondent bank before it reaches the bank account in the destination country. XRP can be exchanged for fiat currency such as Japanese Yen, US dollars, and Euros, as well as crypto-assets such as Bitcoin. This is referred to as the XRP bridge function. This function allows for international remittances such as Japanese Yen to XRP to USD, Japanese Yen to XRP to Thai Baht and so on. In such transactions, the gateway's IOU (I owe you.) or the right to receive a certain amount of XRP is used (Fugger 2004). For example, when sending a certain amount of XRP from A to B, it is not XRP but IOU that is sent to B's account. The gateway guarantees the trustworthiness of the IOU transaction, and is selected under a strict screening process by Ripple. The gateway functions as a bank's interceptor, accepting XRP deposits from users and rewriting the balance in the RTXP payment system. This enables international money transfers using XRP to be processed directly between financial institutions in the two countries, bypassing correspondent banks and thus speeding up and lowering the cost of international money transfers.

8.3 Methods

8.3.1 Centralities in Complex Network

The total amount of currency in the crypto-asset XRP is fixed, making bubble formation and collapse unlikely. Moreover, because XRP is frequently used for international remittances, detecting anomalies such as money laundering and fraud is challenge. As a results, let us attempt to build a network from XRP transaction data and clarify the network's features to detect the anomalies.

The network $G = (V, E)$ consists of $|V| = N$ nodes connected by $|E| = L$ links. In network science, various types of centrality are known as network features (Barabási 2016). Transaction from node i to node j is captured as the directional link with weight w_{ij}. The in-degree of node i $k_i^{(in)}$ is defined as the number of links from other nodes to node i. The out-degree of node i $k_i^{(out)}$ is defined as the number of links leading from node i to other nodes. Similarly, the in-strength of node i $s_i^{(in)}$ is defined as the sum of weight w_{ij} for all inward links to node i. The out-strength of node i $s_i^{(out)}$ is defined as the sum of weight w_{ij} for all outward links from node i.

Using the in-degree of node i $k_i^{(in)}$ and the maximum in-degree $k_*^{(in)}$, the graph in-degree centrality $K_{in}(G)$ is defined by

$$K_{in}(G) = \frac{\sum_{i=1}^{N} k_*^{(in)} - k_i^{(in)}}{N^2 - 3N + 2}. \tag{8.1}$$

Similarly, using the out-degree of node i $k_i^{(out)}$ and the maximum out-degree $k_*^{(out)}$, the graph out-degree centrality $K_{out}(G)$ is defined by

$$K_{out}(G) = \frac{\sum_{i=1}^{N} k_*^{(out)} - k_i^{(out)}}{N^2 - 3N + 2}. \tag{8.2}$$

The average shortest path length $d(G)$ is defined by

$$d(G) = \frac{1}{N(N-1} \sum_{i,j=1,\cdots,N(i \neq j)} d_{ij}, \tag{8.3}$$

where d_{ij} is the shortest path between nodes i and j. The cluster coefficients $C(G)$ of the entire network are calculated by averaging the cluster coefficient of node i C_i of node i:

$$C(G) = \frac{1}{N}\sum_{i=1}^{N} C_i = \frac{1}{N}\sum_{i=1}^{N} \frac{2L_i}{k_i(k_i-1)}. \tag{8.4}$$

Here, L_i is the number of links between k_i neighbors of node i. The degree correlation coefficient, $r(G)$, is defined by

$$\gamma(G) = \sum_{j,k} \frac{jk\left(e_{jk} - q_j q_k\right)}{\sigma^2}, \tag{8.5}$$

$$\sigma^2 = \sum_k k^2 q_k - \left[\sum_k k q_k\right]^2, \tag{8.6}$$

where e_{jk} is the degree correlation matrix and $q_k = (kp_k)/\langle k\rangle$ is the probability that a node of degree k is connected to a randomly chosen link. Furthermore, the degree entropy $S(G)$ can be calculated using the degree distribution p_k as

$$S(G) = -\sum_{k=1}^{N-1} p_k \log p_k. \tag{8.7}$$

8.3.2 Signal Noise Separation

In this section, we extract the characteristics of the entire transaction network using principal component analysis, PCA, an unsupervised learning method, from time series of various network-centrities. The random matrix theory will be used in conjunction with PCA to separate the signal and noise components of the time series.

A time series of N network centralities $t = 1, \cdots, T$ is represented by a matrix $\boldsymbol{x}(t)$ with T rows and N columns. First, to exclude the trend, we calculate the difference of the time series

$$\boldsymbol{r}(t) = \boldsymbol{x}(t) - \boldsymbol{x}(t-1) \tag{8.8}$$

and standardize as

$$\hat{\boldsymbol{r}}(t) = \frac{\boldsymbol{r}(t) - E[\boldsymbol{r}(t)]}{\sqrt{V[\boldsymbol{r}(t)]}}. \tag{8.9}$$

Then, we obtain a correlation matrix with N rows and N columns

$$C = \frac{\hat{\boldsymbol{r}}(t)^T \hat{\boldsymbol{r}}(t)}{T}. \tag{8.10}$$

Next, we consider the eigenvalue problem of the correlation matrix C:

$$C\boldsymbol{v}_i = \lambda_i \boldsymbol{v}_i, \tag{8.11}$$

where, $\boldsymbol{v}_i$ and λ_i are the i-th eigenvector and eigenvalue, respectively, $i = 1, \cdots, N$.

According to random matrix theory (Laloux et al. 1999; Plerou et al. 1999; Yaskov 2015), the eigenvalue distribution corresponding to the noise component is given by

$$\rho(\lambda) = \frac{Q}{2\pi} \frac{\sqrt{(\lambda_{max} - \lambda)(\lambda - \lambda_{min})}}{\lambda}, \tag{8.12}$$

where

$$Q = \frac{T}{N}, \tag{8.13}$$

$$\lambda = [\lambda_{min}, \lambda_{max}], \tag{8.14}$$

$$\lambda_{min} = \left(1 - \frac{1}{\sqrt{Q}}\right)^2, \tag{8.15}$$

$$\lambda_{max} = \left(1 + \frac{1}{\sqrt{Q}}\right)^2. \tag{8.16}$$

Therefore, the signal component corresponds to the N_t eigenvalues satisfying $\lambda_i > \lambda_{max}$ $(i = 1, \cdots, N_t)$ when the eigenvalue is arranged in decreasing order.

Using the eigenvector $\boldsymbol{v}_i$ and the eigenvalue λ_i, the correlation matrix C can be separated into signal component C^{signal} and noise component C^{noise}, as

$$C = C^{signal} + C^{noise} = \sum_{i=1}^{N_t} \lambda_i \boldsymbol{v}_i^T \boldsymbol{v}_i + \sum_{i=N_t+1}^{N} \lambda_i \boldsymbol{v}_i^T \boldsymbol{v}_i. \tag{8.17}$$

Furthermore, with the coefficient

$$a_i(t) = \boldsymbol{v}_i^T \boldsymbol{r}(t), \tag{8.18}$$

the difference time series $\boldsymbol{r}(t)$ can be separated into signal and noise components, as

$$\boldsymbol{r}(t) = \boldsymbol{r}^{signal}(t) + \boldsymbol{r}^{noise}(t) = \sum_{i=1}^{N_t} a_i(t)\boldsymbol{v}_i + \sum_{i=N_t+1}^{N} a_i(t)\boldsymbol{v}_i. \tag{8.19}$$

8.3.3 *Motif Analysis*

A motif is a small pattern contained in a network. For three nodes connected by directed links, there are a total of 16 motifs, including three motifs (motifs 1, 2, and 4) that are only partially connected, as shown in Fig. 8.2. Each motif corresponds to a characteristic of a transaction in the network.

In order to determine which motifs are mostly included in the XRP transaction network, some kind of criterion is necessary. We consider a random graph in which links are randomly reconnected without changing the in-degree and out-degree of each node. By comparing the number of motifs in such a random graph with the number of motifs in the XRP transaction network, we can determine which motifs are mostly included in the XRP transaction network.

The mean number N_k of motif $k (k = 3, 5, \cdots, 16)$ in an ensemble of scale-free networks is theoretically calculated as shown as follows (Itzkovitz et al. 2003):

$$N_3 = \frac{N\langle R(R-1)\rangle}{2}, \tag{8.20}$$

$$N_5 = N\langle KR\rangle, \tag{8.21}$$

$$N_6 = N\langle RM\rangle, \tag{8.22}$$

$$N_7 = \frac{N\langle K(K-1)\rangle}{2}, \tag{8.23}$$

$$N_8 = \frac{\langle K(K-1)\rangle\langle RK\rangle\langle R(R-1)\rangle}{\langle K\rangle^3}, \tag{8.24}$$

$$N_9 = \frac{\langle RM\rangle^2\langle K(K-1)\rangle}{2\langle K\rangle^2\langle M\rangle}, \tag{8.25}$$

$$N_{10} = N\langle KM\rangle, \tag{8.26}$$

$$N_{11} = \frac{N\langle M(M-1)\rangle}{2}, \tag{8.27}$$

$$N_{12} = \frac{\langle KR\rangle^3}{3\langle K\rangle^3}, \tag{8.28}$$

$$N_{13} = \frac{\langle KM\rangle\langle RM\rangle\langle RK\rangle}{\langle K\rangle^2\langle M\rangle}, \tag{8.29}$$

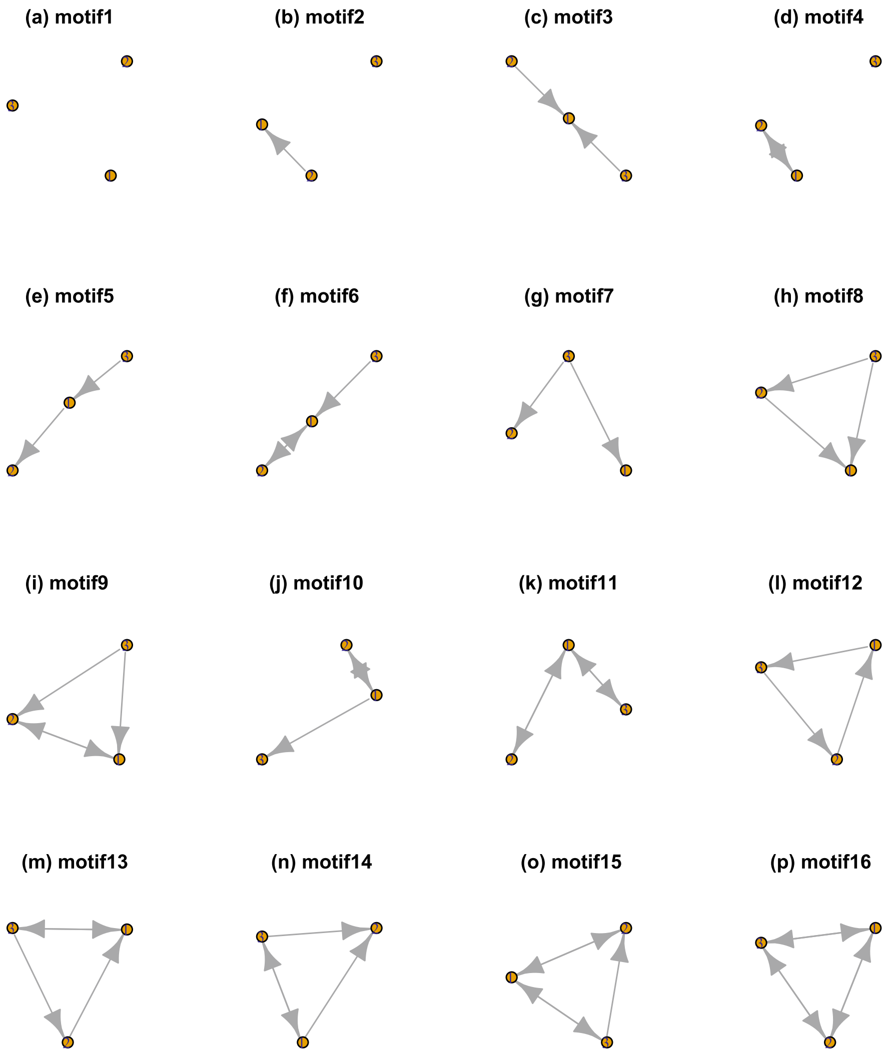

Fig. 8.2 Triangular motifs

$$N_{14} = \frac{\langle KM \rangle^2 \langle R(R-1) \rangle}{2\langle K \rangle^2 \langle M \rangle}, \tag{8.30}$$

$$N_{15} = \frac{\langle KM \rangle \langle RM \rangle \langle M(M-1) \rangle}{\langle K \rangle \langle M \rangle^2}, \tag{8.31}$$

$$N_{16} = \frac{\langle M(M-1) \rangle^3}{6\langle M \rangle^3}, \tag{8.32}$$

with node degrees of node $i (i = 1, 2, \cdots, n)$: in-degree R_i, out-degree K_i, and the number of mutual links M_i. Here, the in-degree and out-degree are counted excluding the mutual links.

8.4 Results

8.4.1 Basic Characteristics of Transaction Network

We constructed monthly transaction networks for crypto-asset XRP from the transactions recorded in RTXP from January 2013 to September 2019. Figure 8.3a, b depict the temporal change in XRP prices in USD from January 2013 to December 2016 and from January 2017 to September 2019. It is worth noting that the price change at the bubble formation in January 2018 shown in Fig. 8.3b is far greater than the two bubbles shown in Fig. 8.3a in December 2013 and January 2015. The price of XRP is relatively stable except for these bubble formations and collapses.

Figures 8.4a, b show the monthly time series of the number of nodes and the number of edges, respectively. The number of nodes and links increases over time, but the number of links appears to be especially high during the bubble formation in 2014 and 2015.

Both complementary cumulative distributions of in-strength $s_i^{(in)}$ and out-strength $s_i^{(out)}$ exhibit the power-law distribution: $P \propto \left(s^{(in)}\right)^{-\gamma_{in}}$ and $P \propto$

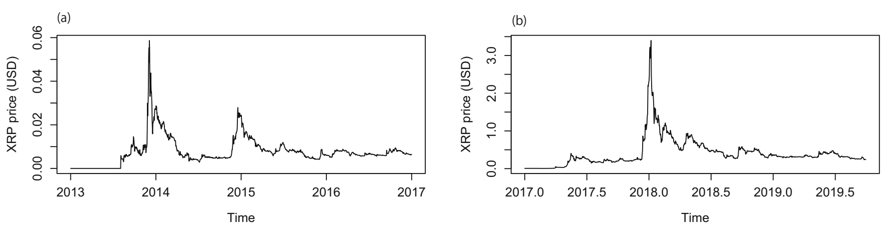

Fig. 8.3 Temporal change of the prices of XRP in USD

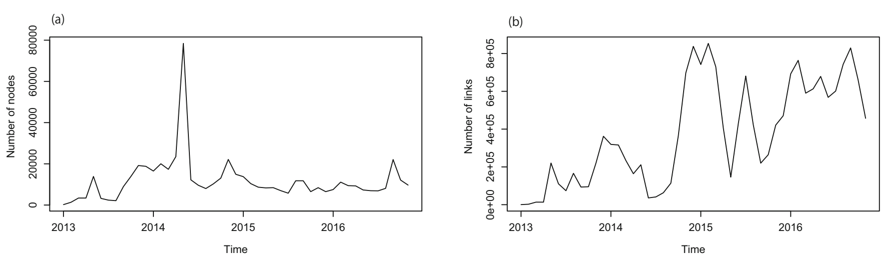

Fig. 8.4 Monthly time series of the number of nodes and edges

$\left(s^{(out)}\right)^{-\gamma_{out}}$. Figure 8.5a, b show the monthly time series of power-law indices γ_{in} and γ_{out}, respectively. Both indices γ_{in} and γ_{out} are slightly less than one for the entire period, except for a period only a few months later than the bubble in 2015.

Figure 8.6a, b show the monthly time series of graph in-degree centrality $K_{in}(G)$ and graph out-degree centrality $K_{out}(G)$, respectively. The graph out-

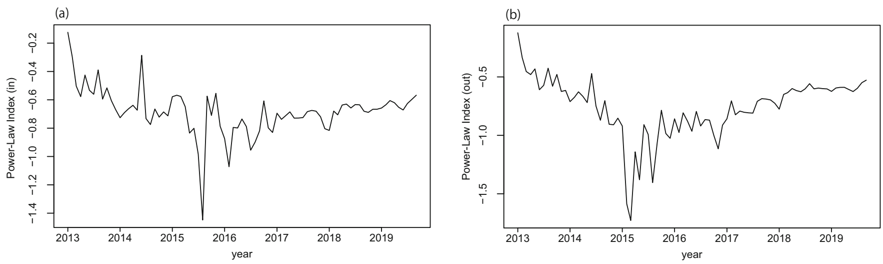

Fig. 8.5 Monthly time series of the power-law indices

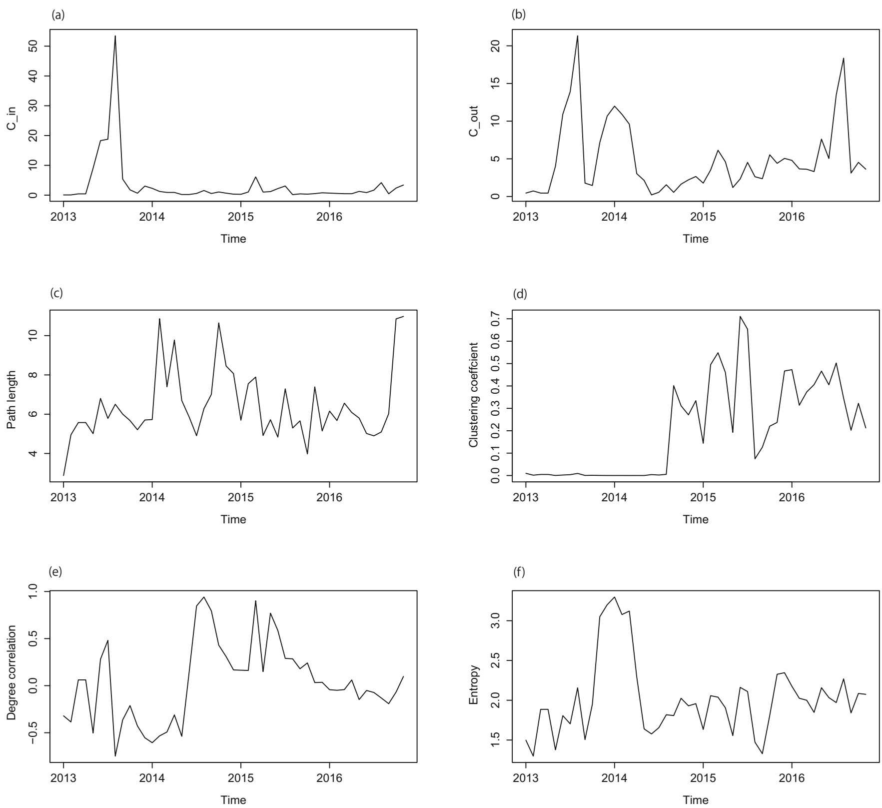

Fig. 8.6 Monthly time series of centralities

degree centrality of XRP in Fig. 8.6b shows peaks at the beginning of 2014 and the first half of 2015, similar to the price trend of XRP in Fig. 8.3a. Figure 8.6c shows the monthly time series of average shortest path length $d(G)$. The temporal change of $d(G)$ does not show a clear structure but fluctuates around six, one of the necessary conditions for exhibiting small-worldness. Figure 8.6d shows the monthly time series of cluster coefficients $C(G)$. The cluster coefficients were very small until the middle of 2014, but they have grown significantly since then, which is another requirement for demonstrating small-worldness. This shift can be attributed to a shift in network structure caused by the spread of XRP, and the transaction network after 2014 is thought to be small-world. The monthly time series of the degree correlation coefficient $\gamma(G)$ is shown in Fig. 8.6e. The degree correlation coefficients are noisy, and it is difficult to read the overall trend, but they appear to be negative. Figure 8.6f shows the monthly time series of degree entropy $S(G)$. Entropy appears to be growing during the first bubble of 2014. However, because there is no change in the 2015 bubble, it is unclear whether this quantity captures overall price changes.

The time series of various centralities shown in Fig. 8.6 may exhibit characteristics change at bubble formations in December 2013 and January 2015, but the relationship is unclear due to various noises in the time series. In the next section, we attempted to separate the overall features from individual movements to show the relationship between the centralities and the bubble formation.

8.4.2 Overall Features and Individual Movements

Using the methods described in Eqs. (8.8)–(8.19), we attempted to separate the overall features (signal component) from individual movements (noise component). The length of the time series is 48 months, from January 2013 to December 2016, therefore $T = 48$. We considered time series of six centralities for XRP transaction network: graph in-degree centrality $K_{in}(G)$, graph out-degree order correlation coefficient centrality $K_{out}(G)$, average shortest path length $d(G)$, cluster coefficient $C(G)$, order correlation coefficient $r(G)$, and degree entropy $S(G)$. We also considered the time series of XRP price in addition to the six centralities, therefore $N = 7$.

Figure 8.7a shows the eigenvalue distribution. The curve is the result of the random matrix theory in Eq. (8.12). The largest eigenvalue of the noise component in Eq. (8.16) is $\lambda_{max} = 1.920$. The first (largest), second, and third eigenvalues are 2.385, 1.236, and 1.167, respectively. If the random matrix theory is strictly applied, only one eigenstate of the first (largest) eigenvalue corresponds to the signal component. However, in this study, we considered the first three eigenstates to be signal components and the remainder as noise components. If a financial transaction exhibits auto-correlation in general, the strict application of random matrix theory for signal noise separation is limited. Figure 8.7b,c show correlation coefficients of seven-time series for signal components and noise components, respectively. The

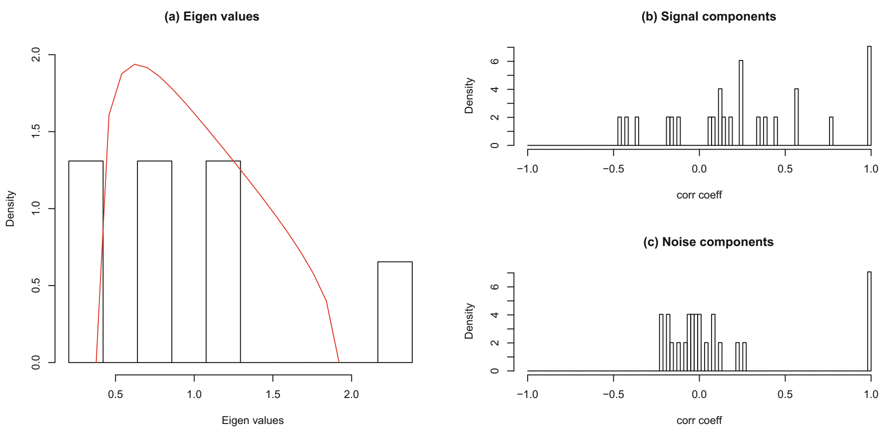

Fig. 8.7 Eigenvalue distribution and correlation coefficients

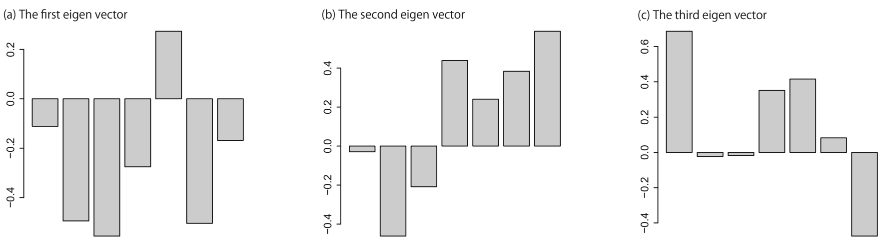

Fig. 8.8 Eigenvectors corresponding the signal components

correlation coefficients equal to one correspond to the correlation with oneself. The correlation coefficients shown in Fig. 8.7c distribute around zero, and therefore the noise components are successfully separated from the signal components.

Figure 8.8a–c show the eigenvectors of three eigenstates corresponding to the signal components. Because these three eigenvectors are orthogonal, the changes in each eigenstate are independent. $K_{in}(G)$, $K_{out}(G)$, $d(G)$, $C(G)$, $\gamma(G)$, $S(G)$, and the XRP price are all included in each vector. All components form one group in the first eigenstate. Changes within the group are generally in the same direction and occur at the same time. $K_{in}(G)$, $K_{out}(G)$, $d(G)$, and $\gamma(G)$ form one group in the second eigenstate, while $C(G)$, $S(G)$, and XRP price form another. Changes within each group tend to be in the same direction, while changes between the two groups change tend to be in opposite directions. The third eigenstate has a small value for the components of $K_{out}(G)$, $d(G)$, and $S(G)$. $K_{in}(G)$ and $C(G)$ form one group, and $\gamma(G)$ and XRP price form another group. Changes within each group, as in the case of the second eigenstate, are generally in the same direction, whereas the two groups change in opposite directions at the same time.

Next, we compare the signal time series and the noise time series for the XRP transaction network. Figures 8.9, 8.10, 8.11, 8.12, 8.13, and 8.14 show

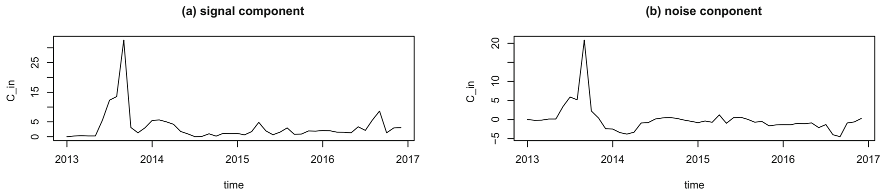

Fig. 8.9 Signal and noise time series of the graph in-degree centrality of the XRP network

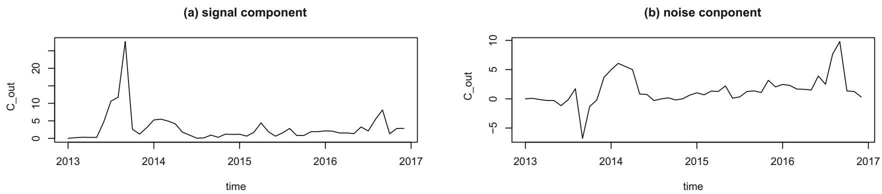

Fig. 8.10 Signal and noise time series of graph out-degree centrality for the XRP network

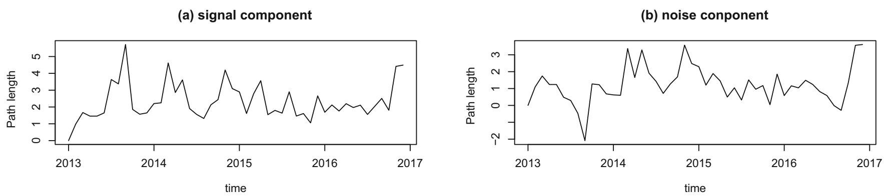

Fig. 8.11 Signal and noise time series of average shortest path length for the XRP network

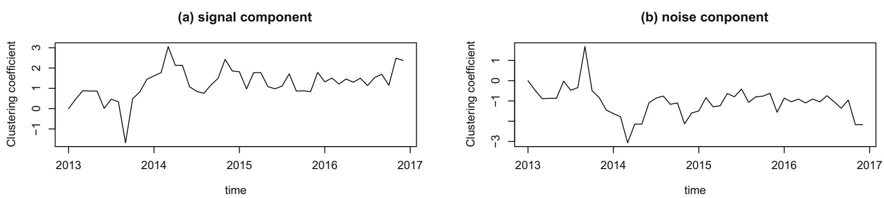

Fig. 8.12 Signal and noise time series of cluster coefficients for the XRP network

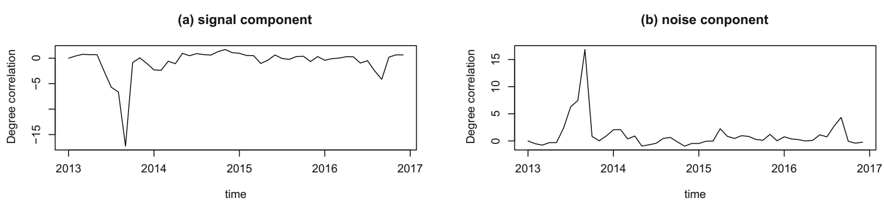

Fig. 8.13 Signal and noise time series of degree correlation coefficient of the XRP network

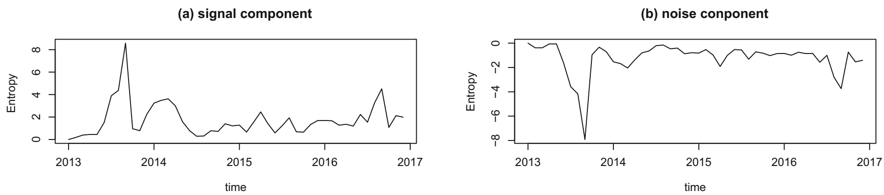

Fig. 8.14 Signal and noise time series of degree entropy of the XRP network

the comparison results of graph in-degree centrality, graph out-degree centrality, average shortest path length, cluster coefficient, order correlation coefficient, and degree entropy, respectively. The signal time series for the graph in-degree and out-degree centrality in Figs. 8.9a and 8.10a show peaks in 2014 and 2015, slightly later than the price peak. The signal is significant for in-degree centrality because the noise time series has no peak in the corresponding period. The noise time series, however, shows a peak of the same magnitude as the signal in 2014 for the out-degree centrality. The significance of the signal is questionable. In addition, the signal component of the average shortest path length in Fig. 8.11a has been around 2 to 4. The signal component of the cluster coefficients, however, shows large average values with large fluctuations in Fig. 8.12a. As a result, these findings are regarded as evidence of small-worldness, as discussed in the preceding section. In Fig. 8.13a, the signal component of the order correlation coefficient is negative throughout the period. The signal components of the degree entropy in Fig. 8.14a has peaked in 2014 and 2014, although the noise components in Fig. 8.14b have the same magnitude. Therefore a simple interpretation of this result is not clear.

Finally, we would like to point out the concern that the time series length is short, $T = 48$. Although the analysis method described in this study appears to be powerful in terms of distinguishing the overall characteristics of the transaction network (signal component) from individual movements (noise component), it is necessary to create a network with a short time horizon, such as weekly or daily, and conduct a similar analysis for a long time series in the future.

8.4.3 Statistically Significant Triangular Motifs

Network motifs are small topological patterns such as triangular sub-graphs that recur in a network significantly more often than expected by chance. We chose the 300 nodes from the entire network with the highest transaction value and built a network of all the nodes that have transactions with these 300 nodes and their 300 nodes to count the number of the 16 triangular motifs shown in Fig. 8.2. We call this network the top-300 node network.

The statistically significant triangular motifs are identified by comparing the observed ratio with the theoretical expectation calculated using Eqs. (8.32)–(8.32).

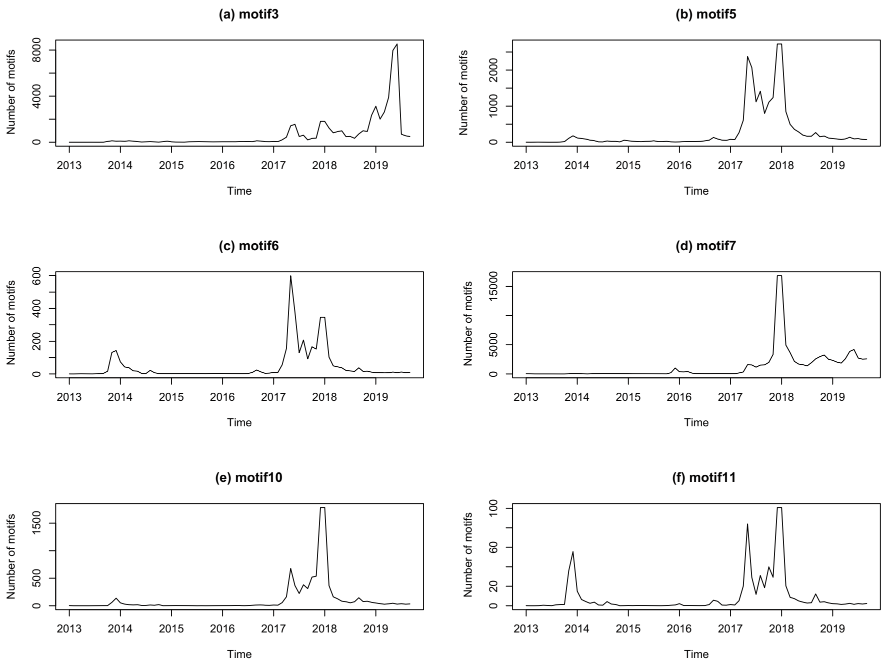

Fig. 8.15 The temporal change of the statistically significant motifs observed in the top-300 nodes network from Jan. 2013 to Sep. 2019

The theoretical expectation for the number of triangular motifs divided by the number of the nodes in the network are $N_3 = 3357$, $N_5 = 1237$, $N_6 = 537$, $N_7 = 356$, $N_8 = 71396$, $N_9 = 8808$, $N_{10} = 151$, $N_{11} = 29$, $N_{12} = 7621$, $N_{13} = 8652$, $N_{14} = 6635$, $N_{15} = 2904$, $N_{16} = 144$, for the network of November 2017. Moreover, the observed number of triangular motifs divided by the number of the nodes in the network are $N_3^{obs} = 22750919$, $N_5^{obs} = 79054373$, $N_6^{obs} = 9700159$, $N_7^{obs} = 214461162$, $N_8^{obs} = 3519$, $N_9^{obs} = 1353$, $N_{10}^{obs} = 34322156$, $N_{11}^{obs} = 1866492$, $N_{12}^{obs} = 2986$, $N_{13}^{obs} = 1748$, $N_{14}^{obs} = 2371$, $N_{15}^{obs} = 959$, $N_{16}^{obs} = 381$, for the network of November 2017. The comparison shows that motif 3, motif 5, motif 6, motif 7, motif 10, and motif 11 are statistically significant. Figure 8.15 depicts the temporal evolution of statistically significant motifs observed in the top-300 node network from January 2013 to September 2019. These statistically significant motifs were discovered to be more prevalent during the bubble-forming periods of 2014 and 2018, and less prevalent throughout the rest of the year. As a result, the observed significant price change is caused by transactions corresponding to statistically significant triangular motifs, and detecting anomalies is possible by observing the triangular motifs.

8.5 Conclusions

We revealed the reality of the financial transaction network of XRP from a network science perspective. We characterized the entire transaction network by drawing on the various centrality features used in network science.

After an overview of blockchain technology and crypto-assets, we explained the reality of the financial transaction network of XRP, a crypto-asset based on blockchain technology, from the perspective of network science. We built monthly XRP transaction networks from January 2013 to September 2019. To reveal the overall characteristics of the transaction network, the following centralities were calculated: graph in-degree centrality, graph out-degree centrality, average shortest path length, cluster coefficient, order correlation coefficient, and degree entropy.

Furthermore, we attempted to separate the signal component from the noise component by using PCA and random matrix theory, a method of statistical physics. It is critical for detecting anomalies such as money laundering and fraud to separate the features of the entire transaction network from individual movements. Although the analysis method described in this study appears to be powerful in terms of distinguishing the signal component from the noise component, it is necessary to create a network with a short time horizon, such as weekly or daily, and conduct a similar analysis for a long time series in the future.

Network motifs are small topological patterns such as triangular sub-graphs that recur in a network significantly more often than expected by chance. The statistically significant triangular motifs were identified by comparing the observed ratio with the theoretical expectation. These statistically significant motifs were more prevalent during the bubble-forming periods of 2014 and 2018, and less prevalent throughout the rest of the year. The result implies that the observed significant price change is caused by transactions corresponding to statistically significant triangular motifs, and thus detecting anomalies is possible by observing the triangular motifs.

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Part IV
Artificial Market Experiments

Chapter 9
The Emergence of Markets and Artificial Market Experiments

Kazuhisa Taniguchi

Abstract Modern financial markets are extremely sophisticated markets that make full use of advanced technology, but historically, markets are as old as the emergence of human society. For many years, the author lectured on the emergence of markets and then conducted artificial market experiments using the U-Mart system designed based on the Tokyo Stock Exchange. The U-Mart system has various advantages, such as allowing students to learn experientially, and it can be used flexibly according to the educational situation. This chapter reports on a series of educational experiments.

Keywords The emergence of the market · Artificial market experiments · The U-Mart system · The educational use · Educational experiments

9.1 Introduction

This chapter reports on economics education using the U-Mart system to conduct virtual market experiments. The U-Mart system is a system that builds an artificial market on a computer network and experimentally trades index futures, and it can be used to conduct excellent research and education. Therefore, although it can be used as a wide-ranging educational tool, the author has used the U-Mart system mainly as a tool for economics education. Usually, most of the financial education provided by university economics faculty is based on the desk lecture format, but education using an artificial market has various merits, such as students learning experientially. Particularly, among virtual market experimental tools, the U-Mart system has distinctive flexibility according to the educational situation. Since the author has been conducting financial education for many years using this system, this chapter will report on the series of educational content.

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9.2 The Emergence of the Markets

Current financial markets, such as the Tokyo Stock Exchange, are extremely sophisticated markets in which advanced technology is used.

However, in modern mainstream economics, the existence and emergence of financial, product, and service markets are given, and their significance and meaning are rarely mentioned. In standard economics textbooks, terms such as "market economy," "market behavior," "market failure," and "perfectly competitive market" appear, but the "market" itself can be explained briefly. The market itself, which plays a crucial role in economic phenomena, is infrequently discussed in economics education.

Therefore, at the "artificial intelligence economics" seminar of the Graduate School of Commerce, Chuo University, we gave a lecture on the emergence of markets according to the works of Adam Smith, Menger, Hayek, and others. Regardless of how sophisticated and advanced markets are, historically, markets are as old as the emergence of human society, and their origins are in gifts and barter before the emergence of money.

9.2.1 Reason for Exchange

In order for a market to generate, there must first be an exchange. Hayek said that when a person first came into contact with a stranger, he or she would have given a gift rather than conducted an exchange. Most likely, he or she left a gift on the border of their tribe in the hope of obtaining a return.[1] The exchange would have started with such a gift. Therefore, why do humans exchange? What is the purpose of exchange?

Adam Smith thought that the reason for exchange was the "propensity to exchange" of human beings, and exchange is unique to humans. However, if the purpose is simply the exchange itself, why not reexchange what was exchanged immediately? Why is exchange irreversible once realized?

Menger thought that the reason to exchange would be to satisfy desires.

> The effort to satisfy their needs as completely as possible is therefore the cause of all the phenomena of economic life which we designate with the word 'exchange'. (Menger 1923, p. 180.)

> If we summarize what has just been said we obtain the following propositions as the result of our investigation thus far; the principle that leads men to exchange is the same principle that guides them in their economic activity as a whole; it is the endeavor to ensure the fullest possible satisfaction of their needs. (Menger 1923, p. 180.)

[1] Hayek (1973, p. 82).

Menger thus thought that the role of exchange was to better satisfy human desires. However, this desire is not a so-called instinctive desire but should be discovered by intellectual activity. This desire is the subject of cognitive efforts and the result of cognitive efforts. Knowledge is required to know this desire, and the desire also includes the desire as a group. For example, the construction of educational facilities and waterworks are collective desires.

9.2.2 Premise of Exchange

If you want to acquire what you desire and be satisfied, you can attain the desire even by plunder or stealing. However, why can we exchange instead of plundering or stealing? It is the fulfillment of instinctive desires for animals to catch their prey, but why do humans not call such behavior of animals plundering or stealing? The following words by Adam Smith express this awareness of the problem surprisingly well:

> Nobody ever saw a dog make a fair and deliberate exchange of one bone for another with another dog. Nobody ever saw one animal by its gesture and natural cries signify to another, this is mine, that yours; I am willing to give for that. (Smith 1776, p. 14.)

In order to acquire goods by exchanging rather than plundering or stealing, the idea of private property (individual ownership) must arise. In addition, the fact that an individual owns an object means that the individual can dispose of the object based on his/her own will and without being forced by another person. Furthermore, when the idea of private property is born, the morality (behavioral rule) that the individual possession should be respected and not violated by the group to which the individual belongs must also be born. The idea of plundering or stealing can exist because of the idea of possession and the morality of keeping the property. There is no idea of plundering when goods cannot be exchanged. Therefore, there is no plundering or stealing in animal society.

Hayek insists that rules of conduct relating to private property, exchange, trade, competition, profit, and privacy have played significant roles in human existence. He discusses, in particular, liberty, property, and justice in one chapter in his book.[2]

First, since abstract awareness is essential to the use of advanced rules of conduct, the acquisition of abstractness should be highlighted. According to Hayek, abstract awareness does not result from intelligence but forms it.[3] Organisms have acquired various capacities for coping with environments in the course of evolution. Homo sapiens acquired abstract awareness as a way to handle difficult situations where environments were so complicated that they could not be completely understood.

Hayek says that no advanced civilization has appeared without a government that mainly aims to protect private property, that private property is the core of every

[2] Hayek (1988, Chapter 2).

[3] Hayek (1973, pp. 29–31).

advanced civilization, and that the concept of private property emerged at a very early stage of human history. He adds that ancient Greece not only discovered the development of individual liberty and private property but also their inseparability to create the world's first civilization by free people.[4] Obviously, the liberty referenced in his book is not political liberty, inner mental liberty, or physical freedom as a form of power but is rather Hayek's interpretation of liberty, i.e., "individual" or "personal" freedom.[5] In other words, Hayek refers to the liberty to dispose of one's own resources for oneself without being forced by other people.

According to Hayek, no individual liberty exists where no private property exists. The reason is that one cannot confirm one's liberty if one does not have the means (private property) to determine whether one is free. In a small band without private property, one can only follow the others in the band, and there is no liberty.

With the birth of liberty, justice was born.[6] Hayek states that justice concerns human-created situations and is only used for human conduct. He adds that people do not say that conduct, which cannot be handled on their own will, is just or unjust.[7] Based on this perception, people may say that conduct, which is not freely conducted but is done under compulsion, is good or bad, but may not say that conduct is just or unjust. It is not possible to demand justice from slaves in the range of conduct where they have no freedom to decide. Consequently, it is supposed that there must have been a glimpse of primitive rules of justice in a free Homo sapiens society since property could not be retained without the existence of rules of justice. If a Homo sapiens' possession was plundered, the unforgivable act of "depredation" does not exist unless there is a practice of condemning depredation as an unjust act in the group. The right to property can only exist in a society where depredation is recognized as "depredation" by the entire group.

Hayek wrote "Such states as 'ownership' have no significance except through the rules of conduct which refer to them; leave out those rules of just conduct which refer to ownership, and nothing remains of it."[8] He also quoted" 'Where there is no property there is no justice,' is a proposition as certain as any demonstration in Euclid" from *Essay Concerning Human Understanding* by John Locke.[9] According to Hayek, rules of justice are also the most abstract and agreeable rules and operate as ultimate values.[10] Justice can be approached by eliminating injustice. However, justice is highly abstract where nobody can confirm that ultimate justice has been reached.[11] It is supposed, therefore, that the highly advanced form of the rules of justice as we have today may not have existed in small-scale blood-related bands

[4] Hayek (1960, Chapter 1).
[5] Hayek (1960, p. 11, Chapter 1).
[6] Hayek (1988, p. 33).
[7] Hayek (1976, p. 31).
[8] Hayek (1976, p. 35).
[9] Hayek (1988, p. 34).
[10] Hayek (1976, p. 15).
[11] Hayek (1976, p. 43).

of Homo sapiens. Nevertheless, there must certainly have been primitive forms of rules of justice, even in those days.

As stated above, whether one is free cannot be determined without the existence of private property. It can be said that liberty itself does not exist under such a situation. It cannot be determined whether a particular conduct is just or unjust without the existence of freedom. Furthermore, private property cannot be retained without the presence of justice. It can be supposed, therefore, that liberty, justice, and private property can never be born separately and that any one of them cannot exist unless all of them are present. This is why liberty, private property, and justice must have been born almost at the same time in the earliest stage of societal and economic evolution.

Exchange is only possible when the concept of possession exists. Conflicts naturally decrease when people can get things they want not by looting but by exchange. Peaceful acquisition helps reduce conflicts between individuals in a group or between one group and other groups. This increases the sustainability of the group. Furthermore, the group can more easily expand. A group that can possess valuable properties also increases its capacity for survival through the ability to exchange. Hayek suggests that barter exchange started when a small band placed things that might be favored by the other bands at the boundary of its territory.[12] Exchange evolved into trade. Trading already existed 30,000 years ago; however, it is difficult to find the origin of trading. The reason is that only durable goods can remain as evidence of trade and consumer goods can never remain. In a place where private property emerged, in order to make it possible to transport durable goods to be used only in a specific place, practical implementation of rules of conduct that might have never been experienced by the people of those days previously became necessary. Once trading began, trade was promoted by the population density increasingly, thereby increasing the population. Through this cycle, humans spread to various places in the world through trading.[13] Markets and currencies must have appeared.

9.2.3 Universality of Exchange

Why can exchange be universally widespread throughout society? Regarding the universality of exchange, let us show a numerical example according to the proof by Shiozawa.[14]

[12] Hayek (1973, p. 82).

[13] Hayek (1988, Chapter 3).

[14] Shiozawa et al. (2019, Chapter 7).

Now, person A and person B own three kinds of goods, and they have different evaluations of v_a and v_b for the goods, respectively. Since this is a vector quantity, it is called an evaluation vector. The evaluation may or may not be the price.

Let these vectors be

$$v_a = (1, 2, 3), v_b = (6, 5, 4).$$

For these evaluation vectors, there is the following vector of goods to be exchanged:

$$u = (x, y, z)$$

We call this vector the exchange vector. Suppose that the following inequality can be created for the scalar product of these evaluation vectors and a certain exchange vector:

$$x + 2y + 3z < 0 < 6x + 5y + 4z$$

For example, $u = (2, -1, -1)$ satisfies this inequality. This is a good vector to be exchanged. In other words, if person A obtains only $-u$ and person B obtains only $+u$ by exchange, the evaluation is $-2 \times 1 + 1 \times 2 + 1 \times 3 = +3$ for A and $2 \times 6 - 1 \times 5 - 1 \times 4 = +3$ for B. This shows that the situation is improved by $+3$ for both people.

The important point is that there is always a certain vector $u = (x, y, z)$ that can create a positive and negative scalar product for the nonnegative and nonproportional evaluation vectors of both people. This guarantees that the exchange will improve the situation. If the evaluation vectors are proportional, then no such vector exists. In other words, the exchange will occur if there are different evaluations between the two. If there are many human beings, they will be diverse, and their evaluation vectors will be more common than proportional. Even for the same person, the evaluation vector will change over time.

In the U-Mart system, index futures are bought and sold, which is the world of zero-sum games. Although it is known in advance that there are both winners and losers in such a game, the game is established, that is, there is a market. The reason is that there are differences in the evaluation vectors of the traders.

It should be noted that this argument shows that it appears in a one-time transaction (buying and selling exchange) and does not mean that the gain that appears in multiple transactions (arbitrage transaction).[15]

[15] See Taniguchi (2019) for the difference between trading and arbitrage.

9.2.4 Market as a Spontaneous Order

Exchange is a fundamental condition for a market to be established, but it will take a long time for mere exchange to evolve into a market. "Spontaneous order" is an important key concept for understanding the market, and we will explain this order using Hayek's "three-fold division."

Hayek said that the division of all phenomena into those that are "national" and those that are "artificial" is misleading.

> Those terms (national and artificial[16]) could be used to describe either the contrast between something which was independent of human action and something which was the result of human action, or to describe the contrast between something which had come about without, and something which had come about as a result of, human design. (Hayek 1967, pp. 96–97.)

> It therefore never became clear that what was really required was a three-fold division which inserted between the phenomena which were natural in the sense that they wholly independent of human action, and those which were artificial or conventional in the sense that they were the product of human design, a distinct middle category comprising all those unintended patterns and regularities which we find to exist in human society and which it is the task of social theory to explain. (Hayek 1967, P.97.)

In this third classification, man-made things are classified into "whether they exist independently of them or are they the result" in terms of "action" and "design," respectively. It can be understood from the fact that the classified contents do not match, as shown in the three-fold division (Fig. 9.1).

There are many things or phenomena that are not intended by humans but are the result of human actions. Some of them are closely related to various elements and draw a certain complicated pattern with regularity. Since these things or phenomena are not intended by humans, their patterns and structures occur spontaneously independent of human intentions. They can have any number of complex structures and have no specific intention. Such a thing or phenomenon is called a spontaneous order.

Markets and money are the spontaneous orders that belong to this three-fold division and are the basis of human civilization. They would not exist without humans, but they are also objective. There are various systems in human society. For example, Japan has a diet, a cabinet, and a court. These are artificial organizations created by humans to maintain Japanese society, and each organization has a purpose. However, the country of Japan itself was not established for any purpose at the beginning. In this way, there is no purpose or intention in a spontaneous order such as a market or money.

Humans cannot escape ignorance. We are not omnipotent and can possess only partial knowledge. That is the root of market order, and it is also due to this ignorance that the present society has taken the form of the market economy. In other words, since the market is an order generated spontaneously in this way, it is

[16] Added by the author.

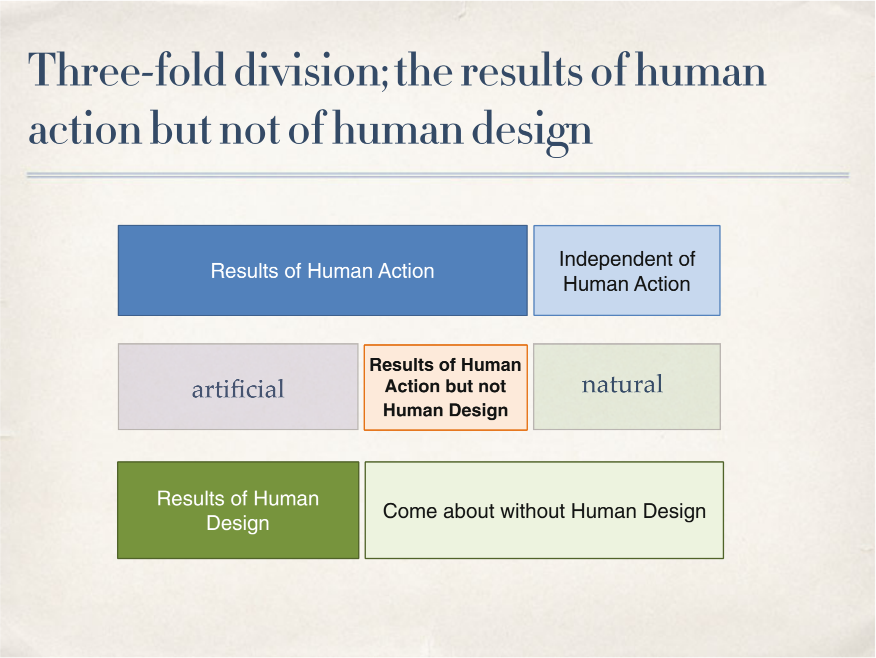

Fig. 9.1 Three-fold division (This figure was illustrated by the author according to Hayek's arguments)

not perfect. Humans have designed the desired market by setting various rules and modifying the imperfect market. Institutional design of the market will need to be constantly made in response to changes in the environment. The artificial market described in the next section offers new possibilities for such institutional design.

9.3 Artificial Market

9.3.1 Financial Markets and Financial Education

The emergence of markets has made it possible to effectively use the knowledge of others, and the society of the market economy has developed. After the Industrial Revolution, financial markets were also born and developed, and these markets were able to gather thin and widespread idle assets in society. Large-scale investment has become possible.

Regarding the financial market, the current composition of financial assets of Japanese households is characterized by a higher proportion of cash and deposits than the United States and Europe. For example, according to the Bank of Japan's "Comparison of Fund Circulation between Japan, the United States and Europe"

(Bank of Japan Research and Statistics Bureau, August 29, 2019), in Japan, "cash and deposits comprise 53.3%, investment trusts comprise 3.9%, stocks comprise 10.0%, and insurance and pension and standard guarantees comprise 28.6%" of the funds circulating; in the United States, "cash and deposits comprise 12.9%, investment trusts comprise 12.0%, stocks, etc. comprise 34.3%, and insurance and pensions and standard guarantees comprise 31.7%" of the funds circulating; and on the Euro area, "cash and deposits comprise 34.0%, investment trusts comprise 8.8%, stocks comprise 18.8%, and insurance and pensions and standard guarantees comprise 34.0%" of the funds circulating.

Therefore, in Japan, indirect finance accounts for a large proportion compared to direct finance, so various introductions have been made to move financial assets from savings to financial investment. For example, NISA (Nippon Individual Savings Account) is a typical example for individual investors. There is a tax exemption for individual investors that started in 2014. Dividends and gains on transfers to stocks and investment trusts are tax-exempt if they are within the tax-exempt investment limit (1.2 million yen per year). Additionally, in 2018, a tax exemption system for small investment called "Tsumitatate (deposit) NISA" started.

In addition, market participation-type educational tools for conducting various stock trading have been developed and introduced into education. An example is the "Nikkei Stock League," which is a stock investment learning program. One can acquire stock experience, such as what company's stock to buy and the stock price trend, by making virtual investments. Then, the "Stock Learning Contest for Junior High School, High School and College Students" is held, and the 20th event was held in 2019. In this way, in Japan, education aimed at fostering individual investors and providing further guidance for individual investors to participate in financial markets is being conducted.

9.3.2 Features of U-Mart System

The U-Mart project integrates social science and engineering. It builds a market for trading stock indexes on a computer network. In this virtual market, both computer program machines (hereinafter, machine agents) and humans (hereinafter, human agents) can participate as traders at the same time. That is, the system can be operated with the simultaneous participation of the machine agent and the human agent, only the machine agent, or only the human agent. Accelerated experiments are possible if experiments are conducted using only machine agents. When the number of human participants is large, the experiment is performed only with the human agent, and when the number of human participants is extremely small, the number of participating agents is adjusted by added machine agents. Being able to operate flexibly according to the number of participants in this way is extremely convenient when used as an educational tool. This is a distinctive feature of the U-Mart system.

Furthermore, since all the data obtained by the experiment are accumulated as log data and available in csv format file, data analysis is possible after the experiment. Since all participants can analyze their own experimental results or the experimental results of others using the data after the experiment, it can also be used as an exercise for data analysis. In addition, although the time depends on the content of the experiment, in the case of an experiment using only machine agents, one experiment can be completed in tens of seconds to a few minutes. Even an experiment in which a human agent participates can be completed within the usual 90-minute lecture time, so it is very convenient as a teaching material in a practical sense.

There are two methods of buying and selling stocks on the Tokyo Stock Exchange: the Itayose method and the Zaraba method. Most of the trades in one day are conducted using the Zaraba method, and the Itayose method is used at the beginning and ending of a day's trading or after the trading is temporarily suspended. Therefore, the U-Mart system is also designed to allow transactions through these two methods. In addition, the trading target of the U-Mart system is the trading of stock indexes. At the beginning of the U-Mart project, J30 provided by the Mainichi News Paper Company was often used.

Even economic phenomena that are difficult to observe frequently in real markets can be easily observed by performing simulations using this system, so this is an extremely useful project for investigating various economic phenomena. The Tokyo Stock Exchange has various rules, such as price range limits, margins, and mark-to-market mechanisms, depending on the type of transaction. Some of these rules have no clear basis and are practiced according to convention. Changing such mechanisms and rules would be very costly. However, it is possible to verify the results of changing such rules by simulation using U-Mart.

The U-Mart project started in 1999 and was presented at the Japan Association for Evolutionary Economics in 2000. At about the same time, a seminar to address educational use was held, and after that, research and education were reported one after another at the conference of the Japan Association for Evolutionary Economics. The work Shiozawa et al. (2008) was published for the purpose of education, and Kita et al. (2016) was published for the purpose of research.

9.3.3 Open Experiment: Joint Seminar of Chuo University Aruga Seminar and Kindai University Taniguchi Seminar

At the beginning of the U-Mart project, an open experiment was conducted at the same time as the conference of the Japan Association for Evolutionary Economics, and then, the experiment including the general public was continued. The open experiment of the U-Mart project began in 2001. Both Aruga and the author (Taniguchi) partly introduced the U-Mart system into their undergraduate seminars mainly for the purpose of financial education, and we held a joint seminar for

Fig. 9.2 Open Experiment and 1st Joint Seminar, Tokyo Institute of Technology, October 2, 2004

our students (Joint Seminar of Commerce Faculty, Chuo University and Faculty of Economics, Kindai University). This joint seminar was held annually from October 2004 to 2014. It was conducted 11 times. Figures 9.2 and 9.3 show the seminars at those times. The results of the experiments while competing for victory or defeat in the U-Mart experiment have also been reported. In addition, the open experiment was continued for a long time and was held at the "National Research Conference of the Society of Economic Education (September 10 (Sat) and 11 (Sun), 2016, University of Marketing and Distribution Science)." In addition, a summer school for engineering graduate students was held every year at the Artificial Intelligence Laboratory of Tokyo Institute of Technology, and one graduate student of the graduate school of Osaka Prefecture University had PhD.

9.3.4 Learning of Experimental Participants

Experiments using the U-Mart system have produced various results in research and education. The author has mainly conducted experiments in which human agents participate as traders. Among the many experimental results, what is impressive to the author is that although most of the experimental participants were students who

Fig. 9.3 Open Experiment and 2nd Joint Seminar, Kyoto University, September 12, 2005

had no trading experience, a small number of strong traders often appeared. At the beginning of the trading experiment, there were no individual differences among the traders, but it was truly interesting that strong traders appeared when the trading experiment was repeated. This section reports on how the participating students understood the U-Mart experiment and what they thought it took to win.

9.3.4.1 Methods for Predicting Stock Price Fluctuations and Zero-Sum Games

There are two types of methods for predicting stock price fluctuations: fundamental analysis and technical analysis. Fundamental analysis is a stock price forecast based on the basic (fundamental) conditions of the economy. Fundamental analysis indicators range from the various management indicators of the company described below to macro indicators of the economy as a whole. As the management indexes of a company, profitability, net assets, dividends, balance sheets, income statements, financial statements, etc., as well as the management ability and sales base of the manager, are used. Macro indicators of the economy as a whole include interest rates, trade balances, exchange rates, unemployment rates, business conditions indexes, and economic growth rates. In addition, current noneconomic factors (political situations, social situations, etc.), natural disasters, technological innovations, etc. are also included.

"Ask the stock price about stocks" is a common saying. Following this, technical analysis is a method of predicting future prices by examining price fluctuations. For example, a graph showing the price movements of past stock prices (which is a stock index in the U-Mart experiment) is called a chart, which is a type of line graph. Technical analysis applies some form or trend to this emerging chart and predicts stock price fluctuations from it. For example, there are many types of technical analyses, such as the golden cross method and dead cross method that use the short-term and long-term moving averages, the trend method that uses the trend of stock prices, and the Bollinger band method that uses the trading volume and the stock price. There is also a figure called the "ruled line" ("Keisen" in Japanese) that is a method unique to Japan that expresses the price movement of stock prices. The ruled line started with a record of fluctuations in the rice market at the Rice Exchange in Osaka during the Edo period, and the inventor was Honma Soukyu. This development occurred 100 years before the grain futures market began in Chicago, USA. Following this, there are roughly two types of stock price forecasting methods, fundamental analysis methods, and technical analysis methods, and in the real market, both are combined for forecasting. Although the long-term trend of stock prices can be understood as a result of only fundamental analysis, there is a limit to the prediction of short-term fluctuations. Therefore, in the real market, stock price fluctuations are predicted using both fundamental analysis and technical analysis.

In the U-Mart experiment, the trading target is an index of the futures market. Since the movement of the spot price is given, the futures price is not affected by the basic economic conditions (fundamentals). Therefore, improving the trading strategy depends only on learning technical analysis. However, although they are learning the analysis method in the same way, not everyone is equally strong. What is the reason? Futures are traded on the U-Mart system. Since the futures market is a zero-sum game, if there is a winner, there will always be a loser. Therefore, even if everyone is familiar with the trading system and has improved their trading method, the degree of improvement will be a relative comparison. Fundamentally, since futures are traded and futures trading is a zero-sum game, participants can win and lose because of the relative comparison of participants.

The reason why the difference appears in transactions is that the way humans react to stock price fluctuations is different. Since there are various types of technical analysis used for trading under various conditions, how to use those analysis methods depends on the characteristics of the individual. For example, in technical analysis, the shape of the chart that can be judged to have bottomed out by forming two valleys is called the "double bottom." The time when the short-term moving average crosses the long-term moving average from top to bottom is called the "dead cross." If the chart has a double bottom and a dead cross, those who value the shape of the chart will implement "buy" actions. In contrast, those who value the moving average will engage in "selling" behavior. One phenomenon occurs with regard to stock price fluctuations, but if there is a difference in the interpretation, a higher standard is required to determine which standard to adopt. Furthermore, even if a certain chart analysis is adopted, the analysis result will be different if the period to which the analysis is applied is different, that is, if the time axis of the referenced chart is different. For example, a buy signal may be given on the daily chart, but a sell signal may be given on the weekly chart. This applies to all analysis methods such as the "moving average method," "Ichimoku Kinko Hyo," and "Bollinger Bands," which are the main chart analysis methods. In addition, the results will vary depending on factors such as proficiency and transaction timing. There are also differences in market knowledge gained through trading experience and consideration of various methods. In order to win, it is necessary to efficiently draw out the advantages of the method and conduct transactions, but the judgment also depends on the individual's trading experience.

What is more important is that even if there is a winning method, if everyone uses that method, there will be no winner because it is a zero-sum game. Therefore, it is unlikely that a method for predicting future stock prices that will surely make profits in the future will be established. If one is established, there will be no losers and no winners. If this happens, the stock market will no longer exist.

9.3.4.2 Example of Trading Strategy (1)

If price movements form some trend and past price movements affect future price fluctuations, we can develop trading strategies that predict future prices from past price fluctuations. Here, let us address one of the strategies that the participants of the U-Mart experiment considered. It is a type of day trader strategy. Figure 9.4 is a schematic diagram, and the advantages of this strategy are as follows:

- You cannot expect high profits by selling and buying once, but you can expect stable profits with low risk.
- Even if the order is not executed, it is hard to lose.
- Since it is easy to align the positions, it is possible to respond to sudden price fluctuations.
- It is hard to miss a favorable order.
- The strategy is easy to use in combination with other strategies.

The disadvantages of this strategy are as follows:

- If the price fluctuation is small, it will be difficult to execute an appropriate price. As a result, the contract frequency decreases.
- Even if the order is executed, and if the set price range line is narrow, large profits cannot be generated.

Figure 9.5 shows the actual trades based on this strategy, which were conducted on May 23 and June 23, 2015. The buy and sell orders placed by the human agent are shown in the chart showing price movements, and it can be seen that they are executed almost as shown in Fig. 9.5.

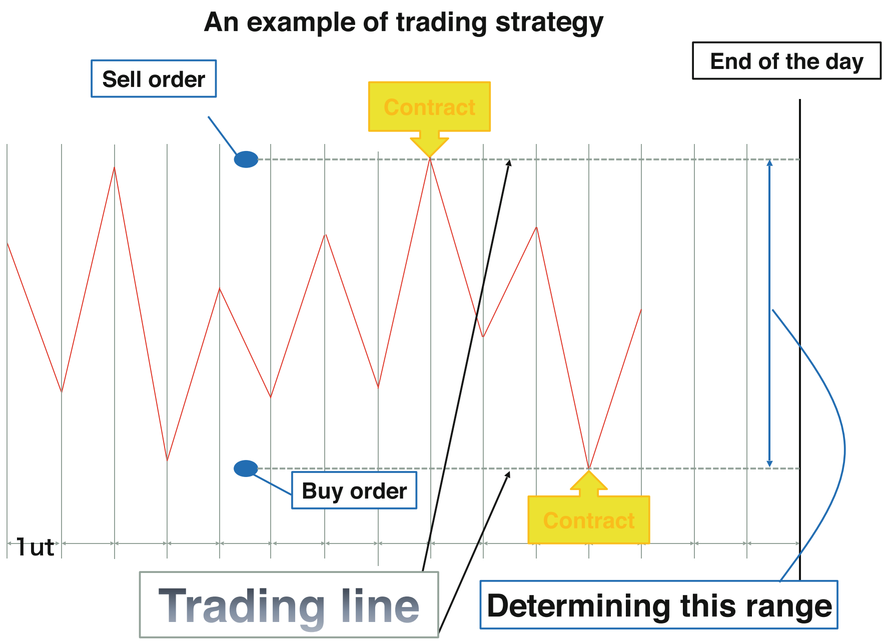

Fig. 9.4 Schematic diagram (by Koji Utaka)

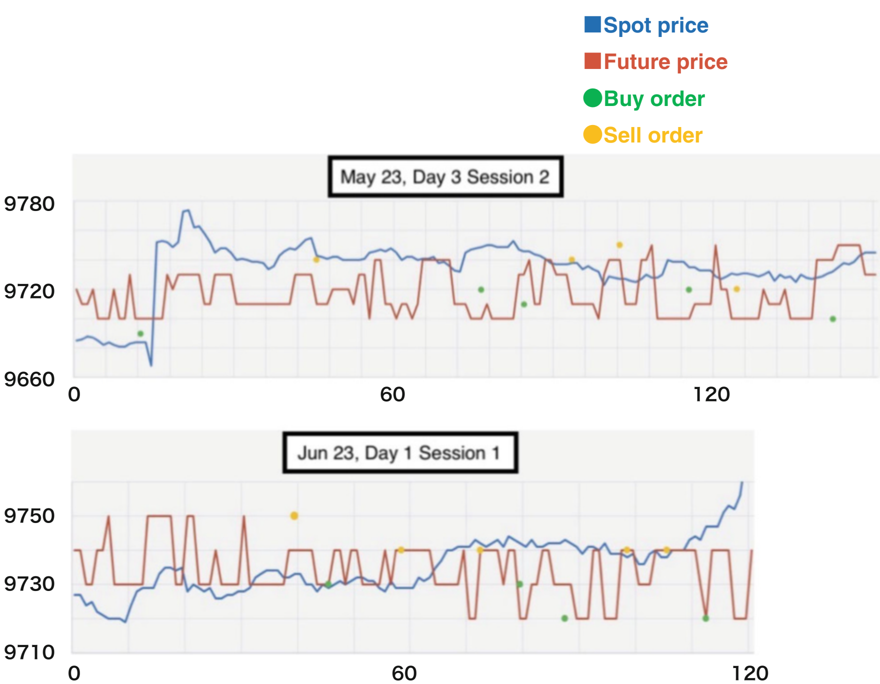

Fig. 9.5 Actual transaction (by Koji Utaka)

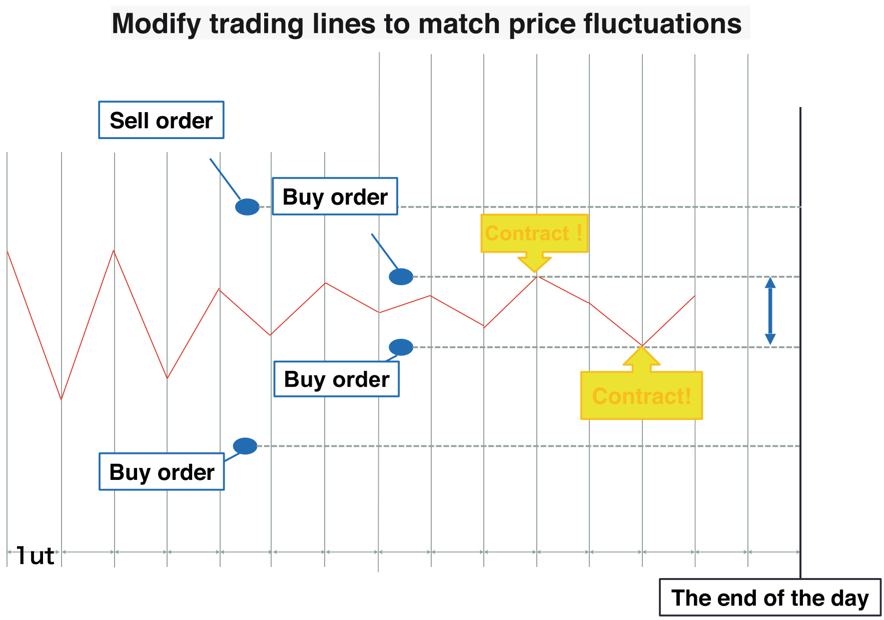

Fig. 9.6 Improved trading method (by Koji Utaka)

However, as mentioned above, this strategy cannot make large profits if the price change is small or it cannot make profits at all. Even if a buy/sell order is executed, and if the price range of the preset buy/sell line is narrow, it is difficult to gain large profits. Therefore, this trader improved the strategy that is seen in the first schematic diagram to the following strategy. That is, as shown in Fig. 9.6, the price range of the trading line scheduled in advance is changed. This is also a type of day trader, but the strategy is to set the base price for trading sell/buy orders in advance and modify the trading line according to market price fluctuations. By implementing this well-thought-out strategy, the trader almost always won.

9.3.4.3 Example of Trading Strategy (2)

In addition, I would like to mention another interesting strategy. This method places multiple sell and buy orders at different prices at the same time. In Zaraba market trading, multiple buy and sell orders are placed almost at the same time within the same u-time. This method sets a second forecasted price with a wider range of forecasts in addition to the forecast price at that time and places an order at the second forecast price. In other words, it responds to price fluctuations with a two-step stance. This always requires fine-tuning the order price setting. This order strategy has the following advantages:

- Within a certain range, it is possible to respond to sudden price fluctuations without placing a market order.
- When the price fluctuates, the order is placed in advance, so there is no need to hurry to place or cancel the order. You can avoid the resulting mistakes.
- Even if the price movement is smaller than expected, no loss will occur because the limit order will not be executed.
- If the price moves as expected and the transaction is successful, you can make large profits from the subsequent rebound.

In addition, the impact on the board will affect the strategies of other traders. In other words, if there are a large number of orders slightly above or slightly below the current price, other traders will say "because there are large buy (sell) orders at that price, the contract price will not be higher (or lower) than the order price." At this time, it is possible to place an order with a higher strategy for such an expectation. This is a fairly advanced strategy.

9.4 Conclusions

Our present-day national affluence is measured by GDP (gross domestic product). This concept of GDP is an important economic indicator discovered by economists approximately 250 years ago. Although there are criticisms that environmental pollution is not reflected as a negative item, it is most often used as an index to measure the wealth of a country. GDP is an added value produced in the product market and is traded in the market. The source of this affluence was in production activities, and there was also the development of a product market that could make good use of the distributed human knowledge. Financial markets that have developed since the Industrial Revolution have become able to intensively utilize the dormant capital that is widespread throughout society. As a result, large-scale investment has become possible. More production activities have become more efficient and large scale, creating a prosperous society. The significance of financial markets must be fully understood, but at the same time, the harmful effects of bloated financial markets must be recognized. Financial markets have become huge and have generated four times as many assets as the product market worldwide. The gap between rich and poor is widening due to digitalization and technological progress. Almost a quarter of a century has passed since the U-Mart project started, and changes in the surrounding environment have become clear.

Since the market is spontaneously generated, its regulation is unavoidable and will be necessary. Strict regulation and transparency are needed, especially for markets based on zero-sum games that do not bring wealth to all market participants. Keynes said the following more than 80 years ago:

> The spectacle of modern investment markets has sometimes moved me towards the conclusion that to make the purchase of an investment permanent and indissoluble, like marriage, except by reason pf death or other grave cause, might be a useful remedy for

our contemporary evils. For this would force the investor to direct his mind to the long-term prospects and to those only. (Keynes (1936, Chapter 12), The State of Long-Term Expectation.)

Arrowhead, which is currently operating on the Tokyo Stock Exchange, is said to execute more than 1000 trades per second. How will we respond to such changes in the market? Artificial market research and education using it will face greater critical problems.

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Chapter 10
Trading Agents for Artificial Futures Markets

Hajime Kita

Abstract Artificial markets are powerful tools for simulation-based experimental study of financial markets. The U-Mart project has studied artificial futures markets for about 20 years through the development of the U-Mart system, an artificial futures market simulator. It consists of a market server and trading agents implementing a variety of trading strategies. This article discusses the aims and implementation of such trading agents.

Keywords Artificial futures market · U-Mart project · Trading strategies · Market follower · Contrarian · Arbitrage

10.1 Introduction

The market is one of the major mechanisms of a modern economy, and it has been studied in various ways such as theoretical studies assuming behaviors of traders, empirical research with real data. The artificial market is a method to study market economy experimentally using virtual markets. With the virtual market, behaviors of trading agents are simulated and their relationship with price formation in the market is studied in a constructive way. In this article, we discuss trading agents in artificial market studies based on the experience of artificial futures market U-Mart which started in 1998 and continued for more than 20 years.

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10.2 Market and Price Formation

10.2.1 Classical Understanding of Market

The market is a social mechanism formed with money economy. In classical understanding, suppliers and consumers of goods or services trade them via price adjustment in the market. With such price formation and resource allocation, under some conditions, socially reasonable resource allocation can be achieved even if the participants' behaviors are selfish, and it gives rationality to the free market. However, in the market economy, there are also observed several problems which are called "failure of market."

Additionally, with progress in information and communication technologies, the market is expanded in various ways, and they show both possibilities and problems of using the market. In the following, we see two examples:

10.2.2 Electric Power Market

Utility industries such as electric power, regional monopoly were allowed before because of their economy of scale, and the price was regulated so as to cover the total cost but not to yield monopolistic profit. Recently in Japan, a policy of separating electrical power production from power distribution and transmission, and deregulation of the electric power market has been pursued.

As economic characteristics of the electric power industry, on one hand, it requires vast amount of fixed cost for facilities. On the other hand, electric power is difficult to store, and demand and supply must coincide in real-time. To have sufficient supply capacity of electric power systems is difficult, and if the time of consumption is different, it should be treated as separate markets, and the law of one price cannot be applied in the temporal direction.

For demand-supply adjustment of electric power with market, ideally, electric power should be treated a vast amount of separate markets, e.g., markets with second-order time interval coexisting toward the future, but it is not realistic. As compromise ways, to match demand and supply, various services such as electric power markets of time-of-use, and ancillary service for short time demand-supply adjustment are sought (Takeuchi 2017).

10.2.3 Financial Market and Uncertainty

In electric power markets, markets are extended in a temporal direction because of its the technical characteristics of the industry. In financial markets, temporal extension is sought because of its economical characteristics. Financial markets are markets of money themselves, and credits and debts are traded. In payback of debts, payment of interests is required, but there exists uncertainty of being unable to pay in the future. Further, in the financial market, credits and debts are intangible and actual costs for possession are extremely low.

In such markets, an asymmetry between buyers and sellers gets small, and it induces speculative trading. Further, financial risk in the future is treated by securitization of debt, and various derivatives have been developed and utilized. Globalization and computerization of the financial markets have enabled high-speed and world-wide trading. In such markets, trading with computer programs is used rather than trading by humans. In such markets, for example, the bankruptcy of Lehman Brothers brought about the financial crisis in 2008.

Thus, contemporary financial markets require the study of dynamic price formation and systemic risk of markets themselves beyond the classical understanding of market economy.

10.2.4 Diversity of Traders and Market

Markets function when both buyers and sellers exist. Classically, the market mediates suppliers of goods or services and their consumers, and therefore sellers and buyers are asymmetric. As for financial markets, traders act both as buyers and as sellers, and they are much more symmetric. If we assume all the traders in a market are rational, and share common information, their trading behaviors have to be identical, and consequently, the market does not function.

If an asset traded in a financial market has some temporal characteristics, especially uncertainty, and traders have different attitudes to the future, it diversifies the traders' behaviors, i.e., some traders want to buy it and some others want to sell. However, even market may function, with rather symmetric traders, the price may change with positive feedback between trading strategies employed by the traders and the price change formed in the market. It may cause instability of the market such as the occurrence and collapse of bubbles.

For studies of markets having aforesaid complexity, experimental studies with virtual markets can be a promising method as well as theoretical and empirical studies.

10.3 Artificial Futures Market U-Mart

10.3.1 Simulation of Market

With a pioneer work by Arthur et al. (1996), the study of market economy with agent-based simulation has attracted attention and is called "Artificial Markets"

(Izumi 2003). It can be considered as one area of agent-based social simulation. Gilbert categorized agent-based social simulation into three, i.e., "abstract models" which simplify the models as much as possible for fundamental studies, "middle range models" which have some complexities and are used to explain stylized facts of social problems, and "facsimile models" that model the society more in detail for study of realistic situations. He also proposed that depending on the categories, validation of models should be carried out in different ways (Gilbert 2008). Artificial futures market U-Mart models institutional aspects of actual financial markets in detail to study them, and it can be categorized into the facsimile models. Concerning this, Koyama called the U-Mart "a second-generation artificial market" (Koyama 2008), and One et al. listed five items "fidelity," "transparency," "reproducibility," "traceability," and "usability" as design guidelines of the U-Mart (Ono et al. 2008).

10.3.2 Artificial Futures Market U-Mart

One of the difficulties in modeling social simulation is to extract an interesting part of social systems which relate to each other. Especially in artificial markets, it is a key issue to characterize what is traded in the virtual market, and how to ground it to reality. Suppose a virtual market that treats a virtual item with virtual money. If trading agents have no way to evaluate the item, we cannot discuss price formation in the market because there is no rational reason for the formed price.

On the other hand, if we try to bring various matters such as events that occurred in the real society, for example, into the model, it makes modeling and validation of simulation results difficult. Artificial futures market U-Mart has tried to answer this question by designing virtual futures market where it treats futures of an existing spot market whose prices are given exogenously. That is, in the virtual futures market, the price of futures has to coincide with that in the spot market at the due date. With this framework, the U-Mart is designed as a virtual market where realistic information is fed into the market.

Another feature of the U-Mart is that it aimed at the study of institutional issues with experimental study of markets. In actual financial markets, various institutional devices such as ways of making a contract, and information provision to traders are introduced. In the U-Mart such institutional devices have been modeled.

Further, the U-Mart enables both gaming simulation played by humans, agent-based simulation played by computer programs, and their hybrid. On one hand, gaming simulation and agent-based simulation share common features as the structure of the simulation environment. On the other hand, as for characteristics of feasible experiments, they are complementary. That is, in gaming simulation, it is played with the intelligence of an actual human, but a possible number of trials are quite limited. In an agent-based simulation, it is played by rather simplified computer programs, but a vast number of simulation runs can be used. Further, gaming simulation is used as a tool of education. It also works as a tool to learn the complexity of the market by researchers before the development of trading agents for their study.

As a research project, the U-Mart has studied the artificial markets since its start in 1998. We have developed several versions of the artificial futures markets and have published some of them. U-Mart Ver. 2 (Shiozawa et al. 2008; Kita et al. 2009) is a version that was published in the early days, and it was a blushed-up version of a trial implementation U-Mart Ver. 1. In this version, the “Itayose” method, a kind of batch auction is employed for order matching and contract making, which is easy to understand and implement. In this method, orders submitted by traders are stored in a certain period, and the market makes contracts by finding a price that achieves the maximum contract volume among the submitted orders. In actual stock markets, it is employed to process orders at the opening of the market to contract orders submitted before the opening of the market.

After that, with experience of a trial implementation as Ver. 3, U-Mart Ver. 4 implemented the “Zaraba” method, a kind of continuous double auction, which is commonly used in Japanese stock markets. Institutional devices related to the Zaraba method are also considered in detail (Kita et al. 2016). Thus U-Mart Ver. 4 enabled more realistic simulation of actual markets. However, implementation of the simulator is much more difficult and complex than the U-mart Ver. 2, because simulation requires more information processing in real-time for quick response in gaming simulation.

10.3.3 Organization of U-Mart

Both in Ver. 2 and Ver. 4, the U-Mart system consists of the following elements:

Market Server It is a simulator of the exchange market of futures. It accepts orders from traders, matches the orders, makes contracts, and adjusts their accounts. It also provides traders with market information such as the prices of the futures.

Trading Agents The U-Mart supports both gaming simulations played by humans and agent-based simulation. Hence, two sorts of trading agents are considered:

- The U-Mart system provides users with a GUI-based trading terminal that communicates the market server for trading by a human.
- In U-Mart, trading by computer programs is processed by building the trading programs into the market server. For this purpose, the U-Mart system supports an interface for ordering and obtaining information from the server. A trading agent obtains its asset status such as its position and possessing cash, time-series information of both futures and spot prices, and remaining trading periods until the due date from the server. Then it makes an order specifying buy or sell, a volume, and a limit price, and submits it to the server.

10.4 Trading Strategies in Financial Markets

In this section, an overview of trading strategies in the financial market is given from several viewpoints to explain the trading agents implemented in the U-Mart.

10.4.1 Fundamental Analysis and Technical Analysis

In the stock market, the stock is ownership of a company, and the market capitalization (value of the company) is given by

$$\text{Market Capitalization} = \text{Price of Stock} \times \text{Number of Issued Share} \tag{10.1}$$

It will depend on the status of society and can change with economic indexes, political situation, and management policy of the company. "Fundamental analysis" is a type of trading strategy that decides orders considering these factors.

Another type of trading strategy considering only time-series information of the stock prices is called "technical analysis." If we accept the "efficient market hypothesis" (see, e.g., Mantegna and Stanley 2008), no useful information for trading can be obtained from the prices of the market where all the traders act rationally. However, the market is not sufficiently efficient, and technical analysis has a chance of making profits. For actual markets, various strategies are proposed as technical analyses.

10.4.2 Market Follower and Contrarian

In thinking about technical analysis, the attitudes of traders to the price trends may different. Suppose we observe a trend of rising prices in a certain period. Some traders may interpret this trend will continue more, and therefore it is a good time to buy the item expecting higher prices in the future. Such trading strategies are called "market followers."

Contrary to this, the observed up-trend can be also interpreted as the price has been already raised more than before, and therefore it is a good time to sell the item. These sorts of trading strategies are called "contrarian."

10.4.3 Moving Average Method

The optimal trading can be achieved by buying the item at the bottom of the price change and selling it at the top of that. The moving average method is a well-known trading strategies seeking this idea. In this method, two moving averages curves with different time windows are drawn. The cross points of these two curves appear near the bottoms and tops of the price change (with some delay). The trader tries to buy or sell at such cross points.

10.4.4 Arbitrage

If the same item is treated in different markets, a trading strategy of buying it in a market that shows a relatively lower price, and selling it in another market of a relatively higher price simultaneously yields profits proportional to the price difference (say split). Such sort of strategies is called "arbitrage." In a futures market, at futures price coincides with the spot price at the due date. Hence, if we observe the price difference (split) between the futures and spot, to by the item in the market of the lower price, and to sell it in the market of a higher price, and possess them until the due date yield profits. If such arbitrage opportunities exist in several markets, arbitragers enter the markets, and consequently, the prices of these markets move closely.

10.4.5 Risk Avoidance

In the financial market, traders buy assets with risks seeking profits. At the same time, avoiding such risk is also an important viewpoint in trading. For that, they also try to change their assets having risks to those of lower risks. For example, if a trader has bought an item at a price, and after that the price gets down, he/she may sell it so as to avoid further loss. If the price of an item that a trader has bought is raised after, he/she may sell it so as to fix its profit and convert it to an asset of lower risk.

10.5 Trading Strategies in the U-Mart

10.5.1 The Standard Agent Set

In the following, we discuss trading strategies in the U-Mart Ver. 2, which is publicly open. In the U-Mart Ver. 2, 10 sorts of trading agents are provided with the system as a standard agent set. Provision of this set has several purposes as follows:

- The Market has to show adequate price formation with this set. Markets fail in price formation without traders that submit orders which match each other. The standard agent set aims at the provision of a start point of market simulation for both education and research including a case of human traders also participating in trading.

- It also aims to show typical trading strategies. It suggests viewpoints in thinking of trading strategies in the artificial futures markets.
- Further, it aims to show points in the implementation of trading agents with example source codes. In actual trading, an agent has to decide not only a decision of to buy or to sell but also it has to decide a limit price and a volume of the order. Further, it also has to consider management of the risk brought about by its asset status and has to adjust its position to avoid too much risk.

10.5.2 Trading Strategies of the Standard Agent Set

In the U-Mart having a structure of futures market, time series of spot prices is available as well as that of futures prices, and therefore various trading strategies can be applied other than ordinary technical analysis while fundamental analysis is out of model scope.

In the U-Mart Ver. 2, the following 10 sorts of trading agents are implemented and the standard agent set consists of these agents, which are stated in the cells of Table 10.1.

Among these, agents of random trading buy or sell randomly with a limit price around the latest price. Market followers and contrarians decide to buy or sell depending on the market trend obtained by the difference of recent two prices. RSI is a trading strategy that uses RSI (Relative Strength Index) of the price time series. It decides orders in a contrarian way using the ratio of up-trend and down-trend during a certain period. Day trading method submits both a buying order with a limit price lower than the latest price and a selling order with a limit price higher than the recent price. If both orders get contracted, it yields profits. It is also employed as an example program of an agent who submits several orders at once.

In U-Mart, only futures can be traded, and hence arbitrage between futures and spot markets is not possible. However, trade of futures using price split between spot and futures is possible, and it can be thought of as pseudo arbitrage.

Table 10.1 Trading strategies contained in the standard agent set of the U-Mart

	Referring time series	
Strategies	Futures prices	Spot prices
Random trading	URandomAgent	USRandomAgent
Market follower	UTrendAgent	
Contrarian	UAntiTrendAgent	
RSI	URsiAgent	USRsiAgent
Moving average method	UMovingAverageAgent	USMovingAverageAgent
Day trading method	UDayTradeAgent	
Pseudo arbitrage	USFSpreadAgent	

10.6 Agents and Behavior of Market

Once we execute U-Mart experiments with the standard agent set, we observe USFSpreadAgent, a pseudo arbitrager, makes a profit steadily. Similar behavior is also observed for USRandomAgent, a random agent which makes orders randomly with limit prices around the spot price. This agent submits random orders, but due to its limit prices around the spot price, the results are similar to those of the pseudo arbitrager. If these agents work, the futures prices stay around the spot prices. If these agents go to bankruptcy due to, e.g., sudden price change in the market, the futures price moves away from the spot price because other agents have no logic to bring the futures price near to the spot price.

The performance of pseudo arbitragers is steady, but if the number of such agents is increased, the profit made by them gets small, and some other agents make profits. In the U-Mart, the spot prices are fed exogenously, and therefore the futures prices formed in the market tend to follow the spot prices with some delay. It is brought about by the asymmetry of futures and spot markets in the U-Mart where actual arbitrage cannot be employed in it.

10.7 Study of Thin Market and Market Makers

In the major stock markets in Japan, contracts are made by matching the selling and buying orders. If the market is "thick," i.e., it has a sufficiently large number of participants, this system works well. However, if the market is "thin," i.e., the number of the participants is small, to match both orders gets difficult, and the market loses its function of finding a price. As for institutional design for such a "thin" market, there is a method of using market makers, special traders obliged to show prices of the listed items and to buy or to sell them at the shown prices and in a small amount.

With the U-Mart as a platform of experimental study of the market, we can experimentally discuss such an issue. On market makers for thin markets, questions such as whether we can set market makers neutral in making a profit, or whether liquidity can be supplied with market makers have been studied (Matsunaga and Kita 2006; Kita et al. 2006; Nakamura et al. 2008).

10.8 Conclusion

This article discussed findings on the study of the artificial futures market U-Mart from a viewpoint of trading agents. The U-Mart overcomes the difficulty of economic validity in modeling by employing an idea of treating virtual futures market of existing spot market whose prices are fed exogenously. This model enables autonomous price formation by trading agents in the artificial market and enables the study of institutional issues of the market. However, study of a market with agents employing fundamental analysis is difficult with the framework of the U-Mart.

Concerning the agent-based simulation with fundamental analysis, another approach of using learning agents trained by actual data is proposed (Izumi 2003; Izumi et al. 2008). With this approach, a market model is not required to provide the meaning of the item traded in the market. Instead, it is achieved by the agents that internalized logic through the learning of actual data. While it assumes the availability of data for learning, it enables the study of agents with fundamental analysis.

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Chapter 11
Default Agent Set for Artificial Futures Market Simulation

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Abstract The origin problem is essential to agent-based simulation. When we developed the artificial financial market simulator named "U-Mart," we needed to develop not only the system itself but also the default environment in which users begin to use the system. Accordingly, we developed the "Standard Agent Set" as a default set of machine agents for the U-Mart System. We used ten well-known but simple technical strategies and estimated the best mixture ratio of them to realize an adequate futures market by simulation.

Keywords U-Mart · Artificial market · Agent-based simulation · Artificial intelligence

11.1 Introduction

The purpose of this chapter is to propose an open problem: "What is the origin of the common testbed for Agent Base Model (ABM)?" In this chapter, we explain how we address the "origin problem" historically, and then, we introduce our first proposal to solve this problem as a clue. The "origin problem" can be thought from several points of view, but it is better to start from practical problems. We are confronted by the origin problem through the activities of the U-Mart Project. We have developed an artificial futures market "U-Mart System" and released it publicly. We have to decide the default conditions including the set of built-in agents and time series.

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11.1.1 The "Origin" Problem

The origin problem is important for investigations of complex systems with agents. To estimate the effect of something that we are focusing on, we compare a particular state with an original state. When we treat a system with sufficient complexity, there are many implicit variables that are given default values without consideration and left as they are. Strictly speaking, we must examine the generality among other sets of hidden parameters.

Agent-based systems have been studied as simple systems. We assume that situations can be divided into clarified conditions and that the application range of the system is deemed to be sufficiently narrow. All assumptions can be selected and examined, and then, they can be defined well.

Considering strategies that control the behaviors of agents, agent-based systems can be seen as benchmarks to estimate such strategies. For each strategy, even if it includes an adaptive or learning system, benchmarks usually can be selected clearly, and there is no doubt regarding the estimation results. However, we are immediately faced with the origin problem when we study strategies that are expected to work in real-world settings. Currently, when we estimate some performance aspects of a strategy, we have two kinds of environments. One is a simple and well-defined benchmark, and the other is a real-world environment. There is a large gap between these environments, and the real world is too complex to analyze, such that the real-world results obtained suffer from the problem of their one-time-only nature. Between these environments, we can find a sufficiently complex environment. Agent-based systems can be seen as benchmarks to strategies. However, once we depart from the well-defined benchmark that estimates an isolated strategy, we have to face the origin problem because there are too many hidden parameters to consider.

Animal experiments are one example. A common species is chosen for each category as an experimental animal, for example, a fruit fly, a mouse, and a rhesus monkey. Then, the species of categories of interest are used for all related investigations. There are many reasons why the species is selected as experimental animal for this category, but the most important point is not how selection is performed but rather that one species is selected, and everyone follows this selection if there is no special reason. If we have a well-defined "origin" system and if we all use this system as the default, then we can concentrate on the parameters of interest and easily compare the results with other investigations.

For us, the origin problem appeared as the default problem of providing a common testbed. To explain this, we introduce our project for providing a common testbed.

11.1.2 What Is the U-Mart Project?

Economic and social systems including financial markets are typical complex systems. Designing such systems is a difficult but urgent issue. At various levels, we measure the influence of constraints on information availability and trade rules to find a way to control the market indirectly. To design a financial market system, we must consider a “cross-reference” mechanism in which individuals and organizations with different abilities, technologies, and experiences join and influence each other while learning and creating. To resolve this difficult issue, we must invite researchers from various fields such as engineering, economics, or psychology to approach the problem from various aspects such as artificial intelligence, artificial markets, cognitive science, or learning theory in addition to conventional market research. U-Mart was developed to provide a common testbed that can be used by researchers who are interested in the dynamics of economic and social systems such as the financial market or behaviors of economic entities under such systems.

The aim of the U-Mart Project is to provide a common testbed for analysis of financial markets for interdisciplinary collaboration (Terano et al. 2002). The U-Mart Project was developed to provide what we have requested. During this term, we groped for an answer to the question of what a “common testbed” is. Now, the U-Mart Project not only provides an artificial futures market system but also conducts social activities to promote realization of these systems. Accordingly, we are faced with the default problem.

The main content released by the U-Mart Project is an artificial futures market system named the “U-Mart System.” We have been developing this system and have opened it to the public. The key concept of the U-Mart System is “seamlessness.” This is a unique point among academic simulators for social science. The first seamless point of contact is the point between experimentation via a network environment and standalone environment, and next is the point between computer simulation and gaming simulation. The look and feel of all applications included in the U-Mart System are almost same. If you join the U-Mart System as a human agent, you do not have to worry that your opponents are in your PC or somewhere connected by a network. If you develop a machine agent, the agent’s behavior can be monitored by the application with the same look and feel as that of the human agent. For real-time experimentation, both human and machine agents can access the U-Mart Server via LAN or internet. Computer simulation and gaming simulation can be used for both real-time experimentation by human agents and accelerated experimentation by a machine agent. Certain regulations, that is, the transaction fee, margin (guaranteed deposits), and time series of spot price, can be set by a setting sheet. The format of logging is unified for all kinds of experiments. Then, the same analysis tools can be used, and they can easily be compared within the same system. For training or accelerated experiments, a set of machine agents and market servers can be used to establish a standalone environment. The U-Mart System is coded by JAVA. Therefore, we can use the system seamlessly among several OSs, including

Windows, Mac OS, Linux, and so on. Due to the reusability and expandability of JAVA, the U-Mart System can be considered amenable to seamless change in the future. A brief explanation of the U-Mart System is provided in Sect. 11.2.

To improve the U-Mart System and to enable chances to use this system, the U-Mart Project also conducts some activities. The activities of the U-Mart Project can be divided into three directions, that is, facilitating research, providing courseware, and promoting open experiments (competitions). We consider that these activities are important to realize the U-Mart System as a common testbed. The three activities are deeply related and mutually support each other. The main subject of investigation for U-Mart is to develop an approach for institutional design of financial markets by agent-based simulation. We estimate the effect of changing institutions, and we want to propose new institutions and rules for practical use. The U-Mart System is also used as courseware for programming practice or market analysis at universities. We have been using U-Mart System in lectures. To improve our lectures, we have compared our lecture approaches with each other, followed by the gradual development of courseware including curriculum, tools, text, and so on. We have held two kinds of annual periodical open experiments (competitions). The aims of these experiments are to enrich the collection of machine agent programs and experimental data, to provide motivation to improve the skills of the agents, and to provide a forum for researchers from various fields. In Sect. 11.3, the three activities are briefly introduced and explained, and in particular, the results of the open experiment are reported.

For a common testbed, a set of simple experimental environments must be included. When you install the U-Mart System, you expect to start without defining settings. With the default settings of the system provided as a common testbed, there should be a basic environment to develop machine agents, to train human agents, and to start investigations. From our experience of releasing the U-Mart System and conducting activities associated with the U-Mart Project, we have encountered the need for well-defined default settings. This is the origin problem that has arisen through our experience.

Variations in future markets can occur from two directions. Internal variations include different market institutions and agent components. External variations include types of time series. Market institutions are the main target of investigation, and the default settings are given by the NK225 futures listed in the Osaka Securities Exchange. As the default component of an agent, the U-Mart Project provides the "Standard Agent Set (SAS)." This SAS includes 10 simple technical agents. One of the aims of the SAS is to provide default opponents of a human agent or machine agent developed by the user. In addition, sample source code of machine agents is provided. For beginners, simple but somewhat smart agents are a good option. The SAS must also play an important role, aiming to locate "origin" of the system. For investigation, we must estimate the effect of control. To do so, it is important to set an origin point. The origin can and must be decided for each investigation, but if there is a common origin, then it is useful for everyone. The U-Mart System is provided as a common testbed, so we aim to propose the SAS as the origin set of agents. In the future, we want to propose a closely examined SAS that can be treated as a set of experimental animals in life science and medical science. We will explain the current trial of the SAS in Sect. 11.4 of this chapter. Time series of spot prices are another important variation. As the default, a time series of an actual daily Japanese stock index named J30 is included. For the open experiment established by the U-Mart Project, four types of coordinated actual time series of stock index are used, that is, ascent, descent, oscillation, and reverse. These types are feasible because each price is given. However, for experiments, especially by human agents, controlled time series are needed. In Sect. 11.4, we will also explain several cases to create time series of prices.

11.2 U-Mart System

The U-Mart System consists of five tools or applications, which are separated by the type of connection and type of agent. Because the U-Mart System provides all tools, setting sheets and logging forms uniformly, experiments via network and standalone environments, real-time experiments and accelerated experiments can be carried out seamlessly. The look and feel of all applications are almost the same. Therefore, if you familiarize yourself with how to use one of the tools, you can easily use the others. All environmental settings can be set in the same way among these experiments, and the form of log data is also the same. This approach helps us both to create experiments and to analyze them. In this section, we will explain these aspects for "seamlessness."

11.2.1 Overview of the U-Mart System

First, the names and roles of the five tools are explained.

Market Server (GUI)
This is the core system of the U-Mart System. If you carry out an experiment via a network, you must control the U-Mart experiment by this application. This component acts as a public futures market (i.e., calculating the total sum of orders and then deciding on market contraction) and account management tool of agents (i.e., controlling login, accepting orders, and adjusting accounts). The U-Mart Server handles built-in machine agents. It is also an information center. It sends market conditions, individual agent's assets, and time series of spot and futures prices. The U-Mart Server has the most informative graphical user interface. By this, we can monitor all activities and conditions of all agents. If you want to monitor the behavior of machine agents, you can use the Market Server. In this case, it can be used in a standalone environment.

Market Server (CUI)
This is the server system for accelerated experiments with built-in agents. By batch processing, we establish many experiments and explore the parameter space.

Market Simulator
This is used for training how to use the U-Mart System with your PC. You can compete with a built-in machine agent.

Human Agent Trading Terminal
This tool is for a human agent to join trading via a network. If you use this, there are send orders and a variety of information provided from the server. The look and feel of the Human Agent Trading Terminal are almost completely the same as those of the other tools.

Machine Agent Adapter
This is used for the machine agent to join the Market Server via a network. The Machine Adapter Agent is used if you develop a machine agent that uses real-time information, for example, current distribution of orders and so on.

11.2.2 Setting, Logging, and Analyzing

For experimentation, the U-Mart System needs two kinds of setting sheets: one is for agents and the other is for the market institution including time series of spot price. Both setting sheets are needed for the Market Server (GUI) and Market Server (CUI) and Market Simulator. The setting sheets are in comma-separated value (CSV) format and are very similar among the tools, so same sheet can be used for another tool. Therefore, if you check the market institution both in a real-time experiment with a human agent and in an accelerated simulation without a human, you can use the same setting sheet for both.

The logging format must also be decided uniformly. Log data contain all things that happen in the experiment, so from the log data, we can trace the experiment perfectly. For each experiment, all logs are saved in the proper folder or directory. Setting sheets used for the experiment are also saved in the folder. Therefore, we do not have to record all settings for each experiment. Furthermore, if we use the setting sheets saved in a given experiment folder, we can replay the same experiment automatically. Because the logging format is uniformly decided, we can easily make a reusable analysis tool. Indeed, the current version of the U-Mart System contains the Logging Tool. With this tool, we can trace the activities of each agent, and we can see the figures of price, profit, position, and so on.

11.3 Three Activities of the U-Mart Project

11.3.1 Overview of Activities

The activities of the U-Mart Project can be divided into three directions: (1) research, (2) education, and (3) open experiment (competition). These three activities are associated with each other. The open experiment has been one of the most important events of the U-Mart Project. The U-Mart Organizing Committee and U-Mart System Operating Committee were organized to plan and hold international open experiments.

Research As one of the major artificial market research projects in Japan, many researchers have joined this project and performed various activities. The major objective of this project is to design a financial market system. More specifically, we hope to establish market control methods. Now, we plan to investigate the effect of controlling the following parameters and institutions: (1) extent and scope of information disclosure regarding circuit breakers, (2) margin, (3) limit of price movement, (4) market maker system, (5) indicative price calculation methods, (6) information update intervals, and so on. We want to measure information value and tradeoffs (e.g., liquidity or stability) for basic research to use information disclosures timing and scope as market control parameters.

Education
The U-Mart System has been used as courseware for both engineering and economics. For engineering, the U-Mart System is used for programming practice. Programming a machine agent is a good assignment for practice, and we note two reasons. The first reason is mobility. A machine agent programmed by a student can trade in futures markets, and the student can the monitor the behavior of his/her agent. Additionally, the agent can compete among agents of other classmates or other agents to obtain a prize in an international competition. These prospects give students good motivation. The second point is size of program. The simplest agent that has participated in an international competition that we held was programmed by only five lines, and the agent was not that weak. Successful trading can be achieved by different ideas, so students can develop agents by their own skill. On the other hand, the problem is open-ended, so we can make the agent as complex as desired. As we will explain next section, in our recent international experiments with machine agents, only agents with online learning methods such as neural networks and genetic algorithms have been able to win the prize.

For students of economics, they can learn the market experimentally. By trading as a human agent, the students can understand the market mechanism in depth. Moreover, they can trace their own behavior by log data. For the first step of statistical analysis, students can study data of interest.

Open Experiments (Competitions)
We have been conducting experiments open to the public, inviting both machine agents and human agents. In recent years, international open experiments named UMIE 20xx series and domestic (Japan-based) open experiments named U-Mart 20xx series have been periodically held. These open experiments are held in workshops or organized sessions at academic conferences hosted by NAACSOS, ISAGA, JAFEE, SICE, and so on. At each event, we collect and report the results of U-Mart research as well as provide experts from various fields with discussion opportunities by having panel discussions.

These three types of activities are inseparably tied. Machine agents are invited to the open experiments to increase the diversity of agent sets used for research. This diversity motivates researchers from various fields to gather at symposiums and workshops, and it serves as a springboard for further open experiments or joint research. The set of tools developed for educational purposes are used for research and events. Many machine agents have been developed through educational courses and have contributed to agent sets used for further research. Many economics students join U-Mart as human agents, providing more experiment opportunities. Additionally, the students have proposed GUI improvement ideas and have contributed to help develop new tools used for event activities. As more open experiments are held, more problems that must be resolved using the artificial market are found, as well as logs to be analyzed. Moreover, as the research has progressed further, the purposes of the open experiments have become clearer, and the rules and systems have changed.

11.3.2 Open Experiment (Competition)

In the U-Mart Project, open experiments are periodically held. Open experiments have served as prefaces to U-Mart's new research, educational targets for programming or financial investment classes, or test cases of various studies (Deguchi et al. 2003). So far, we have performed seven open experiments as follows:

- PreU-Mart2000 Machine Agent, at SICE Souhatu Summer School
- U-Mart2001 Machine Agent and Human Agent, at SICE Souhatu Summer School
- UMIE2002 Machine Agent, at CASOS conference
- U-Mart2002 Machine Agent and Human Agent, at SICE emergence system symposium
- UMIE2003 Machine Agent, at NAACSOS conference
- U-Mart2003 Machine Agent and Human Agent, at ISAGA conference

- UMIE2004 Machine Agent, at AESCS conference
- U-Mart2004 Machine Agent and Human Agent, at JAFEE autumn conference
- UMIE2005 Machine Agent, at Social Informatics Fair
- U-Mart2005 Machine Agent and Human Agent, at Social Informatics Fair

We held the first open experiment, Pre U-Mart 2000, to see if U-Mart's System would work as designed. Therefore, "Pre" meant that it was not a formal experiment. We had many aspects to confirm: Would a machine agent designed based on the "U-Mart Protocol" (SVMP) operate correctly? Would the U-Mart Server appropriately process various commands received from several agents concurrently? Would U-Mart work as a futures market? and so on. Participants brought their own machine agents and laptop PCs to the experiment site to connect to the U-Mart System for the first time. The participants managed to perform all the planned tasks and completed the experiment overnight. As a result, many agents went bankrupt because inflation and collapse occurred often, although most functions of the system including communication using the M-Mart Protocol, U-Mart Market and accounting functions worked correctly. Contrary to our expectations, we found problems with the system as a market through the experimental results. One of the problems, for example, was that random agents (agents randomly selling and buying at around the spot price) developed for debugging always led the market.

One year after the first experiment, our first formal experiment in U-Mart2001 was held to study the artificial futures market. Human and machine agents participated in this experiment according to the first purpose of the U-Mart Project. Machine agents were collected prior to the experiment and participated in several competitions using five types of time series (i.e., random, ascending, descending, reversed, and oscillating), and excellent machine agents received awards. In addition, on the day of the experiment, the "actual" competition was held, and both machine and human agents participated. In the experiment, the absence of random agents led to inflation and collapse, but less frequently than with Pre U-Mart2000. The market became stable after random agents joined. As a result, we found that agents with abundant assets were strong when inflation or collapse occurred, and random agents were very strong in any situation. Because the random agents placed stop orders at around a spot price, their transactions naturally worked like arbitrage trading, such that they were able to secure stable profits and at the same time contributed to the market's stabilization. Although machine agent development kits (to be described later) had been distributed prior to the experiment, the time required to perform the pre-experiment was the same as that of an ordinal experiment (60 min) because machine agents that directly corresponded to the U-Mark Protocol also participated.

In 2002, the first international open experiment was held. For this occasion, the purposes of the open experiment were clarified, and its contents were largely improved. The most major change was that the conditions of two types of open experiments were clarified: only machine agents can participate in international open experiments (UMIE200X), and both human agents and real-time processing machine agents can participate in domestic open experiments (U-Mart200X). For international open experiments, participating strategic-class machine agents can be transferred via e-mail, so participants can join the market from anywhere in the world at any time. If we know that participants are all machine agents in advance, we can invite only machine agents who are free from concern about the number of Itayose (a trading method used when orders are flooded in a market, such that selling/buying orders are collected until the number of both orders; through these experiments, the conditions and rules of the open experiments become the same while adjusting the price according to the volume of orders, and finally, all are sold/bought at the same price) intervals in order to perform an acceleration experiment. In fact, only strategic-class machine agents using machine agent development kits (developed by Professor Kita et al., Tokyo Institute of Technology, for use in class) were invited to the first international open experiment. If you use a machine agent development kit, five types of data (time series of futures market price, time series of spot price, number of future goods currently retained, current cash balance, and remaining possible number of Itayose intervals) are automatically given, and you can develop a machine agent by creating only a class implementing the strategic part for order output. The agent simulator that is developed in the same way is also included in the kit. The agent simulator enables a user to compete with a maximum of ten machine agents simultaneously using his/her own PC, analyze competitors' logs, and track their selling/buying activities. With these features, the actions of machine agents are traceable step-by-step so that more practical algorithm development and more detailed tuning are possible. Because an acceleration experiment can be conducted smoothly, the evaluation criteria for agents have changed. Conventionally, agents who had the highest gains were regarded as excellent and awarded, but that meant that high-risk, high-return investing was more advantageous in the competition. We thought that was not a preferable and improved evaluation method. We set four criteria (winning percentage, maximum gain, average gain, and bankruptcy percentage) and evaluated the scores comprehensively based on Pareto ranking. In 2002, the first international open experiment UMIE2002 was held. In addition, among the participants, an agent developed by students of Tokyo University as a task in class and an agent implementing the decision-support system that used an online learning system developed by Osaka Prefecture University had remarkable scores.

On the other hand, the domestic open experiments U-Mart200X provide university or graduate school students who have used the U-Mart System in classes with good opportunities to gather and compete. Thus, students are more motivated by working toward this open experiment. In addition, because more human agents who are seriously working on investments participate in the experiment, much more practical data are collected. This experiment is also good for testing machine agents with real-time processing functions. Since the data/actions that the agents developed by the agent development kit (strategic-class agents) can use or take are limited, they are not allowed to try many ideas such as using data that change from time to time (e.g., other agents' order information) or investing in collaboration with other agents. Participants are allowed to bring their own PCs, and the experiment is a good opportunity for them to compete with other challenging machine agents. In 2002, another domestic open experiment U-Mart2002 was held, and students at Osaka Sangyo University who had used U-Mart for investment practice in a class, students of Chuo University, and graduate students who had developed machine agents participated. In particular, students who had achieved excellent performance in the class at Osaka Sangyo University (so-called speculators) also scored high marks on the experiment. Among real-time processing machine agents, an agent that exchanged data with other agents and chose the most appropriate strategy on the spot, developed by Team Sawa from Tokyo Institute of Technology, was outstanding. In 2003, teams who had learned from the results of the previous open experiment received high scores. In particular, among machine agents, "agents who used short-run trends" and "agents with online learning ability" mostly achieved high scores. At both UMIE2003 and U-Mart2003, Tokyo Institute of Technology's agent named ClassifireAgent, which was developed based on the experience from the previous experiment, won first prize. A prototype of the U-Mart System Version 2.0 was first used at the domestic open experiment in 2003, U-Mart2003. In UMIE2004, there were four agents who won first prizes: TriDiceP (with reinforcement learning), NN2 (with a neural network), FuzzyB (UMIE2002 winner), and ClassifireAgent (UMIE2003 winner). Well-known learning systems investigated in AI areas and agents developed by undergraduate school students and with traditional ways of trading were hardly high ranking. In this contest, application of an AI method to future market prediction under the simple rules should have been satisfactory. In 2005 and 2006, we proposed new rules and conditions according to our investigation, related to "thin market and market maker." The results and their consideration are somewhat beyond the scope of this chapter, so we omit them here.

In these open experiments or contests, we have incorporated sample agents and time series of spot price into the agent developers' kit and training kit. We call the set of sample agents the "Standard Agent Set (SAS)." For a machine agent submitted to the UMIE200x series, the U-Mart System with the SAS is the first environment to test and be used as a benchmark. For a human agent, the U-Mart

System with the SAS should be the common training environment. Indeed, to estimate how a submitted machine agent compares, the first stage of UMIE series involves experiments of the agent with the SAS. If the performance of the agent with the SAS is majorly different from that with other submitted agents, there may be issues. The time series of price used for the contest also play important roles. We have selected and modified them empirically but analytically. We investigated the log data of UMIE series and estimated the effect of changing the mixture of agents and time series of spot price (Nakajima and Tomomi 2003). In this way, we are confronted by the default problem and origin problem. In the next section, we introduce our first step to address this problem.

11.4 Experimental Environment

The default setting of system has important meanings. In particular, the U-Mart System has been developed as a common testbed, such that the default settings are the default for any investigation. If the default settings are decided carefully and qualified statistically, they can be used as the common origin point for all investigations using the U-Mart System. If so, then these default settings can play the same role as the control in animal experiments. The more users that use the default settings as a control, the more possible that we can compare the results with those of previous investigations using the U-Mart System. In this sense, choosing the default settings is very important. Both internal and external variations can be used. Internal variations include the set of institutions and the set of agents. External variations include the time series of spot price. To select a default set of institutions, we refer to the NK225 futures listed on the Osaka Securities Exchange. In this section, we explain how we try to select default settings of agent sets and the time series of spot price.

11.4.1 Standard Agent Set

We call the default set of built-in machine agents in the U-Mart System the "Standard Agent Set (SAS)." The purposes of the SAS are to provide sample code of agents and default opponents for both human and machine agents. When we use the U-Mart System with the default settings, we expect to realize a "feasible market" tacitly. Generally, when we see related investigations, that is, artificial financial markets, there are two types of default opponents: one is a random-type agent, and the other is an agent who has his/her own strategy. In the latter case, all artificial markets without the U-Mart System are not released for common use, and then, all built-in agents are designed for a particular investigation. For example, the artificial market system AGEDASI TOF developed by K. IZUMI is downloadable (http://staff.aist.go.jp/kiyoshi.izumi/program.html). The built-in traders are all designed for his investigation. Basic designs of traders are common, and variations are given by initial settings of parameters or the result of learning.

A random agent, sometimes called a noise trader, zero-intelligence trader, and so on, is the most common type. If we use these agents as the default, it is easy to control the market. However, a market filled by random agents has too strong a force of restitution to the mean price preferred by them. In actual markets, fluctuations of price tend to show a power law distribution, which can appear when there are trend followers (Sato and Takayasu 1998). In an actual market, each trader has their own way of decision-making. If the efficient market hypothesis (EMH) is right, then we do not want to take the conclusion of the EMH in advance and fill the default market with random agents; rather, we want to construct a default market by a set of several strategies. If, by changing the combination of agents, the market behaves like the market filled by random agents, then we think that the former is more feasible than the latter.

We tentatively select 10 types of strategies. The names and summaries of each strategy are shown in Table 11.1, quoted from documents attached to the U-Mart System. These 10 strategies are selected without explicit reason and are initially prepared as sample code of agents. Through our experience, by balance of influence to the market, (i.e., trend follower, contrarian or neutral, or they prefer the spot price or futures price), by feasibility of futures price, these strategies have been selected gradually.

We tried to adjust the mixture ratio of agents for the SAS to realize feasible future prices by these ten strategies. For the first step, we conduct a simple experiment as follows. Each agent has each strategy without overlap. We control the amount of volume when the agents send an order. Each agent is randomly assigned a value among 0, 5, 13, 34, and 89. These numbers cannot divide each other, so they maintain the stability of price change. During an experiment, all agents always send an order with same volume initially assigned. With this number, we control the impact of each agent. The other experimental institutions or conditions are same as the default settings of the U-Mart System. The initial conditions including cash are the same among agents. Futures are settled at the first price of the 61st day. The market opens every day and conduct four sessions per day. All orders are cancelled automatically at the end of a day. Figure 11.1 shows the price of example cases in a trial. The future price is sometimes close to the spot price and sometimes far away. Let t be the sequential number of sessions, $s(t)$ be the spot price of t, and $f(t)$ be the futures price of t. Suppose that $\mathrm{sp}(t)$ is the absolute value of the difference between $s(t)$ and $f(t)$. We define the distance between spot price and future price as the summation of $\mathrm{sp}(t)$ for all t. To estimate the tendency, we conduct 3000 trials and calculate the distance between spot and future price.

Table 11.1 Summary of standard agent set

Name	Algorithm	Mixture ratio
Random	The agent buys or sells randomly. The limited price on order is set randomly around the latest futures price, and quantity of the order is set randomly within a prescribed range. Position of the agent is also considered in decision making	8.1
AntiTrend	Price 1 = last futures price, and price 2 = second last futures price. If price1 is lower than price 2 then the agent orders buying. If price 1 is higher than price 2 then the agent orders selling. The amount of order is randomly decided	7.2
DayTrade	Basic strategy of day trading. The agent orders selling and buying simultaneously. Limited price of selling order is slightly higher than latest futures price. That of buying order is lower than latest futures price	8.2
MovingAverage	The agent sends an order when the short term moving average line of futures price crosses over the medium term moving average line. If trend of short term moving average line is up, the agent sends buying order and when it is down, he sends selling order	26.4
Rsi	The agent buys or sells based on Relative Strength Index (RSI) of futures price. RSI is one of major technical analysis methods. The limited price is given randomly around the latest futures price, and quantity of the order is given randomly within a prescribed range. Position of the agent is	9.3
Trend	Price 1 = last futures price, and price 2 = second last futures price. If price1 is higher than price 2 then the agent orders buying. If price 1 is lower than price 2 then the agent orders selling. The amount of order is randomly decided	13.2
SRandom	The agent buys or sells randomly. The limited price on order is set randomly around the latest spot price, and quantity of the order is set randomly within a prescribed range. Position of the agent is also considered in decision making	50.8
SFSpread	The agent orders when a spread between spot and future price is wider than threshold. If future price is higher than spot price, the agent send a buying order, and it send a selling order when futures price is lower than spot price	45
SMovingAverage	The agent sends an order when the short term moving average line of spot price crosses over the medium term moving average line. If trend of short term moving average line is up, the agent sends buying order and when it is down, he sends selling order	32.8
SRsi	The agent buys or sells based on Relative Strength Index (RSI) of spot price. RSI is one of major technical analysis methods. The limited price is set randomly around the latest spot price, and quantity of the order is set randomly within a prescribed range. Position of the agent is also considered in decision making	22.6

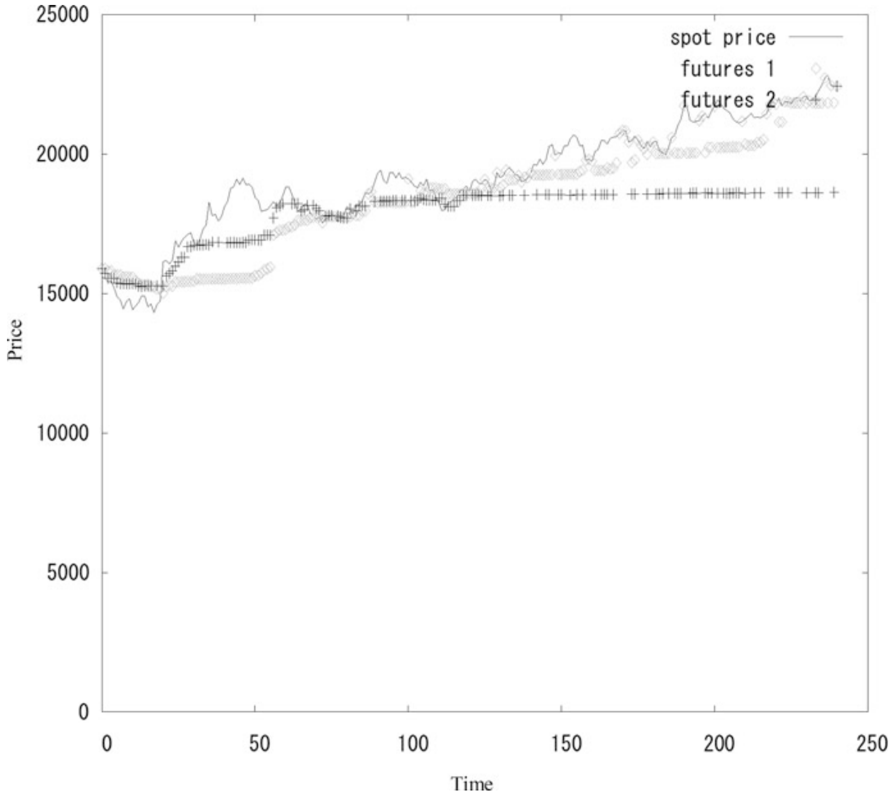

Fig. 11.1 The time series of spot and futures price. *x*-axis: time. *y*-axis: price

From the results of the experiment, Fig. 11.2 shows the case of a random agent. The x-axis is the order of the distance between the spot and future price among the trials. The y-axis is the assigned number of each agent, that is, the amount of order volume. To estimate the tendency, we calculate the moving average of the assigned number toward the order of the spread. Figure 11.3 shows the result of all types of agents when we calculate for a moving average of 200. This figure represents when the spread between the spot and futures price becomes narrow or wide. From left side to right side of Fig. 11.3, the spread tends to widen, so the value of each agent on the left side shows a good mixture ratio of agents. We can grasp how agents affect the spread. The Random, AntiTrend, DayTrade, Rsi, and Trend agents contribute to widening the spread. The SRI, SmovingAverage, and Average are

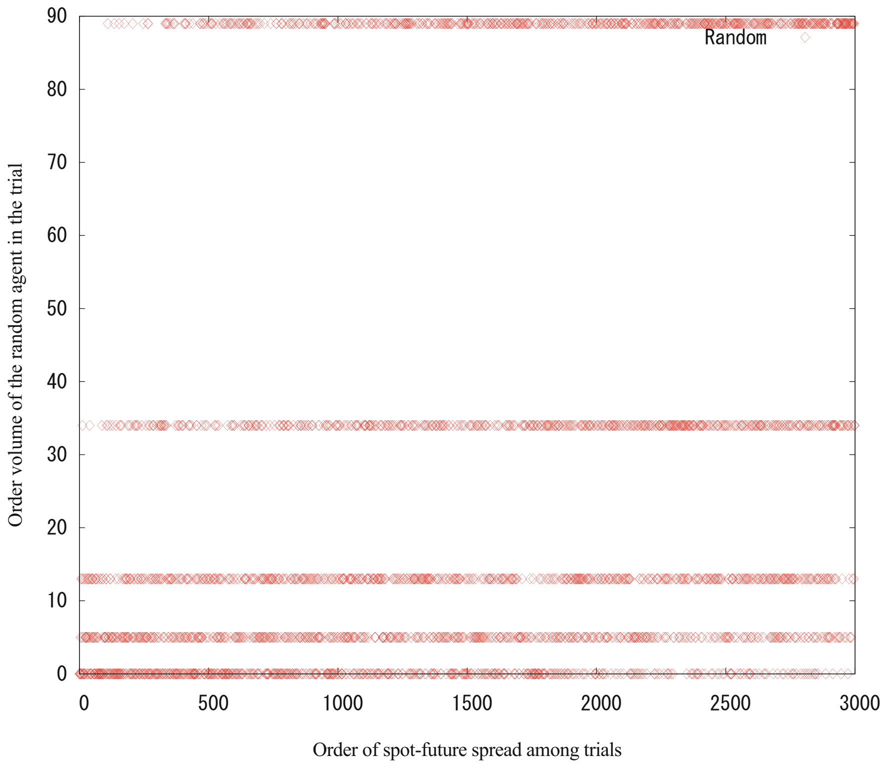

Fig. 11.2 Assigned number of random agent sorted by spread between spot and future price. *x*-axis: order of spot-future spread among trials. *y*-axis: order volume of the random agent in the trial

neutral. The SRandom and SFSpread contribute to narrowing the spread. From the top 200 among 3000 trials ordered by spread, we can propose a tentative mixture ratio of agents for the SAS. The third column of Table 11.1 represents this value. Figure 11.4 presents the relationship between the order, which is used as the *x*-axis of Figs. 11.2, 11.3, and 11.4, and the spread between spot and futures price. The first spread widens linearly according to the order. However, in surrounding areas, the spread becomes extremely wide.

11.4.2 Time Series

For both computer simulation by machine agents and gaming simulation by human agents, time series of spot price play an important role. The reason why we select the future market is the treatment of fundamental information. If the artificial market is a stock market, then we have to provide some kind of fundamental information.

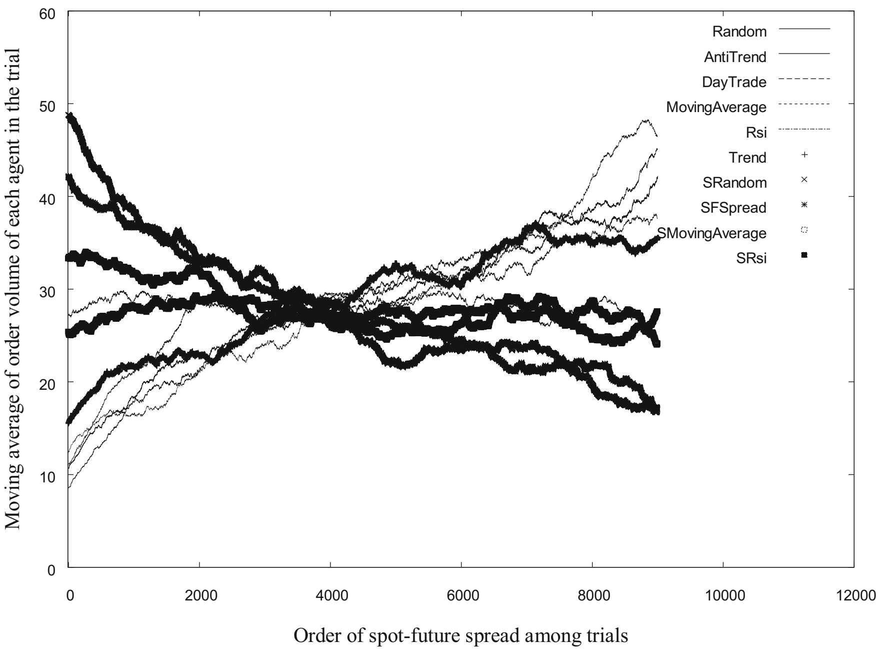

Fig. 11.3 Moving average toward order of spread (the x-axis). The y-axis represents the number of orders. x-axis: order of spot-future spread among trials. y-axis: moving average of order volume of each agent in the trial

However, if we assume the efficient market hypothesis, then we can consider that all fundamental information reflects the current spot price. In this sense, if we select appropriate time series of spot price, the U-Mart System can experience movement as if it exists in a social environment.

We can use two kinds of time series for spot price: the actual price and artificial price time series. Actual data have validity because they appeared in the real world at least one time. However, there is an infinite number of data, and we cannot control the parameters. For the open experiments conducted by the U-Mart Project, four kinds of time series are selected from actual data. Because we test agents in several environments, we try to select data with characteristic trends. These data work well, but it was hard for us to find another set of time series. If we use artificial data, important features might be lacking. However, we can easily control the parameters. We can easily design an experimental plan.

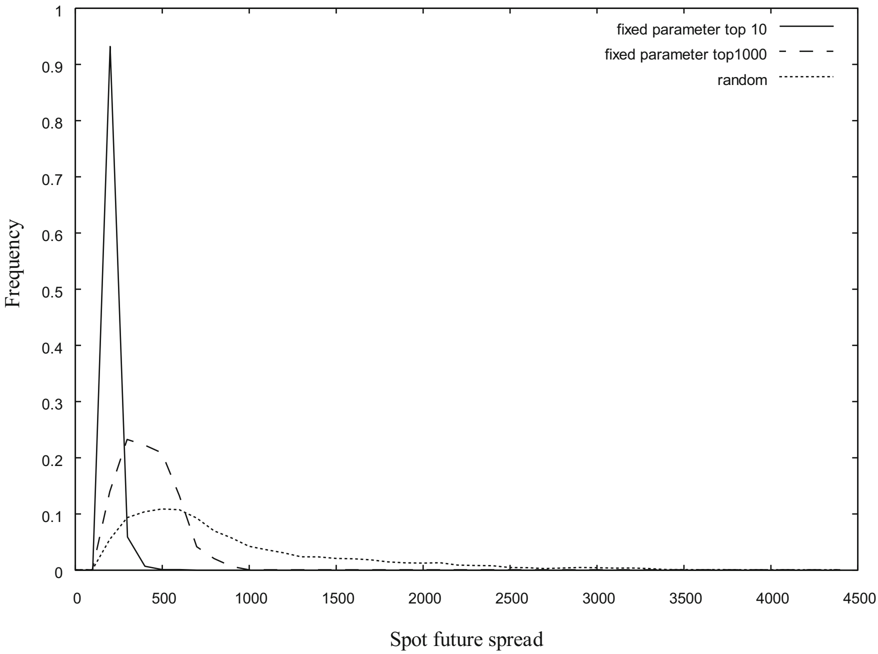

Fig. 11.4 Relationship between the number of orders (x-axis) and spread between spot and future price. x-axis: spot future spread. y-axis: frequency

There are two ways to use artificial data. One approach is using a stochastic process. There are many stochastic process models, and their statistical properties have been studied well. Therefore, we can conduct experiment as much as we like. The other approach is processing actual data. We propose one way as an example. First, let us select one actual time series of price $\{p(t)\}$ and plot the graph. We calculate the formula of a straight line $y(t) = a*t + \mathrm{b}$ that joins the first point (0, $p(0)$) and last point (t, $p(t)$) of the price graph. For each point of t, let us subtract the straight line from price $\mathrm{ap}(t) = p(t) - y(t)$. Then, the graph of the modified price line and the first point and last point become the same. Next, we obtain difference data by $b(t) = \mathrm{ap}(t) - \mathrm{ap}(t - 1)$. Then, we shuffle their order randomly. Subsequently, we accumulate shuffled $\{b(i)\}$. Finally, we obtain a flat line that is similar to the time series of price. Afterward, depending on the experiment, we can add trends. Figure 11.5 shows one example. The upper red line shows the original data, and the three lines below are artificial lines made from the red line. These three lines show variations due to added trends.

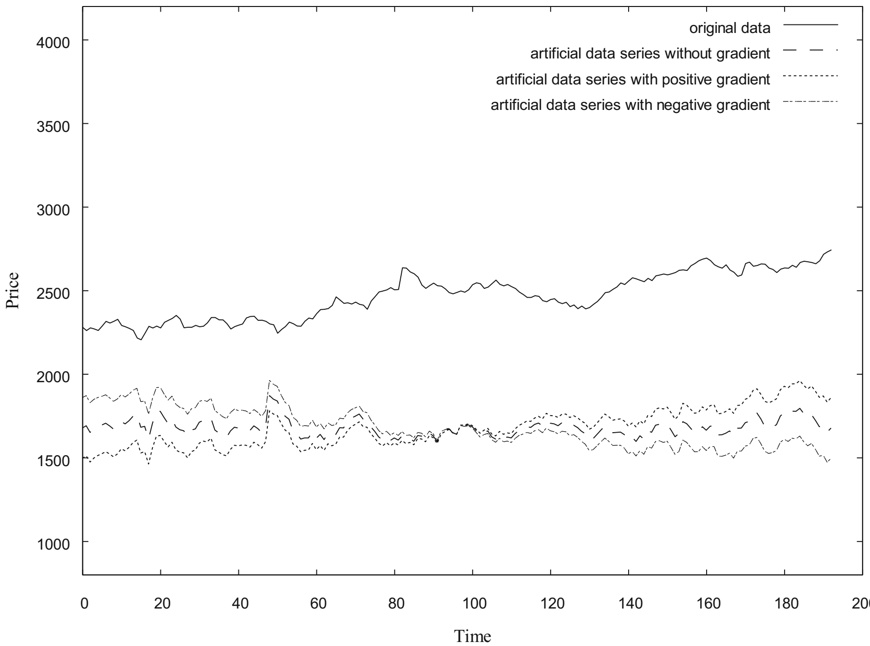

Fig. 11.5 One example of artificial price data. x-axis: time. y-axis: price

11.5 Conclusion

Based on our efforts to release a common testbed and conduct open experiments, we have been confronted by the origin problem. We also realized the importance of origin in social simulation. If there is an origin system such as an experimental animal and many investigations adopt to use it, then it must help investigations of social science. In this chapter, we propose this problem, and to explain this problem concretely, we introduce the activities of the U-Mart Project.

For our first efforts toward solving the problem, we try to establish an appropriate mixture ratio of agents who compose the U-Mart System as the "Standard Agent Set (SAS)." An approach to generate time series of spot price is also proposed. When we arrange the order amount of each agent by the spread between futures price and spot price, we find that the values for each agent have a linear tendency. Some agents help to narrow the spread, some agents widen it and some agents are neutral. From these agents, we can propose a mixture ratio. For external environments, we propose a way to generate artificial time series. These data are from actual time series but are well controlled. This is only a first step, and more detailed analytical investigations are desired.

Acknowledgments This experiment can work for all researchers participating in the U-Mart Project. This research was partially supported by the Ministry of Education, Science, Sports and Culture, Grant-in-Aid for Scientific Research (18K01692).

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Chapter 12
Programmed Trading Agents and Market Microstructure in an Artificial Futures Market

Takashi Yamada

Abstract This chapter is organized as follows: first, it introduces how U-Mart, an artificial futures market testbed, is used at a graduate school of engineering to teach economics/financial markets as well as computer programming and system modeling. Second, it reports a strategy experiment with human subjects and their submitted trading agents by focusing on market microstructure to see the relations between the evolution of their trading strategy and the characteristics of order book. The empirical results confirm that although there are locally mispricing effects of several trading agents; in most cases, market liquidity improves. Future perspectives of related fields are also discussed.

Keywords Teaching economics in classroom · Programming education · Artificial market · Trading contest · Market microstructure

12.1 Introduction

The development of ICT technology has changed financial markets a lot. In earlier years, there were floor traders who were members of a stock or commodities exchange and execute the transactions for their own account there. But as electric trading has become faster and less costly, the floor traders have been replaced and are currently quite rare or even disappeared. In addition, electric trading (or algorithmic trading) is quite popular for individual market participants. Indeed, the

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percentage of volume for algorithmic trading was 15% in 2003, and this rapidly reached to 85% in 2012 (Glantz and Killell 2013).

The abovementioned fact means practitioners and economists as well as engineers need to understand both financial markets and computer programming for their trade or study. Although it is sufficient for some of the individual market participants only to submit their orders via their security firm, the others write and update their trading algorithm on their computer at home. Likewise, while some researchers on financial market not only develop a mathematical model by using a paper and a pencil, the others computationally analyze the financial data or run a computer simulation. Or, the engineers have been required to study market mechanism in accordance with the evolution of trading processes (e.g. Evans et al. 2013).

These trends affect how to teach economics and computer programming. Traditionally, economics has been taught by chalk and talk, and computer programming classes have started with outputting "Hello world!" and progressed such as sort, recursive algorithm, and object-oriented programming. As time passes by, such teaching styles have also evolved. Some of the economics courses are taught by experimental approach, called "Teaching Economics in Classroom"[1] (e.g. Becker and Watts 1998; Bostian and Holt 2009; Egbert and Mertins 2010; Kaplan and Blkenborg 2010; Nungsari and Flanders 2020; Watts and Guest 2010) and tools to learn financial markets have been also developed.[2] Likewise, programming education has been studied (e.g., Robins et al. 2010; Sarpong et al. 2013; Ulloa 1980) and there are several attempts to incorporate serious game playing into computer programming courses (e.g., Kazimoglu et al. 2012; Malliarakis et al. 2014; Miljanovic and Bradbury 2018; Moreno 2012; Pellas and Vosinakis 2018; Vahldick et al. 2014, 2020). In addition, computer programming has become to be taught by using an educational tool such as Scratch,[3] Springin',[4] Viscuit,[5] or Blockly[6] so that not only students but also kids can learn with fun or by introducing game playing method.

The "UnReal Market as an Artificial Research Testbed" (hereafter, U-Mart) is an artificial futures market in which human subjects and trading agents take part in together,[7] and lots of contributions have been made in economic and engineering literature. For instance, Sato et al. have clarified the differences between the behavior of human subjects that of trading agents or profitability of simple technical

[1] A wide variety of contributions are found in https://www.economicsnetwork.ac.uk/themes/games.

[2] For example, https://www.howthemarketworks.com/.

[3] https://scratch.mit.edu/.

[4] https://www.springin.org/.

[5] https://www.viscuit.com/.

[6] https://developers.google.com/blockly.

[7] For more information, see official website (U-Mart project: http://www.u-mart.org/) or the book (Shiozawa et al. 2008).

trading rules (Sato et al. 2003). It has been also widely used in educational program for teaching computational economics and system modeling.

This study reviews (i) how computer programming and system modeling was taught to master's course students who studied engineering at Tokyo Institute of Technology, (ii) what kind of trading agents the students wrote in the trading contests, and (iii) how the market dynamics were from the perspective of market microstructure. In other words, this study deals with teaching computer programming and economics in classroom. In addition, as just mentioned in the last paragraph, this study is something related to experimental economics with human subjects and trading agents.

There is an earlier study which investigated the learning processes of the students by questionnaire surveys from a point of view about acquisition of concepts in computer programming (Okamoto et al. 2009). According to their work, programming concepts were divided into three categories: the concepts that could be understood in classroom lecture, the ones that could be mastered by programming by themselves, and the ones that were difficult to understand. The main difference between their study and this one is that this study focuses on what kind of agents the students employed in the trading contest and how the agents behaved in U-Mart. Therefore, this study does not pay attention to which skill the students really acquired through the contests.

On the other hand, there are several researches on laboratory market with human subjects and trading agents. Das et al. have implemented a coexistence trading market extending the flamework by Das et al. (2001). But the market is not a double-auction one unlike the U-Mart. Glossklags and Schmidt have investigated how the existence of trading agents affects the behavior of human subjects and thereby the market dynamics (Glossklags and Schmidt 2003). The most apparent difference from our framework is that human subjects also created their trading agents, not we offered simple ones. On the other hand, Sonnemans et al. and Hommes et al. have independently conducted strategy experiments[8] in a simple asset pricing model in order to test whether the asset price converges to a theoretical value and how each strategy file evolves over the round (Sonnemans et al. 2004; Hommes et al. 2005).[9] However, since their experiments have assumed a particular utility function in the economy, the excess demand of each strategy file is determined automatically, namely it is not designed so as to investigate market microstructure. Nevertheless, these studies may help incorporate the findings of experiments into the frameworks of agent modeling and vice versa (Duffy 2006).

The rest of this chapter is organized as follows: the next section explains how the course and the trading contests progressed. Section 12.3 shows some computational results focusing on the relations between the submitted trading agents and market microstructure. Section 12.4 gives a couple of concluding remarks.

[8] Other strategy experiments in experimental economics include Brandts and Charness (2011), Linde et al. (2014) and Zhao et al. (2018), for example.

[9] Bao et al. and Sunder give a comprehensive survey in this field (Bao et al. 2021; Sunder 1992).

12.2 System Modeling at Tokyo Tech

12.2.1 Overview

The experiment was implemented as a part of a course "System Modeling," an engineering introduction to computational intelligence and systems science in the graduate school of science and engineering program at Tokyo Institute of Technology. Since this is one of the core courses in this department,[10] participation is a course requirement for master's course students. This course deals with computer programming and system development, and its objectives include (i) the mastery of basic skills of design and development of a highly reliable system with about 10 thousand lines of code, (ii) acquisition of Java programming, (iii) learning of project management, and (iv) improvement of communication skills. For these purposes, this course used U-Mart so that the students were asked to tackle with a programming of trading agent as an individual task and a design of market system as a group work. Note that this course did not intend to teach how to make more money in financial markets.

Table 12.1 shows a timetable in FY2007. This course was held once a week and the duration of each session was two hours and twenty minutes long. There were five instructors and two teaching assistants. As in this table, the first half of the course consists of computer programming and trading contests, while the second half focuses on system modeling. Since the backgrounds of the students are various, computer sciences, engineering, mathematical science, and economics, the skills of computer programming are also various. Some of them were novices and others were nearly experts. Therefore, before starting their group work, the instructors firstly investigated to what extent the students could write a computer program by asking the longest lines that they had ever written to them and then form groups of four or five so that their abilities should be similar.

12.2.2 Tutorial

The objectives of this tutorial were to provide the students with some experiences with operating U-Mart and to give lectures about computer programming. After installing JDK (Ver. 6 Update 12 at that time), Eclipse (Ver. 3), and U-Mart (Ver. 2) for each personal computer, three introductory sessions were held as follows: in the first session (Session 3 in Table 12.1), a trading pre-contest was implemented. In this session, only human subjects with the originally installed trading agents took part in the artificial market in order to grasp how a futures market ran. In the second and third sessions, computer programming lectures were given. While the students were

[10] The other courses are "Adaptive System," "Discrete System," and "Dynamic System."

Table 12.1 Timetable of system modeling at Tokyo Tech in FY2007

Session	Contents
1	Introduction
2	Basics of research skills (Project documentation and presentation)
3	Pre-trading contest
4	Introductory Java (1)
5	Creation of trading agent
6	Introductory Java (2)
7	System Modeling in Life Sciences and Business
8	Trading contest (1)
9	Trading contest (2)
10	Design of market server (1)
11	Design of market server (2)
12	Design of market server (3)
13	Design of market server (4)
14	Design of market server (5)

taught elementary JAVA programming in the first half of the classes, they learned how to create a machine agent using a template file distributed in the second half of the lecture.

To create a trading agent, the students are given three kinds of source files, Strategy.java as a base file, RandomStrategy.java, and MovingAverageStrategy.java as sample files. Both RandomStrategy.java and MovingAverageStrategy.java use Strategy.java as a package and the students are asked to create their own trading agent by referring to and revising these sample files.

- Strategy.java
  This file firstly monitors and records past 120 spot prices and 60 futures ones. Then, it gets current position and cash and sees the remaining trading days. In addition, based on what is written in a file to trade, it submits orders to the market.
- RandomStrategy.java
  This strategy thinks that the futures price follows a random walk with the previous price as mean and a predetermined value as standard deviation. The next position of this agent is also determined randomly, but if both the current and the expected position are over or under a threshold value, then the agent does nothing.
- MovingAverageStrategy.java
  This strategy uses two kinds of moving averages, 10-period moving average and 20-period moving average, for decision-making. It refers to only futures price. After calculating the two moving averages, it determines buy, sell, or doing nothing by comparing these indicators with the preceding ones. Both the order price and the quantity are the same as what RandomStrategy.java does.

12.2.3 Trading Contest

The experiments lasted two weeks, each of which had one round. In each round, the students had to submit a strategy file in Java. They could submit their own strategy any time before the previous day of the contest. In the first round, subjects had about two weeks to create agents, while in the second round they had only one week to revise their strategy. In other words, they could make machine agents after taking all the introductory lectures. The number of submissions was 87 and 89 of 89 registrations, respectively. The instructors and two teaching assistants checked these strategies for not having any bug or error. As a result, two strategies were excluded in Round 1, and three were in Round 2.

In each round, we implemented an experimental asset market with human subjects and submitted strategies only one time. The reason why we could not conduct iterated experiments in case of the market with students is human subjects surely learn from the past events. The two kinds of time series spot data, the one is NIKKEI225 and the other is USD/JPY, were converted such that the mean and the variance were all equal to those of originally installed data, J30. Since each simulation run had 20 days, each of which had eight bid/offer matching done on the order book, one matching could be considered as one-hour long. Moreover, the human subjects had about 20 seconds in each matching for their decision-makings. Market participants were allowed to do infinitely short-selling so long as their budget permitted, but the ones who had gone bankrupt could not take part in the market anymore (other setups are described in Table 12.2). At the end of each round, the subjects received open information about all the source codes, order information, historical data (price and volume), and the rankings of the strategies and human subjects by final wealth. After experiment, students revised their strategy based on the results and submitted for the next competition (even if the third round did not take place).

Problems often addressed by many researchers are motivations of subjects and attempts to obfuscate the market. The former problem would be overcome by letting the participants be financially motivated, namely instructors announced that the most profitable human subject and the student who created the winner agent could receive sweet treats for the amount of 10 dollar. On the other hand, with

Table 12.2 Experimental setup

Item	Memo
Initial wealth	One billion
Initial holdings	No
Ordering for machine agents	Limit order only
Cancellation of orders	Not allowed
Risk free rate	0.1
Trading unit	1000-fold
Commission	300 thousand per unit
Credit taking	Up to 30 million

Table 12.3 Characteristics of submitted strategies

	Round 1	Round 2
Random	5	2
Stop loss	10	11
Trend follower	20	20
Contrarian	4	5
Moving average	22	20
Spot-futures spread	28	31
Others	8	10
Total strategies	87	89

respect to the latter obstacle, we did not prohibit them from making a destabilizing machine agent because we knew that such an attempt would be quite hard to succeed due to the existence of nearly 100 market participants including originally installed machine agents[11] as Hommes et al. have pointed out (Hommes et al. 2005). Fortunately, the strategies submitted which will be explained in the next section were ordinal.

12.3 Results

12.3.1 *How Are Agents Created?*

In agent-based computational finance models, the characters of agents are mostly bounded rational, namely the characters of agents are usually fundamentalists, chartists, deterministic, or ones using evolutionary algorithm. Before presenting the results of market dynamics, we will briefly review general distinctions of submitted strategies.

Table 12.3 shows main characteristics of the strategy files. About one-thirds are arbitragers, namely they think that the futures price will eventually converge to the spot price. The rest strategies are something like Markov property or moving average ones. That is to say, the former strategies can be considered as ones with characters of fundamentalists and the latter ones are chartists. Around 10 strategies employ stop loss orders, which is because the U-Mart allows market participants to do more than two orders at a time. Finally, around 10 other strategies are more complex ones, namely they consist of neural network program, classifier systems, or reinforcement learning.

On the other hand, Fig. 12.1 shows histograms and a scattered plot of the number of lines of the submitted trading agents. Also, Table 12.4 gives its summary

[11] They were as follows: one trend follower, one contrarian, two random walkers, two RSI traders, two moving average strategies, one arbitrager (he/she focuses on the spread between spot price and futures price), and one stop loss trader. For more details, see the textbook (Shiozawa et al. 2008).

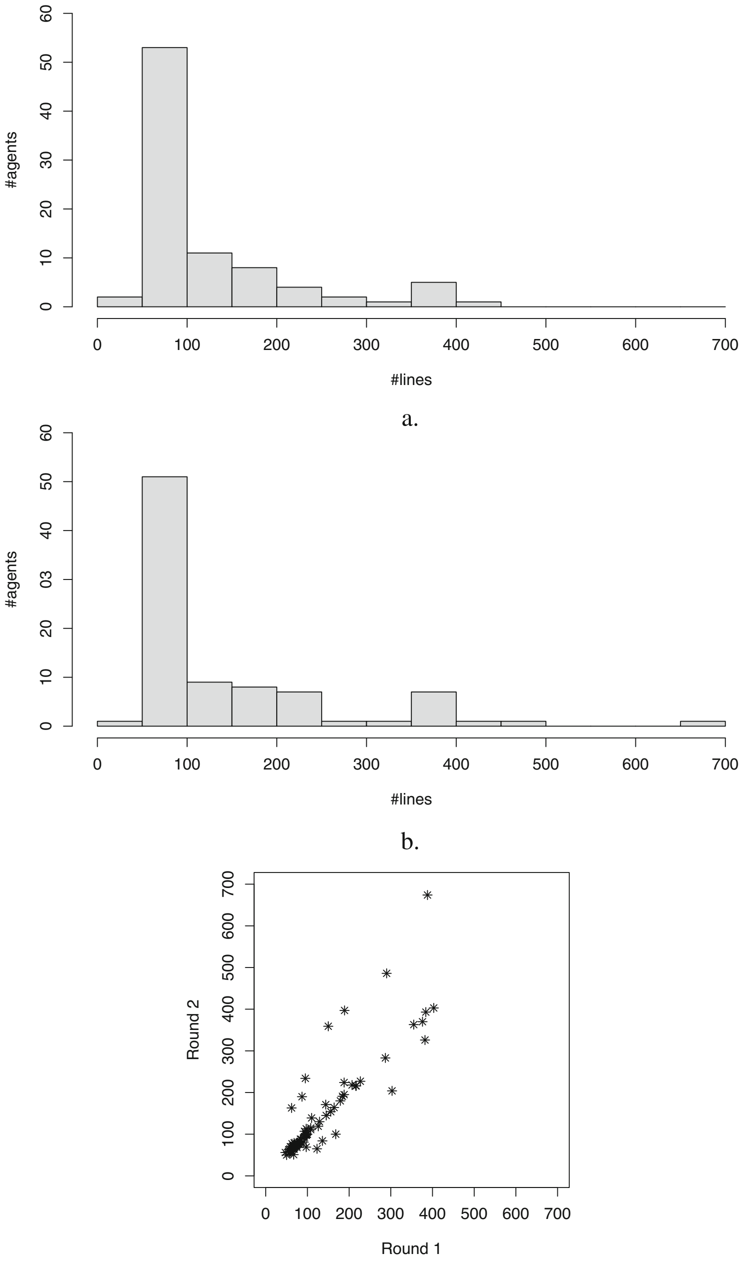


Fig. 12.1 The number of lines of submitted trading agents. (**a**) Contest 1. (**b**) Contest 2. (**c**) Differences between Round 1 and Round 2

Table 12.4 Summary statistics of the number of lines of submitted trading agents

a. Round 1

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
47.0	68.0	91.0	126.0	148.8	403.0

b. Round 2

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
50.0	69.0	88.0	138.6	169.2	674.0

statistics. Note that the number of lines was calculated after all the comments, Javadoc, and blank lines were manually deleted and the source code was reformatted on Eclipse. Also, those of the two sample files, RandomStrategy.java and MovingAverageStrategy.java, were 75 and 154, respectively. As in the table, over the half of the submitted agents were longer than RandomStrategy.java in form but shorter than MovingAverageStrategy.java. Likewise, many of them were less than 100 lines, while a small number of students submitted a strategy file with 300 lines or more. Finally, although about one-third of them did not improve their strategy in Round 2, the students wrote a longer program on average (p-value $= 0.038$ from a paired t-test and Pearson's product-moment correlation coefficient $= 0.878$). These suggest that the students did not employ a complicated or sophisticated strategy, but some of them did their best so that the trading agent could perform better in the contest.

12.3.2 Market Dynamics

Before explaining the experimental results, the author ran agent-based simulation where only the preinstalled agents and the submitted trading agents 10 times for each round. By doing so, we will see how the trading agents affected the market microstructure in U-Mart. In other words, the results and the discussions are mainly based on the agent-based simulations.

Figures 12.2 and 12.3 show a snapshot of trading contest and one of the generated sample paths. Unlike the laboratory experiments with human subjects, there were no price jumps in the economy because market order was not allowed for trading agents.

In order to check if the market with only trading agents successfully led the dynamics observed in actual financial markets, namely "stylized facts" (Hommes 2001; Lux and Marchesi 2000), we conducted the following time series analyses:

- Exchange rates and stock prices have almost unit roots.
- Returns have fat-tailed distributions.
- Returns per se cannot be predicted, namely they have almost zero autocorrelations.

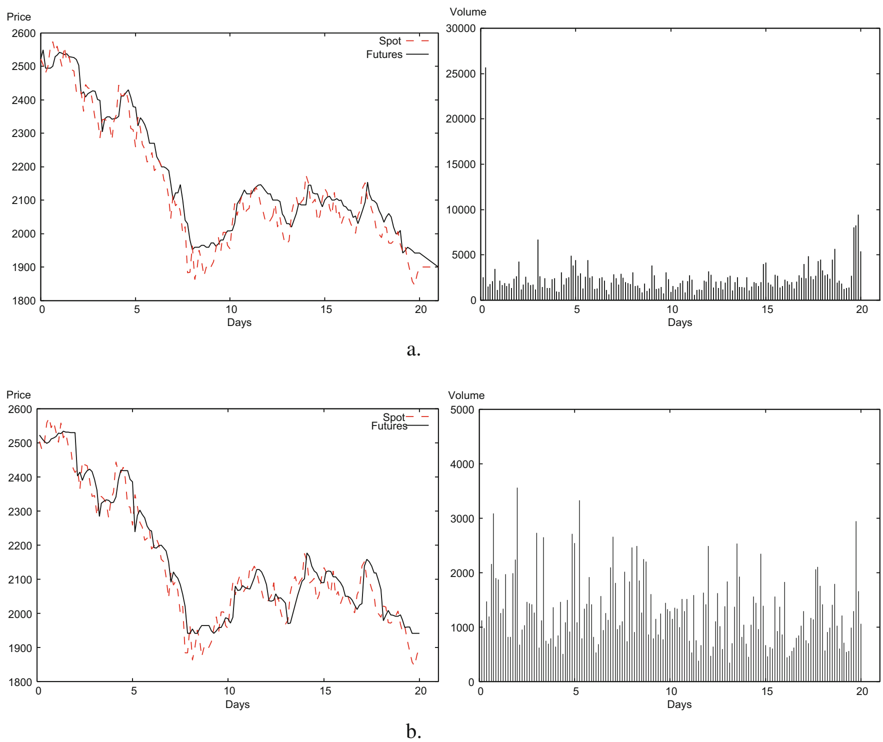


Fig. 12.2 Market dynamics of Round 1 (left panel: price and right panel: volume). (**a**) Trading contest. (**b**) Agent simulation

- Return distribution shows long memory, namely absolute or squared returns are significantly positive and decrease slowly as a function of the lags.

After those analyses, we observed that the time series supported the unit root property and fat-tailed distributions but did not replicate long memory properties. This is because the number of observations is too scarce to be analyzed. Besides, we also confirmed that some trading experiments and knowledge of computer programming seemed to make the prices be closer to a theoretical value.[12]

12.3.3 Market Microstructure

The time series reviewed in the preceding section appears to lead the dynamics observed in real financial markets in some regards. However, that does not

[12] Yamada et al. analyze this in greater detail (Yamada et al. 2008).

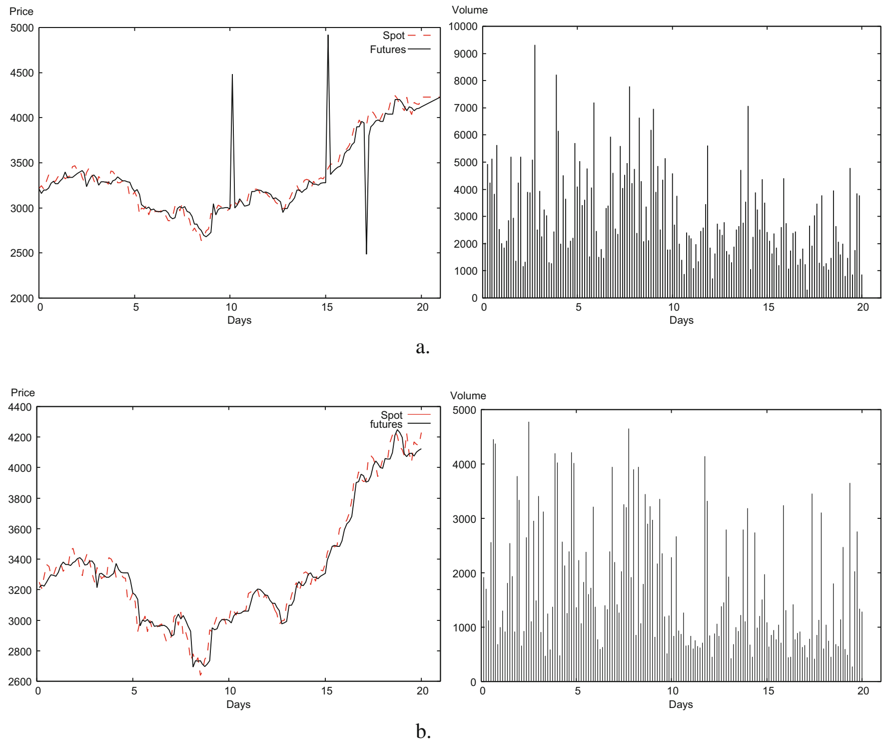


Fig. 12.3 Market dynamics of Round 2 (left panel: price and right panel: volume). (**a**) Trading contest. (**b**) Agent simulation

always mean the students successfully learnt to write a trading agent and trade futures assets. Therefore, in this part of the section, the author investigates market microstructure of each sample path in order to check whether the trading agents become more sophisticated or their behavior is not redundant employing the following four measures:[13]

- Bid-ask spread
  Bid-ask spread is usually the difference between the lowest ask available and the highest bid available calculated as

$$\text{raw spread}_t = P_{ask,t} - P_{bid,t} \tag{12.1}$$

  where $P_{ask,t}$ and $P_{bid,t}$ are the ask price and bid one at time t, respectively. While the measure above represents raw differences between the two quotes,

[13] For more details, please refer to comprehensive surveys (Biais et al. 2005; Madhavan 2000) and an empirical study for Tokyo Stock Exchange (Ahn et al. 2002).

other measures take into consideration the ratio of mid-point, effectiveness (Lee et al. 1993), or all the uncontracted and new orders in the market as

$$\text{mid-point spread}_t = \frac{2(P_{ask,t} - P_{bid,t})}{P_{ask,t} + P_{bid,t}} \tag{12.2}$$

$$\text{effective spread}_t = \frac{2\sum_{i=1}^{N} |P_t - (P_{ask,t} + P_{bid,t})2/|Q_{t,i}}{\sum_{i=1}^{N} Q_{t,i}} \tag{12.3}$$

$$\text{weighted spread} = \frac{\sum_{i=1}^{M} P_{ask,t,i} \cdot D_{ask,t,i}}{\sum_{i=1}^{M} D_{ask,t,i}} - \frac{\sum_{i=1}^{M} P_{bid,t,i} \cdot D_{bid,t,i}}{\sum_{i=1}^{M} D_{bid,t,i}} \tag{12.4}$$

where N is the number of sessions in a day, M is the number of prices offered, $Q_{t,i}$ is the trading volume traded in the i's session at day t, and $D_{t,i}$ is the orders submitted to the market in the i's session at day t.

- Market depth
  Market depth is the quantity of an order which is required to change the prices calculated as follows:

$$\text{depth}_t = D_{ask,t} + D_{bid,t} \tag{12.5}$$

  where $D_.$ is the quantity of bid or ask order at $P_.$. That the market depth is larger means that the market is liquid, namely a large order is necessary to move the market.
- Kyle's measure (Kyle 1985)
  Kyle has developed an illiquidity measure, called λ, which measures how large changes in prices are while the volume of a fixed quantity is formed. In this study, we conduct a linear regression with zero interceptions as

$$\lambda = \frac{\sum_{i=1}^{N} |R_{t,i}| \cdot Q_{t,i}}{\sum_{i=1}^{N} Q_{t,i}} \tag{12.6}$$

  where $R_{t,i}$ and $Q_{t,i}$ are the session i's return of an asset price and trading volume at time t, respectively, and N is the number of sessions/contracts in a trading day. A small λ means that the market has a high liquidity, i.e., larger orders are contracted in a small change in prices.
- Amihud's measure (Amihud 2002)
  Amihud has created an illiquidity measure, called formally *ILLIQ*, which is the daily ratio of absolute return of a risky asset to its currency volume, averaged over some period as follows:

$$ILLIQ_t = \frac{1}{N} \sum_{i=1}^{N} \frac{|R_{t,i}|}{P_{t,i} \cdot Q_{t,i}} \tag{12.7}$$

where N is the number of sessions per day. Additionally, Kyle's λ, a small $ILLIQ$, means that the market is more liquid.

Figure 12.4 and Tables 12.5, 12.6, 12.7, and 12.8 show fundamental statistics of four bid-ask spread of each sample path. With respect to mean values, those in Round 1 seem smaller than those in Round 2 except Table 12.8. In other words, Tables 12.5, 12.6, and 12.7 appear that the trading and programming skills of human subjects did not become expertized. Especially, the maximum values in Round 2 are much larger than those in Round 1. But this is due to some statistical outliers or because some trading agents mispriced the future prices. For instance, as in Table 12.9, after the bid orders at the price of 3376 or higher were all contracted, the highest price of remaining bid orders became 3376. On the other hand, 200 ask orders at the price of 4960 were still on the board. In this case, the bid-ask spread became much larger. Although we did not investigate each strategy file in greater detail, the highest ask was from the mispricing of a trading agent because the difference between the price and the second highest price is over 1500. Instead, the differences between weighted ask prices and those bid ones in Round 2 are much smaller than those in Round 1 (Table 12.8 and Fig. 12.5). These two exhibits explain the following two points: first, some orders in Round 1 were redundant but did not affect the bid-ask spread. Second, mispricing of a few strategy files worsened the bid-ask spread in the market, but the distributions of expected prices became more sophisticated in Round 2. Thus, in this regard, it can be said that the human subjects learned to write a more sophisticated trading agent.

Second, Fig. 12.6 and Table 12.10 summarize market depth of each round. The empirical findings are basically the same as the case of bid-ask spread, i.e., the market depth in Round 1 seems larger than that in Round 2. But, as Fig. 12.6 precisely tells, there are several unrealistic figures observed in Round 1. This is because some trading agents submitted huge orders, and as a result most of their orders were still uncontracted. It is true that the similar situations are observed in Round 2, but the market microstructure in Round 2 sometimes seems normal when taking into consideration the fact that the maximum values of depth in sample paths 6, 9, and 10 are much smaller. Therefore, that the market depth, namely the market liquidity, is small does not mean that the behaviors of trading agents are not random or that the market is still thin.

By the way, Table 12.11 presents the correlation between bid-ask spread and market depth. Usually, those two measures are negatively related to each other; namely, when a bid-ask spread is small (large), the corresponding market depth is likely to large (small). In most cases, the values are negative, but they are not significant level. Possible reasons are that the number of observations is not plenty enough or that there are sometimes huge but meaningless orders in the market. In other words, even if the bid-ask spread is small, (the) large remaining orders affect market depth. Thus, we need to implement long-run simulation to obtain more data. This is one of the problems which agent-based computational finance and experimental economics should resolve.

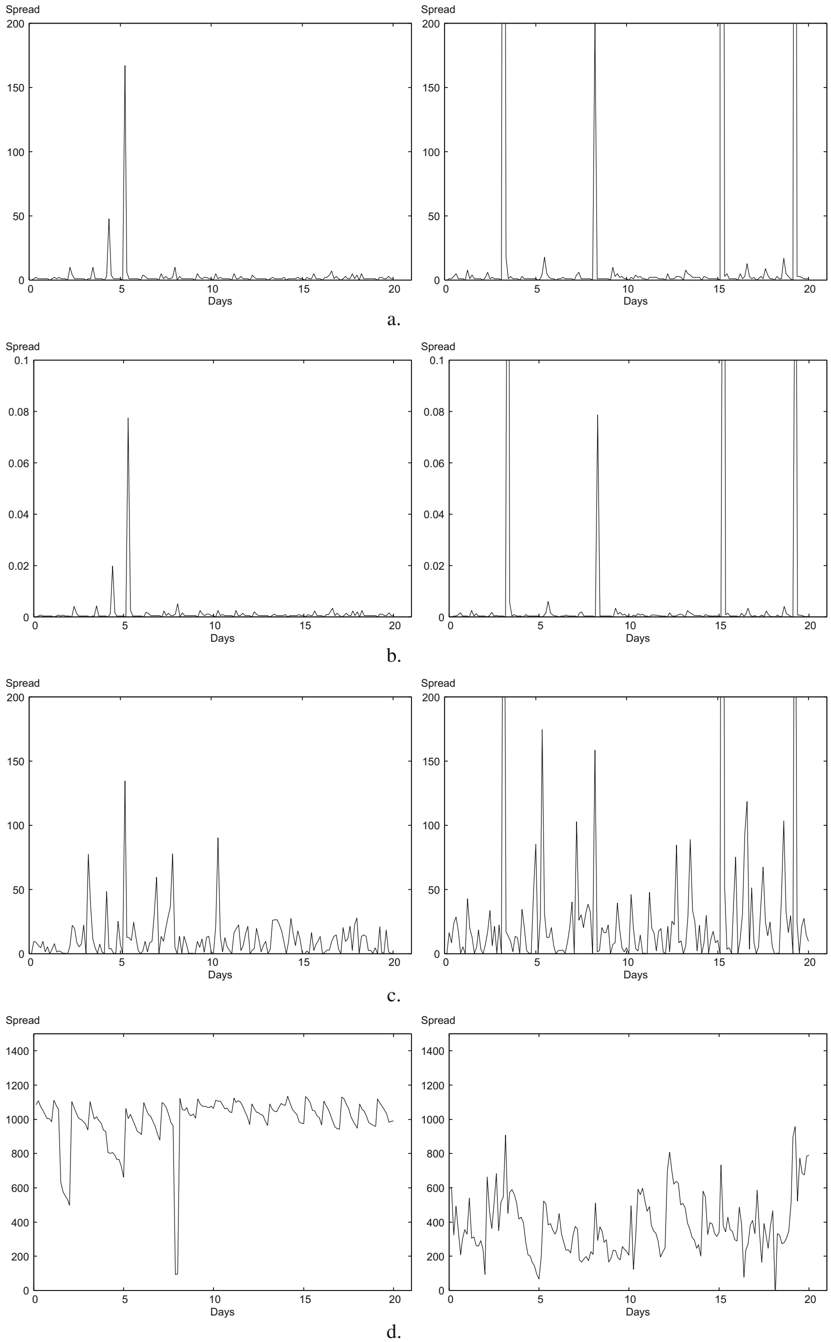


Fig. 12.4 Time series of bid-ask spread (left panel: Round 1 and right panel, Round 2). (**a**) Raw spread. (**b**) Mid-point spread. (**c**) Effective spread. (**d**) Weighted spread

Table 12.5 Bid-ask spread (raw value)

a. Round 1

Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	2.94	13.67	0	1	1	2	167
2	3.15	12.46	0	1	1	2	154
3	2.09	3.04	0	1	1	2	24
4	2.90	13.25	0	1	1	2	167
5	1.92	2.62	0	1	1	2	24
6	3.48	13.85	0	1	1	2	167
7	3.26	12.63	0	1	1	2	150
8	1.94	2.74	0	1	1	2	17
9	3.93	14.78	0	1	1	2	167
10	1.88	2.79	0	1	1	2	26

b. Round 2

Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	23.17	152.86	0	1	1	3	1584
2	15.63	150.01	0	1	1	3	1890
3	9.61	68.34	0	1	1	3	842
4	4.40	16.92	0	1	1	3	204
5	3.36	7.60	0	1	1	3	71
6	8.34	66.26	0	1	1	3	836
7	16.10	145.23	0	1	1	3	1828
8	4.65	18.39	0	1	1	3	205
9	3.90	9.81	0	1	1	3	74
10	4.10	17.18	0	1	1	3	207

Third, Fig. 12.7 and Tables 12.12 and 12.13 illustrate daily market illiquidity measures, both of which are small if the market has more liquidity. Now, we easily confirm that the values in Round 2 are significantly smaller than those in Round 1. Besides, the fact that both the tables do not provide with any abnormal number implies that occasional mispricing did not affect the market liquidity. In summary, these two measures support our earlier results, i.e., the human subjects got accustomed to trading and programming. Interestingly, the correlation between Kyle's λ and Amihud's illiquidity measure gets worse over round unlike the report in Amihud (Table 12.14). To our regret, since we did not find any reason from our past and present investigation, more efforts should be done in the near future.

As well as the financial time series, there exist several stylized facts about intraday market microstructure as follows (Kissell 2013):

Spread — Intraday spreads are high at the open than mid-day but do not spike at the close. Spreads decrease slightly into the close. (p. 67)

Volume — Intraday volume follows J-shaped rather than U-shaped. (pp. 68–69)

Table 12.6 Bid-ask spread (mid value)

a. Round 1							
Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	1.35	6.30	0.00	0.42	0.48	0.95	77.58
2	1.47	5.81	0.00	0.43	0.49	0.94	71.76
3	0.99	1.51	0.00	0.42	0.49	0.97	12.28
4	1.35	6.15	0.00	0.43	0.48	0.98	77.58
5	0.90	1.28	0.00	0.43	0.49	0.97	12.28
6	1.62	6.41	0.00	0.43	0.49	0.97	77.58
7	1.50	5.84	0.00	0.44	0.49	0.89	69.96
8	0.91	1.29	0.00	0.41	0.48	0.95	8.72
9	1.82	6.80	0.00	0.43	0.48	0.97	77.58
10	0.88	1.33	0.00	0.41	0.48	0.94	12.79

b. Round 2							
Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	6.56	40.71	0.00	0.30	0.33	0.77	380.03
2	3.61	30.32	0.00	0.30	0.33	0.73	376.49
3	2.84	19.12	0.00	0.30	0.33	0.93	229.30
4	1.44	6.46	0.00	0.30	0.34	0.92	79.16
5	0.98	2.26	0.00	0.30	0.33	0.94	23.65
6	2.35	18.07	0.00	0.30	0.34	0.92	227.86
7	3.80	29.15	0.00	0.30	0.33	0.98	360.41
8	1.50	6.75	0.00	0.30	0.33	0.90	79.53
9	1.14	2.77	0.00	0.30	0.33	0.99	22.67
10	1.35	6.55	0.00	0.30	0.34	0.99	80.28

Volatility Intraday volatility does not follow U-shaped profile. It is high at the open but does not increase into the close. (pp. 70–71)

Stability Intraday trading stability is high variation in volumes at the open, leveling off mid-day, and decreases into the close. (p. 72)

Of the four facts, it may be relatively meaningful to calculate intraday bid-ask spread and trading volume due to limited period in the contest. Figures 12.8 and 12.9 show the two measures of both trading contest and computer simulation, respectively. As in these figures, neither of them is observed. This may be because the students did not fully understand what futures market is or how call market worked. In addition, as explained before, they did not master computer programming so much or were not so motivated.

Table 12.7 Bid-ask spread (effective spread)

a. Round 1							
Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	11.49	17.14	0.00	1.50	7.00	14.13	134.50
2	12.46	17.98	0.00	1.50	8.25	16.63	143.00
3	11.40	16.93	0.00	1.50	7.00	14.13	142.50
4	11.57	16.75	0.00	1.50	7.50	14.50	146.50
5	12.60	20.10	0.00	0.88	8.00	16.75	162.00
6	12.13	16.41	0.00	1.50	6.75	16.50	125.00
7	11.38	17.04	0.00	1.50	7.25	14.50	144.00
8	12.14	18.01	0.00	1.50	8.00	13.50	132.50
9	12.77	18.02	0.00	1.50	9.00	15.50	141.50
10	11.72	19.35	0.00	1.00	7.00	13.50	162.00

b. Round 2							
Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	30.03	77.32	0.00	2.00	13.50	27.75	732.00
2	27.76	79.18	0.00	3.38	14.00	29.63	961.00
3	24.08	41.05	0.00	2.50	14.50	29.63	403.00
4	21.74	26.00	0.00	4.00	14.50	29.13	143.00
5	22.57	28.12	0.00	3.25	13.25	29.50	169.00
6	22.36	37.70	0.00	2.88	13.25	27.50	397.00
7	27.99	81.39	0.00	4.50	17.25	30.63	1008.00
8	21.32	29.00	0.00	2.38	12.50	26.00	173.00
9	20.70	23.54	0.00	4.50	13.50	25.50	108.50
10	21.73	25.81	0.00	2.88	14.50	29.50	137.00

12.3.4 Classification of the Submitted Trading Agents

In the beginning of this session, the author briefly summarized the submitted trading agents. But, as in Table 12.3, the classification is rather descriptive. Likewise, it can be said that neither the market dynamics nor market microstructure was reproduced in the experiments. Here, to see how the submitted trading agents behaved both in the contest and in the simulations, the author employed cluster analysis. By doing so, when and how many assets the trading agents buy or sell in U-Mart will be quantitatively categorized and characterized.

To conduct the analysis, the author calculated the following items for the trading contest and computer simulation, respectively:

- The frequency of buy/sell orders
- The average bid/ask futures price minus the preceding futures price
- The average amount of buy/sell orders at a time
- The average difference of futures price for a buy/sell order
- The average difference of spot price for a buy/sell order
- The average difference between spot price and futures price for a buy/sell order

Table 12.8 Bid-ask spread (weighted value)

a. Round 1

Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	996.41	153.28	92.71	977.29	1032.43	1075.83	1135.19
2	852.21	184.37	104.27	732.63	884.07	1003.65	1123.06
3	842.80	228.08	81.69	711.79	901.97	1025.61	1128.91
4	999.18	143.13	101.65	972.27	1024.93	1073.52	1128.17
5	959.47	210.60	122.11	961.56	1035.83	1080.80	1132.25
6	966.05	195.89	123.52	960.72	1033.04	1076.68	1136.92
7	965.21	195.84	103.73	959.46	1026.08	1076.39	1132.75
8	937.22	256.90	81.74	962.63	1030.94	1072.30	1136.96
9	960.40	194.06	135.77	956.82	1014.17	1073.87	1131.65
10	818.26	218.78	90.73	631.41	866.71	1017.60	1115.42

b. Round 2

Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	380.86	178.19	−30.45	255.71	345.24	497.42	958.81
2	396.50	188.27	70.56	266.82	357.75	496.56	1068.14
3	399.14	177.39	124.56	275.48	363.55	508.56	1033.15
4	398.39	174.59	22.42	269.81	354.71	527.09	909.45
5	393.74	170.38	−64.71	267.85	379.57	504.90	884.12
6	414.01	148.66	15.65	287.34	381.95	537.59	995.52
7	401.94	186.07	78.73	263.32	352.01	515.48	1000.53
8	402.37	190.72	31.02	259.24	370.34	521.62	988.30
9	417.67	188.68	−111.18	271.91	384.31	543.89	1025.32
10	412.42	177.27	97.52	281.76	367.50	543.55	984.92

Table 12.9 An example of large bid-ask spread in Round 2

a. Before			b. After		
Bid	Price	Ask	Bid	Price	Ask
7792	3386-	632	10	3376	0
0	3391	10	0	3391	0
50	3394	0	0	3394	0
38	3397	0	0	3397	0
57	3401	0	0	3401	0
116	3423	0	0	3423	0
27	3427	0	0	3427	0
354	3561	0	0	3561	0
0	4960	200	0	4960	200

After having a dendrogram[14] in each contest set, the author split them into five (Round 1) or six (Round 2) clusters in Fig. 12.10.[15]

[14] The agglomeration method was “ward.D2” in R.

[15] Before obtaining the dendrogram, the author extracted several trading agents as outliers because the distance is quite large. They are as follows: 1–6, 1–30, 1–50, 1–51, 1–76, and 1–80 in Round 1 and 2–6, 2–30, and 2–80 in Round 2.

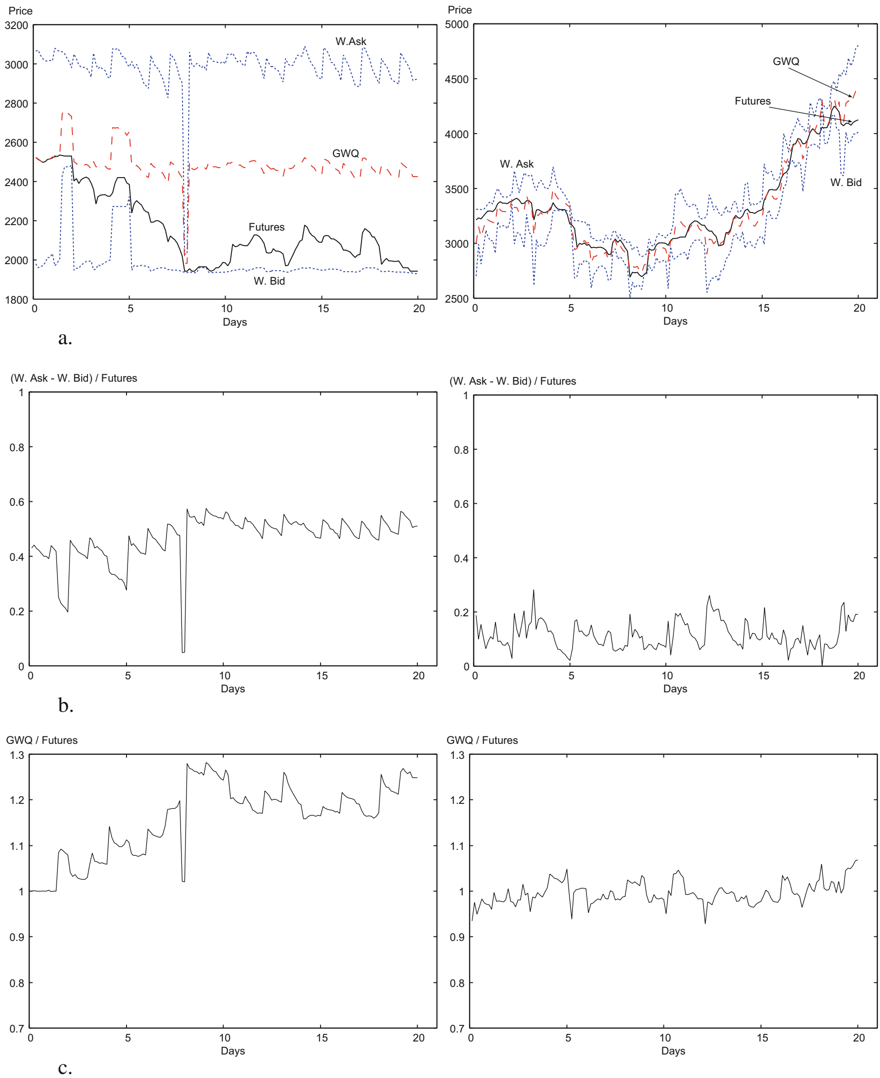


Fig. 12.5 Time series plot of weighted forecast prices (left panel: Round 1 and right panel: Round 2). (**a**) Weighted forecast prices (GWQ is the mid-point price between weighted ask and weighted bid). (**b**) Ratio of the differences between weighted ask and weighted bod to the futures prices. (**c**) Ratio of the mid-point weighted prices to the futures prices

Then, the author compared each of the above defined items between the clusters by Kruskal–Wallis test, and Table 12.15 summarizes which item has statistically significant differences between the clusters. In both rounds, mainly the number of orders, the bid/ask price minus the preceding futures price, and the amount of order

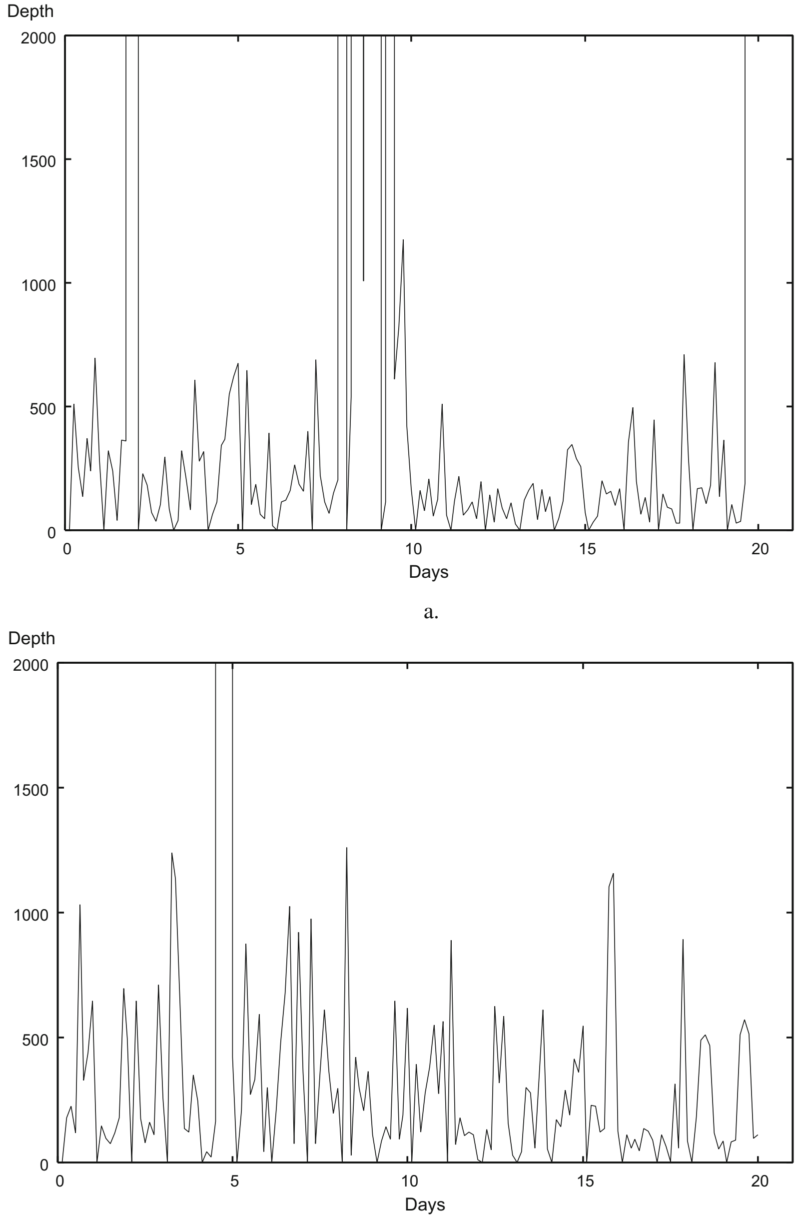


Fig. 12.6 Time series of market depth. (**a**) Round 1. (**b**) Round 2

Table 12.10 Market depth

a. Round 1

Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	13,966.38	65,825.92	0.00	61.75	157.00	344.25	411,099.00
2	10,304.28	56,513.16	0.00	55.25	146.00	311.75	374,437.00
3	16,688.54	81,688.71	0.00	54.00	152.00	312.75	727,892.00
4	6577.53	36,486.69	0.00	67.50	150.00	273.75	316,611.00
5	18,077.68	92,702.55	0.00	83.50	168.00	354.50	730,432.00
6	11,784.24	58,471.56	0.00	82.75	143.00	283.25	418,633.00
7	15,420.16	73,022.77	0.00	77.00	152.50	323.25	473,004.00
8	22,463.97	99,150.62	0.00	69.50	129.50	334.50	727,292.00
9	9049.56	48,289.38	0.00	56.75	117.50	236.25	408,978.00
10	17,221.81	92,618.46	0.00	83.75	164.50	340.50	730,482.00

b. Round 2

Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	5488.78	37,791.34	0.00	79.00	176.00	424.75	280,749.00
2	3896.57	32,185.41	0.00	77.00	184.50	396.00	290,897.00
3	2096.69	22,871.15	0.00	74.00	181.50	390.50	289,560.00
4	2117.66	23,026.47	0.00	68.50	142.00	394.25	291,516.00
5	9360.79	60,497.52	0.00	79.50	157.50	342.50	581,124.00
6	242.23	276.08	0.00	71.50	145.00	353.25	1757.00
7	2094.49	22,498.80	0.00	72.75	176.50	444.75	284,874.00
8	8923.84	57,576.04	0.00	67.75	133.50	343.00	553,698.00
9	288.33	390.83	0.00	53.50	134.00	328.25	2192.00
10	270.17	295.07	0.00	69.00	173.50	367.00	1546.00

are the key factors. From now on, the author will discuss how the trading agents in each category behaved mainly in each round.

- Round 1 (Fig. 12.11)

  The frequencies of order submission were not so different between the clusters when the agents were going to buy or sell,[16] but the amount of their buy/sell orders and the bid/ask price are significantly different: on the one hand, when they were going to buy, the agents of Cluster 5 wanted to buy at a higher price, while the prices at which the others submitted were around the preceding futures one. Instead, the agents of Cluster 5 did not submit so many buy orders. Rather, the amount of the buy orders submitted by the agents of Cluster 3 was around 1250. On the other hand, when they were going to sell, the agents of Clusters 4 and 5 had a tendency to submit a higher price, while those of Clusters 2 and 3

[16] In computer simulations, the agents of Cluster 1 submitted buy orders more often than those of Clusters 2 to 5, whereas those of Clusters 2 and 3 would not submit sell orders compared to those of Clusters 1, 4, and 5.

Table 12.11 Correlations between bid-ask spread and market depth

a. Round 1

Sample path	Raw	Effective	Mid-point	Weighted
1	−0.032	−0.154	−0.031	−0.183
2	−0.027	−0.068	−0.026	−0.153
3	−0.061	0.370	−0.024	−0.404
4	−0.023	−0.128	−0.023	−0.357
5	−0.096	0.688	−0.022	−0.336
6	−0.028	−0.139	−0.027	−0.111
7	−0.043	−0.152	−0.041	−0.096
8	−0.115	0.399	−0.071	−0.524
9	−0.018	−0.026	−0.019	−0.237
10	−0.114	0.723	−0.078	−0.211

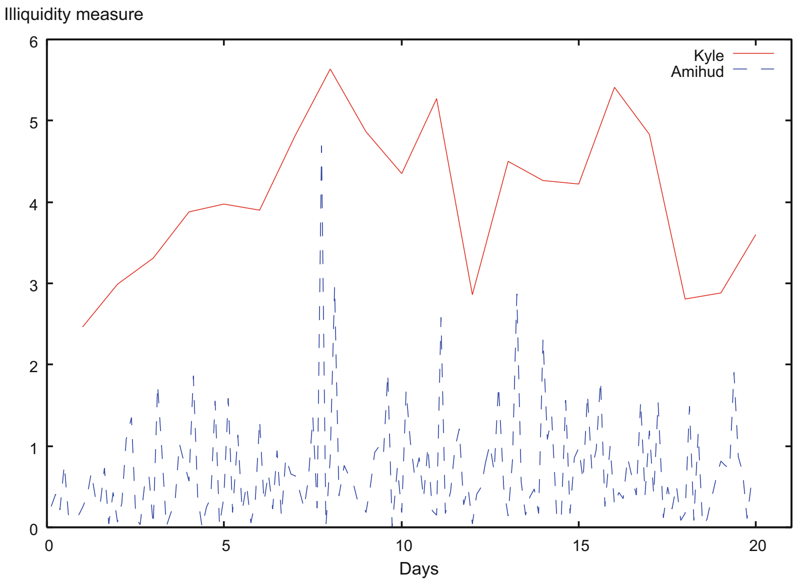
b. Round 2

Sample path	Raw	Effective	Mid-point	Weighted
1	−0.023	−0.032	−0.024	−0.205
2	−0.013	−0.013	−0.014	−0.183
3	−0.011	0.010	−0.012	0.010
4	−0.016	0.024	−0.014	0.018
5	−0.066	0.250	−0.052	−0.263
6	−0.039	−0.068	−0.037	−0.242
7	−0.008	−0.022	−0.008	−0.034
8	−0.038	0.261	−0.028	−0.242
9	0.020	−0.155	0.017	0.020
10	0.234	0.089	0.240	−0.108

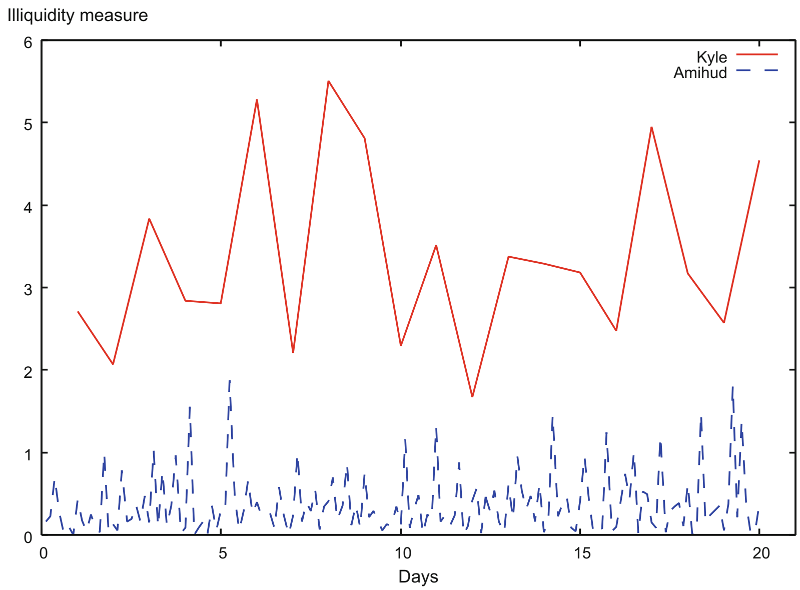
were willing to sell more than those in the other clusters. Note that the outlier agents submitted either so many buy/sell orders or a huge amount of orders.

- Round 2 (Fig. 12.12)

  In terms of buy order, the agents of Cluster 2 did not want to do so, but once they decided to submit their order, their bidding price was quite lower than the preceding settled futures one with more volume. This means they wanted to buy the asset only when the price would drop. The similar trading pattern corresponds to Cluster 6. The agents of Cluster 5 have a tendency to sell the futures asset at a higher price, meaning that they wanted to buy the asset surely whenever they decided to do so. On the other hand, in terms of sell order, the agents of Cluster 2 were going to sell the futures asset at around the preceding settled price, but their orders were relatively small. The behaviors of Clusters 5 and 6 were also similar to those in cases of buy orders. Note that, as just mentioned before, the outlier agents submitted either so many buy/sell orders or a huge amount of orders.



a.



b.

Fig. 12.7 Time series of two market illiquidity measures. (**a**) Round 1. (**b**) Round 2

Table 12.12 Kyle's λ (daily, $\times 10^{-4}$)

a. Round 1

Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	4.04	0.95	2.46	3.23	4.10	4.83	5.64
2	4.01	0.95	2.45	3.05	4.10	4.69	5.54
3	4.06	1.13	2.47	3.05	4.09	4.69	6.99
4	3.99	0.98	2.47	3.24	3.94	4.59	6.45
5	4.01	1.00	2.46	2.99	4.23	4.64	6.13
6	4.01	1.00	2.46	3.31	4.18	4.56	6.45
7	4.00	0.90	2.47	3.30	4.08	4.61	5.70
8	4.05	0.92	2.44	3.11	4.14	4.75	5.69
9	4.07	0.96	2.46	3.22	4.16	4.72	5.75
10	4.04	1.14	2.46	3.02	4.04	4.62	6.80

b. Round 2

Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	3.36	1.13	1.67	2.54	3.18	4.01	5.51
2	3.33	1.04	1.70	2.61	3.19	3.99	5.18
3	3.34	1.14	1.83	2.43	3.13	4.08	5.50
4	3.20	1.14	1.88	2.25	2.89	3.77	5.60
5	3.42	1.10	1.73	2.63	3.32	4.06	5.33
6	3.50	1.17	1.80	2.70	3.28	4.03	5.74
7	3.27	1.09	1.74	2.33	2.97	3.84	5.21
8	3.39	1.15	1.88	2.50	3.24	4.10	5.31
9	3.56	1.28	1.96	2.61	3.19	4.51	5.92
10	3.47	1.12	2.02	2.70	3.23	4.19	5.61

12.3.5 Discussion

It has been about two decades since the birth of U-Mart, and lots of contributions have been made in economic and engineering literature. At the same time, it has been widely used in educational program for teaching computational economics. However, our computational results provide with some possible drawbacks or open questions remaining in the U-Mart. In this part of the section, we address what the U-Mart is required for the future.

First, we guess that not allowing trading agents to cancel their past and uncontracted orders may worsen some bid-ask spread and the market depth. We should implement another experiment taking into consideration this effect.

Second, as well as cancellation of orders, when implementing a laboratory experiment with human subjects and trading agents, the U-Mart project members should make it possible to standardize the experimental designs such as market order or information availabilities. So far, as the author knows, only human subjects are allowed to cancel their mistaken/undesirable orders, submit market orders, or

Table 12.13 Amihud's illiquidity (daily, $\times 10^{-9}$)

a. Round 1

Sample path	Mean	Std. dev.	Min.	25%	Median	75%	Max.
1	6.83	1.90	2.88	5.72	7.21	7.70	10.55
2	6.83	2.20	2.83	5.68	6.60	7.95	10.65
3	6.82	2.39	2.58	5.49	6.69	8.27	12.00
4	6.44	1.55	2.87	5.93	6.63	7.37	9.26
5	6.44	1.93	2.83	5.30	7.01	7.76	10.14
6	6.83	1.87	2.89	5.96	6.99	8.24	9.50
7	6.39	1.75	2.87	5.36	6.53	7.55	9.67
8	6.62	1.92	2.80	5.79	6.94	7.55	9.77
9	6.52	1.71	2.81	5.42	6.88	7.70	9.31
10	6.75	2.49	2.83	5.78	6.21	7.50	13.94

b. Round 2

Sample path	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	3.63	1.07	1.78	2.87	3.77	4.26	5.77
2	3.83	1.31	1.76	2.70	4.01	4.67	6.25
3	3.78	1.28	1.74	2.89	3.95	4.41	5.99
4	3.92	1.32	1.74	2.52	4.27	4.90	4.30
5	3.78	1.20	1.73	2.94	3.63	4.36	6.38
6	4.10	1.30	1.90	3.09	4.41	4.90	6.30
7	3.68	1.30	1.52	2.40	4.02	4.56	6.32
8	4.04	1.50	1.80	2.66	4.12	4.69	7.25
9	4.05	1.15	1.80	2.95	3.78	5.19	6.92
10	3.63	1.21	1.76	2.69	3.55	4.46	5.95

Table 12.14 Correlation between Kyle's λ and Amihud's illiquidity

Round	Mean	Std. Dev.	Min.	25%	Median	75%	Max.
1	0.764	0.075	0.614	0.724	0.761	0.808	0.862
2	0.633	0.132	0.408	0.513	0.691	0.734	0.785

monitor the board in the market. This would hinder detailed investigation except the one on information asymmetry (Ranaldo 2004).

Third, since the U-Mart is an artificial "futures" market, it would be fine if the spot asset is tradable in the market. As some experimental economic researches, introducing futures market leads the prices in spot market to fundamental values and then diminishes the bubble trend (Noussair and Tucker 2006). If it becomes possible to trade not only futures but also spot asset in U-Mart, researchers will be able to reconfirm the market microstructure in another way (Phylaktis and Manalis 2008).

Fourth, more comparison with other studies is also required; for instance, since the time series data used in Round 1 is NIKKEI 225, the comparisons of the

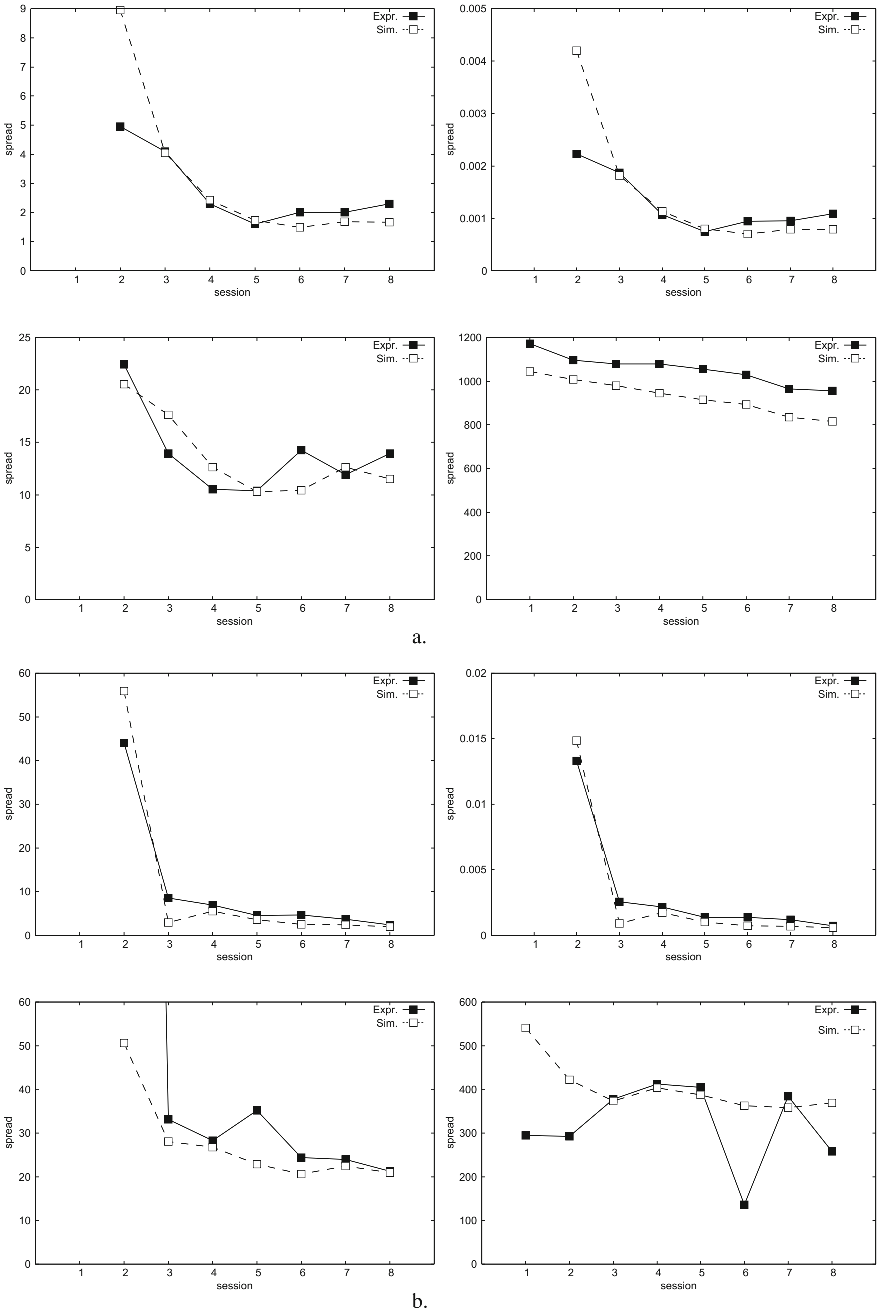


Fig. 12.8 Intraday bid-ask spread (top left: simple spread, top right: mid-point spread, bottom left: effective spread, and bottom right: weighted spread). (**a**) Round 1. (**b**) Round 2

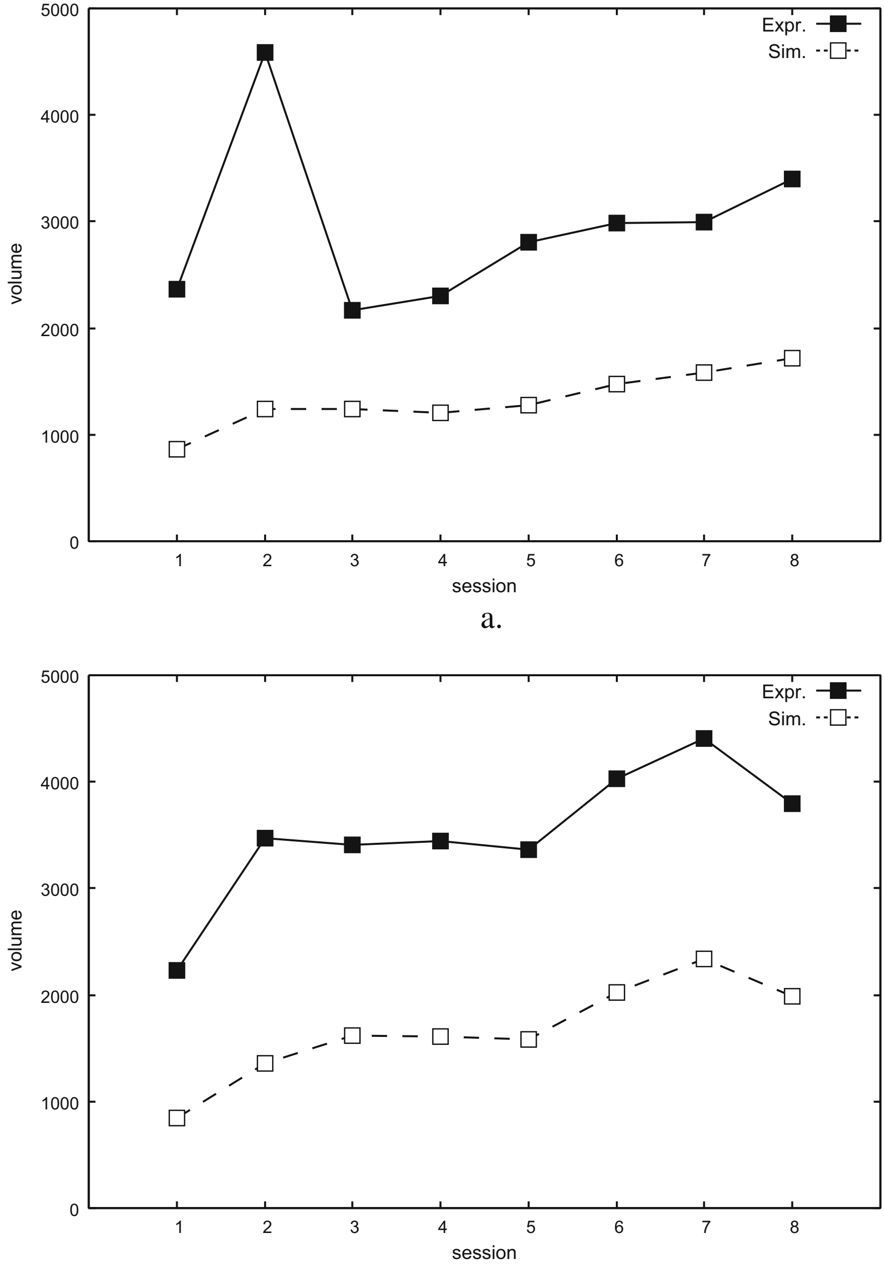


Fig. 12.9 Intraday trading volume. (**a**) Round 1. (**b**) Round 2

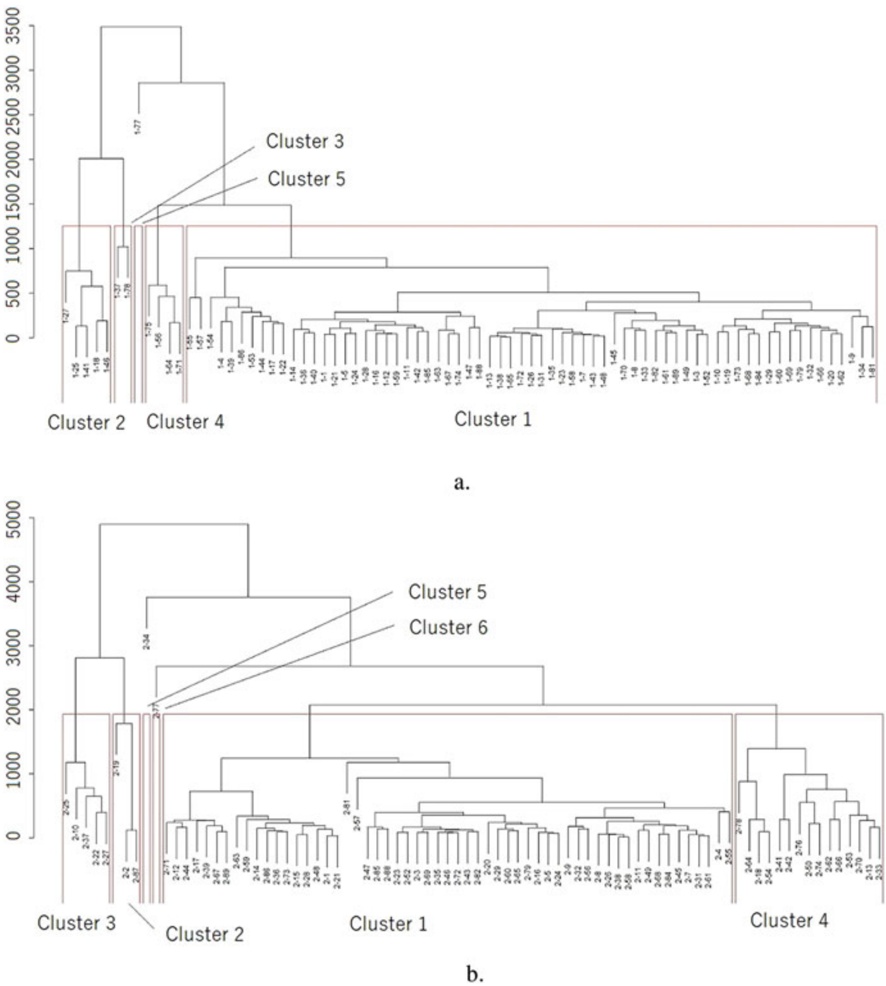


Fig. 12.10 Generated dendrograms after several outliers were deleted. (**a**) Round 1. (**b**) Round 2

computational results and the empirical findings (e.g., Kim et al. 2002) would be helpful to improve the design of laboratory experiment and computer simulation. Or, that the trading agent is allowed to do only limit orders means that it is possible to confirm what is different from the market microstructure in actual limit order books (e.g., Rakiwski and Beardsley 2008). On the other hand, in the experimental economic literature, Bloomfield and O'Hara (1999) and Bloomfield et al. (2005) have investigated the effects of information disclosure on market microstructure and welfare of market participants in an electronic limit order market. Besides, Raberto et al. (2005) and Consiglio and Russino (2007) have employed agent-based approach to investigate the relations between market liquidity and prices. Especially,

Table 12.15 Result of Kruskal–Wallis test (x: statistically significant differences between the clusters at 5% level)

a. Round 1

		Nos.	Price	Volume	ΔFutures	ΔSpot	F-S spread
Expr.	Buy		x	x			
	Sell		x	x			
Sim.	Buy	x	x	x			
	Sell	x	x	x			

b. Round 2

		Nos.	Price	Volume	ΔFutures	ΔSpot	F-S spread
Expr.	Buy	x	x	x			
	Sell	x		x	x		x
Sim.	Buy	x		x			
	Sell	x	x	x			

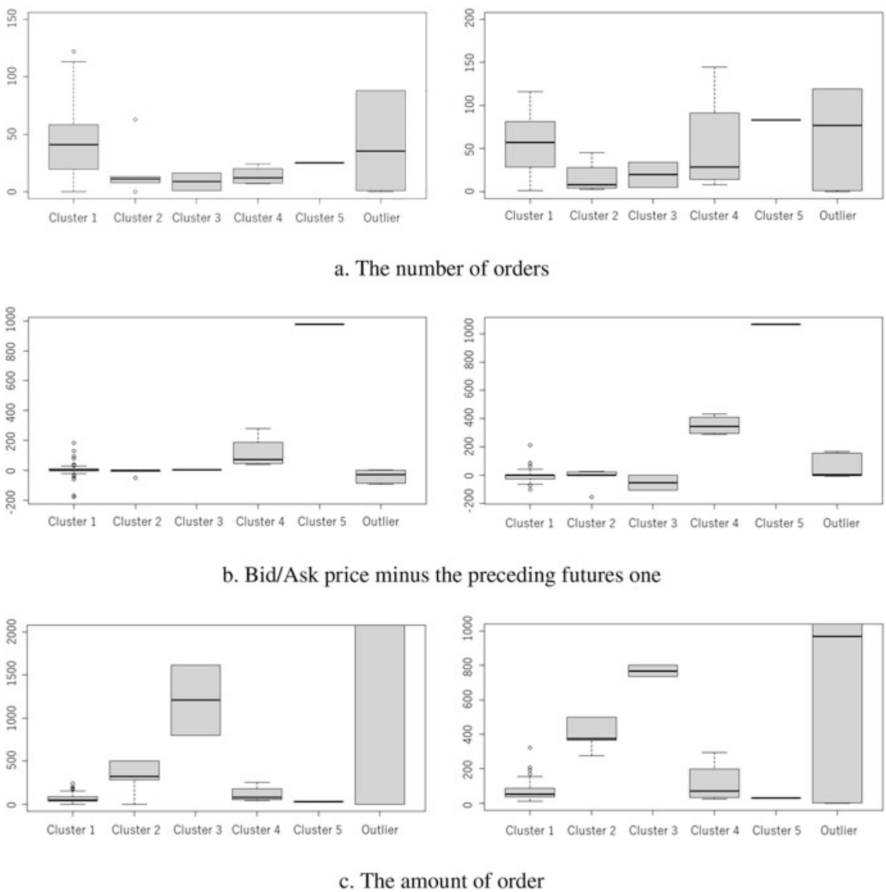


Fig. 12.11 Average behaviors of each cluster in Round 1 (Left panel: Buy, Right panel: Sell)

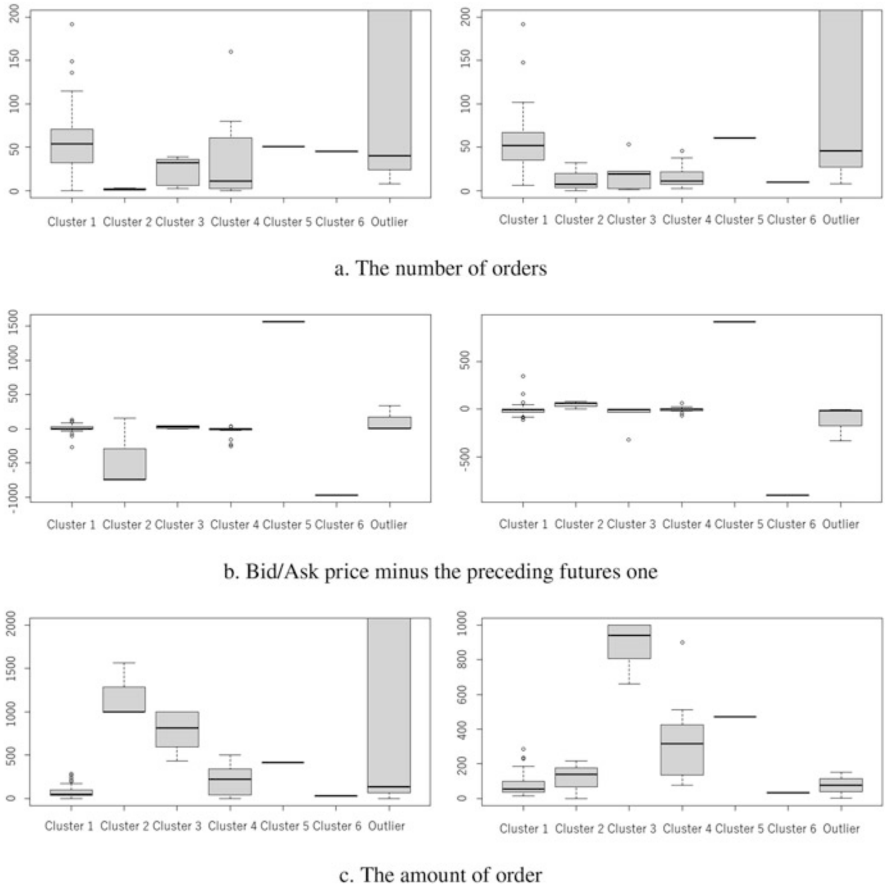


Fig. 12.12 Average behaviors of each cluster in Round 2 (Left panel: Buy, Right panel: Sell)

since the Genoa artificial stock market in Raberto et al. enables the agents to do a market order, it is necessary to check whether the same computational results are obtained in the U-Mart and vice versa.

12.4 Concluding Remarks

This chapter introduces how U-Mart was used at a graduate school of engineering to teach economics/financial markets as well as computer programming and system modeling. Here, the author reports a strategy experiment with human subjects and their submitted trading agents by focusing on market microstructure to see the relations between the evolution of their trading strategy and the characteristics of order book. The analyses are summarized as follows: first, although many of the students did not write a long or sophisticated trading agent, they did their best to improve their strategy. Second, although some mispricing effects failed to replicate the bid-ask spread and the market depth properly in some regards, the appropriate weighted bid-ask spread and two market illiquidity measures, Kyle's λ and Amihud's illiquidity measure, are observed. This chapter also discusses what the U-Mart is required for the future from the viewpoints of experimental economics and teaching economics in classroom.

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Chapter 13
Artificial Intelligence (AI) for Financial Markets: A Good AI for Designing Better Financial Markets and a Bad AI for Manipulating Markets

Takanobu Mizuta

Abstract I introduced a good AI for finance, an artificial market (an agent-based model for a financial market) to design a financial market that works well, and a bad AI for finance, an AI trader that discovers how to manipulate markets through learning in an artificial market. First, I describe an artificial market for designing a financial market that works well. Artificial markets have recently been used to develop and examine rules and regulations such as tick size reduction in actual financial markets. Their influence is growing. A good market design is important for developing and maintaining an advanced economy. Second, I show that an AI trader that learns in an artificial market can discover how to manipulate a market and use that capability as an optimal investment strategy even when the developer of the AI has no such intention, and the result suggests the need for regulation. These stories show that there are both good and bad AIs for society. We should not discuss whether AIs on the whole are good or bad, but rather how to manage them so that they are useful tools. To do that, we should discuss rules, ethics, and philosophy for AIs.

Keywords Agent-based model · Artificial market model · Multi-agent simulation · Market design · Market manipulation · Genetic algorithm

Note that the opinions contained herein are solely those of the authors and do not necessarily reflect those of SPARX Asset Management Co., Ltd.

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13.1 Introduction

In this study, I introduce a good artificial intelligence (AI) for finance, an artificial market model (an agent-based model for a financial market) to design a financial market that works well, and a bad AI for finance, an AI trader that discovers how to manipulate markets through learning in an artificial market even when the person who built the AI trader has no intention of market manipulation.

Artificial intelligences, including those based on machine learning, agent-based models, and so on, are being used more and more often in finance. An agent-based model for a financial market is called as an artificial market model.

Section 13.2 is introduction according to a paper by Mizuta (2020), artificial market models can be used to design financial markets that work well. Designing a financial market that works well is very important for developing and maintaining an advanced economy, but it is not easy because changing detailed rules, even ones that seem trivial, sometimes causes unexpected large impacts and side effects. Therefore, we can say that AIs for market design are good for society.

A computer simulation using an agent-based model can directly treat and clearly explain complex systems where micro processes and macro phenomena interact. In particular, many effective agent-based models have been developed for investigating human behavior. Recently, artificial market models, which are agent-based models of financial markets, have started to be used to develop and discuss rules and regulations for actual financial markets.

In Sect. 13.2, I describe an artificial market model that be of help to design financial markets that work well and an artificial market model of suitable complexity. I discuss the advantages and disadvantages of artificial market models and their validation. Then, I describe a previous study investigating tick size reduction. Note that Mizuta (2016) reviewed other previous artificial market models for designing financial markets. I hope that more artificial market models will contribute to the design of financial markets that work for the benefit of advanced economies.

Section 13.3 describes a trade-execution algorithm using AI that learns in an artificial market (Karpe et al. 2020). Such an algorithm already exists (Karpe et al. 2020). Besides trade-execution AIs, AI traders that learn in artificial markets by trying a variety of trading strategies have been the topic of many studies, including ones on AI technical traders (Izumi et al. 2009) and an AI portfolio manager (Kuo et al. 2021). These algorithms are useful for trading on actual financial markets.

However, no one can predict what kinds of AI traders will emerge in the future. Section 13.4, which is based on the paper by Mizuta (2020), describes an AI trader which discovers how to manipulate markets through learning in an artificial market. This trader learns how to manipulate a market even if it is not the intention of the person who built it. We consider that such an AI is bad for society. The question is thus who should be held responsible when an AI performs market manipulation.

I devised an AI trader using a genetic algorithm that learns in an artificial market simulation. Then, I investigated whether the AI trader can discover market manipulation through learning even though the AI developer had no intention of manipulating the market. The results show that the AI trader discovered market manipulations that it could use as an optimal investment strategy. This suggests that regulation is necessary, such as requiring the developers to prevent AIs from performing market manipulation. The results also suggest that the developers should limit AI traders to avoid impacting market prices.

The final section (Sect. 13.5) concludes this chapter.

13.2 Artificial Market Model: An Agent-Based Model for a Financial Market

This section is an introduction to the paper by Mizuta (2020) on artificial market models for designing financial markets that work well, i.e., good AIs for society.

13.2.1 Importance and Difficulty of Market Design

People have been able to develop advanced economies by cooperating to exchange goods for money. Creation in any industry requires investment to purchase or build tools to make goods. Thus, a financial market that enables smooth investment is an obvious requirement.

The economist John McMillan, who used game theory to investigate many markets, said "a market works well only if it is well designed" (McMillan 2002). The design of a market (of its regulations, rules, etc.) determines whether it works well or poorly. McMillan also concluded that "the economy is a highly complex system. It is at least as complex as the systems studied by physicists and biologists." The computer scientist Melanie Mitchell said "economies are complex systems in which the simple, microscopic components consist of people buying and selling goods, and the collective behavior is the complex, hard-to-predict behavior of markets as a whole, such as fluctuations in stock prices" (Mitchell 2009). A financial market is a highly complex system where the sum total of micro processes (trader behaviors) never accounts for macro phenomena (price formation). Changes to the detailed rules, even ones that seem trivial, sometimes have unexpectedly large impacts and side effects. McMillan illustrated this by stating "both God and the devil are in the details." Designing a market well is thus very important for developing an advanced economy, but it is not easy.

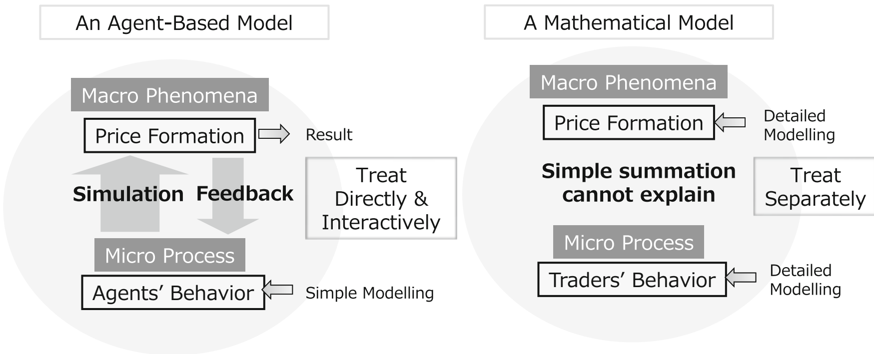

Fig. 13.1 Features of an agent-based model (left) and a mathematical model (right)

13.2.2 An Agent-Based Model Explaining a Complex System

Figure 13.1 shows the features of an agent-based model and a mathematical model. Separately investigating macro phenomena and micro processes unclearly explains complex systems where macro phenomena and micro processes interact. Mathematical models cannot be used to directly treat or clearly explain the interactions because micro processes and macro phenomena are separately modeled and the macro phenomena are not a simple sum of micro processes even if the models are detailed and precise (the right of Fig. 13.1).

A computer simulation using an agent-based model, on the other hand, can directly treat and clearly explain the interactions[1] because, in an agent-based model, macro phenomena are not modeled but outputted as results of simulations of agent behaviors; the macro phenomena are reflected in the complexity of the system even if the micro model is simple (the left of Fig. 13.1). An agent-based model includes agents modeling trader behaviors and shows macro phenomena as a result of their interactions. Agent behaviors that are simple but affect macro phenomena cause complex macro phenomena, which are not a simple sum of the agent behaviors. Thus, an agent-based model can give researchers new knowledge. Moreover, as it requires no data, it is a true computer simulation. These micro–macro interactions sometimes give rise to strong phenomena called "micro–macro feedback loops" or "positive feedback loops" in which some micro processes strengthen some macro phenomena, the macro phenomena strengthen the micro processes, and these strengthenings continue as a loop.

Not only financial markets are complex. Many studies have devised agent-based models of social systems. For example, a study may consider the effect of new roadways on traffic jams or determine an evacuation route in a building on fire

[1] Sabzian et al. provide a comprehensive review of agent-based models for complex systems (Sabzian et al. 2018).

or under terrorist attack. Also, the researchers naturally use various approaches to solve such problems: mathematical model, empirical studies, and agent-based models. Each approach has its advantages and disadvantages and gives researchers various viewpoints and knowledge with which to find unexpected side effects. Here, agent-based models are considered to be as important as mathematical models and empirical studies.

13.2.3 An Artificial Market Model = An Agent-Based Model for a Financial Market

An artificial market model is an agent-based model for a financial market. There are thorough great reviews on such model (LeBaron 2006; Chakraborti et al. 2011; Chen et al. 2012; Cristelli 2014; Todd et al. 2016; Mizuta 2016, 2020). Numerous significant artificial market models (Takayasu et al. 1992; Izumi and Okatsu 1996; Arthur et al. 1997; Lux et al. 1999) have been developed since their first appearance in the 1990s. Because of their generality, they are often qualitative. In particular, artificial markets have been used to investigate the mechanism by which stylized facts[2] (fat-tails, volatility-clustering, and so on) emerge (Takayasu et al. 1992; Lux et al. 1999).

Here, let us briefly examine the nature of financial market phenomena such as bubbles and crashes, as described in Izumi and Okatsu (1996), Arthur et al. (1997). It is said that micro–macro feedback loops have played very important roles in bubbles and crashes, and artificial market models can directly treat such loops. A number of projects have built generic artificial market models, such as the U-mart project in Japan in the 2000s. (Kita et al. provide a comprehensive review of the U-mart project (Kita et al. 2016).) These projects have helped to explain the nature of financial market phenomena and the mechanism by which stylized facts emerge.

Artificial market models, however, have rarely been used to investigate the rules and regulations of financial markets. After the bankruptcy of Lehman Brothers in 2008, some researchers argued that traditional economics had not found ways to design markets that work well but suggested that an artificial market model could do so. Indeed, in Science, Battiston et al. (2016) explained that "since the 2008 crisis, there has been increasing interest in using ideas from complexity theory (using network models and agent-based models) to make sense of economic and financial markets," and in Nature, Farmer and Foley (2009) explained that "such (agent based) economic models should be able to provide an alternative tool to give insight into how government policies could affect the broad characteristics of economic performance, by quantitatively exploring how the economy is likely to react under

[2] A stylized fact is a term used in economics to refer to empirical findings that are so consistent (for example, across a wide range of instruments, markets, and time periods) that they are accepted as truth (Sewell 2011).

different scenarios." Richard Bookstaber, an expert on risk management who has worked for investment banks and hedge funds, wrote a book (Bookstaber 2017) that "provides a nontechnical introduction to agent-based modeling, an alternative to neoclassical economics that shows great promise in predicting crises, averting them, and helping us recover from them." In 2010, Jean-Claude Trichet then, President of the European Central Bank (ECB) (Trichet 2010), stated that "agent-based modelling dispenses with the optimization assumption and allows for more complex interactions between agents. Such approaches are worthy of our attention."

Financial regulators and exchanges, who decide rules and regulations, are especially interested in using artificial market models to design a market that works well. Indeed, the Japan Exchange Group (JPX), which is the parent company of the Tokyo Stock Exchange, has published 36 JPX working papers, including 10 on using artificial market models, as of June 2021.[3]

Also, in Europe, a three-year project (2014–2017) undertaken by the European Commission to integrate macro-financial modeling for robust policy design included a work package named "bridging agent-based and dynamic-stochastic-general-equilibrium modeling approaches for building policy-focused macro-financial model" (Hommes and Breen 2018). The Bank of England also published a working paper investigating the effects of passive funds in a bond market by using an artificial market model (Braun-Munzinger et al. 2016).

Mizuta (2016) reviewed other previous agent-based models for designing a financial market that works well.

13.2.4 Suitable Complexity, Advantages, and Disadvantages

Here, I will discuss features that an artificial market model for designing a financial market should have. Such models aim not to forecast accurately but to design a financial market that works well. To determine what the best design is, acquiring knowledge of what mechanisms affect prices is more important than replicating a real financial market.

Such a model must be able to reveal possible mechanisms that affect price formation through many simulation runs, e.g., searches for parameters or comparing situations before and after specific changes are made. The possible mechanisms revealed by these runs provide new knowledge and insights into the effect of the changes on price formation in actual financial markets. Other methods of study, e.g., empirical studies, would not reveal such possible mechanisms.

Unnecessary replication of macro phenomena leads to models that are overfitted and too complex. Such models would prevent us from understanding and discovering mechanisms that affect price formation because the number of related factors would be so large. Indeed, artificial market models that are too complex are often

[3] https://www.jpx.co.jp/english/corporate/research-study/working-paper/index.html.

criticized as they are very difficult to evaluate (Chen et al. 2012). A model that is too complex not only would prevent us from understanding mechanisms but also could output arbitrary results by overfitting too many parameters. It is more difficult for simpler models to output arbitrary results, so they would be easier to evaluate. Thus, an artificial market model should be built as simply as possible and not intentionally implement agents to cover all the investors in actual financial markets.

As Michael Weisberg mentioned, modeling is “the indirect study of real-world systems via the construction and analysis of models. Modeling is not always aimed at purely veridical representation. Rather, the researchers worked hard to identify the features of these systems that were most salient to their investigations” (Weisberg 2012). Therefore, good models differ depending on the phenomena they focus on. Here, my model is good for the purpose of this study, but it may be not any good for other purposes. An aim of my study is to understand how important properties (behaviors, algorithms) affect macro phenomena and play a role in the financial system rather than representing actual financial markets precisely.

The above discussion holds not only for artificial markets but also for agent-based models used in other fields besides financial markets. For example, Thomas Schelling, who received the Nobel prize in economics, used an agent-based model to discuss the mechanism of racial segregation. The model was built very simply compared with an actual town in order to focus on the mechanism (Schelling 2006). Indeed, while it was not able to predict the segregation situation in the actual town, it was able to explain the mechanism of segregation as a phenomenon.

Harry Stevens, a newspaper writer, simulated an agent-based model to explain the spread of COVID-19 and to find a way how to prevent infection (Stevens 2020). The model is too simple to replicate the real world, but its simplicity enabled it to reveal the mechanism behind the spread.

Michael Weisberg studied what mathematical and simulation models are in the first place and cited the example of a map (Weisberg 2012). Needless to say, a map models geographical features on the way to a destination. The left of Fig. 13.2 is a simple map. We can easily understand the way to the destination. On the other hand, the right of Fig. 13.2 is a satellite photo. The photo replicates actual geographical features very well; however, we cannot easily see the way to the destination.

The title page of the book (Weisberg 2012) cited a passage from a short story by Jorge Borges (1954), “In time, those Unconscionable Maps no longer satisfied, and the Cartographers Guilds struck a Map of the Empire whose size was that of the Empire, and which coincided point for point with it ... In the Deserts of the West, still today, there are Tattered Ruins of that Map, inhabited by Animals and Beggars.” The story in which a map was enlarged to the same size as the real empire to become the most detailed of any map is an analogy to that too detailed a model is not useful. This story gives us one of the most important lessons for when we build and use any model.

Figure 13.3 shows the features of the outputs of an artificial market model and an empirical study. The outputs of the empirical study include only events that happened in a real financial market. The advantage of an empirical study is output

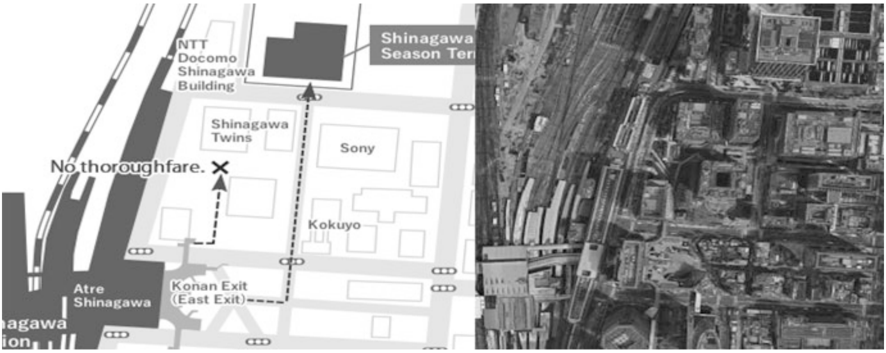

Fig. 13.2 A simple map (left) is a good model to understand a way to a destination, while a satellite photo (right) is a bad model for this purpose even though it replicates actual geographical features very well; (left) from the official web page of Shinagawa Season Terrace (https://shinagawa-st.jp/en/access/train.html) and (right) from Google Maps (Google; Imagery ©2020, CNES/Airbus, Digital Earth Technology, Maxar Technologies, Planet.com, The Geoinformation Group, Map Data ©2020 Google)

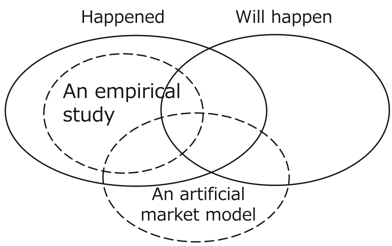

Fig. 13.3 An artificial market model and an empirical study

excludes the all area not happening in the past or future. The disadvantage, however, is output excludes any area happening in the future.

The advantage of an artificial market model is its outputs include possible events in the future. The disadvantage, however, is that its outputs include events that did not occur in the past and will not occur in the future. An artificial market model just outputs "possible" results that reflect the mechanisms of a market. The discussion of whether its outputs will occur or not requires other methods, e.g., empirical studies and mathematical models.

Any discussion on the outputs of an artificial market model must be further informed by knowledge from empirical studies and mathematical models. To work well, a market should be designed by using not one but several methods (an artificial market model, empirical study, and a mathematical model), and these methods should work together to mutually compensate for their disadvantages. As the following subsection shows, an empirical study is useful for validating an artificial market model.

13.2.5 Validation of Artificial Market Model

Many previous studies discussed validations of artificial market models. Here, I recall the argument presented by Mizuta et al. (2016), which asserted that artificial financial market models should replicate at least major stylized facts, i.e., fat-tails and volatility-clustering. A fat-tail means that the kurtosis of price returns is positive. Volatility-clustering means that squared returns have a positive auto-correlation which slowly decays as lag becomes longer.

Many empirical studies, e.g., Sewell (2011), have shown that both stylized facts (fat-tails and volatility-clustering) exist statistically in almost all financial markets. Conversely, they have also shown that only fat-tails and volatility-clustering are stably observed for any asset during any period, because financial markets are generally unstable.

Indeed, the kurtosis of price returns and the auto-correlation of squared returns are stable and significantly positive, but the magnitudes of these values are unstable and vary greatly depending on the asset and/or period. Moreover, the kurtosis of price returns and the auto-correlation of squared returns have been observed to have very broad ranges, about $1 \sim 100$ and about $0 \sim 0.2$, respectively (Sewell 2011).

For the above reasons, an artificial market model should replicate these values as significantly positive and within a reasonable range. It is not essential for it to replicate specific values of stylized facts because the values of these facts are unstable in actual financial markets.

This leads me to the conclusion that an artificial market should replicate macro phenomena existing generally for any asset and at any time, i.e., fat-tails and volatility-clustering.

13.2.6 Case Study: Tick Size Reduction

13.2.6.1 Tick Size Reduction

A typical study of the design of a financial market using an artificial market model is one on tick size reduction (Mizuta et al. 2013) (vol. 2, JPX working paper).

The tick size is the minimum unit of a price change. For example, when the tick size is \$1, order prices such as \$99 and \$100 are accepted, but \$99.1 (\$99 and 10 cent) is not. The Tokyo Stock Exchange used ¥1 as its tick size until 18 July 2014 and has used ¥0.1 (10 sen) since 22 July 2014.

More stock exchanges, especially those in the United States and Europe, are now making full use of information technology (IT) for lowering the costs of their operations. Their market shares of trading volume have caught up with those of traditional stock exchanges. Thus, individual stocks are traded in many stock exchanges at once. Whether such fragmentation makes markets more efficient has been debated (Foucault and Menkveld 2008; O'Hara and Ye 2011). Many factors, such as tick size, speed of trading systems, length of trading hours, stability of trading systems, safety of clearing, and variety of order types, determine the market share of trading volume between actual stock exchanges. A smallness of the tick size is one of the most important factors to be considered when stock exchanges are in competition with one another.

Mizuta et al. (2013) used an artificial market model to investigate competition, in terms of market share of trading volume, between two artificial stock exchanges that had exactly the same specifications except for their tick sizes and initial trading volumes.

13.2.6.2 Model

The model of Chiarella and Iori (2002) is very simple but replicates long-term statistical characteristics observed in actual financial markets: fat-tail and volatility-clustering. In contrast, the model of Mizuta et al. (2013) replicates high-frequency micro-structures, such as execution rates, cancel rates, and one-tick volatility, that cannot be replicated with Chiarella and Iori's model (Chiarella and Iori 2002). Only fundamental and technical analysis strategies that generally exist for any market at any time are implemented in the agent model.

Agents

The number of agents is n. First, at time $t = 1$, agent 1 places an order to buy or sell a stock; then, at $t = 2$, agent 2 places an order to buy or sell. At $t = 3, 4, \ldots, n$, agents $3, 4, \ldots, n$ each place orders to buy or sell. At $t = n + 1$, going back to the first agent, agent 1 places an order to buy or sell, and at $t = n+2, n+3, \ldots, n+n$, agents $2, 3, \ldots, n$ each place orders to buy or sell, and this cycle is repeated. Note that t passes even if no deals have occurred. An agent j determines the order price and buys or sells by using the following process. Agents use a combination of the fundamental and technical analysis strategies to form expectations on the return of a stock. The expected return of agent j at t is

$$r_{e,j}^t = \left(w_{1,j} \log \frac{P_f}{P^{t-1}} + w_{2,j} \log \frac{P^{t-1}}{P^{t-\tau_j-1}} + w_{3,j} \epsilon_j^t \right) / \Sigma_i^3 w_{i,j}, \tag{13.1}$$

where $w_{i,j}$ is the weight of term i for agent j and is independently determined by taking random variables uniformly distributed on the interval $(0, w_{i,max})$ at the start of the simulation for each agent. P_f is the fundamental value and is constant[4]. P^t is the market price of the stock, and ϵ_j^t is determined by random variables taken from a

[4] This enables us to focus on phenomena on short time scales, as the fundamental price remains static.

normal distribution with average 0 and variance σ_ϵ. τ_j is independently determined by taking random variables uniformly distributed on the interval $(1, \tau_{max})$ at the start of the simulation for each agent.[5]

The first term in Eq. (13.1) represents the fundamental strategy: the agent expects a positive return when the market price is lower than the fundamental value, and vice versa. The second term represents the technical analysis strategy: the agent expects a positive return when the historical market return is positive, and vice versa.

The excellent review paper by Chen et al. (2012) summarized previous studies on artificial market models and showed that models including only these two strategies can replicate important stylized facts. As comprehensively reviewed by Menkhoff and Taylor (2007), many empirical questionnaire studies have found these two strategies to be prevalent strategies. An empirical data study gave the same conclusions (Yamamoto 2021).

Laboratory markets in experimental economics have greatly contributed to the above discussion. Parameter fitting of the artificial market model including both fundamental and technical analysis strategies leads to similar results as those of the laboratory market (Haruvy and Noussair 2006). This means that both strategies are needed to replicate the laboratory market, and they may also be needed to replicate real markets.

After the expected return has been determined, the expected price is

$$P_{e,j}^t = P^t \exp(r_{e,j}^t). \tag{13.2}$$

The order price $P_{o,j}^t$ is determined by taking random variables normally distributed with average $P_{e,j}^t$ and standard deviation P_σ, where P_σ is a constant. Whether to buy or sell is determined by the magnitude relationship between $P_{e,j}^t$ and $P_{o,j}^t$:

when $P_{e,j}^t > P_{o,j}^t$, the agent places an order to buy one share, but

when $P_{e,j}^t < P_{o,j}^t$, the agent places an order to sell one share.[6]

Scattering the order prices around the expected price enables the distribution of order prices in a real financial market to be replicated and a simulation to run stably.

Agents always order only one share. The model adopts a continuous double auction, so when an agent orders to buy (sell), if there is a lower price sell order (a higher price buy order) than the agent's order, dealing immediately occurs. Such an order is called a "market order." If there is no lower price sell order (a higher price buy order) than the agent's order, the agent's order remains on the order book. Such an order is called a "limit order." The remaining order is canceled after t_c from the order time. Agents can short sell freely. The quantity of holding positions is not limited, so agents can take any shares for both long and short positions to infinity.

[5] When $t < \tau_j$, however, I set the second term in Eq. (13.1) to 0.

[6] When $t < t_c$, however, to generate enough waiting orders, the agent places an order to buy one share when $P_f > P_{o,j}^t$ or to sell one share when $P_f < P_{o,j}^t$.

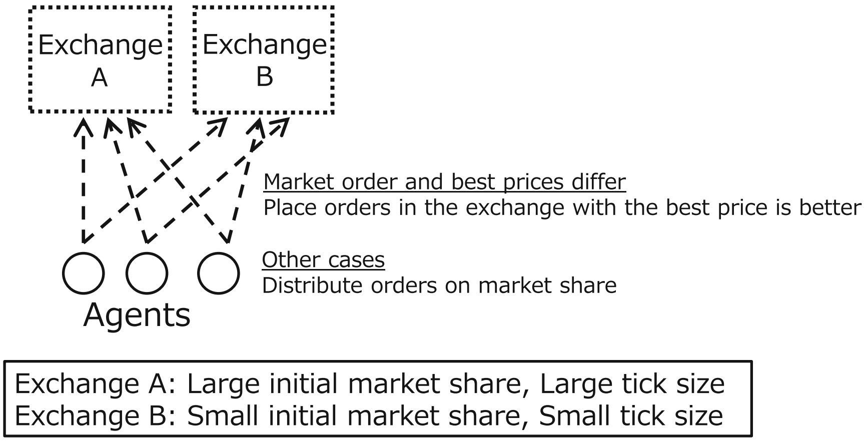

Fig. 13.4 A model selecting a stock exchange to place an order

Selecting a Stock Exchange

The agents trade one stock in two stock exchanges: A and B (Fig. 13.4). The two exchanges have exactly the same specifications except for the minimum unit of a price change (tick size) per P_f, ΔP_A, and ΔP_B. The buy order price is rounded down to the nearest fraction, and the sell order price is rounded up to the nearest fraction. Initial shares of trading volume are W_A and W_B. The agents should decide which exchange they want to make orders in: A or B.

The model of exchange selection is almost the same as the order allocation algorithm (smart order routing, SOR) used in real financial markets. Each agent determines an exchange in which to place every order. When the agent order is "buy" (sell), it searches for the lowest sell (highest buy) orders of each exchange. These prices are called "best prices." When the best prices differ between exchanges and the order is a market order in least one of the exchanges, the agent places an order to buy (sell) in the exchange with the best price, i.e., lower (higher) in the case of the buy (sell) order. In other cases, i.e., when the best prices are exactly the same or the order is a limit order in both exchanges, the agent places an order to buy (sell) in exchange A with probability W_A,

$$W_A = \frac{T_A}{T_A + T_B}, \tag{13.3}$$

where T_A is the trading volume of exchange A within the last t_{AB}, and T_B is that of exchange B. To summarize, if the market order and best prices differ, agents place orders to buy (sell) in the exchange with the best price. In other cases, agents place orders to buy (sell) in exchanges depending on the market share of trading volume.

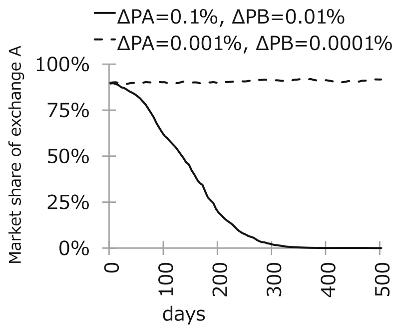

Fig. 13.5 Time evolution of market shares of trading volume where tick sizes are not too small ($\Delta P_A = 0.1\%$, $\Delta P_B = 0.01\%$) and too small ($\Delta P_A = 0.001\%$, $\Delta P_B = 0.0001\%$)

13.2.6.3 Simulation Results

Mizuta et al. (2013) investigated the change in market share of trading volume for two stock exchanges. The two exchanges (A and B) had exactly the same specifications except for tick sizes per P_f, ΔP_A, and ΔP_B and initial market share of trading volume $W_A = 0.9$ and $W_B = 0.1$. They set $n = 1000$, $w_{1,max} = 1$, $w_{2,max} = 10$, $w_{3,max} = 1$, $\tau_{max} = 10000$, $\sigma_\epsilon = 0.06$, $P_\sigma = 30$, $t_c = 20000$, $P_f = 10000$, and $t_{AB} = 10000$ (5 days). The simulations ran to $t = 10000000$.

Figure 13.5 shows the time evolution of market share of trading volume in exchange A, where $\Delta P_A = 0.1\%$, $\Delta P_B = 0.01\%$ and $\Delta P_A = 0.001\%$, $\Delta P_B = 0.0001\%$. In the cases of $\Delta P_A = 0.1\%$, $\Delta P_B = 0.01\%$, and ΔP_B being 1/10th of ΔP_A, exchange B took a market share of trading volume from exchange A. On the other hand, in the $\Delta P_A = 0.001\%$, $\Delta P_B = 0.0001\%$ which is 1/100th of that in the previous case, exchange B could not take a market share despite ΔP_B being 1/10th of ΔP_A. These results show that competition under tick sizes that are too small does not affect taking of market share of trading volume.

Figure 13.6 summarizes the above discussion. When ΔP_A is larger than $\overline{\sigma_t}$ that is the standard deviation of returns for one tick time, which was found approximately 0.05% (Fig. 13.6 top), if ΔP_B is smaller than ΔP_A, there is a large amount of trading in exchange B inside ΔP_A. Thus, exchange B takes a market share of trading volume from exchange A. When ΔP_A is smaller than $\overline{\sigma_t}$ (Fig. 13.6 bottom), even if ΔP_B is very small, price fluctuations cross many widths of ΔP_A and sufficient price formations occur only in exchange A. Thus, exchange B can rarely take any market share of trading volume from exchange A.

Mizuta et al. (2013) showed more detailed results and performed an empirical analysis, comparing its results with the simulation results.

13.2.6.4 Summary

An exchange having a tick size larger than its volatility will lose market share of trading volume to other exchanges. In contrast, an exchange having a tick size

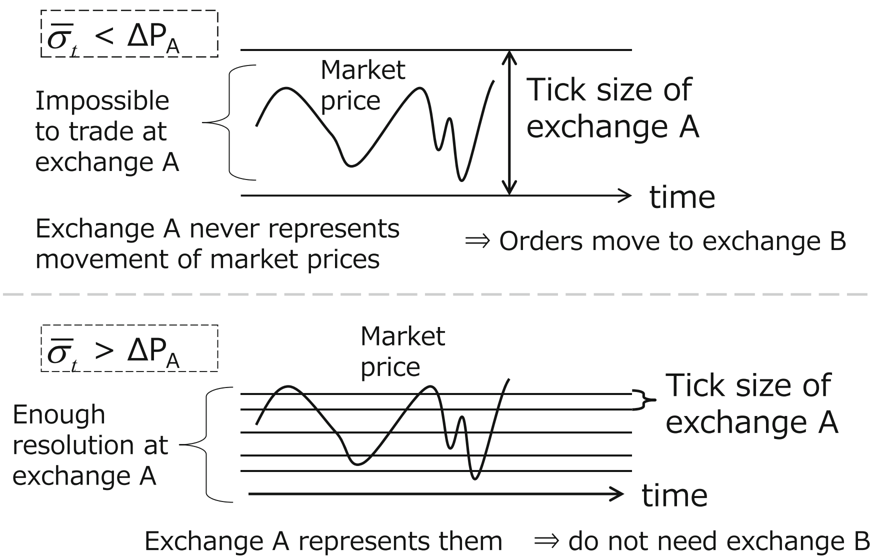

Fig. 13.6 Mechanism of taking market share of trading volume

smaller than its volatility will rarely lose market share to other exchanges, even if the tick size is larger than those of other exchanges. A tick size smaller than its volatility rarely affects competition for market share between stock exchanges, whereas a tick size larger than the corresponding volatility enlarges the volatility and prevents adequate price formation.

This simulation study is the first to discuss an adequate tick size.[7] An empirical study cannot investigate tick sizes that have never been used in an actual financial market or isolate a direct effect on price formation that is affected by many factors. In contrast, an artificial market model can isolate the effect of changing the tick size on price formation and simulate tick sizes that have never been used before. An artificial market model has these advantages over an empirical study.

The mathematical model of Nagumo et al. (2017) achieved the same results as the simulation study of Mizuta et al. (2013). They both showed that an artificial market model can indicate new problems that studies using mathematical models and empirical analysis should be able to solve. Of course, there have been studies using other artificial market models besides the one of Collver (2017), Yang et al. (2020), Zhao et al. (2020).

[7] Darley and Outkin (2007) investigated tick size reduction using an artificial market model when NASDAQ, a stock exchange in the USA, was planning a tick size reduction. They showed, for example, that a market can become unstable when some investment strategies become more prevalent. However, their model had too many parameters and they focused on which investors earned more, which prevented them from examining factors contributing good design of financial markets.

13.3 A Trade-Execution AI Learning in an Artificial Market

This section introduces a trade-execution algorithm using AI that learns in an artificial market.

The 1st ACM International Conference on AI in Finance[8] was held in October 2020. Sponsored by JP Morgan Chase & Co., the conference featured many presentations on artificial market studies,[9] including ones on trade-execution algorithms using AI.

When buying or selling a large amount of a particular stock, investors should place only a few orders at a time because placing them all at once would impact market prices significantly. A trade-execution algorithm divides the orders and automatically places orders a few at a time. A better trade-execution algorithm enables an investor to trade a large amount with better prices; therefore, the performance of the algorithm is very important especially for larger investors like as institutional investors. Karpe et al. (2020) build an execution algorithm using AI that learns in the artificial market based on the model developed by Byrd et al. (2019).

An artificial market model for investigating a trade-execution algorithm should replicate stylized facts of high-frequency micro-structures like an order book because the performance of trade-execution algorithm would depend on the structures. Vyetrenko et al. (2019) investigated whether the model of Byrd et al. (2019) could replicate the stylized facts of the micro-structure and indicated many problems. The model of Byrd et al. (2019) implemented many and deeply detailed components; for instance, the agent repeated the orders of actual financial markets and replicated the latency, which is delay of order information between investors and exchanges. This level of detail, however, might make it too complex to understand the mechanism how the trade-execution performs.

13.4 Bad AI Performing Market Manipulation

This section, which is based on the paper by Mizuta (2020), describes an AI trader discovers how to manipulate a market through learning in the artificial market even when the person who built it has no intention of manipulating the market; this sort of AI is bad for society.

Numerous studies have discussed the question of who should be held responsible when AI accidentally performs illegal actions. In the financial sector specifically, it is necessary to address AIs that manipulate markets. Market manipulation refers to traders artificially increasing or decreasing market prices for profit. Such a practice is prohibited in many countries as it leads to unfair trades.

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[8] https://ai-finance.org/. It was originally scheduled to be held in New York but was held virtually.

[9] I presented there together with co-author Yagi et al. (2020).

Scopino indicated that the developer who has no intention of manipulating a market should not be held responsible when his/her AI trader manipulates a market at its own discretion, according to the present regulations of the United States (Scopino 2016). This means that even though market prices are manipulated, no one is held responsible. This situation presents difficulties in maintaining the integrity of the market.

An AI trader must automatically learn the impact of its trades on market prices in order to discover that market manipulation earns a profit. AI traders are usually evaluated by backtesting, in which the profit is estimated as if the AIs were trading on the basis of historical past market prices. In backtesting, an AI trader cannot learn the impact of its trades on market prices because market prices are fixed as real historical data. As a result, the AI trader will not discover that market manipulation earns a profit when it uses backtesting as its learning process. Thus, as long as backtesting is implemented, there is no chance of an AI trader performing market manipulation at its own discretion.

However, an artificial market simulation enables an AI trader to automatically learn the impact of its trades on market prices, because the trades alter the market prices in the simulation. As I mentioned in the previous section (Sect. 13.3), Karpe et al. (2020) built a trade-execution AI by having it learn in an artificial market. The AI of Karpe et al. (2020) will not manipulate a market because it places only a few orders at a time. Note that there are many other studies on AI traders learning in artificial markets such as on AI technical traders (Izumi et al. 2009) and AI portfolio managers (Kuo et al. 2021), and I cannot predict what kinds of AI traders will emerge in future. AI traders might emerge that learn in artificial markets by adopting a variety of trading strategies.

In the following subsections, I describe an AI trader, shown in Fig. 13.7, that operates by using a genetic algorithm[10] that learns in an artificial market simulation. I investigated whether the AI trader can discover how to manipulate a market through learning even when its developer has no intention of manipulating a market.

13.4.1 Model

A developer building an AI trader gives it potential trading strategies and makes it learn which strategies and parameters earn more. This study focuses on whether an AI trader can discover how to manipulate a market through such learning even when the builder has no such intention.[11]

[10] A genetic algorithm is a calculation method inspired by evolution and natural selection that searches for an approximate optimal solution. Input values are represented as genes, and a surviving gene that has a higher adaptability (output value) leads to an optimal solution, that is, the input value that results in the highest output value (Goldberg 1989).

[11] In reality, the builder always intends certain strategies to be selected when modeling possible strategies. However, it is crucial for this study that the developer has no intention of any strategies

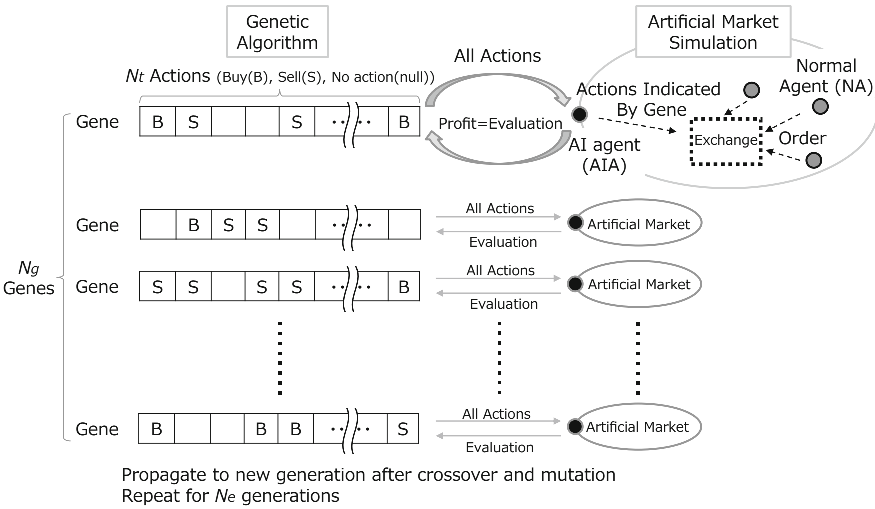

Fig. 13.7 My model

Figure 13.7 schematically shows the model developed in this study. An AI trader with no trading strategy is modeled using a genetic algorithm in which a gene includes all trades. Each gene is evaluated in the artificial market simulation. The artificial market includes an AI agent (AIA) that trades as one gene indicates. The gene is evaluated by AIA's profit in the simulation. The genetic algorithm searches for the gene that earns the most profit. This search corresponds to how the AI trader learns which trades profit.

Although AIA's trades impact market prices in the artificial market, for the purpose of comparison, I also investigated the case of backtesting in which the trades do not impact market prices.

In the following, I explain the artificial market simulation that evaluated each gene. Then, I describe the genetic algorithm that searched for the gene that earns the most profit.

including market manipulation. Therefore, I did not intentionally model trading strategies, and my model directly searched for all the optimal trades in an artificial market environment. Because there are no models of trading strategies, my model does not output in an out-sample forecast; thus, no one can test my model in an out-sample forecast. I argue, however, that this study does not need such evaluations because it focuses on whether an AI trader can discover market manipulation strategy through its own learning despite the builder having no intention of market manipulation. This study does not aim to use the model to out-sample forecast.

13.4.1.1 Artificial Market Simulation and Normal Agent (NA)

The artificial market model was built by adding an AIA to the model that I mentioned in Sect. 13.2.6.2. Hereafter, I will refer to a "normal agent" (NA) as being the sort of agent described in Sect. 13.2.6.2. To replicate the nature of price formation in actual financial markets, I implemented the NA to model a general investor.

AI Agent (AIA)

At every δt tick time, AIA takes one of the three actions: buy one share (at the lowest sell order price on the order book), sell one share (at the highest buy order price on the order book), or no action.[12] AIA takes actions $N_t = (t_e - t_c)/\delta t$ times in one artificial market simulation, where the simulation runs until tick time t_e. The actions are given by one gene in the genetic algorithm as described below.

13.4.1.2 Genetic Algorithm

Genes and Artificial Market

Figure 13.7 shows the model of the AI trader. An AI trader has no trading strategy and is modeled using a genetic algorithm. The number of genes is N_g. A gene contains information on actions, and the number of actions one gene has is N_t. There are three possible actions: buy one share, sell one share, or no action. Each gene is evaluated by AIA's profit in an artificial market, where AIA trades at every δt tick time by taking N_t actions as indicated by one gene. If AIA is holding stocks at the end of a simulation, the stocks are evaluated as P_f. All artificial markets have exactly the same NAs using the same random numbers. Therefore, if AIA makes the same trades, the artificial markets output the same market prices and the same NAs' trades.

Inheritance by Next Generation

The top N_{ge} genes that earned the most are not changed and inherited by the next generation.

Non-top N_{ge} genes are replaced with a probability of R_c by a crossover gene containing two genes, g_0 and g_1, randomly selected from the top N_{ge} genes. In the crossover, all actions are replaced with those of the gene g_0, and then the i_0th to

[12] AIA does not take any action before tick time t_c to stabilize the simulations. As mentioned in footnote 6, the purpose of the period before t_c is to generate enough waiting orders.

i_1th actions (i_0 and i_1 are randomly determined) are replaced with those of gene g_1. After crossover, the actions of the non-top N_{ge} genes are mutated with a probability of R_m. The mutated actions are changed with the same probability as buying, selling, or no action.

This inheritance by the next generation is repeated N_e times.

In the first generation, all of the genes' actions are determined with the same probability as buying, selling, or no action.

13.4.2 Simulation Results

The parameters for the artificial market were set to $n = 900$, $w_{1,max} = 1$, $w_{2,max} = 100$, $w_{3,max} = 1$, $\tau_{max} = 1000$, $\sigma_\epsilon = 0.03$, $P_d = 1000$, $t_c = 2000$, $\delta P = 0.01$, $P_f = 10000$, and $\delta t = 10$. Simulations were run until $t = t_e = 10000$. The parameters for the genetic algorithm were set to $N_t = (t_e - t_c)/\delta t = 800$, $N_g = 10000$, $N_{ge} = 400$, $R_c = 0.65$, $R_m = 0.2$, and $N_e = 1500$. This resulted in $N_g \times N_e = 1.5 \times 10^7$, meaning that the simulation of the artificial market was run 15 million times. In the following, I use the AIA of the optimal gene in the final generation.

Figure 13.8 shows the time evolution of market prices (mid-prices) with and without AIA. AIA amplified the variation in the market prices.

Figure 13.9 shows the time evolution of market prices with AIA and trading volume (positive and negative numbers indicate buying and selling, respectively) aggregated every 200 tick times. Around $t = 2000$, AIA bought many stocks, causing the market prices to increase. Around $t = 3000$, market prices continue to increase even though AIA did not buy many stocks. Given the fundamental

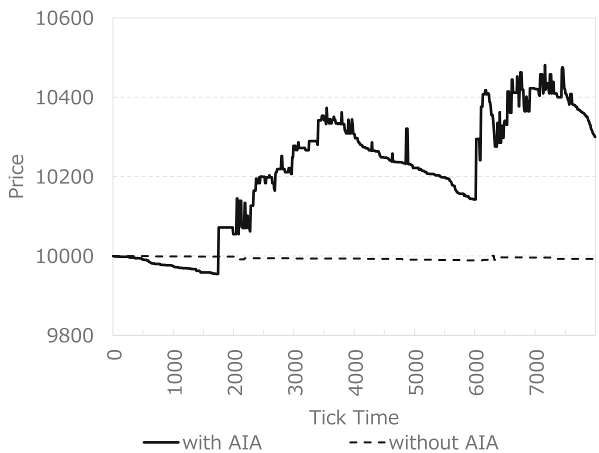

Fig. 13.8 Time evolution of market prices (mid-prices) with and without AI agent (AIA)

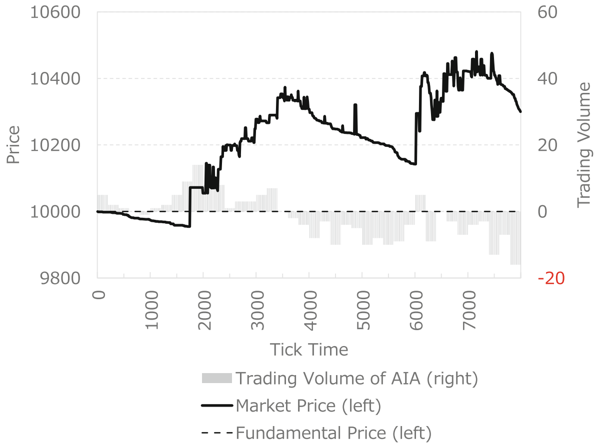

Fig. 13.9 Time evolution of market prices with AIA and trading volume (positive and negative numbers indicate buying and selling, respectively) aggregated every 200 tick times

strategy of normal agents in the first term of Eq. (13.1), a negative return was expected because the market prices are over the fundamental price. On the other hand, because of the technical analysis strategy in the second term of Eq. (13.1), a larger positive return was expected because of the historical positive return around $t = 2000$ at which AIA had increased market prices by itself. Therefore, the market prices were able to increase even though AIA did not buy many stocks. Afterwards, from around $t = 4000$ to around $t = 6000$, AIA was able to sell stocks at higher prices than when they were bought at around $t = 2000$, because the market prices continued increasing until around $t = 3000$.

AIA's trades are evidently market manipulation. This indicates that an AI can discover market manipulation as an optimal investment strategy through learning with an artificial market simulation.

Figure 13.10 shows the time evolution of market prices and trading volume without an impact on market prices (backtesting) as in Fig. 13.9. Note that Fig. 13.10 has a different scale for the vertical axis than those in Figs. 13.8 and 13.9. The time evolution of market prices is the same as that without AIA because AIA's trades never impact market prices, as can be seen in Fig. 13.8. AIA tended to buy stocks because the market prices were lower than the fundamental price. Its trades corresponded to its fundamental strategy; thus, in the case of backtesting, it could not discover market manipulation as a trading strategy.

This indicates the possibility that an AI cannot discover market manipulation through learning with backtesting.

Mizuta (2020) showed the results of ten additional simulation runs through learning with an artificial market and with backtesting. These results were similar to the above result. This implies that an AI trader can easily discover market manipulation as an optimal investment strategy and yet the possibility that it cannot

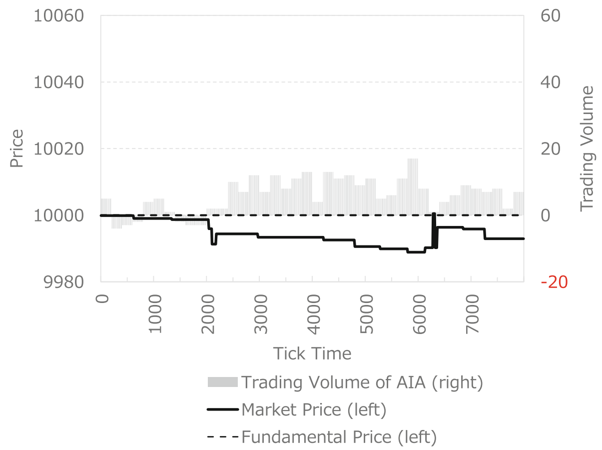

Fig. 13.10 Time evolution of market prices and trading volume in case without impact on market prices (backtesting)

discover market manipulation when the learning is done with backtesting in which there is no impact on market prices.

13.4.3 Summary

I constructed an AI trader using a genetic algorithm that learns in an artificial market simulation. Then, I investigated whether the AI trader could discover how to manipulate a market through its learning even though I had no intention of building such a capability into it.

The results showed that the AI trader discovered how to manipulate a market as an optimal investment strategy. This indicates that even though the developer may have no intention of market manipulation, an AI trader can discover how to do so as an optimal investment strategy in an artificial market simulation in which it automatically learns the impact of its trades on market prices. However, the results also indicate the possibility that an AI trader cannot discover how to manipulate a market manipulation when the learning employs backtesting in which there is no impact on market prices.

The results suggest the need for regulation, such as obligating AI developers to prevent AIs from performing market manipulation. Another suggestion is that developers should limit trades performed by AI to avoid impacting market prices.

13.5 Conclusion

I introduced a good AI for finance, an artificial market model to design a financial market that works well, and a bad AI for finance, an AI trader discovers on its own how to manipulate markets through learning in the artificial market even when the person who built it has no intention of market manipulation.

Section 13.2 introduced an artificial market model, which is an agent-based model for a financial market, to design a financial market that works well. Artificial market models have been used to discuss rules and regulations of actual financial markets such as tick size reduction. Their contribution has not been so significant but will become greater in the coming years.

Some readers may think that tick size reduction is a trivial matter for a financial market. It is, however, important and should not be underestimated. Making small rules changes sometimes has an unexpectedly large impact and side effects. John McMillan illustrated this feature of markets as "both God and the devil are in the details" (McMillan 2002). Detailed designs can determine whether a financial market develops or destroys an advanced economy. Designing a market well is thus very important for developing and maintaining an advanced economy, but it is not easy.

I hope that more artificial market models will contribute to designing financial markets that further develop and maintain advanced economies.

Section 13.4 introduced an AI trader using a genetic algorithm that learns in an artificial market simulation. Then, I investigated whether the AI trader discovers market manipulation through learning even when the person who built the AI trader has no intention of market manipulation.

The results showed that the AI trader discovered market manipulation as an optimal investment strategy. This indicates that even if the developer has no intention of market manipulation, the AI trader can discover market manipulation as an optimal investment strategy through learning in an artificial market simulation in which it automatically learns the impact of its trades on market prices. The results also indicate the possibility that an AI trader cannot discover market manipulation if its learning is done with backtesting in which there is no impact on market prices.

The results suggest the need for regulation, such as obligating AI developers to prevent AIs from performing market manipulation. They also suggest that developers should limit trades performed by AI to avoid impacting market prices.

There are both good and bad AIs for society. We should not discuss whether AIs on the whole are good or bad, but rather how to manage them so that they are useful tools. To do that, we should discuss rules, ethics, and philosophy for AIs.

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Part V
The Randomness and High Frequencies in the Financial Data

Chapter 14
Possible Relationship of the Randomness and the Stock Performance

Mieko Tanaka-Yamawaki and Yumihiko Ikura

Abstract The RMT test, formulated by one of the authors as a tool for labeling big data by means of randomness, is applied on the real-data of price fluctuation recorded by each second in Tokyo market. It is suggested that a sudden deterioration of randomness level of the tickwise price fluctuation predicts a future decline of the market price, based on the example found in analyzing tick data of the TOPIX index.

Keywords Big data · RMT test · Randomness · Price fluctuation · Prediction

14.1 Introduction: Is There a Rule to Govern the Performance of Stock Prices?

In almost any occasion, we make predictions. Whether we notice or not, we try to establish our own hypotheses based on experiences and attempt to verify them in the new situation. For example, I have my own regulation to cross street when a signal is about to change and control my speed. I would run if I am confident to cross street before a signal change. Or, I walk slowly to wait for the next green. Similarly, professional stock investors set up various hypothesis on possible surge or crash of the market, by looking at the price charts every day. Those regulations, however, do not necessarily guarantee the future performance. Just like the above-mentioned hypothesis on the speed of walk before crossing the road, the prediction fails with finite probability. Moreover, those hypotheses are often hard to formulate precisely. Above all, it is difficult to write down its algorithm.

Meanwhile, data collection became easy substantially in recent years. At the same time, power of the computer processing helped by a high-speed computer offers us a big chance of a decision-making using such data. The application of artificial intelligence (AI) has offered us a chance to quickly classify the visual as

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well as audio patterns. Great success of the deep learning technique has opened up a wide application of AI in the financial business. However, the answer of AI is not sufficient. We human still need to grasp what kind of factors played the most important role. We also want to understand how they worked out in those events. In other words, we need a scenario to convince ourselves by human words.

In case of physical phenomena such as weather forecast, we can utilize the established knowledge of physical sciences, by using the high precision data, such as air pressure, temperature, wind speed, etc. In the case of financial forecast, however, the basic phenomena are the human mind and behavior. There is no established rule for the financial forecast. Accordingly, the formulation is not easy, and high level of accuracy cannot be expected. If there are no solid regulations in a financial prediction at all, one remaining possibility could be the use of randomness to characterize the gross nature of big data. Obviously, we cannot expect a high level of precision from this. Still there may be a possibility to expect some sort of prediction on the direction of the economic cycles.

There is a long history of the theory of price fluctuation. The first reference is known as the random walk hypothesis by Louis Bachelier (Bachelier 1900). This idea has been the corner stone of financial engineering for a long time. Especially, in the statistical treatment of high frequent price fluctuation, the statistical distribution of price increments is assumed to be the Gaussian (normal) distribution. On the other hand, the fluctuation of the market price often deviates from the simple random walk and exhibits self-similarity property, especially when the market is in the critical situation, such as a market crash. In the term of statistical distribution, it is called as the long-tailed, or non-Gaussian distribution. Due to the similarity to the critical phenomena in condensed matter physics, this problem has attracted much attention in the community of physicists and stimulated to form a new field of statistical physics called "econophysics" (Mantegna and Stanley 2000).

Meanwhile, thanks to the rapid progress of information technology, the amount of data that we can use has expanded rapidly. This situation allowed us to use sufficient data for statistical analyses on relatively short time period. Based on substantial experience on such data, we have learned that the market moves between two states of Gaussian (highly random) and non-Gaussian (less random). This observation has led us to seek for a good labeling of those states. That label seemed to be related to the degree of randomness of time series.

A hint came from our course of study on the methodology of the RMT-based PCA. The RMT is an abbreviation of the random matrix theory (Mehta 2004). It was used by E. Wigner in the field of nuclear physics (Wigner 1958), then used in many other fields of science. Around the turn of the century, we encountered some pioneering works (Laloux et al. 1999; Plerou et al. 2002) in which RMT was applied on cross-correlation matrix of high-frequency stock price time series in order to extract the principal components of stock markets. We have applied that methodology on various data including high-frequency data of Tokyo market in various time ranges. We successfully extracted major sectors at each time interval (Tanaka-Yamawaki et al. 2012a, 2013). The main tool of this study was the mutual correlation matrix between pairs of two stocks and compare the eigenvalue distribution of such correlation matrix to the theoretical counterpart of the random matrix theory (RMT) (Sengupta and Mitra 1999). The essential secret of this methodology was the separation of a few principal components and the rest of random components. Converting this idea, we realized that the same methodology can be used to measure the randomness of a single data string. Namely, we use the self-correlation matrix between two different parts of one price time series (Yang et al. 2011, 2012, 2013a; Tanaka-Yamawaki et al. 2012b, 2015), instead of mutual correlation matrix.

In other words, the dominant assumption in our idea is that the "randomness" is the primary feature of price time series, and the characteristics of each data are determined by the degree of deviation from the randomness. Qualitatively speaking, the financial market keeps stability when large number of participants have diverse opinion, and it becomes unstable when the diversity of the opinion distribution is lost. In the analogy of the assembly of many small magnets, the random state is the case when the directions of those small magnets are diverse, and the less random state is the case when the directions of those small magnets is lost, the diversity and the alignment to a certain specific direction occur.

Obviously, the stock price is determined by many factors, and it is hard to identify which factor effects and how much. Simply, the price rises when more investors want to buy that stock. Inversely the price falls if more investors don't want to buy but sell. Usually, the speed of rising stock price is rather slow compared to the speed of falling. Following the prospect theory (Kahneman and Tversky 1979), the reason for this tendency can be understood by the fact that people's fear of losing money is much stronger than the joy of earning profit. Especially, the big decline occurs when many people feel the fear of declining at the same time.

14.2 Randomness as a Label of a Bulk Data

The first thing we do, when we deal with big data, is to measure various labels to characterize each data, such as the size, data-type, or the time when the data are taken. A good label would greatly reduce the burden of big data analysis. Our thrust is to add the "randomness of the time series" as a new label to characterize a string of price data. Considering the fact that the price moves almost randomly, it is quite natural to explore this possibility. To do this, we need a handy tool to measure the randomness of large-sized numerical data. However, the value of every tool depends on its purpose. Then what kind of tool is suitable to measure the randomness of the price time series?

One solution is to use the RMT test that the authors have proposed recently as a new tool to measure the randomness of given data sequences, as a byproduct of the RMT-PCA. The RMT test is a way of measuring the degree of randomness based on the random matrix theory (RMT) applied on the cross-correlation matrix between financial time series. The qualitative version of the RMT test (Yang et al. 2011) is suitable to visualize the randomness by comparing the eigenvalue distribution of the cross-correlation matrix of data sequence to its theoretical counterpart derived by means of the RMT. This is suitable to view intuitively the degree of randomness of real data that are relatively low in randomness.

The quantitative version of the RMT test (Tanaka-Yamawaki et al. 2012b) represents the degree of randomness by the error represented by the difference between the 6th moment of the eigenvalue distribution of the correlation matrix and its RMT theoretical counterpart. This method has been applied to distinguish subtle difference between reputed pseudo random generators, and the physical random generators installed in the super computers (Mikamori et al. 2013). Also, this method is shown to be comparable to the standard NIST randomness test in terms of empirically evaluating the randomness level of artificially created random sequences after shuffling an ordered sequence (Mikamori et al. 2013).

14.3 Methodology of the RMT Test

The method of the RMT test is outlined as follows. We aim to test the randomness of a long one-dimensional sequence of numerical data, S. At the first step, we cut S into N pieces of equal length L, then shape them in an $N \times L$ matrix, $S_{i,j}$, by placing the first L elements of S in the first row of the matrix $S_{i,j}$, and the next L elements in the 2nd row, etc., by discarding the remainder if the length of S is not divisible by L. Each piece, $S_i = (S_{i,1}, S_{i,2}, ..., S_{i,L})$, is converted to a normalized vector $x_i = (x_{i,1}, x_{i,2}, ..., x_{i,L})$ by means of

$$x_{i,t} = \frac{S_{i,t} - < S_i >}{\sigma_i} \qquad (i = 1, \ldots, N; t = 1, \ldots, L) \tag{14.1}$$

$$< S_i >= \frac{1}{L}\sum_{t=1}^{L} S_{i,t} \tag{14.2}$$

$$\sigma_i = \sqrt{< {S_i}^2 > - < S_i >^2} \tag{14.3}$$

such that every row in the new matrix x has mean = 0, variance = 1. Since the original sequence S is random, in general, all the rows are independent, i.e., no pair of rows is identical. The cross-correlation matrix $C_{i,j}$ between two stocks, i and j, is constructed by the inner product of the two time series, $x_{i,\,t}$ and $x_{j,\,t}$,

$$C_{i,j} = \frac{1}{L}\sum_{t=1}^{L} x_{i,t} x_{j,t} \tag{14.4}$$

thus the matrix $C_{i,j}$ is symmetric under the interchange of i and j. A real symmetric matrix C can be diagonalized by a similarity transformation $V^{-1}CV$ by an orthogonal matrix V satisfying $V^t = V^{-1}$, each column of which consists of the eigenvectors

$$v_k = \begin{pmatrix} v_{k,1} \\ v_{k,2} \\ \vdots \\ v_{k,N} \end{pmatrix} \tag{14.5}$$

of C, where

$$\sum\nolimits_{j=1}^{N} C_{i,j} v_{k,j} = \lambda_k v_{k,i} \quad (k = 1, \ldots, N) \tag{14.6}$$

and λ_k are the eigenvalues of C numbered in the descending order of k.

$$v_k \cdot v_l = \sum\nolimits_{n=1}^{N} v_{k,n} v_{l,n} = 0 \tag{14.7}$$

$$v_k \cdot v_k = \sum\nolimits_{n=1}^{N} \left(v_{k,n}\right)^2 = 1 \tag{14.8}$$

In the case of perfectly random sequence, the RMT tells us that the eigenvalues are distributed in the range of

$$\lambda_- < \lambda_i < \lambda_+ \tag{14.9}$$

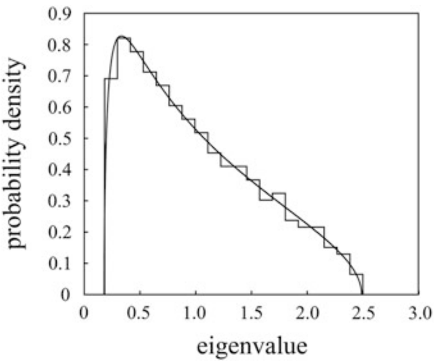
where

$$\lambda_\pm = 1 + \frac{1}{Q} \pm 2\sqrt{\frac{1}{Q}}\lambda_\pm = \left(1 \pm Q^{-1/2}\right)^2 \tag{14.10}$$

But some eigenvalues become larger than the theoretical limit λ_+ as the randomness goes lower. This fact can be used to measure the randomness of a data sequence. Also, the following quantity

$$\Delta\lambda = \lambda_{\max} - \lambda_+ \tag{14.11}$$

the distance between the largest eigenvalue $\lambda_{\max}$ and the theoretical maximum λ_+ can be used as a rough measure of the degree of randomness of a data string. For the parameter $Q = 3$, $\lambda_+ = 2.488$.



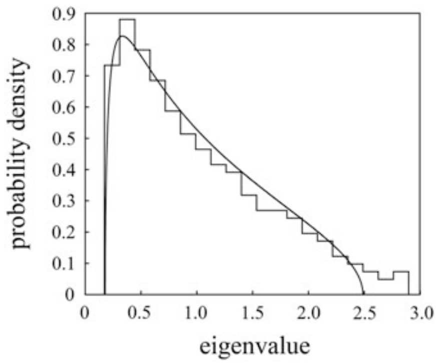


Fig. 14.1 Highly random data (left) and less random data (right) in the qualitative test

14.3.1 Qualitative Version of the RMT Test

The qualitative version of the RMT test compares the theoretical curve derived in the RMT and the histogram of eigenvalue distribution of the cross-correlation matrix made by the inner-product of N pieces of time series of length L. The randomness of the time series is high if the histogram matches the theoretical curve, and it is low if they do not match. A typical example can be seen in the two figures of Fig. 14.1, where a case of highly random time series in the left hand side is compared to a case of less random time series in the right hand side. Both the figures compare the histograms of the eigenvalue distribution computed from the TOPIX index price per second, at a highly random term (4/20 to 6/1, 2012) and less random term (3/8 to 30, 2018), respectively. The former figure shows a good match of the histogram and the theoretical curve in the solid line, while the latter figure clearly shows a deviation of the histogram from the theoretical curve.

14.3.2 Quantitative Version of the RMT Test

The quantitative version of the RMT test is used to discriminate subtle difference of randomness among good random numbers. The kth moment of the eigenvalues

$$m_k{}^{\mathrm{EXP}} = \frac{1}{N}\sum\nolimits_{i=1}^{N} (\lambda_i)^k \tag{14.12}$$

is compared to the corresponding theoretical moments derived from $\mathrm{P_{RMT}}$ of the random matrix theory.

$$m_k{}^{\mathrm{RMT}} = \int_{\lambda_-}^{\lambda_+} \lambda^k P_{\mathrm{RMT}}(\lambda)\, d\lambda \tag{14.13}$$

The theoretical moments up to $k = 6$ can be explicitly obtained as a function of $Q = L/N$ as follows.

$$m_1^{\mathrm{RMT}} = 1$$

$$m_2^{\mathrm{RMT}} = 1 + \frac{1}{Q}$$

$$m_3^{\mathrm{RMT}} = 1 + \frac{3}{Q} + \frac{1}{Q^2}$$

$$m_4^{\mathrm{RMT}} = 1 + \frac{6}{Q} + \frac{6}{Q^2} + \frac{1}{Q^3}$$

$$m_5^{\mathrm{RMT}} = 1 + \frac{10}{Q} + \frac{20}{Q^2} + \frac{10}{Q^3} + \frac{1}{Q^4}$$

$$m_6^{\mathrm{RMT}} = 1 + \frac{15}{Q} + \frac{50}{Q^2} + \frac{50}{Q^3} + \frac{15}{Q^4} + \frac{1}{Q^5} \tag{14.14}$$

The quantified criterion of (inverse) randomness is defined by the deviation rate of the experimental value of the kth moment from its theoretical counterpart

$$D_k = \frac{{m_k}^{\mathrm{EXP}}}{{m_k}^{\mathrm{RMT}}} - 1 \tag{14.15}$$

This value D_k for $k = 6$ successfully discriminate the randomness between two random generating programs (LCG, Mersenne Twister = MT) and three physical random generating boards (Toshiba, Hitachi, Tokyo Electron Device = TED), as shown in Table 14.1. Since the random data fluctuate at every time, values shown in the table are the average of 100 independent tests, together with the standard deviation in the parentheses. It is shown that D_6 is consistently smaller for MT compared to LCG. Among three random generation boards, the latest TED performs better than the others. Based on this experiment, we use D_6 for the quantitative version of the RMT test.

Table 14.1 Comparison of D_k for five random generators (data length 750,000)

k	Algorithm: LCG	Algorithm: MT	Board: Toshiba	Board: Hitachi	Board: TED
2	−0.0004 (0.0010)	−0.0004 (0.0009)	−0.0004 (0.0010)	−0.0004 (0.0010)	−0.0004 (0.0009)
4	−0.0018 (0.0047)	−0.0014 (0.0041)	−0.0019 (0.0046)	−0.0019 (0.0044)	−0.0015 (0.0044)
6	−0.0036 (0.0100)	−0.0022 (0.0085)	−0.0033 (0.0096)	−0.0037 (0.0092)	−0.0021 (0.0093)

14.4 Application to the Stock Performance

It is customary to convert the price time series $p_1, p_2, ...,$ to the log-return time series $r_1, r_2, ..., r_L$

$$r_i = \log\left(\frac{p_{i+1}}{p_i}\right) \tag{14.16}$$

in the financial analysis, in order to eliminate the unit/size dependence of different stock prices (Mantegna and Stanley 2000). However, this process involves the same p_i for r_i r_i and r_{i+1}. Because of this, the time series of log-returns lose the randomness that existed in the original price time series and a certain pattern specific to the log-return time series emerges. This effect can be eliminated if we take the non-overlapping log-return by giving up the half of the total elements of r_i ($i =$ even or odd), in exchange of the length of data L to one half of the original. Using this fact, we analyze the randomness of the stock price with non-overlapping log-return series.

Tick data of stocks in TOPIX 500 in the period of 2007–2009 per minute satisfying the appropriate conditions are selected and used for analysis (Yang et al. 2013b). Tick data mean the time series stamped in seconds or minutes recording the information of traded or quoted prices. Since trades or quotes may not occur at every time period, the lengths of the tick data are not fixed. For this reason, some work is required to prepare the fixed-length time series to serve for analysis. The blanks are filled by copying the previous data as long as the added part is less than the 20% of the total length in order to calculate equal time correlation of each stock price. As a result, the data length (L) and the number of stocks (N) are different year by year. The values of L and N for each year used in this chapter are summarized in Table 14.2.

The RMT test involves a free parameter, $Q = L/N$, to be determined beforehand. The condition required by the RMT is $Q > 1$ and $N \to \infty$. The ranking of randomness in 2007 is shown in Table 14.3 in which the stock of the highest randomness in 2007 is 9504 in the sector of Electric/Gas. As expected, the degree of randomness for the stock price is significantly large compared to the random numbers. The typical randomness of the algorithmic random numbers (LCG, MT) and physical random numbers from the random number generating boards expressed by the deviation D_k are the order of a few percent, as can be seen in Table 14.1. Compared to this, the deviation D_k for the stock time series, in Table 14.3, are larger by the order of more than two digits.

Table 14.2 Data used for analysis

Year	Data length (L)	Number of stocks (N)
2007	66,338	211
2008	66,338	240
2009	65,945	229

Table 14.3 Randomness ranking computed from the 1-minute stock price in Tokyo Market 2007

Order	Classification	Code	Deviation rate (D_6)
1	Power supply	9504	0.264
2	Machinery	6460	0.376
⋮	⋮	⋮	⋮
209	Chemistry	4043	8.00
210	Steel	5541	10.01
211	Vehicle	7201	12.1

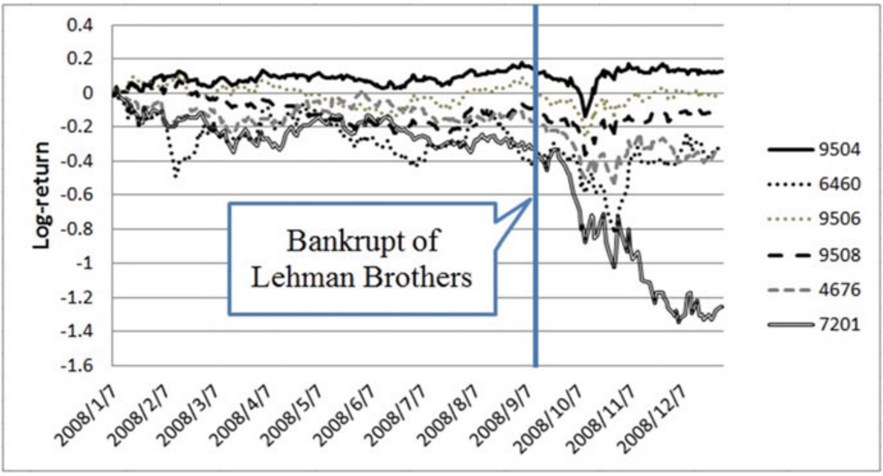


Fig. 14.2 The five stocks of the highest randomness in 2007 perform better than 7201 in 2008

The stock of the lowest randomness in 2007 is 7201 in the sector of "Transportation and Equipment." Figure 14.2 shows the log-return of the top five stocks of code number 9504, 6460, 9506, 9508, 4676 having the highest randomness comparing with the stock of the lowest randomness 7201. As a result, the top five stocks perform better than 7201 and effect very little by the financial crisis. On the contrary, the 7201 which has the lowest randomness in 2007 fell down enormously due to the effect of Lehman shock that occurred in September 2008. Based on this observation, the authors conclude that the stock which has the highest randomness is stable and safe under a bear market (Tanaka-Yamawaki et al. 2012b; Yang et al. 2012).

In short, we conclude that the following inequality is held for the performance of two stocks 9504 (electric power supply: most random time series in 2007) and 7201 (automobile manufacture: least random time series in 2007) throughout the following year before the Lehman shock.

$$7201 < \text{Nikkei Average Stock Price} < 9504 \qquad (14.17)$$

A corresponding analysis on the bull (rising) market has been performed by using S&P500 index for 1993–1996 in American market. The parameters are chosen to be $L = 628$ and $N = 157$ for 1993, and $L = 624$ and $N = 156$ for 1994, 1995, and

Table 14.4 The empirical rule "high randomness means low risk" is tested in the period of the rising market, 1993–1994

	1993–1994	1994–1995	1995–1996	1996–1997
5 most random stocks	+**0.11**	+0.33	+**0.27**	+**0.39**
5 least random stocks	−0.06	+**0.43**	+0.11	+0.24

Bold figure shows a higher return each column

1996, so that we have the best value of $Q = 4$. By evaluating the randomness each year in the period of 1993–1996, we compare the performance of the stock return next year. As shown in Table 14.4, the average returns of the top 5 stocks in terms of randomness in 1993–1995 perform better in the next year compared to the bottom 5 stocks. However, the rule does not hold in 1994. Thus the empirical rule "high randomness means low risk" is satisfied in three out of four cases.

Summarizing the above result, we conclude that the empirical rule stating that "the higher randomness of minute-wise profits of individual stock indicates the better performance compared to other stocks of lower randomness" is shown to hold at least in the period of 2007–2009 in Tokyo market, which was the typical bear market (Tanaka-Yamawaki et al. 2015; Yang et al. 2012, 2013a). This rule is further discussed in this chapter by investigating the real-world price time series found in the period of 1993–1996 in the US market, which was the typical bull market (Yang et al. 2013b).

14.5 Sudden Decrease of Randomness Predicts Future Decline of Stock Index

Finally, we show our latest result of applying the randomness of the price fluctuation computed by our method of the RMT test, to investigate the relationship to the future stock performance. The method itself is the same as the one in Sect. 14.4. However, this time we use a single price index, TOPIX index of 1-s period, and attempt to predict the future performance of the stock index by using the current value of randomness. In Sect. 14.4, we computed the randomness D_6 of different stock codes using data length of 1 year for each stock and found that the most random stock, for which the randomness measure D_6 is the smallest among all the stocks considered, was the best performer in the following year, and the least random stock was the worst performer. The reason we needed a very long data for 1-year period was the irregularity of time interval of stock trades. Some stocks are not traded every second, or minute, or even hour. For this reason, we had to select stocks that are traded at least once at every minute, then selected representative price out of multiple prices during a fixed time interval. In this process, the number of stocks we can use became as small as 200 or around. Also, the time interval was not shorter than 1 min.

This time we have obtained a data set of TOPIX index of 1-s interval for 10 years of 2010–2019. Having one trade per second, we have $60 \times 60 \times 5 = 18{,}000$ data points per day, 90,000 data points per 5 days. On the other hand, the RMT test requires 750,000 data points for $N = 500$, $L = 1500$, that is more than 2 months. Usually, the ups and downs of stock index occurs in a few months or shorter. Thus we choose $N = 200$, $L = 600$ to have 120,000 data points, equivalent to a little shorter than 7 days for 1 set of data to compute D_6. Considering there are at most 5 working days a week, 7 days means a week and a half. For the sake of consistency, we also compute D_6 for wider range of data, $N = 300$, $L = 900$ to have 270,000 data points, equivalent to 15 days and also $N = 400$, $L = 1200$ to have 480,000 data points, equivalent to 26 or 27 days. We also use $\Delta\lambda$ in Eq. (14.11) for a crosscheck. This is computed from Eq. (14.10). For $Q = 3$, $\Delta\lambda$ can be calculated by $\Delta\lambda = \lambda_{max} - 2.488$.

We aim to show that notable price declines are related to a sudden rise of randomness of price time series. Note that we must exclude price collapse caused by an external effect, such as the case of March 11, 2011 caused by the earthquake and the collapse of the nuclear plant. A price decline by the internal, endogenous cause and a price collapse by an external or exogenous cause are completely different and only the endogenous type can be predicted by the sudden decrease of randomness. People do not dream of such accident. It happens with no signs at all beforehand. Naturally, the level of randomness does not change beforehand, as shown in Table 14.5. A sharp decline of the price in Fig. 14.2 occurs suddenly together with a sudden increase of $\Delta\lambda$ and D_6.

On the other hand, the price decline caused by the endogenous effect usually occurs gradually. The main driving force of the endogenous effect is the psychological factor which is ruled by the fear that a reaction seems to come after a long-term bull market, or a rumor on the increase of the interest rate, etc. The diversity level of the market participants increases and the price moves with higher amplitude than ever. This type of price declines, of endogenous effects, can be observed around April 3, 2012, that follows the sudden increase of randomness of price fluctuation in the period of March 23 to April 2. The largest eigenvalue is 3.2, larger by 0.7 than the theoretical maximum 2.5. Then the price declines after April 3, 2012. This situation is depicted in Table 14.6 and Figs. 14.3 and 14.4.

Table 14.5 An exogenous price fall is not caused by a decline of the degree of randomness

Term	$\Delta\lambda$	D_6	Price
2011.2.14–2.24	0.00	0.12	–
2011.2.24–3.7	0.00	0.06	–
2011.3.7–3.17	4.67	52.5	Decline
2011.3.17–3.29	0.02	0.08	–

Table 14.6 A price decline by an internal effect can be anticipated by precautious increase of $\Delta\lambda$ and D_6

Term	$\Delta\lambda$	D_6	Price
2012.3.13–3.23	0.12	0.22	
2012.3.23–4.3	**0.73**	**0.47**	
2012.4.3–4.11	0.00	0.05	**Decline**
2012.4.11–4.20	0.10	0.12	

Bold figure shows a higher return each column

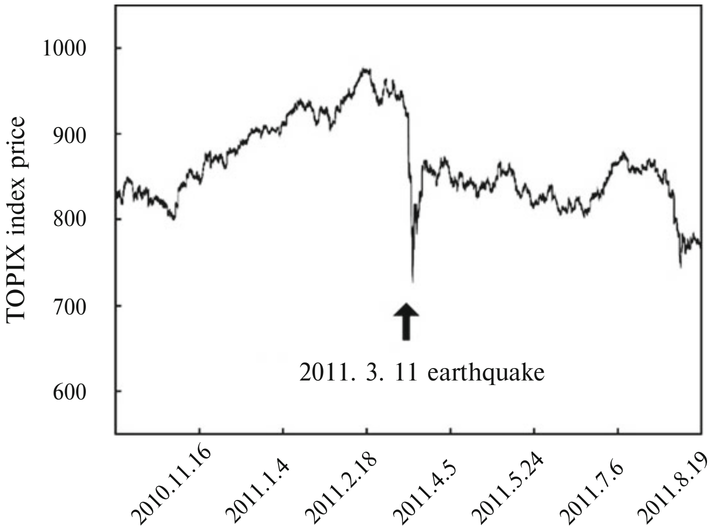


Fig. 14.3 TOPIX index price sharply fell at the 3.11 earthquake in March 2011

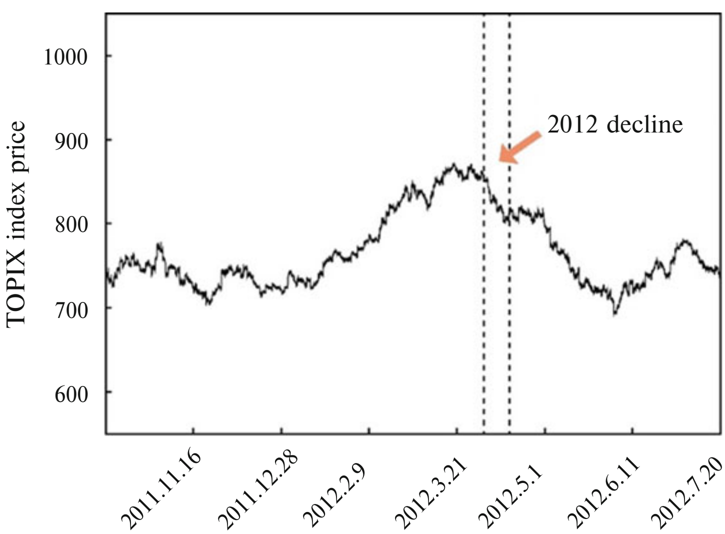


Fig. 14.4 The TOPIX declined in April 2012 after the deviation D_6 increased in March 2012

14.6 Summary

We explored a new method of evaluating the randomness level of large-sized data string, by using the RMT-oriented methodology, and applied this method on a high-frequency stock index price, TOPIX per 1-s price time series in the period of 2010.10 to 2019.9. We cut this time series into pieces of 120,000 data points, corresponding to the parameters $Q = 3$, $N = 200$, $L = 600$, and computed two factors of randomness, $\Delta\lambda$ and D_6, shown in Sect. 14.4. It is found that the index price declines after a sudden increase of those parameters, indicating the decrease of randomness of the secondary time series. One clear example is presented in Sect. 14.5 for the decline in the period beginning on April 3, 2012, right after a sudden increase of $\Delta\lambda$ and D_6 in the previous period of March 23 to April 2, 2012. This fact can be viewed as an example of price decline caused by an endogenous effect based on market psychology, that is discriminated from the accidental change of market condition by exogenous effect such as the 3.11 earthquake and the following disorder of the nuclear plant. However, there are other examples in which a sudden increase of $\Delta\lambda$ and D_6 does not necessarily results in the price decline. In fact, not many good examples of price decline caused by the endogenous effect are found in the period of 2010–2019.

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Chapter 15
Random Matrix Theory (RMT) Application on Financial Data

Takuya Kaneko and Masato Hisakado

Abstract In this study, we show results from application of random matrix theory (RMT) on various kinds of financial data. The random matrix theory is expected to play an important role in big data analysis. Small sized stock price data and mainly portfolio data (basket of stocks) are utilized in previous researches. Here, we use middle scale price data and apply RMT on stock portfolios and each single product, respectively. We apply on twenty-five single products. They are cryptocurrencies, foreign exchange rates, and commodities. In application of RMT on stock portfolios, we see interesting results that are completely different from the previous papers due to our more appropriate treatment for missing values of stock prices. In application of RMT on single products, cryptocurrencies have closer distribution to the theoretical shape than other products although it is being said as wider price fluctuation than other financial products. In this chapter, we briefly explain theoretical background of RMT and review previous key papers. And we introduce results of numerical experiments and targets in our future works.

Keywords Random matrix theory (RMT) · Eigenvalues of Wishart matrix · Marchenko-Pastur law

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15.1 Introduction

It is becoming available to collect a huge amount of data (these are called as big data) in the various kinds of research fields. In each research field, many analytical methods have been continuously developed. We choose random matrix theory (RMT) for analyzing financial data among developed tools. It has been utilized in Mathematical Statistics first and applied in Physics, Biological Science, and so on. Also, it is used to investigate mechanism of deep learning's escaping from overfitting. Recently, costs of purchasing large-scale storage medium are becoming reasonable and machine calculation speed is also enhancing remarkably year after year. These thing enable us to collect/save large scale financial time series data and give us opportunities to challenge for studying their structure. So far, RMT is mainly utilized for studying data structure of portfolio composed of stocks to find ideal portfolio allocation to minimize risk. And RMT is utilized to investigate price move characteristics of individual stocks. Researchers calculate empirical moments and compare them with the theoretical values.

In the following sections, we show results from RMT applications on following various kinds of financial data. They are 1. Bitcoin/US Dollar FX Spot Rate (BTC/USD), 2. Ripple/US Dollar FX Spot Rate (XRP/USD), 3. Ethereum/US Dollar FX Spot Rate (ETH/USD), 4. Euro/US Dollar FX Spot Rate (EUR/USD), 5. US Dollar/Japanese Yen FX Spot Rate (USD/JPY), 6. UK Pound Sterling/US Dollar FX Spot Rate (GBP/USD), 7. US Dollar/Swiss Franc FX Spot Rate (USD/CHF), 8. Australian Dollar/US Dollar FX Spot Rate (AUD/USD), 9. US Dollar/Canadian Dollar FX Spot Rate (USD/CAD), 10. New Zealand Dollar/US Dollar FX Spot Rate (NZD/USD), 11. Euro/Japanese Yen FX Cross Rate (EUR/JPY), 12. Euro/Swiss Franc FX Cross Rate (EUR/CHF), 13. Euro/UK Pound Sterling FX Cross Rate (EUR/GBP), 14. US Dollar/Brazilian Real FX Spot Rate (USD/BRL), 15. US Dollar/Chinese Yuan Offshore FX Spot Rate (USD/CNH), 16. US Dollar/Indian Rupee FX Spot Rate (USD/INR), 17. US Dollar/South African Rand FX Spot Rate (USD/ZAR), 18. US Dollar/Russian Ruble FX Spot Rate (USD/RUB), 19. NYMEX Light Sweet Crude Oil Electronic Energy Future Continuation 1 (WTI), 20. CBoT Soybeans Composite Commodity Future Continuation 1 (SOY), 21. CBoT Corn Composite Commodity Future (CORN), 22. Gold Spot Multi-Contributor (XAU), 23. CBOE Market Volatility Index (VIX), 24. Japan 10 Year Benchmark (JGB), and 25. Nikkei 225 Index (NKY). Also, we occasionally hear that cryptocurrencies move volatile and irregularly (Mackintosh 2021). We especially pay attention on the results from cryptocurrencies and compare with others. In the following sections, we briefly review important previous papers and overview their findings. And we show/review results from our RMT application on financial data after explaining calculation process about theoretical moments based on Marchenko–Pastur law.

15.2 Reviews on Important Previous Papers

15.2.1 Random Matrix Theory (RMT)

In this section, we briefly explain RMT. Now let M be a real-valued symmetry matrix and its size is $N \times N$ ($N \in \mathbf{N}$). Each element M_{ij} is an independent and identically distributed (iid) random variable. Figure 15.1 indicates histogram of eigenvalues of sample matrices. The size of matrix for the left figure N_{left} is 200 (i.e., $M_{left} \in 200\times200$) and the size of right figure N_{right} is 1000 (i.e., $M_{right} \in 1000\times1000$). Elements of these matrices are randomly set based on the uniform distribution $[-1, 1]$. The theoretical density curve of eigenvalues in $N \to \infty$ is shown in Eq. (15.1). This is well known as the Wigner semicircle law (Wigner 1958).

$$\rho_W(\lambda) = \frac{1}{2\pi\sigma^2}\sqrt{4\sigma^2 - \lambda^2}, \quad \text{if } |\lambda| \leq 2\sigma, \tag{15.1}$$

where λ is eigenvalue and σ^2 is the variance of eigenvalues.

Next, let M be a real-valued rectangle matrix ($L \times N$) and i and j be natural numbers ($i \in [1, L]$, $j \in [1, N]$). Each element of the matrix M_{ij} is random numbers and independent and identically distributed (iid). Let Q be a ratio of $\frac{L}{N}$ under $N \to \infty$ and suppose that $L \geq N$. Let C be a correlation matrix

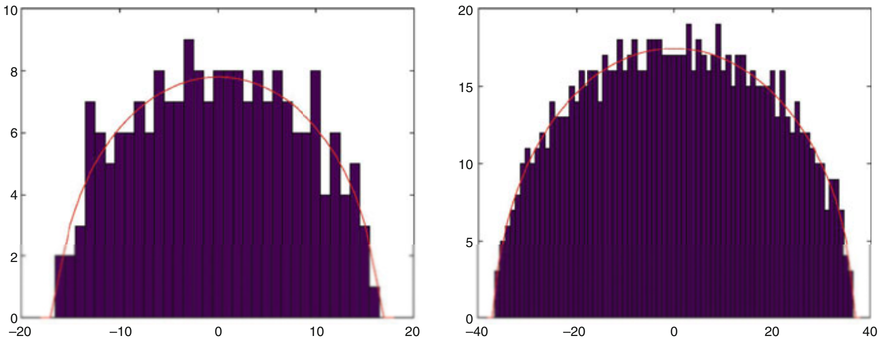

Fig. 15.1 Histograms of eigenvalues: the horizontal axis indicates the value of eigenvalues and the vertical axis indicates the number of eigenvalues that are included in each mesh. The mesh spans are set as 1 for both the figures. The left figure is the eigenvalue histogram of 200 × 200 size real-valued symmetry matrix and the right figure is also eigenvalue histogram of 1000 × 1000 size real-valued symmetry matrix. Variance (σ^2) of λ is set as $n \times \frac{1}{12}\{\text{Range}_{max}(= 1) - \text{Range}_{min}(= -1)\}^2$ by referring (Sengupta and Mitra 1999). Then, the variance of the left figure (${\sigma_{left}}^2$) is $\frac{200}{3}(= 66.667)$, and the variance of the right figure (${\sigma_{right}}^2$) is $\frac{1000}{3}(= 333.333)$. The eigenvalue range for the left is $[-16.33, 16.33]$ and the right range is $[-36.52, 36.52]$. The theoretical curves are adjusted to fit the histograms. They are multiplied by the number of eigenvalues (n)

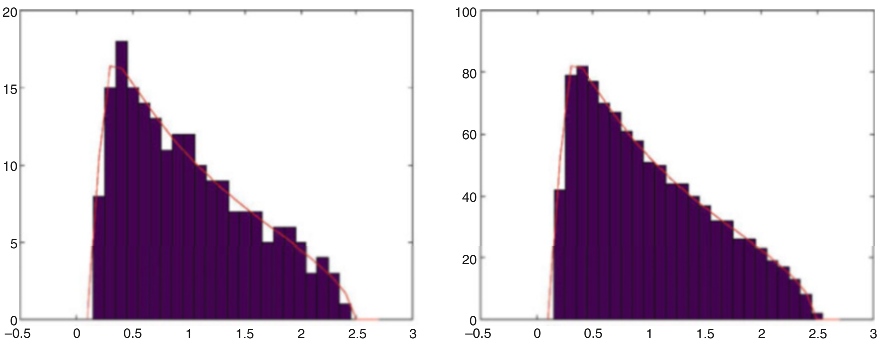

Fig. 15.2 Histograms of eigenvalues: the horizontal axis indicates the value of eigenvalues and the vertical axis indicates the number of eigenvalues that are included in each mesh. For both the figures, mesh spans are set as 0.1 and Q is 3. Then, λ_+ is 2.488034 and λ_- is 0.178633. The left figure is the eigenvalue histogram of 200 $\times$ 200 size correlation matrix and, the right figure is also eigenvalue histogram of 1000 $\times$ 1000 size correlation matrix. These correlation matrices are calculated based on 600 $(L)\times$ 200 (N) iid random numbers for the left figure (i.e., 120,000 iid random numbers are generated for the left figure) and 3000 $(L)\times$ 1000 (N) for the right (i.e., 3,000,000 iid random numbers are generated for the right figure). Random numbers are from uniform distribution $[-1, 1]$. The theoretical curves are adjusted to fit the histograms. They are multiplied by the mesh size $\times$ the number of eigenvalues (N)

calculated based on M and its size is $N \times N$. Each element of C_{ij} is inner product of vector $\bar{M}_{i\cdot}$ and vector $\bar{M}_{j\cdot}$. The bar symbol over each vector indicates that vectors are standardized with their averages and standard deviations. The matrix C is known as the Wishart type matrix, and also the eigenvalues of this type of matrix follow Marchenko-Pastur law (Marcenko and Pastur 1967) as shown in Eq. (15.2) (Fig. 15.2).

$$\rho_{MP}(\lambda) = \frac{Q}{2\pi\lambda}\sqrt{(\lambda_+ - \lambda)(\lambda - \lambda_-)}, \quad \lambda_\pm = 1 + \frac{1}{Q} \pm 2\sqrt{\frac{1}{Q}}. \tag{15.2}$$

The theoretical moments are calculated as follows:

$$\mu_k = \mathbf{E}\left[\lambda^k\right] = \int_{\lambda_-}^{\lambda_+} \lambda^k \rho_{MP}(\lambda)\mathbf{d}\lambda. \tag{15.3}$$

By inserting Eq. (15.2) into Eq. (15.3), the theoretical moments are obtained. These are known as Narayana polynomial. They are Catalan number and their calculation processes are shown in the following section:

$$\mu_1 = 1$$

$$\mu_2 = 1 + \frac{1}{Q}$$

$$
\begin{aligned}
\mu_3 &= 1 + \frac{3}{Q} + \frac{1}{Q^2} \\
\mu_4 &= 1 + \frac{6}{Q} + \frac{6}{Q^2} + \frac{1}{Q^3} \\
\mu_5 &= 1 + \frac{10}{Q} + \frac{20}{Q^2} + \frac{10}{Q^3} + \frac{1}{Q^4} \\
\mu_6 &= 1 + \frac{15}{Q} + \frac{50}{Q^2} + \frac{50}{Q^3} + \frac{15}{Q^4} + \frac{1}{Q^5} \\
&\cdots
\end{aligned}
\tag{15.4}
$$

For $Q = 3$, μ_2 is 1.333, μ_3 is 2.111, μ_4 is 3.704, μ_5 is 6.938, and μ_6 is 13.597. From the above simulation, empirical sample moments are calculated as μ_2^{200} is 1.332, μ_3^{200} is 2.109, μ_4^{200} is 3.701, μ_5^{200} is 6.943, μ_6^{200} is 13.639 for the left figure ($N = 200$). μ_2^{1000} is 1.333, μ_3^{1000} is 2.111, μ_4^{1000} is 3.706, μ_5^{1000} is 6.948, and μ_6^{1000} is 13.632 for the right figure ($N = 1000$). The right figure is close to the theoretical distribution more than the left figure by comparing these empirical moments.

15.2.2 RMT Application on Financial Data

Here, we briefly introduce a few important previous papers which applied RMT on financial data. In there, the authors analyze portfolio composed of US stocks and investigate ideal portfolio allocation which minimizes the risk of portfolio by using RMT. In the first paper (Plerou et al. 2002), RMT is adapted to three time series stock price data. They are: (1) 30-min returns of 1000 US stocks for the 2-year period 1994–1995, (2) 30-min returns of 881 US stocks for the 2-year period 1996–1997, and (3) 1-day returns of 422 US stocks for the 35-year period 1962–1996. They suppose that stock price process is log normal and convert stock prices into their returns. Let $S_i(t)$ be issuer i's stock price at time t and $R_i(t)$ be issuer i's stock return at time t, $R_i(t) = \ln S_i(t + \delta t) - \ln S_i(t)$. Inner products $C_{ij} = \sum_{t\in[0,T]} \bar{R}_i(t) \times \bar{R}_j(t)$ are calculated after standardizing returns, respectively,[1] and utilized this correlation matrix (this matrix is real-valued symmetry, and this is the Wishart type matrix) to calculate eigenvalues and their corresponding eigenvectors. They check if almost eigenvalues are included in RMT bound $[\lambda_-, \lambda_+]$ and analyze the largest eigenvalue that corresponds to an influence in all stocks (this is called as market factor). In the second paper (Laloux et al. 1999), RMT is applied to the financial data. The authors focus on the noise included in the correlation matrix, especially when the data length for calculating correlation matrix is not enough long compared to N assets. They utilize 406 assets included

[1] t indicates discrete time interval within the range of $[0, T]$.

in S&P500 during the years 1991–1996. They investigate the smallest eigenvalue and its corresponding eigenvector which determine the minimum risk portfolio of CAPM theory in Markowitz (1952). In these papers, the authors check the histograms of eigenvalues and found that they are enough close to the theoretical distribution except for a few eigenvalues.

15.2.3 RMT Application on Japanese Financial Data

Some papers (see, e.g., Tanaka-Yamawaki et al. (2015)) apply RMT on stock price data in Japan. They utilize stock prices listed on the Tokyo Stock Exchange during the years 2007–2009, more specifically 211 stocks with 66,338 minutely price data in 2007, 240 stocks with 66,338 minutely price data in 2008, and 229 stocks with 65,945 minutely price data in 2009. By using these data, they tried to extract characteristics of stock price direction. Also, they frequently checked ratios between theoretical moment and empirical moment obtained from stock price fluctuations. Most characteristic differences between the previous researches and these are not only using stock price data in Japan but also analyzing single stock. They prepare enough length of stock price data and convert them into returns like above. In the next step, they truncate these return data into N pieces. Each truncated pieces has $L(= N \times Q)$ length of return data. They rearrange them in matrix format (i.e., the truncated first L return is the first column of the matrix M and the truncated Nth return is the last column of the matrix M). Its matrix size is L (rows) $\times N$ (columns); namely the matrix contains only single firm's time series stock prices. This matrix is corresponding to L data length N assets matrix in the above papers (financial portfolio application cases). An example matrix is shown in Fig. 15.3. After that, they follow usual steps introduced in the previous papers, namely calculate correlation matrix and its eigenvalues, and they compare theoretical and empirical moments by their ratio and also draw theoretical density function and empirical histogram for graphical comparison.

$$\mathbf{R}_{pf} = \begin{pmatrix} \bar{r}_1(t_1) & \bar{r}_2(t_1) & \cdots & \bar{r}_N(t_1) \\ \bar{r}_1(t_2) & \bar{r}_2(t_2) & \cdots & \bar{r}_N(t_2) \\ \vdots & \vdots & \ddots & \vdots \\ \bar{r}_1(t_L) & \bar{r}_2(t_L) & \cdots & \bar{r}_N(t_L) \end{pmatrix}, \qquad \mathbf{R}_{\#i} = \begin{pmatrix} \bar{r}_i(t_1) & \bar{r}_i(t_{L+1}) & \cdots & \bar{r}_i(t_{(N-1)L+1}) \\ \bar{r}_i(t_2) & \bar{r}_i(t_{L+2}) & \cdots & \bar{r}_i(t_{(N-1)L+2}) \\ \vdots & \vdots & \ddots & \vdots \\ \bar{r}_i(t_L) & \bar{r}_i(t_{2L}) & \cdots & \bar{r}_i(t_{NL}) \end{pmatrix},$$

Fig. 15.3 The above two matrices are composed of standardized return ($\bar{r}_i(t)$). The left matrix contains N kinds of stocks and each data length is L. This is utilized for portfolio analysis, and the right contains only single stock time series price (return) data. As explained, returns in the left matrix have different numbers of i, while returns in the right figure have consistent subscript. For single stock analysis, we need to prepare N times longer price data than portfolio analysis

15.3 Numerical Experiments

Before showing results of RMT application on financial data, we write the calculation process of Narayana polynomial.

15.3.1 *Marchenko–Pastur Distribution, Motzkin Number, and Narayana Number*

We can obtain the theoretical moment by using Marchenko–Pastur distribution: Eq. (15.2).

$$\mu_k = \mathbf{E}\left[\lambda^k\right] = \int_{\lambda_-}^{\lambda_+} \lambda^k \rho_{MP}(\lambda)\mathbf{d}\lambda$$
$$= \frac{2}{\pi}\int_{-1}^{1}\left\{2\sqrt{\frac{1}{Q}}x + \left(1+\frac{1}{Q}\right)\right\}^{k-1}\sqrt{1-x^2}\mathbf{d}x, \tag{15.5}$$

where

$$x = \frac{\lambda - (1+\frac{1}{Q})}{2\sqrt{\frac{1}{Q}}}.$$

We divided the cases when $k = 2m+1$ and $k = 2m+2$, $m = 1, 2, \ldots$. In the case $k = 2m+1$, we expand the first term by x, and the odd powers of x become 0,

$$\mu_k = \sum_{i=0}^{m}\binom{2m}{2i} C_i \left(1+\frac{1}{Q}\right)^{2m-2i}\frac{1}{Q^i}$$
$$= \sum_{i=0}^{m} T(k-1, i)\left(1+\frac{1}{Q}\right)^{2m-2i}\frac{1}{Q^i}, \tag{15.6}$$

where $T(k-1, i)$ is the number of Motzkin paths, Mozkin number, of length $k-1$ with i up steps. Mozkin number, M_l, is defined as $M_l = \sum_{i=0}^{\lfloor l \rfloor} T(l, i)$, where $\lfloor l \rfloor$ is the floor function. We show the Motzkin paths for $k = 5$ in Fig. 15.4.

In this calculation, we use the relation

$$\int_{-1}^{1} x^{2i}\sqrt{1-x^2}\mathbf{d}x = \frac{\pi}{2^{2i+1}}C_i, \tag{15.7}$$

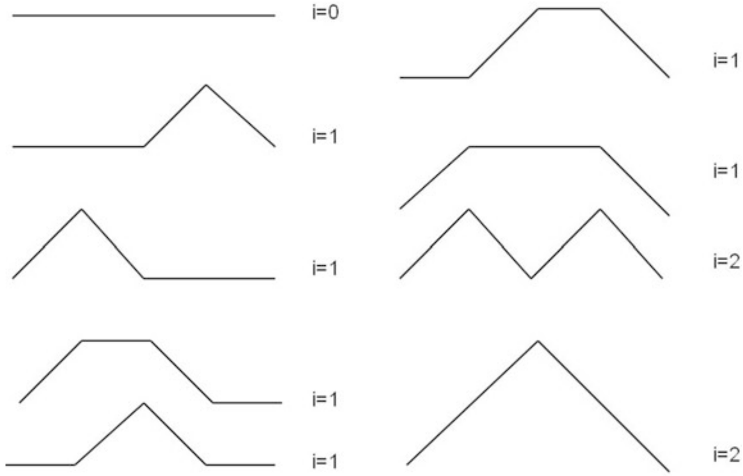

Fig. 15.4 Motzkin paths for $k = 5$. We can confirm $T(4,0) = 1$, $T(4,1) = 6$, $T(4,2) = 2$, and $M_4 = 9$

and C_i is the i-th Catalan number

$$C_i = \frac{1}{i+1}\binom{2i}{i}. \tag{15.8}$$

We expand Eq. (15.6) more,

$$\begin{aligned}\mu_k &= \sum_{i=0}^{m}\binom{2m}{2i} C_i \left(1+\frac{1}{Q}\right)^{2m-2i}\frac{1}{Q^i} \\ &= \sum_{i=0}^{m}\sum_{l=0}^{2m-2i}\binom{2m}{2i}\binom{2m-2i}{l} C_i \frac{1}{Q^{l+i}}.\end{aligned} \tag{15.9}$$

Here, we use $j = i + l + 1$ instead of l

$$\begin{aligned}\mu_k &= \sum_{j=1}^{k}\sum_{i=0}^{m}\binom{2m}{2i}\binom{2m-2i}{j-1-i} C_i \frac{1}{Q^{j-1}} \\ &= \sum_{j=1}^{k}\frac{1}{k}\binom{k}{j}\binom{k}{j-1}\frac{1}{Q^{j-1}}\end{aligned} \tag{15.10}$$

$$= \sum_{j=1}^{k} N(k, j) \frac{1}{Q^{j-1}}$$

$$= \mathcal{N}_k \left(\frac{1}{Q} \right), \tag{15.11}$$

where we use the following identity (Simion and Ullman 1991):

$$\frac{1}{k} \binom{k}{j} \binom{k}{j-1} = \sum_{i=0}^{\lfloor (k-1)/2 \rfloor} \binom{k-1}{2i} \binom{k-2i-1}{j-1-i} C_i. \tag{15.12}$$

$N(n, j)$ is the Narayana number and $\mathcal{N}_n(x)$ is the Narayana polynomial. Narayana number is the number of Dyck paths of length $2k$ with j peaks. In Fig. 15.5, we show the Dyck paths of length 6 with j peaks. The sum of the Narayana number becomes the Catalan number.

When $k = 2m + 2$, we can obtain in the same way

$$\mu_k = \sum_{i=0}^{m} \binom{2m+1}{2i} C_i \left(1 + \frac{1}{Q}\right)^{2m+1-2i} \frac{1}{Q^i}$$

$$= \sum_{i=0}^{m} T(k, i) \left(1 + \frac{1}{Q}\right)^{2m+1-2i} \frac{1}{Q^i}$$

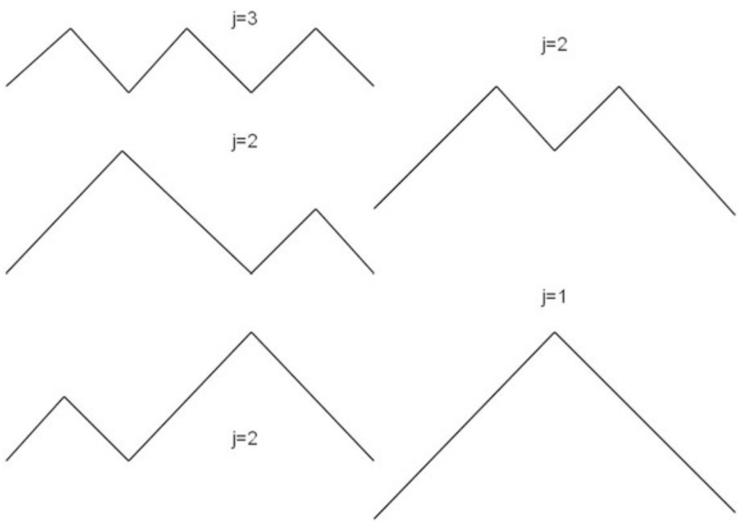

Fig. 15.5 Dyck paths for $k = 3$. We can confirm $N(3, 1) = 1$, $N(3, 2) = 3$, $N(3, 3) = 1$, and $C_3 = 5$

$$= \sum_{j=1}^{k} \frac{1}{k} \binom{k}{j} \binom{k}{j-1} \frac{1}{Q^{j-1}}$$

$$= \sum_{j=1}^{k} N(n, j) \frac{1}{Q^{j-1}} = \mathcal{N}_k \left(\frac{1}{Q} \right). \tag{15.13}$$

In summary, we can obtain the moment μ_k as the Motzkin polynomial in the left side and Narayana polynomial in the right side,

$$\begin{aligned}
\mu_1 &= 1 = 1 \\
\mu_2 &= \left(1 + \frac{1}{Q}\right) = 1 + \frac{1}{Q} \\
\mu_3 &= \left(1 + \frac{1}{Q}\right)^2 + \frac{1}{Q} = 1 + \frac{3}{Q} + \frac{1}{Q^2} \\
\mu_4 &= \left(1 + \frac{1}{Q}\right)^3 + 3\left(1 + \frac{1}{Q}\right)\frac{1}{Q} = 1 + \frac{6}{Q} + \frac{6}{Q^2} + \frac{1}{Q^3} \\
\mu_5 &= \left(1 + \frac{1}{Q}\right)^4 + 6\left(1 + \frac{1}{Q}\right)^2 \frac{1}{Q} + 2\frac{1}{Q^2} = 1 + \frac{10}{Q} + \frac{20}{Q^2} + \frac{10}{Q^3} + \frac{1}{Q^4} \\
\mu_6 &= \left(1 + \frac{1}{Q}\right)^5 + 10\left(1 + \frac{1}{Q}\right)^3 \frac{1}{Q} + 10\left(1 + \frac{1}{Q}\right)\frac{1}{Q^2} \\
&= 1 + \frac{15}{Q} + \frac{50}{Q^2} + \frac{50}{Q^3} + \frac{15}{Q^4} + \frac{1}{Q^5} \\
&\cdots
\end{aligned} \tag{15.14}$$

In general, it can be expressed as $\mu_k = \mathcal{N}_k(\frac{1}{Q}) =_2 F_1(1-k, -k; 2; 1/Q)$. As the special case when $1/Q = 1$, the momentum, μ_k, becomes the Catalan number, and when $1/Q = 2$, the momentum becomes the Schröder–Hipparchus numbers.

15.3.2 RMT Application on the Financial Data

Firstly, we apply RMT on portfolio data. We use Nikkei 225 which is well known as benchmark stock price index in Japan and S&P500. Both of them are 30-minutely price data to consistently compare with figures in the previous papers. Before using these data, we check prices one by one whether they are missing price (blank data) or not. When we find missing price, namely the product was not traded in the time span (30 minutes), we use the previous trading price. We strictly arrange prices to be consistent to each trading time period. Probably then, we see high

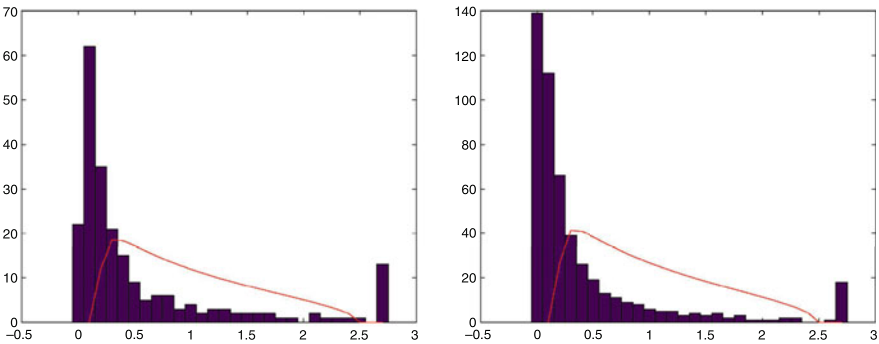

Fig. 15.6 Histograms of eigenvalues for stock portfolios: the horizontal axis indicates the value of eigenvalues, and the vertical axis indicates the number of eigenvalues that are included in each mesh. For both the figures, mesh spans are set as 0.1 and Q is 3. Then, λ_+ is 2.488034 and λ_- is 0.178633. The left figure is the eigenvalue histogram of Nikkei225. N is 225 and L is 675. We use 30-minutely price data from 2021/3/30 9:00 am to 2021/6/22 10:30 am. The right figure is the eigenvalue histogram of S&P500. N is 503 and L is 1509. We use 30-minutely price data from 2020/7/16 23:30 (JST) to 2020/11/31 0:00 (JST)

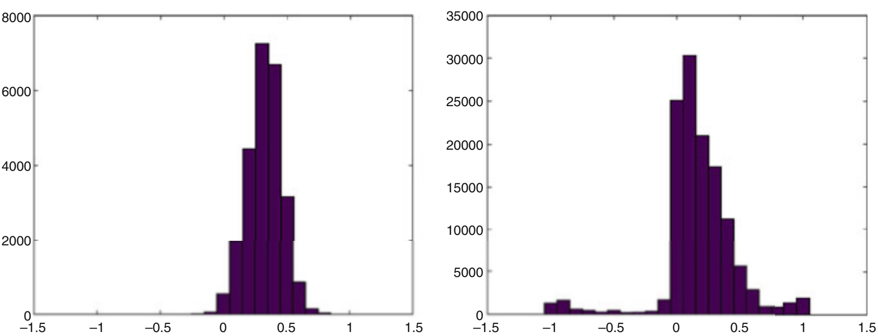

Fig. 15.7 Histograms of correlations: the horizontal axis indicates the value of correlations and the vertical axis indicates the number of correlations that are included in each mesh. For both the figures, mesh spans are set as 0.1. The left figure is based on Nikkei 225 which is exactly same data with RMT application, and the right figure is based on S&P500 which is also exactly the same with above. The left figure contains 25,200 (=225×224/2) correlations, and the right figure contains 126,253 (=503×502/2) correlations

correlation as shown in Fig. 15.7, and this might be easy to predict because of our frequently seeing simultaneous price appreciation and depreciation even among different sectors/industries. This is completely opposite to the iid assumption of RMT. That is why we had Fig. 15.6 which histograms of empirical eigenvalue are completely different from the theoretical curves. When the absolute value of correlations is not so high, we tend to have histograms like Fig. 15.8, which indicates that the histogram of empirical eigenvalues is close to the theoretical curve. This

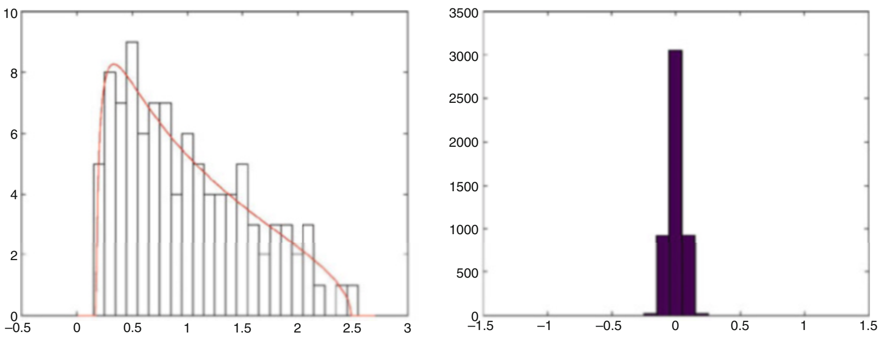

Fig. 15.8 The left figure is the histogram of eigenvalues based on BTC/USD price data. The horizontal axis indicates the value of eigenvalues, and the vertical axis indicates the number of eigenvalues that are included in each mesh. N is 100 and Q is 3. The right figure is histogram of correlations based on the same BTC/USD price data. The horizontal axis indicates the value of correlations and the vertical axis indicates the number of correlations that are included in each mesh. We use minutely price data (30,000) from 2020/6/4 3:36 (JST) to 2020/6/24 23:41 (JST)

implies that relation between histogram of empirical eigenvalues and its theoretical curve is tightly related to the correlations.

Secondly, we apply RMT on individual financial products, and their details are shown in Table 15.1. We set N as 100 and Q as 3 except for JGB and NKY due to data limitation. N is 55 and Q is 3 for JGB. N is 70 and Q is 3 for NKY. We prepare different price data by shifting time window and calculate 10 times for each asset to mitigate specific data dependency. For JGB, there are 445 values which are less than zero out of 9127 and it is impossible to convert into log format. Then, we replaced them to the tiny value: 0.001. Before starting to explain results, we simply check normal volatility price average ratio (this is equal to standard deviation of price divided by average price) to grasp price fluctuation level. BTC/USD (6.233%), XRP/USD (16.410%), ETH/USD (11.434%), EUR/USD (1.320%), USD/JPY (0.645%), GBP/USD (1.079%), USD/CHF (1.212%), AUD/USD (1.511%), USD/CAD (1.351%), NZD/USD (1.529%), EUR/JPY (0.879%), EUR/CHF (0.400%), EUR/GBP (0.347%), USD/BRL (3.462%), USD/CNH (0.619%), USD/INR (1.034%), USD/ZAR (2.236%), USD/RUB (1.082%), WTI (4.965%), SOY (4.821%), CORN (4.595%), XAU (2.701%), VIX (11.667%), JGB (89.979%), and NKY (65.117%). NKY and JGB are daily data, and then their ratios are naturally high. Except for NKY and JGB, cryptocurrencies ratio is the highest and commodities ratio is the second highest. Results including average and standard deviation of moments are shown in Table 15.2 and found that moments based on cryptocurrencies (BTC, XRP, and ETH) are quite close to the theoretical moments. Furthermore, by comparing with empirical moments obtained based on NKY225: 28.588 (μ_2), 2060.759 (μ_3), 158134.651 (μ_4), 12200792.096 (μ_5), 941975811.564 (μ_6), and S&P500: 58.826 (μ_2), 6564.445 (μ_3), 768328.742 (μ_4), 90965894.144 (μ_5), 10826369286.114 (μ_6) in Fig. 15.6, moments from cryptocurrencies are reasonably close to the theoretical numbers.

Table 15.1 Data spec

No.	Data name	Data category	Data period	Data span	Data length
1	BTC/USD	Cryptocurrency	2021/6/4 3:36–2021/7/15 19:49	Minutely	60, 000
2	XRP/USD	Cryptocurrency	2021/6/4 3:30–2021/7/15 19:00	Minutely	60, 000
3	ETH/USD	Cryptocurrency	2021/6/4 3:39–2021/7/15 19:52	Minutely	60, 000
4	EUR/USD	Foreign exchange	2021/5/19 4:03–2021/7/15 19:53	Minutely	60, 000
5	USD/JPY	Foreign exchange	2021/5/19 4:54–2021/7/15 19:53	Minutely	60, 000
6	GBP/USD	Foreign exchange	2021/5/19 18:36–2021/7/15 19:55	Minutely	60, 000
7	USD/CHF	Foreign exchange	2021/5/19 10:30–2021/7/15 19:55	Minutely	60, 000
8	AUD/USD	FX (natural resource)	2021/5/19 18:10–2021/7/15 19:56	Minutely	60, 000
9	USD/CAD	FX (natural resource)	2021/5/19 20:22–2021/7/15 19:57	Minutely	60, 000
10	NZD/USD	FX (natural resource)	2021/5/19 12:18–2021/7/15 19:58	Minutely	60, 000
11	EUR/JPY	FX (cross pair)	2021/5/18 19:32–2021/7/15 19:59	Minutely	60, 000
12	EUR/CHF	FX (cross pair)	2021/5/18 13:20–2021/7/15 20:00	Minutely	60, 000
13	EUR/GBP	FX (cross pair)	2021/5/19 1:06–2021/7/15 20:00	Minutely	60, 000
14	USD/BRL	FX (BRICS)	2021/4/15 20:01–2021/7/15 6:01	Minutely	34, 047
15	USD/CNH	FX (BRICS)	2021/5/18 23:47–2021/7/15 20:04	Minutely	60, 000
16	USD/INR	FX (BRICS)	2021/4/15 20:04–2021/7/15 20:04	Minutely	45, 134
17	USD/ZAR	FX (BRICS)	2021/5/18 16:55–2021/7/15 20:05	Minutely	60, 000
18	USD/RUB	FX (BRICS)	2021/5/11 13:37–2021/7/15 20:06	Minutely	60, 000
19	WTI	Commodity	2021/5/17 7:01–2021/7/15 19:57	Minutely	56, 525
20	SOY-beans	Commodity	2021/4/19 9:01–2021/7/15 19:57	Minutely	38, 483
21	CORN	Commodity	2021/4/19 9:01–2021/7/15 19:59	Minutely	41, 113
22	XAU	Commodity	2021/5/17 9:45–2021/7/15 20:10	Minutely	60, 000
23	VIX	Commodity	2021/4/15 20:11–2021/7/15 19:56	Minutely	48, 106
24	JGB	Government bond	1996/10/31–2021/7/15	Daily	9127
25	NKY225	Stock index	1965/1/5–2021/7/15	Daily	14, 886

Table 15.2 Individual results

No.	Data name	μ_2	μ_3	μ_4	μ_5	μ_6
0	Theoretical value	1.333 (0.000)	2.111 (0.000)	3.704 (0.000)	6.938 (0.000)	13.597 (0.000)
1	BTC/USD	1.335 (0.004)	2.120 (0.013)	3.74 (0.040)	7.043 (0.111)	13.090 (0.302)
2	XRP/USD	1.356 (0.007)	2.162 (0.027)	3.862 (0.085)	7.376 (0.242)	14.747 (0.662)
3	ETH/USD	1.341 (0.007)	2.145 (0.030)	3.811 (0.098)	7.251 (0.290)	14.467 (0.819)
4	EUR/USD	1.380 (0.010)	2.297 (0.039)	4.261 (0.117)	8.463 (0.324)	17.599 (0.867)
5	USD/JPY	1.373 (0.007)	2.266 (0.030)	4.160 (0.103)	8.169 (0.319)	16.786 (0.935)
6	GBP/USD	1.353 (0.007)	2.120 (0.031)	3.975 (0.101)	7.720 (0.291)	15.751 (0.790)
7	USD/CHF	1.400 (0.008)	2.381 (0.034)	4.525 (0.114)	9.221 (0.349)	19.696 (1.027)
8	AUD/USD	1.368 (0.005)	2.249 (0.022)	4.123 (0.070)	8.101 (0.209)	16.695 (0.606)
9	USD/CAD	1.419 (0.008)	2.448 (0.028)	4.716 (0.082)	9.732 (0.218)	21.038 (0.568)
10	NZD/USD	1.373 (0.003)	2.269 (0.017)	4.177 (0.070)	8.234 (0.242)	17.010 (0.767)
11	EUR/JPY	1.375 (0.008)	2.273 (0.003)	4.180 (0.094)	8.222 (0.267)	16.940 (0.733)
12	EUR/CHF	1.430 (0.003)	2.494 (0.016)	4.856 (0.055)	10.113 (0.164)	22.032 (0.456)
13	EUR/GBP	1.402 (0.003)	2.385 (0.015)	4.533 (0.055)	9.237 (0.180)	19.738 (0.562)
14	USD/BRL	1.349 (0.002)	2.175 (0.010)	3.901 (0.034)	7.502 (0.113)	15.154 (0.354)
15	USD/CNH	1.409 (0.008)	2.416 (0.034)	4.644 (0.110)	9.595 (0.337)	20.835 (1.005)
16	USD/INR	1.364 (0.010)	2.223 (0.038)	4.072 (0.120)	7.963 (0.348)	16.341 (0.978)
17	USD/ZAR	1.352 (0.005)	2.181 (0.023)	3.907 (0.077)	7.483 (0.233)	15.000 (0.660)
18	USD/RUB	1.348 (0.006)	2.167 (0.026)	3.871 (0.081)	7.401 (0.022)	14.832 (0..591)
19	WTI	1.336 (0.005)	2.123 (0.019)	3.741 (0.058)	7.046 (0.163)	13.894 (0.443)
20	SOY	1.333 (0.003)	2.111 (0.013)	3.703 (0.041)	6.933 (0.122)	13.569 (0.344)
21	CORN	1.327 (0.056)	2.080 (0.024)	3.603 (0.076)	6.651 (0.209)	12.829 (0.541)
22	XAU	1.342 (0.007)	2.145 (0.034)	3.802 (0.116)	7.205 (0.342)	14.295 (0.947)
23	VIX	1.336 (0.007)	2.117 (0.027)	3.713 (0.085)	6.960 (0.254)	13.669 (0.736)
24	JGB	1.330 (0.036)	2.102 (0.014)	3.692 (0.042)	6.950 (0.117)	13.731 (0.317)
25	NKY	1.324 (0.049)	2.081 (0.020)	3.637 (0.064)	6.819 (0.186)	13.433 (0.512)

15.4 Conclusion

In this research, we updated important findings in the previous papers by using current data. We found at least three interesting points through this research and study the following points in our future works. Firstly, empirical moments based on cryptocurrencies are not far from the theoretical moments and are even closer than other financial products although these prices move volatilely and irregularly including frequent jumps. We know that this has to be cautiously tested on larger scale data to let results/findings be more stable. Secondly, the absolute value of correlations on portfolio analysis is far larger than other cases and might have put huge influence on their empirical moments; then, we had far different figures from the previous studies. We investigate the mechanism to compose ideal portfolio (minimizing portfolio risk) by improving findings in previous researches. Thirdly, we think that auto-correlations are also effecting on correlations and eigenvalues eventually. This is also targeted to study in our future work. Additionally, we test our findings/results on larger scale data like tick-by-tick data or far longer length of minutely data.

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Chapter 16
How Does the Entropy Function Explain the Distribution of High-Frequency Data?

Hiroyuki Moriya

Abstract In financial markets, price movements are stipulated by financial practitioners, regulators, and market organizers to realize smooth and liquid trading and achieve fair market conditions for all participants. These forces determine the minimum allowable price increment, enabling trades in multiples of this value. We utilize large deviation theory and analyse the distribution of high-frequency data under the assumption that the majority of economic agents trade with this minimum price increment. By introducing an entropy function and focusing on the exponential decay of distributions, it is found that such economic agents play central roles in markets and that transaction data can move unpredictably in a wider and more skewed manner than that predicted by the central limit theorem and even the strong law of large numbers.

Keywords Entropy function · Realized volatility · High-frequency data · Market microstructure

16.1 Introduction

The prediction and control of the risks corresponding to trading and investment in financial markets are the main applications of probability and statistical theory. The law of large numbers and the central limit theorem are major tools for analysing the ranges of price fluctuations. We emphasize the logarithm of multiplicity that connects the macro phenomena and micro phenomena in markets. The exponential decay of the distribution of the sum of squared price increments may explain the properties of realized price movements. Our empirical analysis with respect to the Nikkei 225 mini stock exchange explains the mechanism of price fluctuations. The sample size N and the limiting mean are the key elements of the analysis. Price

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movements are unpredictably wider and exhibit more skewness than that predicted by probability theory.

Section 16.2 introduces basic tools for analysing transaction data. We introduce the basic concepts of transaction data: the minimum price increment and the sum of squared price increments. These basic ideas for modelling are obtained from Aoki (1996). Then, we explain various product and probability measures. Motivated by Ellis' introduction to the large deviation metric and its application in statistical mechanics (Eliss 1985), we use the exponential decay of probability distributions to analyse the given transaction data. An excellent review of the recent developments of large deviations in mathematical finance is provided by Pham (2008) including rare event simulations and credit risk and portfolio loss management. We model the probability distribution of transaction data under the condition of a strictly isolated market after a brief discussion of the law of large numbers and the exponential decay of probability. Then, we propose a distribution for tick data by fixing the average of the sum of squared price increments.

Section 16.3 explains the market structure of the transaction data obtained from the Nikkei 225 mini stock exchange and the back-test process. Data from August 2016 to November 2018 comprise three sets for our analysis. One dataset contains the data without any price movements; another represents bid-ask bounce (Hausman et al. 1992), which is a basic phenomenon in the financial market related to market making; and the third dataset contains price movements outside the bid-ask bounce. We explain how to obtain the third dataset. After the data are cleaned, we perform the back tests by focusing on 10, 100, and 1000 data points to obtain the basic properties of the exponential decay of the distributions.

Section 16.4 explains and discusses the results of the empirical data analysis.

16.2 Modelling Transaction Prices

We model transaction price data, which are the highest frequency data in financial markets.

16.2.1 Minimum Price Increments and Price Process

The Nth trade at a given price at time $t \geq 0 \in \mathbb{R}$ is described as

$$x_N(t) = x_0(t) + \sum_{j=1}^{N} y_j(t),$$

where $N,\ j \in \mathbb{Z}$. $x_0(t)$ is an initial transaction price at time t, $x_N(t) > 0$, for $y_j \in \Gamma$,

$$\Gamma = \{\gamma_i;\ i = -r, \cdots, -1, 1, \cdots, r\},$$

where the ith price increment γ_i must be a multiple of the minimum price increment ($|\gamma_1|$) that takes values in Γ. The γ_i are arranged in increasing order while taking the properties of $\gamma_{-i} = -\gamma_i$ and $\gamma_i = i \cdot \gamma_1$ into account; this rule may be restated as

$$\gamma_{-r} = -\gamma_r < \cdots < \gamma_{-1} < 0 < \gamma_1 \cdots < \gamma_r.$$

$\Delta(t)$ is a closed bounded interval with a nonempty interior at time t and its upper and lower boundaries are the highest and lowest prices of $x_j(t)$, respectively. A number N of discrete transaction prices are modelled by the movements in $\Delta(t)$. The prices rise and fall in $\Delta(t)$, which is divided into the following sub-boundaries:

$$\delta_1(t) < \delta_2(t) < \cdots < \delta_{m-1}(t) < \delta_m(t),$$

where $\delta_1(t)$'s lower bound is the lower bound of $\Delta(t)$ and $\delta_m(t)$'s upper bound is the upper bound of $\Delta(t)$. The movements continue up and down in $\delta_i(t)$ until the price reaches $\delta_{i+1}(t)$ or $\delta_{i-1}(t)$. The transactions continuously and repeatedly traded in the same sub-boundary $\delta_i(t)$ are called the "bid-ask bounce" (Hausman et al. 1992).

The transactions at time t are represented by the microstates $\omega(t) = (\boldsymbol{x}(t), \boldsymbol{y}(t))$, where $\boldsymbol{x}(t) = (x_1(t), \cdots, x_N(t))$ and $\boldsymbol{y}(t) = (y_1(t), \cdots, y_N(t))$. For each $t \geq 0$, $\omega(t)$ is a microstate and a point N price increment configuration space, which is the set

$$\Omega_N = \{\omega : \omega = (x_1, \cdots, x_N, y_1, \cdots, y_N),\ \text{with}\ x_j \in \Delta,\ \text{and}\ y_j \in \Gamma\} = \Delta^N \Gamma^N.$$

Price processes in financial markets are derived from many factors. Since we cannot obtain all information related to the subjects of interest, it is natural to treat the prices and price increments of the N trades as random. We denote them as $\{X_j;\ j \in \mathbb{Z}\}$ and $\{Y_j;\ j \in \mathbb{Z}\}$, respectively, where $x_j = X_j(\omega)$ and $y_j = Y_j(\omega)$.

We restate the above processes:

$$\begin{aligned} x_N(0) &= \quad x_0(0) + y_0(0) + y_1(0) + \cdots + y_N(0) \\ x_N(1) &= \quad x_N(0) + y_0(1) + y_1(1) + \cdots + y_N(1) \\ &\vdots \\ x_N(t) &= x_N(t-1) + y_0(t) + y_1(t) + \cdots + y_N(t). \end{aligned} \tag{16.1}$$

16.2.2 The Sum of Squared Price Increments

We assume that market participants trade a risk-free asset without any interest rate and one risky asset in a frictionless market with a self-financing strategy (Harrion and Kreps 1979; Cox and Leland 2000). These participants only allocate funds between the risk-free asset and the risky asset, and their endowment is sufficiently large to settle the transactions. We isolate these financial markets from the external environment. Money, market participants, and information are not affected by external environments. The available funds for trading, the properties of market participants, and regulations determine the initial statistics.

We introduce $U_N(t) = \sum_{j=1}^{N} y_j(t)^2$ and want to assume that $U_N(0) = U_N(t)$ with a fixed number of $U_N(t)/N$. $U_N(t)$ is the realized volatility for tick data, as introduced by Andersen et al. (2001). We define the set A as a closed subinterval (γ_1^2, γ_r^2) with a nonempty interior, where $U_{N,A}/N = \{\omega \in \Omega_N : N^{-1}\sum_{j=1}^{N} y_j(t)^2 \in A\}$. However, it is best to start with a value of $U_N(0)/N \in A$ that is as small as possible. A restricts the price movements and must include the limiting mean of $U_N(t)/N$ or u_ρ. The microstates of the price movements can be any points in $A_{U_N} = \{\omega \in \Omega_N : \sum_{j=1}^{N} y_j(t)^2 \in A\}$, and it is reasonable to assign an equal probability to all microstates in A_{U_N}.

16.2.3 Product and Probability Measures

We topologize Δ, Γ, and Ω_N. Δ is defined via relative topology as a subset of $\mathbb{R}$ on $\mathscr{B}(\Delta)$ and Borel σ fields. Γ and Ω_N are defined by the discrete topology and the product topology, respectively. $\mathscr{B}(\Gamma)$ and $\mathscr{B}(\Omega_N)$ are the respective Borel σ fields.

Lebesgue measure on $\mathscr{B}(\Delta)$ is introduced and normalized with $\lambda\{\Delta\} = 1$. We define the uniform measure ρ on $\mathscr{B}(\Gamma)$ for $\rho_i = \rho\{y_i\}$ for each $y_i \in \Gamma$. For a subset of Γ $\mathscr{A}$, $\rho\{\mathscr{A}\}$ equals $\sum_{1\le|i|\le r} \rho_i \delta_{y_i}\{\mathscr{A}\}$, where $\delta_{y_i}\{\mathscr{A}\} = 1$ if $y_i \in \mathscr{A}$ and $\delta_{y_i}\{\mathscr{A}\} = 0$ if $y_i \notin \mathscr{A}$.

We define $L_N(\omega, \cdot) = N^{-1}\sum_{j=1}^{N} \delta_{Y_j(\omega)}(\cdot)$ corresponding to the sequence $Y_1(\omega), Y_2(\omega), \cdots Y_N(\omega)$. It is an empirical measure that takes values in the set $\mathscr{M}(\Gamma)$ containing the probability measures determined on $\mathscr{B}(\Gamma)$. $\mathscr{M}(\Gamma)$ is metrizable and is a completely separable metric space. For each ω, the numbers $\{v_i; |i| = 1, \cdots, r\} \in \mathscr{M}(\Gamma)$ provide probability measures and have the form $\sum_{1\le|i|\le r} v_i \delta_{\gamma_i}$, and $\sum_{1\le|i|\le r} v_i = 1$. The vector $\{\rho_i\}$ is the limiting mean of the random vector $\{v_i\}$.

The finite product measure on $\mathscr{B}(\Omega_N)$ with one-dimensional marginals ρ is defined by

$$\Pi_N P_{\lambda,\rho}(d\omega) = \lambda(dx_1)\cdots\lambda(dx_N)\rho(dy_1)\cdots\rho(dy_N),$$

where $P_{N,\lambda,A}$ denotes the probability measure determined on the configuration space Ω_N for the isolated market. $\Pi_N P_{\lambda,\rho}$ represents the restriction structures of price movements via U_N/N. This restriction becomes the conditional measure of $P_{N,\lambda,A}$, where

$$P_{N,\lambda,A}(d\omega) = \Pi_N P_{\lambda,\rho}\{d\omega|U_N/N \in A\}.$$

Under the restriction of $P_{N,\lambda,A}(d\omega)$, the prices and price increments of n transactions are described as

$$\omega(t,\omega_0) = (x_1(t), x_2(t) \cdots x_N(t) \text{ with } y_1(t) \cdots y_N(t)),$$

where $\omega_0 \in \Omega$, $t > 0$ and $\omega(0,\omega_0) = \omega_0$. It defines the microstate. Please refer to Durrett (2019) for measure-theoretic probability theory.

16.2.4 The Law of Large Numbers and Exponential Decay of Probability

We can estimate the macrostates in terms of microstates such that $U_N = \sum_{j=1}^{N} y_j^2$. Let $A_{u,\varepsilon}$ be the closed set $\{u \in \mathbb{R} : [u-\varepsilon, u+\varepsilon]\}$ for $\varepsilon > 0 \in \mathbb{R}$. $\Psi_N(\cdot)$ denotes the distribution of the sample average, and the weak law of large numbers (WLLN) explains $\Psi_N\{A_{u_\rho,\varepsilon}\} \to 1$ as $N \to \infty$ in probability.

If $u \neq u_\rho$ and $0 < \varepsilon < |u - u_\rho|$, then $\Psi_N\{A_{u,\varepsilon}\} \to 0$. The events represented by $\Psi_N\{A_{u,\varepsilon}\}$ have fluctuations of U_N/N order of $|u-u_\rho|$ away from the limiting mean. $\Psi_N\{A_{u,\varepsilon}\}$ is called a large deviation probability and represents a very rare event. The strong law of large numbers (SLLNs) states that $\Psi_N\{(u-\varepsilon, u+\varepsilon)\}$ decays to 0 exponentially fast. SLLN states the exponential convergence. If a number of $N = \Xi(A_{u,\varepsilon}) > 0$ exists and

$$\Psi_N(A_{u,\varepsilon}) \leq \exp(-N\Xi) \text{ for all sufficiently large } N$$

holds, the sample average converges almost surely towards the expected value as $N \to \infty$.

For fixed N and $i \in \{-r, \cdots -1, 1, \cdots, r\}$, k_i is the number of times γ_i appeared in the sequence $Y_1(\omega), \cdots, Y_N(\omega)$. Let us define

$$A_L = \left\{ v \in \mathscr{M}(\Gamma) : \max_{1 \leq |i| \leq r} |v_i - \rho_i| \geq \epsilon \right\},$$

where $0 < \varepsilon < \min_{1 \leq |i| \leq r}\{\rho_i, 1-\rho_i\}$. Then, we have empirical probability

$L_{N,i}(\omega) = k_i/N$ and $L_N(\omega, \cdot) \in A_L$ if and only if $\boldsymbol{k} = (k_{-r}, \cdots, k_r)$ is in the set

$$A_{L,N} = \{\boldsymbol{k} = (k_{-r}, \cdots, k_{-1}, k_1, \cdots, k_r) \text{ with } k_i = (0, 1, \cdots, N), \\ \textstyle\sum_{1\le|i|\le r} k_i = N, \max_{1\le|i|\le r} \left|\frac{k_i}{N} - \rho_i\right| \ge \varepsilon\right\}, \text{ respectively.}$$

For a fixed $\boldsymbol{k} \in A_{L,N}$, we define

$$C(N, \boldsymbol{k})\rho^{\boldsymbol{k}} = \frac{N!}{k_{-r}! \cdots k_r!}\rho_1^{k_{-r}} \cdots \rho_r^{k_r} \text{ or}$$

$$\log C(N, \boldsymbol{k})\rho^{\boldsymbol{k}} = \left(\log N! - \sum_{1\le|i|\le r} \log k_i! + \sum_{1\le|i|\le r} k_i \log \rho_i\right), \tag{16.2}$$

where $C(n, \boldsymbol{k})$ is the number of points $\omega = (\omega_1, \omega_2, \cdots, \omega_N) \in \Omega_N = \Gamma^N$ for which $L_{N,\,i}(\omega) = k_i/N$ for each i. $\Psi_{N,L}$ denotes the distribution of $L_N(\omega, \cdot)$ on $\mathscr{M}(\mathbb{R})$. Since U_N is a function of price increments, $\Pi_N P_\rho$ is defined as the finite product measure Ω_N with ρ:

$$\Psi_{N,L}\{A_L\} = \sum_{k\in A_{L,N}} \Pi_N P_\rho\{\omega \in \Omega_N : L_{N,i}(\omega) = k_i/N \text{ for each } i\} = \sum_{k\in A_{L,N}} C(N, \boldsymbol{k})\rho^{\boldsymbol{k}}.$$

Let us attempt to determine how the right-hand side of the above equation governs the left-hand side. Since $\Psi_{N,L}\{A_L\}$ has no more than $(N + 1)^{2r}$ terms in the sum, we replace $\sum$ with max, where

$$\max_{k\in A_{L,N}} C(N, \boldsymbol{k})\rho^{\boldsymbol{k}} \le \Psi_{N,L}\{A_L\} \le (N + 1)^{2r} \max_{k\in A_{L,N}} C(N, \boldsymbol{k})\rho^{\boldsymbol{k}}.$$

We additionally apply an increasing function of log:

$$\begin{aligned}\max_{k\in A_{L,N}} \left[\frac{1}{N} \log(C(N, \boldsymbol{k})\rho^{\boldsymbol{k}})\right] &\le \frac{1}{N} \log \Psi_{N,L}\{A_L\} \\ &\le \frac{2r \log(N + 1)}{N} + \max_{k\in A_{L,N}} \left[\frac{1}{N} \log C(N, \boldsymbol{k})\rho^{\boldsymbol{k}}\right].\end{aligned}$$

Thus, we can see that the asymptotic behaviour of $\Psi_{N,L}\{A_L\}$ is regulated by the asymptotic behaviour of the largest summand in $\sum_{k\in A_{L,N}} \log C(N, \boldsymbol{k})\rho^{\boldsymbol{k}}$.

Utilizing a simple combinatorial calculation with a weak form of Stirling's approximation for all $N \ge r$, $\log(n!) = n \log n - n$, we can restate $C(N, \boldsymbol{k})\rho^{\boldsymbol{k}}$ as

$$\frac{1}{N} \log[C(N, \boldsymbol{k})\rho^{\boldsymbol{k}}] = -\sum_{1\le|i|\le r} \frac{k_i}{N} \log\left[\left(\frac{k_i}{N}\right)/\rho_i\right].$$

We define the measure $v_{\boldsymbol{k}/N} = \sum_{i=1}^{r}(k_i/N)\delta_{y_i} \in \mathscr{M}(\Gamma)$ and restate

$$\frac{1}{N}\log \Psi_{N,L}\{v_{\boldsymbol{k}/N}\} = \frac{1}{N}\log[C(N,\boldsymbol{k})\rho^{\boldsymbol{k}}] = -I_{\rho,L}(v_{\boldsymbol{k}/N}),$$

and

$$\frac{1}{N}\log \Psi_{N,L}\{A_L\} = \max_{k\in A_{L,N}}\{-I_{\rho,L}(v_{\boldsymbol{k}/N})\}.$$

Defining the set $\{v \in \mathscr{M}(\Gamma) : v = v_{\boldsymbol{k}/N}$ for some $\boldsymbol{k} \in A_{L,N}\}$, we obtain

$$\lim_{N\to\infty}\frac{1}{N}\log \Psi_{N,L}\{A_L\} = -\lim_{N\to\infty}\frac{1}{N}\log \Pi_N P_\rho\{L_N(A_L)\} = -\lim_{N\to\infty}\min_{\boldsymbol{k}\in A_{L,N}} I_{\rho,L}(v_k, N).$$

$U_N/N = \sum_{i=1}^{r}\gamma_i^2 v_i$, U_N/N is contained in the set $A_U = \left\{u \in \mathbb{R} : |u-u_\rho| \geq \varepsilon\right\}$ where $0 < \varepsilon < \min\{u_\rho - \gamma_1^2, \gamma_r^2 - u_\rho\}$ if and only if U_N is in the set of measure $B_L = \{v \in \mathscr{M}(\Gamma) : |\sum_{1\leq|i|\leq r}\gamma_i^2 v_i - u_\rho| \geq \varepsilon\}$. Thus

$$\lim_{N\to\infty}\frac{1}{N}\log \Psi_{N,U}(A_U) = \lim_{N\to\infty}\frac{1}{N}\log \Psi_{N,L}(B_L) = -\min_{\boldsymbol{k}\in B_L} I_{\rho,L}(v).$$

We conclude that

$$I_{\rho,U}(u) = \begin{cases}\min\{I_{\rho(v),L} : v \in \mathscr{M}(\Gamma), \sum_{1\leq|i|\leq r}\gamma_i^2 v_i = u\} & u \in [\gamma_1^2, \gamma_r^2].\\ \infty & u \notin [\gamma_1^2, \gamma_r^2].\end{cases}$$

We may heuristically state

$$\Psi_{N,U}(A_{u,\varepsilon}) \approx \exp[-NI_{\rho,U}(u)].$$

Ψ_N has an entropy function I_ρ. Roughly speaking, when $\{\Psi_N\}$ has a function I_ρ, it is lower semicontinuous and has compact level sets. This is known as the large deviation property. Please refer to Eliss (1985, Chapter 2 Definition II.3.1).

We are interested in $\Psi_{N,L}$ for a small sample size N:

$$\Psi_{N,L}(B_L) \approx \exp[-NI_{\rho,L}(v)].$$

16.2.5 The Cylinder Set

Formula (16.1) is the simplest form of a cylinder set, which is introduced to compare the speed of exponential decay of the probability distribution with U_N/N. Eliss (1985) introduced three levels of large deviations developed by Donsker and

Varadhan (1983). The level-1 entropy function is our $I_{\rho,U}$ and the level-2 entropy function is our $I_{\rho,L}$. The level-3 function is for a cylinder set $\Sigma \subseteq \Omega$ that has the form

$$\Sigma = \{\omega \in \Omega : (\omega_{m+1}, \cdots, \omega_{m+l}) \in G\}, l > 0, m \in \mathbb{Z}, F \subseteq \Gamma^l.$$

Let us define $\mathscr{M}_s(\Omega)$ as the set of strictly stationary probability measures on Ω. We define the empirical process $R_N(\omega, \cdot)$ in $\mathscr{M}_s(\Omega)$, which is metrizable and as a completely separable metric space. In our model, cylinder sets have the form

$$\Sigma = \{\omega \in \Omega : \omega_{m+1} = x_{i_1}, \omega_{m+2} = x_{i_2}, \cdots, \omega_{m+l} = x_{i_l}\}.$$

$R_N(\Omega, \Sigma)$ gives the empirical frequency of the string $\{x_{i_1}, x_{i_2}, \cdots, x_{i_l}\}$. However, in our model, $\{x_{i_1} = x_{i_2} =, \cdots, = x_{i_l}\}$. Thus, $R_N(\Omega, \Sigma)$ is considered to be $L_N(\Omega)$.

16.2.6 Distribution Obtained by Fixing u

Set A is a closed subinterval $[\gamma_1^2, \gamma_r^2]$ with a nonempty interior. We introduce Φ

$$\Phi = \int_\Gamma y^2 \rho(dy) = \sum_{1 \le |i| \le r} \gamma_i^2 \rho_i,$$

and we define $u(A)$ so that if $\Phi \in A$, $u(A) = \Phi$.

We define K as the closed set $\{u \in \mathbb{R} : |u - u(A)| \ge \varepsilon, \varepsilon > 0\}$. Thus $P_{N,\Delta,A}\{|U_N/N - u(A)| \ge \varepsilon\}$ is equal to $P_{N,\Delta,A}\{U_N/N \in K\}$. We show that $P_{N,\Delta,A}\{U_N/N \in K\} \le \exp(-N\Xi)$ for all sufficiently large N. The small intervals $K \cap A$ form a nonempty interior, and if $\Pi_N P_\rho\{U_N/N \in A\} > 0$, we have

$$P_{N,\Delta,A}\{U_N/N \in K\} = \Pi_N P_\rho\{U_N/N \in K \cap A\} \cdot \frac{1}{\Pi_N P_\rho\{U_N/N \in A\}}.$$

$K \cap A$ and A are a continuity set. This means that

$$\begin{aligned}
&\lim_{N\to\infty} \frac{1}{N} \log P_{N,\Delta,A}\{U_N/N \in K\} \\
&= \lim_{N\to\infty} \frac{1}{N} \log \left[\Pi_N P_\rho\{U_N/N \in K \cap A\} \cdot \frac{1}{\Pi_N P_\rho\{U_N/N \in A\}} \right] \\
&= - \left[\inf_{u \in K\cap A} I^*_{\rho,U}(u) - \inf_{u\in A} I^*_{\rho,U}(u) \right].
\end{aligned}$$

If $\Phi \in A$, then $u(A) = \Phi$, and $\inf_{u\in A} I^*_{\rho,U}(u)$ is attained at the unique point $u = u(A)$. The existence of $u(A)$ represents the unique equilibrium state.

The empirical measure $L_N(\omega, \cdot)$ takes v from the set $\mathscr{M}(\Gamma)$ of probability measures on $\mathscr{B}(\Gamma)$. For a real t, we define

$$\rho_{t,i} = \frac{\exp(ty^2)\rho_i}{\int_{\mathbb{R}} \exp(ty^2)\rho(dy)} = \frac{\exp(t\gamma_i^2)\rho_i}{\sum_{1\le|j|\le r} \exp(t\gamma_j^2)\rho_j}. \tag{16.3}$$

The cumulant generating function of ρ is given by

$$\begin{aligned}
c_\rho(t) &= \log \int_{\Gamma^N} \exp(tU_1) d(\Pi_N P_\rho) \\
&= \log \int_\Gamma \exp(ty^2)\rho(dy),\, t \in \mathbb{R} \approx \sup_{t\in\mathbb{R}}\{tu - I^*_{\rho,U}(u)\},\, u \in \mathbb{R}.
\end{aligned}$$

Taking the derivative of $c_\rho(t)$ with respect to t, we have

$$\frac{dc_\rho(t)}{dt} = c_\rho(t)' = \frac{\int_\Gamma y^2 \exp(ty^2)\rho(dy)}{\int_\Gamma \exp(ty^2)\rho(dy)}.$$

We obtain a unique value $\Upsilon = \Upsilon(u)$.

$$c_\rho(t)'(-\Upsilon) = \int_\Gamma y^2 \rho_\Upsilon(dy) = u.$$

ρ_Υ is the probability measure $\sum_{1\le|i|\le r} \rho^*_{\Upsilon,i}\delta_{v_i}$ (please see equation (16.4)). If ρ denotes the $\Pi_N P_\rho$ distribution of γ_1^2, then $c_\rho(t) = \log \int_{\mathbb{R}} \exp(t\gamma^2)\rho(d\gamma)$. We can obtain a unique real number $\Upsilon = \Upsilon(u(A))$ by solving

$$u(A) = \int_\Gamma \gamma^2 \rho_\Upsilon(d\gamma).$$

Υ is the inverse of the limiting mean of U_N/N as $N \to \infty$.

16.2.7 Distribution Obtained by Fixing Υ

In the isolated market, the market participants execute trades with $A_{u,\varepsilon}$ that are as small as possible, and as a consequence, the specific value of the sum of squared price increments $u = u(A)$ is achieved. However, when the participants construct trading strategies and manage their risks, they require the limiting mean of the relevant sum of squared price increments, which is the inverse of Υ. Now, we discuss the distribution of the state of the market system obtained by fixing Υ.

Given $\Upsilon > 0$, we define

$$\rho^*_{\Upsilon,i} = \frac{\exp(-\Upsilon\gamma_i^2)\rho_i}{\int_\Gamma \exp(-\Upsilon y^2)\rho(dy)} = \frac{\exp(-\Upsilon\gamma_i^2)\rho_i}{\sum_{1\le|j|\le r}\exp(-\Upsilon\gamma_j^2)\rho_j}. \tag{16.4}$$

The distribution of the mean of the squared price increments obtained by fixing Υ might be the product measure $P_{N,\Delta,\Upsilon}(d\omega)$ on Ω_N defined by

$$P_{N,\Delta,\Upsilon}(d\omega) = \lambda(dx_1)\cdots\lambda(dx_N)\rho^*_\Upsilon(dy_1)\cdots\rho^*_\Upsilon(dy_N),$$

where ρ^*_Υ is the probability measure $\sum_{1\le|i|\le r}\rho_i^*\delta_{\gamma_i^2}$ on $\mathscr{B}(\Gamma)$ and the configuration space is $\omega = (x_1, \cdots, x_N, y_1, \cdots, y_N) \in \Omega_N$.

$u = u(A)$ is the specific limiting mean value of the sum of squared price increments and $\Upsilon(u)$ is the corresponding inverse. Then we denote $P_{M,\Delta,\Upsilon(u)}$ as the limiting marginal distribution of the prices and the price increments of M labelled trades with respect to the distribution of the sum of squared price increments for the M trades as $N \to \infty$. The $M > 0 \in \mathbb{Z}$ trades are a subset of the N total trades. When we consider the isolated market, each trader attempts to achieve a value of A that is as small as possible. Now we focus on the market governed by the limiting mean of the sum of squared price increments, for example, when long-term investors who face unpredicted problems must sell some of their assets immediately, this may cause the corresponding market volatility to increase. We assume the type of market chosen has a facility to avoid such selling and a capability to stabilize market volatility. This facility is called a reservoir and is achieved by $N - M$ non-labelled trades. As $N \to \infty$, $P_{M,\Delta,\Upsilon}$ equals P_{N,Δ,Υ^*}, which is the product measure of N trades on the configuration space Ω_N. These measures can be given by

$$P_{N,\Delta,\Upsilon^*}(d\omega) = \frac{\exp[-\Upsilon^* U_N(\omega)]\Pi_N P_{\lambda,\rho}(d\omega)}{\int_{\Omega_N}\exp[-\Upsilon^* U_N(\omega)]\Pi_N P_{\lambda,\rho}(d\omega)}, \tag{16.5}$$

where the inverse of Υ^* is the expected value of U_N.

16.3 Testing the Large Deviation Property

We test the exponential decay of a data distribution obtained from the electrical open limit order book of the Japan Exchange Group.

16.3.1 Data

We use Nikkei 225 mini (Japan Exchange Group 2021a) transaction data from August 2016 to November 2018 including 573 trading days and a total of approximately 106 million executed trades. Nikkei 225 mini (Japan Exchange Group 2021b) is the most liquid futures contract in Asia.

Its trading hours are divided into two sessions: 8:45–15:15 (day session) and 16:30–6:00 (night session). Each session consists of opening and closing auctions and the regular session. The contract tick size is ¥5. We do not distinguish between morning sessions and night sessions or between opening and closing auctions and regular sessions.

Since Nikkei 225 mini applies quarterly and monthly contract systems, we connect the data that are closest to the quarterly contract months (March, June, September, and December) at the end of February, May, August, and November each year.

16.3.2 Basic Properties of the Data

We have approximately 106 million transaction data, among which almost 94% of the data are traded without any price movements. This means that nearly 7 million data exhibit price movements. The 86% level can be classified as the bid-ask bounce. This means that we obtain 908,062 data points that move freely in the range of Δ for each of the 1147 sessions, which is equal to 791 transactions/sessions. If we select $|\gamma_i| \leq 10$, we have 905,167 data points.

16.3.3 Bacsk-Test Process

We only analyse the case in which $r = 2$, that is, $\Gamma = \{-10, -5, 5, 10\}$ because we are making the assumption that most investors prefer trading with minimum price increments. Price increments with $r \geq |15|$ are removed.

When we estimate $P_{N,\Delta,\Upsilon}$, we use

$$P_{N,\Delta,\Upsilon^*}(N,\Delta,\Upsilon^*,U_N,\rho)=\frac{\exp[-\Upsilon^* U_N]\exp\{\log[\Pi_N P_{\lambda,\rho}(N,U_N,\rho)]\}}{\sum_{U_N^*}\exp[-\Upsilon^* U_N]\exp\{\log[\Pi_N P_{\lambda,\rho}(N,U_N,\rho)]\}},$$

where $U_N^*=\{U_N\}=$

$$\left\{\boldsymbol{k}\cdot\boldsymbol{\gamma}:\boldsymbol{k}=(k_{-r},\cdots,k_{-1},k_1,\cdots,k_r)\text{ with }k_i=(0,1,\cdots,N),\right.$$
$$\left.\sum_{1\le|i|\le r}k_i=N\text{ and }\boldsymbol{\gamma}=(\gamma_{-r},\cdots,\gamma_{-1},\gamma_1,\cdots,\gamma_r)\right\},$$

and the inverse of Υ^* is its expected value.

In our analysis, since $N\in\{10,100,1000\}$ is very small for Sterling's approximation method, we use the numerical method of Windschifl's formula (Lu et al. 2014) to obtain accurate results:

$$2\log\Gamma(z)\sim\log 2\pi-\log z+z\left(2\log z+\log\left(z\sinh\frac{1}{z}+\frac{1}{810z^6}\right)-2\right),$$

where Γ denotes the gamma function. We apply this to formula (16.2) and predict the exponential decay of the proposed model.

We use the root mean square error and the adjusted root mean square error to evaluate the deviations between the theoretical values and the empirical distributions. The latter is the root mean square error for the empirical probability of data that are ≥ 0.01.

We state that $\Delta(t)$ is the closed bounded interval at time t. We consider time t to be a session number. Thus, the $\Delta(t)$s are determined by the highest and lowest prices of each session. The δ_is are also computed during each session and used as data to classify the bid-ask bounce.

We set the empirical values of ρ_1 and ρ_2 for $|\gamma_1|=5$ and $|\gamma_2|=10$, respectively.

16.4 Results

The exponential decay of the distribution predicts much a wider distribution than that produced by the central limit theorem. The smaller the number of samples is, the wider the distribution is. Our back-test results are more complicated.

The back-test results are shown in Tables 16.1, 16.2 and Figs. 16.1, 16.2, 16.3, 16.4, 16.5, 16.6, 16.7, 16.8, 16.9, 16.10, 16.11, 16.12.

Table 16.1 Evaluation of model predictions

	Adj. rmse				rmse			
	All	$\Delta \leq 100$	$100 < \Delta \leq 350$	$350 < \Delta$	All	$\Delta \leq 100$	$100 < \Delta \leq 350$	$350 < \Delta$
$N = 1000$	0.0613	0.0497	0.0597	0.0396	0.0330	0.0497	0.0367	0.0297
$N = 100$	0.123	0.0886	0.102	0.112	0.0560	0.0767	0.0487	0.0606
$N = 10$	0.00953	0.00498	0.00562	0.0167	0.00605	0.00606	0.00422	0.0114
No of data points	905,167	51,826	609,019	251,729				
ρ_1	0.987	0.993	0.991	0.977				
ρ_2	0.013	0.007	0.009	0.023				

Table 16.2 Evaluation of model predictions by mode and mean

	Mode				Mean			
	All	$\Delta \leq 100$	$100 < \Delta \leq 350$	$350 < \Delta$	All	$\Delta \leq 100$	$100 < \Delta \leq 350$	$350 < \Delta$
$N = 10$ emp	250	250	250	250	259	255	257	267
Estimation	250	250	250	250	257	254	255	263
$N = 100$ emp	2500	2500	2500	2500	2595	2549	2566	2671
Estimation	2575	2500	2500	2650	2592	2548	2564	2666
$N = 1000$ emp	25,150	25,150/25,375	25,225	25,225	25,946	25,489	25,665	26,710
Estimation	25,900	25,450	25,600	26,650	25,943	25,481	25,662	26,700

16.4.1 All Data

The model predicts the behaviour of the sum of squared price increments in Fig. 16.1. In Fig. 16.2, the theoretical distribution has a kink, but the empirical values do not. In Fig. 16.3, the theoretical mode is shifted to the right of the empirical mode. In Table 16.1, the root mean square error and adjusted root mean square error for $N = 10$ are small; however, they are larger for $N = 100$ and $N = 1000$. Additionally, $\rho_1 = 0.987$ and $\rho_2 = 0.013$, for which minimum price increments dominate the transactions. From Table 16.2, the means of the empirical distribution and the theoretical distribution have a good fit. However, the modes of these two distribution are the same for $N = 10$, while those for $N = 100$ and $N = 1000$ deviate. These results are consistent with the graphical presentations.

To explain the widening of the distribution of U_N as N increases, we present propositions in which several types of investors may act in the market, most of them prefer trading with minimum price increments, and the others do not. Such investors' behaviour is represented by ρ_1 and ρ_2. These two values can form a function of the price fluctuation in the associated session.

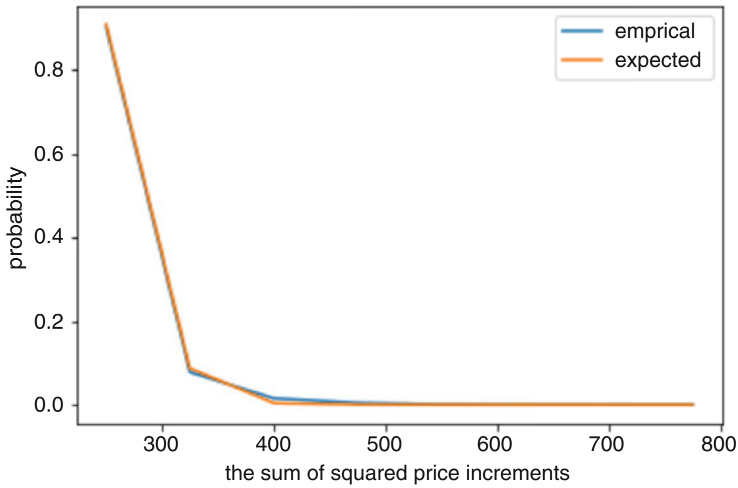

Fig. 16.1 All data: $N = 10$

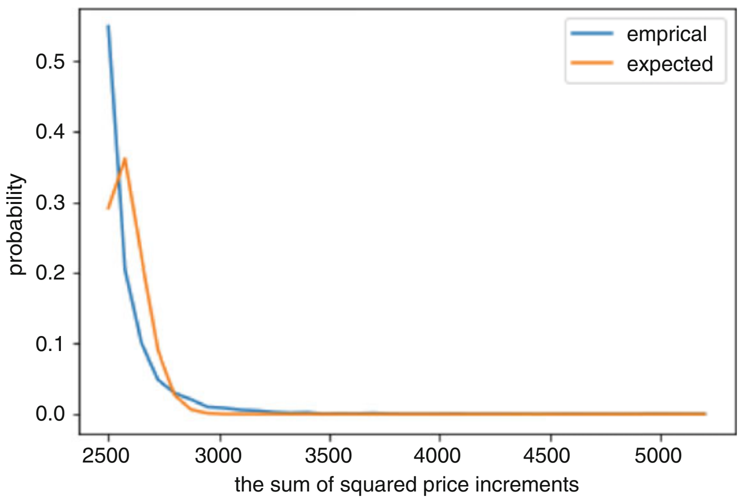

Fig. 16.2 All data: $N = 100$

16.4.2 Data Classified by Δ

To clarify the propositions, we subdivide the data into three groups of $\Delta(t) \in \{\Delta \leq 100, 100 < \Delta \leq 350, 350 < \Delta\}$. These cutoff points of 100 and 350 can be replaced by any number in increasing order.

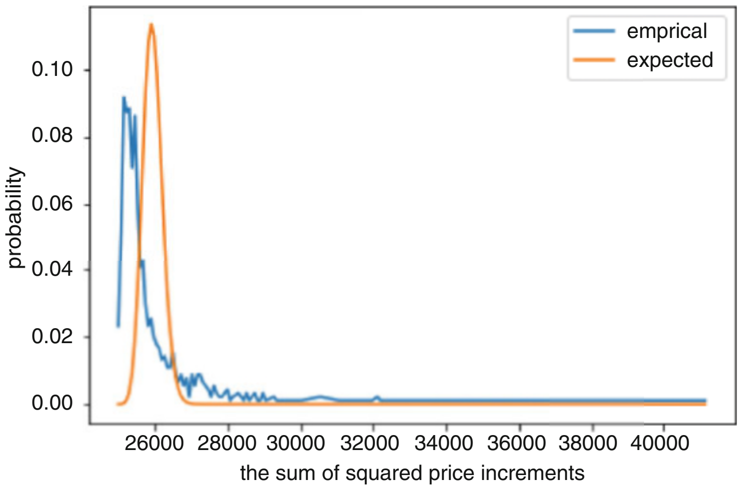

Fig. 16.3 All data: $N = 1000$

16.4.2.1 $\Delta \leq 100$

In Table 16.1, approximately 6% of the total transactions belong to this price range. We obtain the lowest error with $N = 10$ and 100 for the adjusted root mean square error. As expected, $\rho_1 = 0.993$ is the largest number in any range of Δ. From Table 16.2, the means and modes of the empirical distribution and the theoretical distribution achieve a good fit.

Figure 16.4 is almost a perfect fit. Figure 16.5 shows small deviations between the empirical distribution and the theoretical distribution. Figure 16.6 shows reasonable deviations between the empirical distribution and the theoretical distribution.

16.4.2.2 $100 < \Delta \leq 350$

In Table 16.1, almost 67% of the data belong to this range. In terms of the root mean square error, $N = 10$ and $N = 100$ yield the best fitting effects. In Table 16.2, the difference between the modes of the empirical and theoretical distributions for $N = 1000$ is 375, i.e., 1.5%. Figures 16.7 and 16.8 display similar results to those of Figs. 16.1 and 16.2. However, Fig. 16.9 presents better results than those shown in Fig. 16.3.

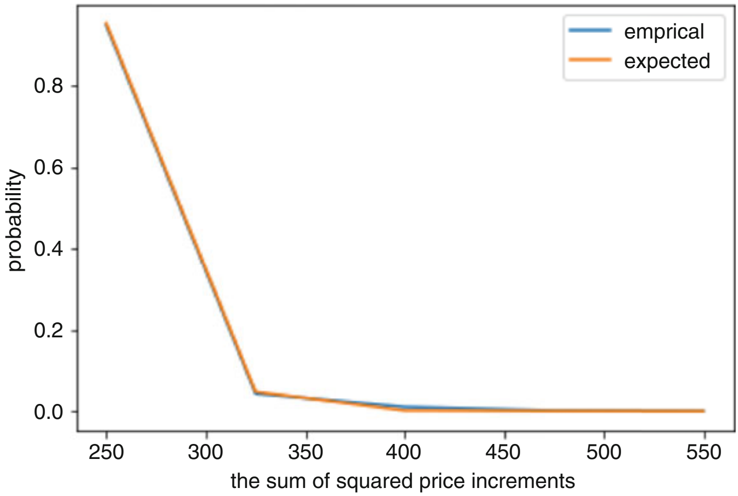

Fig. 16.4 $\Delta \leq 100$: $N = 10$

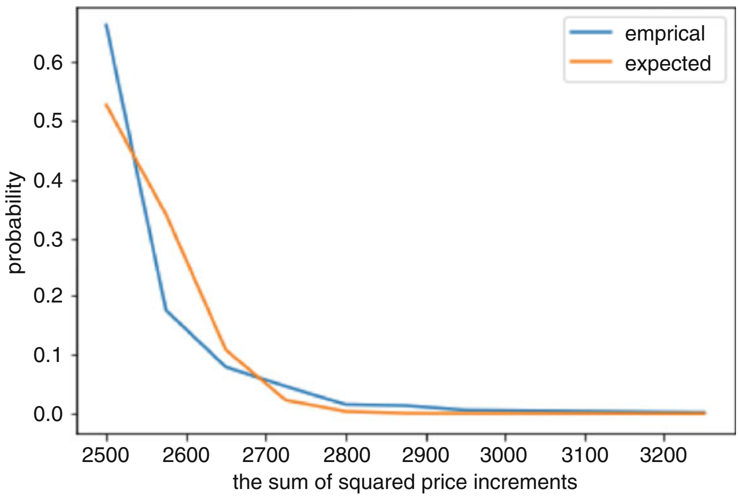

Fig. 16.5 $\Delta \leq 100$: $N = 100$

16.4.2.3 $350 < \Delta$

In Table 16.1, nearly 27% of the data belong to $350 < \Delta$. In terms of both the root mean square error and adjusted root mean square error, $N = 1000$ produces the best fitting effect. ρ_1 has the largest value. In Table 16.2, the two modes of $N = 100$ and $N = 1000$ have some deviations.

Figure 16.10 shows an almost perfect fit. Figure 16.11 contains a slightly large deviation. Figure 16.12 presents similar results to those of Fig. 16.3.

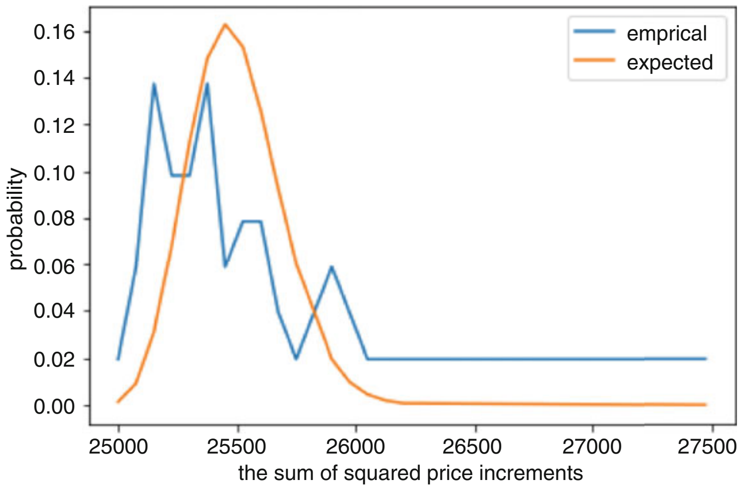

Fig. 16.6 $\Delta \leq 100$: $N = 1000$

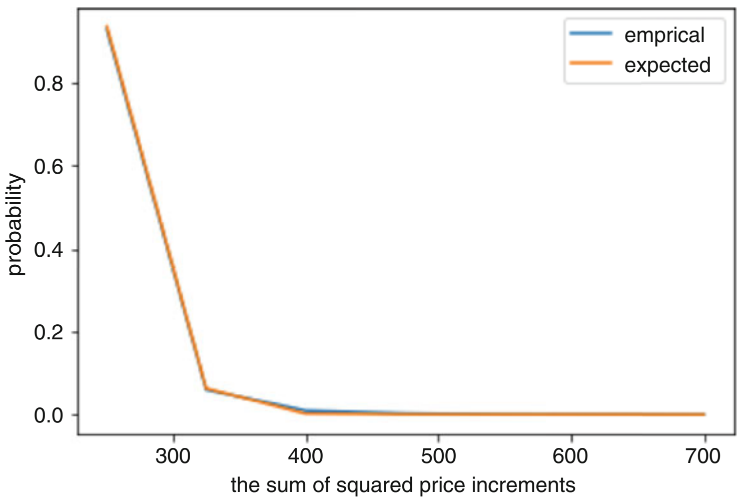

Fig. 16.7 $100 < \Delta \leq 350$: $N = 10$

16.4.3 Interpretation of the Results

We define the microstates as descriptions of the N transactions' prices and price increments and the sum of squared price increments as the macro value in the market. The large number of transactions provides an infinite number of possible microstates, which exhibit a limiting mean of u_ρ. If $N \to \infty$, then $U_N/N \to u_\rho$. When all the accessible microstates are equally likely, the maximum number of configurations represents the most likely macroscopic state.

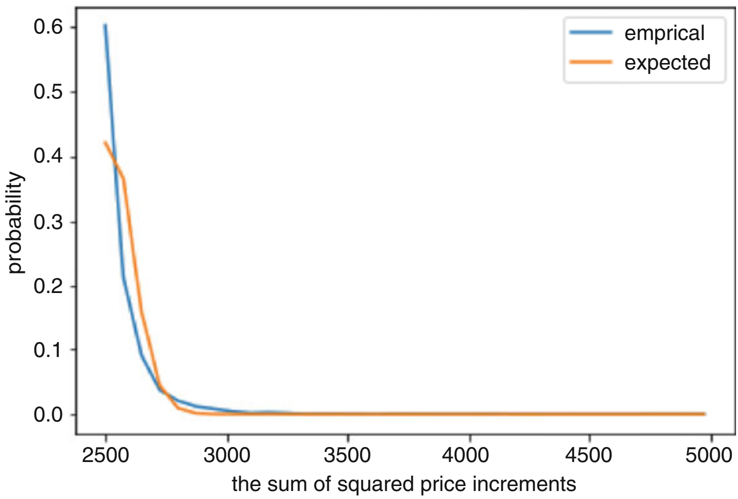

Fig. 16.8 $100 < \Delta \leq 350$: $N = 100$

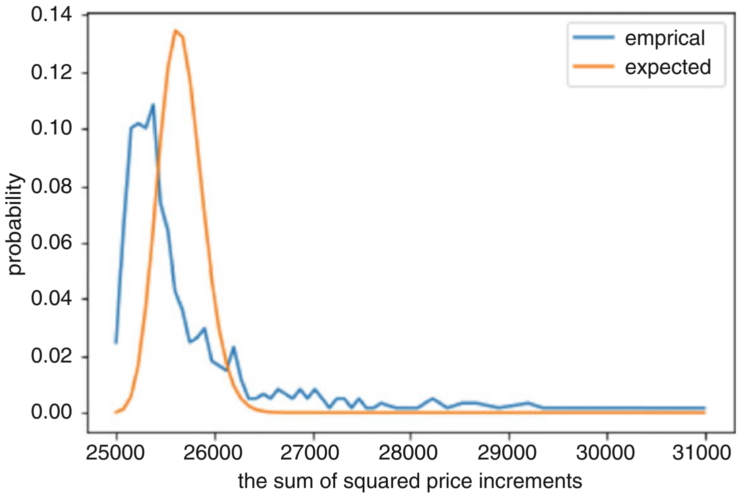

Fig. 16.9 $100 < \Delta \leq 350$: $N = 1000$

The macroscopic state is characterized by the distribution of the microstates. The set of microstates comprises a statistical distribution that contains the probability of each microstate. The set of microstates with an associated probability distribution depends on the set of market constraints faced by economic agents. A different constraint results in a different configuration. We introduce a completely isolated market and a market that can access a financial product (acting as a reservoir). The former is described by formula (16.3), and the latter is described by the formula (16.5).

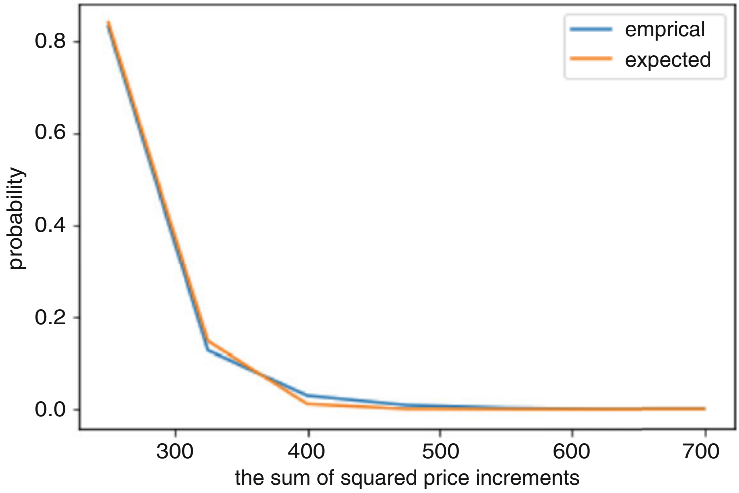

Fig. 16.10 $350 < \Delta$: $N = 10$

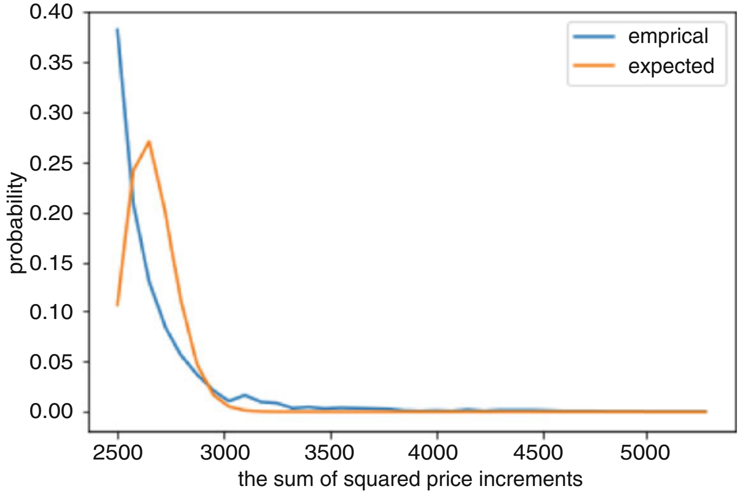

Fig. 16.11 $350 < \Delta$: $N = 100$

The probability distribution of microstates might be a function of some elements in the market. A microstate with some restrictions makes its own distribution skewed, so ρ_i might be far away from $1/r$. The state is theoretically described as $N \to \infty$; however, the sample size is limited. The entropy function adjusts the effects of the size of N. How close u_ρ is to the macroscopic state is characterized by an empirical distribution.

When N is fixed, the elements make the probability distribution of U_N/N deviate from the limiting mean by only ρ_i. In our back test, when $N = 10$, the

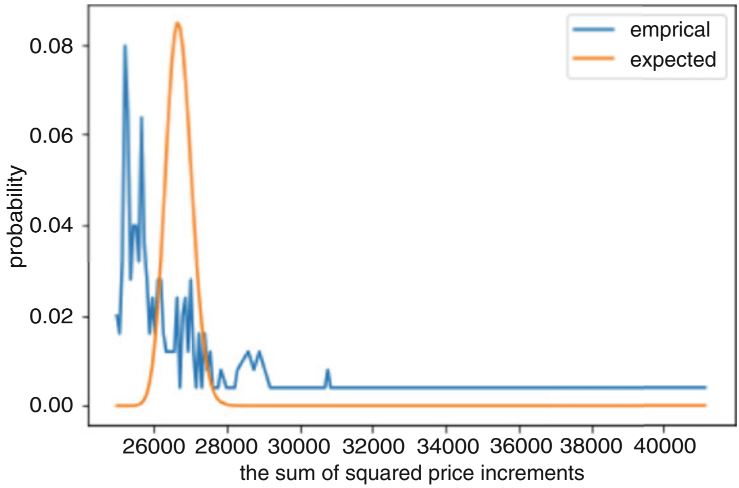

Fig. 16.12 $350 < \Delta$: $N = 1000$

entropy function explains the sample distributions with minimum errors. However, as N increases, the deviation from the theoretical distribution becomes larger. This is because the entropy functions might not adjust the sample size properly. Alternatively, u_ρ may not be stable due to continuous changes in regulations and financial policies, the exits and entries of some economic agents, the continuous replacement of technology, etc. Furthermore, the deviations might be explained by the mixture of the u_ρ. The larger N is, the wider Ψ is, which might state that the sum of squared price increments only accumulates the effects of a wide variety of events realized in the past. We find that the larger the price range Δ is during a session, the smaller the value of ρ_1 is. This means that the larger Δ is, the smaller the proportion of investors trading with the minimum price increment. However the decrease in the proportion of economic agents trading with the minimum price increment is limited. In case with large N, the empirical distribution does not merely shift to the right; it appears to become wider to the right when fixing the left-hand side.

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Part VI
Other Trading Strategy Issues and the Effects of AI Usage

Chapter 17
The Emergence of Periodic Properties of Ordering Strategies Under Disruption in the Beer Game

Hiroshi Sato

Abstract Whether to keep effective management of supply chain even in the disasters has become a crucial issue for the manufacturing industry because modern supply chain networks spread global and complex, and the behaviors of the network are hardly predictable. The Beer Game is a simple but beneficial supply chain network model. The game consists of four sectors: factory, distributor, wholesaler, and retailer. The game's goal is to deliver the beer to the customers in just proportion. Many business schools adopt it to learn the critical point of the supply chain. In this study, evolving computer agents by genetic algorithm play the game instead of humans. We examine how the agents handle the game significantly when some parts of the supply chain are disrupted for some reason. Through simulations, we confirmed that effective ordering strategies are different between sectors, and the positions of the sectors are an essential factor in their strategies.

Keywords Supply chain management · Disaster mitigation · Agent-based simulation · Genetic algorithm · The Beer Game

17.1 Introduction

A supply chain is a flow of a product from factory to consumer (Hugos 2011). Nowadays, the supply chain has become a global and complex network. This network produces effective productivity in peacetime, but the function of the supply chain will lose when a disaster occurs. For example, a large number of supply chains were forced to stop their operation after the 2011 Tohoku earthquake and tsunami and the 2011 Thailand floods (MacKenzie et al. 2012). Therefore, the research of resilience of the supply chain is an urgent issue to establish a stable supply of

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products. Many cases mentioned above are studied, but it is not easy to draw general knowledge from them because each case has its properties.

This chapter takes up the Beer Game (Sterman 1992) as the benchmark of supply chain management. This game is a straightforward model of a supply chain, but it can reproduce essential issues such as bullwhip effects (Jarmain 1963; Sterman 1989). Human players usually play the Beer Game. However, in this study, the computer agents play the game. We analyze the performance of computer agents in the supply chain, especially when some part of the network breaks down because of disasters such as an earthquake. Our purpose is to get the simple rules of thumb such as "should we focus on the flow, or should we focus on stock?" because the more straightforward the rules become, the easier the managers of each sector handle the situation.

The following of this chapter consists of five sections. Section 17.2 introduces the supply chain network model used in this study. Section 17.3 explains how we implement an agent-based simulation of the Beer Game. Section 17.4 explains the optimization of the agents' parameters using a genetic algorithm. Section 17.5 shows the results of computer simulation. Finally, Sect. 17.6 concludes this study and points out some future works.

17.2 Minimal Model of Supply Chain Network

In this section, we introduce the Beer Game—a minimal supply chain network model used in this study. We also explain the essential properties of the game called the "Bullwhip effect."

17.2.1 The Beer Game

The Beer Game was invented in the 1960s in the Massachusetts Institute of Technology business school. It has been used as an educational tool and a research tool. The supply chain in the Beer Game consists of four sectors: "factory," "distributor," "wholesaler," and "retailer" (Fig. 17.1). These four players make the team. The goal of the team is to minimize the total cost of operation. Every turn, the players decide how much case of beer they will order. The game's turn is called "week," and the total cost is the sum of inventory fee and the loss of backorder. During the game's play, players cannot communicate with each other. Only they can see the beer flow in the supply chain.

The players have to estimate the demand for the future and to make an appropriate order based on their strategies. This uncertainty makes the mismatch of demand and supply and unstableness in the supply chain (Strozzi et al. 2007).

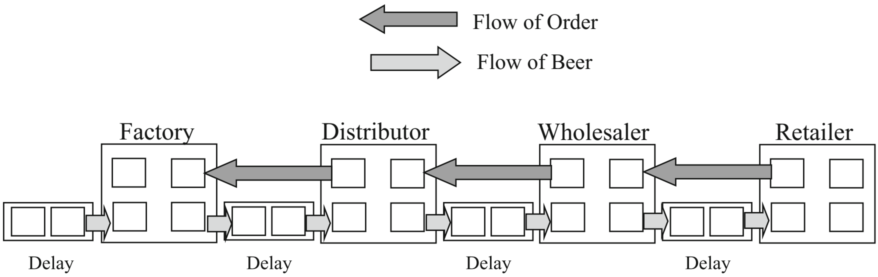


Fig. 17.1 The flow of orders and products in the Beer Game

17.2.2 Bullwhip Effect

The Beer Game has a fascinating property. The bullwhip effect is the most exciting and catastrophic phenomenon where we can see the enormous swings of inventories in response to the change of demand. Figure 17.2 shows the typical situation of the Bullwhip effect. For example, in Fig. 17.2, a slight change of the order at the retailer causes a significant change in the production at the factory.

The cause of this oscillation comes from the player's psychological factors, such as misperception and panic, and the operational factors, such as forecast error and lead-time variety. The previous studies on preventing the occurrence of the bullwhip effect are classified into two categories. The studies in the first category focus on the detection of the point where the demand of the customer changes (O'Donnell

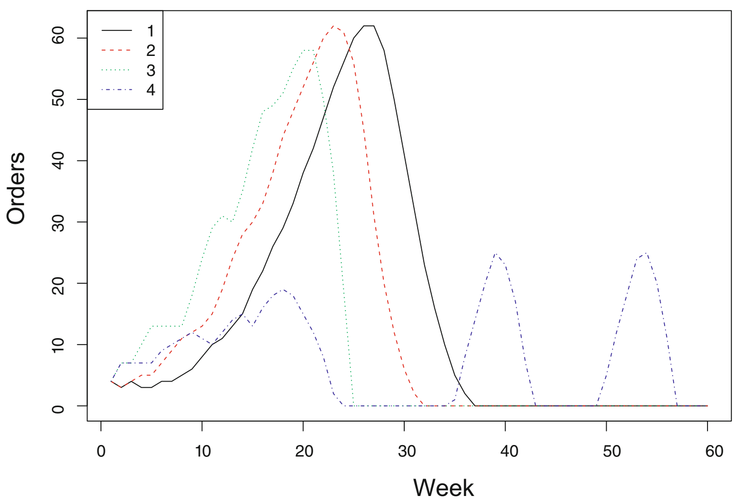


Fig. 17.2 A typical situation of the Bullwhip effect. The legend in the figure shows the layer of the supply chain: 1—factory, 2—distributor, 3—wholesale, and 4—retailer

et al. 2006; Kimbrough et al. 2002), and those in the second category study the appropriate policies in each sector (Strozzi et al. 2007). These studies assume there is no failure or accident during the operation. However, our concern is finding resilient strategies even when a disaster strikes the supply chain.

17.3 Implementation of the Beer Game by Agent-Based Modeling

In this study, we adopt Strozzi's model (Strozzi et al. 2007) for implementing the Beer Game by computer agent. There are four layers of agents in the Beer Game: factory, distributor, wholesaler, and retailer. All agents have the same structure. Figure 17.3 shows the structure of an agent at i-th layer.

The following are the state variables of the agent:

- $IS_i(t)$: incoming shipment at time t
- $INVi(t)$: inventory of the beer at time t
- $DINV_i$: desired inventory (constant)
- $OSi(t)$: outgoing shipment at time t
- $ASL_i(t)$: adjustment of supply chain at time t
- $SL_i(t)$: supply chain at time t
- DSL_i: desired supply chain (constant)
- $AS_i(t)$: adjustment of stock at time t
- $ED_i(t)$: expected demand at time t
- $OP_i(t)$: orders placed at time t
- $BL_i(t)$: backlog of orders at time t
- $IO_i(t)$: incoming orders at time t

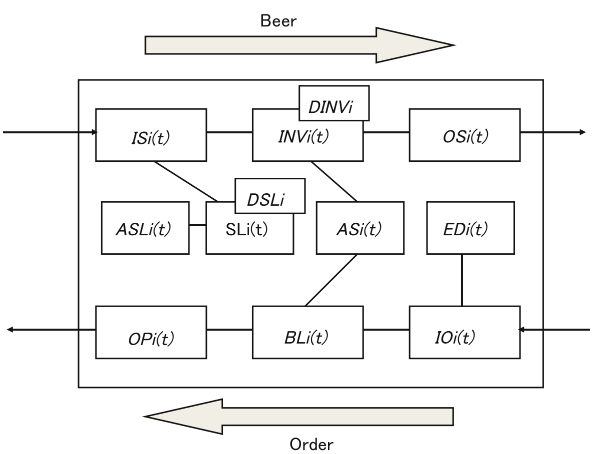


Fig. 17.3 The basic structure of the agent on i-th layer at time t in the Beer Game

The transition of the states is determined by the following equations:

$$INV_i(t) = \begin{cases} INV_i(t-1) + IS_i(t-1) - BL_i(t-1) - IO_i(t-1) \\ \quad \texttt{if} \;\; INV_i(t-1) + IS_i(t-1) \\ \quad\quad \geq BL_i(t-1) + IO_i(t-1) \\ 0 \quad \texttt{otherwise} \end{cases} \tag{17.1}$$

$$IS_i(t) = OS_{i-1}(t-1) \tag{17.2}$$

$$BL_i(t) = \begin{cases} BL_i(t-1) + IO_i(t-1) - INV_i(t-1) - IS_i(t-1) \\ \quad \texttt{if} \;\; BL_i(t-1) + IO_i(t-1) \\ \quad\quad \geq INV_i(t-1) + IS_i(t-1) \\ 0 \quad \texttt{otherwise} \end{cases} \tag{17.3}$$

$$OS_i(t) = \min(INV_i(t-1) + IS_i(t-1), BL_i(t-1) + IO_i(t-1)) \tag{17.4}$$

$$ED_i(t) = \theta IO_i(t-1) + (1-\theta)ED_i(t-1)) \tag{17.5}$$

Here, θ $(0 \leq \theta \leq 1)$ is a control parameter,

$$OP_i(t) = max(0, \theta IO_i(t-1) + (1-\theta)ED_i(t-1)) \tag{17.6}$$

$$ASL_i(t) = \alpha_{SL}(DSL - SL_i(t)) \tag{17.7}$$

$$AS_i(t) = \alpha_S(DINV_i(t) - INV_i(t) + BL_i(t) \tag{17.8}$$

$$SL_i(t) = WIS_i(t) + IO_{i-1}(t) + BL_{i-1}(t) + OS_{i-1}(t) \tag{17.9}$$

Let $\beta = \alpha_{SL}/\alpha_S$, and $Q = DINV + \beta DSL$, then we get

$$OP_i(t) = max(-, ED_i(t) + \alpha_S(Q - INV_i(t) + BL_i(t) - \beta SL_i(t) \tag{17.10}$$

We assume $\alpha_S \leq \alpha_{SL}$ and $\beta \leq 1$. A point (α_S, β) represents the characteristic of agents: if $\alpha_S > \beta$, the agent pays attention to inventory, and if $\alpha_S < \beta$, the agent pays attention to the supply chain. In this study, we examine the evolution of using a genetic algorithm.

17.4 Genetic Algorithm

In order to search the appropriate characteristic parameter (α_S, β) of each agent, we use a genetic algorithm (GA). The followings are the procedures of the GA.

17.4.1 Fitness Function

As a fitness function of GA, we use the cost function of the Beer Game. The objective is to minimize the cost. There are two types of cost. The first one is the cost of inventory (0.5$ per case per week). The second one is the penalty of backlog (2$ per case per week). Equation (17.11) is the fitness function.

$$Fitness = \sum_{t=1}^{T} \sum_{i=1}^{m} (2BL_i(t) + 0.5INV_i(t)) \tag{17.11}$$

where T is the total number of weeks and m is the number of sectors.

17.4.2 Coding and Crossover Operator

We adopt real number coding instead of binary coding. As crossover operator, we use REX (Akimoto et al. 2007). REX is a multi-parent crossover and it is known for its high performance. Let x be the representation of individual that is a real-coded vector of n dimension and k is the number of parents for the crossover. The children are

$$\mathbf{x}_c = \mathbf{x}_g + \sum_{i}^{n+k} \phi(0, \sigma^2)(\mathbf{x}_i - \mathbf{x}_g) \tag{17.12}$$

where $\phi(0, \sigma^2)$ is a random number chosen from the probability distributions with average 0 and variance σ^2. In this study, we use the normal distribution as $\phi(0, \sigma^2)$.

17.4.3 Generation Alternation Model

The performance of crossover strongly depends on the generation alteration model. In this study, we use JGG (Kobayashi 2009). The procedure of JGG is as follows:

1. (Initialization) Create m individuals as the initial population and evaluate them.
2. (Selection for reproduction) Select parents from the population by random sampling without replacement.
3. (Reproduction) Repeat crossover to parents and generate children.
4. (Selection for survival) Select the best individual from children and replace with parents.
5. Go to 2.

JGG requests a sufficiently large number of children be generated during the crossover.

17.5 Computer Simulation

The purpose of this simulation is to obtain the effective policy of each agent in the Beer Game when one sector breaks down during some time period. Previous studies show effective policies in a normal situation. Therefore, we compare the policies for a normal situation and the policies for an emergency situation.

17.5.1 Baseline Result

Here, we present the result of the normal situation without any disruption. In this case, we use the following scenario (Jarmain 1963):

- Inventory of each sector is initialized with 12 cases of beer.
- Orders of each sector are initialized with 4 cases of beer.
- The time delay from the passing of orders and shipments from one place to the next is one week (unit time of the game).
- The production time at the factory is three weeks, and it is assumed that the production capacity of the factory can be adjusted without limits.
- Each week, customers order beer from the retailer, which supplies the requested quantity out of its inventory.
- Customer's demand is four cases of beer per week until week four and steps to eight at week five.
- The whole game period is 60 weeks.

Figure 17.4 shows the result of the evolution of each sector's strategy with GA. In Fig. 17.4, the maximum order volume is 12, and order volumes are converged to 8 soon. Comparing the result of the bullwhip effect (Fig. 17.2), changes in the order volumes are small and stable. We can say that all sectors can find their appropriate order strategies after the evolution.

17.5.2 Adaptation of Ordering Policy Corresponding to Disruption

We assume a breakdown may occur in any one sector from wholesaler, distributor, or factory. As with the previous research (O'Donnell et al. 2006), we neglect the case in which the retailer breaks down. Omit the possibility of the breakdown in the retailer's position because we cannot see the Bullwhip effect if the retailer cannot place their orders.

The timing of breakdown is set to be at any one of the following two periods: disruption in the early stage (from week 11 to week 15) or disruption in the middle stage (from week 21 to week 25).

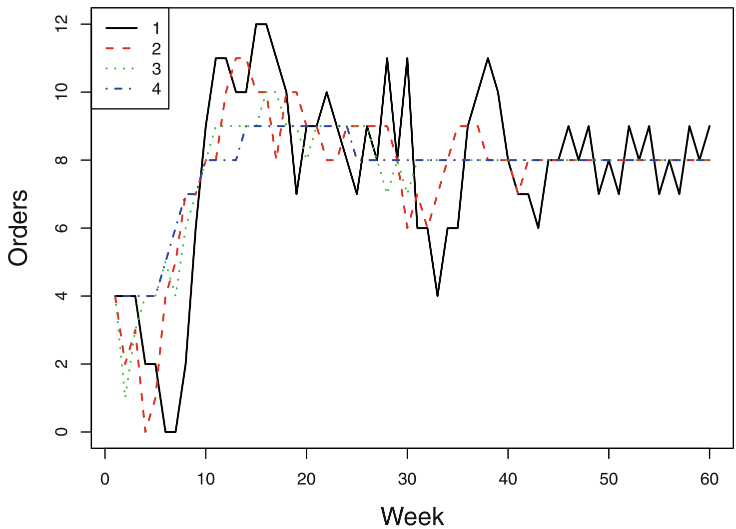


Fig. 17.4 Ordering behaviors after the evolution in a normal case. The legend in the figure shows the layer of the supply chain: 1—factory, 2—distributor, 3—wholesale, and 4—retailer

17.5.2.1 Disruption in Early Stage

Figures 17.5, 17.6, and 17.7 show time variation of the order volume of each sector when the disruption occurs in the early stage. It seems to be difficult to cope with this situation because the disruption occurs just after the customers' orders change. You can see that the spike of the order volume is getting higher from Figs. 17.5 to 17.7. We can say that the disruption downstream generates a more negative impact on the supply chain. However, the heights of the spikes are still lower than that in the Bullwhip case. This means that the obtained policies prevent the Bullwhip effect.

17.5.2.2 Disruption in the Middle Stage

Figures 17.8, 17.9, and 17.10 show time variation of the order volume of each sector when the disruption occurs in the middle stage. In this case, the spike of the order is quite small. If the time gap between the change and accidents is large, the sectors can find effective strategies. This means that the obtained policies prevent the Bullwhip effect very well.

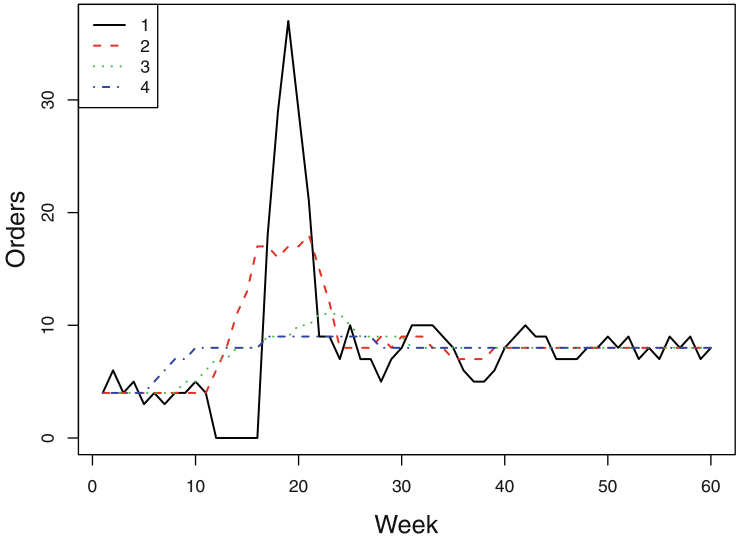


Fig. 17.5 Ordering behavior after the evolution in disruption case: at factory in the early stage. The legend in the figure shows the layer of the supply chain: 1—factory, 2—distributor, 3—wholesale, and 4—retailer

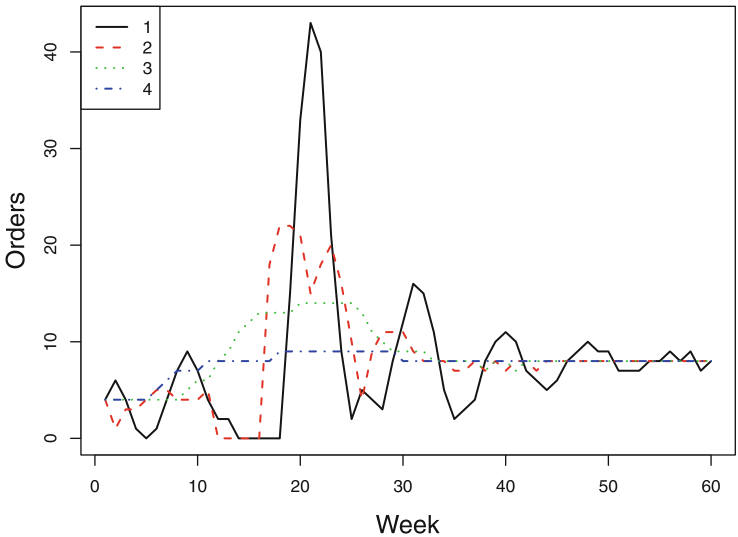


Fig. 17.6 Ordering behavior after the evolution in disruption case: at distributor in the early stage. The legend in the figure shows the layer of the supply chain: 1—factory, 2—distributor, 3—wholesale, and 4—retailer

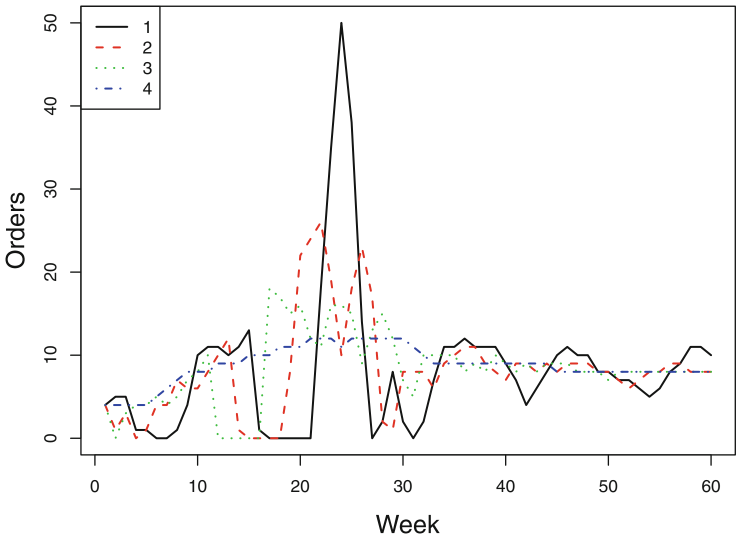


Fig. 17.7 Ordering behavior after the evolution in disruption case: at wholesaler in the early stage. The legend in the figure shows the layer of the supply chain: 1—factory, 2—distributor, 3—wholesale, and 4—retailer

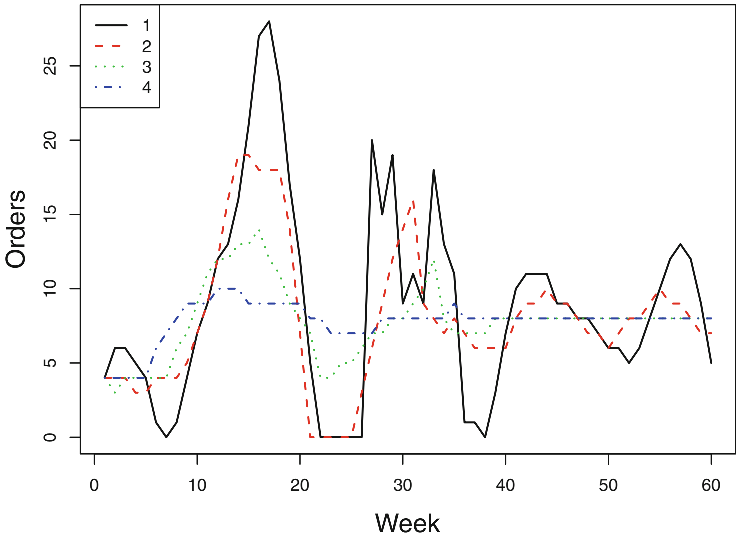


Fig. 17.8 Ordering behavior after the evolution in disruption case: at factory in the middle stage. The legend in the figure shows the layer of the supply chain: 1—factory, 2—distributor, 3—wholesale, and 4—retailer

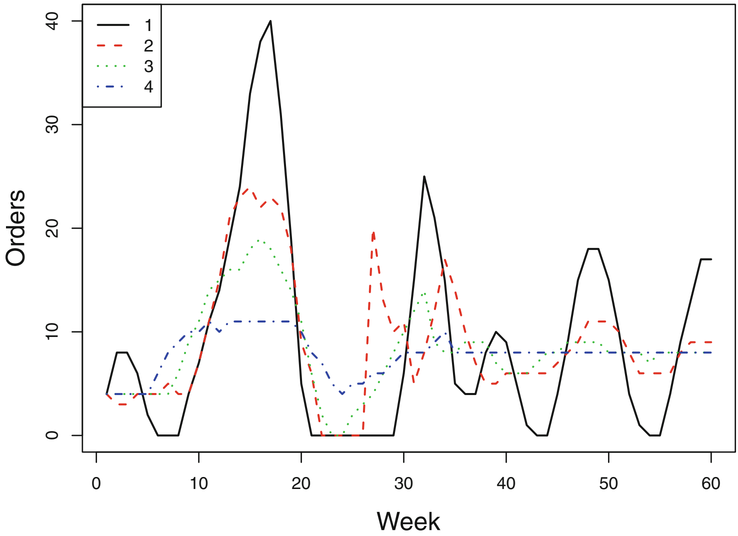


Fig. 17.9 Ordering behavior after the evolution in disruption case: at distributor in the middle stage. The legend in the figure shows the layer of the supply chain: 1—factory, 2—distributor, 3—wholesale, and 4—retailer

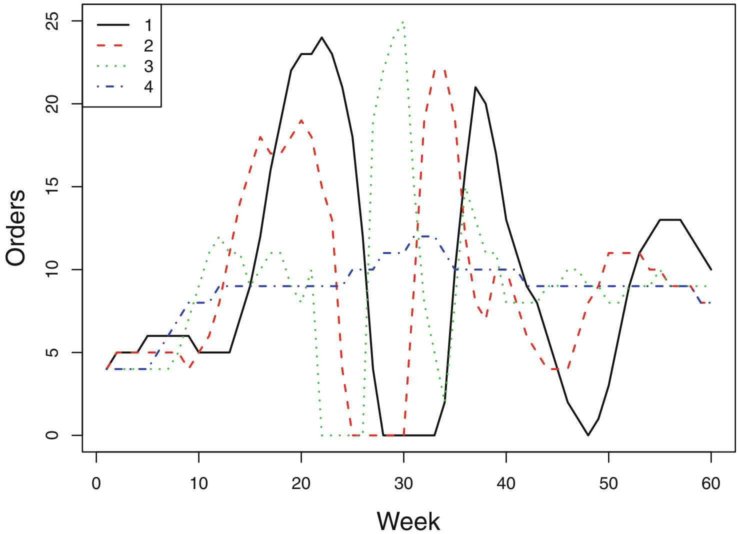


Fig. 17.10 Ordering behavior after the evolution in disruption case: at wholesaler in the middle stage. The legend in the figure shows the layer of the supply chain: 1—factory, 2—distributor, 3—wholesale, and 4—retailer

17.5.3 Trend of Agents' Parameters

We can see the trend of the agents' parameters by comparing each case. Figure 17.11 shows the parameters of each agent in each case. A point in this space (α_s, β) represents the parameter of an agent. Case (a) shows the parameters in normal case—no disruption. You can see factory and wholesaler are on the right side of the space, and distributor and retailer are on the upper side of the space. As mentioned in Sect. 17.3, the region where $\alpha_s > \beta$ means that an agent pays attention to inventory (= stock-sensitive), and the region where $\alpha_s < \beta$ means that an agent pays attention to supply chain (= flow-sensitive). In this case, factory and wholesaler are stock-sensitive, and distributor and retailer are flow-sensitive.

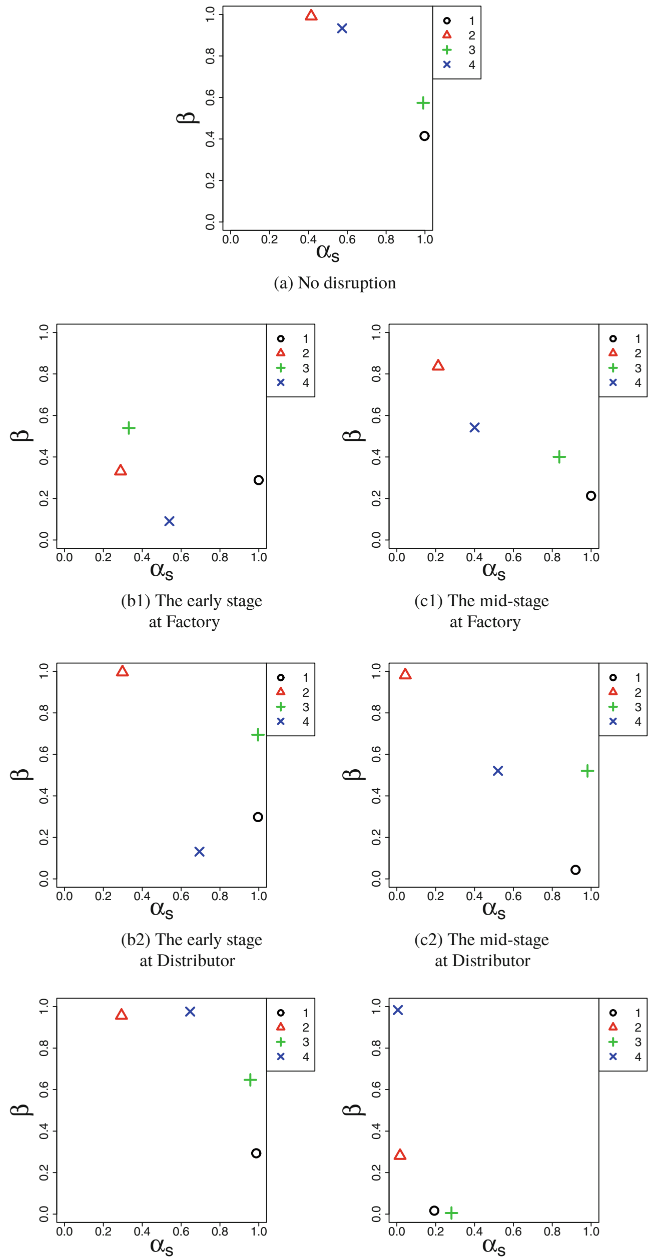
From (b1) to (c3), we can see that the parameters shift when disruption occurs. However, they tend to stay in the same region of parameter space. The figures show that factories and wholesalers are still stock-sensitive, and distributors and retailers are still flow-sensitive.

17.5.4 Cases in Longer Supply Chain

Here, we will extend the model, which has a longer supply chain, and see what happens. In this case, we extend the length of the supply chain from 4 to 8 and 12, and only one sector in the middle of the chain breaks down during mid-term (from 21st week to 25th week) in the period of 60 weeks. The demand of the customer is the same as the original beer game (first four weeks: 4 cases per week, after that: 8 cases per week).

Figures 17.12 and 17.13 show the ordering behaviors after the evolution. Figure 17.12 shows the results of the supply chain, which consists of 8 sectors. Figure 17.13 shows the results of the supply chain, which consists of 12 sectors. The upper graphs of each figure show that the volume of the order remains small. On the other hand, the lower graphs of each figure have a spike of order, but not so high. We can say that the Bullwhip effect can be suppressed.

Figure 17.14 and 17.15 show the results of the evolved parameters in each case. Figure 17.14 shows the result of the supply chain, which consists of 8 sectors. Figure 17.15 shows the results of the supply chain, which consists of 12 sectors. In the same way as the supply chain, which has four sectors, the parameters of each agent tend to stay in the same region of parameter space.



(a) No disruption

(b1) The early stage at Factory

(c1) The mid-stage at Factory

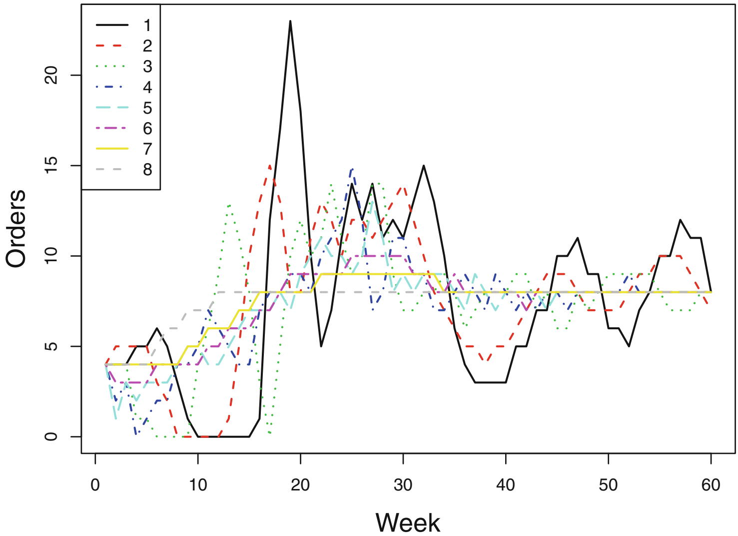
(b2) The early stage at Distributor

(c2) The mid-stage at Distributor

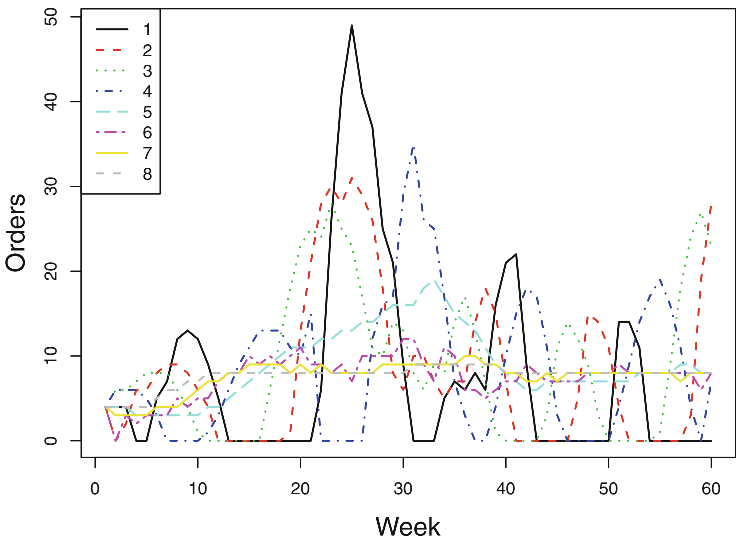
(b3) The early stage at Wholesaler

(c3) The mid-stage at Wholesaler

Fig. 17.11 The evolved parameters (α, β) of each agent. (**a**) normal case, (**b1**)–(**b3**) disruption case at early stage, and (**c1**)–(**c3**) disruption case at the middle stage



(a)



(b)

Fig. 17.12 Ordering behavior after the evolution. The length of the supply chain is 8. (**a**) No disruption case and (**b**) disruption case

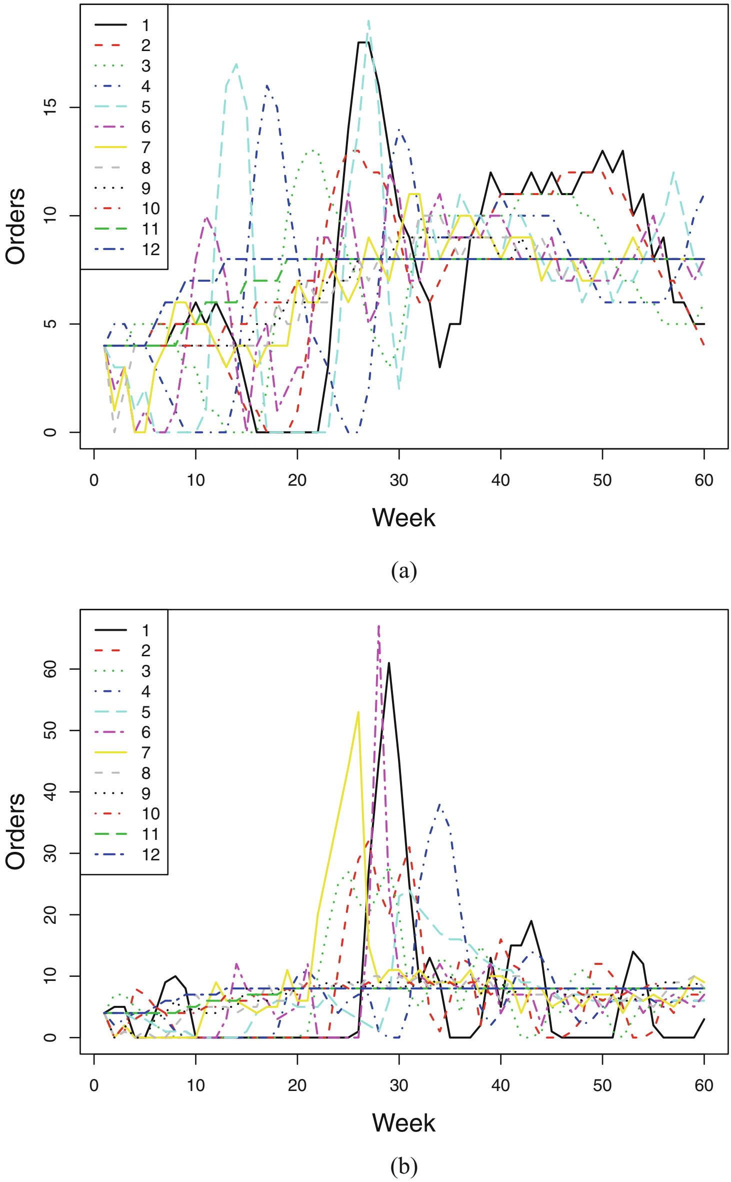


Fig. 17.13 Ordering behavior after the evolution. The length of the supply chain is 12. (**a**) No disruption case and (**b**) disruption case

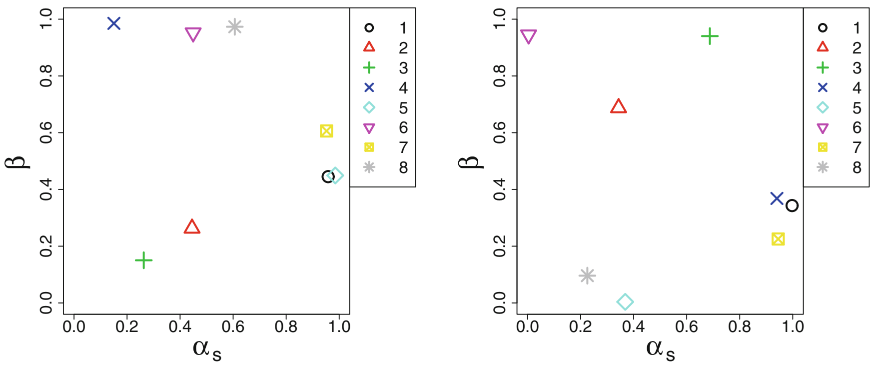


Fig. 17.14 Parameters of ordering policies (α_s, β) of best agents obtained by GA. The length of the supply chain: 8; normal condition (left) and malfunction condition (right)

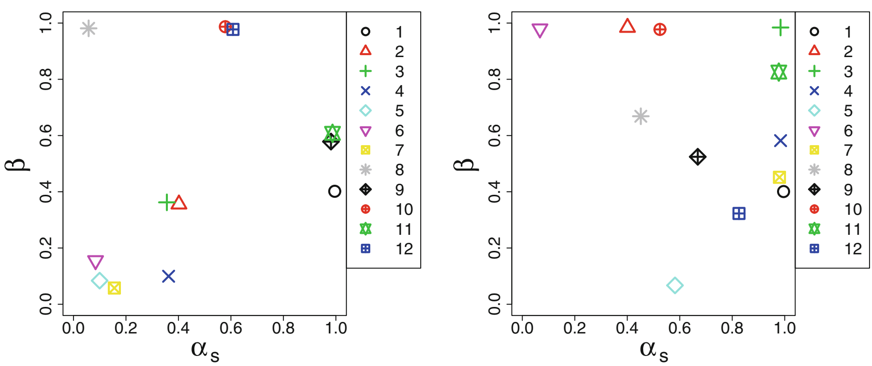


Fig. 17.15 Parameters of ordering policies (α_s, β) of best agents obtained by GA. The length of the supply chain: 12; normal condition (left) and malfunction condition (right)

17.6 Conclusion

In this chapter, we investigated the effective ordering policy of the supply chain in the situation that there is a disruption in one sector. We adopted the Beer Game as an example of a supply chain and used genetic algorithms in order to find the best strategy. We introduce two changes in the original Beer Game. One is the disruption of a sector during the simulation, and the other is the extension of the length of the supply chain. From the simulation results, we obtained the fact that the sensitivity of each sector tends to be the same. The flow-sensitive sectors tend to be flow-sensitive even when a disruption occurs and vice versa. Getting a more precise policy of each sector and using the more complex supply chain network are our future work.

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Chapter 18
Network of Investment-Oriented Social Media

Masachika Sueki

Abstract This study explores the network structure of social media dedicated to equity investment. We used network data from over 40,000 individual investors. The data were part of more than 450,000 investors on this social media dedicated to equity investment. Unlike other popular social networks such as Facebook and LinkedIn, this network was not created from a human relationship perspective. However, investors need to interact with others to share their investment ideas. This is a valuable feature of the investment community on the internet.

First, an analysis of the entire network revealed that it consists of a few individual investors with numerous links and numerous individual investors with a few links. Except for the scale-free nature of this network, there was no network-wide characteristics. Next, we adopted the Modularity Q method and divided the entire network into several subnetworks. Subnetwork statistics completely differ from the entire network statistics. Most subnetworks have several hubs or authorities.

After discovering some features of subnetworks, we tested two hypotheses about investor motivation for investors to create links with other investors. The first hypothesis is related to investment performance, which helps understand why investors want to network with high-performance investors for tips on stock selection, investment strategies, and financial analysis, among other aspects. The second hypothesis relates to stock selection. Similar to the first hypothesis, investors may be interested in other investors' views on the stocks they invest in. In this hypothesis, investors establish links with investors who own the same stock as them. The characteristics of subnetworks are much more complex than the hypothesis tested in this study, and our hypothesis could not find a clear reason for its formation.

Keywords Social network analysis · Individual investor · Social media

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18.1 Introduction

This study surveyed the network of investment-oriented social media. Individual investors play an important role in all capital markets worldwide. They not only bring money to the market but also provide stability in price fluctuations. Moreover, they might bring positive effects other than this.

Since the advent of the Internet, individual investors have become effective in obtaining and analyzing information and making investment decisions. As such, the disadvantages are reduced compared to institutional investors. The Internet has also improved the ability of individual investors to share investment-related information and ideas effectively. Sharing information and ideas among investors to the minimum is beneficial from the perspective of investment strategy planning. It is not widely talked about, but it is happening in a closed investor society such as institutional investors. For a long time before the Internet appeared, most individual investors were isolated within the investment community. Investment-oriented social media made it possible for individual investors to share information and ideas, and such information is shared by posts like any other social media.

Significant differences exist in the quality, quantity, and accuracy of information between institutional investor's societies and social media. We must exclude inappropriate posts when analyzing the activity of information sharing. We use the nature of the network structure to distinguish the information shared by investors on the network in terms of effectiveness.

In fact, investors post a lot on social media every day. Hence, most posts are of low information value, and other investors ignore them. However, some posts contain useful information, and other investors may take them up from their perspective. Here, other investors on this social media will help distinguish effective posts. If other investors rate this particular investor positively, they may create a link to the investor who posted the effective post. When a link between investors is created, a network is also created. The network analysis of the actual state of individual investors' information sharing can be used to improve the return of individual investors, thereby improving the role of individual investors in the investment society.

18.2 Review of Related Literature

Chen et al. (2016) used data collected from Seeking Alpha to investigate posts on the Internet using natural language analysis. Their research aimed to find a relationship between the sentiment contained in the post and the return that investors mentioned in the post.[1] They also considered interactions between investors, such

[1] The term "sentiment" refers to investors' prediction of whether to buy or sell in the area of stock investment.

as information sharing. At the beginning of the analysis, they grouped the post by the difference between positive and negative sentiment. They found that the excess returns for the negative post were significantly negative and confirmed stocks with a negative post related to wire news, press releases, and financial information. These findings suggest that post on the Internet is of beneficial value only if the sentiment is negative. Thus, their findings may evidence that most investors are not willing to share positive private information.

Meanwhile, Giannini et al. (2019), Bagnoli et al. (1999), and Zaima and Harjoto (2006) indicated or partially indicated the positive forecasts or returns of individual investors on the Internet.

Moreover, Das and Sisk (2003) used data collected from Yahoo Finance, The Motley Fool, Raging Bull, and Silicon Investor. These are Internet services for individual investors. They grouped investors investing in the same stock by eigenvalue vector centrality and compared the volatility, covariance, and return among subnetworks. This study presented two findings. First, the return in large subnetworks was higher than that in smaller subnetworks, and the covariance of return was small. Second, stocks with high eigenvalue vector centrality showed higher covariance than stocks with lower eigenvalue vector centrality. Moreover, investors in large subnetworks tend to perform well, suggesting possible interactions between other investors in the subnetwork.

18.3 Data

18.3.1 Data Source

This study uses social media data provided by Minna-no-kabushiki, which is operated by Minkabu the Infonoid Co., Ltd.[2] The main participants in this social media are individual investors who intend to share information related to equity investments and/or foreign exchange margin trading. Investors who want to participate in this social media would first need to create an account and a dedicated web page. Next, if necessary, they enter their information, such as investment experience, strategy, favorite information sources, and budget, in the input frame of the page (Table 18.1). Needless to say, the information provided by investors is not always true. As for return, it is automatically tracked when a user investor enters a stock code, price, and trading date into the system.

Like any other social media, this service includes links to other investors, blogging services, community groups, and so on. These links build a network of investors that we pay attention to, which are of two kinds: one is an outbound link to another investor, and the other is an inbound link. These two links are overlapped

[2] Minna-no-kabushiki, https://www.minkabu.jp/.

Table 18.1 Key contents on the owner page

Group	Name	Description
Investment history	Transaction in progress	Date of transaction, return (at the sample collected day), current and purchase price, comments from oneself and other investors
	Completed transaction	Term, return, price, comments from oneself and other investors
	Profile	Investment experience in years, investment style, resource of information, broker
	Blog	Blog system
Activity on the social media	Respect	Other investors whom they emulate
	Followings	Other investors whom they follow
	Followers	Other investors who they are followed
	Community	BBS on general topics

in most cases, but they are not the same from a network science perspective. This survey uses inbound links (follower links) for social network analysis.

18.3.2 Sample

The sample collection period was from April 15, 2016, to April 30, 2018. All investors on this social media are automatically assigned a serial number as their ID. At the end of the sample collection period, the latest ID number was 453,573. The following investors are excluded from the sample set: (a) investors who trade only foreign margin exchange transactions (352,081); (b) those without a dedicated web page (45,292); and (c) those who have no stock investment record (14,601). Consequently, 41,599 investors were included in the sample set.

Table 18.2 presents the overview of the sample. The average number of stock code-based buys was 5.4, and the average number of stock code-based sells was 1.2. These numbers include both spot trading and futures. The maximum total number of stock code-based buys was 2999 by an investor, and the maximum total number of stock code-based sells was 3724. These numbers may be multiple counts, as investors may have bought and sold the same stock multiple times in their trading history.

18.3.3 Fundamental Network Stats

The following are overviews of fundamental network statistics. As explained earlier, links between investors emerge when an investor follows another investor. These links build a network of directed graphs.

Table 18.2 Fundamental stats of investors' activity

Stats	Value
The number of investors on this social media	41,599 IDs
Average number of buy per investor[a]	5.4
Median number of buy per investor[a]	2.0
Standard deviation of the number of buys[a]	41.1
Maximum number of buy per investor[a]	2996
Minimum number of buy per investor[a]	0
Total number of buy by all investors[a]	225,677
Average number of sell per investor[a]	1.2
Median number of sell per investor[a]	0.0
Standard deviation of the number of sells[a]	29.2
Maximum number of sell per investor[a]	3724
Minimum number of sell per investor[a]	0
Total number of sell by all investors[a]	48,147

As of Apr. 30, 2018
[a] Count by stock code

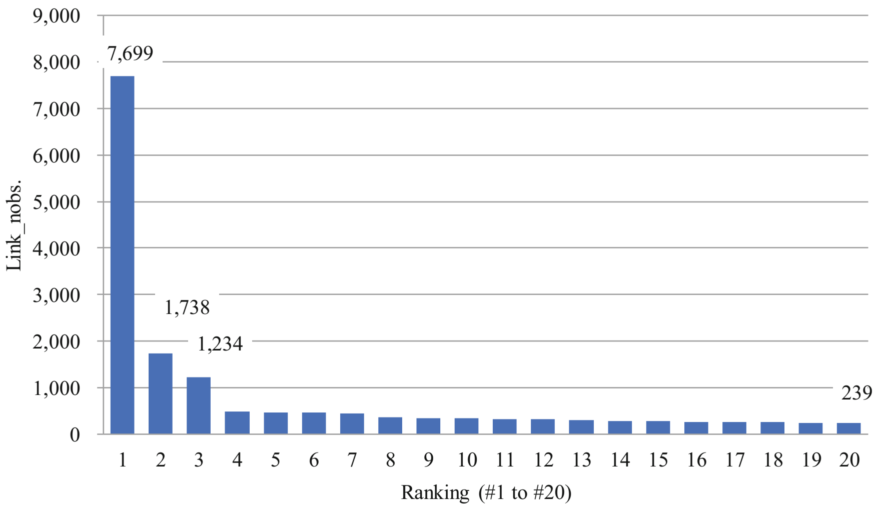

Fig. 18.1 The number of links (top 20 investors)

There are two kinds of network statistics. One is related to individual investors, which is commonly referred to as nodes or edges in network science. The other is related to the entire network graph. Node-related statistics are the distribution of links, degree centrality, PageRank, and rank–size plots. Meanwhile, network graph-related statistics are density, cluster coefficients, diameter, and average path length.

18.3.3.1 Number of Links and Degree of Centrality

The distribution of links is concentrated in few investors (Fig. 18.1). Only three investors have above 1000 links, whereas 53 investors have more than 100 links.

Table 18.3 Number of investors by link class

Link_nobs.	Number of investors		Link_nobs.	Number of investors	
1000~	3	0.01%	41–50	29	0.1%
501–1000	0	0.00%	31–40	64	0.2%
401–500	4	0.01%	21–30	103	0.2%
301–400	6	0.01%	11–20	298	0.7%
201–300	13	0.03%	2–10	3756	9.0%
101–200	27	0.06%	1	5308	12.8%
51–100	66	0.16%	0	31, 922	76.7%

Table 18.4 Stats of links per investor

Stats	Value
Average number of inbound links	1.3
Median of inbound links	0.0
Maximum number of inbound links	7699
Minimum number of inbound links	0.0

Most investors have less than 10 links. In addition, over 76% of investors do not have a link and are isolated within this social media (Table 18.3). The average link is 1.3, and the median is 0.0 (Table 18.4). Whether these numbers show an appropriate distribution remains unclear. The distribution of links may have scale-free characteristics.

18.3.3.2 Scale-Free Feature of the Distribution

As aforementioned, the distribution of links might have scale-free characteristics. We ran a rank–size plot to determine whether the distribution of links had this characteristic. The vertical axis of the rank–size plot is the logarithm of the investor's ranking. The investor with the most links is ranked first, and the investor with the fewest links is ranked last. Meanwhile, the horizontal axis is the logarithm of that investor's number of links (Fig. 18.2).

Looking at Fig. 18.2, we can easily see three dots in the lower right corner representing the top three investors who have many links (Fig. 18.1). The upper left portion is investors with few links. Next, we performed a linear regression on the rank–size plot. The regression model is

$$\text{Log (Link\_Rank)} = C - a \times \text{Log (Link\_nobs)}$$

If the parameter a is close to -1 and significant, the distribution of links is considered a scale-free network, where C is constant. Regression results show that the coefficient is significant, that is, -0.93, which was close to -1. Meanwhile, the distribution of links in the range 1.5–2.5 shows that the distribution has a scale-free feature.

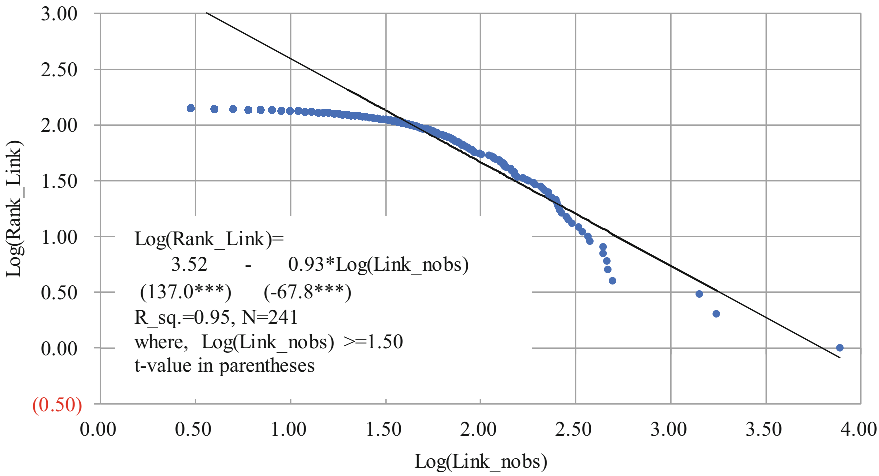

Fig. 18.2 Rank size plot of links. The straight line shows −45°

18.3.4 Network Statistics

18.3.4.1 Network Density, Average Cluster Coefficient, and Average Path Length

From the following, investors without links have been removed from the sample set. Due to this limitation, the remaining sample was 15,944 investors with 60,313 links. The network density, the average cluster coefficient, and the average path length were 0.000, 0.183, and 2.999, respectively. Considering these statistics, we present the following.

First, low network density indicates that there are not many links between investors, and the average cluster coefficient decreases accordingly. These results may be due to low activity in the interconnection of links. Second, the average path length is smaller compared to the sample size. Moreover, the entire network may consist of multiple subnetworks instead of one huge network, or it might have characteristics of small worldness. However, note that in this network, the characteristics of the small world are unimportant because the objective of investors participating in this social media is not to build personal relationships like other social media, but to obtain information that can be used for high returns.

18.3.4.2 PageRank

Indeed, degree centrality is an important and clear measure of an investor's presence in the network, but it simply means measuring the number of the investor's connections. Suppose an investor is important in the meaning of disseminating

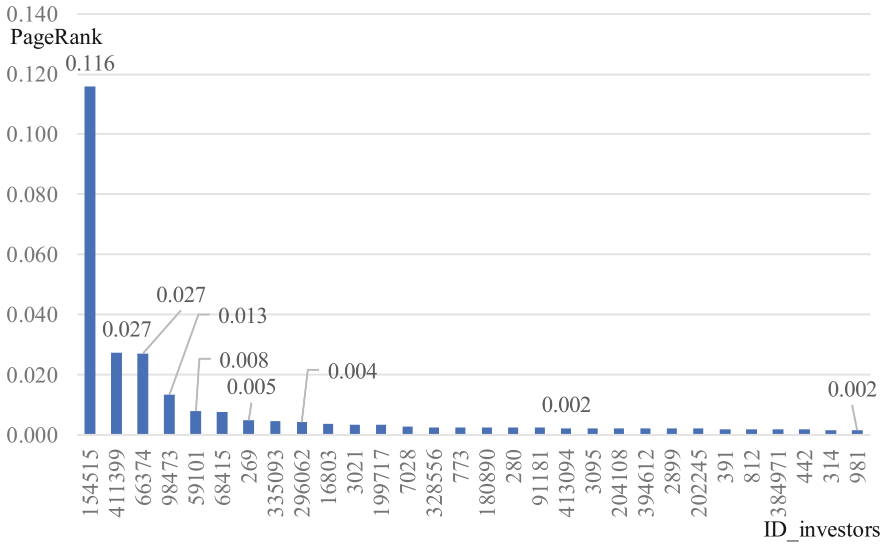

Fig. 18.3 PageRank (top 30 investors). ID_investors denote only for identification

information; in that case, many other investors may be linked to this investor. In particular, this key investor has a higher percentage of links from other key investors than other general investors.

In this regard, PageRank is a measure that considers the importance of links from other nodes, that is, other investors. Therefore, investors are worth valuing with PageRank. Almost all investors have a PageRank of less than 0.1, which is not high. The distribution is also biased (Fig. 18.3). Contrary to expectations, the attempt to use PageRank to assess the importance of investors on the network was unsuccessful.

However, when comparing the PageRank and the degree centrality, we may find relative differences between them. When a scatter plot was drawn, the correlation coefficient between the number of links and PageRank was 0.69. This score suggests a strong relationship, but some differences remain. Next, we performed a regression analysis between PageRank and degree centrality because a 45-degree analysis is inappropriate for analysis between PageRank and degree centrality. These two are not essentially the same. The regression results reveal that 36 investors have PageRank higher than the degree centrality (Fig. 18.4). These investors may have special perceptions from other investors regarding the information they provide.

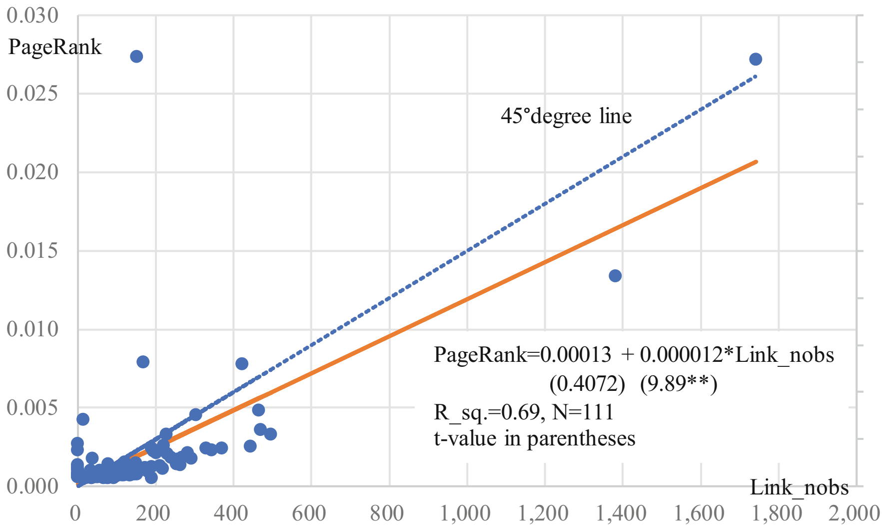

Fig. 18.4 Correlation of link and PageRank. The dotted line indicates 45° and the solid line is the regression line by OLS

18.4 Network Structure

In the previous section, we focused on individual investor's network statistics. In this section, we look at the network structure of investment-oriented social media.

18.4.1 Network Graph

Of the 41,599 investors who meet the sample selection criteria, 15,946 have links, and the number of links is 60,318. Using these investors and links, we draw the network graph using the Force ATLAS2 algorithm (Fig. 18.5).[3] At first glance, it is difficult to find the characteristics of the entire network.

18.4.2 Subnetwork

As aforementioned, some characteristics cannot be easily derived from the entire graph, which consists of small subnetworks based on different interests. Investors

[3] Fort Atlas 2 algorithm has the advantage of being faster than other algorithms, such as Fruchterman-Rheingold and Yifan Hu. See Jacomy et al. (2014) for more information.

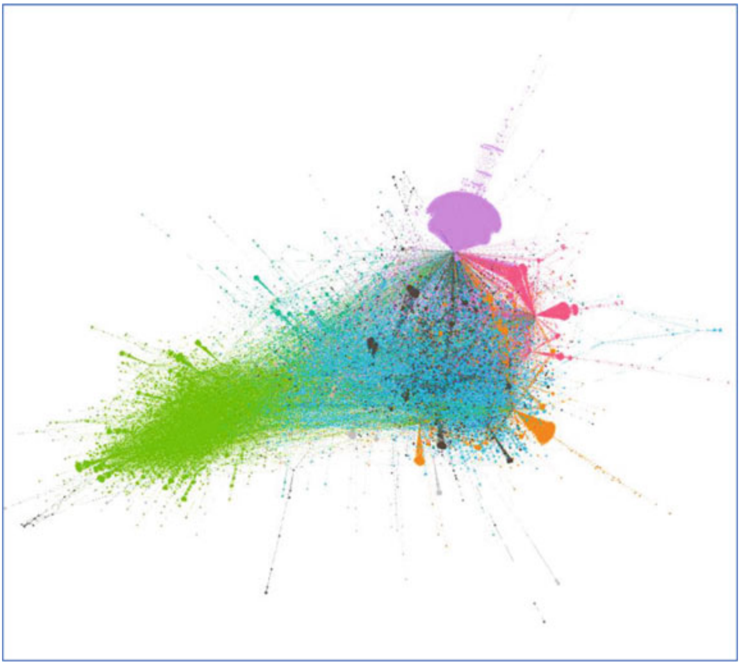

Fig. 18.5 Network graph of entire sample. Color differences indicate subnetworks

may participate in investment-oriented social media based on their unique interests. Therefore, it makes sense to split the network into multiple subnetworks for detailed analysis.

The entire network was divided on the basis of the modular Q algorithm; thus, the network was divided into 131 subnetworks. These subnetworks also differ in the number of investors (Fig. 18.6). For instance, subnetwork 4 comprises about 6000 investors, whereas the remaining 125 subnetworks have less than 1000 investors.

18.4.3 Network Statistic of Subnetwork

In the following, we will focus on the subnetworks with more than 100 investors and analyze their structure. The ID numbers of these subnetworks are No. 4, 1, 10, 9, 3, 2, 6, 8, 0, and 5 in descending order of the number of investors (see Fig. 18.6). The basic network statistics show that network density and the average cluster coefficient (Avg. Cluster_coeff.) are low (Table 18.5). Subnetworks have small sub-subnetworks (Nobs_sub-subnetwork) within themselves.

Figure 18.7 is a network graph of the 10 major subnetworks. Looking at these graphs, we may distinguish subnetwork graphs into several types. For example, the

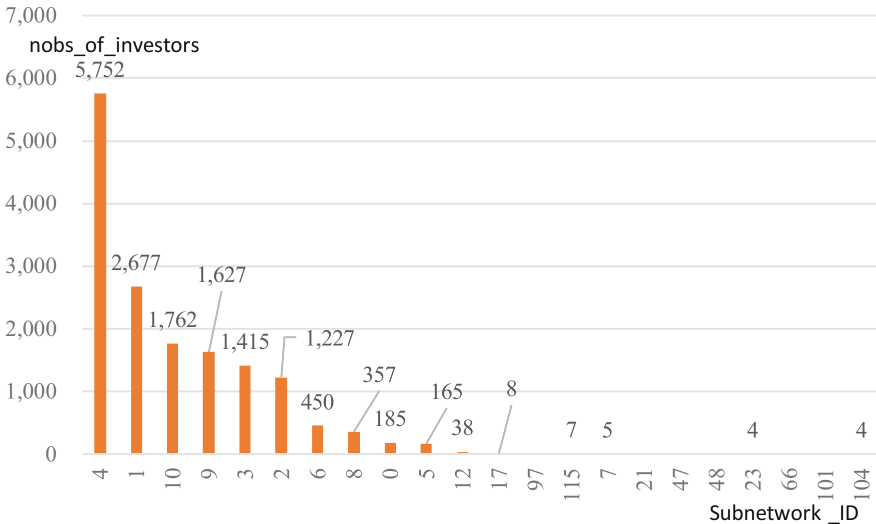

Fig. 18.6 The number of investors (top 22 subnetworks). Subnetwork_ID denote only for identification. Subnetworks with 3 or less investors are omitted

type of network structure of subnetworks No. 1 and 10 is chaotic. Meanwhile, subnetworks No. 0, 2, 3, 4, 6, and 9 are also chaotic, but they include several investors with a high degree of centrality. Subnetwork No. 4 has a single investor with a high degree of centrality.

Next, we look at the correlation matrix between the network statistics of the subnetworks (Table 18.6). Unsurprisingly, each statistic has a positive correlation.[4] However, the correlation coefficient is low, but the correlations between the number of subnetworks (Nobs_subnetwork) and the average cluster coefficient (Avg. Cluster_coeff), diameter (Diameter), and average path length (Avg. Path_length) are negative. From these statistics, it can be inferred that the subnetworks contain smaller sub-subnetworks inside. Moreover, many investors are concentrated in such sub-subnetworks, with sparse links to other sub-subnetworks.

In some subnetworks, we have found core investors. However, what role these investors will play in the subnetworks remains unclear. Therefore, we calculated the value of Hubs and Authorities to investigate the role of investors with a high degree of centrality (Fig. 18.8). Considered along with the network graph (see Fig. 18.7), subnetworks can be classified into four types.

[4] For example, if the number of links (Link_nobs) is large, the average degree (Avg. Degree) will naturally be high. Hence, the larger the diameter (Diameter), the longer the average path length (average Path_length). Additionally, a negative correlation of −0.5 or less exists between density (Density), the number of investors (Nobs_of_investors), and number of links (Link_nobs), which is also a natural tendency based on the density calculation formula.

Table 18.5 Stats of major subnetwork

Subnetwork_ID	Nobs_of_Investors[a]	Link_nobs	Avg. degree	Density	Nobs_sub-subnetwork[b]	Avg. Cluster_coefficient	Diameter	Avg. path_length
0	232 (185)	341	1.470	0.006	21 (11.0)	0.066	4	1.932
1	3082 (2677)	16, 630	5.396	0.002	12 (256.8)	0.262	7	3.024
2	2019 (1277)	3961	1.962	0.001	28 (72.1)	0.122	10	2.441
3	1679 (1415)	2692	1.603	0.001	23 (73.0)	0.106	8	2.858
4	8327 (5752)	11, 155	1.340	0.000	128 (65.1)	0.018	5	2.018
5	287 (165)	494	1.721	0.006	11 (26.1)	0.078	9	3.324
6	725 (450)	1514	2.088	0.003	11 (65.9)	0.088	9	3.366
8	685 (357)	1434	2.093	0.003	14 (48.9)	0.104	11	3.530
9	2596 (1627)	6282	2.420	0.001	13 (199.7)	0.152	8	2.917
10	2872 (1762)	15, 413	5.367	0.002	8 (359.0)	0.141	9	3.575

[a] Nobs_of_investors are different from those in Fig. 18.6. Subnetworks contain inbound links from investors belonging to other subnetworks. Therefore, when defining the number of investors, such investors should be included in the subnetwork. The numbers in parentheses are the same as in Fig. 18.6

[b] The average number of investors per sub-subnetwork is in parentheses

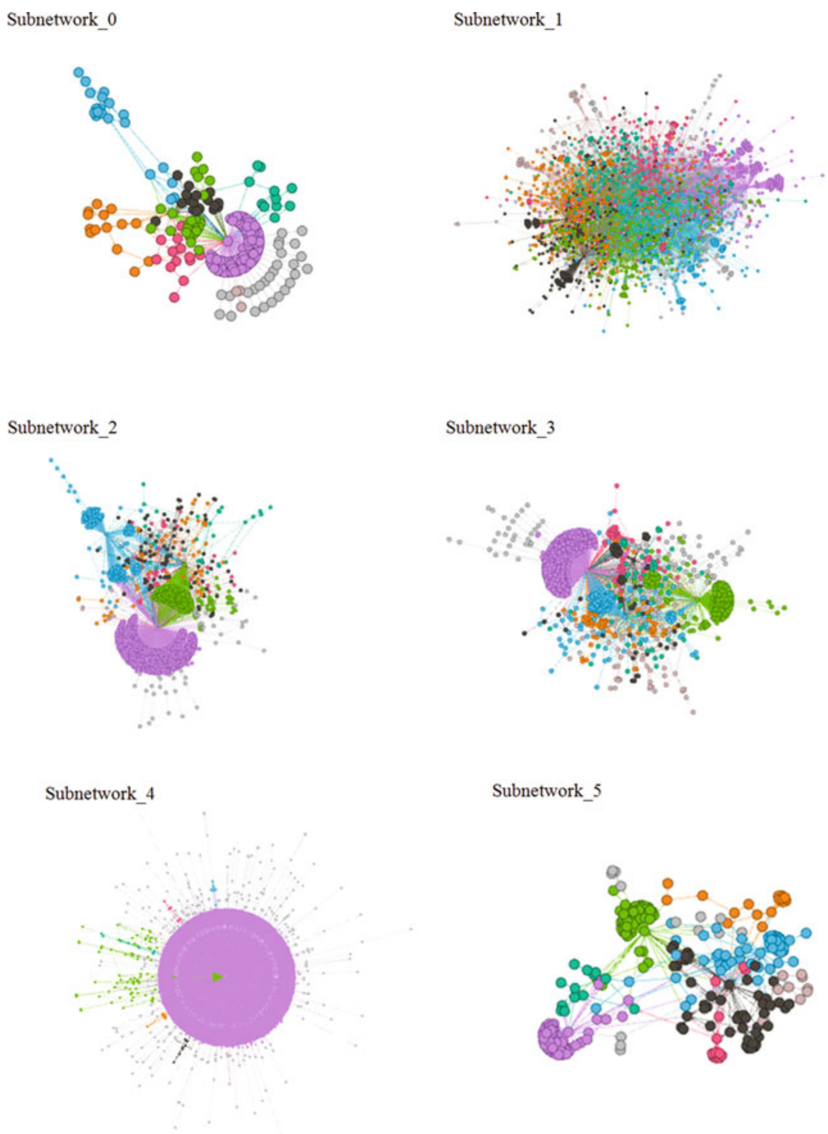

Fig. 18.7 Network graph of subnetworks

- Type 1: the network structure is chaotic, but the relationship between the hub and authority is aligned (subnetworks No. 1, 8, and 10).
- Type 2: investors are biased to the score of authority (subnetworks No. 0 and 3).
- Type 3: conversely to type 2, investors are biased to the hub (subnetworks No. 2, 5, 6, and 9).
- Type 4: the rest of types 1 to 3.

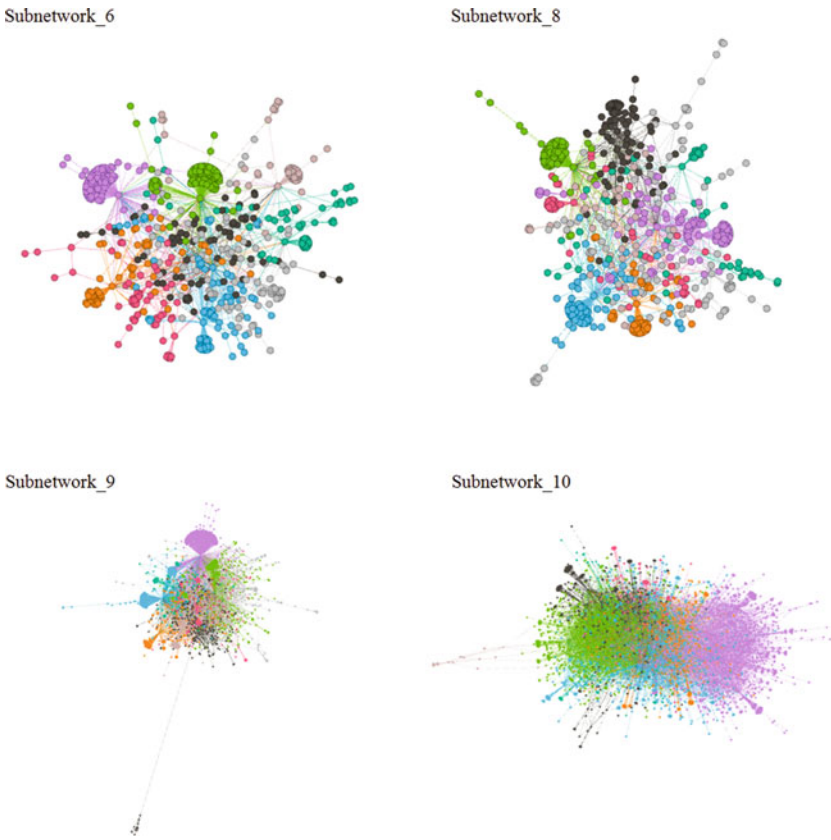

Fig. 18.7 (continued)

Generally, most subnetworks have low density and short average path length. These findings suggest that subnetworks have characteristics of the small world. However, given the nature of investment-oriented social media, the characteristics of the small world may not be essential to investor's performance. We found that subnetworks are categorized into three using PageRank and frequency, and four categorized using Hubs and Authorities. Why the entire network is made up of such subnetworks is still unclear. In the next section, we will try determining the rationale using two factors: investor stock selection and return.

Table 18.6 Correlation matrix of network stats

	Link_nobs	Avg. degree	Density	Nobs_subnetwork	Avg. Cluster_coefficient	Diameter	Avg. Path_length
Nobs_of_Investors	0.636	0.080	−0.692	0.871	−0.147	−0.410	−0.413
Link_nobs		0.816	−0.510	0.220	0.549	−0.181	0.072
Avg. degree			−0.156	−0.363	0.796	0.137	0.466
Density				−0.449	−0.179	−0.099	0.106
Nobs_subnetwork					−0.547	−0.502	−0.625
Avg. cluster coefficient						0.225	0.378
Diameter							0.771

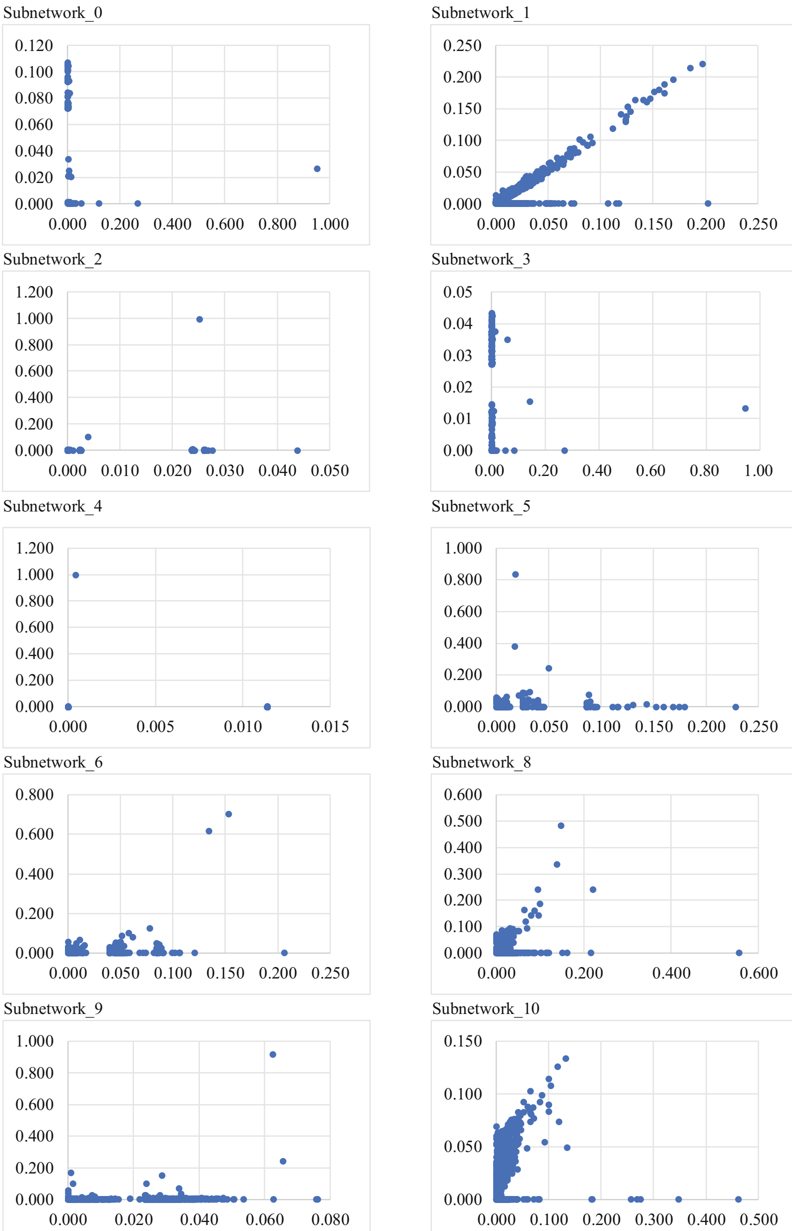

Fig. 18.8 Correlation between hub and authority score of investors. The vertical axis is authority and the horizontal axis is hub

18.5 Relation Between Subnetwork and Return, Stock Selection

In the previous section, we focused only on the network structure. From this section, we analyze network structures in consideration of investor's stock selection and return.[5]

18.5.1 Relation Between Return and Subnetwork Formation

Some subnetworks (subnetworks No.0, 2, 3, 4, 5, 6, 7, and 9) seem to have some investors who act as hubs (see Fig. 18.7). These investors might have the potential to become Hubs due to their return, which attracts links from other investors (Table 18.7, Panel A). To test this hypothesis, we examined the correlation between return and PageRank and the correlation between return and degree of centrality (Table 18.7, Panel B). The results show that both correlation coefficients are less than ± 0.1. This means little correlation. In the next analysis, we excluded investors with a few links from the sample because they, unfortunately, add noise to the network analysis. Due to this limitation, the sample comprises investors with the top 10% of links in the subnetworks.

Correlation coefficients vary between subnetworks. One subnetwork has high positive correlation coefficient (subnetwork No. 5), and the other subnetworks are negative (subnetworks No. 0 and 4). Therefore, it is hard to say that good investors are collecting many links from other investors. In summary, the emergence of links may have reasons other than return.

18.5.2 Relation Between Stock and Subnetwork Formation

It is natural to think that every investor may plan an investment strategy first. Some investors use fundamental analysis to develop their strategies, while others use technical analysis and other methods. Next, investors will select a stock based on their strategy. After choosing an equity, they may try finding other investors on the network who have invested in the same equity. It may be worth checking on social media for the activities and messages of investors who have invested in the same equity. If the link positively impacts returns from an information-gathering perspective, the investor links to another investor who has invested the same stock. These investor-motivated links create subnetworks on social media.

[5] Return was calculated only for completed transactions. Data on ongoing investments were excluded. Most investors in this social media were individual investors; thus, returns are not risk-adjusted.

Table 18.7 Fundamental stats of return (panel A), correlation between return and other stats (panel B)

	Panel A: return ($N = 6858$)[a]				Panel B: correlation			
Subnetwork_ID	Avg. (%)	Median (%)	SD	Max. (*100%)	Return and PageRank	Return and C.Degree[b]	Return and C.Degree[c]	PageRank and C.Degree
0	−1.3	−2.0	0.432	4	−0.03	0.06	−0.94	0.60
1	0.8	1.0	0.458	21	0.02	0.02	−0.11	0.97
2	3.4	0.0	0.466	48	0.02	0.03	−0.00	1.00
3	2.9	−1.0	0.580	40	−0.01	−0.00	−0.02	0.98
4	4.9	0.0	0.777	114	−0.01	−0.03	−0.40	0.57
5	2.0	−1.0	0.664	11	0.11	0.06	0.42	0.92
6	3.2	1.0	0.557	52	−0.01	−0.01	−0.06	0.99
8	−13.4	−10.0	0.154	0	−0.05	−0.05	0.03	0.95
9	4.5	−2.0	0.626	34	0.01	0.00	−0.04	0.93
10	1.5	−2.0	0.586	54	−0.04	−0.05	−0.02	0.89

[a] Investors who have not completed their investment were excluded from the sample. For this reason, the number of investors is different from it of Table 18.5
[b] Based on a sample of all investors in the subnetwork. *C* Degree denotes degree of centrality
[c] Based on upper 10% of investors who have many links

To confirm the above hypothesis, we must first validate the difference in the stock code included in each subnetwork. The sample is 1,002,965 investment records. These records are made of 5019 equity and exchange-listed funds by 6703 investors (Table 18.8). In the sample, investors are not overly focused on a particular stock. Even the stock with the highest share of the sample is 0.77%. The cumulative share of the top 100 is 18.4% (Fig. 18.9). These numbers indicate that different characteristics may exist among the subnetworks. In other words, a subnetwork might be made up of different investors who invest in different stocks.

Table 18.8 The number of investor by subnetwork and overall number of invested projects

Subnetwork_ID	Nobs_of_investors[a]	Overall number of investment	Number of investments per investor
0	85	1343	15.8
1	1580	78,748	49.8
2	651	74,452	114.4
3	504	99,945	198.3
4	1799	44,647	24.8
5	83	19,313	232.7
6	349	35,593	102.0
8	212	18,252	86.1
9	545	158,034	290.0
10	895	472,638	528.1
Total	6703	1,002,965	149.6

[a] Investors who have not completed their investment were excluded from the sample. For this reason, the number of investors is different from it of Fig. 18.10

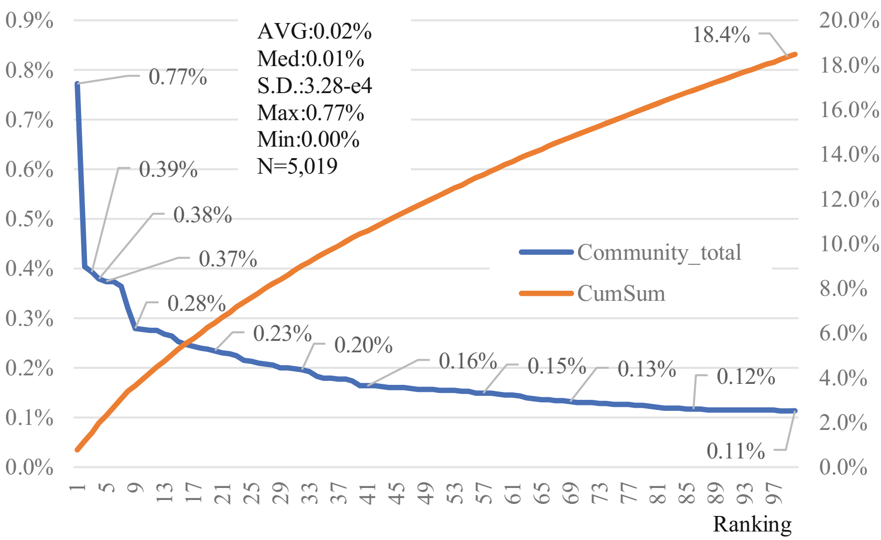

Fig. 18.9 Share of investment numbers by stock code (top 100)

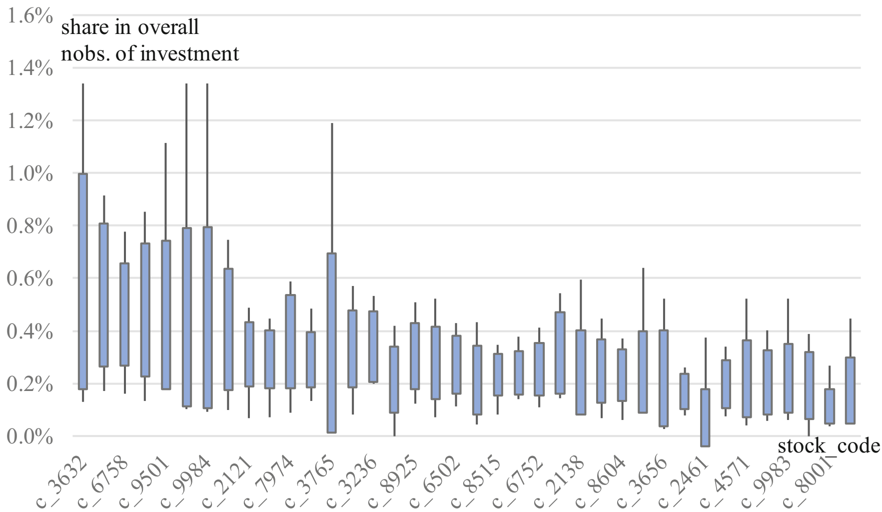

Fig. 18.10 Distribution of subnetwork on share of investment numbers by stock code. This figure shows the difference in invested stocks (by stock code) among subnetworks. The range of distribution indicates the degree of concentration of a stock in a particular subnetwork. The wider the range, the more concentration on a particular subnetwork. The securities code is that of the Tokyo Stock Exchange. Some stock codes are not displayed on the axis due to placement restrictions

To confirm the presence or absence of this characteristic, we analyzed the distribution of the number of investments in each subnetwork of an individual stock (Fig. 18.10). Some stock codes have many investments for them that vary from stock to stock (e.g., c_3632Gree Inc., c_9984 Softbank Group Corp., c_3765 GungHo Online Entertainment, Inc.). However, the share of investment stocks in each subnetwork does not vary widely.

We ran an independence test to see if certain stocks were concentrated in a particular subnetwork. The test was conducted 1026 degrees of freedom and 28,916 sum of squared errors. The hypothesis of independence was rejected with a *p*-value of 2.2×10^{-16}. This result suggests that certain stock may be concentrated to some extent between subnetworks. However, which stocks are concentrated in which subnetworks remains unclear. Further analysis is needed.

18.5.3 Analysis

This section examined the characteristics of the subnetwork based on investor's stock selection. At the beginning of this analysis, we expected that the attractiveness of high-performance investors formed the subnetworks, but this hypothesis was not supported. Next, another hypothesis tested is that subnetworks were formed with a particular stock as the core. If this hypothesis applied, core equity could vary between subnetworks. Statistical tests rejected the hypothesis that no difference existed between subnetworks for stocks invested by investors.

18.6 Conclusion

In this chapter, we surveyed the network of investment-oriented social media. Analysis of the entire network yielded few results other than chaotic structures, but deriving subnetworks from the entire network gave some results. First, we found several types of subnetworks. Second, the presence of high-performance investors might not play an important role in the formation of subnetworks. Third, some individual stocks might attract investors, resulting in the emergence of links within the subnetwork, which made subnetwork's characteristics.

In future analysis, we are planning to extract more detailed characteristics of the network structure and determine how links between investors affect return. Naturally, network links alone cannot explain or predict return. Fortunately, relevant data such as individual investors' investment history and return, investment styles, and messages between investors are available on social media systems. These data are useful for analyzing the network structure and the investment performance of the investors belonging to it.

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Chapter 19
Student Learning in the Age of AI

Yoshifumi Kono

Abstract This chapter discusses student learning in the age of artificial intelligence (AI). With the advent of AI, it is important to make an effort to think for ourselves. However, the Internet makes it easy to retrieve a variety of thoughts and ideas from it. Therefore, some people simply accept and pass on the information they find on the Internet. Such behavior is not desirable, especially in the age of AI. This is because it may lead to accepting an AI's opinion as it is. Even though an AI gives us rational answers based on data, it is important to understand something based on our own experiences and to explain it in our own words. College students, especially, must learn to reflect and express on their own. However, some of them are reluctant to think for themselves and to construct sentences in their own words. We call such students, who save their cost of thinking, "thought-saving learners" and analyze education from the perspective of learners' thinking cost. Our research suggests that in trying to save their thinking cost, students affect their learning outcome negatively.

Keywords Education economics · Embodied learning · Human capital · Signaling theory · Thought-saving learners

19.1 Introduction

In the age of artificial intelligence (AI), the coexistence of AI and human knowledge is essential. In the field of education, learning must adapt to the AI age. Learning in this age is not about competing with AI for computing power, as AI is capable of processing and evaluating large amounts of information that humans cannot handle.

In some fields, AI has even surpassed human capabilities. For example, in the world of Go and Shogi, AI software is now capable of beating top professional

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players. In 2016, AlphaGo, developed by Google DeepMind in the UK, stunned the world by overwhelming the world's top professional Go players at the time.

The advantage of AI software over humans is the extensive accumulation of match records. Matches between AI software generate a large amount of game record data. AI software that learns from this data can sometimes make moves that are beyond human understanding. In the 2016 game of AlphaGo, a professional commentator struggled to explain a new move played by Alpha Go. According to Yamaguchi (2017), who was watching the game live on air, deep learning from the data of 30,000 game records per day led to the discovery of a new joseki that cannot be explained by humans.

However, in a talk with Professor Shinya Yamanaka, Mr. Yoshiharu Habu, a professional Shogi player, described the new moves played by AI software as a creation that is clearly different from that based on human ideas (Yamanaka and Habu 2018).

Habu said that the difference comes from the human sense of esthetics. According to him, this esthetic sense is based on the stability and security that comes from the continuity and consistency to which we are accustomed. In contrast, AI software is not limited to esthetics based on continuity and consistency. The AI software only calculates the best solution based on past data and makes risky moves that a human would never choose.

According to Habu, AI software does not have the fear of self-preservation and survival instincts. In contrast, humans who must protect themselves instinctively sense danger from their opponents' moves, even in a game. Habu said that no matter how strong a player is, when the king is in check, they sense danger.

We act within our environment. Taking Shogi as an example, a game between humans is not just a matter of reading the opponent's moves and choosing one's own move. During a game, the player constantly senses the opponent's facial expressions and body movements.

Embodiment is important in thinking about human knowledge, not only in games. From one perspective, the body and intellect are inseparable. Nakashima (2013) argued that intelligence depends partly on the environment and that disembodied intelligence is inconceivable.

When intelligence and embodiment are inseparable, embodiment becomes important in education as well. Suwa (2012) emphasized the importance of embodied learning, defined as the act of understanding things in relation to one's own body, consciousness, life, and society. For example, Japanese universities are now emphasizing the need for career education. Career-related embodied learning means thinking about work as a personal matter and its relationship to life and society. If students are satisfied with only learning the definition of a career, then their learning is not embodied.

Suwa (2012) asserted the importance of crafting one's own words. According to Suwa, the opposite of embodied learning is second-hand knowledge. Now that everyone has easy access to the Internet, there is no end to speaking and writing directly from the opinions and thoughts of others. However, there is a lack of awareness of the subject who creates the knowledge.

To embody the knowledge that others speak of, we need to learn it for ourselves by comparing it to our experiences and learnings. Then, we should express the knowledge we acquired using our own words. We should not blindly accept the opinions and thoughts of others on the Internet. According to Suwa, though it takes time and conscious effort, it is important to think about things in relation to one's own experiences, life, and society.

However, the time and conscious effort required to put knowledge into words is an economic cost. In economics, the behavior of learners depends on the benefits and costs of learning. Without incentives that are worth the cost, we cannot expect learners to be motivated. Students who are unwilling to pay the economic cost of sentence construction in the classroom are more likely to be reluctant to learn. In contrast, students who appreciate the value of sentence construction more than the cost are expected to actively participate in the class. In light of these learning costs, it is important to analyze learner behavior and its economic performance.

We consider such thinking activities by learners as an investment in human capital. Then, we analyze the relationship between the costs and benefits of that investment from the individual learner's perspective. In particular, we focus on learners trying to save the economic cost of thinking in the classroom. We call such learners "thought-saving learners" and analyze their impact on learning outcomes. This study makes a novel contribution to the literature on the economics of education by analyzing education in terms of the learners' thinking cost.

First, in Sect. 19.2, we present a framework for an economic analysis of education. In Sect. 19.3, we study the benefits and costs of individual educational investment from the learner's perspective and theoretically analyze the differences between students who actively learn in class and those who do not. Next, in Sect. 19.4, we discuss the survey conducted on the presence of learners who try to save on thinking costs and their learning outcomes.

19.2 Economic Analysis of Education

Two of the most popular economic analyses of education are human capital theory and signaling theory. Both theories view education as a kind of investment, but the two theories differ in how they evaluate the benefits of education. According to Oshio (2002), human capital is a general term for workers' knowledge, skills, education, and know-how. According to Becker (1994), a major contributor to human capital theory, a school is an organization dedicated to the production of training, and through this training, students form human capital. Momma (2016) investigated the wage gap between college-educated workers and high-school-educated workers in Japan and found that despite the relative increase of college-educated workers to high-school-educated workers, there is no obvious downward trend in the college-educated wage premium. From the perspective of the human capital theory, the formation of human capital through university education is the reason why the wages of university graduates are higher than those of high school graduates.

In contrast, the signaling theory (Spence 1973) focuses on the asymmetry of information between sellers and buyers in the labor market. As buyers of labor, companies have limited information about the capabilities of the applicants they are considering hiring. In this case, education is a signal of the applicant's ability. If an applicant's academic background lowers the cost of a firm's recruitment efforts, then education is useful as a signal of a worker's ability.

A great deal of research has been conducted on human capital and signaling theories. However, it is not easy to empirically compare the two mechanisms in terms of their economic effects. This is because even if the difference between the wages of high school graduates and those of college graduates is real, it is difficult to distinguish whether it is due to human capital or signals. It would therefore be appropriate to interpret this as a function of both signaling theory and human capital theory.

In addition, when education is viewed as an investment, its outcome is uncertain. For example, as Oshio indicates, parents who send their children to cram schools from an early age with the goal of attending a top university do not necessarily achieve that goal. The same applies to the learners being educated. For example, there will be variations in grading among students taking the same lecture at a university. No matter how hard a student studies, they might not always get a high grade.

In addition, some abilities that are acquired through learning are difficult to evaluate. For example, unlike degrees and credits, it is not always easy to ascertain how much basic literacy has been acquired through a university education. Compared to the specialized knowledge and skills learned in university, it is not easy to assess how basic literacy will affect future wages. When learning outcomes are uncertain, learners' expectations of education are likely to vary. Learners who value the benefits of human capital are more likely to be engaged in learning than those who do not. Expectations from one's human capital affect the behavior of the learners.

Both the expectation of the benefits of learning and learning costs will affect the behavior of learners. Learning costs include direct costs, such as tuition and commuting costs, as well as indirect costs, such as the time and effort required to learn. Many students earn money through part-time jobs. The more time they spend learning, the less time they will have for part-time jobs.

We should analyze how learners' expectations of education and the cost of learning affect their actual learning behavior.

19.3 Economic Analysis of Students' Learning Behavior

Two issues need to be considered separately in analyzing students' demand for education. One is determining the level of education, and the other is how much to study. For example, in the case of higher education, students can choose the level of education, such as four-year college or junior college. After joining college, they also have to decide how much time and effort they are willing to put into their studies. For example, the learner chooses how much time and effort they will devote to the tasks assigned by the instructor in the class. Out-of-class study time can also be determined to some extent by individual learners.

In addition, Oshio and Senoh (2003) identified the characteristics of the group being educated together as one of the inputs that define the educational outcome. Active discussion among students will affect educational outcomes. The more actively they are involved in the discussion, the greater the learning outcomes. However, while some students actively participate in the discussion, others do not because the thinking involved in these discussions is burdensome for students who are reluctant to learn. The level of education differs depending on whether a person is studious or not.

Kono (2021) analyzed how students determine their demand for education. In Kono's model, the level of education chosen by the individual and the amount of learning by the individual were analyzed separately. He separately analyzed the individual's choice of educational service and their subsequent choice of how much to learn.

To analyze learning behavior, the following assumptions are made referring to Kono (2021). Individuals distinguish between the effects of the level of education they receive and the effects of their own learning efforts. Individuals use part of their labor for learning, subject to the constraints imposed by the education they choose. Individuals also distinguish between the human capital formation effects of their learning and the signaling effects of their education. In other words, individuals distinguish between the rate of return they expect on education and the rate of return they expect on learning.

To simplify the discussion, the model in this section makes the following assumptions based on Oshio (2002): Individuals live in two periods, the first and the second, and education is received only in the first period. The level of individual utility depends on the level of consumption during these two periods. There is no utility gained from education or learning itself. In other words, we did not consider education as consumption.

We denote the utility function of an individual as u,

$$u = u\left(c_1, c_2\right), \quad \frac{\partial u}{\partial c_1} > 0, \frac{\partial u}{\partial c_2} > 0,$$

where c_1 and c_2 are the consumption in periods 1 and 2, respectively.

The budget constraint equations for the first and second periods are

$$c_1 = w\left(L - L_E\right) - aE - s,$$
$$c_2 = wL + \left(1 + \rho_L\right) wL_E + \left(1 + \rho_E\right) aE + (1 + r)\, s.$$

Here w is the wage rate, s is the savings, r is the interest rate. L is the amount of labor, such as working hours, that an individual can invest in each period, and L_E is the effort that an individual invests in learning, such as the time spent in learning. We assume that $L \geq L_E$. In addition, E is the educational level, such as the duration of study. a is the direct cost of education, such as tuition, and ρ_L and ρ_E are the expected rate of return on learning and the expected rate of return on education, respectively.

If we spend L_E effort on learning in the first period, it will cost wL_E, but in the second period, we can expect additional income equal to $(1 + \rho_L)$ times that cost. Similarly, an education of E in the first period costs aE, but in the second period, one can expect an additional income of $(1 + \rho_E)$ times that cost.

By combining the two equations above, we can obtain the budget constraint equation for these two periods,

$$c_1 + \frac{c_2}{1+r} = \frac{2+r}{1+r} wL + \frac{\rho_L - r}{1+r} wL_E + \frac{\rho_E - r}{1+r} aE.$$

When both the expected rate of return on education ρ_E and the expected rate of return on learning ρ_L are below the rate of interest r, the individual should not opt for higher education. Conversely, when the expected rate of return on education ρ_E and the expected rate of return on learning ρ_L, both exceed the rate of interest r, individuals should go on to higher education and spend as much effort on learning as possible.

In the case of enrolled university students, the expected rate of return on university education is likely to be high. However, educational expectations do not always directly lead to a high evaluation of learning.

A problem in learning behavior occurs when the expected rate of return on education ρ_E exceeds the interest rate r but the expected rate of return on learning ρ_L is less than the interest rate r. In other words, there is a discrepancy between the expectation of academic background and the expectation of ability formed by learning. In this case, they will consider going on to higher education, but will try to save as much effort as possible in their learning.

The problem that can be derived from the above theoretical study is the existence of students who distinguish between the level of education as a signal and the level of learning for human capital formation, and try to save their effort in learning. In other words, these are students who entered higher education with high expectations for signals, but not for human capital formation, and who are not motivated to learn. It is necessary to analyze how these student behaviors affect their learning outcomes.

19.4 A Survey of Thought-Saving Learners and Their Learning Outcomes

Some assignments in the class, like a reaction paper, require students to react to the instructor's lectures or readings by giving their personal opinions and conclusions.

The content of a reaction paper is valuable to the instructor because it contains a wealth of qualitative information.

However, it is burdensome for students to write reaction papers. In fact, Tatsumi and Sawaguchi (2014), who studied the use of online reaction papers, introduced the voices of students and pointed out this burden. The content and description varies considerably among students. While some write long answers in small letters in a limited space, many others write only simple and short answers and some others write almost nothing.

Though reaction papers are burdensome for students, the content and description provide important information to instructors. For example, students who write long responses spend more than just time on reaction papers. The amount of effort spent on thinking is also expected to increase with the length of the responses. The thought process of organizing one's thoughts, summarizing them into an opinion, and describing it in writing with evidence requires a reasonable amount of thought and a large number of words. The length of students' responses can be seen as an indicator of the amount of effort put into their classroom learning.

To determine whether students are thought-saving or not, we asked them a simple question. The length of responses by the students was used as an indicator of whether the students were thought-saving or not.

We then examined how thought-saving learners' behavior affects their learning outcomes. For learning achievements, we used the evaluation scores of the exercises assigned to the class. Students who are willing to put in the effort to construct sentences are enthusiastic about the exercises and are expected to rank higher. In contrast, the ranking of thought-saving students should be lower than that of motivated students.

19.4.1 Methods

Fifty-nine college students taking a class to think about their careers participated in the survey. The class was taught by three instructors including the author. The survey was conducted in the author's class. Students were given an option to give their opinions on learning in an open-ended format. At the time of the survey, students were informed that their answers would only be used for lecture and research purposes and would not affect their grades.

19.4.2 Results and Discussion

The number of Japanese characters in the answers was counted, including punctuation. The relationship between the character count data and students' assignment evaluation was analyzed. The assignment assessments used in the analysis were given and graded by a different instructor. The number of letters in the free responses of 59 respondents was counted and the average was found to be 33 (M=33.1, SD=34.7). Thirteen respondents did not answer, and the longest response was 144 characters.

Considering the number of characters in the open-ended questions, about 80% of the responses were less than 60 characters long and 40% were less than 20 characters long. Among the respondents who wrote less than 20 words, several were close to no answer. For example, there were five cases with no opinions, such as "none" and "nothing," in particular.

Respondents who wrote less than 20 words but more than 10 characters made their thoughts apparent. For example, "I want to study something directly related to my future" (19 characters in Japanese) and "I think it is necessary, but I don't like it" (17 characters in Japanese).

In contrast, the responses that only expressed feelings and impressions, not the respondents' thoughts, tended to be shorter. For example, "I don't want to do it if possible" (10 characters in Japanese) or "It feels too long" (five characters in Japanese). When we counted the number of responses that was less than 10 words as a criterion for shortness, we received 19 responses, including no responses. These respondents are considered to be thought-saving.

The table shows the difference in performance between thought-saving and non-thought-saving learners (Table 19.1). Respondents with less than 10 words in their response were classified as "thought-saving" and those with more than 10 words were classified as "non-thought-saving. The "characters" in the table are the mean and standard deviation of the number of Japanese characters in the responses. The mean of the descriptions of thought-saving learners was very small because it included non-respondents. The "score" in the table is the assessment of the assignments that the students worked on in the class. Each student's evaluation score is an aggregate of the evaluations from the classes prior to the one in which the questionnaire was given, and the full score was 40.

There was a large difference in the mean scores of the thought-saving and non-thought-saving learners. An unpaired t-test for the difference in mean scores between the two learners showed a statistically significant difference ($t(57) = 4.27$, $p < .001$). This result suggests that there are students who avoid thinking in class, and their learning outcomes are inferior.

Statistical analyses were performed using the statistical analysis software R (R version 3.6.2).

Table 19.1 Length of response and assignment score

	Thought-saving ($n = 19$)		Non-thought-saving ($n = 40$)	
	Mean	S.D.	Mean	S.D.
Characters	1.0	1.7	48.3	32.4
Score	14.8	9.2	24.2	7.1

19.5 Conclusions

AI is playing a major role in our increasingly digitalized society. In the age of AI, education and learning must be adapted to the times. The key to this learning is embodiment, the strength of humans over AI. As Suwa (2012) argued, we need to learn with our bodies in light of our own experiences, not by relying on what we hear from others. It is also important to spend time and conscious effort to share in our own words in order to learn with our body. People can claim to understand only if they can explain what they learned in their own words. However, in an age where information is easy to retrieve from the Internet, there is no end to the number of people who simply accept and pass on information found on the Internet.

In the classroom, some students try to avoid thinking and constructing sentences in their own words. The time and effort needed to construct one's sentences is a cost from the economic perspective. Students who expect education to be more effective as a signal than human capital are likely to be reluctant in constructing their own sentences in the classroom.

We analyzed students' free responses to the instructor's questions not related to their grades. Students who answered with reasons should have longer answers. In contrast, those who try to save on thinking costs should have shorter answers. There is a concern that such student behavior may affect their learning outcomes. Our research suggests that the attempt to save the thinking cost negatively affects students' learning outcomes.

In an increasingly digitalized society, we are expected to coexist with AI. The existence of learners who try to save the economic cost of thoughts while learning is a major issue in fostering human intelligence in this age. Coexistence with AI does not mean that we should just believe the opinions presented by AI. Though it gives us rational answers based on the data it has accumulated, it is important to understand based on one's own experiences and to explain in one's own words.

In light of the results of this study, it is necessary for learners to understand the benefits of human capital accumulated through such learning. When learners understand the benefits, then we expect them to be motivated to learn. Future research should explore ways to help learners understand the benefits of embodied learning.

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