Evolutionary Economics and Social Complexity Science 4

Hajime Kita
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Realistic Simulation of Financial Markets

Analyzing Market Behaviors by the Third Mode of Science

Springer

Evolutionary Economics and Social Complexity Science

Volume 4

The Japanese 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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Editors

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Foreword

Everyday human life, on a mass global scale, is ushering in the era of a new mode of interaction called social information and communication technology (ICT). Our lives are rapidly becoming integrated with artificial intelligence in various spheres of our socioeconomic systems. In many fields, both civilian and military, human contributions to decision-making are at times being replaced by algorithm-based agents. Algorithms not only coexist with humans, but are also becoming increasingly preferred to human-made decisions. This move also naturally applies to markets. As sophisticated high-frequency trading (HFT) demonstrates, the computing power of algorithms in financial exchanges overwhelmingly triumphs over human ability and instinct; thus, understanding of the market system is no longer grounded in human-initiated transactions. There is keen anticipation of a simulation system compatible both with people and algorithms to clarify how the market can work through heterogeneous interaction between the two parties.

The U-Mart Project for an artificial-intelligence-based market, addressed in this book, is a compelling challenge for grasping this new approach and satisfying HFT's many requirements. This project, begun at the end of the twentieth century, was in fact far-sighted with regard to the advent of HTF and was continually updated intensively and extensively to keep pace with the Tokyo Stock Exchange's new features. This book's group of authors has published several books on U-Mart, both in Japanese and English. The first English-language book was published by Springer in 2008. This book marks the second English release on the topic of U-Mart. I hope the readers will enjoy looking in on a new form of realistic simulation and examining its implications toward a new type of modern exchange.

Tokyo, Japan
January 2015

Yuji Aruka

Preface

This book reports on a study about realistic simulation of financial markets, based especially on the core study which is the U-Mart Project. In 1998, one of the authors of this book, Professor Kita along with other authors invited one of the authors, Professor Shiozawa, to give a discourse at the 4th Emergence Systems Symposium under the auspices of the Society of Instrument and Control Engineers. This actually led the birth of the U-Mart Project. In 1999, major members of the U-Mart Project were determined and the study was kicked off. In the autumn of the same year, the specifications of the artificial futures market were almost determined in order to achieve the aim of U-Mart Project. The building of the entire system was then started. The prototype was completed in 2000, while demonstrations were presented at the Japan Association for Evolutionary Economics and our first open experiment was also conducted around this time. Afterward, open experiments have been conducted every year. Last year marked the 14th open experiment conducted. At the same time, international open experiments have also been conducted. In addition, lectures related to U-Mart have been held for the purpose of educational utilization of the U-Mart system in several universities. A book about U-Mart based on education of economics was published in Japanese in 2006. The same book but in English was published and released by Springer in 2008. A summer school targeting the students of technical engineering graduate schools was also started. Another U-Mart book for the teachers and students in the technical engineering field was published in Japanese in 2009.

There exist two kinds of trading methods in Tokyo Stock Exchange in Japan. One is the call auction method which is called *Itayose* trading method in Japanese and the other one is the continuous double auction method which is called *Zaraba* trading method. Initially, the U-Mart system was developed with the focus on the Itayose trading method to be used for experiments (U-Mart Ver.2). The version that supports the Zaraba trading method was developed later (U-Mart Ver.4). The U-Mart system currently supports both trading methods and is used for experiments. Specifications have been changed through development, while the system was divided into modules. This development actually produced a graduate school student who finished a doctorate. The U-Mart system currently supports the arbitrage transactions for spot trading and futures trading, while producing a wide variety of research and educational achievements.

The market is primarily an important study objective of economics. It has been about 250 years since economics became an independent field of learning, where researchers tried to describe and analyze economic phenomena by defining concepts based on language. Adam Smith well explained the function of the market by using "the invisible hand." With such insights, the conception of a self-organizing structure of the market began to dawn upon mankind. Since markets had been self-organized and appeared before mankind as a spontaneous order, we became able to grasp them. As a result, economics came into the world.

The concept of differentiation discovered by Newton and Leibniz could reveal the motions of celestial bodies clearly in the seventeenth century. These outstanding achievements of physics introduced the concept of differentiation into economics and brought about the Marginal Revolution in economics in the nineteenth century. This enabled mathematical analysis on markets in addition to language-based analysis. As an anecdote, "to search for what we have lost on a dark street at night at well-lit places" was born; however, the analyses of standard economics separated us almost completely from understanding the actual markets. A glorious history of economic theory actually came to a dead end.

However, the development of computer technology brought about many findings in complicated phenomena, and chaos is included as one of them. This technological advancement also made it possible to conduct simulations, which has enabled to conduct realistic economic analysis. That is to say, agent-based simulations (hereafter ABS) appeared. There exist a wide variety of ABS types. The U-Mart system supports simultaneous participation of computer-programmed machine agents and human agents. This flexibility in participants significantly characterizes the U-Mart system as an ABS. This book describes the significant meaning of the U-Mart system and the system components that were built, along with a comprehensive report of the findings obtained through the U-Mart system.

Markets continually evolve and develop new products. When comparing those goods that appeared in paintings drawn 200 years ago and the goods we currently handle in our daily life, we clearly notice that there is a world of difference between both of them. New products are being born not only in product markets, but also in financial markets. In addition to the product kinds, transaction methods have also changed. Comparison of the additional values produced between product markets and financial markets gives us the fact that the additional values produced in financial markets have increased by about three times the values produced in product market in a period of only 30 years after 1980. The recent financial crises clearly show that events happening in financial markets have had disastrous impact on product markets. Amid such drastically changing market conditions, first of all, we must understand what is actually happening in financial markets. As for the trading conducted in a modern stock exchange, however, transaction information is exchanged about 1000 times per second, while preprogrammed computers participate in trading as traders. For us, the detail mechanism of a market and what happens in a millisecond where financial transactions are conducted have been shrouded in darkness. In such an era, ABS is strongly required not only to offer breakthrough for economic theory facing a dead end, but also to serve as a tool to understand a market that continues to evolve and become more and more complicated. The U-Mart Project will surely play a part of this role.

Let me give a simple description on the content of how this book is composed. Part I contains four comprehensive papers based mainly on the U-Mart system.

Chapter 1 is authored by Professor Yoshinori Shiozawa, the mother of the U-Mart Project. This chapter describes how ABS-based studies can be positioned in the history of economics. Readers can understand the meaning of "the third mode of scientific research" which is also found in the title of this book. With the description of the dead end in which economics after the 1970s fell off, this chapter gives basic direction and methods for economics in order to break through this blind alley situation. It is suitable to start this book as the first chapter written based not on the mere academic history of economics, but on historical backgrounds of theoretical issues that economics has to overcome. We would like not only for younger researchers studying economics, but also those scientific researchers engaging in studies of ABS to read this book.

Chapter 2 is authored by another mother of the U-Mart Project, Professor Hajime Kita. In this chapter the author gives us an overview of social simulations including ABS. This chapter gives explanations regarding the advantages and limitations of each model for modeling in an easy-to-understand fashion. This chapter is also for researchers that are unfamiliar with this particular field. The engineering-related ABS model might present an unfamiliar impression for researchers of economics. However, reading this chapter will help such researchers understand that ABS is actually applicable to economic phenomena.

Chapter 3 gives the description of the U-Mart system written by Professor Isao Ono and Professor Hiroshi Sato who have engaged in the development of the U-Mart system from the beginning of this project. This chapter describes the fundamental buildings of the U-Mart system, individual trading agent, differences from other artificial markets, and the unique features of the U-Mart system. Use of the U-Mart system requires a certain amount of knowledge with regard to the system specifications. This chapter not only contains this required knowledge, but also reports on the U-Mart system including its fundamental design policies. We also believe this will surely be of interest to researchers of engineering.

Chapter 4 gives a future perspective on U-Mart and related ABS written by Professor Takao Terano who is also one of the founders of U-Mart project. The author states that U-Mart Project is very small; however, it has the unique characteristics of a big project, and we should switch the principles of conventional artificial intelligence approach into ones to ravel out intelligence as a group through agent-based modeling. The requirements for ABS toward a new research scheme are summarized; in addition, necessity of the mezzo-scopic structure between the microscope and the macroscopic level for social and economic processes is introduced. In spite of the short chapter, it includes stimulating contents for many readers.

Part II introduces applications of artificial markets, containing four papers. The study of artificial markets based on ABS as the third mode of science has only a short history. The current state of the research is a mere starting point. However, Part II suggests specific examples providing a wide variety of possibilities that could be used in the future.

Chapter 5 is authored by Professor Naoki Mori and reports on machines that can obtain the best strategy. Market participants including machine agents try to enter the market trading using certain trading strategies. At that time, they plan such strategies based on fundamental economic information consisting of general economic activities and based on technical trading information, such as prices and board information. It is quite difficult for humans to learn this technical information on a real-time basis especially in security exchange markets where ultrahigh-speed trading is conducted. From this point of view, machines become more advantageous when compared to humans. Professor Mori developed a trading machine that can automatically obtain the best trading strategy that is equipped with a genetic programming for evolutionary calculation. Using this machine, he conducted several experiments.

Chapter 6 is a research report regarding market makers, authored by Professor Yoshihiro Nakajima. To start with, when certain traders place buy or sell orders, the market does not make any sense if there are no traders that can or will respond to the order placed. For this reason, market traders, who are called market makers (in a sense that they actually create a market), that respond to buy and sell orders placed by customers (market traders) are essential for security exchange markets. However, can the market makers that are able to secure market liquidity as well as avoid suffering loss really exist? If such market makers do exist, what kind of strategies do they use? Professor Nakajima created some agents with alternative strategies while associating these strategies with market spread and the positions of market makers, and conducted experiments under multiple market environments and conditions.

Chapter 7 is a report authored by Professor Hiroyuki Matsui and his PhD student Ryo Ohyama regarding the adequateness of the concept, resilience. In theoretical analysis of security exchange markets in general, a wide variety of concepts are used, such as liquidity, depth, and spread. When trying to confirm the results of market theoretical analysis based on these concepts, we notice that it is an unexpectedly difficult task to accomplish considering the vague definition of each concept. Focusing on the concept of resilience, which is one of the fundamental concepts of market analysis, they confirmed the definition of resilience and provided empirical proof by conducting artificial market experiments based on the representative preceding models. This is a study that could only be done because of the artificial market experiments that have become available to conduct.

Chapter 8, authored by Professor Kazuhisa Taniguchi, attempts to understand markets through observation of artificial market experiments with human agents as the subject. Humans have spread all over the world since they were able to obtain certain benefits through market transactions. Where can we find the universality of market establishment? Throughout human history, money appeared and exchange evolved into buying and selling. But why are completely opposite activities, buying and selling, executed? This chapter considers the reasons based on the point of view of the Exchange Principles. Moreover, this chapter examines the causes why arbitrage behavior can be seen in a market, where buying and selling is continuously conducted based on an evolutionary-economic approach from the point of view of human agnosticism.

This book targets economic researchers and engineering researchers. Graduate school students trying to advance into their individual study domains are also included. Researchers of economics might feel overwhelmed by the artificial market study based on ABS. After reading through this book, however, they will be able to find out that it is surprisingly easy to get into this field of study. In addition, graduate school students that are going to learn economics need to study the history of economics in order to position their own studies in the domain of economics. This book also helps them when they explore positions of their studies in this particular domain of economics. At the same time, reading this book enables them to set sail for large unexplored academic domains where a vast amount of academic achievements can be expected because of the potential for academic exploration based on ABS.

By reading this book, engineering researchers can understand the meaning of the birth of this project when learning the historical background of economics. They must be able to understand the significance of ABS in social science from deep inside. Similarly to graduate school students of economics, the graduate school students of engineering who read this book will surely realize a large domain spreads out in front of their eyes where a vast amount of academic achievements can be expected.

Since the beginning of the development stage, the U-Mart Project that integrates the social science and engineering has been supported by many people including researchers that participated in the project from diverse academic fields. This project is a study based on the actual security exchange markets. Therefore, we had not only academic researchers, but also business practitioners from the actual related industries and stock exchange markets in the U-Mart workshop. The students and graduate school students of universities where the authors of this book belong to were the individuals that mainly participated in our experiments, while a cumulative total of hundreds of individual agents participated in experiments as traders. It is difficult to enumerate all the names of the project participants, though we would like to express our gratitude to all individuals that engaged in this U-Mart Project.

Osaka, Japan Kazuhisa Taniguchi
November 2015

Acknowledgements

This book is the result of the collaboration of social scientists and engineers. In our view, the scope reflects the breadth of the research. Accordingly, the projects have been supported by a great many people, including not only academic researchers, but also business practitioners and university (graduate) students. It is difficult to enumerate all of the participants in this project. We wish to express our gratitude to all who have supported this research. Of the people whose names we remember, those mentioned here are only a few. We would like to ask for the understanding of all those unmentioned.

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Contents

Part I U-Mart System: The First Test Bed of the Third Mode of Science

1 A Guided Tour of the Backside of Agent-Based Simulation 3
Yoshinori Shiozawa

2 Research on ABS and Artificial Market 51
Hajime Kita

3 Building Artificial Markets for Evaluating Market Institutions and Trading Strategies 59
Isao Ono and Hiroshi Sato

4 A Perspective on the Future of the Smallest Big Project in the World 87
Takao Terano

Part II Applications of Artificial Markets

5 Evolution of Day Trade Agent Strategy by Means of Genetic Programming with Machine Learning 97
Naoki Mori

6 How to Estimate Market Maker Models in an Artificial Market 117
Yoshihiro Nakajima

7 The Effect of Resilience in Optimal Execution with Artificial-Market Approach 137
Hiroyuki Matsui and Ryo Ohyama

8 Observation of Trading Process, Exchange, and Market 171
Kazuhisa Taniguchi

Index 195

Part I
U-Mart System: The First Test Bed of the Third Mode of Science

Chapter 1
A Guided Tour of the Backside of Agent-Based Simulation

Yoshinori Shiozawa

Abstract Agent-based simulation brings a host of possibilities for the future of economics. It provides a new analytical tool for both economics and mathematics. For a century and a half, mathematics has been the major tool of theoretical analysis in economics. It has provided economics with logic and precision, but economics is now suffering; economics in the twentieth century made this clear. Theorists know that the theoretical framework of economics is not sound and its foundations are fragile. Many have tried to sidestep this theoretical quagmire and failed. Limits of mathematical analysis force theorists to adopt mathematically tractable formulations, though they know these formulations contradict reality. This demonstrates how economics lacks a tool of analysis that is well suited to analyzing the economy's complexity. Agent-based simulation has the potential to save economics from this dead end and can contribute to reconstructing economics from its very foundations. Achieving this mission requires those engaging in agent-based simulation to have an in-depth understanding of economics based on its critical examinations. This guided tour leads readers around the backside of economics, tells what is wrong with economics and what is needed for its reconstruction, and provides hints for a new direction open to incorporation of agent-based simulation.

1.1 Introduction

This chapter is not intended to be an original report of recent results and development of agent-based simulations (ABSs) and agent-based computational economics (ABCE) in particular. The chapter instead intends to introduce beginners in the field the basic facts about why ABCE is required now and what types of tasks and possibilities it enables for the development of economics. It also intends to explain to economists, but not specialists in the field, how ABCE relates to old theoretical problems that arose many years ago.

ABCE and ABS in general place a heavy burden on beginner economists to acquire computer programming abilities and skills. Beginners in ABCE generally do

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not have enough time to make historical surveys of the development of economics for the last half century. Many specialists have begun to use ABCE without engaging in any deep reflection on why ABCE and ABS in general are required as a new method in economics and how they are related to old methods of economics. It is rather rare to address this topic as a main issue associated with ABCE. However, knowledge of the history of economics is important in situating ABCE research projects correctly in a wider perspective. This chapter provides a brief overview of the history of modern economics, mainly from the 1970s to the present, focusing on problems left unsolvable within the framework of standard economics.

This paper will also be interesting for economists who are not specialists in ABCE. These economists sometimes show keen interest in ABCE. They have come to know several models of various topics and believe that computer simulation may illustrate certain aspects of economic behavior, but they do not usually imagine that ABCE provides a new tool in economics, which is comparable to mathematics, and that this new tool may mark a breakthrough and open a way to a new scope in economics.

Computer simulation is a new tool in economics. This does not mean that simulation has totally replaced two older methods: the literal or conceptual method and the mathematical method. All three methods are complementary. The same researchers may use all three methods in appropriate fields and for appropriate tasks.[1] However, ABCE is not a simple method added to the standard economics. In fact, it has the task of remedying a malaise that has prevailed in economics for a long time.

The ill of modern economics lies in the fact that it attacks only problems that one can formalize and analyze by mathematical methods. The typical framework is that of equilibrium and maximization. This framework has dominated mathematical analysis. A monumental achievement in this direction was the work of Arrow and Debreu [5] on the existence of general competitive equilibrium. As a framework of the market economy, the general equilibrium theory (GE theory) contained serious defects, but it became an ideal model for mathematical economics. The term "theoretical" became a synonym for "mathematical," and the term "mathematical economics" was replaced by the term "theoretical economics." The main tendency of "theoretical economics" was to follow the track of the GE theory. People searched for problems that they could formulate and solve mathematically. They did not examine the validity of formulations. They could formulate and solve the problem. They were satisfied interpreting this fact as a demonstration that the formulation was right.

The 1950s was a time of euphoria for mathematical economics and for GE theory. People believed in the possibility of economics. They imagined that mathematical economics plus the use of computers (meaning econometrics) might turn economics into an exact science like physics. This general mood continued almost through the 1960s. At the same time, some economists began to reconsider the possibility

[1]Gray [27] states that data-centered science can count as the fourth paradigm in methods of scientific research. I will discuss this matter in Sect. 1.4.

of mathematical economics and acknowledged that mathematical methods have a fundamental weakness in treating economic phenomena. In the mid-1960s, there was a continuous debate now called the Cambridge capital controversy [9, 33]. It revealed that a serious logical problem lies at the root of the simple expression of the production function. Economists became more reflective and critical on the state of economics. Maurice Dobb [20] called the 1960s "a decade of high criticism."

Many criticisms of the basis of economics appeared in the first half of the 1970s. Many economists, including leaders of mainstream economics, posed a question on the very basis of economic science and the usefulness of the mathematical method.[2] Many asked what was wrong with economics and called for a paradigm change. In 1973, Frank Hahn [29], one of the leaders of general equilibrium analysis, described the mood of the time as "the winter of our discontent."

Those in young generations may have difficulty imagining the atmosphere of that time. It is helpful to remember the shock and disarray among economists that occurred just after the bankruptcy of Lehman Brothers. Paul Krugman, the Nobel Laureate in Economics for 2008 and famous *New York Times* columnist, was famously cited as stating that "most work in macroeconomics in the past 30 years has been useless at best and harmful at worst."[3] The expressions used in the 1970s were not as strong and catchy as Krugman's statement, but the reflections on the state of economics were more profound and deeply considered. Many economists questioned the very framework of economics based on the concepts of equilibrium and maximization.

In the mid-1970s, the atmosphere changed. The Vietnam War (or the American War in Vietnam) ended. Protest songs changed to focus on self-confinement. A shift of interest occurred in the theory fields, too. Rational expectation became a fad. Game theory hailed a second boom. The winter of our discontent ended suddenly. Enquiries into the theoretical framework were discarded. In the mid-1990s, Arrow [6, p.451] still viewed GE theory as "the only coherent account of the entire economy."

The economists who were critical of the main tendency of "theoretical economics" reacted rather irrationally. Many of them, from Marxists to ontological realists, blamed mathematics as the main vehicle that led economics to the present-day deplorable state. They also confused theory and mathematics. What we should blame is not mathematics but the theoretical framework. Mathematics is a tool. It is a powerful tool, but not a unique one. The stagnation of economics arose partly because of the underdevelopment of new tools suitable for analyzing complex economies. ABCE is an effort to develop new analytical tools.

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[2]Heller [36] provided a strong testimony. Although he was against it, he recognized the existence of "our current fashion of telling the world what's wrong with economics." He cited names such as J.K. Galbraith, W. Leontief, F. Hahn, G.D.N. Worswick, E.H. Phelps Brown, J.H. Blackman, S. Maizel, B. Bergman, G. Myrdal, R. Heilbroner, and P. Sweezy among those who had publicly deplored the dismal state of our science. See the Introduction to Sect. 1.2 for a rough summary.

[3]Cited in an article in *The Economist* (June 11 2009). The original statement was expressed a bit differently [46, 14th minute in the video].

ABCE provides a new analytical tool, but it is not the final target. It has a different mission: to reconstruct economics from the very foundations of the discipline. The reconstruction of economics requires the development of a new and powerful method, perhaps as powerful as mathematics, that is suitable for the analysis of the wider situation of the real economy.

It is important for those who work with ABCE to understand this mission. A strong magnetic field exists. It attracts every effort to the neoclassical traditions. There is no tabula rasa in economics (or in any other science). If researchers are not aware of it, they cannot escape this magnetic field. It is necessary to situate their research in the long history of theoretical polemics around GE theory. They should also know what has been left unsolved and how deformed most of the questions were by the "theoretical necessity of the theory."

Therefore, my discussion goes back to the first half of the 1970s, when reflections erupted among many eminent and leading economists. I even go back further, to when discussions paved the way for the eruption of the 1970s. I also summarize how these criticisms of the 1970s were accepted and what types of attempts were made. Some of this history is famous among heterodox economists. Young economists rarely have time to learn this sinuous history, and ABCE practitioners who started in information engineering have practically no chance to learn these questions. As a result, the present paper will also be useful for all types of ABCE specialists.

This chapter is organized as follows. The tour of the past is composed of two parts. Section 1.2 starts with an introduction that shows how a critical mood permeated economics in the 1970s. The subsequent subsections examine three major controversies that led to the critical mood of the first half of the 1970s. All three controversies have a common point. The theoretical problems raised were unsolvable under the general equilibrium framework of economics. Section 1.3 examines the later developments of the GE framework after the 1970s and various trials to extend and rescue the framework. My conclusion is simple. The GE framework is suffering from a scientific crisis and needs a paradigm change. A comprehensive paradigm shift requires a new research tool. Agent-based simulation is a promising candidate as a new tool. Section 1.4 argues what kind of significance and possibilities it has for the future of economics.

1.2 General Crisis of Economics: State of Economics During and Before the First Half of the 1970s

Let me start my discussion with the state of economics in the 1970s. I started economics in the 1970s, but it is not the reason that I chose this period as the starting point. For most young economists, the 1970s are the old days that they know only through the history of economics. Many of those economists may not know and even cannot imagine the atmosphere of the time. Mainstream economics often ignores this period. When it comments on this period, there is a tendency to underrate the meaning of the discussions presented during the period. The typical attitude is something like this: people presented many problems and difficulties in the 1960s and 1970s, but economics has overcome them and developed a great deal since that time.

The fact is that some problems remained unsolved. The only difference between the first and second halves of the 1970s is that people ceased to question those difficult problems, which may require the reconstruction or even destruction of existing frameworks. After 1975, a strong tendency appeared among young economists who believed that the methodology debate was fruitless and it was wise to distance themselves from it. However, understanding the criticism presented in the first half of the 1970s is crucial when one questions the fundamental problems of economics and aims to achieve a paradigm change.

The first half of the 1970s was indeed a key period when the two possibilities were open. Many eminent economists talked about the crisis of economics. The list of interventions is long. It was common for presidential addresses to take a severely critical tone. Examples of interventions included Leontief [49], Phelps Brown [61], Kaldor [40], Worwick [94], and others.[4] Other important interventions were Kornai [44], J. Robinson [67, 68] and Hicks [38]. These eminent economists expressed many points of contention and asked to change the general direction of economic thinking. Leontief warned against relying too much upon governmental statistics. Kornai recommended an anti-equilibrium research program. Kaldor argued that the presence of increasing returns to scale made equilibrium economics irrelevant to real economic dynamics. Robinson asked to take into consideration the role of time. Alternatives were almost obvious. The choice was either to keep the equilibrium framework or to abandon it in favor of constructing a new framework.

In terms of philosophy of science, the question was this: Is economics now undergoing a scientific crisis that requires a paradigm change? Or is it in a state that can be remedied by modifications and amendments to the present framework? These are difficult questions to answer. The whole of one's research life may depend on how one answers them. To search for answers to these deep questions, it is necessary to examine the logic of economics, how some of the debates took place, and how they proceeded and ended.

1.2.1 Capital Theory Controversies

Let us start with the famous Cambridge capital controversy [9, 33]. The controversy concerned how to quantify capital. Cambridge economists in England argued that capital is only measurable when distribution (e.g., the rate of profit) is determined. This point became a strong base of criticism against the neoclassical economics of the 1960s.

The 1950s were a hopeful time for theoretical economics. In 1954, Arrow and Debreu [5] provided a strict mathematical proof on the existence of compet-

[4] See Footnote 2 for many other names.

itive equilibrium for a very wide class of economies. Many other mathematical economists reported similar results with slightly different formulations and assumptions. As Alexei Leijonhufvud [48] caricatured in his "Life Among the Econ," people placed mathematical economics at the top of the economic sciences and supposed that it must reign as queen. The 1950s were also a time when computers became available for economic studies, and Laurence Klein succeeded in building a concrete econometric model. Many people believed that mathematical economics plus computers would open a new golden age in economics just like physics at the time of Isaac Newton and afterward. In the 1960s, a new trend emerged. Hope changed to doubt and disappointment.

Some of the doubts were theoretical. The most famous debate of the time was the controversy on capital theory, which took the form of a duel between Cambridge in England and Cambridge, Massachusetts, in the United States. In the standard formulation of the time, the productivity of capital, the marginal increase in products by the increase of one unit of capital, determined the profit rate. This was the very foundation of the neoclassical distribution theory. The opposite side of this assertion was the marginal theory of wage determination. The theory dictates that the productivity of labor determines the wage rate. The exhaustion theorem, based on a production function, reinforced these propositions. A production function represents a set of possible combinations of inputs and outputs that can appear in production. A production function that satisfies a standard set of assumptions is customarily called the Solow-Swan type. The assumptions include the following conditions: (1) The production function is in fact a function and defined at all nonnegative points. The first half of the condition means that the products or outputs of production are determined once the inputs of the production are given.[5] (2) The production function is smooth in the sense that it is continuously differentiable along any variables. (3) The production function is homogeneous of degree 1. This means that the production function f satisfies the equation $f(tx, ty, \ldots, tz) = tf(x, y, \ldots, z)$ for all nonnegative t.

The exhaustion theorem holds for all Solow-Swan-type production functions. If a production function f is continuously differentiable and homogeneous of degree 1, then the adding up theorem

$$f(K, L) = rK + wL$$

holds, where

$$r = \partial f / \partial K \quad \text{and} \quad w = \partial f / \partial L.$$

The proof of the theorem is simple. Using the differentiability of the function, one can easily obtain the formula by the Leibnitz theorem on the derivation of a composite function. The adding up theorem indicates that all products can be

[5] This assumption is not often mentioned but, in my opinion, it is the most critical one.

distributed among contributors to the production as either dividends or wages. No profit remains for the firm. This is what the exhaustion theorem claims and the basis of the neoclassical theory of distribution.

In this formulation, capital is a mass that is measurable as a quantity before prices are determined. Let us call this conception "the physical mass theory." Samuelson called it the "Clark-like concept of aggregate *capital*."[6] The story began when a student of Cambridge University named Ruth Cohen questioned how techniques could be arranged in an increasing order of capital/labor ratios when reswitching was possible. Reswitching is a phenomenon in which a production process that becomes unprofitable when one increases the profit rate can become again profitable when one increases the profit rates further. Piero Sraffa [89] gave an example of reswitching in his book.

Joan Robinson of Cambridge University shone a spotlight on this phenomenon. If reswitching occurs, the physical mass theory of capital is not tenable. Robinson claimed that the standard theory of distribution is constructed on a flawed base. Samuelson and Levhari of MIT (in Cambridge, Massachusetts) tried to defend the standard formulation by claiming that the reswitching phenomenon is an exceptional case that can be safely excluded from normal cases. They formulated a "non-switching" theorem for a case of non-decomposable production coefficient matrix and presented a proof of the theorem [52]. As it was soon determined, the theorem was false (see Samuelson et al. [72]).[7] In his "A Summing Up," P.A. Samuelson admitted that "[reswitching] shows that the simple tale told by Jevons, Bohm-Bawerk, Wicksell, and other neoclassical writers … cannot be universally valid."

The symposium in 1966 was a showdown. The Cambridge, England, group seemed to win the debate. A few years after the symposium, people refrained from apparent use of production functions (with a single capital quantity as their argument). However, some peculiar things happened, and the 1980s saw a revival of the Solow-Swan-type production function, as if the Cambridge capital controversy had never occurred.

The resurgence occurred in two areas: one was the real business cycle theory and the other was the endogenous growth theory. Both of them became very influential among mainstream economists. The real business cycle (RBC) theory adopted as its main tool the dynamic stochastic general equilibrium (DSGE) theory. DSGE was an innovation in the sense that it includes expectation and stochastic (i.e., probabilistic) external shocks. Yet the mainframe of DSGE relied on a Solow-Swan-type production function. The endogenous growth theory succeeded in modeling the effect of common knowledge production. It also relied on a Solow-Swan-type production function. Its innovation lay in the introduction of knowledge as an argument of the production function. In this peculiar situation, as Cohen

[6] In the original text, the italic "capital" is in quotation marks.

[7] The Symposium included five papers and featured contributions from L. Pasinetti, D. Levhari, P.A. Samuelson, M. Morishima, M. Bruno, E. Burmeister, E. Sheshinski, and P. Garegnani. P.A. Samuelson summed it up.

and Harcourt [15] put it, "contributors usually wrote as if the controversies had never occurred." At least in North American mainstream economics, the capital controversy fell completely into oblivion.[8]

How could this situation take place? One may find a possible answer in Samuelson's 1962 paper [71], written in the first stage of the controversy. Samuelson dedicated it at the time of Joan Robinson's visit to MIT. He proposed the notion of a surrogate production function in this paper. This concept was once rejected by Samuelson himself, and it is said that he resumed his former position later. The surrogate production function, however, is not our topic. At the beginning of the paper, Samuelson compared two lines of research. One is a rigorously constructed theory that does not use any "Clark-like concept of aggregate capital." The argument K in a production function is nothing other than the capital in the physical mass theory. Another line of research is analysis based on "certain simplified models involving only a few factors of production." The rigorous theory "leans heavily on the tools of modern linear and more general programming." Samuelson proposed calling it "neo-neoclassical" analysis. In contrast, more "simple models or parables do," he argued, "have considerable heuristic value in giving insights into the fundamentals of interest theory in all its complexities."

Mainstream economists seem to have adopted Samuelson's double-tracked research program. The capital controversy revealed that there is a technical conceptual problem in the concept of capital. This anomaly occurs in the special case of combinations of production processes. While simple models may not reflect such a detail, they give us insights on the difficult problem. Their heuristic value is tremendous. Burmeister [13] boasted of this. In fact, he asserted that RBC theory, with its DSGE model,[9] and endogenous growth theory are evidence of the fecundity of a Solow-Swan-type production function. He blamed its critics, stating that they had been unable to make any fundamental progress since the capital controversy. In his assessment, "mainstream economics goes on as if the controversy had never occurred. Macroeconomics textbooks discuss 'capital' as if it were a well-defined concept, which is not except in a very special one-capital-good world (or under other unrealistically restrictive conditions). The problems of heterogeneous capital goods have also been ignored in the 'rational expectations revolution' and in virtually all econometric work" [13, p.312].

Burmeister's assessment is correct. It reveals well the mood of mainstream economists in the 1990s and the 2000s just before the bankruptcy of Lehman Brothers. This mood was spreading all over the world. Olivier Blanchard [11] stated twice in his paper that "[t]he state of macro is good." Unfortunately for Blanchard, the paper was written before the Lehman collapse and published after the crash.

Of course, after the Lehman collapse, the atmosphere changed radically. Many economists and supporters of economics such as George Soros started to rethink

[8] A topic not addressed here is the aggregation problem. See [23].

[9] Two originators of RBC theory, Prescott and Kydland, were awarded the Nobel Memorial Prize in Economic Sciences for 2004.

economics.[10] A student movement, the Rethinking Economics network, was started in 2012 in Tübingen, Germany, and has spread worldwide. The mission of the organization is to "diversify, demystify, and reinvigorate economics." The students who launched the network acknowledge that mainstream economics has something wrong with it and claim plurality in economics education. It became evident that the abundance of papers does not indicate true productivity in economics. We should develop a new economics, and we need a new research apparatus. ABCE can serve as such an apparatus. This is the main message of this chapter.

Blanchard [11] emphasized the "convergence in vision" (Section 2) and in methodology (Section 4) in recent macroeconomics. The term "New Consensus Macroeconomics" frequently appears in newspapers and journals. This does not mean, however, that macroeconomics comes close to the truth. It only means that economists' visual field became narrower. Students are revolting against this contraction of vision.

1.2.2 Marginal Cost Controversy

The capital theory controversy concerned macroeconomics. Although it is not as famous as the capital theory controversy, another controversy erupted just after World War II in the United States. It concerned microeconomics. The controversy questioned the shape of cost functions and the relevance of marginal analysis. It is now called the marginalist controversy [35].[11]

R.A. Lester [50] started the controversy in 1946. Lester was a labor economist, and minimum wage legislation was his concern. He employed the question paper method. One of his questions was this: What factors have generally been the most important in determining the volume of employment in firms during peacetime? Out of 56 usable replies, 28 (50 %) rated market demand as the most important factor (with 100 % weight) in determining the volume of employment. For the other 28 firms, the average weight for market demand was 65 %. Only 13 replies (23 %) included wages among the factors considered.

The equality of a marginal product and price were the very basis of the neoclassical theory of the firm, and it was this condition that determined the volumes of production and employment. Other questions revealed unfavorable facts for marginal analysis. Many firms did not calculate the marginal cost at all. The average cost function was not U shaped as the standard theory usually assumed.

[10]Soros started the Institute for New Economic Thinking just after the Lehman collapse. Many eminent economists are collaborating on the institute.

[11]The "marginal cost controversy" was different. It was an issue mainly in the United Kingdom. The concern was the pricing of the products of a public firm whose average cost is decreasing. The study started before World War II and took the form of a controversy after the war. One of the main proponents was R.H. Coase. See [28, 57] for a German Controversy.

It was reasonable to suppose that the marginal cost either remained constant for a wide range of production volumes or decreased until the capacity limit was reached. Combining personal observations and informal communications, Lester argued that standard marginal analysis had little relevance in determining the volume of production. He also questioned whether the marginal productivity of labor determines wages. This was a scandal among neoclassical economists.

F. Machlup [55] first responded to Lester's attack. He wrote a long paper that was published in the same volume as Lester's (but in a different issue). He was an acting editor of the *American Economic Review (AER)* and had a chance to read the papers submitted to *AER*. Machlup argued that the marginal theory is the foundational principle of economics and that criticism of this basic principle requires a thorough understanding of economic theory. He claimed that economics (in a narrow sense) is a science that explains human conduct with reference to the principles of maximizing satisfaction or profit. In view of this definition, he argued, "any deviations from the marginal principle would be extra-economic." He also argued that it is inappropriate to challenge the marginal theory of value using the question sheet method. Machlup's reaction to Lester reminds me of two books that are closely related to Austrian economics. The first is L. Robbins [65], and the second is L. von Mises [59]. Robbins [65, p.16] gave a famous definition of economics as follows: "Economics is the science which studies human behaviour as a relationship between ends and scarce means which have alternative uses." This definition is frequently cited even today. Von Mises preferred to use the term "praxeology" instead of economics. He believed that praxeology is a theoretical and systematic science and claimed that "[i]ts statements and propositions are not derived from experience. They are, like those of logic and mathematics, a priori" [59, 1, II. 8]. Machlup held the same apriorism as Robbins and von Mises. We understand well why Machlup reacted vehemently to the empirical research work raising doubt about marginal analysis. The two antagonists had very different views of what economic science is and ought to be.

In the following year, *AER* published Lester's answer to Machlup's criticisms, Machlup's rejoinder to the answer, and a critical comment by G.L. Stigler [90]. Hansen's paper [32] was sympathetic to Lester, although the main subject matter was Keynes' theory of employment. At the end of 1947, Eiteman's short paper [21] appeared in *AER*, and in 1948, R. Gordon's paper [26], which was also critical of the standard theory, followed. Eiteman's intervention raised a new series of debates about the pros and cons of the marginal theory. Articles from R.B. Bishop [10] and W.W. Haines [30] also appeared in *AER*. In December of that year, H. Apel [4] entered the debate from the standpoint of a defender of the traditional theory. In the following year, Lester [51] and Haines [31] exchanged criticisms.

Three years later, Eiteman and Guthrie [22] published the results of a more complete survey. To respond to the criticisms made by many defenders of marginal theory, they conducted a carefully organized questionnaire survey and gathered a large number of responses. They posed questions after they had explained the research intentions and the meanings of questions to avoid the criticism that the respondents did not understand the meaning of the questions well. Eiteman and

Guthrie briefly and clearly explained the meaning of average cost. They showed a set of curves in figures and asked which shapes the functions of their firms obeyed.

The report described the results in detail. For 1,082 products on which they obtained answers, only 52 answers corresponded to the five figures that reflected the neoclassical theory of the firm. The sixth figure, in which the average cost decreased until it reached a point very close to the lowest cost point and then increased a bit afterward, accounted for 381 products. The seventh figure, in which the average cost decreased until it reached the capacity limit, accounted for 636 % or 59 % of the answers. The case of the sixth figure was rather favorable to anti-marginalist claims, but there remained a possibility of objections from marginalists. However, the number of answers for the seventh figure numbered close to 6 out of 10. This showed that a majority of the firms were not obeying the rule advanced by the marginalists.

It is easy to show this reasoning by a simple calculation. The marginalist principle assumes that, given the market price, firms choose the production volume (or supply volume) at the point where they can maximize their profit. A simple calculation shows that the marginal cost should be equal to the price or $m(x) = p$ at the point where the profit is maximal. Here, the function $m(x)$ is defined as the marginal cost at the production volume x. The result that Eiteman and Guthrie obtained implies that it is impossible for this formula to be satisfied.

This logical relation easily turns out as follows. Let the function $f(x)$ be the total cost at the production volume x; the average cost function $a(x)$ is expressed as $f(x)/x$, and the marginal cost function m is given by $m(x) = f'(x)$. The following equation obtains

$$a'(x) = \{f(x)/x\}' = \{m(x)x - f(x)\}/x^2. \tag{1.1}$$

If $m(x) = p$, then each member of the above equations is equal to $\{p \cdot x - f(x)\}/x^2$, which is the profit divided by x^2. This means that if firms are making a profit in the ordinary state of operations, then the left member of equation (1.1) must be positive. If the marginalist theory is right, then the average cost must rise. What Lester found and Eiteman and Guthrie confirmed was that the average cost decreased at the normal level of production. Lester was right when he concluded that the marginalist theory of the firm contains a serious flaw.

In the face of this uncomfortable fact, two economists who believed in marginalism rose to defend the theory: A.A. Alchian [3] and Milton Friedman [24]. Alchian's paper appeared not in *AER* but in the *Journal of Political Economy*, and it was published prior to Eiteman and Guthrie's final report. Alchian partly accepted Lester's contentions and other anti-marginalists' arguments that factory directors did not even know the exact value of the marginal cost and did not much care to behave according to the marginalist rule. From this retreated position, Alchian developed an astute argument that compromised the new findings and the marginalist principle. He admitted that some of the firms may not be producing at the volume where they achieve maximal profit. However, he went on to state that, in the long term, firms that are not maximizing their profit will be defeated by competition and ousted from the market. As the result of this competition for survival, firms with maximizing behavior will prevail.

Alchian's paper [3] is often cited as the first to introduce the logic of evolution in the economic analysis. Indeed, it is a seminal paper in evolutionary economics. However, we should also note that the simple argument borrowed from Alchian contains two false claims. First, it is not true that competition leads necessarily to maximal behavior even if it exists. It is possible that the evolutionary selection process remains at a suboptimal state for a long time. Second, the marginalist rule gives maximal profit only when a particular condition is satisfied. Indeed, the marginalist rule implicitly assumes that firms can sell as much as they want at the given market price. If this is true, the total sales equal to $p \cdot x$, where p is the market price and x is the volume of production, and equal to the quantity sold. Then, if f is the total cost function, the profit is given by the following expression: $p \cdot x - f(x)$. If the function f is differentiable, the maximal is attained only at the point where

$$p = f'(x) = m(x). \tag{1.2}$$

If this equation is satisfied at a point and the marginal cost is increasing at that point, the maximal profit is obtained when firms operate at volume x. This is what the marginal principle indicates. However, this argument includes a crucial misconception. Firms normally face limits in demand. The marginal cost remains constant for a wide range of production volumes. What happens when they cannot sell as much as they want? In that case, $p \cdot x$ would not be the actual sales. Formula (1.2) does not give the maximal profit point. The marginalist rule gives the maximum profit in a particular situation, but that particular situation is extremely rare, and wise firms adopt rules other than the marginalist rule. Alchian was wrong in forgetting this crucial point.

The second person who rose to defend the marginalist principle was Milton Friedman [24]. Citing Popper's theory on the impossibility of the confirmation of scientific statements, Friedman went a step further. Friedman argued that propositions have positive meanings when they are falsifiable. A statement is scientifically valuable when the statement seems unlikely to be true at the first examination. Friedman argued as follows. Trees develop branches and leaves as if they are maximizing sunlight reception. It is unlikely that the trees plan to achieve that. Likewise, many economic assumptions are not realistic at all. However, if one supposes that people act as if they are maximizing their profits and utilities, one can obtain a good prediction of their actions. This is the reason that the maximization principle works, and this principle is more valuable when it seems more unrealistic.

Friedman totally ignores the fact that science is a system of propositions and that the propositions of this system should be logically consistent with each other. Many economic assumptions are observable. One can determine whether those assumptions are true. The proposition included in an assumption is a predictive rule with the same title as what Friedman refers to as prediction. If assumptions turn out to be false, these assumptions should be replaced by new assumptions that are consistent both with observations and with the propositions of the system.

Friedman denies one of the most important factors that led modern sciences to their success: the consistency and coherence of a science or at least a part of a science. Modern science developed on the basis of experiments. Logical consistency helped very much in developing it. Friedman denied this important maxim of modern sciences. It is true that sciences faced a phase of inconsistency in various observations and theories. Science developed in trying to regain consistency, not simply in abandoning it.

Friedman's arguments were extremely dogmatic and apologetic. Popper argued that science develops when someone finds a new phenomenon that the old system of science cannot explain and when the discoverer or some other person finds a new theory (i.e., a new system of concepts and propositions) that is consistent with the new discovery. Friedman pretended to rely on Popper and betrayed him in content. It is quite strange that Friedman named his methodology "positivist." It is more reasonable to abandon the old marginalist principle in favor of a new principle or principles that are consistent with the new observations. Alchian's idea is applicable at this level. Economic science evolves. The consistency of principles and observations is one of the motivating forces that drive economics to develop.[12]

There is a profound reason that marginalists could not adopt such a flexible attitude. A stronger motive drove them: the "theoretical necessity" of the theory (I use this phrase in a pejorative way). In other words, the framework they have chosen forces them to cling to the marginalism, though they face facts that contradict their analysis. This is the coupling of equilibrium and maximization. How it happens is explained in the next section. Two important concepts are defined in preparation. A firm is in increasing returns to scale when the average cost is decreasing, and it is in decreasing returns to scale when the average cost is increasing. Lester and Eiteman confirmed that most firms are operating in the increasing returns-to-scale regime, whereas the marginal theory of value supposes the decreasing returns-to-scale regime. These are two conflicting conceptions of the conditions of production, named laws of returns.

1.2.3 "Empty Boxes" Controversy and Sraffa's Analysis on Laws of Returns

There was a precursor to the marginalist controversy. As early as 1922, J.H. Clapham, the first professor of economic history at Cambridge, wrote a paper titled "Of Empty Economic Boxes"[14]. In the same year, A.C. Pigou, also a professor of economics at Cambridge, wrote a "Reply"[62] to Clapham. Two years later, D. Robertson published a paper titled "Empty Boxes"[66], and Pigou commented on

[12] A basic observation of evolutionary economics is that important categories of the economy, such as commodities, economic behavior, production techniques, and institutions, evolve. Economics itself evolves as part of our knowledge. See [78].

it [63]. Robertson described the debate between Clapham and Pigou "a battle of giants." This debate (and Robertson's intervention) is sometimes called the "empty boxes" controversy.

Clapham [14] criticized the concepts of increasing and decreasing returns as useless. One can classify industries into these two types of returns, but they are empty boxes with no empirical and theoretical basis. He also pointed out that a conceptual problem lay in the notion of increasing returns. Alfred Marshall, the real founder of the English neoclassical school, knew these concepts well and was aware of the problem. Increasing returns inside firms were contradictory to a competitive market. Marshall excluded the internal economy (the name given by Marshall to increasing returns in a firm) and confined it to the external economy. The external economy appears as an increase in returns for all firms in an industry when the total scale of production increases.

The fundamental idea of neoclassical economics is simple. It is based on the assumption that the best method of economic analysis is to investigate equilibrium. Marshall preferred to analyze partial equilibrium. Leon Walras formulated the concept of general equilibrium (GE). An economy is in GE by definition when the demand and supply of all commodities are equal and all subjects are maximizing their objectives (utility or profit). The basic method was to search for prices that satisfied these conditions. Marshall, who was a close observer of the economic reality, never believed that GE was a good description of reality, but he could not present a good and reasonable explanation that partial equilibrium analysis is much more realistic than the GE framework.

In both frameworks of equilibrium, general or partial, increasing to returns was a problem. In 1926, Piero Sraffa published an article titled "On Laws of Returns under Competitive Conditions"[88]. He knew both of the analytical schemes: general equilibrium and partial equilibrium. He did not mention any names of people who were involved in the empty boxes controversy. Whether he knew of it or not, the controversy prepared readers to examine Sraffa's new paper closely. Sraffa addressed mainly the Marshallian tradition, but the logic was applicable to the Walrasian framework.

Sraffa examined the logical structure of the equilibrium theory in a rather sinuous way. Sraffa showed first that laws of returns either decreasing or increasing have no firm grounds. The explanations given in Marshall's textbook are more motivated by the "theoretical necessity" of the theory than by the results of observations of actual firms. The law of decreasing returns was rarely observed in modern industry. The law of increasing returns was incompatible with the conditions of a competitive economy. As a conclusion, Sraffa suggested that firms were at a first approximation in constant returns.

This simple observation implies dire consequences for economics. As seen in the previous subsection, firms cannot determine their supply volume on the basis of the equation $p = m$, when the marginal cost remains almost constant. This denies the possibility of the very concept of supply function that is defined based on increasing marginal cost. Neoclassical economics is founded on the concepts of supply and demand functions. If one of the two collapses, the whole framework collapses.

Sraffa's conclusion was simple; he suggested a radical reformulation of economic analysis. He observed that the chief obstacle, when a firm wants to increase the volume of its production, does not lie in the internal conditions of production but "in the difficulty of selling the larger quantity of goods without reducing the price, or without having to face increased marketing expenses" [88, p.543]. Each firm, even one subjected to competitive conditions, faces its own demand, and this forms the chief obstacle that prevents it from increasing its production.

Sraffa proposed a true revolution in economic analysis, but it simply meant a return to the common sense of businesspeople.

First, he recommended changing the concept of competition. The neoclassical theory of competition supposed: (1) competing producers cannot affect market prices, and (2) competing producers are in circumstances of increasing costs. In these two points, Sraffa emphasized that "the theory of competition differs radically from the actual state of things" [88, p. 542]. Many, if not all, firms set their product prices, yet they are competing with each other fiercely. Most firms operate with constant or decreasing costs when considering overhead. The concept of competition was indeed radically different from actual competition.[13]

Second, as mentioned above, it was not the rise of the production cost that prevented firms from expanding their production. Without reducing prices or paying more marketing costs, they cannot expect to sell more than they actually do. Put another way, firms produce as much as the demand is expressed (or expected) for their products. Based on this observation, we may establish the principle that firms produce as much as demand requires.[14]

This was really a revolution. Before Sraffa pointed it out, all economists implicitly supposed that firms could sell their products as much as they wanted, at market price. The concept of the supply function depends on this assumption. The supply function of an industry is the sum of individual firms' supply functions. The supply function of a firm is, by definition, the volume it wants to offer to the market at a given system of prices. This concept implies that the firm has, for each price system, a supply volume that it is willing to sell but does not want to increase its offer beyond that volume. The marginalist rule (rule 3 in the previous subsection) is fulfilled only if (a) firms are producing in conditions of increasing costs and (b) firms can sell their products as much as they want. Sraffa rejected these two assumptions, observing closely what was happening in the market economy.

As Robertson [66] witnessed, many economists knew that a majority of firms are producing in the state of decreasing costs (or increasing returns in our terms). More precisely, unit cost is the sum of two parts: variable costs and overhead costs per

[13]There is a widespread misunderstanding that Sraffa recommended building a new theory of incomplete or monopolistic competition; Sraffa recommended a new conception of competition. As he explicitly stated, the concept of imperfections constituted by frictions was "fundamentally inadmissible" [88, p.542].

[14]It would be convenient to call this principle Sraffa's principle. This is the firm-level expression of Keynes' principle of effective demand.

unit. Variable costs are normally proportional to the volume of production. Overhead costs decrease when the volume of production is expanded. Consequently, unit costs normally decrease. The major results that Lester and Eiteman discovered are, in fact, confirmations. The vehement reaction from the marginalists testifies to how difficult these simple facts were to digest.

At the time when he wrote the paper, Sraffa might not have had any clear intent to pursue this revolutionary destruction. In the last half of the paper, he discussed various aspects of price determination and the degree of monopolies. However, after he published this paper, Sraffa kept silent, except for a few papers, notably including a discussion of Hayek's theory of interest. Not only was he busy in the preparation of the Collected Works of Ricardo but he also did not know how to proceed. He moved slowly but deeply. More than 30 years later, in 1960, he finally published a small book [89] with a rather long title: *Production of Commodities by Means of Commodities*. The book was subtitled *Prelude to a Critique of the Political Economy*.

Between 1926 and 1960, the theoretical landscape of economics changed greatly. Indeed, these 30 years were the most fruitful period of mathematical economics. The first move occurred in the 1930s in Vienna. Scholars including Carl Menger, the son of the founder of Austrian economics Carl Menger, began inquiring about the positive solvability of the systems of equations that appeared in economics. Before that, people were satisfied with counting the number of equations and the number of variables and examining if the two coincided. Now, they questioned whether there was a nonnegative system of solutions. However, it was a turbulent period. The Nazis invaded Austria in 1938. Many intellectuals were forced to escape from Vienna. Many of them moved to Britain and then to the United States. After World War II, the United States became the center of mathematical economics. In 1954, Arrow and Debreu published their seminal article on the "Existence of Competitive Equilibrium"[5]. Many other related contributions appeared around this period. Arrow and Debreu's theory was beautiful as a formulation and perfect as mathematics.

In view of this development, Sraffa's concern was outside the current. His thought was, however, deep enough to undermine the very basis of the now mathematically complete general equilibrium theory. The next section examines what types of problems there are in the GET as economic formulations. Then, the development of equilibrium theory after the 1970s and return to the question why equilibrium analysis was doomed to fail are addressed.

1.3 Possibilities and Limits of General Equilibrium: State of Economics After the 1970s

After the 1970s, many macroeconomic theories took the form of general equilibrium theory. We may ask one question here. Are they really general equilibrium theories? Many models pretend to be so. They are in the sense that they deal with all major aspects of the economy. They are not in the sense that (in most cases) they assume one good and single representative agent for producers and consumers. A typical case is dynamic statistical general equilibrium theory.[15]

1.3.1 Assumptions of Arrow and Debreu's Formulation

There are several versions of general equilibrium theory (GET). Arrow and Debreu's formulation was accepted as the standard model of the GET. Because of its generality and elegance, Arrow and Debreu's formulation was superior to all other models proposed at that time. Morishima [60] objected to this from an economic point of view, but he remained in the minority.

Arrow and Debreu's theory assumes a very general situation. It assumes an economy with many consumers or households, many firms or producers, and many goods and services. Each consumer possesses his/her own preference, expressed by a smooth, convex, and non-satiable utility function. It was assumed that preferences are independent of the preferences and consumption of others. Each firm is expressed by a production possibility set, which represents the technology of the firm. Each individual possesses an initial endowment and satisfies a subsistence condition. In addition to endowments in nature, individuals possess shares of firms. With some assumptions on the shape of production possibility sets, Arrow and Debreu proved the existence of a competitive equilibrium.

The generality of the model was important. The modern market economy is a system composed of an enormous number of people and commodities. GET was conceived as a unique theory that explains theoretically how this enormous system works. This is the reason that, after many years of critical reflection, Arrow [6, p. 451] claimed that the GET remained "the only coherent account of the entire economy."

Most of the conditions assumed were very general and seemed harmless. However, the beautiful formulation hides big problems. Objections to Arrow and Debreu's GET were numerous. As it became a kind of central dogma of theoretical economics, it attracted many criticisms. We may group them into two categories. One contains criticism of the unrealistic assumptions of the model. The other concerns interpretations of the model.

Concerning the assumptions of Arrow and Debreu [5], the criticisms centered on two parts:

1. Preferences
2. The production possibility set

[15]Those seeking more information about the flaws of mainstream economics can read, for example, [2, 42]. Also see [8]. These offer a wide scope for a new economics not based on equilibrium analysis.

Many in radical economics have argued that individuals' preferences are dependent on each other. They emphasized the endogenous evolving nature of preferences. The dynamic and interpersonal character of preferences is indicative of the need for agent-based simulations (ABSs). This may give a good theme for ABS. Yet this is a weak criticism. If we add one or two minor changes in formulation of preferences, Arrow and Debreu's framework can well overcome these objections.

More fundamental and fatal flaws hide behind the assumption that people can find a maximal solution. To define the demand function, it is supposed that consumers maximize their utility under the condition of budget constraints. Let us examine this point in detail.

Let u be the utility function. A consumer with a budget B maximizes

$$u(x_1, x_2, \ldots, x_N) \tag{1.3}$$

under the condition that

$$\begin{aligned} &x_1 p_1 + x_2 p_2 + \cdots + x_N p_N \leq B, \\ &x_1 \geq 0,\ x_2 \geq 0,\ \ldots,\ x_N \geq 0. \end{aligned} \tag{1.4}$$

Here, $\mathbf{p} = (p_1, p_2, \ldots, p_N)$ is a price vector. Let us suppose that all p_k are positive for the simplicity of explanation. Then, the set Δ of points $\mathbf{x} = (x_1, x_2, \ldots, x_N)$ that satisfies condition (1.4) is closed and bounded. If function u is continuous on the bounded closed domain, by Weierstrass's theorem of several variables function, u attains a maximal value $v = u(z_1, z_2, \ldots, z_N)$ at some point $\mathbf{z} = (z_1, z_2, \ldots, z_N)$. In the mathematical locution, $\mathbf{v}$ is the maximal value, and $\mathbf{z} = (z_1, z_2, \ldots, z_N)$ is the maximal solution. Evidently, the maximal value is unique for any maximization problem, whereas solutions may not be unique. If the utility function satisfies the usual conditions, the set of maximal solutions is a closed, convex, and bounded set. The demand function is a correspondence between $\mathbf{p} = (p_1, p_2, \ldots, p_N)$ and the set of all maximum solutions. This correspondence is upper hemicontinuous.[16] Then, Kakutani's fixed-point theorem gives the existence of an equilibrium.

What this formulation neglects is the cost of the consumers' calculation. If we interpret the above maximization problem as an integer problem, i.e., for a problem that seeks solutions with integer values for all components of solutions, there is no big difference in real business. Most exchanges take place by counting units of commodities. We pose a simplifying assumption. Let utility function u be linear with integer coefficients. This interpretation and specification reveals a hidden difficulty behind the above simple maximization problem. Indeed, the integer maximization problem with a linear condition is what one calls the "knapsack problem" in the field of computational complexity [75, §6, pp.90–91]. We can easily solve this problem

[16] A set-valued function or a correspondence f from X to Y is defined as upper hemicontinuous when the set $\{(x,\ y) \mid y \in f(x)\}$ is closed in $X \times Y$.

Table 1.1 Computation time increases with the number of commodities

Number of commodities	10	20	30	40	50	60	70	80
Computation time	1×10^{-3} seconds	1 second	17 minutes	12 days	35 years	36×10^3 years	37×10^6 years	36×10^9 years

with no difficulty for some special instances.[17] An example is the case where $p_1 = p_2 = \cdots = p_N$. Then, the problem is to find the biggest coefficient of linear function u. To solve the problem in general, however, the solving procedure becomes much longer, and it normally requires computation time that is asymptotically proportional to 2^N. The exponential function increases rapidly. Even for a rather small number of commodities N, the calculation becomes practically impossible because it takes too much time. The use of computers is not very helpful, for it only enlarges the limits by less than 100. The following is an example of the estimated time when one wants to solve an integer problem by, say, a personal computer (Table 1.1. Of course, the time depends on many factors, including the algorithm used and the speed of the computer; the table is just an indication of how rapidly the computation time increases).

In economics taught in schools, the number of commodities is always 2 or 3. As an illustration, this is justified. When one wants to draw a figure on a paper, this sort of simplification is inevitable. However, a real economy includes a relatively large number of commodities. We have no detailed statistics about the number of commodities. The Japan Standard Commodity Classification contains 13,757 items for the finest classification (six-digit classification, 1990 revision). This classification is not sufficient to specify a commodity. Even a standard type of convenience store deals with around 5,000 items. In a country like Japan, it is not exorbitant to assume that there are more than 100 billion items. Even if people maximize their utility, they cannot arrive at a solution even after billions of years. If one estimates the computing time, it is a tremendous error to assume that consumers are maximizing their utility.

Defenders of the GET would say that they are not assuming that consumers are really maximizing their utility. It is sufficient, they think, to assume that consumers maximize their utility only approximately. These defenders of the GET are making an error, confusing maximal value and maximal solutions. If consumers use approximate solutions, the obtained utility value is close to the maximal value. In the construction of a demand function, what matters is the composition of the solutions. Let $(y_1, y_2, \ldots, y_N)$ be a solution that satisfies condition 2, and suppose that the utility value $u(y_1, y_2, \ldots, y_N)$ is very close to the maximal value $u(z_1, z_2, \ldots, z_N)$. In the integer problem like those under conditions 1 and 2, the set

[17] We now know that a majority of instances have a rapidly solvable algorithm that gives the maximal solution. Unfortunately, these algorithms are not usable except for a specific class of instances. Any known general algorithm has an estimated exponential time.

of positive y_j may be completely different from the set of positive z_j. Approximation does not ensure that solutions are near and approximate [75].

The question of computing time is only an instance of a more general problem of economics: the assumption of perfect rationality. The same question arises for producers. Most textbooks on microeconomics demand that readers choose prices or quantities that maximize the firm's profit. If the problem is a stylized one, a routine process gives the answer. There are also problems that require deliberation. Any deliberative decision-making situation is always so complicated that no maximization problem applies. The human ability to engage in rational calculation and information gathering is limited. Herbert A. Simon [86] summarized these human limits using the key word "bounded rationality." If human rationality is unlimited, as Simon [85, 3rd Edition p.220; 4th Edition p.322] stated in his seminal book, administrative theory "would consist of the single precept: Always select that alternative, among those available, which will lead to the most complete achievement of your goal." The seemingly innocent formulation of Arrow and Debreu contains a fundamental flaw in assuming a perfect or unbounded rationality for economic agents.

Once we abandon the assumption of perfect rationality, we should formulate the behaviors of consumers and producers differently. This is why we need an evolutionary economics point of view. Agents are no longer maximizing decision-makers except in very special situations where maximization is possible. In such situations, we can formulate the behavior of agents as routines. Each agent has its own rules of conduct: in one case, they act in one way, and in another case, they act in another way. In the simplest form, we can represent an agent as a set of routine behaviors. A routine behavior consists of the set of behaviors and rules. Its conduct may become more complicated, for the if-then rules take a complex chain structure. One of the simplest but sufficiently complex formulations is Langton's "classifier system," first introduced for his artificial life world.

All these behaviors are "rule-based behaviors." A person is an agent with a set of rule-based behaviors. He or she classifies a situation as a particular case, searches a conduct rule in his repertory of conduct, and acts in accordance with the chosen rule. Each behavior is a simple rule. We know that we can easily mimic these behaviors. It is not difficult to reproduce the social interactions of these behaviors in a virtual world in a computer. ABS is suitable for this kind of analysis and this is discussed in Sect. 1.4.

As Arrow [6] suggested, GET can incorporate bounded rationality, for what matters for the proof of the existence of competitive equilibrium is the hemi-continuity of demand correspondence. If we can achieve such a correspondence, whether agents behave rationally or not does not matter. However, once we abandon complete rationality, the mathematical formulation of consumers' behavior becomes too complex and does not permit mathematical analysis. While GET seems very general, it is in reality confined to a very narrow world.

Another flaw in Arrow and Debreu's formulation is concerned with the production possibility set. The assumptions imposed on the shape of the possibility sets are very simple. Setting aside such conditions as the impossibility of net positive production, two crucial conditions are closedness and convexity. The mathematical meanings of these conditions are clear. If a series of production $x(i)\{i = 1, 2, \ldots\}$ is possible and the series converges to a vector $\mathbf{x}$, it is plausible to assume that production $\mathbf{x}$ is also possible. Convexity is much simpler. If two productions $\mathbf{x}$ and $\mathbf{y}$ are possible, convexity means that the production $\alpha\mathbf{x} + \beta\mathbf{y}$ is also possible for any nonnegative α and β when $\alpha + \beta = 1$. If the scaling down and addition of production are always possible, the production possibility set is convex. Thus, upon first examination, the assumptions on possibility sets seem plausible and harmless. This is a simple trick.

The most important problem of the convexity assumption is that it excludes increasing returns to scale. In this point, the Arrow-Debreu formulation inherits the same flaw as the neoclassical framework for production. Producers face constant or decreasing returns to scale. In the Arrow-Debreu formulation, the higher cost of production prevents producers from producing more. The logic is the same as that of the Marshallian framework. There is nothing mysterious in this coincidence. The Arrow-Debreu model assumes the concept of the supply function (or excess demand function), and this concept requires decreasing returns to scale. The abstract character of the mathematical model often obscures the real constraints that it assumes implicitly.

Defenders of GET were aware of this flaw and tried to extend the GET framework to include increasing returns to scale. I will discuss the history of this attempt in Sect. 1.3.4.

1.3.2 Problems of Interpretations of the Arrow-Debreu Theory

The criticism of flaws in the assumptions is, in a sense, extrinsic. A close examination reveals more intrinsic problems with the theory.

The first question is rarely discussed. What kind of situation does the Arrow-Debreu equilibrium describe? Is it a long-term equilibrium or a short-term equilibrium? There are many careless misinterpretations. Many people believe that the Arrow-Debreu equilibrium is a long-term one. Defenders of GET say that equilibrium may not establish itself instantaneously, but it will appear, sooner or later, after a sufficient time of the "tâtonnements" (groping process).

If this interpretation is to be plausible, only two cases are possible. In case I, all endowments are given constantly by nature, and there are no futures markets. In case II, some endowments are the result of past acts of accumulation and transaction. In case I, futures markets play no role, because they simply do not exist. In case II, futures markets play an important role. To understand this point, we must consider the time structure of the model. The first point to grasp is that the Arrow-Debreu equilibrium expresses markets at a point in time, say T, and futures markets are also open at time T. The only difference between a futures market with a spot market is that the transacted good is a future good and delivery takes place in the future. The transaction is a promise to deliver a specified good at a determined time. Let us assume that traders keep their promises. Futures markets generate flows of goods. The delivery of a good at a future time means that the trader receives it as an endowment. Therefore, the existence of futures markets generates flows of endowments that are dependent on past transactions. The case II interpretation presupposes a shifting economy behind the equilibrium. If the case II scenario produces a stationary state, the conditions of equilibrium must contain many other equations that do not appear in Arrow and Debreu's formulation. Without these conditions, what seems like an equilibrium may generate a fluctuation of the shifting economy. Arrow and Debreu did not examine this possibility. There is no guarantee that this fluctuation converges to a stable state. Indeed, we can construct an example in which one cannot extend the shifting economy beyond a certain point in time.

As a conclusion, Arrow and Debreu introduced the dated good market, but it was not as successful as many researchers thought. Mathematically, it was a simple generalization. Economically, the logic of futures markets is not well incorporated in the GE framework. GE with futures markets can be a component of a dynamic development analysis, but nobody pursued that line of investigation. Even at that time, the question of the instantaneous establishment of GE remains.

This issue is only a symptom indicating that there is some misconception in the GET research program. It cannot be a long-term or a short-term theory. The term "general equilibrium" bewildered people. Despite its apparent generality, the Arrow-Debreu formulation is only a description of an equilibrium state at a point in time. It simply means that the equilibrium state will not change if the same initial endowments and other conditions, such as preferences, are given. The existence of such a state does not teach us much about real market transactions.

The second question is a famous one. A short explanation will be sufficient. The Arrow-Debreu equilibrium includes no role for money. This is true for any other forms of general equilibrium, for equilibrium means equality of demand and supply for every good. No room remains for money as a medium of exchange.

1.3.3 Shapes of Excess Demand Functions

In the 1970s, there were new discoveries. Hugo Sonnenschein [87] found in 1973 that a very wide class of functions could be an aggregate excess demand function of an economy. We know that an aggregate excess demand function satisfies two characteristic conditions:

1. It is continuous and homogeneous of degree zero.
2. It satisfies Walras' law.

Suppose that there are N types of goods. Let Π be a set of all price vectors in R^N that satisfy conditions $p_i \geq 0$ for all $i = 1, 2, \ldots, N-1$ and $p_N = 1$. Let $\Pi(\epsilon)$ be a subset of Π that satisfies conditions $1/\epsilon \geq p_i \geq \epsilon$ for $i = 1, 2, \ldots, N-1$. A Walras function is a vector-valued function $(f_1, f_2, \ldots, f_N)$ that satisfies conditions 1 and 2. A typically polynomial Walras function is a Walras function whose functions are polynomials of first $N-1$ price variables. Sonnenschein proved that any typically polynomial Walras function is indeed an aggregate excess demand function of an economy with normal insatiable convex utility functions. Weierstrass' theorem states that any Walras function has an approximate polynomial function. This means that any Walras function can be uniformly approximated on $\Pi(\epsilon)$ by typically polynomial Walras functions. In other words, typically polynomial Walras functions are dense in the set of all Walras functions. This means that an aggregate demand function can take approximately any function on Π.

Rolf Mantel [56] reported that Sonnenschein's theorem can be extended to include all continuously differentiable functions with a certain C^* property. Gerard Debreu [17] provided a stronger theorem than Sonnenschein's. Debreu showed that one could take any continuous function as a possible approximate aggregate demand function. Like Sonnenschein, Debreu assumed that the functions are homogeneous of degree zero and satisfy Walras' law. The new theorems are true over any ϵ-trimmed price spaces $\Delta(\epsilon) = \{\mathbf{p} = (p_1, p_2, \ldots, p_N) \mid 1/\epsilon > p_j > \epsilon \text{ for all } j\}$.[18] Debreu's result means that any Walras function can be the aggregate demand function of an economy on this trimmed price space.

Mantel and Debreu examined a sufficient number of persons to get the above result. Mantel showed that the number of individuals needed in the economy is at a maximum of $2N$ and conjectured that N would be sufficient. Debreu showed that N is sufficient and that it is the minimum of such numbers.

Although these are rather technical results, their impacts were tremendous. The GET has a standard set of research programs. This set includes uniqueness, stability, and comparative statics. All these analyses supposed a well-behaved aggregate excess demand function. The Sonnenschein-Mantel-Debreu theorem (SMD theorem) means that assumptions that guarantee good behavior at the individual level do not carry over to the aggregate level. Thus, the SMD theorem destroyed standard research programs of the GET.

The SMD theorem changed the general orientation of research programs. To obtain an aggregate demand function with certain nice properties, it became clear that it is necessary to assume some special distributions for initial endowments, thus departing from the generality of theory assumptions. The SMD theorem was, in this sense, very influential, but the influence remained within the framework of the GET. It only demonstrated that the Arrow-Debreu-type model can be much more complicated than it was assumed before the theorem. It is also important to point out that the instability shown by the SMD theorem indicates nothing on the movement of the real economy. Comparative statics teach us almost nothing in the real dynamics of economic adjustment.[19]

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[18]Debreu's formulation is slightly different from that of Sonnenschein. The definition of the ϵ-trimmed price set is revised to adapt to the new formulation.

[19]Study and discussion on the testability of GET seem futile, for it is too influenced by positivist science philosophy à la Milton Friedman. Tests and refutation of a theory are not confined to the

As for trials outside of GET, Rizvi [64, pp. 230–231] sums them up concisely: Thus in the 10 years following the Shafer-Sonnenschein [74] survey, we find a number of new directions in economic theory. It was around this time that rational-choice game theory methods came to be adopted throughout the profession, and they represented a thoroughgoing change in the mode of economic theory. Even so, following a growing realization of formal difficulties with rational-choice game theory as well as experimental evidence that did not agree with some of its predicted outcomes, a group of practitioners turned to evolutionary game theory. Indeed, the rise of experimental economics itself represents an important development in the growth of alternative approaches in the wake of general equilibrium theory's difficulties.

1.3.4 GET and Increasing Returns to Scale

Whereas the SMD theorem shows the difficulties within the research program of GET, the questions of increasing returns to scale include much wider contents and perspectives. Indeed, increasing returns to scale are a common phenomenon. We can observe them widely in most of industrial production.[20]

There were several approaches to "solve" the questions raised by the existence of increasing returns to scale. The first of such attempts was made by Alfred Marshall. Marshall knew very well that increasing returns inside a firm would eventually lead to a monopoly and destruction of the competitive economy. When Marshall was editing his *Principles of Economics* (1st edition, 1890; 8th edition, 1920), Great Britain and the United States were witnessing the emergence of giant companies through a process of mergers of many companies. Marshall was more concerned about the consistency of theory rather than incorporating the new trend that he observed in the real world. His astute invention was the concept of "externality." He admitted the existence of increasing returns to scale that are external to firms and internal to industry and denied the existence of increasing returns to scale that are internal to firms. With this conception, Marshall succeeded in saving the logical consistency of his system. As we have seen, what Sraffa criticized was this "solution."

The second attempt was to deny the importance of increasing returns to scale. Many economists admitted the possibility of increasing returns to scale but tried to confine these phenomena to special industries such as railways and utility

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aggregate results. We can question micro-behavioral assumptions and logical consistency. See [64] for a history of these discussions.

[20]Increasing returns sometimes indicate the phenomenon in which production techniques improve and the cost of production decreases. This is the dynamic notion of increasing returns. Increasing returns here concern the phenomenon in which cost decreases without any change in production techniques. This is the static notion of increasing returns. The theoretical difficulty with regard to increasing returns to scale belongs to the static notion.

supplies (such as gas, water, and electricity). In these industries, they thought, a public authority should control these monopolies. These monopolistic firms are usually called public-purpose enterprises. This doctrine continues to be taught in undergraduate economics courses. According to this "solution," we observe no strong increasing returns to scale, and if they were observed, they have no serious significance.

Some economists emphasized the general validity of convexity assumptions concerning a production possibility set. Indeed, if we admit that productions are additive and divisible, we can logically deduce the convexity of the production possibility set. The flaw in this reasoning lies with the divisibility assumption. Another tricky explanation emphasized the generality of input substitutions. If we fix one or some inputs and increase other inputs, decreasing returns are general rules. We should not confuse input substitution and increasing returns to scale. In increasing returns to scale, the best combination of inputs should be chosen.

These constitute apologetic reasoning. They have no power for serious observers and theorists. By and by, particularly after the 1980s, increasing returns to scale became recognized as one of the most important anomalies or irregularities that should be incorporated into the framework of GET.

A major attempt in the new direction was to change the behavior of producers. One method was to assume that firms are no longer price takers and have a pricing rule. Many alternative assumptions were proposed. Three of them were as follows:

1. Average cost-pricing rule
2. Two-part marginal pricing rule
3. Constrained profit maximization rule

All these rules induce a correspondence from $P \times F$ to P, which is upper hemicontinuous with nonempty, closed, and convex sets as values. Here, F stands for the Cartesian product of the N set of weakly efficient production points, and P stands for the price simplex. If a pricing rule induces a correspondence with the above properties, it is possible to apply Kakutani's fixed-point theorem and prove the existence of an equilibrium in which all consumers and firms have no need to change their plans.

Average cost pricing is one of the rules that can be imposed by society on public-purpose firms. As for the behavior of competitive firms with increasing returns to scale, pricing rules with quantity constraints deserve closer examination. Two different formulations are possible. One was proposed by Scarf [73] and the other by Dehez and Dréze [18]. The first sets constraints on inputs, whereas the second sets constraints on outputs. Both of them tried to show that the equilibrium is compatible with "voluntary trading."

I will skip the details of the concept of voluntary trading.[21] It is a good characterization that includes both price-taking behavior for decreasing returns-to-scale producers and supply behavior for increasing returns-to-scale producers. In fact, for a producer with a smooth convex production set (the case of a "normal" producer with decreasing returns to scale), a minimal output price under voluntary trade implies that the output quantity of the producer is the same as the profit-maximizing quantity under given input and output prices. Another important feature of voluntary trade is the supply behavior of the increasing returns-to-scale producers. If the producer is operating at the output price p and output quantity y, it is ready to produce more when the market demand is bigger than y. This attitude is similar to the behavior of producers described by Sraffa [88]. He emphasized that what limits production to the actual level is not the increase in cost but the constraint of demand for the producer's product.

The result obtained by Dehez and Dréze [18] is astonishing. They proved two theorems for a private ownership economy under several standard conditions, except that, for the production sets, they did not assume convexity:

Theorem V. Under assumptions C.1 to C.3 and P.1 to P.4, a voluntary trading equilibrium exists.

Theorem M. Under assumptions C.1 to C.3 and P.1 to P.4, a minimal voluntary trading equilibrium exists.

The concepts of the equilibria are given as follows. A voluntary trading equilibrium is a set of a price vector $\mathbf{p}$; a list of production plans $\mathbf{y}^1, \mathbf{y}^2, \ldots, \mathbf{y}^N$; and the list of consumption plans $\mathbf{x}^1, \mathbf{x}^2, \ldots, \mathbf{x}^M$ that satisfies the following three conditions:

1. Excess demand is nonpositive with the free goods rule.
2. Consumption plan $\mathbf{x}^i$ is the best choice for each consumer i given the vector price $\mathbf{p}$ and profits.
3. For each producer j, the price vector $\mathbf{p}$ and the production plan $\mathbf{y}^j$ satisfy the voluntary trade condition for the production set Y_j.

The same set is defined a minimal voluntary trading equilibrium when, in addition to conditions 1, 2, and 3, the minimal output price condition is satisfied. (I omit the definition of this last condition.) Note that theorem M is stronger than theorem V.

At a first glance, it seems that Dehez and Dréze's results [18] were a victory of the long-continued efforts to extend the GET to include increasing returns to scale. In reality, it is not.

Let us examine closely Dehez and Dréze's results. A concave producer has a production possibility set, the complement of which is convex in an appropriate

[21] When $\mathbf{y}$ and Y are, respectively, the production vector and the production possibility set of a firm and $\mathbf{p}$ the market price, *voluntary trading* for the firm is defined as a condition wherein the price vector $\mathbf{p}$ and production vector $\mathbf{y}$ satisfy the condition $\mathbf{p} \in VT(\mathbf{y})$, where $VT(\mathbf{y}) = \{\mathbf{p} \in R^N \mid \mathbf{p} \cdot \mathbf{y} \geq \mathbf{p} \cdot \mathbf{y}' \text{ for all } \mathbf{y}' \in Y \text{ such that } \mathbf{y}' \leq \mathbf{y}_+\}$ and $\mathbf{y}_+$ denotes the vector in R^N with coordinates $\max\{0, y^{jh}\} (h = 1, \ldots, N)$.

half space. This means that the increasing returns to scale apply at all points of production. Theorem M proves the existence of an equilibrium even in the non-convex (i.e., increasing returns-to-scale) environment. Theorem M states that there is an equilibrium where concave producers operate without profit, for the output price is equal to the average cost that is minimal in the voluntary trade price set. In other words, the concave producers always produce at the break-even point.

A minimal voluntary trading equilibrium permits convex (i.e., decreasing returns-to-scale) producers to get positive profits but does not permit concave producers to get any positive profits. This is exactly the opposite of what we usually observe in a real (but not in a theoretical) market economy. Even in the paradigm of GET, this result is disastrous because the equilibrium is consistently not Pareto efficient.

At the end of my discussion on increasing returns to scale, it is worth adding some words on the same topics in the macroeconomic literature. Indeed, eminent economists such as Josef E. Stiglitz, James M. Buchanan, Robert E. Lucas, and Martin Weitzman showed a keen interest for the effects of (static and dynamic) increasing returns. Buchanan and Yoon [12] edited an anthology on this theme. David Warsh [93], a *Boston Globe* columnist, wrote a journalistic book titled *Knowledge and the Wealth of Nations*. He contrasted the pin factory parable (increasing returns) against the invisible hand parable (equilibrium) and pointed out that the two theories are logically contradictory, so the pin factory discourse was suppressed in favor of the invisible hand logic. In the latter half of the book, Warsh discussed the role of Paul M. Romer [70] in this "increasing returns revolution" in economic thought. In this and other papers, Romer treated knowledge as the third input, together with capital and labor, to the aggregate production functions. He avoided the usual difficulties in introducing increasing returns by assuming the spillover effects of knowledge. Increasing returns appear only in the macroeconomic analysis. By introducing the logic of externality, Romer succeeded in incorporating increasing returns, just as A. Marshall did. As for the logic of explanation, Marshall and Romer were structurally the same.

Dixit and Stiglitz [19], Krugman [45], and others have made other attempts concerning monopolistic competition. Using the Dixit-Stiglitz utility function, Krugman succeeded in explaining that a degree of diversity occurs under monopolistic competition. He explained that this would show why intra-industry trade is increasing in volume and in proportion. This result relies too much on the symmetric assumptions on both the producers' and consumers' sides. It is rather a poor result. It does not explain how specialization occurs between countries, for specialization takes place purely by chance in Krugman's symmetric world.[22]

[22]See Shiozawa [79] and subsequent papers [80–82]. They explain why intra-industry specialization occurs within a general framework of Ricardian trade theory.

1.3.5 Computable General Equilibrium

Some computer simulation researchers believe that the GET is not so bad and is even useful in some ways, for computable general equilibrium models (CGE models) are constructed and actually used.

It is necessary to distinguish two different aims of economic models. GET is primarily an "algebraic theory."[23] It does not aim to provide a prediction. That understanding is simply a Friedmanian misconception. GE models contain many variables and functions, but it is normally difficult to replace them with observed data. An algebraic theory teaches us the principle of a system. In the case of economics, a good theory teaches us how the market economy works [7]. As Arrow and others insisted, GET gave a coherent account of how an economy as worldwide network works with no directing headquarters. As a parable, GET has produced a fine picture. However, it contains various fatal flaws. GE is a refined theory as mathematics but a fanciful confabulation as economics. The insight that GET gives is far from reality and often toxic. That is why we have determined that we should reject GET. It has no future.

The second aim of economic models is to give predictions. They are conceived as policy tools. Many economic models, private and public, are working for this purpose. As positive science, there are many insufficiencies in these models. They are like fortune-telling. People misuse economic models thinking that they express causal relations between variables. Despite these problems, it is an inevitable work. As Keynes hinted, in the field of predictions and policymaking, we should be as humble as dentists who try to ease the client's pain without knowing its real cause. We should also note that basic medical sciences, empowered by the recent development of biophysics, have improved treatment tremendously. In economics, we should pursue both sides: practical treatment and basic science. It is yet important to know that practice and theory may have a great distance between them.

Broadly speaking, CGE models are a type of GE model. In contrast to other GE models, their aim is to be useful for concrete economic analysis. On this point, they are closer to most macroeconomic models. The difference between mainstream econometric models and CGE models lies in their orientations. Mainstream econometric macro models are constructed as simply as possible. They use a small number of aggregate variables and a small number of equations. CGE models contain a large number of variables and equations. They rely heavily on detailed statistical data. CGE models descend from Leontief's input-output table and have the aspect of a new form of a system of national accounts.

This difference between mainstream econometric models and CGE models comes from different philosophies in useful model building. Mainstream models

[23] Hayek [34] used this phrase after J.W.N. Watkins's suggestion. See [7, p. 54] for more information.

aim for speed and accuracy. CGE models aim to be usable in various analyses in policy assessment before any concrete implementations.

In the 1960s and even in the 1970s, there was a widespread belief that, if we can build a large-scale econometric model, we can get more accurate results. This belief was abandoned a long time ago. The economy is a huge network that includes tremendous number of variables. Interactions between them are very complex, and the introduction of new variables and equations does not help very much to improve models.

1.3.6 Dynamic Stochastic General Equilibrium Models

Another strand of computable macroeconomic models is called dynamic stochastic general equilibrium (DSGE) models. This type of model is much more popular among macroeconomic specialists for more than 20 years. The Royal Swedish Academy of Sciences awarded the Nobel Prize in Economic Sciences in 2004 to Kydland and Prescott, who were major promoters of DSGE models.

DSGE models have incorporated expectations and substitution between consumptions at two points in time. As they are actually popular models, be they abstract or computable, there are many versions, but most of them have a very simple structure. They assume one type of good and a unique representative agent. The agent represents consumers who have identical preferences.[24] They choose how much they consume this unique good at a given time. In this sense, goods are differentiated as time-specific goods. If they expect inflation, consumers prefer to consume more now than later. The word "general" means simply that the agent chooses these differentiated goods. "Dynamic" means only that agents have expectations of future events. Preference and the production function remain the same. In the proper sense of the words, DSGE is but a static model. "Stochastic" means that there are external shocks to the economy. Whatever happens, an agent is ready to adapt its behavior and redress the disturbed equilibrium. With these characteristics, DSGE models are normally understood to be rigorous models that have firm microfoundations. Based on this assessment, discussions and observations of neoliberal new classical economists and more liberal new Keynesians are both mainly based on one DSGE model or another.

However, criticism of DSGE models abounds and became much stronger after the Lehman Brothers bankruptcy. We cite here a short historical assessment in a paper by Colander and others [16, p. 237] prepared and published before the shock:

> The exaggerated claims for the macro models of the 1960s led to a justifiable reaction by macroeconomists wanting to "do the science of macro right", which meant bringing it up to the standards of rigor imposed by the General Equilibrium tradition. Thus, in the 1970s

[24] In view of the Sonnenschein-Mantel-Debreu theorem, it will not be easy to generalize this assumption.

> the formal modeling of macro in this spirit began, including work on the micro foundations of macroeconomics, construction of an explicit New Classical macroeconomic model, and the rational expectations approach. All of this work rightfully challenged the rigor of the previous work. The aim was to build a general equilibrium model of the macro economy based on explicit and fully formulated micro foundations.

The authors' conclusion was as follows:

> Einstein once said that models should be as simple as possible but not more so. If the macro economy is a complex system, which we think it is, existing macro models are "more so" by far. They need to be treated as such. We need to acknowledge that our current representative agent DSGE models are as ad hoc as earlier macro models. There is no exclusive right to describe a model as "rigorous". This does not mean that work in analytical macro theory should come to a halt. But it should move on to models that take agent interaction seriously, with the hope that maybe, sometime in the future, they might shed some direct light on macro policy, rather than just provide suggestive inferences.

1.3.7 Why did the Mainstream Research Program Fail?

The above conclusions of Colander and others [16] are fairly natural, but it would be better to add some words about symptomatic observations on the present state of economics.

If we examine the situation with an open mind, symptoms of economic science's crisis are evident. All difficulties of economics come from the fact that it cannot escape the equilibrium framework. Equilibrium is a framework that treats the economy as if it is in a static state. However, the economy is a dynamical entity. Stock prices and foreign exchange rates fluctuate by the minute. An economy is always changing: competition, the business cycle, the boom and collapse of financial markets, and growth and stagnation. Commodities, people's behaviors, technology, institutions, and organizations change over a longer period.

Since the time of John Stuart Mill, economists have known that the basic method of analysis should be switched from static to dynamic. Many economists espoused this ideal, but it was never realized. Even nonspecialists in economics knew that the economy is always changing. To rescue economics from the yoke of statics, J. R. Hicks devised the idea of shifting equilibrium. Under this interpretation, the economy is a series of equilibria at any moment in time but shifts from equilibrium to equilibrium. Another mode of thinking is to examine inter-temporal equilibrium conditions. A typical example is dynamic stochastic general equilibrium models Despite these palliative ideas, analysis based on equilibrium framework cannot escape its essential character of being static. As Ichikawa Atsunobu [39] emphasizes, it is necessary to see the potential limits of the present system of a science. As he tells us, there is always a margin between the actual state of a system and its limits. If one is bewildered by the small remaining margin of development, one cannot achieve a breakthrough. It is, rather, time to abandon the old framework. If we do not, we cannot go further.

Why did people adhere so closely to the GE framework? It is a conundrum. To solve this, it is necessary to make a short detour into the history of science. Economics is a part of science and was strongly influenced by the general methodology of scientific investigation. Throughout the nineteenth century, this thinking involved measurement and mathematics. Newtonian analysis was extended to the various fields of physics and engineering, and it was believed that this method could be applied to such a field as economics. Fortunately (or, in reality, unfortunately?), economics succeeded in incorporating mathematical analysis into economic reasoning, and it could take the form of a scientific field. However, this pseudo-success paved the way to the present state of economics.

Emerging in 1930s in Vienna, mathematical reasoning in economics became much more refined throughout the twentieth century.[25] One of the highest peaks in this direction was Arrow-Debreu's theory of a general equilibrium model [5]. In the 1950s and 1960s, there was a kind of fever or blind trust in economics: mathematical economics, together with econometrics, was expected to become a real science, comparable to physics. Criticism in the first half of the 1970s was a reaction to this euphoria. This history of economics is closely related to a major change in scientific research modes and will be explained in Sect. 4.2.

Arrow and Debreu's success was conditioned on two factors. Their theory was based on two orientations: maximization and equilibrium. These two research frameworks helped very much in the successful application of mathematics, but they also indicated the limits of mathematical analysis.

Once the hypothesis of maximization was abandoned, economists were obliged to stand in an uncomfortable position. Economic agents' behaviors are no longer determined uniquely. How do economic agents behave? There are no leading principles by which to formulate economic behaviors a priori. Economists must start their analysis with observations of actual economic behavior. However, this was not an easy attempt, for it required sharp insight and the power of abstraction. Moreover, this method is in some sense contradictory to the well-established custom of economics. It is still believed that economics can be constructed as an axiomatic science from such principles as rational decision-making.[26] Many theoretical economists were afraid to lose mathematics as a tool of analysis. They knew that real agents were not behaving as utility or profit maximizers, but they preferred to conserve tools rather than to abandon them.

Similar logic had worked with regard to the equilibrium framework. In any market economy, prices and quantities are mutually dependent. This kind of mutual dependence can be analyzed by two methods: one is equilibrium analysis and the other is process analysis. In equilibrium analysis, all relevant variables are thought to be constant through (probably virtual) time. An important related question, whether the economy has any mechanisms to arrive at equilibrium, was seldom questioned.

[25] See Sect. 2.3 for a short overview of this movement.

[26] Curiously, this claim was typically advanced by economists in the Austrian tradition. See von Mises [59]. Machlup in the marginalist controversy belongs to this tradition.

If an economy is in equilibrium, the analysis becomes drastically simple. If we confine ourselves to the analysis of equilibrium, it is sufficient to inquire whether a system of equations has a solution and whether solutions are unique or not. For the existence of an equilibrium state, one could use Kakutani's fixed-point theorem, one of the most general forms of fixed-point theorems. This was one reason that Arrow and Debreu's theory was successful.

If we abandon the equilibrium framework, then all variables become dependent on time. Process analysis becomes necessary, but the researchers' burden becomes much heavier. This approach was tried sporadically, but it was doomed to remain fruitless because there were no good tools to pursue the processes systematically. Process analysis was extremely difficult if the main tool of analysis was limited to mathematics alone. Except for models with one or two variables (as attempted in macroeconomic analysis) and for linear system cases, very few results were obtained. Process analysis was ideal but impractical, as the formula became complicated and did not permit an easy understanding of the meaning. Simply speaking, process analysis was intractable if we wanted a certain level of reality for the analysis.

This was the deep reason that economists resisted so strongly admitting the deficiency of their framework despite the repeated criticisms against GET and other neoclassical frameworks. Mathematics (or at least formula calculation) is not well adapted to analyzing complex phenomena. These days, however, complexity has become a popular topic, and many have understood that mathematical formula calculation has an intrinsic limit as a tool of analysis. Agent-based simulation (ABS) or agent-based computational economics (ABCE) changed this status quo. This is the very reason that a long guided tour was necessary to understand the deep mission and the possibility of the ABS.

1.3.8 What Happened During this Century and a Half?

As a conclusion to our brief tour over the history of economics over more than a century and a half, let us cite a paragraph in Sraffa's 1926 paper [88, p. 536]:

> In the tranquil view which the modern theory of value presents us there is one dark spot which disturbs the harmony of the whole. This is represented by the supply curve, based upon the laws of increasing and diminishing returns. That its foundations are less solid than those of the other portions of the structure is generally recognized. That they are actually so weak as to be unable to support the weight imposed upon them is a doubt which slumbers beneath the consciousness of many, but which most succeed in silently suppressing. From time to time someone is unable any longer to resist the pressure of his doubts and expresses them openly; then, in order to prevent the scandal spreading, he is promptly silenced, frequently with some concessions and partial admission of his objections, which, naturally, the theory had implicitly taken into account. And so, with the lapse of time, the qualifications, the restrictions and the exceptions have piled up, and have eaten up, if not all, certainly the greater part of the theory. If their aggregate effect is not at

once apparent, this is because they are scattered about in footnotes and articles and carefully segregated from one another.

This paragraph describes the intellectual atmosphere during the first quarter of the twentieth century and is still prophetic if we reflect on what happened during these 40 years since 1970s and what is happening now. We know that foundations of neoclassical economics "are actually so weak as to be unable to support the weight imposed upon them." There were many who expressed their doubts, and they were "promptly silenced, frequently with some concessions and partial admission of [their] objections, which, naturally, the theory had implicitly taken into account." This was the history that was continually repeated over the century and a half after the rise of neoclassical economics. It continues to be repeated [91].

The most important lesson to draw from this history is that something was missing in our efforts on reconstructing economics. Much of the criticism was addressed and then accumulated. This is necessary but not sufficient for the reconstruction of economics. Mathematics provided economics with a powerful tool for analysis, but singular reliance on this tool is now the main cause of the current troubles with economics. We must introduce or create a new analytical tool as powerful as mathematics. A promising candidate is computer simulation or agent-based simulation. The next section discusses what kind of possibilities agent-based simulation has for the future of economics.

1.4 Tasks and Possibilities of ABS

We have made a long journey through economics, before and after the 1970s. We have seen that economic science is seriously ill. The history of economics after the 1970s teaches us the necessity for a paradigm change in economics itself. A research program that seeks a modification and redressing of mainstream economics is deemed to fail. We should pursue a breakthrough. To achieve a breakthrough, it is not sufficient simply to rearrange concepts and theorems. A new tool for economic analysis is necessary. Its reconstruction requires something very new. ABS or ABCE is one such possibility.

1.4.1 New Bag for a New Wine: ABS as a New Tool for Economics

If we summarize the history of economic analysis very briefly, we can detect three stages. The period before the 1870s was characterized by a method of analysis that employed literary explanations and history, and concept making played an important role. The second period ranges from the 1870s to the present. A new tool of economics, mathematics, was introduced. In the latter half of the twentieth century, mathematics was a synonym for the theory. At that time, what was mathematically formulated was considered theoretical and therefore scientific. Now we are standing at the starting point of the third period. There are overlaps in every periodization. We are in a phase of transition.

This transition may have started around the 1970s at the earliest and in the 1990s at the latest. In the meantime, two important events occurred. First, a new style of mathematics emerged. Chaos, fractals, and power laws were discovered in every field of science. People acknowledged that reality is much more complex than those that the classical tools, such as differential equations, can describe well. The second event was the advent of personal computers. Calculation became faster and easier beyond comparison. This made agent-based simulation possible.

The new mathematics was a new conception of the world. From Newton to Poincaré to René Thom, the world was differentiable. The world was considered a dynamical system. This meant that everything could be described by a system of differential equations. However, the world has changed much since the arrival of new mathematics. Fractal dimensions were introduced. The forms were no longer differential. We must remember that, in the nineteenth century, a Weierstrass function was thought to be most pathological and barely accepted with astonishment. The discovery of chaos was another big impact that changed the worldview, even though it was based on a dynamical system. The standard classical view of the regular world was discarded in favor of acknowledgment of the complex world.

The new mathematics contributed to the establishment of this new worldview, but it also revealed the limited bounds of mathematics. It was dethroned from omnipotence and sent into retreat, where mathematical reasoning is useful only in a fortunate, simple situation. However, we should be pleased. At the same time as the arrival of the new mathematics, another powerful tool came to the rescue[27]: computer simulation. ABS models are a part of this general trend [47].

Economics changed much when it began to use mathematics as a tool of analysis. In the last quarter of the nineteenth century, mathematics was a new tool for economics, and it opened a new big possibility. Without mathematization of economics, no strict reasoning was possible. However, as we have seen above, mathematics was a trap for economics. Even when we recognized many anomalies, contradictions in the theory, and its irrelevance to reality, mainstream economics wanted to remain loyal to mathematics and, as a consequence, to maximization and to the equilibrium framework. A majority of economists thought that there was no choice other than mathematics. To change the status quo, it is not sufficient to change our minds. Without developing a new tool, we must continue to use an old tool. It is absolutely necessary to seek a new tool of analysis. Now it is time to pour new wine (new contents) into a new bag (new tool). The introduction of ABS models has such a meaning in economics. As such, it is important for new researchers to know the merits and tasks that we face with regard to this new tool. It will be a crucial

[27]Evidently, the new mathematics was helped by the arrival of computers.

knowledge for the further development of economics and to lead our inquiry in the right direction.

Although ABS can provide a powerful tool for economics, it is not yet an experienced and mature tool. It is not sufficient to use ABS models as a convenient set of analyses, but it is necessary to develop ABS as a good tool. It provides a big possibility and task. To make it effective, we should be good model builders. As many have pointed out, it is rather easy to build an ABS, but few models are good ones. Once a computer model is implemented, it can produce enormous amounts of results, but if the assumptions used in the model are wrong, they are meaningless. ABS models have a strong tendency to result in "garbage in, garbage out." A good ABS model satisfies many requirements of different levels. We will discuss the question of how to formulate agents' economic behavior in Sect. 1.4.4. The problem of ABS, however, does not stop here. We should also consider more subtle, meta-level problems. They may be classified into two groups.

The first group of problems is concerned with the conditions needed to be a good model. For example, we can easily cite the following three tasks:

1. Build a simulation model that is relevant to real-world questions
2. Build a simulation model that helps to understand what is happening in a real economic process
3. Build a meaningful simulation model

The first two tasks are easy to understand. The third task may include tasks 1 and 2, but it can imply a different meaning. A simulation model is useless if it can only give a result that is obtained by mathematical formulations. If a mathematical proof is possible, the simulation can only afford a verification check. In that case, there is no raison d'être for ABS as a new tool.

The second group of tasks is concerned with how to obtain scientific knowledge and how to confirm that it is true. In simulations, for example, we always face the following tasks:

4. Find a method to discover an interesting phenomenon
5. Find a method to establish general tendencies or laws
6. Find a criterion to estimate the generality of a tendency or a law

All these tasks are difficult problems. We may not arrive easily at first-step solutions. Despite the difficulties, it is necessary to attack these tasks so that ABS can become a truly scientific method. Indeed, it is not only economics that faces these tasks. Many science fields face similar and common problems.

This is not surprising, as we are entering a new phase of scientific research. The experiences of other fields may be helpful. At the same time, the history of experimental sciences may be indicative. Experiments are now the most fundamental mode of modern scientific research, but this method did not come to the world easily and swiftly. It took many hundreds of years before experiments became a firm mode of scientific research. ABS researchers should learn from the history of the development of experimental sciences. In this regard, it will be necessary to make a short detour into the history of science and situate ABS in the long-range history of scientific research.

1.4.2 The Third Paradigm in Scientific Research

Let us review the history of science as a development of different modes of scientific research so that we can understand the situation of ABS and ABCE.

The first mode or paradigm of scientific research was theory. This mode of scientific research originated in Ancient Greece, or Classical Greece. Many people may be surprised to read this. If we see that the word "theory" came from the Greek word "theōri'a" ($\theta\epsilon\omega\rho\iota'\alpha$), which means "speculation" or "contemplation," my contention may become more plausible. Theō'ri'a is a derivative of the verb "theō'rēō," meaning "I look at." The word "speculation" is based on the Latin word of the same original meaning. Observe and contemplate! This was the original method of theoretical effort. "Theorem" comes from the Greek word "theō'rēma," meaning "proposition to be proved."

The same types of contemplations and speculations must have occurred in Ancient India and Ancient China. It was Greece that developed logical reasoning to an extreme. Mathematics as a logical science emerged in Greece. Euclid's *Elements of Geometry* was a compilation of known theorems arranged in a logical order. Theorems are known in India, China, Egypt, and Mesopotamia, but only in Classical Greece were different theorems arranged in a logical order beginning with the first principles, i.e., postulates and axioms. It is amazing that the Greeks proceeded so deeply into logical reasoning. It is not strange that *Elements* remained a must-read textbook for more than two millennia. The idea that an indefinite number of theorems can be derived from a small number of postulates and axioms is quite unusual, although it became one of the indispensable pillars of modern science. This is demonstrated by the fact that Chinese scholars could not understand the significance of arranging theorems in a logical order when Euclid's *Elements* were imported and translated in seventeenth-century China.

The second mode or paradigm of scientific research came very late compared with theory. It was experiments. A clear date for the beginning of experimentation was not marked until Galileo Galilei established modern experimental science. His falling bodies experiment from the Leaning Tower of Pisa is the best known of his experiments. We should also note that Galileo used a telescope to observe the sun, moon, and planets. He discovered the rings of Saturn and satellites of Jupiter. The telescope served as an extension of the sensory organs. He became the first person to change our thinking by means of observations.

Observations are not usually considered a part of experiments, but observation by using special instruments is very close to an experiment. Although observation is an important aspect of speculation, it became a scientific research tool only after the arrival of modern experimental science. Experiments and observations are an inseparable pair. We can include observation as a kind of experiment.

The origin of experiments is quite vague. We may go back to medieval alchemy and further to Archimedes. All empirical studies had some characteristics of experiments or observations. It took many centuries for burgeoning experimentation to grow into a scientific research tool.

Observation is a part of the experimental mode. Experiments, instruments, and observations form a triplet in experimental science. Experiments and observations existed before experimental science was established as modern science. Observations became an indispensable element of experiments when observation became a controlled act of data gathering with the use of instruments. The latter helped to obtain accuracy and reproducibility and extended our ability to perceive beyond our five senses.

Experiments together with instruments and observations became a scientific research method only after various procedures were stipulated. The result of an experiment, if it is an important one, is recognized as an established fact only when other independent experiments confirm the result. History shows that experiments required a much greater understanding of scientific research methods. This point gives us a valuable lesson when we think of making agent-based simulation a true scientific research method.

The third mode or paradigm of scientific research is computer simulation. As computers are rather new devices, computer simulation has only a short history. In a science such as chemistry, computer simulation has become a well-established method of research, as it is thought that a complete research project should contain three parts: a theoretical examination, an experiment, and a computer simulation. In astronomy, computer simulations are often used to show graphically how the universe evolves. Even in physics, computer simulations are used to generate statistical movements of large-scale systems. In other fields, such as biology, computer simulations are used as parables. Artificial life is a famous example, but its relevance to biology is still ambiguous.

In addition to the aforementioned three paradigms of scientific research, Gray [27] proposed a fourth paradigm: data exploration.[28] Others named it e-Science. We are living in an age of data deluge. Data exploration comprises all activities related to data processing: data capturing, data curation, data analysis, data visualization, and all related operations. Implementation requires millions of lines of code for a large-scale experiment. As Gray pointed out, the software cost dominates many large-scale experiments. Data exploration itself is a field of engineering rather than a science, but science and engineering go together. We should recall Galileo's telescope and the arrival of computers. They changed the mode of scientific research enormously. Engineering not only helped science but changed scientific research methods tremendously. The same thing is happening now in the domain of data processing. Data exploration is indeed changing the mode of scientific research, and we may say that it has marked the arrival of a new paradigm [54].

[28] Explanations of the first two paradigms are different from mine. Gray explains that empirical study started a thousand years ago, whereas the "theoretical branch" started a few centuries ago.

The four modes of research are not exclusive. No research effort is possible without depending on other modes. They are complementary. The trouble with ABS lies with two factors. First, we lack a firm theoretical basis. Second, ABS is still young, and we lack a good metatheory by which we orient and control our research. The second factor is common to all simulation experiments, and we can and must learn from other disciplines where more experience and theoretical examination are accumulated. The first factor is proper to economics, but we should not be discouraged by this. Economics went astray because it depended too much on mathematics, which was not well suited to study complex phenomena. In contrast, we can expect that ABS may serve as a good tool for reestablishing economics. The mission of ABS is as great as this.

As experiments needed a long time, perhaps centuries, to be established, simulation study will require a long time before it will be established firmly as a mature mode of scientific research. It needs much work and reflection in building simulation models, implementing models, interpreting simulation results, finding a law assessing the relevance of models, and other tasks. On the basis of these activities, we need a kind of new philosophy by which to lead our meta-level reflections. We do not yet have a concrete vision on this level, but one will emerge as research through simulation proceeds. It may reveal the strengths and weaknesses of simulations, but at the same time, research will teach us how to compensate for weaknesses by combining other modes of scientific research. We should be patient. Experimentation was not built in a day. We need many years, if not centuries, before simulations become a full-fledged scientific research method. In this regard, all computer-based science faces similar problems. We should promote transdisciplinary communications and discussions. Learners of ABS and ABCE should build the ability to communicate and discuss common problems with researchers in other fields.

1.4.3 Complexity and Tractability

Process analysis is not only more general than equilibrium analysis. It opens a new logic that has so far been impossible in economic analysis. For example, as discussed at length, increasing returns to scale were a vexing question, but process analysis can easily incorporate it into its logic. It is sufficient to assume that firms produce their products at the same rate at which they are sold (Sraffa's principle; see page 17).[29]

ABS has, of course, some special features that are not common to computer simulation in general. Simulations are used in macroeconomics, but the latter is not fully exploiting the possibility of computer simulations. They are used only in lieu

[29]We are preparing a new book on process analysis based on this principle: *Microfoundations of Evolutionary Economics* (to appear in the same series as this book).

of solving a system of equations algebraically. Researchers use computers only to obtain numerical solutions. This kind of simulation has no power to rehabilitate economics. What ABS aims at is quite different. ABS may provide a foundation for a new economics not based on equilibrium.

An example of such a new possibility is the process analysis of sequential development of economics states. Sequential analysis is one of the old tools of economics. Stockholm school economists and English economists, such as Hawtrey, Keynes, and Robertson, discussed monetary problems in this framework in 1920s and 1930s. They used it extensively but could not obtain firm results, and Keynes returned to more traditional equilibrium analysis in his *General Theory* [43]. The reason for this moderation is simple. If the sequence is traced by calculating mathematical expressions, the algebraic formula becomes too complicated and exceeds our manipulation ability. When expressions include max or min operators, distinguishing cases become too large to do a thorough case analysis. When, instead, the sequence is pursued numerically, we can get a result more easily, but we are not sure whether the obtained result reflects any general rule. Such a concern was partly eliminated when computers were introduced. Starting from different initial conditions, we can trace and see what happens in general more easily.

Sequential analysis is also called process analysis. The landscape of process is very different from that of equilibrium. In some sense, they stand at opposite extremes. Process seeks to clarify the mechanisms of change at every move. Equilibrium neglects all these changes and seeks to determine at what state the process ceases to change. If such a state exits, analysis becomes extremely simplified. If we know the mapping from one period to the next, the equilibrium is a fixed point of the mapping, and there is no need to know how the state evolves outside of equilibrium.

At the edge of intractability, this simplifying assumption was in some domains very useful. Equilibrium analysis was widely used in mechanics and thermodynamics. In economics, too, in the first phase of mathematical analysis, it was useful as the first approximation. It was reasonable to assume that demands were nearly equal to supplies. However, at some point in economics, equilibrium became a dogma. When we encounter a case where the equilibrium framework is not applicable, every kind of apology was added, and the framework was saved. Instead of trying to produce a new framework, the majority of economists wanted to conserve their old framework. These reactions can be interpreted as a model case of protective belt making in the face of anomalies, in Imre Lakatos' terms. Research programs with equilibrium changed from progressive to degenerating.

Process analysis is much more complicated than equilibrium. Instead of analyzing only fixed points, it was necessary to analyze, so to say, the mapping itself. A general theory was sometimes too difficult to construct. Even a simple second-order mapping such as

$$x(n) = a \cdot x(n-1)\{1 - x(n-1)\}$$

is extremely complicated when we want to classify different behaviors of the series $x(n)\{n = 1, 2, 3, \ldots\}$ when the coefficient a changes. Li and Yorke [53] found a theorem: any continuous mapping that maps an interval into itself shows the behavior referred to as "chaos" if the mapping has a fixed point of period 3. This was the starting point of chaos theory.

The Li-Yorke theorem destroyed the classical image of the dynamical system. The classical image of the dynamical system was rather simple. There are some isolated fixed points. If the initial points are, by chance, off the fixed points, the points converge to one of the fixed points. Indeed, in the case of a two-dimensional system of differential equations, the solution paths are classified in three cases. One is the convergence to a fixed point, i.e., the equilibrium point. The second is divergent cases. The points go out of any bounded set. The third is a limit cycle. The path approaches a closed curve, i.e., a limit cycle. Then, except for the cases of divergence, the limiting state of any dynamic process is either equilibrium or a closed cycle, showing periodic ups and downs like a trade cycle. However, this image was justifiable only when we are working with a low-dimensional differential dynamical system. If the system becomes high dimensional or even in a low-dimensional case if the system is described by difference equations, the limiting behavior becomes astonishingly complex. Li-Yorke's chaos is a simple example of the latter case. Many types of strange attractors have been discovered since then. Convergence to an equilibrium point or to a limit cycle is a rather exceptional case.

1.4.4 Features of Human Behavior

ABSs have two characteristics as a method of analysis: (1) they are constructed as interactions from the behavior of economic agents, and (2) they investigate the process of how the economy proceeds and changes. As for the first point, ABS models are different from macroeconomic models but have common characteristics as microeconomics. As a tool of analysis, the second characteristic is more important. Because of this characteristic, we can implement many phases of human behavior, which was practically impossible when we were confined to equilibrium analysis. Therefore, let us start with the second characteristic.

A process analysis proceeds as follows. The analysis is divided into steps. In each step, agents do what they can do. This may sound trivial, but in fact, this is a crucial point. Human agents are entities with limited capabilities. As the subject of an action, we can point out three aspects[30]:

1. Limited range of information gathering (limited sight)

[30]The three-type classification of limits of human abilities was inspired by Jacob von Üexküll's idea of a "functional cycle" [92]. This was discussed at length in my book *The Science of the Market Order* (in Japanese) [76, Chap. 11, "Human Behavior in a Complex World"]. See also [78, §6].

2. Limited ability in information processing (limited rationality)
3. Limited ability to carry out something (limited executive capacity)

Each agent at each step observes a few variables, makes decisions almost instantaneously, and acts. In ABS models, it is equivalent to use some limited number of values that are already determined, calculate some simple formulas, and change some variables. Simon (1984) discussed the first two aspects under the subject of *bounded rationality*.

Process analysis can take different time spans. Much decision-making is done habitually, but a few important decisions are made deliberately, consuming many hours and much labor. Katona [41] contrasts habitual or routine behavior and genuine decision-making. Production workers' movements are mostly habitual. Mintzberg [58] reports that a factory manager makes more than 1,000 decisions in a day. Those decisions must be habitual ones, whereas a decision to build a new factory or to launch a new product must be a highly genuine one. Habitual behavior or routine decisions have a shorter time span, and genuine decision-making requires long deliberation and is done with a long interim period.

It is necessary to employ different time scales for different layers of decisions and actions. Various kinds of adjustments take the form of routine behavior and have a proper time span according to the purpose and nature of adjustments.

The ability to build a good ABS requires many capabilities, such as a good and critical knowledge of economics, a good observer's view of economic affairs, good formulations of human behavior, or good skill in implementing a model. To obtain a good formulation, a basic knowledge of human behavior is necessary. Routine behavior is relatively easy to formulate since it can be formulated as a chain of if-then directives. This formulation has a quite wide coverage. The *Turing machine* idea is based on the fact that any computable function can be represented as an ordered set of directives of the form $q_1S_1S_2q_2$ [78, Subsection 6.4.]. We can reasonably suppose that any routine behavior can be depicted as an ordered set of if-then directives of the form $q_1S_1S_2q_2$.

We can derive two important lessons from this: (1) it is the internal state q1 that determines what will be observed and (2) the action to be taken S_2 should be within the limit of executive capacity. The first point expresses the active and subjective aspect of the agent, and the second point indicates that a change that an agent can make is a small part of the world. These aspects of human behavior can be fully incorporated into ABS models. Contrary to equilibrium analysis, which generally assumes maximizing behavior of the agents, there is no need for ABS to assume that human agents are fully rational and farsighted in space and time. Human agents in ABS are thus myopic entities and respond to a small number of variables that they can observe. The effects of their actions diffuse slowly, from part to part and step by step, on an entire economy.

Differences between the equilibrium and process analysis are listed in Table 1.2.

We lack the space to explain each row of difference in detail, but we can observe from this table that process analysis with the aid of ABS can dispense with various unrealistic assumptions that are often required for equilibrium analysis.

Table 1.2 Comparison between equilibrium and process analysis

Equilibrium analysis	Process analysis
Unbounded rationality	Bounded rationality
Farsighted	Myopic
Limit state	Step-by-step examinations
Infinitely rapid effect	Finite velocity of effects
Static	Dynamic
Barter economy	Exchange with money
Instantaneous adjustment	Gradual adjustment
Fixed behavior	Evolutionary change in behavior

Another merit of process analysis lies in its systematic decomposition into step-by-step examinations. This eases the burden of implementation enormously, as the decomposition of process to periods can be easily programmed as a repetition of a cycle. Once a program for a series of events in a period is written, it can be used for another period. This type of repeated work is most easily done by computers. Agents' behavior and the total process can thus be implemented in an ABS model. As a conclusion of this subsection, we can safely say that process analysis and computer simulation in the form of ABS have good chemistry.

1.4.5 Evolutionary Economics and Micro-Macro Loops

We have listed the merits of ABS models. There is another important advantage that equilibrium analysis does not have. It is likely that ABS will open up new possibilities for evolutionary economics.

Evolutionary economics emphasizes that major categories of economic entities can be better understood when we conceive of them as something that evolves [78]. Seven categories are notable: commodities, technology, economic behavior, institutions, organizations, systems, and knowledge.[31] ABS models are a suitable tool of analysis for an evolutionary study of rules of conduct.

ABS may include learning and even evolution. There is no need to keep the set of rules of conduct fixed for all periods. The number of rules may increase or decrease. Some rules may be excluded from the set, and some others may be included in the set. The voluntary acquisition of new rules of conduct might be called learning, whereas involuntary or unconscious changes in rules of conduct might be better called evolution. However, there is no essential difference between learning and evolution. As with genetic algorithms (GAs), it is also possible to implement selection. Unlike standard GA, fitness function is not given a priori in ABS models. Selection mechanisms may be different for different categories. Firms

[31]In [78], I pointed out five categories: commodities, technology, institutions, economic behaviors, and knowledge. Later, I added two categories: organizations and systems.

are extinguished when they go bankrupt. A behavior pattern will be propagated by a more complex feature depending on experience, rumors, and reputation.

At any rate, ABS and the research agenda of evolutionary economics have much in common. However, the possibilities of ABS do not stop here. The introduction of new rules of conduct may change the mode of movement of an economy, and this changed mode may influence the selection. Then, we should study the *micro-macro loops* that can be observed in the economy.

A micro-macro loop is a kind of "coevolution" between behaviors of the agents and behaviors of the market. However, the term "coevolution" should be better reserved for coevolution between two species or two entities of the same level. The concept of a "micro-macro loop" has been proposed to indicate mutual conditionings between different levels [78]. In sociology, a similar term, "micro-macro link," is used. However, in the latter expression, the evolutionary point of view is rather lacking, and it risks being interpreted as an example of general conditioning between two different levels.

It will be easier to understand this notion with an example [83, Chapter 6]. The daily volatility of the Nikkei index has decreased considerably since around 2004. Many explanations are possible, and it is difficult to determine the main reason that pushed down the volatility. One possible explanation is that the number of Web traders has increased, while transaction costs have decreased. As a consequence, the number of day traders also increased. One of their preferred trade patterns is to place twin orders to sell and buy in the same quantities. Selling prices are set 1 % higher than the opening price of the day, and buying prices are set 1 % lower than the opening price. If both orders are executed, the trader can get 2 % of the margin minus the transaction cost. If the transaction cost is less than 0.5 %, then the trader can get a 1 % profit net of the transaction cost. This kind of trading behavior should have the effect of suppressing the width of daily ups and downs (this is the precise definition of "daily volatility"). It is possible that this has influenced the volatility of the Nikkei index.

However, the story does not stop here. The expected profit rate of the day traders is conditioned by the daily volatility. When the daily volatility exceeds an average of 2 %, the traders' chance of success is rather high. However, if the daily volatility decreases on average to 1 %, the chance that the trader can effectively contract both of the twin orders decreases. If none of the orders is contracted, there is no harm. However, if only one of the twin orders is contracted, the trader is obliged to offer the counter order to keep his or her position neutral. If this is done successfully, the trader should bear a certain loss from the trade. The expected rate of profit for the traders depends sharply on the level of daily volatility. It is possible that the daily volatility will be pressed down such that the expected profit rate nears zero. If this is true, this is a beautiful example of micro-macro loops.

We can observe many different micro-macro loops in the economy. Another example is the micro-macro loop that we can observe between the foreign exchange rate of a country and the country's productivity improvement [25, §6]. Productivity improvement is a result of a change on workers' behavior (labor productivity), production processes, institutional and organizational improvement, and other factors. If the general level of productivity of a country increases, the foreign exchange rate changes, in the long run (probably 4 to 5 years' time), in favor of the country. This means that the real wages of the country have increased and that firms and workers are obliged to improve productivity to maintain competitiveness. Thus, this micro-macro loop generates truly dynamical development. Another example is related to the so-called Japanese mode of management [77, 78].

At a more basic theoretical level, micro-macro loops play an important role. This is observed in the production adjustment process when firms produce according to Sraffa's principle. If firms react to the present demand, the economy-wide adjustment process is normally divergent even if the demand flow is stationary. However, if firms adjust their production based on a demand prediction with a demand average of more than five periods, the economy-wide adjustment process converges to a constant production level that corresponds to the given demand [84].

We can observe many micro-macro loops in economic processes. The typical time structure of micro-macro loops deserves a remark. Each loop has two arrows of causation. One is an effect from micro to macro, and the other is an effect from macro to micro. The first effect is easy to see and instantaneous. The behavior of each agent generates the total process. The second effect is more complicated and depends on an eventual change in the agents' behavior. Thus, this is an evolutionary process. Behavioral evolution requires more time than micro-macro effects. Micro-macro loops are observable when we examine an economic process with a relatively long time span.

Micro-macro loops are an interesting topic in themselves, but they have grave consequences for the methodology of social sciences. Neoclassical economics stands on methodological individualism. Sociology is divided into two stances. One is methodological individualism, and the other is methodological holism. The existence of micro-macro loops signifies that neither methodological individualism nor holism is valid because the actual state is determined as a result of evolutionary development and structured by micro-macro loops. In this sense, micro-macro loops overcome the old dichotomy between methodological individualism and holism. Both of them are insufficient. We must observe micro-macro loops.

Micro-macro loops cannot be clarified by equilibrium analysis. They have not been investigated deeply and analytically because of a lack of appropriate tools. ABS models have the possibility to provide those tools. When they succeed in this task, economics will change enormously.

1.5 Conclusions

Economics is now seriously ill. It needs a fundamental change in its framework. Renovation requires new paradigms in both principles and research methods. ABS, as the third paradigm of scientific research, offers a good chance at the required renovation. As a new mode of research, it has the possibility to change economics as greatly as mathematics changed it in the twentieth century (even if it went in the wrong direction). ABS makes it possible not only to solve present problems more smoothly but also to make new problems possible and tractable. When ABS is developed, we will be liberated from the yoke of the equilibrium framework. Researchers who work on ABS models have a duty to develop them. Building a good ABS model requires a good critical knowledge of economics, a deep understanding of human behavior, and a good knowledge of ABS as the third mode of economic research. This is a heavy burden. This guided tour aims to be helpful for young ABS researchers.

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Chapter 2
Research on ABS and Artificial Market

Hajime Kita

Abstract This chapter gives an overview of the agent-based simulation (ABS) that includes artificial markets (AM), market models based on ABS. First, various methods of computer simulation for social sciences are briefly introduced and the characteristics of ABS are discussed relative to other methods. Next, important issues related to ABS are examined. Gaming simulation, which is based on human subjects, offers an alternative to computer simulation for studying social systems, and hybridization of gaming and ABS are also discussed. Finally, artificial market models are introduced and the characteristics of the U-Mart are clarified.

2.1 Social Simulation

2.1.1 Methods for Social Simulation

Various methods have been developed for computer simulation of social systems. To clarify the characteristics of ABS, this section gives a brief overview of such methods. For more detail, see Gilbert et al. [7].

2.1.1.1 System Dynamics: Models Using Macroscopic Variables

System dynamics is a model that describes the evolution of macroscopic variables with (nonlinear) differential (or difference) equations. A model is constructed as the evolution of state variable $\boldsymbol{x}(t)$. A model in differential equations takes the following form:

$$\frac{d\boldsymbol{x}(t)}{dt} = \boldsymbol{g}(\boldsymbol{x}(t), \boldsymbol{u}(t)) \tag{2.1}$$

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where $\boldsymbol{u}(t)$ is an exogenous factor. A discrete time model fit for computer simulation takes the following difference equation form:

$$\boldsymbol{x}_{t+1} = \boldsymbol{x}_t + \boldsymbol{G}(\boldsymbol{x}_t, \boldsymbol{u}_t) \tag{2.2}$$

State variables $\boldsymbol{x}$ are often considered as stock variables. $\boldsymbol{G}$ can be divided into inbound flow $\boldsymbol{I} \leq 0$ and outbound flow to the stock variables $\boldsymbol{O} \leq 0$, and the above equation can then be rewritten as

$$\boldsymbol{x}_{t+1} = \boldsymbol{x}_t + \boldsymbol{I}(\boldsymbol{x}_t, \boldsymbol{u}_t) - \boldsymbol{O}(\boldsymbol{x}_t, \boldsymbol{u}_t) \tag{2.3}$$

This method is suitable for studying trends in macroscopic social data, such as population. Treating macroscopic values as the state variables ensures that the model remains small, as does the computational load of simulation. However, formulating the model only at the macroscopic value level ignores detail of microscopic behavior such as that of individuals. "The Limit of Growth" by Meadows et al. [9] is a groundbreaking work using the World Model, a system dynamics model. A similar idea is used in models of mathematical ecology, specifically the cohort survival model of population and the SIR model of disease spread.

2.1.1.2 Models Using Microscopic Variables

The previous subsection presents a model that uses macroscopic variables such as population number. Another approach to simulate social systems is to use a model of microscopic variables such as individual behaviors. This category contains several types of models:

Queuing Model: The queuing model, or the discrete event model, is a model of queues. Objects processed by a machine arrive randomly at that machine, resulting in the formation of a queue in which other objects should also be waiting for processing. The machine performs processing of the objects at the head of the queue in a prescribed time. Thus change in the queue is simulated. Connecting these waiting queue models in the form of a network enables the description of complex systems.

Microsimulation: Microsimulation simulates social change at the individual level. For example, in population simulation, initial individuals are set, and life events such as birth, aging, death, etc. occur randomly to each individual with the prescribed probabilities. Population thus is simulated. While microsimulation resembles agent-based simulation, usually individuals in a microsimulation model work independently and interaction among them is not considered.

Cell Automata: Cell automata are another type of model that simulates society at the microscopic variable level. Cells arrayed in line or in two-dimensional grid are elements of the model. Given initial states and state transition rules, the state of each cell changes depending on the states of surrounding cells.

Agent-Based Simulation: Agent-based simulation (ABS) uses a more complicated individual model. Individuals, or agents, are constructed as software agents. They interact with other agents and the external environment via a social interaction model. Hence ABS can be applied to complex social interactions and agents' behaviors. ABS is further discussed in the next section.

2.1.2 Research with Simulation

Research using simulation differs methodologically from research using other methods such as theoretical analysis using mathematics. Research using simulation consists of the following steps

1. Model construction
2. Implementation as a simulator
3. Parameter selection
4. Verification and validation of the model/simulator
5. Conducting simulation runs
6. Data analysis of the simulation results
7. Discussion using the analysis

Model construction, simulator implementation, and execution of simulation runs are central issues in simulation-based research. However, other steps are also important and may be more time-consuming. The above process may be applied repetitively for model revision to obtain satisfactory results.

Simulators of the agent-based model become rather complex, and implementation of the simulator and related tools for parameter selection is challenging, as in the visualization of the results. To provide the simulation environment, several simulation platforms are proposed. Some are general purpose simulators, while others are platforms for specific domains.

2.2 Agent-Based Simulation

2.2.1 Structure of the Agent-Based Models

The agent-based model for social simulation comprises two parts, as shown in Fig. 2.1, i.e., a set of software agents and a social interaction model in which agents interact with each other and the environment.

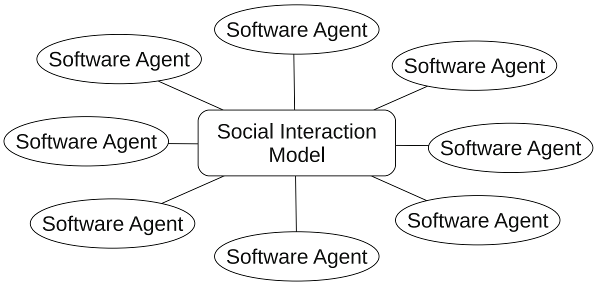

Fig. 2.1 Structure of an agent-based model

2.2.1.1 Implementation Issues of Agent

Rationality such as optimization of a utility function is a key concept in constructing mathematical theory in social sciences, and there exists criticism that bounded rationality should be considered. While theoretical study on bounded rationality may be difficult, ABS enables study assuming agent-bounded rationality. The following are typical agent constructions:

Routine Agents: Routine is a fixed behavior adopted by humans in a particular situation. To construct agents that adopt a routine observed from real situations is one approach adopted in ABS to the bounded rationality. If the routine is sufficiently clear, it can be described as a computer program. ABS allows the discussion of social system behavior even when mathematical analysis is difficult.

Learning Agents: Another alternative of the modeling agent of bounded rationality is considering learning. That is, an agent or a population of agents changes its behavior through its experiences. Various techniques, such as neural networks, classifier systems, fuzzy logic, and genetic algorithms, developed in artificial intelligence [10] can be used. However, human learning behavior is complex, and large differences exist between human learning and the learning of software agents using AI techniques.

2.2.1.2 Interaction Structure of Agents

As for social interaction among agents, several structures are used. As shown in Fig. 2.2a, an array of agents in a two-dimensional grid is often used. If agents are assumed to be distributed geographically and to interact with surrounding agents, this model is a natural implementation [5, 11]. Furthermore, an array of agents in a two-dimensional grid is easy to visualize on a computer display. However, the relationship among agents in the society is not limited to such structures, and it may be dangerous to utilize the gird structure without consideration of actual relationships among agents. As for the market, it has a simpler star structure as

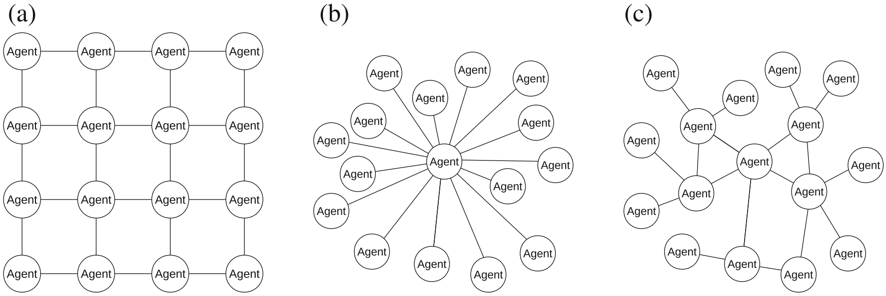

Fig. 2.2 Interaction structure of agents. (**a**) Grid. (**b**) Star. (**c**) Network

shown in Fig. 2.2b. That is, there exists a central agent that plays the role of the exchange market, and all other agents that trade in the market are connected only to the central agent. Generally, social interaction can be modeled in a network as shown in Fig. 2.2c, and social behavior depends largely on network characteristics [4].

2.2.2 Simulator Granularity

Simulator granularity[1] is also an important issue related to social simulation purpose. Gilbert categorizes simulators into the following three types [6]:

Abstract Models: The abstract model is rather simple and is used to study fundamental characteristics of social systems widely applicable to various situations. Hence, the abstract model relates to theoretical analysis of mathematical models rather than actual cases. These purposes require that the model be as simple as possible. This is known as the “keep it simple, stupid (KISS)” principle and was first advocated by Axelrod who conducted pioneering work on the iterated prisoner’s dilemma [2, 3].

Middle Range Models: Models in this category are structurally more complicated than the abstract model. Such models are designed to study specific situations of social systems. However, the study with the model is focused on qualitative study such as the reproduction of stylized facts rather than quantitative ones.

Facsimile Models: Models in this category aim to study actual social systems in more detail and quantitatively. For example, the evaluation of actual social policies requires models of this type because trade-offs may exist among evaluation criteria and implementation constraints.

[1] In Chap. 3, a similar characteristic of a simulator is expressed by the word ‘fidelity’.

2.3 Hybridization with Gaming

Gaming simulation is also an important tool for education and research in social sciences. In gaming simulation, a social issue of interest is designed as a game and is studied through observation of how human subjects play the game. Compared with experimental economics or experimental psychology which sets up a simplified situation to confirm a hypothesis regarding human behavior, games designed for gaming simulation are rather complex and designed to study social situations through game playing. Conventionally, simulation games are designed using boards and cards, but games mediated by computer are also a promising approach. Figure 2.3a shows the gaming structure.

Comparing the structure of ABS shown in Fig. 2.1 with that of gaming shown in Fig 2.3a reveals a structural similarity between ABS and gaming simulation. By substituting "software agents" with "human players" and attaching an appropriate user interface connecting the social interaction model on the computer with human player, ABS can be easily converted to a gaming simulation. Furthermore, we can also conduct a simulation played by both software agents and human players as shown in Fig. 2.3b. That is, a hybridization of ABS and gaming simulation.

While ABS and gaming share structural similarity, they have complementary study characteristics. As for the quality of experiments, experiments based on gaming strongly exploit human abilities and remain difficult for software agents to implement in advance. Experiments using gaming simulation provide suggestions about key factors of human behaviors in particular situations which in turn are modeled as software agents for ABS. Another point is experiment cost. Since gaming simulation uses human players, it is expensive to perform, and it is not realistic to conduct numerous simulation runs or simulations involving large numbers of players. In contrast, simulation by the agent-based approach is limited only by computational power, and large-scale simulation and multiple runs are permitted only under conditions of availability of machines and time.

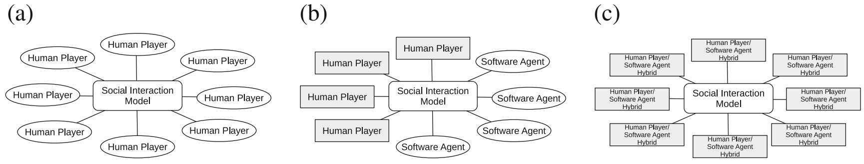

Fig. 2.3 Hybridization of ABS and gaming. (**a**) Gaming. (**b**) ABS-gaming hybrid. (c) Hybrid players

Furthermore, players themselves can be mixed, as shown in Fig. 2.3c. That is:

- Humans play the game with the assistance of software agents that monitor the situation and give adequate information to allow understanding by humans.
- Human players supervise playing software agents. That is, the human player monitors the play of his/her agents and then tunes the parameters of the agent to fit the changed situation.

2.4 Characteristics of U-Mart as an Agent-Based Simulation Model

In actual markets, particularly financial markets such as stock markets and currency markets, we observe complex dynamic price behaviors such as the inflation and collapse of price "bubbles." Such behaviors mean markets display anything but a static picture of equilibrium. Market prices are decided through interaction among many sellers and buyers who observe the market itself, and therefore are an emergent phenomenon. Furthermore, actual markets involve various institutional mechanisms that serve as stabilization function and allow rapid price finding in response to changes in the social situation relating to markets.

Because of the emergent nature of markets, agent-based simulation is an important research method for studying them [1, 8] and is particularly called "artificial markets." Most artificial market models are focused on studying the fundamental dynamics of market prices and can be classified as "abstract models" or "middle-range models" in terms of their granularity. However, among such artificial market models, the U-Mart has the following unique characteristics:

- U-Mart has been developed to study the institutional design of financial markets. U-Mart considers various institutional factors of markets in detail, and in terms of granularity is a facsimile model.
- From the beginning, U-Mart has considered hybridization of agent-based simulation and gaming simulation. It helps people understand complex institutional matters of financial markets through both playing and reading documentation. Further, in "The Zaraba-based U-Mart System" introduced in Chap. 3, we provide human players with rich information through trading terminal software. It is a good example of the "hybrid player" discussed in the previous section.
- U-Mart aims not only to be used by the authors but also to serve as an open platform of agent-based study of markets by other researchers. While U-Mart has client-server architecture to support both agent-based simulation and gaming simulation, its design is based on considerations of portability and usability so as to allow easy handling by researchers in both social sciences and computer science.

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Chapter 3
Building Artificial Markets for Evaluating Market Institutions and Trading Strategies

Isao Ono and Hiroshi Sato

Abstract This chapter[1] focuses on building artificial market simulators based on the agent-based modeling approach for evaluating market institutions and trading strategies. Artificial market simulators for evaluating market institutions and trading strategies should meet the following five requirements: (1) high fidelity, (2) high transparency, (3) high reproducibility, (4) high traceability, and (5) high usability. In this chapter, we introduce two types of artificial market simulators that meet the five requirements well, namely, the Itayose U-Mart system (U-Mart system Ver.2) and the Zaraba-based U-Mart system (U-Mart system Ver.4). We also explain how to develop trading agent programs for the Itayose U-Mart system and the Zaraba-based U-Mart system. Furthermore, we show simple experiments and what we can do using the Zaraba-based U-Mart system.

3.1 The Fidelity of Models: From KISS Principle to High-Fidelity Models

In this section, we discuss the fidelity of models which is one of the most important issues when we build computer simulation models. We often build a computer simulation model of a phenomenon in order to understand it. Especially in computer simulation models, the degree of model fidelity is very important because they have a high degree of freedom.

Generally, low-fidelity models are utilized in the field of science, while high-fidelity ones are employed in the field of engineering, which means that models

[1]The contents of this chapter are based on [4].

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in the field of science are simpler than those in the field of engineering. In the field of science, it is important to capture the nature of a phenomenon. In this context, it is desirable to make a computer simulation model as simple as possible under the criterion that the model can reproduce the phenomenon because such a model reveals the essence of the mechanism causing the phenomenon. On the other hand, in the field of engineering, computer simulation models are used for realistic decision-making. Computer simulation models for engineering should be of high fidelity so that the models take into consideration decision variables to be designed and their effects. Computer simulation models for engineering should be applied to domains where experiments with prototype models in the real world are difficult to perform because the experiments are expensive, dangerous, or unethical. The complexity of a computer simulation model should be realistically computable.

In the domain of addressing physical phenomena, the computer simulation has been an absolutely essential tool for not only science but also engineering. Physical phenomena are easy to model because they are governed by primitive equations. However, precise models are not realistic in terms of computability. Before computer simulation models for engineering are put to practical use in the domain where physical phenomena are addressed, there have been various innovations such as developing high-speed and high-capacity computers; improving methods of modeling, numerical calculation, and visualization; and inventing highly developed methods of experiment and observation for validating the computer simulation models. A typical example is a simulation of global warming. Recently, the effect of human activity related to changes in atmospheric temperature in the future has become predictable by computer simulations [3].

In the domain of treating social phenomena, the KISS (keep it simple, stupid) principle [1] has been proposed as a guideline for building computer simulation models for science. As shown in Fig. 3.1 by ensuring that there is always a link to mathematical analysis, computer simulation models for science should provide some results that cannot be obtained by mathematical analysis. Recently, building high-fidelity computer simulation models for engineering in the domain of social simulations is becoming important, aiming at seeking suggestions for realistic institutions. Needless to say, it is very difficult to build computer simulation models for engineering in the domain of social simulations for the following reasons: (1) we do not have primitive equations, (2) modeling societies and humans is difficult, (3) it is difficult to construct experimental systems in the real world, and (4) available practical data is limited. As shown in Fig. 3.1, computer simulation models for engineering have a connection to experiments by prototype models in the real world.

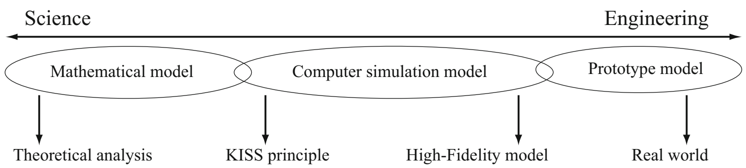


Fig. 3.1 The KISS principle and high-fidelity models

3.2 Requirements for Artificial Market Simulators for Evaluating Market Institutions and Trading Strategies

This section presents five design requirements which we consider when we build artificial market simulators for evaluating market institutions and trading strategies. The five requirements are as follows:

- **High Fidelity**
  As discussed in the previous section, an artificial market system should have high fidelity in order to evaluate various institutions and trading algorithms. In order to achieve high fidelity, the following conditions should be considered:

  1. All the market institutions in a real market can be built into the system.
  2. Market institutions should be duplicated precisely.
  3. The effects when system parameters are being changed in the market can be examined.
  4. Phenomena that occurred in real markets can be reproduced accurately.

- **High Transparency**
  Machine agents and human agents should be able to participate in the market under the same conditions at the same time for two purposes. One is to analyze human trading behaviors and make machine agents that behave like human agents, which is important for fidelity. The other is to compare the results obtained by experiments using only machine agents with those using human agents in order to verify the validity of the experiments using only machine agents.
- **High Reproducibility**
  The same results should be obtained if the experiments are performed under the same conditions with the same random seeds.
- **High Traceability**
  All the internal states of agents and a market should be stored in files in order to reconstruct and understand what happens in the market at arbitrary times.
- **High Usability**
  It should be easy for computer novices to install, configure, and manage the system, which is an important factor in enabling various kinds of users in the economics field to make full use of the system.

3.3 Itayose U-Mart System (U-Mart System Ver.2)

The Itayose U-Mart system is an order-driven artificial market that adopts the batch auction method, which is called Itayose in Japanese. Figure 3.2 shows the structure of the Itayose U-Mart system. This system is a model of a single exchange managing

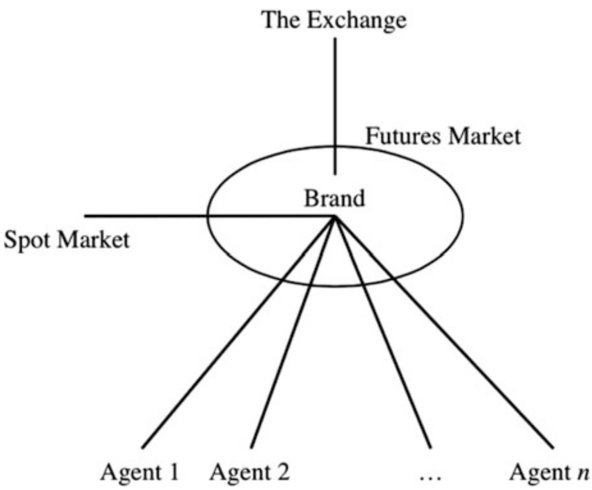


Fig. 3.2 The structure of the Itayose U-Mart system

a single futures market of a single brand. This system deals with a single brand. Agents trade a virtual futures index of an existing spot index which is traded outside of the system such as Nikkei 225 and S&P 500. The futures prices in the virtual market emerge as the results of interactions among trader agents. Human agents as well as machine agents can participate in the market via the network at the same time.

3.3.1 System Configuration

Figure 3.3 shows the configuration diagram of the system. The system is designed as a client-server model. It consists of the market server and the human agent trading terminal.

The market server is modeled on a stock exchange in the real world. It is responsible for order control, account management, contract process, and so on. The market server comprises multiple modules as shown in Fig. 3.3. The reproducibility is achieved by executing agent programs synchronously within the market server. The following information gives a detailed description of the time management, the transaction method, and the GUI tools of the Itayose U-Mart system.

3.3.1.1 Time Management in the Itayose U-Mart System

The time in the Itayose U-Mart system is represented by day and session. A day consists of several sessions and post-trading period. Figure 3.4 is an example of the schedule of the Itayose U-Mart system. The schedule has six sessions per day. During trading period, the exchange of the Itayose U-Mart system accepts orders

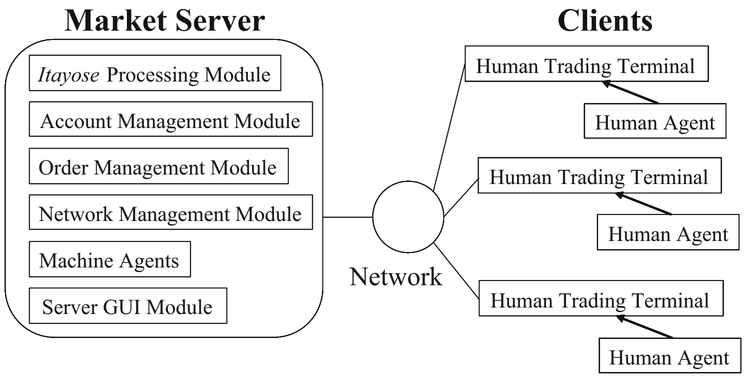


Fig. 3.3 The configuration diagram of the Itayose U-Mart system

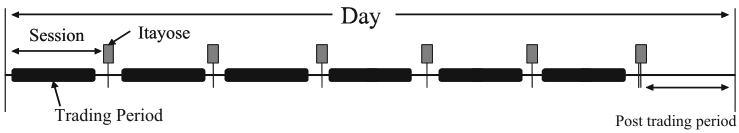


Fig. 3.4 An example of the schedule of the Itayose U-Mart system

from traders. At the end of every session, the contract price is determined by the Itayose method. Mark to market is done daily in post-trading period. Settlement is done using the spot price at the due date.

3.3.1.2 The Transaction Method in the Itayose U-Mart System

Itayose is a trading method in which all buy and sell orders are compared and a price is determined so that the number of executed orders is the maximum as shown in Fig. 3.5. The priority of the orders is as follows:

1. **Order-type priority**
   Market orders have priority over limit orders. A limit order is an order to buy/sell at no more/less than a specific price. A market order is an order to be executed at the current market price.
2. **Price priority**
   A sell/buy limit order at a lower/higher price has a higher priority. If there are many orders indicating the same price, the rule of time priority is applied.
3. **Time priority**
   If two orders indicate the same price, the older one has a higher priority than the newer one. If these two orders are placed in the same session, the priority is determined randomly.

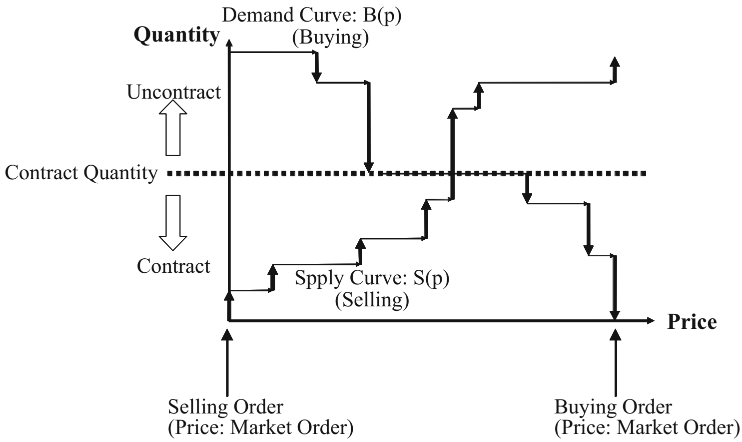


Fig. 3.5 Itayose trading method

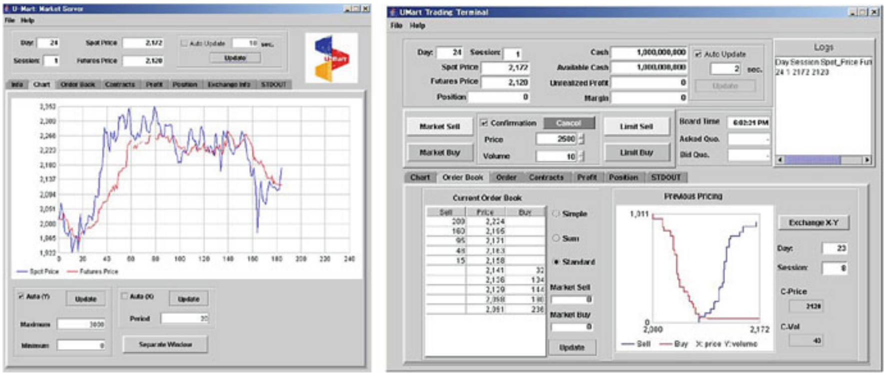


Fig. 3.6 Screenshots of the Itayose U-Mart system (*Left*, server; *Right*, client)

3.3.1.3 GUI Tools of the Itayose U-Mart System

The left figure in Fig. 3.6 shows the GUI (graphical user interface) of the market server. The screenshot on the right in Fig. 3.6 shows the GUI of the human agent trading terminal. The human agent trading terminal is a GUI program that is used by a human in order to participate in trade over the network. In terms of transparency, the GUI program is designed to provide an intuitive and easy-to-use environment.

3.3.2 Implementation of Itayose Market Server

In this section, we introduce the internal structure of the Itayose market server designed by object-oriented modeling (OOM) [5]. The system is implemented in Java which is an object-oriented programming language. Java has many features: it runs on multiple platforms, such as Windows, Linux, and Mac, it supports easy-to-use parallel processing and networking, and it provides various class libraries, such as GUI libraries. The core system of the Itayose market server, except the GUI system, consists of about 150 classes.

Figure 3.7 is the overview of the Itayose market server in UML class diagram [2]. As shown in Fig. 3.7, the UMart class, UMartNetwork class, and UServerManager class play central roles. The UMart class manages the whole stock exchange and is the parent class of the UMartNetwork class. The UMartNetwork class is for the network environment. The UServerManager class provides a start-up mechanism of the Itayose market server. The UMart class has the UServerStatus class, the UReadWriteLock class, the UCmdExecutableChecker class, classes for managing accounts, classes for managing orders and contracts, classes for managing local machine agents, and classes for managing data and logs. The UServerStatus class manages date, session, and the server status. The UReadWriteLock class prevents the server status from being disrupted by processes running in parallel. The UCmdExecutableChecker class examines whether or not a command from an agent can be executed under the current server status. The classes for managing accounts are shown in Fig. 3.8. The classes for managing orders and contracts are shown in Fig. 3.9. The classes for managing local machine agents are shown in Fig. 3.10. The classes for managing data and logs are shown in Fig. 3.11. The UMartNetwork class has classes for managing network clients shown in Fig. 3.12.

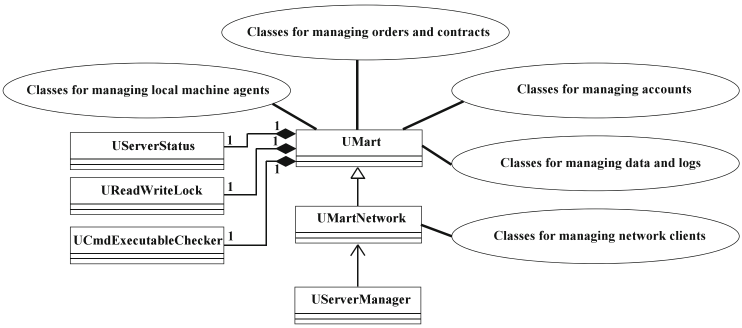


Fig. 3.7 An overview of the Itayose market server

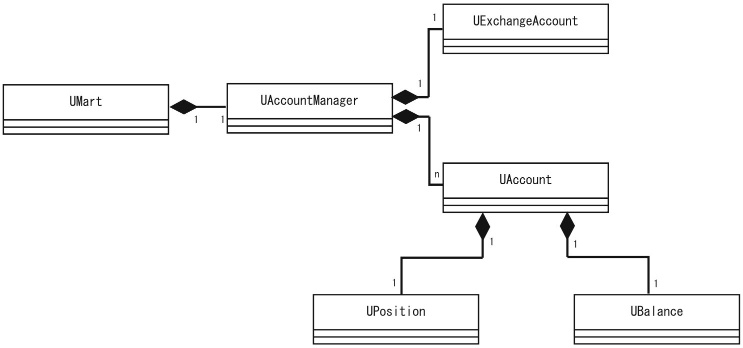


Fig. 3.8 Classes for managing accounts in the Itayose market server

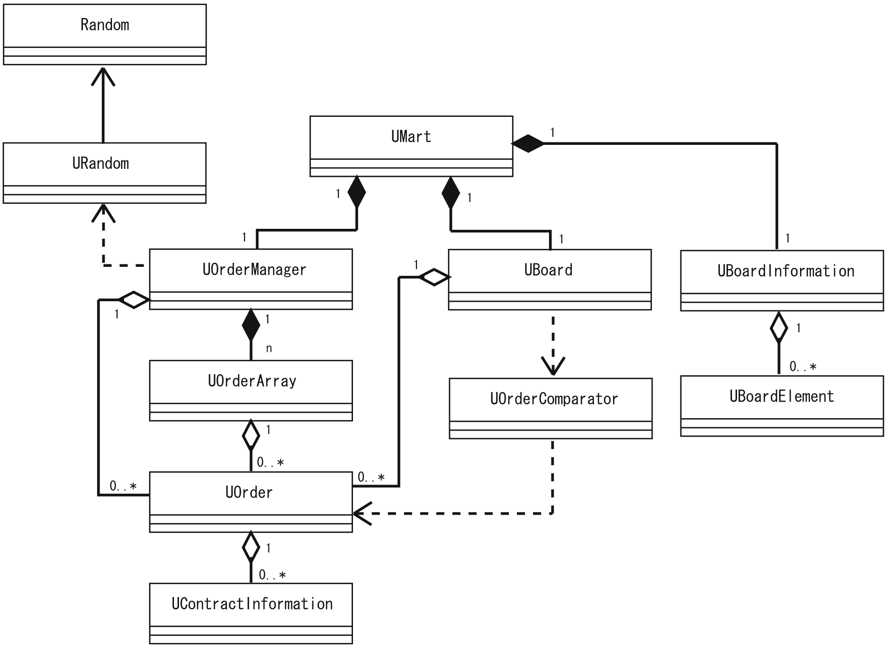


Fig. 3.9 Classes for managing orders and contracts in the Itayose market server

3.3.3 How to Develop Trading Agents for Itayose U-Mart System

This section provides information necessary to design trading strategies for the Itayose U-Mart system. The Itayose U-Mart system is designed by object orientation and implemented by Java programming language. For this reason, it is necessary to understand the basic concept of object orientation and Java programming language

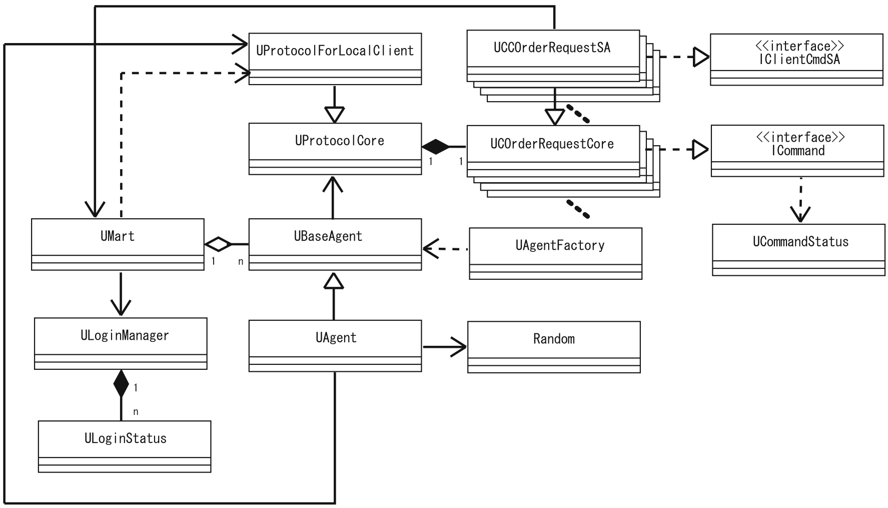


Fig. 3.10 Classes for managing local machine agents in the Itayose market server

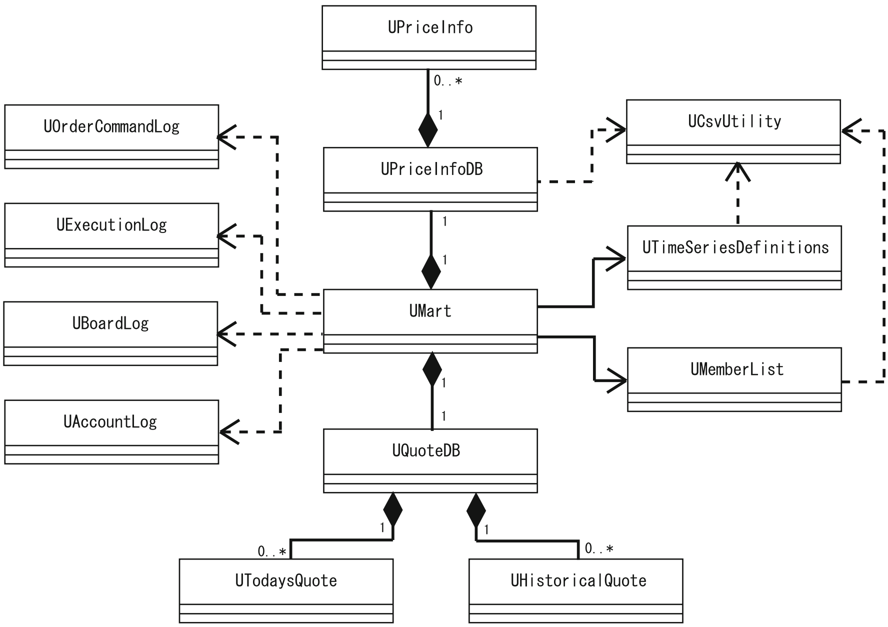


Fig. 3.11 Classes for managing data and logs in the Itayose market server

before making programs of trading agents for the Itayose U-Mart system. However, it is possible to design trading strategies without the knowledge of object orientation and Java programming language.

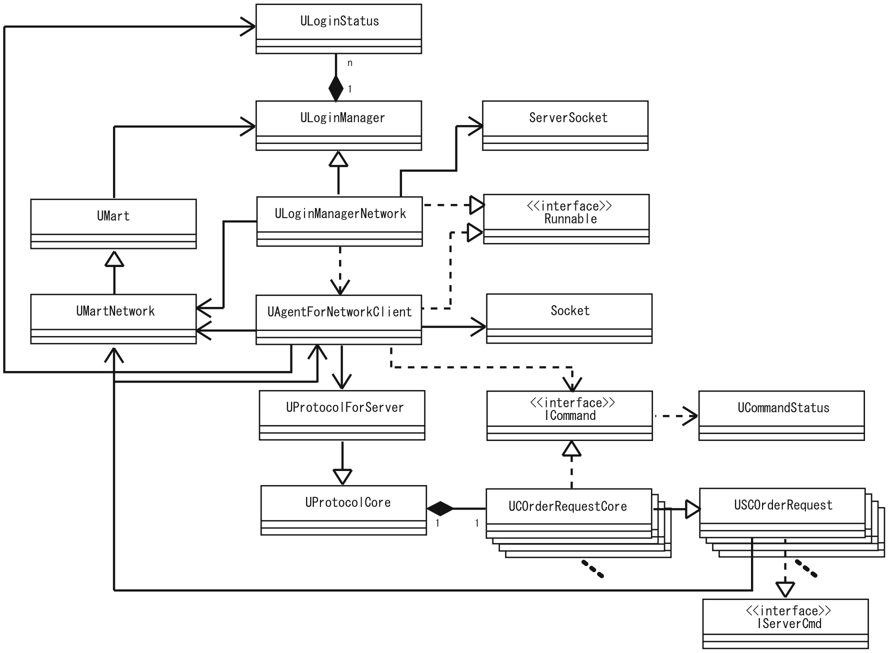


Fig. 3.12 Classes for managing network clients in the Itayose market server

At the start of each session, an agent receives the following observation from the exchange:

- The current date
- The current session
- The transaction period
- The number of sessions per day
- The past spot price series
- The past futures price series
- The current position
- The current cash balance

Then, the agent decides whether or not it makes orders according to its trading strategy and the observation from the exchange. If the agent places orders, the agent determines if the orders are buy or sell and limit or market. If the orders are limit orders, the order prices also have to be specified. The order volumes also have to be determined. Finally, the agent makes order forms according to its decision and submits them to the exchange. The agent can cancel its orders before they are contracted. The Itayose U-Mart system provides some typical and simple trading agents called the standard agent set. The standard agent set includes the following agents:

- **RandomStrategy**
  The RandomStrategy agent chooses sell or buy randomly. It randomly determines the order price according to a normal distribution with a mean value of the latest futures price and a standard deviation given by a user in advance. It randomly chooses the order volume between the user-defined ranges. If the absolute value of the position is expected to get larger than a user-defined threshold by the order, no action is taken.
- **SRandomStrategy**
  The SRandomStrategy agent chooses sell or buy randomly. It randomly determines the order price according to a normal distribution with a mean value of the latest spot price and a standard deviation given by a user in advance. It randomly chooses the order volume between the user-defined ranges. If the absolute value of the position is expected to get larger than a user-defined threshold by the order, no action is taken. The difference between RandomStrategy and SRandomStrategy is its reference price.
- **TrendStrategy**
  The TrendStrategy agent makes a buy (sell) order if the previous futures price is higher (lower) than the futures price in the previous two sessions. It randomly determines the order price according to a normal distribution with a mean value of the latest futures price and a standard deviation given by a user in advance. It randomly chooses the order volume between the user-defined ranges. If the absolute value of the position is expected to get larger than a user-defined threshold by the order, no action is taken.
- **AntiTrendStrategy**
  The AntiTrendStrategy agent makes a buy (sell) order if the previous futures price is lower (higher) than the futures price in the previous two sessions. It randomly determines the order price according to a normal distribution with a mean value of the latest futures price and a standard deviation given by a user in advance. It randomly chooses the order volume between the user-defined ranges. If the absolute value of the position is expected to get larger than a user-defined threshold by the order, no action is taken.
- **MovingAverageStrategy**
  The MovingAverageStrategy agent places orders when the short-term moving average line and the midterm moving average line have intersections. If the short-term moving average tends to go up (down), it buys (sells) at a price that is according to a normal distribution with a mean and a standard deviation. The mean is the latest futures price plus (minus) a user-defined value. The standard deviation is a user-defined value divided by four. It randomly chooses an order volume between the ranges given by a user. If the position is expected to get larger than a user-defined threshold by the order, no action is taken.

- **RsiStrategy**
  The RsiStrategy agent makes decisions by using the relative strength index (RSI) of the futures price series. RSI is a famous method of technical analysis. It randomly determines the order price according to a normal distribution with a mean value of the latest futures price and a standard deviation given by a user in advance. It randomly chooses the order volume between the user-defined ranges. If the absolute value of the position is expected to get larger than a user-defined threshold by the order, no action is taken.
- **SRsiStrategy**
  The SRsiStrategy agent makes decisions by using the relative strength index (RSI) of the spot price series. RSI is a famous method of technical analysis. It randomly determines the order price according to a normal distribution with a mean value of the latest spot price and a standard deviation given by a user in advance. It randomly chooses the order volume between the user-defined ranges. If the absolute value of the position is expected to get larger than a user-defined threshold by the order, no action is taken.
- **DayTradeStrategy**
  The DayTradeStrategy agent places a sell order and a buy order at the same time. The sell order is put at a price which is a little higher than the latest futures price. The buy order is put at a price which is a little lower than the latest futures price. It randomly chooses the order volume between the ranges given by a user. If the position is expected to get larger than a user-defined threshold by the order, no action is taken.

A user can make an original agent program by designing a trading strategy and implementing it by Java programming language. The user can register the original agent program to the Itayose U-Mart system and run it with the standard agent set.

3.3.4 Features and Problems of the Itayose U-Mart System

This section summarizes the features and the problems of the Itayose U-Mart system in terms of the requirements discussed in Sect. 3.2.

The features of the Itayose U-Mart system are as follows:

1. **Fidelity**
   In the market of the Itayose U-Mart system, futures of the existing stock index are traded. The price of the futures in this virtual market emerges as a result of interaction among agents while maintaining a relationship to the real-world market. The Itayose U-Mart system introduces several factors taken from the real markets: Itayose is used as a pricing scheme and a closing out position is used as settlement.
2. **Transparency**
   The Itayose U-Mart system is implemented so that machine agents and humans can participate in the market equally. SVMP (Simple Virtual Market

Protocol) is defined as an interaction protocol between the market server and the clients. The GUI of the human agent trading terminal is designed to be used easily because it is important for humans not to have any difficulty in trading operations.

3. **Reproducibility**
   Time in the Itayose U-Mart system is discretized. Orders that are placed in the same session have the same priority.
4. **Traceability**
   All the information of the order book and the requests of order/cancel/change are saved in log files. The log files are provided in CSV format for convenience to economists.
5. **Usability**
   The Itayose U-Mart system needs only the Java runtime environment. The GUI of the market server is also designed for ease of use.

The problems of the Itayose U-Mart system are as follows:

1. **Fidelity**
   The Itayose U-Mart system has three problems in terms of fidelity. Firstly, the pricing method used in the Itayose U-Mart system is different from that employed in most stock exchange markets in the real world. Secondly, the Itayose U-Mart system does not support market institutions for preventing prices from jumping up and down such as circuit breakers and the daily limit of the price. Thirdly, the Itayose U-Mart system does not support multiple brands.
2. **Usability**
   The GUI of the trading terminal of the Itayose U-Mart system does not provide rich information such as technical indicators for users to make decision easily and quickly.

3.4 Zaraba-Based U-Mart System (U-Mart System Ver.4)

This section introduces the Zaraba-based U-Mart system (U-Mart System Ver.4). The Zaraba-based U-Mart system has been developed to remedy the four problems of the Itayose U-Mart system pointed out in Sect. 3.3.4. Firstly, the Zaraba-based U-Mart system supports the continuous double auction method, which is called the Zaraba method in Japanese, in addition to the Itayose method as pricing methods. The Zaraba method is adopted in almost all the money markets in the world including the Tokyo Stock Exchange (TSE) [6]. Secondly, various institutions can be easily investigated in the Zaraba-based U-Mart system. Users not only can use predefined institutions for preventing prices from jumping up and down which are adopted in TSE but also can define original institutions to investigate their effect. Thirdly, the Zaraba-based U-Mart system supports spot and/or futures market(s) of multiple brands. Agents can trade not only futures but also spot of multiple brands in the Zaraba-based U-Mart system, while they can trade only futures of a single brand

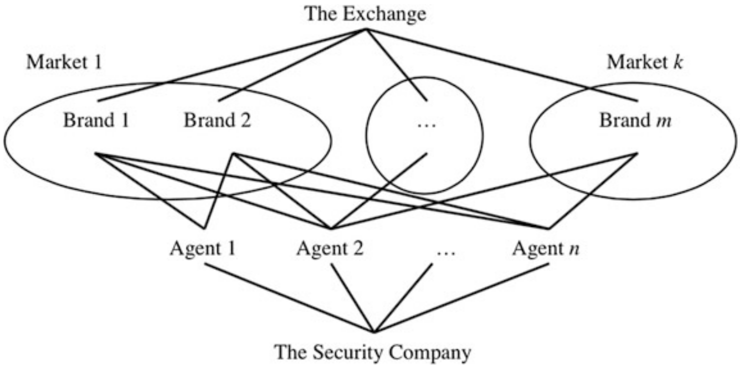


Fig. 3.13 The structure of the Zaraba-based U-Mart system

in the Itayose U-Mart system. This enables users to investigate correlation of spot and futures prices of multiple brands. Fourthly, the Zaraba-based U-Mart system provides a new easy-to-use trading terminal for human agents. The new trading terminal provides user rich information such as technical indicators. This enables users to make decisions easily and quickly. Figure 3.13 shows the structure of the Zaraba-based U-Mart system.

3.4.1 System Configuration

Figure 3.14 shows the configuration diagram of the system. The Zaraba-based U-Mart system consists of the market server and the human agent trading terminal as well as the Itayose U-Mart system. The market server comprises multiple modules as shown in Fig. 3.14. Each module in the Zaraba-based U-Mart system has been modified significantly from the Itayose U-Mart system because the time management system is different from that of the Itayose U-Mart system. The parts that differ most are the time management, the transaction method, and the GUI tools. The following are the descriptions of these three differences.

3.4.1.1 Time Management in the Zaraba-Based U-Mart System

Time management of the Zaraba-based U-Mart system is done by day, session, and unit time (*ut*). One *ut* is the minimum unit of time in the Zaraba-based U-Mart system. Figure 3.15 is an example of the schedule of the Zaraba-based U-Mart system. Opening and closing prices are determined by the Itayose method and other prices by the Zaraba method as done in the TSE. The reproducibility is realized by executing agent programs synchronously within the market server.

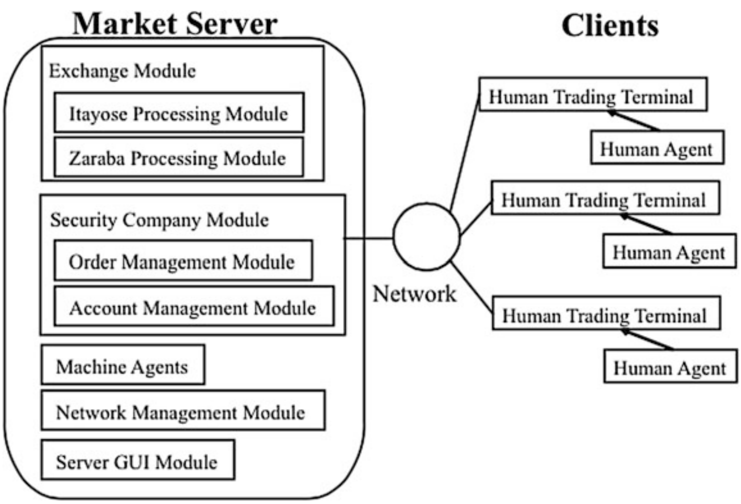


Fig. 3.14 The configuration diagram of the Zaraba-based U-Mart system

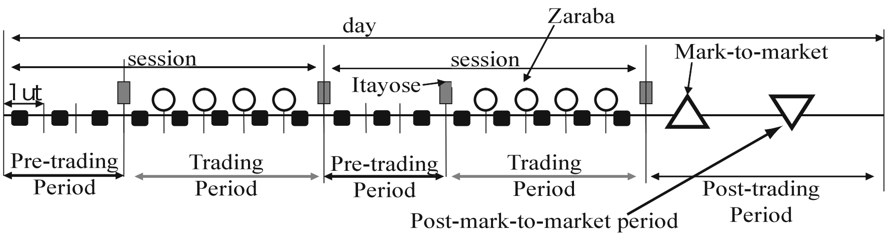


Fig. 3.15 An example of the schedule of the Zaraba-based U-Mart system

3.4.1.2 The Transaction Method in the Zaraba-Based U-Mart System

The schematic diagram of the transaction process in the Zaraba-based U-Mart system is shown in Fig. 3.16. As shown in Fig. 3.16, market institutions such as the circuit breaker and the price limitation are checked twice per transaction, which allows the Zaraba-based U-Mart system to simulate various markets in the real world. The following is the explanation of the transaction process in the Zaraba-based U-Mart system:

1. Pre-checking Market Institutions: Check whether each market institution should be followed or not. If a market institution should be followed, follow the institution.
2. Temporal Contract: Make contracts temporarily.
3. Checking Market Institutions: Check whether each market institution should be followed or not. If a market institution should be followed, discard the contracts and go to step 5.
4. Contract: Make contracts.
5. Output of the Contracts: Output the contracts.

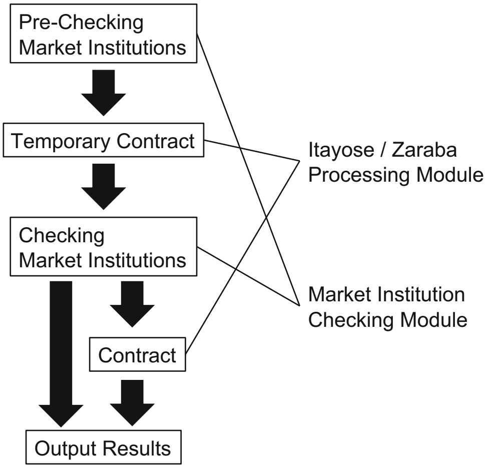


Fig. 3.16 The transaction process in the Zaraba-based U-Mart system

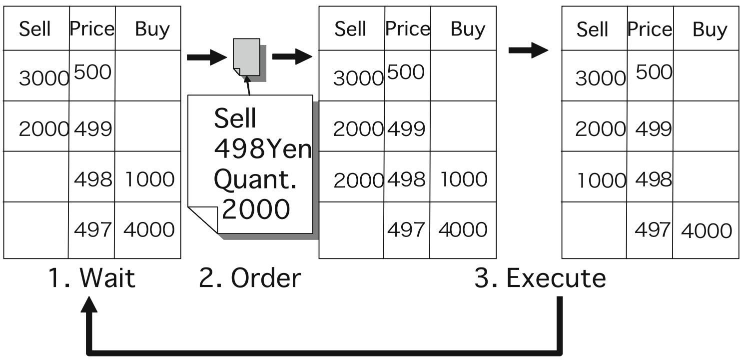


Fig. 3.17 The Zaraba trading method

Zaraba is a trading method in which a new order is matched with existing orders and a price is determined by auction-like process as shown in Fig. 3.17. The priority of the orders is as follows:

1. **Order-type priority**
   Market orders have priority over limit orders. A limit order is an order to buy/sell at no more/less than a specific price. A market order is an order to be executed at the current market price.
2. **Price priority**
   A sell/buy limit order at a lower/higher price has a higher priority. If there are many orders indicating the same price, the rule of time priority is applied.
3. **Time priority**
   If two orders indicate the same price, the older one has a higher priority than the newer one. If these two orders are placed in the same session, the priority is determined randomly.

In the Zaraba trading method, there are two kinds of additional parameters which are not employed in the Itayose trading method:

- **Tick size**
  A tick size is the smallest increment in price. Tick size is an increment by which prices move. Table 3.1 shows the tick sizes in the TSE. There are large differences among tick sizes, while no theoretical evidence is provided. Tick size would have a big effect on price determination. Therefore, analysis and evaluation are needed.
- **Quote parameters**
  Quote parameters define the range of price fluctuation. The next execution price must be within some range around the most recently executed price. Table 3.2 shows the quote parameters of the TSE. There are large differences among quote parameters, while no theoretical evidence is provided. Quote parameters would have a big effect on price determination. Therefore, analysis and evaluation are needed.

Table 3.1 Tick size in Tokyo Stock Exchange [2]

Price (JPY)	Tick size (JPY)	Change rate (%)
0–2,000	1	0.05
2,000–3,000	5	0.166
3,000–30,000	10	0.333
30,000–50,000	50	0.01
50,000–100,000	100	0.01
100,000–1,000,000	1,000	0.01
1,000,000–20,000,000	10,000	0.05
20,000,000–30,000,000	50,000	0.166
30,000,000–	100,000	0.333

Table 3.2 Quote parameters in Tokyo Stock Exchange [2]

Price (JPY)	Quote parameters (JPY)	Change rate (%)
0–499	5	1.00
500–999	10	1.00
1,000–1,499	20	1.33
1,500–1,999	30	1.50
2,000–2,999	40	1.33
3,000–4,999	50	1.00
5,000–9,999	100	1.00
10,000–19,999	200	1.00
20,000–29,999	300	1.00
30,000–49,999	400	0.80
50,000–69,999	500	0.70
70,000–99,999	1,000	1.00

[2]The current regulation of TSE has been changed from this setting.

Fig. 3.18 Screenshots of the Zaraba-based U-Mart system (*Left*, server; *Right*, client)

3.4.1.3 GUI Tools of the Zaraba-Based U-Mart System

Figure 3.18 shows the GUI of the market server and the human agent trading terminal, respectively. The human agent trading terminal is a GUI program that is used by a human in order to take part in trade over the network. In terms of transparency, the GUI program is designed in order to provide an intuitive and easy-to-use environment. The new trading terminal provides user rich information such as technical indicators. This enables users to make decision easily and quickly.

3.4.2 Implementation of Zaraba Market Server

The Zaraba-based U-Mart system has been developed based on OOM as well as the Itayose U-Mart system. In this section, we introduce the internal structure of the Zaraba market system designed by OOM. The complete system of the Zaraba market system consists of about 300 classes.

3.4.2.1 The Exchange Module

The Zaraba-based U-Mart system can handle multiple brands by managing multiple transaction modules. This system has a database which contains the public information of all brands from which it retrieves the information. This enables users to perform various experiments because the system can calculate new indices based on prices stored in the database to provide users the indices. Figure 3.19 is the class chart of the exchange module of the Zaraba market system.

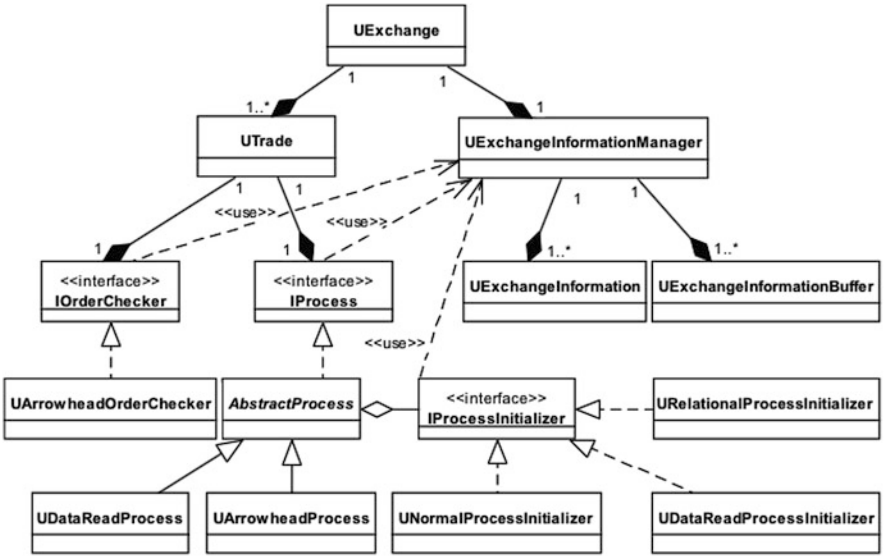


Fig. 3.19 An overview of the exchange module of the Zaraba-based U-Mart system

The following is a brief explanation of the classes in Fig. 3.19:

- **UExchange**: This class controls the market.
- **UTrade**: This class controls the transaction process.
- **IProcess**: This interface defines a transaction module.
- **AbstractProcess**: This abstract class defines a general transaction process.
- **UArrowheadProcess**: This class simulates the transaction process of TSE.
- **UDataReadProcess**: This class provides the real transaction data from outside of the system.
- **IOrderChecker**: This interface defines the acceptance judgment of orders used in a transaction module.
- **UArrowheadOrderChecker**: This class checks whether an order should be accepted or not in UArrowheadProcess.
- **IProcessInitializer**: This interface initializes a transaction module.
- **UNormalProcessInitializer**: This class initializes a general transaction module.
- **URelationProcessInitializer**: This class initializes a transaction module based on the information of relevant brands.
- **UDataReadProcessInitializer**: This class initializes UDataReadProcess.
- **UExchangeInformationManager**: This class manages the information of each transaction module.

- **UExchangeInformation**: This class contains the information of each transaction module.
- **UExchangeInformationBuffer**: This class works as temporal memory for updating the exchange information.

3.4.2.2 The Security Company Module

As mentioned above, the Zaraba-based U-Mart system can handle multiple brands. Therefore, the settlement should be done across the brands. This mechanism enables users to deal with not only usual trading but also margin trading. Figure 3.20 shows the class chart of the security company that manages user accounts.

The following briefly explains the classes in Fig. 3.20:

- **USecuritiesCompany**: This class controls the security company.
- **IBankrupt**: This interface defines a bankrupt process.
- **AbstractBankrupt**: This abstract class defines a general bankrupt process.
- **UCashBankrupt**: This class determines the bankrupt based on the cash.
- **UAgentInformationManager**: This class manages the information of each agent.
- **UAgentInformation**: This class contains the information of agents.
- **UOrderManager**: This class manages the orders from agents.
- **UAccountManager**: This class manages the accounts of agents.
- **URepayOrderInformation**: This class contains the information of open orders.
- **ISettlement**: This interface defines a process of settlement.
- **AbstractSettlement**: This abstract class defines a general process of settlement.
- **USpotSettlement**: This class performs settlement of the spot trade.
- **UMarginSettlement**: This class performs settlement of the margin trade.
- **UFuturesSettlement**: This class performs settlement of the futures trade.
- **UPosition**: This class manages positions of an agent.
- **IFee**: This interface defines a fee.
- **UFeePerVolume**: This class calculates the fee according to the volume of the contract.
- **IProxyServer**: This class defines a proxy of an agent.

3.4.3 How to Develop Trading Agents for the Zaraba-Based U-Mart System

The Zaraba-based U-Mart system is designed by object orientation and implemented by Java programming language as well as the Itayose U-Mart system. The Zaraba-based U-Mart system provides more various information to agents than the Itayose U-Mart system. So a user can make more complex strategies in the Zaraba-based U-Mart system than those in the Itayose U-Mart system. This section provides

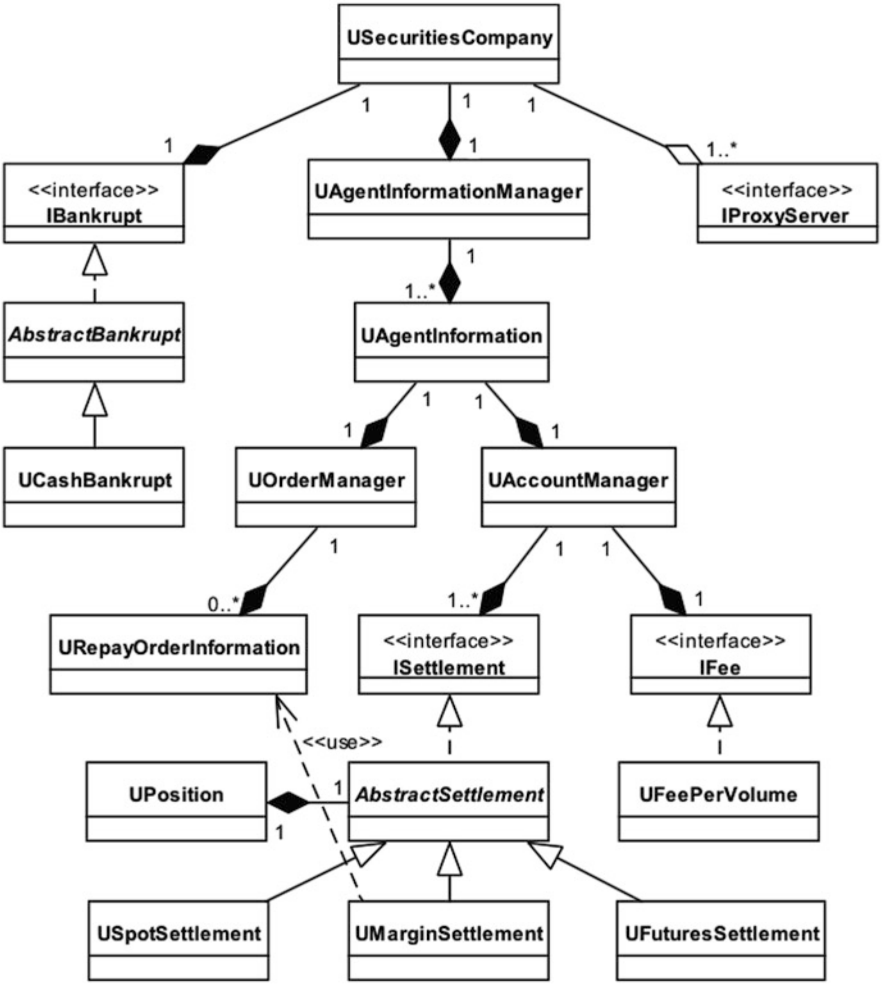


Fig. 3.20 An overview of the security company module of the Zaraba-based U-Mart system

information necessary to design trading strategies for the Zaraba-based U-Mart system.

At the start of each *ut*, an agent receives the following information from the exchange:

- The current date
- The current session
- The current *ut*
- The maximum date
- The number of sessions per day
- The number of *ut*s per session

- Its initial cash
- Its cash
- Its cash purchasing power
- Its margin collateral
- Its margin collateral rate
- Its status (the normal state, the forced settlement or bankrupted)
- Its list of the orders which have not be contracted yet
- Its list of the contracted orders
- Its list of the unpaid orders
- Its long position
- Its short position
- Its closed long position
- Its closed short position
- The brand names available
- The trading type of each brand (normal, margin)
- The history of the latest prices and transaction volumes of each brand whose size is the number of *ut*s per day
- The history of prices and total transactions of each brand in the current *ut*
- The history of daily transactions of each brand (the opening price, the closing price, the highest price, the lowest price, and the transaction volume)
- The order book of each brand
- The minimum tick size
- The quote status (normal, special quotes; sequential trade quotes)
- The margin rate of each brand
- The interest for buy of each brand
- The interest for sell of each brand
- The trading unit of each brand

Then, the agent decides whether or not it makes orders for each brand according to its own trading strategy and the information received from the exchange. When the agent makes orders, it determines if the orders are buy or sell and limit or market. If the orders are limit orders, the order prices also have to be specified. The agent also has to determine order volumes. Finally, the agent makes order forms according to its decision and submits them to the exchange. The agent can cancel orders before they are contracted.

The Zaraba-based U-Mart system provides some typical and simple trading agents called the standard agent set. The standard agent set consists of the following agents:

- **URandomStrategy**
  The URandomStrategy agent randomly places a sell order or a buy order for a brand which is specified by an external configuration file. No action is taken if the absolute value of its position is larger than a position threshold or if its cash purchasing power is less than a cash-purchasing-power threshold. The position threshold and the cash-purchasing-power threshold are specified in the external configuration file. The order price follows a normal distribution with a mean

and a standard deviation. The mean can be set to be the current price, the best bid price, or the best ask price of a specified band. Which price and what brand to use are specified in the external configuration file. The standard deviation is specified in the external configuration file. The order volume is randomly chosen from the range given in the external configuration file. The interval of making orders can be chosen from a fixed number or a normally distributed random number. Which to choose as the interval, the fixed number, the mean, and the standard deviation of the normal distribution is specified in the external configuration file.

- **UTrendStrategy**
  The UTrendStrategy agent places a buy (sell) order if the price of a specified brand rises (drops) successively for a specified period. The brand and the period are specified in an external configuration file. No action is taken if the absolute value of its position is larger than a position threshold or if its cash purchasing power is less than a cash-purchasing-power threshold. The position threshold and the cash-purchasing-power threshold are specified in the external configuration file. The UTrendStrategy determines the order price, the order volume, and the interval of making orders in the same way as the URandomStrategy agent.
- **UAntiTrendStrategy**
  The UAntiTrendStrategy agent places a buy (sell) order if the price of a specified brand drops (rises) successively for a specified period. The brand and the period are specified in an external configuration file. No action is taken if the absolute value of its position is larger than a position threshold or if its cash purchasing power is less than a cash-purchasing-power threshold. The position threshold and the cash-purchasing-power threshold are specified in the external configuration file. The UAntiTrendStrategy determines the order price, the order volume, and the interval of making orders in the same way as the URandomStrategy agent.
- **UMovingAverageStrategy**
  The UMovingAverageStrategy agent places orders when the short-term moving average line and the midterm moving average line have intersections. If the short-term moving average tends to go up (down), it buys (sells). The numbers of uts of the short term and the midterm are specified in an external configuration file. No action is taken if the absolute value of its position is larger than a position threshold or if its cash purchasing power is less than a cash-purchasing-power threshold. The position threshold and the cash-purchasing-power threshold are specified in the external configuration file. The UMovingAverageStrategy determines the order price, the order volume, and the interval of making orders in the same way as the URandomStrategy agent.
- **URsiStrategy**
  The URsiStrategy agent makes decisions by using the relative strength index (RSI) of the price series of a brand specified in an external configuration file. RSI is a famous method of technical analysis. The parameters of RSI are specified in the external configuration file. No action is taken if the absolute value of its position is larger than a position threshold or if its cash purchasing power is less than a cash-purchasing-power threshold. The position threshold and the cash-

purchasing-power threshold are specified in the external configuration file. The URsiStrategy determines the order price, the order volume, and the interval of making orders in the same way as the URandomStrategy agent.

A user can implement original agents by designing trading strategies and implementing them by Java programming language. The user can register the original agents to the Zaraba-based U-Mart system and run them with the standard agent set.

3.4.4 Features

This section summarizes features of the Zaraba-based U-Mart system. The Zaraba-based U-Mart system has the following features in terms of fidelity and usability in addition to those of the Itayose U-Mart system:

- **Fidelity**
  - The Zaraba-based U-Mart system supports the continuous double auction as a pricing method. This enables the Zaraba-based U-Mart system to simulate various real markets because many stock exchanges in the real world adopt the continuous double auction.
  - The Zaraba-based U-Mart system supports multiple brands. This enables the Zaraba-based U-Mart system to simulate various real markets because usual stock exchanges in the real world have multiple brands in them.
  - The Zaraba-based U-Mart system provides a mechanism which allows users to define various institutions. This enables the Zaraba-based U-Mart system to simulate various market institutions in the real world.
- **Usability**
  - The GUI of the trading terminal in the Zaraba-based U-Mart system provides richer information of the market than that of the Itayose U-Mart system. In the Zaraba-based U-Mart system, human traders can see typical technical indicators such as the candlestick chart or the Bollinger bands directly on the trading terminal.

3.5 An Example of Numerical Experiments: An Effect of a Futures Market on Its Spot Market

This section gives an example of numerical experiments with the Zaraba-based U-Mart system to demonstrate the usefulness of the Zaraba-based U-Mart system. These experiments investigate the effect of a futures market on its spot market. It is known that the movement of spot prices of a brand has strong correlation with that of its futures prices. However, it is very difficult to manipulate real markets in order to analyze such correlation. These experiments compare the statistics of spot prices when there is only a spot market of a single brand with those when there are a spot market of a single brand and its futures market. The result suggests that a spot market becomes more stable when its futures market exists.

3.5.1 Experimental Settings

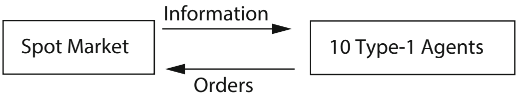
This experiment uses the following four types of agents:

1. [**Type 1**] The type-1 agent randomly places a sell or buy order per *ut* in the **spot** market. The order price follows a normal distribution with a mean and a standard deviation. The mean is the best bid in the **spot** market if the order is buy and the best ask if sell. The standard deviation is 2.5 times the tick. The order volume is randomly chosen between one and ten.
2. [**Type 2**] The type-2 agent randomly places a sell or buy order per *ut* in the **futures** market. The order price follows a normal distribution with a mean and a standard deviation. The mean is the best bid in the **spot** market if the order is buy and the best ask market if sell. The standard deviation is 2.5 times the tick. The order volume is randomly chosen between one and ten.
3. [**Type 3**] The type-3 agent randomly places a sell or buy order per *ut* in the **spot** market. The order price follows a normal distribution with a mean and a standard deviation. The mean is the best bid in the **futures** market if the order is buy and the best ask if sell. The standard deviation is 2.5 times the tick. The order volume is randomly chosen between one and ten.
4. [**Type 4**] The type-4 agent randomly places a sell or buy order per *ut* in the **futures** market. The order price follows a normal distribution with a mean and a standard deviation. The mean is the best bid in the **futures** market if the order is buy and the best ask if sell. The standard deviation is 2.5 times the tick. The order volume is randomly chosen between one and ten.

Using the above four types of agents, this experiment constructs the following two environments as shown in Figs. 3.21 and 3.22:

1. [**Environment A**] Environment A consists of only a single spot market with ten type-1 agents as shown in Fig. 3.21.
2. [**Environment B**] Environment B consists of a spot market with five type-1 and five type-3 agents and its futures market with five type-2 and five type-4 agents.

Fig. 3.21 Environment A



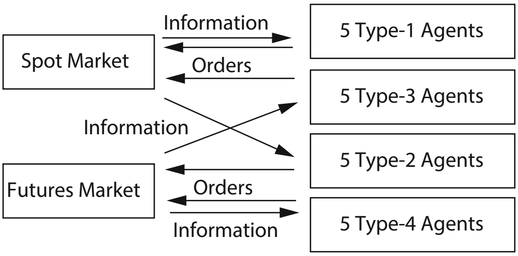


Fig. 3.22 Environment B

The number of days is 20, and one day consists of the morning session (120 *ut*s) and the afternoon session (150 *ut*s). One hundred trials are done. The initial price is 9,347 JPY which is given by Nikkei average of Tokyo Stock Exchange (TSE) on 29th of May in 2009. The institutions of the spot and the futures markets are the same as the institutions of TSE.

3.5.2 Results

Table 3.3 shows the averages and the standard deviations over 100 trials of the average, the standard deviation, the skewness, and the kurtosis of the prices for 20 days. Table 3.4 shows the result of t-test with α level of 1 and 5 %. The hypothesis of this test is that the spot prices of environment A and those of environment B are the same. In this table, the standard deviation and the kurtosis of the prices are significant in 1 % and 5 %, respectively. Table 3.5 shows the result of t-test with α level of 1 %. The hypothesis of this test is that the spot prices and the futures price of environment B are the same. In this table, no elements are rejected. This result suggests that a spot market becomes more stable when its futures market exists.

Table 3.3 The averages and the standard deviations over 100 trials of the average, the standard deviation, the skewness, and the kurtosis of the prices for 20 days in each market

	Average	Standard deviation	Skewness	Kurtosis
Spot (environment A)	9339.81 (94.386)	69.164 (24.676)	−0.02876 (0.3947)	−0.1988 (0.7729)
Spot (environment B)	9350.40 (75.180)	55.282 (17.828)	0.06708 (0.3484)	0.1204 (1.0116)
Futures (environment B)	9350.37 (75.318)	55.451 (17.774)	0.05675 (0.3472)	0.1157 (0.9920)

Table 3.4 The t-test of the averages of the average, the standard deviation, the skewness, and the kurtosis of the spot prices in each environment

Reject rate	Average	Standard deviation	Skewness	Kurtosis
1 %	Not rejected	Rejected	Not rejected	Not rejected
5 %	Not rejected	Rejected	Not rejected	Rejected

Table 3.5 The t-test of the averages of the average, the standard deviation, the skewness, and the kurtosis of the spot prices and the futures prices in environment B

Reject rate	Average	Standard deviation	Skewness	Kurtosis
1 %	Not rejected	Not rejected	Not rejected	Not rejected

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Chapter 4
A Perspective on the Future of the Smallest Big Project in the World

Takao Terano

Abstract This chapter gives my personal view of a perspective of U-Mart: the smallest big project in the world. So far, we have included many people to U-Mart project and got fruitful results through the collaborative interdisciplinary research. Considering the results, the objective of the chapter is to give a future perspective on U-Mart and related agent-based modeling and simulation projects. Thus, first, we start the discussions on the characteristics of a big project and why we consider U-Mart as a big project; second, I explain unique features of agent-based simulation on social and economic complex systems; third, we give a future perspective on the roles of agent-based modeling and simulation studies; and finally, concluding remarks will follow.

4.1 Characteristics of a Big Project and U-Mart

Let us give some examples of big projects: (1) Apollo Project in 1960s, by which they planned to reach to the moon by a human-operated spaceship within 10 years; (2) Human Genome Project in 1990s, in which they stated that all the genome sequences of a human would be read and the meanings would be decoded; (3) currently developing RoboCup Project, whose goal is to win, by robot players team, against the world champion of human player football team; and (4) Human Brain Project just started in 2010, in which understanding the human brain, they will develop both new treatments on brain disease and new computing technologies. They have very smart and charming keywords.

The common characteristics of such big projects include that (1) the missions are simply and clearly stated so that many people has a sympathy to it; (2) when succeeding the clear goal, not only the wonderful direct result but also, as by-products, so many practical novel technologies will be developed; (3) the goal cannot be achieved by only single discipline but required interdisciplinary collaborative research with so many kinds of experts; and (4) planning and scheduled projects cover so many years, and the project require so much budgets.

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Compared with these examples, U-Mart is a very small project; however, U-Mart has the unique characteristics of a big project. It is because of the following reasons:

- We are developing a common platform or common tool to communicate the research topics among economics and engineering communities through the methodology of a real-time virtual market with human and computer participation.
- We are trying to develop a new academic field, which covers the frontiers of social sciences and system sciences, by deploying a simple virtual market simulator.
- To achieve the goal, we need the wide range collaboration of experts in economics, psychology, sociology, financial engineering, computer sciences, artificial intelligence, agent-based modeling, or even big data analytics.
- The development, deployment, and research experiments have taken over 15 years; however, the budgets are very small compared to the other big projects; thus, we call U-Mart as the smallest big project in the world.

In U-Mart project, as the collaborating researchers have their own expertise and their own independent research themes, they are able to discuss the U-Mart-related topics without any barriers of the research boundaries. Therefore, to give a perspective of the future of U-Mart, we must cover various kinds of topics. In the following, we will focus on the principles of agent-based modeling in order to extend the smallest big project in the future.

4.2 Agent-Based Modeling Toward New Social System Sciences

As described in the previous chapters, U-Mart virtual market system has several unique features. In this section, based on our own experience on U-Mart experiments, lectures, and discussions, we explain the importance of agent-based modeling for new social system sciences.

Traditionally, study of social system sciences explored their task domain problems through cases and/or numerical techniques. In case studies, researchers examine existing documents or field investigations on the specific affairs. In numerical techniques, they develop mathematical and/or statistical models with some survey data. They often use tools from statistical physics, for example, in economic and financial problems. In financial engineering, accordingly, the market is assumed to satisfy certain given conditions like physical laws in the natural world. However such assumptions usually do not hold. That is because the market is affected by decisions and actions of individuals, who compose the market, and they are able to change the trading rules on the market. Unlike natural phenomena, such artificial assumptions intrinsically contain so many unclear parameters to formalize them. On the other hand, the recent advances in computer technologies enable us to treat the models from global phenomena to individuals. We are able to observe how individuals, or agents, will behave as a group through intensive computer simulation studies.

Of course, studies on simulation techniques in organizational systems have a long history. For example, the book written by Cyert and March [3] is a starting point of organizational simulation. The garbage can model is well known in organizational decision-making behavior [2]. The strength of the agent-based simulation approach is that it stands between the case studies and mathematical models. It enables us to validate social theories by executing programs, along with description of the subject and strict theoretical development.

In agent-based simulation, behaviors and statuses of individual agents are coded into executable computer programs. The researchers also implement information and analytical systems in the environment. Even when the number or variety of agents increases, the complexity of simulation descriptions itself will not increase very much. Though they cannot cope with computational complexity or combinatorial explosion in the simulation, agent-based models are very effective to analyze complex social phenomena with simple description. We should switch our principles of conventional artificial intelligence approach [5], which tries to make agents smart, into ones to ravel intelligence as a group through agent-based modeling.

Under such agent-based modeling principles, results of scientific study will be communicated in a form comprehensible to other researchers, and when it involves experiments, the results will be reproducible. Emphasis on the keep it simple, stupid or KISS principle in agent-based simulation is to respond to these two requirements[1]. Needless to say, agent-based simulation is merely understanding and executing a certain aspect of a phenomenon, but it has the potential to greatly advance the frontier of existing studies when it is used as a supplement to the theory or when theory is used as a supplement to it[6].

4.2.1 Requirements on Agent-Based Simulation Models

The strength of the agent-based simulation approach is that it stands between the case studies and mathematical models. It enables us to validate social theories by executing programs, along with description of the subject and strict theoretical development. However, to convince the approach to the researchers of the other domains or general intelligent people, there remains some difficulty. Below, I summarized the requirements for simulation experiments, especially agent-based simulation of economic and social complex phenomena:

- It will produce results that agree with reality

  Unlike natural phenomena, social phenomena are not reproducible. However, there are established theoretical systems to explain phenomena, such as financial engineering and economics. It is important that simulation provide results that agree with these theories and actual phenomena.

- It will present phenomena difficult to explain by existing theories

  It is also important that phenomena that are difficult to explain by existing theories but exist in reality will be reproduced in a limited manner. For example, the fat tail phenomenon, which is observed in stock price distribution, is difficult to explain by existing theories, but it can easily be reproduced in simulation, and an explanation is provided by economic physics.

- It will produce satisfactory results

  Simulation study of social phenomena requires numerous parameters. Therefore, we can produce desired results by parameter tuning. Results unsatisfactory to the researchers of model builders are meaningless. Researchers must at least be convincing in the literature regarding simulation results.

- The models should be carefully verified

  As well known, program codes in use usually contain some faults or bugs. Although the developers would like to implement their desires, requirement specifications are always insufficient from their desires. Moreover, to cope with unclear social and economic phenomena, it is very hard to specify the correct desires. Verification tasks in software engineering are defined so as to make a system right. To verify the programs, they adopt various mathematical techniques and support tools. We also use such techniques to make our computer programs right.

- The results will be rigorously validated

  When a simulation experiment is performed, it produces some results. However, it is extremely difficult to demonstrate the validity of the results. In software engineering, the validation means to make right systems. The results will lack persuasion without a theory upon the simulation is based, a basis for the functions equipped to the agents, accuracy of the program, strict sensitivity analysis of the results, and so on.

- The simulation models and results should be accredited

  Accreditation means how and to what extent the simulation results are reliable. To understand social and economic complex systems, the concept of the accreditation should not be so rigorous compared with conventional engineering simulation results. However, to convince the results, we must consider the accreditation tasks in mind.

- The results is capable of approaching the issues difficult to explain by existing theories

  Existing theories are based on the assumption that there is some sort of rationality in the agents' behavior or decision-making. In actual phenomena, however, this rationality assumption often does not hold. Simulation may provide a systematic explanation for and reveal hidden conditions of such issues.

4.2.2 *Toward a New Research Scheme for Agent-Based Simulation in Social and Economic Complex Systems*

In order to meet the requirements in the previous subsection, we would like to propose a new research scheme for agent-based simulation [4]. To follow the scheme, of course, we must develop various methods, techniques, and tools; however, the approach will be promising.

The proposed scheme introduces a mezzo-scopic structure between the microscopic (members) and the macroscopic (market) level. The reason is that problems on social and economic processes have the following difficulties: (a) the problems are too complex to treat with numerous factors in hierarchical structures, and (b) each structural behavior strongly depends on the member's awareness and decisions. Such complex systems have been often described from the micro-macro loop viewpoint.

We regard it is essentially important that the problems exist in the mezzo-scopic level in which they don't have enough scale differences to neglect their corporations' uniqueness nor heterogeneity of their members. On the other hand, though econophysics approaches adopt the outcomes from the experimental economics or the behavioral economics, they tend to explain macrolevel phenomena by regarding the microlevel members as the homogeneous set of agents or particles.

Figure 4.1 illustrates these difficulties from the viewpoints of the interactions between micro-, mezzo-, and macroscopic levels. The arrow "A" indicates that the microlevel (members) numerous factors affect the mezzolevel (organization) states. The arrow "B" shows the mezzolevel influence on the microlevel actors' awareness and decisions. Introducing both the diversity of microlevel agent's awareness and/or decisions without off-scaling and an intermediate level structure.

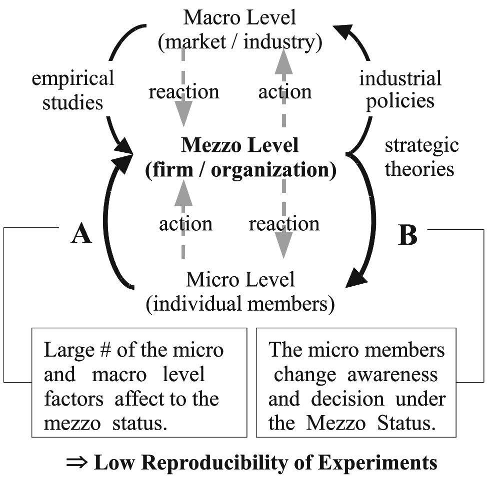

Fig. 4.1 Macro-, mezzo-, and microlevel mutual interaction scheme for agent-based modeling

Actual social and economic processes include both "A" and "B" inter-level interactions. Those bring the low reproducibility of the problems. Single experiments are not effective to explore the problems. Therefore, we need to apply appropriate simulation experiment-based approaches to each "A" and "B." Of course, besides "A" and "B," the environmental fluidity of the systems also exists as a critical factor, which will be discussed elsewhere.

Here we discuss testing and evaluating the hypotheses and theories on the influence from the microlevel factors to macrolevel states (the arrow "A" in Fig. 4.1). At first, we need to build bottom-up organizational models, which include the microlevel agents' behaviors and their influence on the macrolevel states. Then, we conduct the simulation experiments for test and evaluation. However, these organizational models have numerous parameters, which represent the characteristics and conditions of the organization. So not only descriptive statistics but also single-factor comparisons hardly explain any meaningful implications. Therefore, we insist that the combination of the organizational bottom-up simulations and the orthogonal designs of experiments is an effective methodology for the exploration on the "A" in Fig. 4.1.

4.3 Concluding Remarks

In this chapter, we have described (1) why U-Mart research is a big project and why we must extend the project, (2) the importance and difficulties in agent-based modeling, (3) the requirements for agent-based modeling, and (4) the proposal of the new scheme. To close this chapter, we would like to add the following three messages for the future directions:

- The best way to predict the future is to invent it

  This is a famous statement by Alan Kay, who proposed the concept of personal computers as Dynabook. As he said, when we use agent-based models for complex social and economic systems, we always invent a new world or a new bird-view-like point of view, because we are able to design the simulation world as we would like to. Therefore, when we use agent-based models, we are predicting some future. We already have had new tools for predicting the future: agent-based modeling (ABM) is a new modeling paradigm.
- Art is a lie that helps us see reality

  Pablo Picasso, a painter, recorded the statement in his art museum in Barcelona. We would like to slightly change the statement for our future research: agent-based modeling is a lie that helps us see reality. Because of our limited ability of the bounded rationality, we are not able to completely design and analyze social and economic systems; agent-based modeling is an important principle to see reality.

- Everything is Obvious: Once You Know the Answer

  The statement is a title of the book written by Duncan Watts, a scientist in complex networks. Again, we would like to slightly change the statement for our future research: Something may be obvious once you know agent-based simulation. So far, research in social sciences has only succeeded in making clear interpretation and/or explanation about things already happened. However, with agent-based modeling, we are able to uncover the principles of social and economic phenomena beforehand.

Then, let us start new (small) big projects.

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Part II
Applications of Artificial Markets

Chapter 5
Evolution of Day Trade Agent Strategy by Means of Genetic Programming with Machine Learning

Naoki Mori

Abstract The Evolution of Day Trading Strategy by Means of Genetic Programming and Machine Learning

5.1 Introduction

Recently, the number of investor by Internet security companies has increased rapidly. Since Internet security companies provide various online trade services, people can get lots of information about stock easily. However, it is difficult to utilize those information for trading because lots of information are sometimes too complex to understand the situation of market.

There have been reported lots of studies [1] on forecast of stock prices based on the closing price. However, there are few researches which utilize real-time information such as bid and ask price.

On the other hand, evolutionary computations (ECs) [5, 6] have been applied to various kinds of problems, and the advantages of ECs have been reported. The application field of ECs has been expanded to not only science and engineering but also art such as design, music, and economics [2, 9, 10]. Combining ECs and machine-learning technique is one of the promising approaches to solve complex problems in real world.

In this section, we show a novel method of evolving day trade strategies by means of the genetic programming (GP) [7] which is one of the powerful ECs and support vector machine (SVM) [11] which is one of the excellent machine-learning techniques. We focus on the order book information and several technical indices. The performance of the proposed method is shown by means of Day Trade Agent Framework (DTAF) [9] which can reproduce the situation of real stock markets. We show the effectiveness of the proposed method by computer simulations taking three typical real Japanese stocks as examples.

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5.2 Day Trading

Day trading is a short-term investment strategy by which an investor buys and sells equities within the same day. While day trading is insusceptible to long-term risks because equities are held for a very short time, the gain obtained in a single trade is small. Accordingly, to make a handsome profit, an investor must make a large number of trades, which require advanced techniques.

5.2.1 Advantage of Day Trading

Medium-term and long-term investment known as familiar investment styles are exposed to greater risks because they are subject to uncertainties such as changes in economic conditions and the performance of companies, and the time during which the investor cannot control the equity position is longer. Moreover, because the frequency of trades in a single day is low, the need for real-time data is not strong.

In this study, we focus on day trading which handles an enormous quantity of data and requires high-speed computing. Day trading has a high affinity to automatic trade by computer because quantitative technical analysis is more important than fundamental analysis which is hard to treat by computers. One of the important advantage points of day trade is the low risk of being affected by a rapid change in social conditions because positions are settled within the same day.

5.2.2 Order Book Information

In day trading, one of the most important data for decision-making is "order book information." The "order book" is a table in which the order status for a specific stock is displayed. You can view what quantities of orders are being placed at what prices for the stock. A single price is displayed for a stock. However, investors should consider two values: "best ask price," which is the lowest price for sell , and "best bid price," which is the highest price for buy. Figure 5.1 shows an example of order book information. In Fig. 5.1, the best ask price is 103 and the best bid price is 100.

The units of indicative prices are called "tick sizes." They are uniformly set according to the price zones of equities. Table 5.1 shows tick sizes of the Tokyo Stock Exchange.

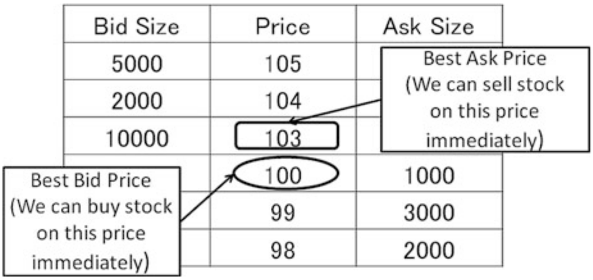

Fig. 5.1 Example of an order book

Table 5.1 Tick size

Stock price (yen)	Tick size (yen)
∼2,000	1
2,000 ∼ 3,000	5
3,000 ∼ 30,000	10
30,000 ∼ 50,000	50
50,000 ∼ 100,000	100
100,000 ∼ 1,000,000	1,000
1,000,000 ∼ 20,000,000	10,000
20,000,000 ∼ 30,000,000	50,000
30,000,000 ∼	100,000

5.2.2.1 Spread

The "spread" is the difference between indicative prices quoted on the order book. The difference between the best ask price and the best bid price is called the "bid-ask spread." In Fig. 5.1, the bid-ask spread is 3. In daytime trading, the definite price at which stocks bought at the best ask price can be immediately sold is the best bid price. Accordingly, investors have the risk of the bid-ask spread just after they purchase a stock. In the field of economics, it is known from the study [4] by Farmer, et al. that spreads have a close relationship with the behavior of stock prices.

5.2.2.2 Thickness

When large quantities of orders are placed on the order book, the order book is said to be "thick." When order quantities are small, the order book is "thin." Since more contracts are needed for the stock price to fluctuate when the order book is thick, the stock prices tend to move toward a thin order book.

5.2.3 Technical Analysis

Values calculated based on stock prices, trading volume, days, and other elements are called technical indices. Analyses using technical indices are mainly divided into two types: trend analysis and oscillator analysis. Trend analysis is suitable for measuring the general direction of market prices, while oscillator analysis is suitable for measuring the behavior of market prices over a relatively short-term period.

These technical analyses are easily processed by computers because the data necessary for the analyses are expressed in numerical values.

5.3 Day Trade Agent Framework

In order to train trading agents, the stock market simulator which can reproduce the real market is required. To achieve this, we have proposed "Day Trade Agent Framework" (DTAF) [9]. DTAF has three parts: market replay system, agent learning part, and the system of applying trading agents to real market. Figure 5.2 shows outline of DTAF.

5.3.1 Market Replay System

Market replay system has two parts: Data-collecting part corrects stock data in the daytime, and data-providing part supplies the corrected data and reproduces the market.

5.3.1.1 Data-Collecting Part

Data-collecting part stores real-time stock data to the database. Table 5.2 shows collecting variable of this part.

Fig. 5.2 Outline of DTAF

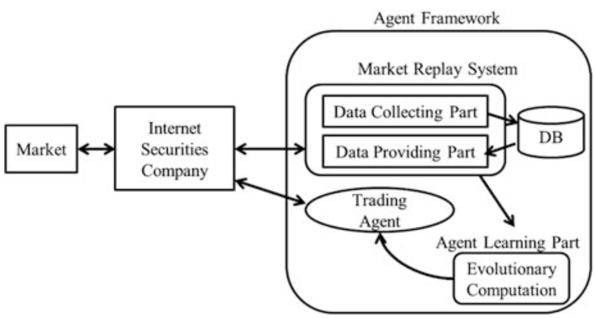

Table 5.2 Collect variable of data-collecting part

Correct item
Stock price
Stock price time
Turnover
Weighted average of turnover
Bid price
Bid size
Ask price
Ask size
Transition of the stock price

5.3.1.2 Data-Providing Part

Data-providing part takes data from the database and reproduces stock market situation after formatting data. This part can reproduce the real order book at every few seconds.

In this section, we only use the data obtained by data-collecting part, but data-providing part can use any kind of data such as artificial price data.

5.3.2 Agent Learning Part

Agent learning part can obtain the effective trade strategy by evolutionary computation or machine-learning technique. We assume that the amount of trading between our agents is too small to affect the situation of real market. If the trading in stock market simulator is only based on stock price, there is a problem that the result of contract becomes unclear. To solve this problem, we utilized the best bid price and best ask price to execute the contract. This condition makes trading difficult, but the results of stock market simulator are near to that of real market.

5.3.3 Trading Agent

Trading agent trades with the strategy, which is obtained by agent learning part in the real stock market.

We can realize the result of the trading agent's in real stock market. The result of trading agent in real stock market shows the exact effectiveness of strategy with risk.

And we can find difference between trading in real stock market and trading in market replay system by real trade of agents. We can tune the agent learning part by the above difference. We only use the market simulator; however, applying our trade agents to real market is an important future work.

5.4 Genetic Programming and Support Vector Machine

5.4.1 Genetic Programming

The evolutionary computation (EC) is a search and optimization technique based on the mechanism of natural evolution. The genetic algorithm (GA) is one of the famous ECs which represents the solution by binary strings. GA consists of the selection, the crossover, and usually the mutation operators. In the selection operation, an individual having larger fitness value is allowed to yield more offsprings in the next generation. There have been reported lots of studies applying GA to various problems with effective results. Though GA is a useful optimization method, GA has one defect that GA cannot represent complex solutions.

To solve these problems, the genetic programming (GP) has been proposed. The most important feature of genetic programming is that GP represents the solutions by tree structure. In utilizing tree structure, GP can represent not only simple solutions but also program, function, and strategy by decision tree.

5.4.2 Support Vector Machine

Support vector machines [3, 11] (SVMs) are one of the powerful supervised learning models used for classification and regression analysis. Each data of given training set is marked as one of two categories. The SVM tries to build a model that assigns new examples into certain category.

A model of SVM is represented by one separating hyperplane in data set space. The data set space is divided into two by this separating hyperplane, and the new examples are predicted to belong to a category based on the separating hyperplane. The interesting point of SVM is that the separating hyperplane is decided as a maximum-margin hyperplane.

In addition, the SVM can efficiently perform a nonlinear classification using kernel trick. The basic kernel of SVM is linear kernel, but radial basis function kernel (RBF kernel) which has high ability to represent the nonlinear features is utilized in this section.

5.5 Evolution of the Day Trading Strategy by Genetic Programming

5.5.1 Individual Expression of the Day Trade Strategy

This section uses genetic programming (GP) to find effective trading strategies. In GP, solution candidates are represented as a decision tree. Any kind of subtree represents a particular trading strategy. Decision node of the tree is a certain function whose inputs are various stock information.

On the other hand, end nodes of the tree represent three typical actions of a trading agent: “buy” (buying the stock at best bid price), “sell” (selling the stock at best ask price), and “wait” (not doing any act).

The main advantage of using GP is the ability to represent different trading rules in a natural way. We show two advantages of using decision tree representing a trading strategy.

1. We can set several conditions to buy and sell conditions.
2. We can represent both buy conditions and sell conditions by only one decision tree.

The functions used at a decision tree are defined as a condition which is used with order book information and technical indices. In the economics field, Farmer reported that spread impacts the fluctuation of stock prices. However there are few researches in engineering field to apply this. So we adopt spread as a condition in decision node.

And we also use a function with an order book thickness data in the decision tree. Figure 5.3 shows order book information utilized in GP. In Fig. 5.3, bid order book thickness (N_a) is the sum of bid size from best bid price to next N_a lower price. Ask order book thickness (N_b) is the sum of ask size from best ask price to next N_b

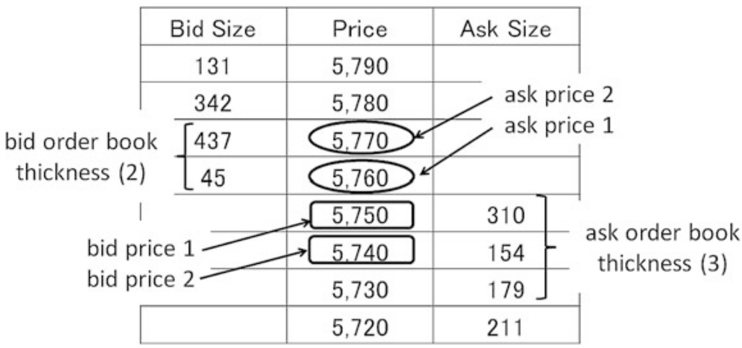

Fig. 5.3 Order book information utilized in GP

higher price. By comparing bid order book thickness with ask order book thickness, we can find the trend of the stock price.

Technical indices are calculated with the numerical data such as stock price, turnover, and so on. Technical indices is usually calculated with daily charts; however, we calculate with minute charts because our research target is short-term day trading.

Table 5.3 shows input value of decision nodes in GP. Functions in decision nodes return Boolean value, “true” or “false.”

These are calculated by comparing the input data and the value we set. The value compared with input data in a function is calculated with the input data of the day before the trading days. Figure 5.4 shows an example of a decision tree.

In Fig. 5.4, S_2 is compared with 2.0 in root node. First, if this decision tree returns “true,” then the decision node whose function is calculated with V_3 is evaluated. Next step, V_3 is compared with 4.0, and then the decision node returns “false.” Finally, the decision tree returns “buy” action.

Table 5.3 Input value in decision node of GP

S_1	(Bid price 2 – Bid price 1)/Tick
S_2	(Bid price 1 – Ask price 1)/Tick
S_3	(Ask price 1 – Ask price 2)/Tick
V_1	Bid order book thickness (1)/Ask order book thickness (1)
V_2	Bid order book thickness (2)/Ask order book thickness (2)
V_3	Bid order book thickness (3)/Ask order book thickness (3)
B_1	Difference from moving average
B_2	Bollinger bands
O_1	RSI
O_2	RCI
O_3	William % R
O_4	Volume ratio
M_1	MACD (12–26 min)
M_2	M_1 – moving average during 9 min
M_3	M_2 on 1 min before

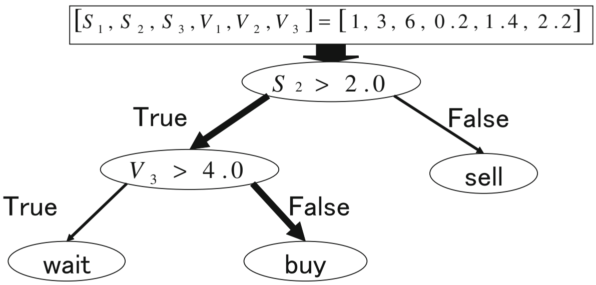

Fig. 5.4 An example of a decision tree

5.5.2 Action of the Trade Agent

Figure 5.5 shows business hours of Japanese stock market. After opening the market, if a decision tree returns a buy signal, the trading agent buys the stock at best bid price.

On the other hand, if a sell signal is returned by a decision tree and the agent has any stocks, the agent sells all the stock at best ask price. If the agent has no stock, the agent acts nothing by sell signal.

The agent can buy in succession without sell stock. The maximum number of buy action is a parameter.

On the market closing time, the agent sells all the stock at closing price. If a decision tree returns no buy signal during business hours, the profit got by the agent is set 0.

5.5.3 Fitness Measure

The fitness measure is the sum of profit got by a trading agent. Profit is always calculated when agent action is "sell." Agent sells all the stock after "sell" action, so we consider t-th times "sell" action.

The profit p_t is defined as following equation:

$$p_t = \sum_{i=1}^{N_t} (s_t - b_i^t) \tag{5.1}$$

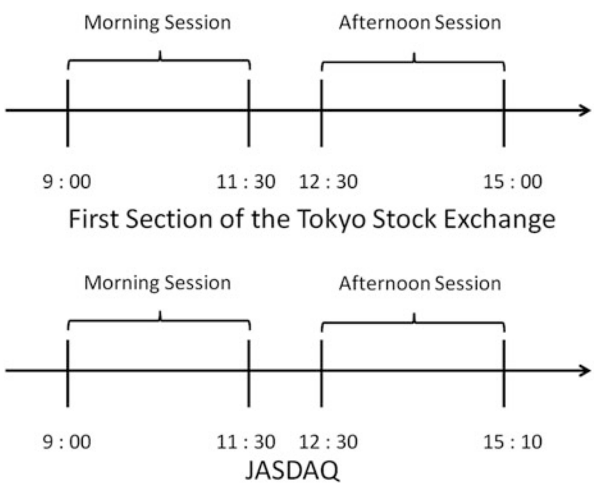

Fig. 5.5 Business hours of Japanese stock market

where s_t represents the sell price of t-th "sell" action and b_i^t represents the buy prices from just after previous "sell" action. We set 0th "sell" action which represents no action just after opening. N_t represents the number of "buy" action between $(t-1)$-th "sell" action and t-th "sell" action.

Total profit of p is obtained by following equation:

$$p = \sum_{t=1}^{N_{\text{sell}}} p_t \tag{5.2}$$

where N_{sell} represents the total number of "sell" action.

In this section, we ignore a commission and tax in a real trading. We also ignore the impact of agent trade to the real market. The reason is that the total volume of trading agent is negligible compare to that of real market.

5.5.4 Learning Term

In this study, we only focus on trading days of market. In GP, we use the total profit represented by equation (5.2) got in previous days as fitness measure. We call these days "learning term." The strategy for the target day is learned by using the data of latest n days before target day. To confirm the effectiveness of GP, we apply the elite individual's strategy obtained by evolution in learning term to the target day. If the target day moves to next day, the learning term also moves dynamically. Figure 5.6

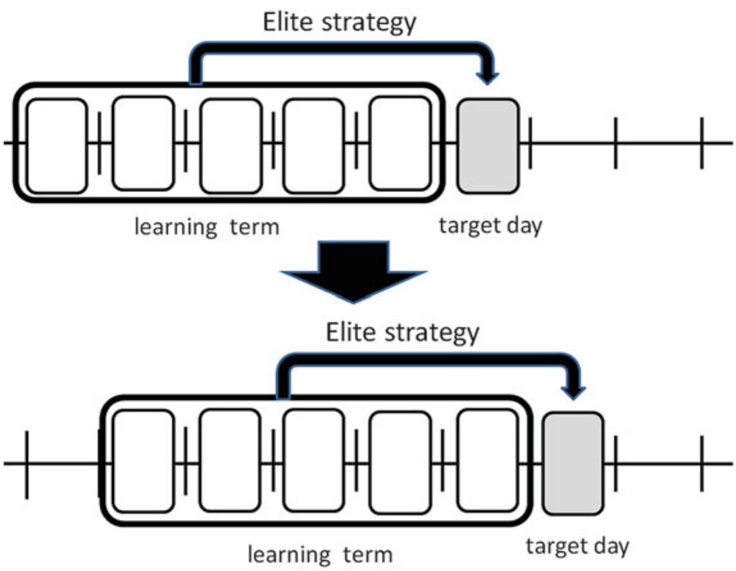

Fig. 5.6 Target day and learning term

shows the relation between target day and learning term and dynamical change of learning term.

5.6 Propose Method

The prediction of fluctuation of stock prices at the trading day is much important to avoid a risk to get loss. In this section, we propose the method to get the trading strategy with GP at the trading day at which stock price fluctuation is predicted by support vector machines(SVMs).

5.6.1 Prediction of Fluctuation of Stock Prices with SVMs

We use two SVMs to predict fluctuation of stock prices at the target trading day. Libsvm [8] which is one of the most famous SVM libraries is utilized. First, SVM predicts the degree of fluctuation of the stock prices $|f|$. We define this SVM as *volatility SVM*. The fluctuation f is defined as the following equation:

$$f = \frac{P_{\text{closing}} - P_{\text{opening}}}{P_{\text{opening}}} \tag{5.3}$$

where P_{closing} represents the closing price and P_{opening} represents the opening price at the trading day.

Volatility SVM estimates whether the fluctuation is large or small by predicting if $|f|$ is over α which is calculated with the data before the target day. Volatility SVM learns the latest 240-day data of the target day. Table 5.4 shows input value used at volatility SVM.

Next, second SVM predicts plus or minus sign of f based on the prediction of the volatility SVM. We define this SVM as *P/N SVM*. To make training data of P/N SVM, we first divided past data into two groups: G_1 and G_2. G_1 consists of all data of $|f| > \alpha$, and G_2 consists of all data of $|f| \leq \alpha$. In this case, f is calculated based on real stock price. If the prediction of volatility SVM of target day is $|f| > \alpha$, P/N SVM is trained by the latest 240 data in G_1. On the other hand, the prediction of volatility SVM is $|f| \leq \alpha$, P/N SVM is trained by latest 240 data in G_2.

Table 5.4 Technical indices used the data of SVMs

Difference from moving average (25 days)	William %R (14 days)
DMI(14 days)	RSI (14 days)
Volume ratio (14 days)	RCI (22 days)
MACD (12 days, 26 days, 9 days)	

We predict the volatility, the positivity, and the negativity of the fluctuation of stock prices at the target day by those 2 SVMs.

The threshold of volatility α is decided as follows:

1. Set $\alpha = 0.005$, $\alpha_{\max} = 0.005$, $p_{\max} = -\infty$, $p = 0$.
2. Set test term to latest 20 days.
3. Train volatility SVM and P/N SVM with current α.
4. Agent trades with "Buy & Hold" strategy at only days in test term that the prediction of volatility SVM is $|f| > \alpha$ and that of P/N SVM is $f > 0$.
5. Set p to the total profit of 20 test term.
6. If $p > p_{\max}$ then $p = p_{\max}$ and $\alpha_{\max} = \alpha$.
7. Add 0.001 to α. If $\alpha > 0.05$ then set final α to $\alpha_{\max}$ and exit. Otherwise, go to 3.

5.6.2 *Evolution of Trading Strategy by GP*

We described the detail of how to introduce SVMs results into GP search.

5.6.2.1 The Method to Apply the Individual of GP

In this section, learning term of GP is set to the latest 20 days at which the prediction of volatility SVM is $|f| > \alpha$ and that of P/N SVM is $f > 0$. Learning term must be selected within latest 60 days from the target day.

5.6.2.2 Nodes of GP Individual

Each GP individual node is related to one input value shown in Table 5.3. GP nodes compare input value to certain constant value. Each input value has one constant values set. When GP node is created, one input value is assigned to the node and then randomly selected constant value in the constant value set of input value. GP node compares input value of real market to constant value in order to decide the next node in decision tree. Once constant value is decided, this value is never changed in GP search. Those constant values set are very important, but there are no concrete methods to get constant values set. To solve this problem, we proposed the following method: Constant values set of target day is decided by distribution of input values of previous day. In this study, the size of constant values set is 5. The constant values set C_X of certain input value X is decided as follows:

1. Define S_X as the set of all the input values X in previous day.
2. Define S'_X as sorted set of S_X in ascending order. Set $N_X = |S'_X|$.
3. Set $C_i = \{S'_X\}_{\lfloor \frac{iN_X}{6} \rfloor]}$, $i = 1, 2, 3, 4, 5$

In addition to input values in Table 5.3, we use the current profit rate. We use $\{0, -0.025, -0.05, -0.075, -0.1\}$ as constant values set of total profit rate.

5.7 Computer Experiments

To confirm the effectiveness of the proposed method, computer simulation is carried out. We use the trading days in 2013 as the target of this experiment.

5.7.1 Experiment Condition

Table 5.5 shows the target brands of this experiment. We denote the brand as stock code.

Table 5.6 shows parameters of GP in this experiment. Initial tree depth limit is the max depth limit of the decision tree in initial population. And subsequent tree depth limit shows the max depth limit of the decision tree in the population during GP search.

GP makes decision trees in initial population randomly. Next, the processes, crossover, mutation, and selection is repeated for the number of generation. At a crossover, the two decision tree is selected as parents randomly. And new two trees are made by exchanging a subtree of parents. Mutations are introduced by using a randomly generated tree in place of the tree selected with mutation rate. We use subtree mutation.

In applying crossover or mutation, if the depth of the tree exceeds the limit depth, we apply crossover or mutation again till maximum repeat times 100. If we cannot obtain a regal offspring by 100 trials, crossover or mutation is failed. We use the elitism as selection. Table 5.7 shows the input values set for GP at each stock name.

The kernel function of SVM is RBF.

Table 5.5 The brands used at experiment

Stock code	Brand	Market
3323	RECOMM CO., LTD	JASDAQ
6773	Pioneer Corporation	First section of the Tokyo Stock Exchange
9984	SoftBank Corp.	First section of the Tokyo Stock Exchange

Table 5.6 Setting of GP

Population size	500
Generations per run	50
Selection	Tournament
Tournament size	6
Crossover rate	0.9
Mutation rate	0.02
Initial tree depth limit	5
Subsequent tree depth limit	15
Number of trials	5
Interval to buy	Over 30 min
Contract limit	15

Table 5.7 The input values used in GP at each stock name

Stock code	The input value
3323	$S_1, S_2, S_3, V_2, V_3, M_1$
6773	V_1, V_2, V_3, M_1
9984	$S_1, S_2, S_3, V_2, V_3, M_1$

5.7.2 *The Prediction of the Fluctuation of Stock Prices with SVMs*

In this section, we confirm the effectiveness of the method shown in Sect. 5.6.1.

In this study, we utilized two kinds of SVM called volatility SVM and P/N SVM. Since output of both SVMs has two classes, this problem is a four-class task. We call the combination of volatility SVM and P/N SVM as fluctuation SVMs. Table 5.8 shows accuracy rate of fluctuation SVMs and P/N SVM. The column of accuracy rate of fluctuation SVMs shows the accuracy rate of four-class task and the ratio of **correct answer/total data** is shown in parentheses. The column of accuracy rate of P/N SVM shows the three kinds of accuracy rates of P/N SVM for total data, data in case of $|f| > \alpha$, and data in case of $|f| \leq \alpha$ separately. The ratio of **correct answer/total data** is shown in parentheses. The column of baseline of P/N SVM shows the three kinds of baseline of P/N SVM for total data, data in case of $|f| > \alpha$, and data in case of $|f| \leq \alpha$ separately. All of accuracy rates of fluctuation SVMs in Table 5.8 are better than baseline of four-class task 25 %. All of accuracy rates of P/N SVM in Table 5.8 are also better than baseline. This results show our SVMs can classify trade day type based on volatility and P/N of stock price fluctuation. It is important that even if the output of fluctuation SVMs is wrong, there is possibility that GP part recovers failure of SVMs and gets profit.

And Table 5.9 shows total profit with "Buy & Hold strategy." Buy & Hold strategy is one of the simplest trading strategy that the investigator buys the stock at the market opening time and then sells all the stocks at the market closing time.

The column of $|f| > \alpha$ and $f > 0$ shows the profit that we apply Buy & Hold strategy only when the prediction result of fluctuation SVMs is $|f| > \alpha$ and $f > 0$.

Table 5.8 Accuracy of each SVM

Stock code	Accuracy rates of fluctuation SVMs (%)	Accuracy rates of P/N SVM		Baseline of P/N SVM	
		$\|f\| > \alpha$	$\|f\| \le \alpha$	$\|f\| > \alpha$	$\|f\| \le \alpha$
3323	46.53 (114/245)	61.22 (120/196)	67.35 (33/49)	52.55 (103/196)	57.14 (28/49)
6773	55.51 (136/245)	67.95 (136/167)	67.94 (53/78)	65.27 (109/167)	69.23 (54/78)
9984	31.84 (78/245)	52.42 (108/206)	56.41 (22/39)	52.42 (108/206)	56.41 (22/39)

Table 5.9 Total profit got with "Buy & Hold Strategy"

Stock code	The prediction is $\|f\| > \alpha$ and $f > 0$	$f > 0$	All day
3323	3439	4133	2332
6773	208	206	−223
9984	3142	2907	1446

And the column of $f > 0$ shows the profit that we apply Buy & Hold strategy only when the prediction result of fluctuation SVMs is $f > 0$. The column of all trading days shows the profit of all days.

From the viewpoint of brands, we can see the following from Tables 5.8 and 5.9.

The accuracy rate of P/N SVM, both of the case of $|f| > \alpha$ and $|f| \le \alpha$, is higher than baseline in the case of 3323. From the result shown in Table 5.9, introducing P/N SVM is effective to get much profit.

Table 5.8 shows that the result of accuracy rate of 6773 is the best among all brands. The result of 6773 profit in Table 5.9 shows that system can get positive profit by utilizing fluctuation SVMs or P/N SVM though the profit of all days is negative.

In the case of 9984, the result of fluctuation SVMs is the worse among all brands, and accuracy rates of P/N SVM in the case of $|f| > \alpha$ is equal to baseline. However, the 9984 profit with SVMs in Table 5.9 is higher than profit of all days.

Thus, those results show that selecting trade day by SVMs is effective to get positive profit. This is because the threshold of volatility SVM α is decided based on the profit during the latest 20 days. We have to say important point that the error of SVM output is harmful of course, but is not critical because trading strategy may improve the SVM error in the real trade.

5.7.3 The Strategy in GP

Table 5.10 shows the total profits of three methods. GP & SVMs are our proposed method that applies GP after applying fluctuation SVMs shown in Sect. 5.6.2. GP is the compared method that applies GP without SVMs. Buy & Hold strategy with fluctuation SVMs is the method that applies Buy & Hold strategy to market only

Table 5.10 Total profit with each method (Japanese yen)

Stock code	GP & SVMs	GP	Buy & Hold strategy with fluctuation SVMs
3323	4818.2	5484	3439
6773	310.4	−624	206
9984	12562.0	−7898	3142

when results of fluctuation SVMs are $|f| > \alpha$ and $f > 0$. These total profits of GP and SVMs and GP are calculated by the mean value of 5 trials in GP.

Table 5.10 shows that the total profit of GP & SVMs is lower than the profit of GP in the case of 3323. However, both methods GP & SVMs and GP to 3323 show higher performance than Buy & Hold method with SVMs.

In the case of 6773, even if total profit of GP is negative, the total profit of GP & SVMs is the highest and positive. The profit of Buy & Hold method with SVMs is also positive. Those results indicate that utilizing fluctuation SVMs to select target days is useful to avoid getting loss in some brands.

The total profit of GP & SVMs at 9984 shows the best performance among all brands. On the other hand, the profit of GP is negative. The main reason of this is that the type of days in market is high in variety, so the learning term of GP must be classified by fluctuation SVMs. If we utilize only GP, it is dangerous to apply individuals of evolving in completely different type of days.

Thus, those results show that our proposed method combined with the GP with fluctuation SVMs is effective to get profit in the stock market.

Figure 5.7 shows the transition of the total profit with the GP & SVMs and "Buy & Hold Strategy" without SVMs. In Fig. 5.7, the performance of GP & SVMs is much higher than that of "Buy & Hold strategy," especially after 09/24.

Figure 5.8 shows the transition of the total profit with the GP & SVMs and "Buy & Hold Strategy" without SVMs.

Figure 5.9 shows the transition of the total profit with the GP & SVMs and "Buy & Hold strategy" without SVMs. "Buy & Hold strategy" without SVMs represents the method just applying "Buy & Hold strategy" to all days. In Fig. 5.9, the performance of GP & SVMs is robust and high, especially after 06/01. Comparing Figs. 5.7, 5.8, and 5.9, The fluctuation of Fig. 5.7 is the smallest among 3. This is because brand 3323(RECOMM) has a small capitalization stock, and the liquidity is low. On the other hand, since brand 6773(PIONEER) and brand 9984(SOFTBANK) are both Nikkei 225 Companies, there are high liquidity which makes Figs. 5.9 and 5.8 complex variation. Those results show that selecting adequate brands are important issue in this work.

We can show the effectiveness of proposed method GP & SVMs from the viewpoint of genotype of GP.

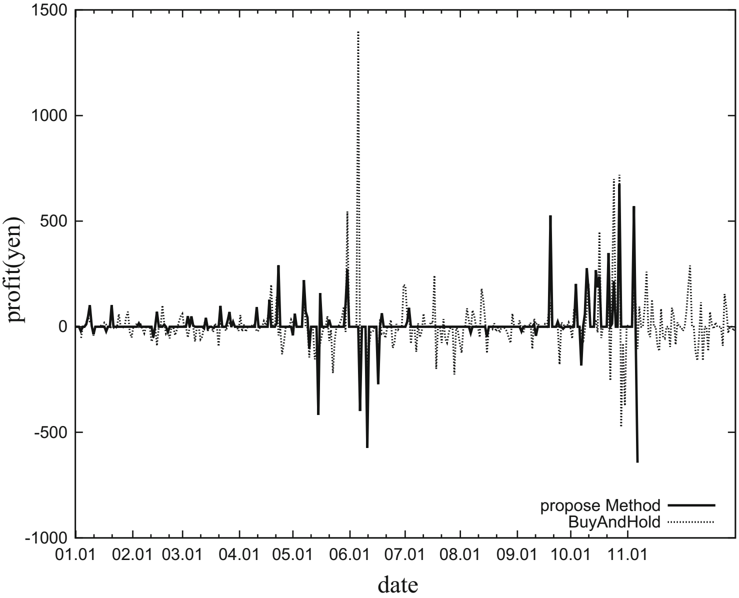

Fig. 5.7 Result: 3323

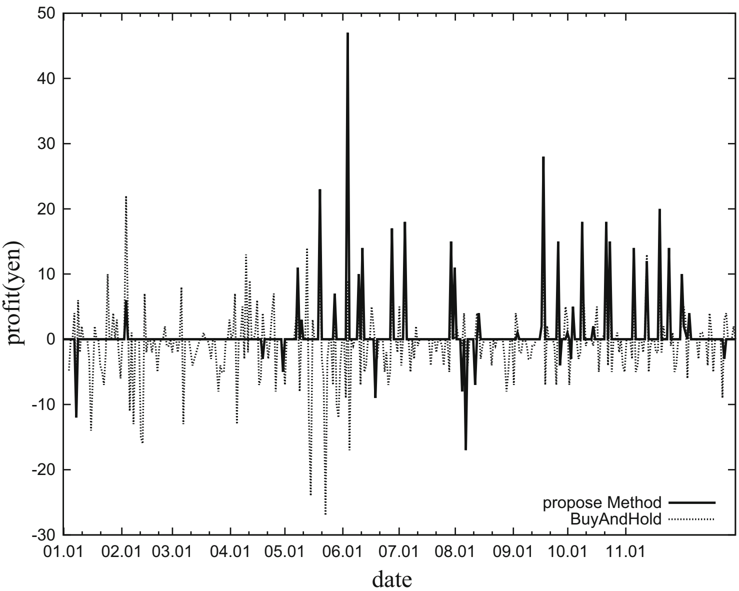

Fig. 5.8 Result: 6773

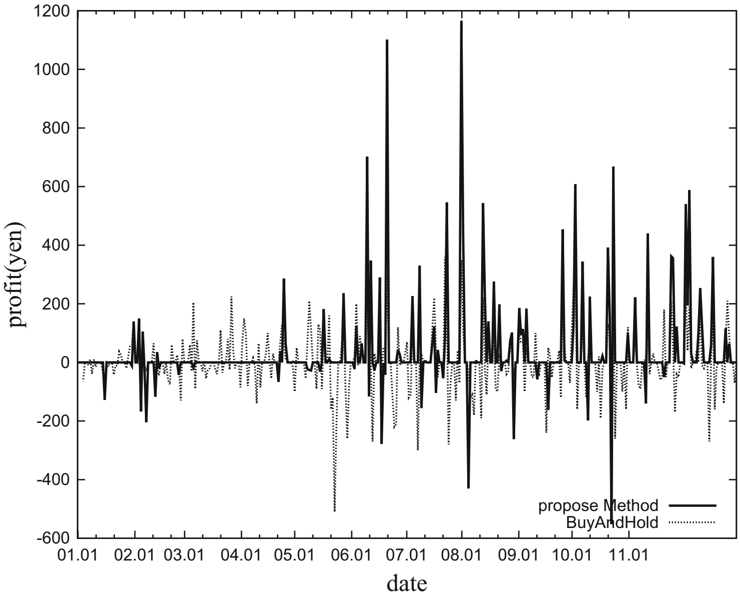

Fig. 5.9 Result: 9984

5.8 Conclusion

In this section, we proposed the novel evolutionary trading method which the fluctuation SVMs and GP to show the effectiveness of automatic trading by computer agents. The results of computer experiments show that selecting trading days and learning term of GP by fluctuation SVM is useful to avoid getting loss. The performance of the proposed method in DTAF is good in several brands. By applying proposed method to various brands and analyzing the genotype of elite individual during trade, more details are subjects of further study. Applying proposed method to artificial market such as U-Mart is also important subjects of further study.

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Chapter 6
How to Estimate Market Maker Models in an Artificial Market

Yoshihiro Nakajima

Abstract In this chapter, market makers and their estimation will be demonstrated as one example of an application using an artificial market. Three kinds of simple market maker models, which decide ask and bid prices by their own positions, are proposed and estimated by acceleration experiments and real-time experiments with human in an artificial market, "U-Mart." These models can accumulate profits stably or at least keep their profits fluctuating in a narrow range. These results suggest the possibility of developing a market maker algorithm working in the real market to provide enough liquidity.

6.1 Introduction

In this chapter, market makers and their estimation will be demonstrated as one example of an application using an artificial market based on investigations by Nakajima et al. [6, 7]. Several models of market makers, which decide bid and ask prices only by their own positions, will be proposed, and they will be estimated empirically by two methods, efficiency and feasibility, in the artificial financial market system of U-Mart.

Recently, with the development and growth of information and communication technology, the number of individual traders who trade via the Internet and algorithm traders is increasing in stock and derivatives markets. Accordingly, the number of orders and the market volume is increasing as well. However, the development and growth of information and communication technology have induced worldwide competition among stock and derivatives markets because temporal and spatial restrictions are being lifted.

Many financial derivative products have been produced. In terms of institution, there are many new products better than currently popular products. However, many new products have been ignored because their markets cannot provide enough liquidity. For example, futures of the Nikkei 225 are rich in liquidity,

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but their underlying asset, that is, the Nikkei 225 stock index, is said to have some problematical points. The Nikkei 225 stock index is strongly affected by the movement of high-priced stocks, it ignores floating share ratios, the identity of the index has been changed by the replacement of stocks, and so on. The FTSE Japan stock index was developed to alleviate these problems, and futures of this index were listed on the Osaka Securities Exchange on July 15, 2002. However, FTSE Japan index futures were rarely traded and ultimately delisted on September 10, 2004. This tells us that, regardless of how constructive a financial product itself is, it will not be traded when the market cannot provide rich liquidity. Therefore, it can be supposed that there are many potential markets that can be realized if we can provide enough liquidity.

It might be dangerous to send orders to a market without enough liquidity because the orders might be ignored for a long time, and unpredictable accidents, which could cause market crashes or sharp rises, might occasionally happen during the ignored term.

Ho et al. [4] pointed out that limit orders left in a market for long time could be regarded as a kind of option without a premium. At the same time, if a trader holds stocks whose market lacks liquidity, he will have difficulty selling his stocks at an adequate price, so traders tend to hesitate to hold stocks whose markets lack liquidity. Sustained lack of liquidity is caused by negative feedback. It is not favorable when markets for worthy stock or financial products cannot function because of a lack of liquidity.

The most common and direct measure and policy to address a lack of liquidity is the introduction of market makers. Market makers are brokers who always offer bid and ask quotes and accept orders from common traders. A market maker can give participants an opportunity to trade financial products. There are market makers in major financial markets in the USA and Europe, the NASDAQ, the NYSE, and the LSE, though their institutions are different. Conversely, for historical reasons, market maker specialists have never been encouraged in Japan. Therefore, practical market maker skills are strongly required in Japan.

Kyle [5] proposed that liquidity in a continuous auction, which is generally adopted in most securities markets, could be divided into three components: tightness, depth, and resiliency. He also defined the measure of liquidity called Kyle's lambda. Kyle's arguments have been a standard hypothesis in market microstructure research, and many studies have used his ideas to propose market maker models.

Stoll [9], Ho and Stoll [4], and O'Hara and Oldfield [8] proposed market maker models to determine bid-ask spread to minimize inventory and transaction costs. Copeland and Galai [2] and Kyle [5] proposed market maker models that calculate an optimum bid-ask spread by the component rate of informed and noise traders. Beltratti et al. [1] proposed market maker models that have a learning method.

However, Kyle's arguments were theoretical, and he assumed an informed market maker who knows true values through perfect foresight as well as the existence of a distribution of orders including potential ones. The arguments are too complex to design market maker models, which will actually provide liquidity by trading in real "thin markets" in the first step. Here, we will examine market maker models to develop software for algorithm trading that will work in a real market and provide liquidity in "thin markets" in which orders are rarely sent and almost no limited orders are left in the order book. In the next section, I will discuss "thin markets" to clarify what type of lack of liquidity is thought to be solved by the market maker models mentioned below.

6.2 Thin Market

Table 6.1 represents the order books of the Mizuho Financial Group on March 24, 2006 at 9:57 a.m. on the Tokyo Stock Exchange (TSE). Table 6.2 shows the books for the Osaka Stock Exchange (OSE). The center column lists the price, and to the left side of each price is listed the ask volume at the given price. The right side shows the bid volume.

In Japan, stocks of many companies with long histories had been listed on both the TSE and OSE. Almost all stocks had been traded on the TSE.[1] In 2006, the market share of the OSE was only around 5 %. The Mizuho Financial Group is one of the biggest banks, and the market capacity of the company's stock is huge. On

Table 6.1 Market information for the Mizuho Financial Group on the Tokyo Stock Exchange (March 24, 2006, 9:57 a.m.)

Ask volume	Price	Bid volume
362	934,000	
431	933,000	
495	932,000	
333	931,000	
562	930,000	
	929,000	195
	928,000	156
	927,000	116
	926,000	102
	925,000	183

Table 6.2 Market information for the Mizuho Financial Group on the Osaka Stock Exchange (March 24, 2006, 9:57 a.m.)

Ask volume	Price	Bid volume
1	973,000	
2	970,000	
1	960,000	
8	931,000	
	928,000	8
	900,000	1

[1]The TSE and OSE merged in 2013.

the Tokyo Stock Exchange, many stocks were traded, but trade was hardly seen on the Osaka Stock Exchange.

In the example represented in Table 6.1, 12,405 stock units had been traded up to 9:57 a.m., but no trade occurred on the Osaka Stock Exchange. In the distribution table of orders on the TSE, we can see that the best bid price was 929,000 yen and the best ask price was 930,000 yen, so the spread was only 1,000 yen. For each price, hundreds of units were in the order book. At the same time, the best bid price on the Osaka Stock Exchange was 928,000 yen, and the best ask price was 931,000 yen. The order volume in the book was also poor; fewer than 10 units were in the order book in total. Additionally, outside of the best ask and bid quotes, the prices are far from the best prices.

Both the best price and number of orders in the order book were disadvantage against new orders on the Osaka Stock Exchange, and then traders might obviously choose the Tokyo Stock Exchange to trade the stock of the Mizuho Financial Group. This is an example of a huge company, and the stock is listed in two different stock markets. However, even if we consider stocks listed only on the Tokyo Stock Exchange, if the distribution of orders on their order book were like that of the Mizuho Financial Group indicated in Table 6.2, traders might hesitate to trade the stock because of a lack of liquidity. On the JASDAQ Securities Exchange, the stock market for small or venture companies, around 10 % of stock brands have not been traded. This suggests that many brands of stock are ignored by traders because of a lack of liquidity. In this investigation, a "thin market" is a market that lacks liquidity, and their order book is usually empty. Market makers play a role in providing liquidity through their orders to recover their normal functions of the markets.

Can algorithm traders, which send orders automatically, operate in real thin markets to provide liquidity as market makers? The market makers mentioned here must satisfy the following conditions: (1) they must keep markets with limited orders on both the ask and bid sides, and (2) they must earn profits constantly in the long term as a consideration of providing liquidity. The first condition arises from effectiveness. The second is related to the feasibility of the market makers because no one will participate as market makers if they will not be able to earn appropriate profits through their service. Practical algorithm market makers trade in real markets; therefore, there is a possibility of suffering a loss. Under Kyle's argument, it is assumed that a market maker can know information about potential distributions of orders and their future conditions. The three indicators of liquidity proposed by Kyle can be calculated from such potential and future information. However, practical market makers cannot know such information.

This investigation is the first step in asking the above question "Can algorithm traders provide liquidity as market makers?" We will propose several simple market maker models using information from a real market. We will examine the efficiency and feasibility of these models using acceleration experiments in an artificial market. This investigation is only the first step; therefore, we assume very strong conditions as follows. The first condition is that the market maker cannot predict prices and orders in the future. In a real market, traders, including market makers, can obtain

(1) fundamental information that is published or broadcasted, (2) time series of past prices and the current distribution of orders, and (3) their own position. Stipulations 1 and 2 are related to Fama's efficient market hypothesis [3]. When we consider the thin markets mentioned here, it is better to start with stronger restrictions, so we should begin here by examining models using only information concerning stipulation 3.

The second condition is that we will examine the number of trades or contracts to estimate the efficiency of market makers. Three types of liquidity proposed by Kyle are all important in discussing market liquidity. However, when we consider thin markets here, all of these liquidity types can hardly be calculated without potential and future information; furthermore, it is hard to compare markets with and without market makers. Therefore, we consider liquidity more simply.

The third condition is that traders other than market makers send orders with identical probability. Essentially, by increasing the number of orders, their normal market function will be restored, and then it can be expected that more and more orders will be made. However, in this investigation, we will ignore such a positive or negative feedback for the sake of simplicity.

The fourth condition is that the feasibility of market makers is estimated by their total profit in the long term. As mentioned above, practical market makers will trade stocks in a real market, so they will often suffer losses in the short term. Additionally, the performance of traders, including market makers, should be estimated by the relationship between risk and return. However, here, we point out only long-term profit for the sake of simplicity.

Strictly speaking, market systems with and without market makers are classified as quote-driven market systems and order-driven market systems. In a quote-driven market, ordinal traders must trade against market makers, and all orders can be contracted in an order-driven market. In this sense, market makers who always send both ask and bid orders to provide liquidity in order-driven market are sometimes called "liquidity providers" to distinguish market makers in order-driven markets from those in quote-driven markets. In this investigation, we concentrate on the estimation of market makers without differentiating between market systems. Therefore, we consider only order-driven markets.

Order-driven markets can be classified roughly into continuous-auction markets, in which all orders are continuously contracted, and batch-auction markets, in which orders are collected during a waiting time and completed at a scheduled time. Most main stock markets are continuous-auction markets, but for the sake of simplicity, we adopt a batch-auction market. The artificial market U-Mart Ver. 2 implements a batch-auction market, and U-Mart Ver. 4 implements both batch- and continuous-auction markets. The details are explained in Chap. 6.[2] We use U-Mart Ver. 2 in this investigation.

[2]In other chapters, the continuous-auction market is called "Zaraba," and the batch-auction market is called "Itayose."

6.3 Market Maker

There are many market maker specialists in major financial markets. It can be supposed that they use some type of program to calculate offer prices. However, these programs and their algorithms are not open to the public, and we cannot analyze them through academic investigations. In contrast, in an academic context, market makers have been investigated [1, 2, 4, 5, 8, 9]. These investigations have addressed the place where market makers can exist, but they hardly indicate how market makers trade in thin markets.

We interviewed specialists who worked as market makers. As a result, we realized that the main point of market making is position control [6]. They are always forced to neutralize their position. Market makers suffer damage when a market is filled with one-sided orders. When a market crash occurs, traders tend to sell one-sidedly. Market makers are forced to provide bid orders, and they must accept such one-sided orders. As a result, they increase their long position. In this situation, market makers no longer want to increase their long position, and they try to sell to neutralize their position. Therefore, market makers reduce both bid and ask prices. From this simple observation, we propose simple market maker models.

6.3.1 Three Models of Simple Market Maker

How do market makers set bid and ask prices in actual markets? In Japan, some stocks on the JASDAQ Security Exchange used a market maker system until 2008. We analyzed the relationship between the last price and the last quote for all JASDAQ stocks on March 3, 2004. Table 6.3 shows the spread from the last price to the last bid quote and the last ask quote, respectively. It shows that the spread between the bid quote and last price and the spread between the ask quote and the last price are not symmetric, suggesting that market maker controls both ask and bid quotes.

To construct market maker models that calculate bid and ask quotes, respectively, from their position, the following notations are given. To estimate models defined by the following notations in U-Mart Ver. 2, we consider a futures market.

Table 6.3 Spreads provided by market makers on March 3, 2004 on the JASDAQ Securities Exchange. Upper Spread. (US): Ask Price—Last Price Lower Spread, (LS): Last Price—Bid Price

	US (%)	LS (%)	Bid-Ask (%)
MAX	8.9	15.2	14.3
MIN	−0.9	−3.4	0.2
Average	1.4	1.1	2.5
Standard deviation	1.5	1.5	2.0

Notations listed blow are used to represent models

- x position ("+" means that the market maker holds a long position; "−" means that the market maker holds a short position)
- $p(t)$: futures price at the tth period
- $ls(x)$: lower spread (spread between last futures price and bid price when the market maker's position is x)
- $us(x)$: upper spread (spread between last futures price and ask price when the market maker's position is x)
- a, b, c: constant (parameter)
- $ap(t)$: ask price at t
- $bp(t)$: bid price at t

where

$$\begin{aligned} ap(t) &= (1 + us(x))p(t-1) \\ bp(t) &= (1 - ls(x))p(t-1) \end{aligned} \tag{6.1}$$

We propose three types of market maker models as follows:

6.3.2 Market Maker Model 1 (MM1, Simple Spread Type)

$$us(x) = b, \quad ls(x) = b \tag{6.2}$$

First, for the sake of contrast, we propose the simplest market maker model, named MM1. MM1 has a proper spread and gives quotes based on it. Figure 6.1 depicts the upper and lower spreads when $us(x) = ls(x) = b = 0.01$. The X-axis is the market maker's position, and the Y-axis shows the spread. Figure 6.2 shows the bid and ask prices calculated by formulas (6.1) and (6.2). The X-axis of Fig. 6.2 is the market maker's position, and the Y-axis is the relative price when $p(t-1) = 1$.

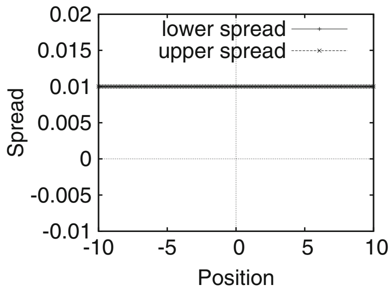


Fig. 6.1 *Upper* and *lower spreads* from last price of MM1

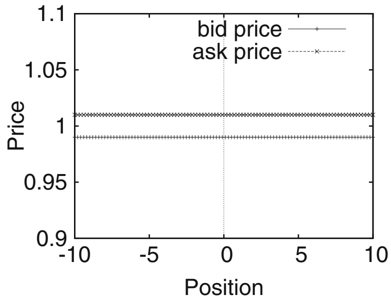


Fig. 6.2 *Ask* and *bid price* quoted by MM1 at its position is x

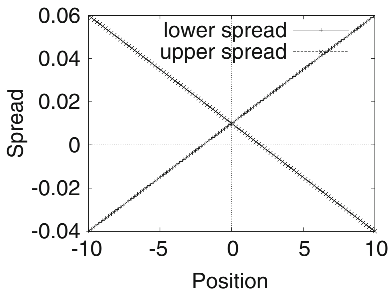


Fig. 6.3 *Upper* and *lower spread* of MM2

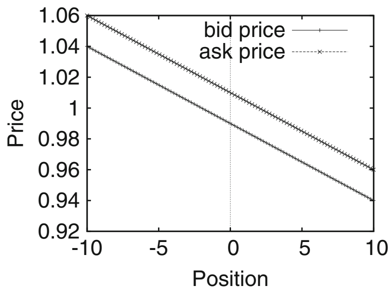


Fig. 6.4 *Ask* and *bid prices* of MM2

6.3.3 Market Maker Model 2 (MM2, Linear Type)

$$us(x) = -ax + b, \quad ls(x) = ax + b \tag{6.3}$$

MM2 simply realizes the behavior that occurs when the market maker holds a long position; he reduces the bid price to avoid increasing the long position further and reduces the ask price to neutralize his position. Figure 6.3 is the upper and lower spread of MM2, and Fig. 6.4 shows relative bid and ask prices quoted by MM2 when $a = 0.005$ and $b = 0.01$. When his position is zero, that is, $x = 0$, the bid and ask prices quoted by MM1 and MM2 are the same. From this, MM1 can be considered a special case of MM2 such that $a = 0$.

6.3.4 Market Maker Model 3 (MM3, Polynomial Type)

$$us(x) = -ax^3 + c|x^3| - b, \quad ls(x) = ax^3 + c|x^3| - b \tag{6.4}$$

MM3 realizes the asymmetry between the upper spread and lower spread from the last price. This is the situation pointed out by Table 6.3. When MM3's position is close to zero, he quotes bid and ask prices by a proper spread, like MM1. With a continuous trend or a steep change in price, when he will have to increase his position, he will try to neutralize his position by controlling the bid and ask prices. There are many functions to realize this behavior, but the simplest one is a cubic function. Thus, the basic function of MM3 can be given as $us(x) = -ax^3 + b$, $ls(x) = ax^3 + b$. To neutralize his position, (1) he avoids further increasing his position, and (2) he tries to decrease his position. The asymmetry shown in Table 6.3 suggests that actual market makers execute condition 1 first and then condition 2. When the position of the market maker is positive—that is, he holds a long position—he reduces the bid price and avoids buying any more. Then, he reduces ask price; that is, he tries to sell at a bargain price. This can be realized when the rate of decrease in the bid price is larger than that of the ask price. The following formula can realize this situation:

$$up(x) = -\left(a - \frac{cx}{|x|}\right)x^3 - b, \quad lp(x) = \left(a + \frac{cx}{|x|}\right)x^3 + b \tag{6.5}$$

Formula (6.4) is derived from formula (6.5). Parameter "b" represents the basic spread, parameter "a" represents the intensity of the position adjustment, and "c" represents the intensity of asymmetry. Note that the roles of parameters "a" and "b" correspond to those of "a" and "b" in MM1 and MM2. Figures 6.5 and 6.6 show the spread and price of MM3 when $a = 0.0001, b = 0.01$, and $c = a/2$.

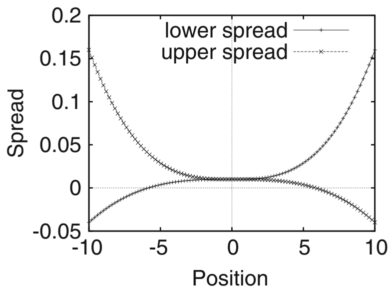


Fig. 6.5 *Upper* and *lower spreads* from the last price of MM3

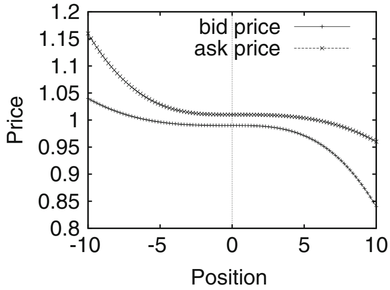


Fig. 6.6 *Ask* and *bid prices* of MM3

6.4 Efficiency and Feasibility of Market Maker Models

Now we examine the efficiency and feasibility of the market maker models proposed here. The efficiency of a market maker is mainly recognized as liquidity and is assumed to be simply estimated by the contract rate. Market makers must obtain a stable income, so their feasibility can be estimated by their profits.

6.4.1 Contract Rate of a Market with Random Agents

To estimate the efficiency of a market maker, we must consider a thin market in which traders other than market makers rarely send orders. As mentioned above, an actual thin market should have some kind of feedback mechanism. However, if we build such a mechanism into a market, the market becomes too complex to estimate the effects of the market maker. Additionally, such a feedback mechanism unavoidably introduces arbitrariness or strong assumptions. Therefore, in this investigation, we seek to estimate market makers in a simple market without a feedback mechanism.

Suppose that a market has a given time divided into sessions. In each session, traders decide to send orders. At the end of the session, orders are contracted at a price that will maximize contract volume. All traders are random agents characterized by order rate p. An agent sends an order with probability p. He decides on an ask or bid order randomly. Limited prices for each order are given by a random variable with a normal distribution around the last spot price. The variance of the distribution to determine the limit price is given as a parameter. When there are N such traders in a market, what is the contract rate?

In one session, the probability that k traders of N send orders is ${}_N C_k pk(1-p)N-k$. In this situation, the probability that h traders in k will send sell orders and the rest will send buy orders is ${}_k C_h(\frac{1}{2})k$. Suppose that the distribution of the limited prices is the same among k traders. The contract rate can be calculated as 1 minus the uncontracted rate. When all limited ask prices are higher than any limited bid prices, no order will be contracted. The probability of this situation is $\prod_{i=0}^{h-1}\frac{h-i}{k-i}$. We

Table 6.4 Analytical and empirical results for contract rate

Number of agent	Analytical Value (%)	Empirical Average (%)	SD (%)
8	5.7	5.7	0.7
10	8.6	8.6	0.8
12	11.8	11.9	0.9
14	15.3	15.5	1.0
16	18.9	19.0	1.0
18	22.6	22.8	1.0
20	26.4	26.5	0.9

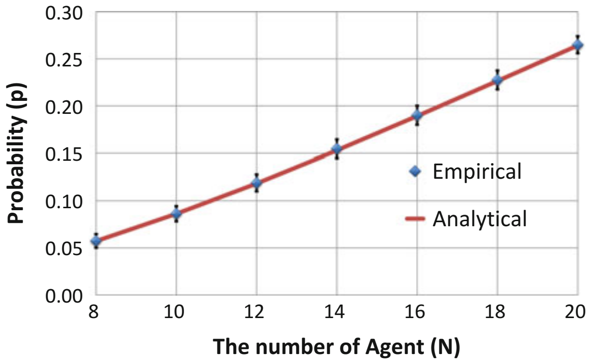


Fig. 6.7 Analytical and empirical results for contract rate

can obtain the contract rate as follows.

$$CR(N, P) = \sum_{k=2}^{N} \left\{ {}_N C_k (1-p)^{N-k} \sum_{h=1}^{k-1} \left\{ {}_k C_h \left(\frac{1}{2}\right)^k \left(1 - \prod_{i=0}^{h-1} \frac{h-i}{k-i}\right) \right\} \right\} \tag{6.6}$$

Table 6.4 and Fig. 6.7 represent the contract rate calculated by formula (6.6) and experimental results in an artificial market with random agents, respectively.

6.4.2 *Experimental Environments Given by the U-Mart Artificial Futures Market*

To estimate the efficiency and feasibility of the market maker models, we adopt the artificial U-Mart System Ver. 2 futures market as a simulator to conduct acceleration experiments. The U-Mart system is provided by the U-Mart Project as a common test bed for agent-based simulation [10]. The U-Mart Project not only provided a simulator but has also conducted open experiments using machine agents (trade algorithms) and human agents (human traders) and provided courseware for graduate- and undergraduate-level courses. With this system, we have a chance to estimate the performance of models in several environments, such as with human agents or machine agents with an artificial intelligence method that showed good performance in past contests that were open to the public. It is uncommon to analyze a futures market, but a futures market is better for simulation because all fundamental information is embedded into spot prices if we assume the efficient market hypothesis.

Adding to the three market maker models, we include two other random agents. One is called a naive market maker (MR), who always sends sell and buy orders, like MM1, MM2, and MM3, but limited prices are given randomly, and ask prices are higher than bid prices. The other agent is a random trader addressed in Section 4.1; that is, he sends orders randomly with probability p. We call him a random agent (RA). In the following experiments, only RA adopts the latest spot price as the latest price, p(t-1), and the others, MM1, MM2, MM3, and MR, use the latest futures price as the latest price. In this sense, we assume that RA can use more profitable information than market makers can.

In the following experiments, all parameters are the same as described above, and the order size of all market makers and random traders is one. The final profits of all traders, including market makers, are given by settlement at the spot price in the next to last session.

6.4.3 Results of Experiment 1 (In Geometric Brownian Motion)

Suppose that a simple market consists of ten random traders (RAs) with order probability $p = 0.1$. According to equation (6.6), the expected contract rate is 8.6 %. We conduct numerical experiments with 11 agents (ten random agents and one market maker or random agent among MM1, MM2, MM3, MR, and RA). We conduct 10 trials with 1,000 sessions for each combination. Spot prices are given by a stochastic process of geometric Brownian motion given the following formula and parameters:

$$p(t) = p(t-1) + 0.8p(t-1) + 0.9p(t-1)2\sqrt{3}w(t) \tag{6.7}$$

where $w(t)$ is white noise.

Table 6.5 shows the results. With any type of market maker, contract rates increase over three times. Considering the standard deviation of the contract rates, the efficiency of the market maker can be confirmed. The contribution rate is calculated as follows: (number of contracts of market maker)/(total number of contracts). The results mean that all market maker agents play the role of a market maker; that is, a contract rate of around 80 % occurs between traders and a market maker. The profit results are different among the models. The average profits of MM2 and MM3 are greater than three times the standard deviation. If their profit distributions follow the normal distribution, the probability that MM2 will suffer a

Table 6.5 Contract rate of each market and contribution rate and profit of market makers

	Contract rate		Contribution rate		Profit	
Agent type	Average (%)	SD (%)	Average (%)	SD (%)	Average (Yen)	SD
MM1	28.6	1.1	80.2	2.6	3,922,600	1,411,406
MM2	28.9	1.6	80.6	2.4	3,231,100	645,763
MM3	27.8	1.5	79.1	1.7	4,196,900	1,086,071
MR	28.6	0.8	79.6	2.2	−3,287,100	3,042,503
RA	10.1	1.2	18.4	2.8	−1,978,600	872,671

Fig. 6.8 Profits of MM1

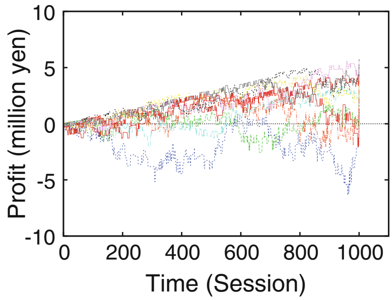
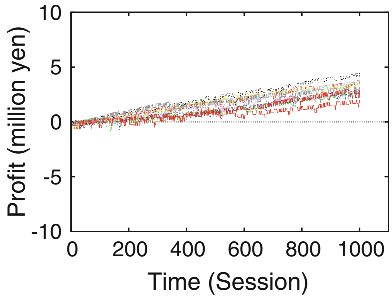


Fig. 6.9 Profits of MM2



loss is 0.00003 %, and that of MM3 is 0.00557 %. These are small enough to ignore. In contrast, the average profit of MM1 is large, but the standard deviation is large as well, so his probability of suffering a loss is 0.272 %.

Figures 6.8, 6.9, 6.10, 6.11, and 6.12 represent the transitions of profits of MM1, MM2, MM3, MR, and RA, respectively. The X-axis represents time (sessions), and the Y-axis represents profits. In each figure, there are ten curves, which indicate the result of each trial. MM1, MM2, and MM3 experience repeated short-term losses and gains, but they tend to increase their profits almost linearly in the long term. MM1 shows some cases of relatively large losses, but for MM2 and MM3, losses are small, and they steadily accumulate profit in the long term. MR and RA suffer big losses in all trials. Because the number of orders for RA is small, his profits move stepwisely.

When we compare RA with MM1, MM2, and MM3, even the simplest one (MM1) is more stable in terms of profit. This suggests that merely fixing the spread

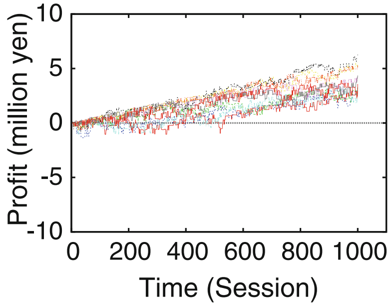


Fig. 6.10 Profits of MM3

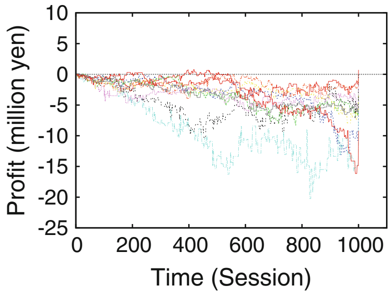


Fig. 6.11 Profits of MR

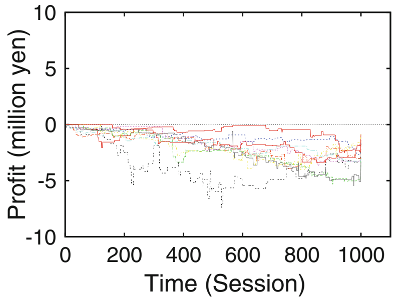


Fig. 6.12 Profits of RA

might stabilize the profits of market makers. It can also be seen that, if market makers accumulate profit, their total profits increase linearly. This suggests that information on their own position is useful in keeping their profit stable. In contrast, as shown in Figs. 6.8 and 6.11, when the market maker suffers a loss in long term, the profit curves fluctuate as in the random walk.

6.4.4 Results of Experiment 2 (GARCH Process)

Next, we examine a case in which spot prices are given by the GARCH process, a common unstable stochastic process that is well known as a model of systems that experience sudden increases or decreases, such as stock prices. The GARCH process also realizes the power law distribution and volatility clustering, which are observed in stock price fluctuations and considered stylized facts that distinguish properties of stock and derivative markets. All conditions without spot prices are the same as in previous experiments. The formula and parameters of the GARCH process are as follows:

$$\begin{aligned} p(t) &= p(t-1) + Q(t) \\ Q(t) &= 0.99Q(t-1) + \sqrt{S(t)w(t)} \\ S(t) &= 1.0 + 0.1w(t-1) + 0.85S(t-1) \end{aligned} \tag{6.8}$$

where $w(t)$ is white noise.

Table 6.6 shows the results of the experiments. The results for the contract rate and contribution rate are almost the same as those shown in Table 6.5. However, the profits of market makers are different. In all cases, even for MM2 and MM3, it cannot be said that market makers obtain stable profits.

Figures 6.13, 6.14, 6.15, 6.16, and 6.17 represent the transitions of profits of MM1, MM2, MM3, MR, and RA, respectively. The X-axis represents time (sessions), and the Y-axis represents the profits. In several trials, MM2 and MM3 accumulate profits stably and can increase their total profits linearly, but sometimes they suffer losses. This suggests that no type of model has sufficient feasibility in a real market. However, the profit curves fluctuate in a determinate range. In several trials, MM1 also succeeds in accumulating profits linearly but sometimes suffers

Table 6.6 Efficiency and feasibility of market makers in the GARCH process

	Contract rate		Contribution rate		Profit	
Agent type	Average (%)	SD (%)	Average (%)	SD (%)	Average (Yen)	SD
MM1	28.6	1.5	78.3	3.2	−179,080,700	319,222,200
MM2	29.2	0.9	80.9	2.9	32,066,800	33,379,910
MM3	26.5	1.6	76.3	2.3	15,009,700	48,603,810
MR	24.4	1.2	80.4	2.0	1,795,900	134,634,400
RA	10.2	0.9	17.5	5.6	33,394,300	49,384,510

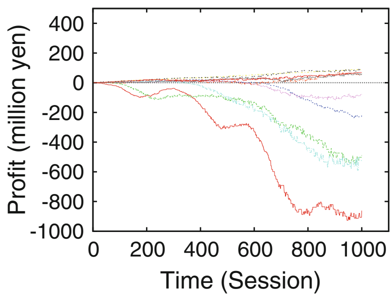


Fig. 6.13 Profits of MM1

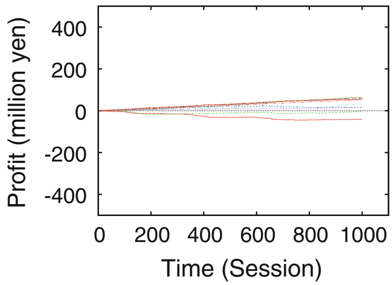


Fig. 6.14 Profits of MM2

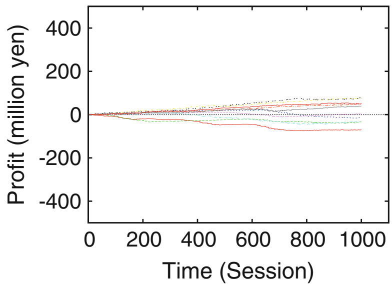


Fig. 6.15 Profits of MM3

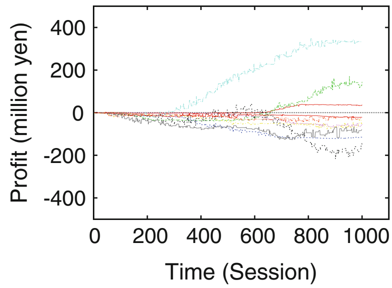


Fig. 6.16 Profits of MR

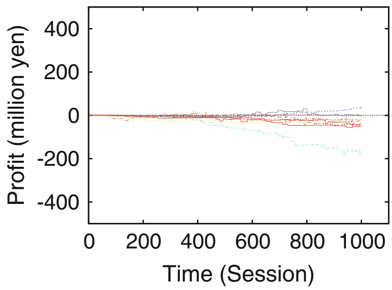


Fig. 6.17 Profits of RA

big losses. RA also ends with profit in several trials, but in both profitable and unprofitable trials, the profit curves fluctuate widely. Market makers who considered their own position relatively keep their profits stably.

6.4.5 Human Agent (U-Mart 2005)

The U-Mart Project has conducted annual international public experiments. Mainly undergraduate students who have used the U-Mart system in their educational courses have participated. They attended as human agents; that is, they have traded themselves in the public experiment, or they submitted a machine agent that they developed themselves. The five machine agents implemented in the market maker models, MM1, MM2, MM3, MR, and RA, participated in U-Mart 2005, conducted at Kyoto University in 2005; in total, 29 human agents and 30 machine agents participated. These public experiments, because human agents were involved, were conducted in real time.

At U-Mart 2005, two trials were conducted. In Trial 1, each session had a wait time of 20 s to gather orders from agents, and 90 sessions were held. In Trial 2, the wait time was 10 s, and there were 192 sessions. The spot price series reflected a real stock index.

Table 6.7 shows the final profits of each machine agent. In both Trial 1 and Trial 2, all agents except RA ended with profits. In particular, the profits of MM2 and MM3 are similar both in Trial 1 and Trial 2. Figures 6.18 and 6.19 show the profit curves of the machine agents. The curves of MM1 and MR fluctuate widely, but those of MM2 and MM3 fluctuate relatively stably, and they succeeded in accumulating profits steadily, as in the experiments described above. Of course, we can conclude nothing based on only two trials. However, it can be pointed out that, though the machine agents are simple, they were able to end with profits, and their profit curves were stable.

Table 6.7 Final profits of models at U-Mart2005

	Trial 1 (Yen)	Trial 2 (Yen)
MM1	2,090,000	2,711,000
MM2	480,000	4,321,000
MM3	780,000	4,891,000
MR	2,799,000	5,662,000
RA	−265,000	4,990,000

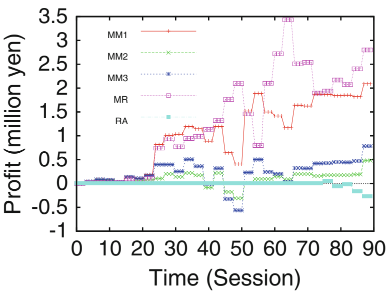


Fig. 6.18 Profits of each model in Trial 1 (20 s per session, 3 sessions per day, 30 days)

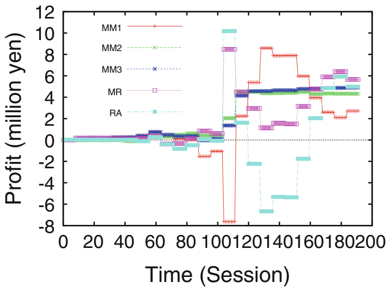


Fig. 6.19 Profits of each model in Trial 2 (10 s per session, 8 sessions per day, 24 days)

6.5 Conclusion

We proposed simple market maker models that use only their own position and always keep their ask and bid orders in the order book. We estimated their efficiency and feasibility by conducting experiments in an artificial market, U-Mart Ver. 2. We conducted three types of experiments: (1) acceleration experiments with spot price time series given by geometric Brownian motion, (2) experiments using the GARCH process, and (3) real-time experiments with human agents and strategic machine agents with a real stock index.

In assessing the efficiency of the market maker models, in all acceleration experiments, we were able to confirm that market makers drastically increase the contact rate. In assessing the feasibility of the market maker models, we sought to determine whether the market maker models were able to earn adequate profit because of their service of providing liquidity. In the experiment with spot price time series given by geometric Brownian motion, MM1 was able to earn profits relatively more stably than RA. The models using their positions, that is, MM2 and MM3, were able to accumulate profits stably. However, in the experiment with the GARCH process, which realizes more realistic time series for stock prices, both MM2 and MM3 faced possible losses even in the long term, and their profit curves fluctuated in a narrow range. This result suggests that MM2 and MM3 are not sufficient to use as autonomous market makers in real markets, but we may be able to develop models based on them. MM2 and MM3 accumulated profits stably in spite of the fact that the other participants were human agents and machine agents that were not random agents but had intelligence.

The models proposed here are simple and estimated in an environment with the conditions driven by strong assumptions. MM2 and MM3 used information only on their position and the latest futures prices, and they used only low-degree polynomials to decide on behavior. However, their profit curves fluctuated in a narrow range even in the worst case, and in many cases, the curves increases linearly.

This investigation is only the first step, and there are many ways to modify the models and experiments. For example, all parameters of the models were fixed in this investigation. The time series of real stock prices and GARCH show volatility clustering. Therefore, based on past price time series, market makers change their parameters automatically depending on the current volatility. In this investigation, all other traders behaved randomly, but it is necessary to estimate the models in markets with intelligent agents. The U-Mart Project has conducted annual public experiments for 15 years, and hundreds of machine agents have participated. Many machine agents use AI and other modern methods. By modifying the models and estimations, we expect to develop market maker models that can be used in real markets and provide liquidity to realize functional markets in many areas.

In this chapter, we introduced the investigation as a method to apply artificial markets. The U-Mart system provides an experimental environment in which we can easily estimate the efficiency and feasibility of market maker models through acceleration experiments and real-time experiments with human agents. The Tokyo Stock Exchange changed the unit of bidding prices in 2014. Artificial markets provide experimental environments in which to estimate the effects of such institutional changes. We hope that artificial markets will contribute to investigations in the future.

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Chapter 7
The Effect of Resilience in Optimal Execution with Artificial-Market Approach

Hiroyuki Matsui and Ryo Ohyama

Abstract This chapter reexamines the optimality of Obizhaeva and Wang's strategy by replacing their assumption of resilience given in functional form with resilience caused by trader behavior. This attempt is based on the idea that trading causes every financial market phenomenon. In other words, stock price change occurs only as the result of trades. In that sense, resilience exogenously given in a functional form is not realistic since it does not consider trading behavior. This thesis focuses on the modeling of trader behavior. Three models are proposed and examined to determine their validity. We name these models the full, low, and zero intelligence models, respectively. The three models are named according to how strategic they are. After examining the validity of each model, we try to simulate the strategies of Bertsimas and Lo and Obizhaeva and Wang by replacing resilience given in a functional form with each validated model. Through simulation of the total execution costs of each optimal strategy, we can check which strategy is better. Obizhaeva and Wang's strategy is said to always outperform that of Bertsimas and Lo under the assumption that resilience follows a certain functional form. This thesis casts doubt on this assumption owing to its arbitrary nature.

7.1 Introduction

7.1.1 Background

For traders as financial market participants, it is extremely rational to set goals, formulate optimal strategies to achieve those goals, and make investments based on the formulated strategies. However, uncertainty exists in financial markets. Therefore, goals and strategies are not always successfully realized. Optimal investment strategy, which is difficult to practice, has attracted much academic interest. There have been a number of studies on this area, including one on portfolio selection by Markowitz [20].

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Particularly, the concept of implementation shortfall proposed by Perold [26] has recently been considered to have important implications. Perold indicated that a significant dissociation could be generated between theoretical and actual investment performance. This phenomenon is clearly observed in institutional traders operating with a significant amount of investment funds. Chen et al. [8] and Yan [33] have already demonstrated this phenomenon by showing an inverse correlation between fund scale and performance.

Market impact, which is included in implementation shortfall, is important to heavy traders. This phenomenon is such that individual investment behavior causes asset prices to fluctuate. Focusing on execution cost where market impact is taken into consideration, Bertsimas and Lo [4] defined optimal investment strategy as minimizing the expected value of execution cost, and so tried to obtain the optimal solution using a dynamic programming method. Obizhaeva and Wang [23] derived the optimal investment strategy based on more realistic assumptions by applying the framework proposed by Bertsimas and Lo [4] to limit order board markets.

However, multiple complex factors intertwine in financial markets, and we have to make assumptions based on certain factors. For example, this study focuses on the factor of resilience, the primary concept of which is well understood. However, the principles of this factor remain insufficiently clear. Obizhaeva and Wang [23] indicated that resilience would follow an exponential function. However, no factual evidence has been presented, and hence the parameters of the exponential function given have not been clarified.

When considering assumptions that are impossible or difficult to observe in actual markets, we must explore their adequacy using other means or methods. As one of the effective methods, the artificial-market simulation method has recently been advanced. According to Izumi [14], an artificial market comprises two factors, the behavioral entity in the market, called the agent, and the price decision mechanism. Numerous requirements exist for the artificial market to become valuable. However, this method has potential to give new interpretations to those objectives, which have been impossible to verify through conventional theories or quantification methods, by modeling market-related hypotheses and hypotheses associated with traders.

Chin [6] performed a representative study based on specific use of artificial markets. Chin [6] expressed the depth of a limit order board market by changing the number of agents. By doing so, he explored the optimal split of transactions across the investment period for minimizing the execution cost. This study involved nine different agent types, making asset price fluctuations extremely complicated. However, the use of the simulation method contributed to the analysis.

7.1.2 Objective

In this study, we take up Bertsimas and Lo [4] and Obizhaeva and Wang [23] who discussed the same objective regarding optimal investment strategies adopted by risk-neutral traders to minimize execution cost. Their two models derived different optimal investment strategies. This results from different market hypotheses. We focused on the factor called resilience, which is given exogenously according to Obizhaeva and Wang [23]. Here we try to model this factor as a trader behavior by using an artificial market to establish a more realistic market environment. While conducting simulations based on this market environment and considering the effect of resilience on the optimal investment strategy, we discuss the validity of assumptions proposed by Obizhaeva and Wang [23].

7.1.3 Meaning of Using U-Mart in This Preset Research

Izumi [14] summarizes the problems in traditional financial market theories as follows:

Traditional financial market theories assume rational market participants. This creates a problem where we face difficulty in providing persuasive explanations regarding irrational market phenomena that often cannot be observed. In many cases, hypotheses regarding the market can be simplified within the modeling process. Therefore, it can be difficult to apply such hypotheses to the actual market. Moreover, traditional theories can contain factors that are difficult to measure, such as the thoughts of market participants, which are difficult to verify.

When taking a stand from the viewpoint of overcoming the abovementioned problems, we have developed the need to use an artificial market in financial market studies. Restated, by using the artificial market, we can make flexible models that include factors, such as traders that are not necessarily rational or that become irrational only under certain conditions. This allows us to explain irrational phenomena. Additionally, the building of a system that follows the actual market system, such as the U-Mart system (Akimoto [1], Kita et al. [17], Ono [24], Ono et al. [25]), can bring market-related hypotheses closer to reality. Therefore, the occurrence of particular phenomena in the artificial market suggests that they might also occur in the real world. Finally, verification of factors that are difficult to measure in the actual world can be enabled by programming and simulation to ensure consistency with the actual world.

In the U-Mart system, future goods to be traded are associated with the actual world by giving spot price data. As we will discuss later, in this study, fundamental price plays an important role. Consequently, in this study, we conduct simulation based on an assumption, which is difficult to verify in the actual world, where traders exist who know fundamental prices and consider the spot price to be the fundamental price.

Additionally, in financial market theories, hypotheses are always simplified in the modeling process, and this tendency is especially notable in the market system. For example, Bertsimas and Lo [4], whose work provides the basis for the simulation in this study, do not refer to any transaction methods. The model of Bertsimas and Lo is quite simple, but doubts exist about its applicability to the actual market. Obizhaeva and Wang [23] came one step closer to the reality in terms of applying the model of Bertsimas and Lo [4] to the limit order board market. Therefore, when limit order boards are used, it is essential to conduct simulations based on limit order boards to examine the differences between the two optimal investment strategies. In this sense, we can say the U-Mart system Ver. 4.0 offers an ideal market environment.

Two factors, market impact and resilience, are important in this study. There exists a possibility where resilience results from trader behavior in response to the perception of market impact as a signal. It is very difficult to obtain analytical solutions for the dynamism of such interactions among traders. To clarify such phenomena, artificial-market-based simulation thus is necessary. Particularly, we strongly recommend the U-Mart system Ver. 4.0. The point here is that the U-Mart system Ver. 4.0 can conduct simulations under realistic market environments as mentioned above.

Based on information obtained through simulation, in this research, we analyzed the execution costs of heavy traders and time-series data of futures price systems. As mentioned earlier, the U-Mart system Ver. 4.0 saves all data during the simulation and is an excellent system for smooth data treatment and processing. For example, whereas the execution cost itself is not saved as data, it can be calculated by multiplying the execution price by the volume. This enables computations using transaction history. This gives the U-Mart system a significant advantage because of the ease of data processing according to the study needs.

7.2 Optimal Investment Strategies in Financial Markets

7.2.1 What Is an Optimal Investment Strategy?

Traders formulate their optimal investment strategies according to their own goals and execute their investments based on those goals.[1] There exist a number of studies on optimal investment strategies, starting with the earliest study on Portfolio Selection, conducted by Markowitz [20]. These studies have continued to attract attention from researchers in this particular field. In discussing optimal investment strategies, it is important to consider how a certain strategy can be identified as optimal. Additionally, conclusions can vary depending on the factors included in optimization. Consequently, we are unable to determine the best strategy with different purposes and factors simply by comparison with preceding studies. However, some studies have developed based on improvement and modification of existing studies, and we do not consider it meaningful to make comparisons with such studies. Focusing on Bertsimas and Lo [4] and Obizhaeva and Wang [23], our study is based on the same objective function, namely, optimal investment strategies adopted by risk-neutral traders, and we try to consider differences in the strategies these traders adopt.

[1]Unless otherwise noted, our discussion is limited to investment in the form of purchasing stock, but the basic concept remains applicable to other types of investment.

From a strategic perspective, it is important to formulate optimal investment strategies before any investment occurs and to execute investment based on the strategies formulated. The question thus arises of whether mathematically derived optimal investment strategies are optimal under real-world conditions. For example, does the real-world implementation of an investment strategy focused on execution cost minimization really result in the lowest cost? Related to this point, Perold [26] proposed the concept of implementation shortfall (IS). He defined IS as difference between the calculated performance of a paper-based portfolio and the performance of the same portfolio measured based on actual market transactions. IS furthermore comprises two factors, execution cost and opportunity cost.

The execution cost includes the difference between the "paper-based" execution price and the execution price charged on the actual execution of trading, called market impact,[2] in addition to fixed expenditures, such as charges and taxes associated with buying and selling.

The opportunity cost is defined as expenditures associated with investments that were not executed, including cases where orders were not placed immediately because of limit orders or separation orders or cases where orders were not established. These cases can control the price impact generated by placing immediate orders; but execution is time-consuming. This time can provide other traders with the chance to change their strategies, potentially resulting in missed opportunities.

As this example shows, the execution cost conflicts with the opportunity cost. However, Perold [26] took the case of one fund, which outperforms the annual average market return of 20 % if measured using a "paper-based" portfolio, but when measured using real-world trading activity achieved an annual average return of just 2.5 %. He concluded that most of this difference resulted from execution cost. Chen et al. [8] and Yan [33] indicated the existence of an inverse correlation between the fund scale and performance. Additionally, Yan [33] showed that market impact increased with fund scale.

This suggests it is more important to include execution cost among necessary factors to be considered when investment strategies are formulated for heavy traders with large investments.

7.2.2 Classification of the Preceding Studies

Diverse preceding studies on optimal investment strategies can be classified according to (1) goals, (2) period, (3) decision-making timing, and (4) market-related hypotheses.

[2]Perold [26] uses the term "price impact," referred to as "market impact" in many other studies. Therefore, we also use this term, market impact, in our study.

(1) Goals

When optimal investment strategies are specified according to the goals of traders, we can identify setting goals as the most important factor in formulating optimal investment strategies. In a mathematical sense, this corresponds to a set of objective functions. The risk appetites of traders are reflected in the objective functions to be set. For example, Bertsimas and Lo [4] assumed traders were risk-neutral; therefore, the optimal investment strategy proposed by this study was the minimization of execution cost. Assuming risk-adverse traders, Almgren and Criss [3] set the expected value of IS of the asset sale price as the objective function and proposed the optimal investment strategy to minimize the constant multiplication sum of the standard deviation of this expected value. Shied and Schoneborn [27] attempted to divide utility functions according to cases by changing the measure of risk aversion to derive the optimal investment strategy for each case.

(2) Period

An estimated investment period varies depending on trader type. Specifying the termination of the investment period as T, many studies have discussed how traders split the investment period in attempting to optimize it. However, these studies have not reached particular conclusions regarding the optimal investment period. Bertsimas and Lo [4] cited Chan and Lakonishok [7] and Keim and Madhavan [15], saying that approximately 20 % of typical institutional traders complete their investment in one day, while 53 % split it across more than four days. Judging from these points, we can estimate that at least one day or more is assumed as the period T that was set in the model proposed by Bertsimas and Lo [4]. In contrast, the recently popular theory of market microstructure assumes markets and traders operate within minimum time intervals measured in seconds. The data used in this theory are referred to a s tick data or high-frequency data. As shown above, the time axis is based on independent assumptions for each case and actually varies from one model to another. In the sense that such an assumption regarding the time axis can influence market-related hypotheses, we consider the time axis an important factor.

(3) Decision-Making Timing

It is natural to make decisions before an investment and for the investment to be based on those decisions. If we refer to this method as static decision-making, preceding studies have been conducted on an investment strategy in which traders conduct dynamic decision-making by making additional decisions and correcting their strategies during the investment period. Based on the model proposed by Almegren and Criss [2] , Almgren and Lorenz [3] discussed how, during investment execution, modifying subsequent strategies according to previous investment circumstances can reduce the expected values of objective functions.

(4) Market-Related Hypotheses

Market-related hypotheses include those regarding asset prices and those regarding market systems. Many hypotheses regarding asset prices assume that asset prices follow a random walk under the discrete time axis and follow Brownian motion under the continuous time axis. Under either the discrete or continuous time axis, both arithmetic and geometric processes can be considered. In the arithmetic process, the asset price could be negative. However, as described in a footnote of Almgren and Criss [2] , differences between these processes can be ignored when observed over a short period. As it stands now, the arithmetic process, which is easier to handle mathematically, has been the main focus of many preceding studies. Hypotheses regarding market systems have often been abstracted during the modeling process in preceding studies. For instance, we can focus on movements in asset prices, which are referred to as tick size. In reality, tick sizes corresponding to stock prices are specified in many stock markets. However, many hypotheses consider asset prices to be continuous in the modeling process. This could be rational in terms of mathematical ease of handling. If we try to apply theories to the actual market, we must pay attention to such a market system, which could be factors in divorcing theories from reality. Some preceding studies on these numerical simulations focus on this point. Smith et al. [29] simulated whether changing tick size could reproduce the market characteristics observed in the actual market.

7.2.3 *Introduction of Optimal Investment Strategies of Risk-Neutral Heavy Traders*

This section introduces two models based on almost identical assumptions when classified in accordance with the previous section. Next, this section discusses differences in optimal investment strategies between these two models by using specific numerical samples, to observe resilient relationships that cause strategic differences.

7.2.3.1 Bertsimas and Lo Model

Bertsimas and Lo [4] defined an optimal investment strategy that allowed risk-neutral traders to purchase a volume of only X_0 while minimizing the execution cost during investment period, T. In this study, the investment period T is split into $t = 1, 2, \ldots, T$, and execution cost minimization is attempted by dividing X_0 into x_t within the investment period. As a market-related hypothesis, the asset price P_t is considered to be transient, as shown in the equation below.

$$P_t = P_{t-1} + \theta x_t + \epsilon_t, \qquad \theta > 0, \quad \mathrm{E}[\epsilon_t \| x_t, P_{t-1}] = 0 \tag{7.1}$$

In other words, it is assumed that the asset price would follow an arithmetic random walk if there were no investments and would transform into a form upon the addition of market impact proportionate to the investment volume.

Bertsimas and Lo [4] formulated this issue as a dynamic optimization problem.

$$\min_{x_t} \mathrm{E}[P_t x_t] \quad \text{s.t.} \quad \sum_{t=1}^{T} x_t = X_0 \tag{7.2}$$

The optimal solution below is obtained using the dynamic programming method.[3]

$$x_t^* = \frac{X_0}{T} \tag{7.3}$$

7.2.3.2 Obizhaeva and Wang Model

Like Bertsimas and Lo [4], Obizhaeva and Wang [23] also examined optimal investment strategies adopted by risk-neutral traders. However, Obizhaeva and Wang [23] modeled optimal investment strategies as trading on the limit order board. Thus, market-related hypotheses were increased in Obizhaeva and Wang [23] compared with Bertsimas and Lo [4].

Depth q and spread s are introduced as variables that indicate the limit order board condition. The depth is defined as a limit order volume per unit price, and Obizhaeva and Wang [23] assume q to be constant. The spread refers to divergence between the best bid price and the best ask price. Additionally, the average of the best bid price and the best ask price is termed the average price.

Obizhaeva and Wang [23] divided market impact into temporary and permanent impacts. Temporary impact arises from a temporary imbalance between supply and demand, the influence of which gradually fades over time. In contrast, permanent impact is the impact permanently reflected in the asset price due to fundamental price fluctuation owing to investments. Bertsimas and Lo [4] implicitly assume the permanent impact to be the same as the market impact. Obizhaeva and Wang [23] express the differences in these two types of impact using the average price V_t, ask price A_t, and spread s. Let us suppose here that before investment, the average price is the same as the fundamental price F_t.

In Fig. 7.1, before executing investment, $V_t + \frac{s}{2}$, namely, the fundamental price with half of the spread added, is consistent with A_t (a). On placement of a large sell order, a temporary impact is generated for Δp_+, and this causes the fundamental price to deviate from the ask price. Afterwards, as the temporary impact effect fades, the difference between these prices gradually declines (c). After a sufficiently

[3]Refer to Bertsimas and Lo [4] for the details of proof.

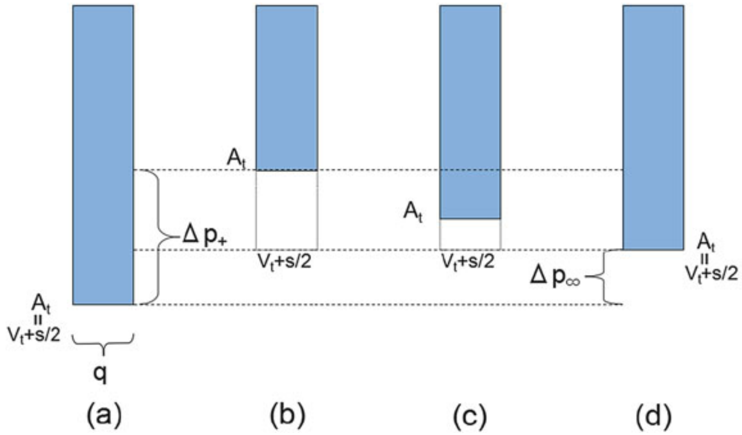

Fig. 7.1 Differences between temporary impact and permanent impact

long period, only the permanent impact Δp_∞ remains, and then the price difference disappears (d) (Fig. 7.1).

In this model, based on $q\Delta p_+ = x_t$, the temporary impact at the investment volume x_t is calculated as $\Delta p_+ = \frac{x_t}{q}$. Given a permanent impact of $\Delta p_\infty = \theta x_t$, based on these calculations, it is supposed than an investment with volume x_t is conducted at time 0. The ask price immediately after investment is calculated as $A_{0+} = V_{0+} + \frac{s}{2} + \frac{x_0}{q}$ and finally as $A_\infty = V_\infty + \frac{s}{2} + \theta x_0$. Obizhaeva and Wang [23] assumed this price difference would reduce exponentially and set ρ as a parameter for this reduction difference, while expressing this as resilience. Therefore, the ask price at time t is expressed as follows:

$$A_t = V_t + \frac{s}{2} + x_0 \kappa e^{-\rho t}, \quad \kappa = \frac{1}{q} - \theta \tag{7.4}$$

Next, necessary preparations are undertaken for an optimal investment strategy. With regard to the purchase cost for investment volume x_t, where the ask price is A_t, as described above, this price is increased to $A_t + \frac{x_t}{q}$ by the investment. The total purchase cost $c_t(x_t)$ thus is expressed as follows:

$$\begin{aligned} c_t(x_t) &= \int_0^{x_t} (A_t + \frac{x}{q})dx \\ &= (A_t + \frac{x_t}{2q})x_t \end{aligned} \tag{7.5}$$

Next, supposing the investment is split into n transactions by the time t, this is expressed as $n(t)$. The following relationship is derived between the average price

V_t and the fundamental price F_t.

$$V_t = F_t + \theta(X_0 - X_t) = F_t + \theta \sum_{i=0}^{n(t)} x_{t_i} \tag{7.6}$$

Here, $X_0 - X_t$ indicates the total purchase volume until time t. Additionally, based on equation 7.4, the ask price at this time is expressed as follows:

$$A_t = V_t + \frac{s}{2} + \sum_{i=0}^{n(t)} x_{t_i} \kappa e^{-\rho(t-t_i)} \tag{7.7}$$

Suppose that the investment period T is equally divided, and the number of transactions during the investment period is set to $t_n = n\tau, n = 0, 1, \ldots, N$. From this the following optimization problem is derived as a minimization of the total execution cost J_0.

$$J_0 = \min_{x_0,\ldots,x_N} \mathrm{E}_0\Big[\sum_{n=0}^{N} [A_{t_n} + \frac{x_n}{2q}] x_n\Big] \tag{7.8}$$

$$s.t. \quad A_{t_n} = F_{t_n} + \theta(X_0 - X_{t_n}) + \frac{s}{2} + \sum_{i=0}^{n-1} x_i \kappa e^{-\rho\tau(n-i)}$$

By using the dynamic programing method, the optimal solution for equation 7.8 can be obtained as follows[4]:

$$\begin{aligned} x_n^* = -\frac{1}{2}\delta_{n+1} \quad & [D_{t_n}(1 - \beta_{n+1} e^{-\rho\tau} + 2\kappa\gamma_{n+1} e^{-2\rho\tau}) \\ & -X_{t_n}(\theta + 2\alpha_{n+1} - \beta_{n+1}\kappa e^{-\rho\tau})] \end{aligned} \tag{7.9}$$

$$\text{where} \quad D_{t_n} = A_{t_n} - V_{t_n} - s/2 \tag{7.10}$$

Here, each coefficient can be obtained iteratively as follows:

$$\alpha_n = \alpha_{n+1} - \frac{1}{4}\delta_{n+1}(\theta + 2\alpha_{n+1} - \beta_{n+1}\kappa e^{-\rho\tau})^2 \tag{7.11}$$

$$\begin{aligned} \beta_n = \beta_{n+1} e^{-\rho\tau} + \frac{1}{2} \quad & \delta_{n+1}(1 - \beta_{n+1} e^{-\rho\tau} + 2\kappa\gamma_{n+1} e^{-2\rho\tau}) \\ & (\theta + 2\alpha_{n+1} - \beta_{n+1}\kappa e^{-\rho\tau}) \end{aligned} \tag{7.12}$$

[4]Refer to Obizhaeva and Wang [23] for details about the proof.

$$\gamma_n = \gamma_{n+1}e^{-2\rho\tau} - \frac{1}{4}\delta_{n+1}(1 - \beta_{n+1}e^{-\rho\tau} + 2\gamma_{n+1}\kappa e^{-2\rho\tau})^2 \tag{7.13}$$

$$\delta_{n+1} = [\frac{1}{2q} + \alpha_{n+1} - \beta_{n+1}e^{-\rho\tau} + 2\gamma_{n+1}\kappa^2 e^{-\rho\tau}]^{-1} \tag{7.14}$$

$$\text{with} \quad \alpha_N = \frac{1}{2q} - \theta, \;\; \beta_N = 1, \;\; \text{and} \;\; \gamma_N = 0 \tag{7.15}$$

7.2.3.3 Comparison of Two Strategies Based on Numerical Samples

Equation 7.3 clearly shows that the optimal investment strategy of the model proposed by Bertsimas and Lo [4] is to make investments via equal-sized transactions. The optimal investment strategy of the model proposed by Obizhaeva and Wang [23] is expressed in a very complicated fashion such that we cannot intuitively understand its function. Figures 7.2 through 7.4 specifically show this strategy (Figs. 7.2, 7.3, and 7.4).

In Figs. 7.2 through 7.4, each parameter is indicated as follows: $X_0 = 100{,}000$, $q = 5{,}000$, $theta = 1/(2q)$., and $T = 1$. Additionally, N indicates

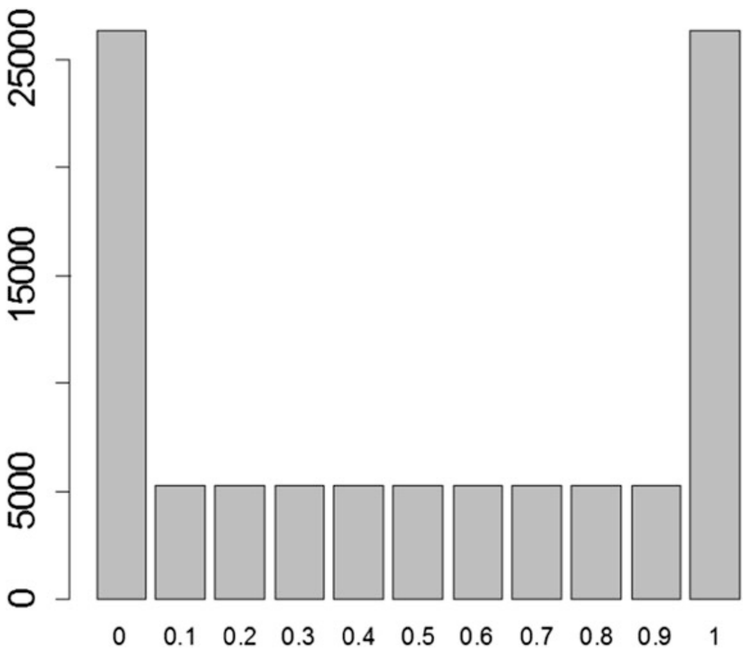

Fig. 7.2 $N = 10$

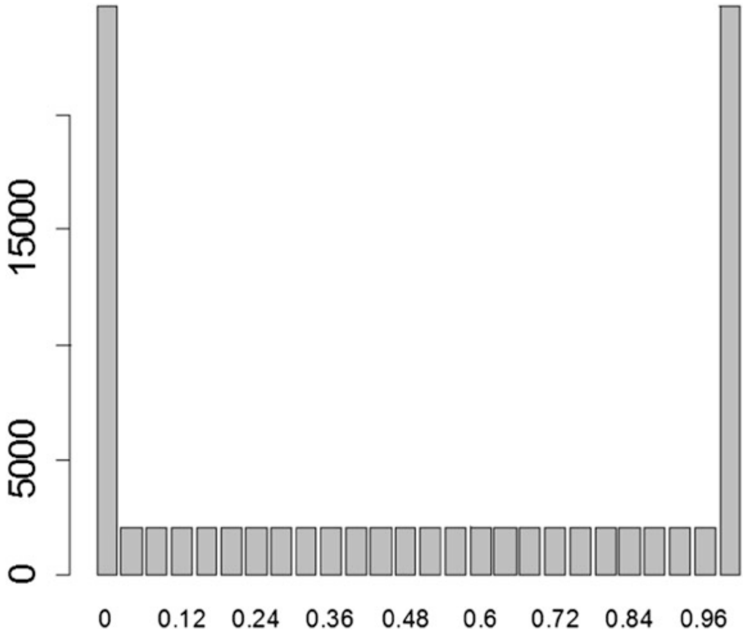

Fig. 7.3 $N = 25$

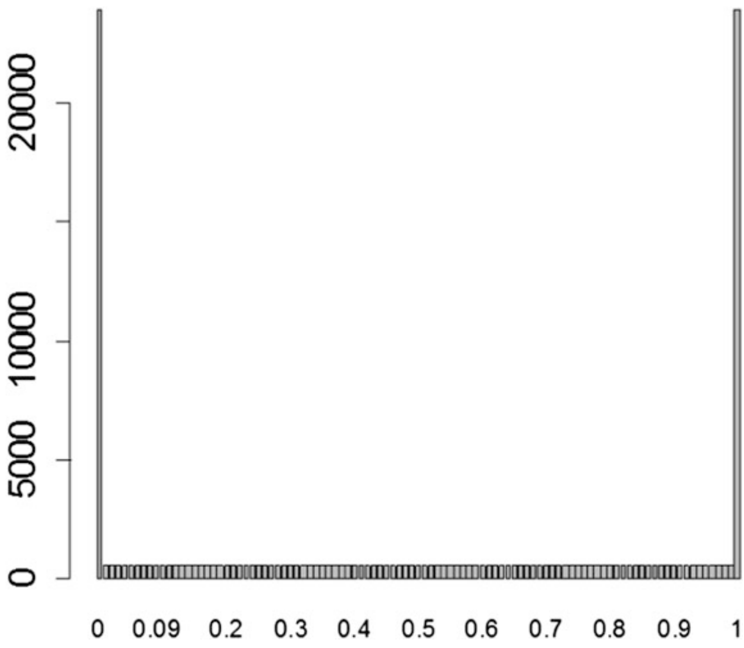

Fig. 7.4 $N = 100$

the number of transactions into which the investments are divided. As each figure shows, the optimal investment strategy here is to make significant investments at both the beginning and end of the investment period, with the remaining investment volume equally divided throughout the remainder of the investment period. Here, ρ is expressed as $\rho = 2.231$; however, Obizhaeva and Wang [23] do not explicitly show this for any particular reason. The optimal situation is to invest approximately 25 % at both the beginning and the end of the investment period when the parameters are set as above.

It is not clearly shown what specific figure is given to ρ . However, Obizhaeva and Wang [23] indicate that in Bertsimas and Lo [4] this parameter ρ was implicitly assumed to be infinite. This suggests that the influence of temporary impact disappears instantaneously, leaving only that of permanent impact. Actually, in the numerical samples of Figs. 7.2 through 7.4, where ρ is changed to $\rho = 10{,}000$ while other parameters remain the same, the results shown in Figs. 7.5 through 7.7 are obtained. This demonstrates that investment via equal-sized transactions as in the model proposed by Bertsimas and Lo [4] is the optimal investment strategy (Figs. 7.5, 7.6, and 7.7).

There is an assumption that the asset price (fundamental price) follows an arithmetic random path in these investment strategies. Thus, we conducted a Monte Carlo simulation to see what differences exist. Restated, we tried to see when an

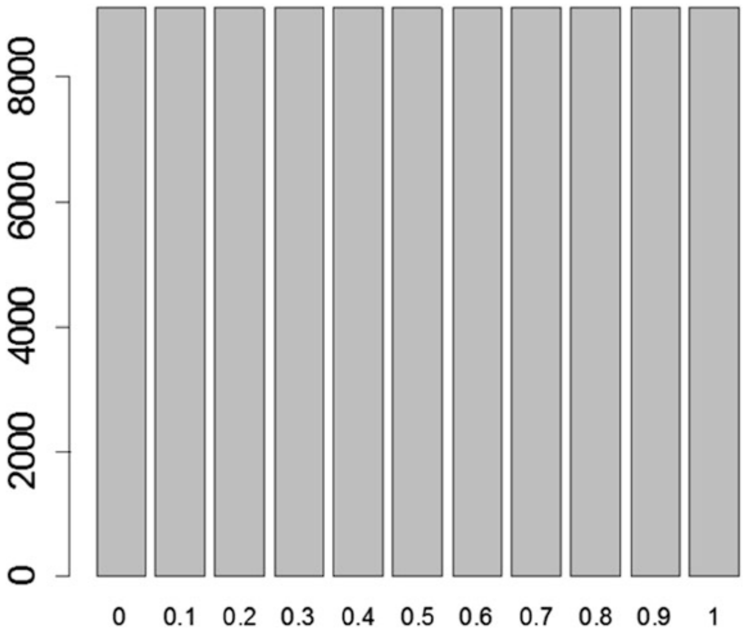

Fig. 7.5 $N = 10$

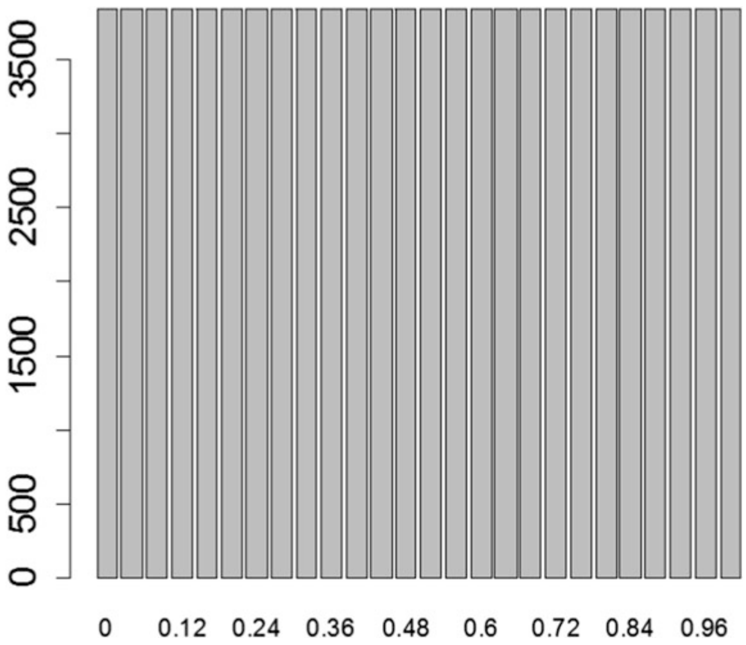

Fig. 7.6 $N = 25$

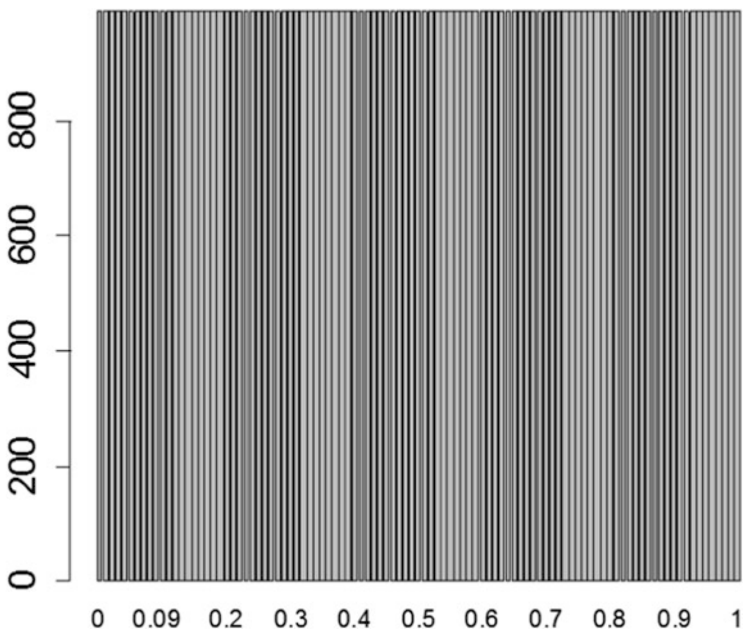

Fig. 7.7 $N = 100$

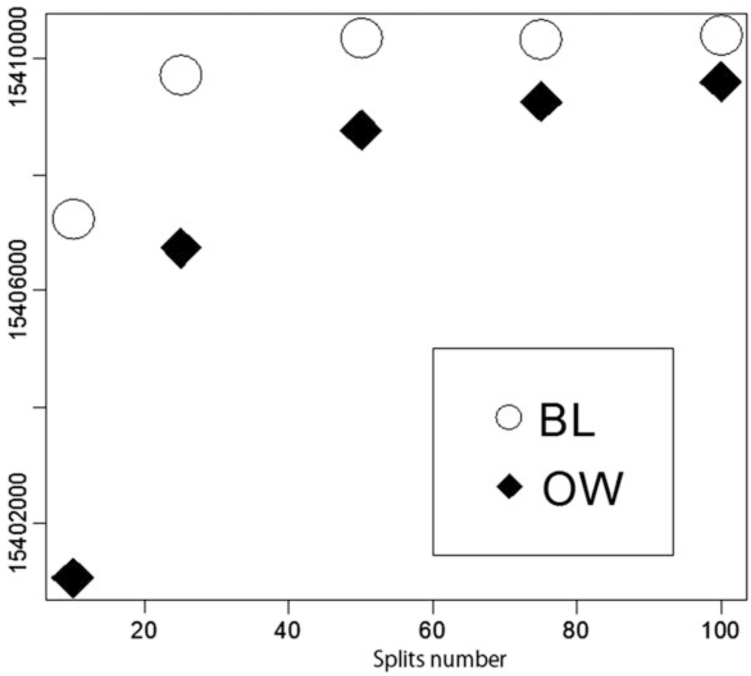

Fig. 7.8 Differences in the execution cost between Bertsimas and Lo (BL) and Obizhaeva and Wang (OW)

equivalent investment is conducted and the extent to which the execution cost differs from the optimal investment strategy of Obizhaeva and Wang [23].

Here, the initial value of the asset price was 10,000, while the volatility was 100. Additionally, to make it fit into the unique simulation of this study that will be described in Sect. 7.4, we also set the following parameters: $X_0 = 1{,}500, q = 5$ and $\theta = 0.5$. We used the value of ρ, $\rho = 2.231$, previously used by Obizhaeva and Wang [23]. In this case, the total execution cost of the two investment strategies shown in Fig. 7.8 was obtained (Fig. 7.8).

Setting the number of transactions into which investments are divided to 10, 25, 50, 75, and 100, the average results of a Monte Carlo simulation run 100 million times are plotted. As we can see from Fig. 7.8, the difference in execution cost decreases as the number of divisions into which transactions are divided increases.

7.2.4 *Is It Appropriate to Give Resilience Exogenously?*

As previously noted, Obizhaeva and Wang [23] did not clearly mention that the resilience parameter is provided exogenously and resilience follows exponential functions. The next chapter introduces how previous studies have recognized resilience as a concept; however, to date discussion of the principles of resilience has been superficial. However, as long as price fluctuations are caused by trader buying and selling behaviors, it is easy to imagine that resilience is also attributed to trader behaviors. In this study, we attempted not to provide resilience exogenously as a parameter, but rather provide it endogenously as a trading model. Setting a more realistic market based on this attempt, we tried to develop a discussion of the results the abovementioned optimal investment strategies would have in the assumed market.

7.3 Resilience in the Optimal Investment Strategy

7.3.1 What Is Resilience?

The term "resilience" was originally used in physics and engineering. Recently, however, the term has appeared in various other areas, such as sociology, psychology, and disaster prevention. To clarify the meaning of resilience in financial markets, this section introduces definitions and interpretations proposed by preceding studies to explore resilience as an abstract concept included in a model.

Harris [13] defined resilience as a factor in price prompting, which fluctuates due to unexpected imbalanced orders placed by traders, which can be restored to their original state. Additionally, Kyle [18] positioned resilience as one of the three factors that specify market liquidity, being followed by tightness and depth. For reference, "tightness" indicates the spread between the bid-ask spread, while "depth" indicates the order volume per unit price on the order board. According to Muranaga [22], resilience can be considered to indicate information regarding potential supply and demand currently not placed as an order. We can interpret that this information becomes obvious depending on change in the balance between supply and demand.

Ultimately, the following two principles can be obtained regarding resilience based on these factors. One is that the spread appears reduced, while the volume of orders randomly placed between the expanded bid-ask spread appears to increase with imbalance of supply and demand. The other is that imbalance between supply and demand signals to traders an influx of unusual orders, to which traders respond by trying to restore the original state of balance. In either case, the source of resilience clearly should be attributed to principles underlying trader behavior. It is possible to take the model of Obizhaeva and Wang [23] a step further to model it as trader behavior.

However, previous studies have tried to determine the source of resilience in market systems. Wuyts [32] defined resilience as an ability of the trading system to produce liquidity shock. Wuyts [32] used the VAR model to examine how shocks, such as best bid and ask prices and depth, could influence liquidity, while ignoring what actually causes resilience. Large [19] estimated parameters while assuming resilience follows a Hawkes process. Similarly to Wuyts [32], he did not mention what generates resilience.

7.3.2 *Meaning of Considering Resilience in the Optimal Investment Strategy*

The previous chapter already described that considering market impact, generated due to temporary imbalance of supply and demand, could be a key when optimal investment strategies are taken into consideration. We can interpret resilience as a force resulting from imbalance that has the effect of attempting to restore the original balance of supply and demand. It is natural to consider the principles of resilience, and especially its source. Doing this corresponds to the principle that market impact arises from an imbalance of supply and demand.

Bertsimas and Lo [4] did not reference resilience, while having an implicit assumption of infinite resilience, similar to the proposal of Obizhaeva and Wang [23]. However, Obizhaeva and Wang [23] assumed that in resilience, the process of market impact convergence, from when the market price received a temporary impact to when only the influence of a permanent impact remained, would follow the exponential function. This assumption has not been theoretically and empirically rationalized. Therefore, doubt persists when applying the optimal investment strategy proposed by Obizhaeva and Wang [23] to actual markets. From Obizhaeva and Wang [23], we can infer that based on the assumption that resilience is nonlinear, resilience can be positioned as an unusual force when compared with relative normal trading time. This study models this “something” and simulates how differences in models might influence optimal investment strategies.

7.3.3 *Proposal of Resilience Models*

7.3.3.1 Resilience Brought About by Trader Investment Behaviors of Traders

As mentioned by some preceding studies, when optimal investment strategies for heavy traders are considered, we can create uncomplicated models by simplifying factors other than heavy traders as much as possible. On the other hand, we need to pay special attention that doing so could lead to missing other important factors, while holding out the possibility to loosing consistency with the actual market. In this study, we tried to model resilience, which was assumed to be given exogenously according to Obizhaeva and Wang [23], as a trader’s behavior in order to observe how the results of optimal investment strategies could vary. Here, this section tries to model the following three trader types in order to attempt to make resilience endogenously, while the next section verifies the validity of these trading models.

7.3.3.2 Zero Intelligence Model

The simplest resilience model is to have random-investment traders in the market while assuming that resilience is generated simply due to random orders. Here, this trader type is referred to as the zero intelligence model hereinafter. This model is based on the concept of Gode and Sunder [11]. In a university's classroom, Smith [28] demonstrated the law of supply and demand originally proposed by Walrus that the trading price would be converged to the node of the demand-and-supply curve even under the situation where no bidders existed. Gode and Sunder [11] conducted artificial-market simulation in order to verify whether this law could be established by human intelligence or by market systems based on having nothing to do with human intelligence.

They discovered that simply providing random-investment traders with budget restrictions could lead to obtaining market balance almost equivalent to the market where human agents participated. In other words, although there were objections, they demonstrated the possibility that the law of supply and demand would be established by market systems unrelated to human intelligence. They referred to the traders they used at that time as zero intelligence. Many researchers subsequently started to seek another direction to see whether various market characteristics called stylized facts, which could be observed in the actual markets, could be explained by using the simplest trader's behavior as possible. Of these researchers, Maslov [21] demonstrated that long-term correlation, such as fat tail and volatility, could be reproduced based on simple trader models. Withanawasam et al. [31] slightly corrected this algorithm and indicated qualities closer to the reality could be obtained by comparison with the actual stock price movements.

Hereinafter, the trader model proposed by Withanawasam et al. [31] is referred to as the zero intelligence (ZI) model in the sense that it is the simplest model in comparison with other models that will be described later. The following shows the algorithm of the ZI model:

1. Buy, sell, or do nothing
2. Limit price or market price

Select 1 or 2 at the equivalent rate. Furthermore, at 2, where the limit order is placed,

3. select $\Delta = 1, 2, 3, 4$ at the equivalent rate
4. Order price $= \begin{cases} \text{Best bid price} + \Delta \text{ if Selling} \\ \text{Best ask price} - \Delta \text{ if Buying} \end{cases}$
5. The order volume is to be a uniform distribution from 1 to 5

7.3.3.3 Full Intelligence Model

Obizhaeva and Wang [23] defined permanent impact as what influences the fundamental price. Based on this definition, we can consider that if there exists traders who know the fundamental price, which is varies due to large investments, along with arbitrage traders focusing on divergence between the fundamental price and the futures price would play a role in resilience. If the futures price is converged into the fundamental price, profits would surely be gained. In this sense, this trader type is referred to as the Full Intelligence (FI) model hereinafter. As Sect. 7.1.3 introduced, the U-Mart system is capable of producing FI-model traders by providing the spot price exogenously as the fundamental price. The following shows the algorithm of the FI model.

Compare the spot price (P) with the best bid price (hereinafter, BBP) and the best ask price (hereinafter, BAP)

1. Where BBP<P<BAP
   The buying limit price is assigned to [BBP,P] or the selling limit price to [P,BAP] at the equivalent rate
2. Where P<BBP<BAP, the selling limit price is assigned to [P,BAP]
3. Where BBP<BAP<P, the buying limit price is assigned to [BBP,P]
4. Check board information every 1Ut, cancel the order if each condition is not met
5. The order volume is to be a uniform distribution from 1 to 5

7.3.3.4 Low Intelligence Model

As indicated by Kimura and Akiyama [16], where there are three spreads or more, orders are often placed so that the spread gradually reduces at the next time point. Based on this, modeling of resilience is attempted. Namely, this model controls load distribution on the probability that orders are easily placed at a price closer to the best bid and ask prices given the existence of three or more spreads, and the model adopts the same algorithm as the ZI model where there are two spreads or fewer. This trader type is referred to as the Low Intelligence (LI) model in the sense that it is positioned between the ZI and FI models. The LI model is possibly closer to reality than the LI model, and it is not clear whether there realistically exist traders similar to the FI model that make their investments based on knowledge of the fundamental price. If this were the case, few such traders would exist. As described later, the ZI model could be insufficiently effective as a resilience model. The algorithm of the LI model is shown as follows:

1. Where there are three spreads or more
   (1) Select buying or selling at the equivalent rate
   (2) Conduct load distribution on the probability of placing orders between spreads for orders of values closer to the best bid and ask price
       E.g., When a selling order with spread = 4
       BAP-1: 4/10, BAP-2: 3/10, BAP-3: 2/10, BAP-4: 1/10

2. Where spreads are two or less

   (1) Buy, sell, or do nothing
   (2) Limit price or market price

   Select (1) or (2) at the equivalent rate. Furthermore, at (2), where the limit order is placed,

   (3) Select $\Delta = 1, 2, 3, 4$ at the equivalent rate
   (4) Order price $= \begin{cases} \text{Best bid price} + \Delta & \text{if Selling} \\ \text{Best ask price} - \Delta & \text{if Buying} \end{cases}$
   (5) The order volume is to be a uniform distribution from 1 to 5

7.3.4 How Should Resilience Be Quantified?

7.3.4.1 Resilience Movements

Many studies quantify and evaluate resilience mainly using liquidity-related indexes. For example, Muranaga [21] or Kimura and Akiyama [16] used the reduction rate based on the proportion of spreads at two points of time as the resilience index. Biais et al. [5] did not use the term "resilience," but calculated the order distribution conditioned with the order at the previous time point based on past order data of the Paris Bourse. They discovered a phenomenon known as the diagonal effect. This phenomenon sees limit orders placed inside the spread.

However, as pointed out by Degryse et al. [10], resilience is a dynamic concept. Therefore, it is difficult to express resilience properly simply by examining the spread reduction rate or the relationship between two time points, such as an order distribution conditioned by the order at the previous time point. Accordingly, Degryse et al. [10] used limit order board data 10 ticks before and 20 ticks after large orders were placed and analyzed the variation in the best bid and ask prices and depth. By doing so, they tried to interpret resilience dynamically. They also graphically illustrated the results, to express resilience visually. However, this method of Degryse et al. [10] described the transitions of the best bid prices and the best ask prices separately. This left a disadvantageous blur regarding the movements of the entire limit price board.

7.3.4.2 Quantification of Resilience Conducted by Christalla

By overcoming the abovementioned resilience quantification issue of Degryse et al. [10], Christalla [9] attempted to quantify resilience by formulating Exchange

Liquidity Measures (XLM) developed by Gomber and Schweickert [12], as follows:

$$\mathrm{XLM}_{B,t}(V) = \frac{P_{B,t}(V) - MQ_t}{MQ_t} \tag{7.16}$$

$$\mathrm{XLM}_{S,t}(V) = \frac{MQ_t - P_{S,t}(V)}{MQ_t} \tag{7.17}$$

These equations quantify how much the price could diverge from the average at both the buy and the sell when investments with volume V are made at time t. $P_{B,t}(V)$ and $P_{S,t}(V)$ indicate the average purchase price and average sales price, respectively. This means that the larger the price divergence, the greater the price fluctuation. Therefore, liquidity is evaluated as low. XLM is defined as the sum of equation 7.16 and equation 7.17. As the previous section referred to the movements of resilience, XLM is measured at each time point. Therefore, examination of time variation can measure the degree of liquidity variation. Additionally, this enables us to see the differences in variations of the selling and buying boards in an integrated fashion, identified as a quantification issue by Degryse et al. [10].

7.3.4.3 Evaluation of Three Models Based on Resilience

This section evaluates the three models proposed in the previous chapter, ZI, FI, and LI, by using XLM. As a given setting, where the dividing number is 10 with the OW model, 381 buy orders are placed at time 1Ut. The following examines how XLM changes at time 1Ut through 120Ut. The averages of Monte Carlo simulations conducted ten times are plotted on the charts in Figs. 7.9 through 7.11 below. This simulation was conducted by changing random numbers while changing the number of each trader type from 1 to 5, 10, and 20 (Figs. 7.9, 7.10, and 7.11).

Figure 7.9 shows that XLM of ZI increases with time. This shows that the board status diverges from its original situation, suggesting the ZI model is inappropriate to express resilience. In other words, resilience is a possibility rather than merely an influx of random orders. In the FI and LI models, XLM tends to decline over time. Additionally, we can see that the decline in velocity accelerates when there are many traders. These results show that these two FI and LI models can serve as the resilience function, where resilience strengthens with increasing number of traders.

Moreover, on the charts of the FI and LI models, XLM is based on the assumption that resilience follows the exponential function, which was provided exogenously in the case of the OW model and is overlapped. Other than $\rho = 2.231$ provided in the previous chapter, $\rho = 10, 50$ is also plotted. As we can see from these figures, the hypothesis $\rho = 2.231$ assumes that resilience works moderately. From the viewpoint of XLM transitions, the rate of change of the FI model with one trader resembles that of the LI model with five traders. Focusing on other cases, in the FI model, the case with 10 traders and that where $\rho = 50$ show similar

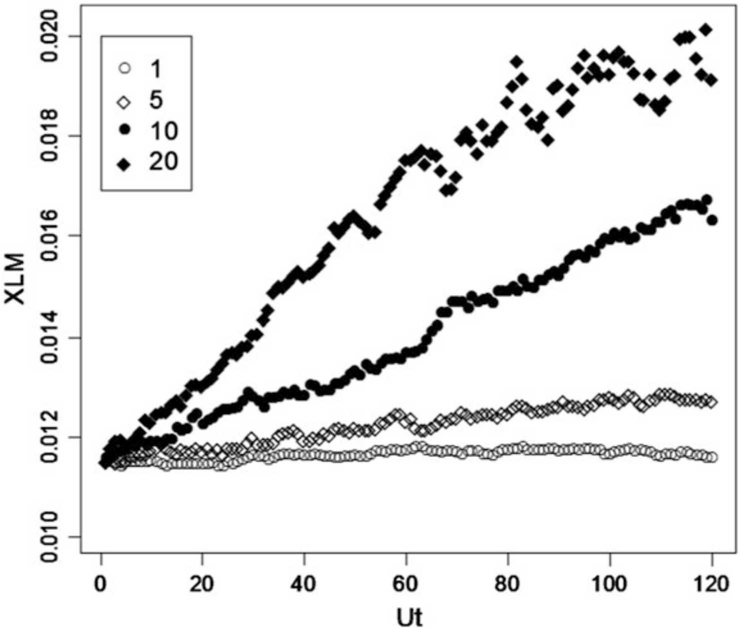

Fig. 7.9 Zero Intelligence Model

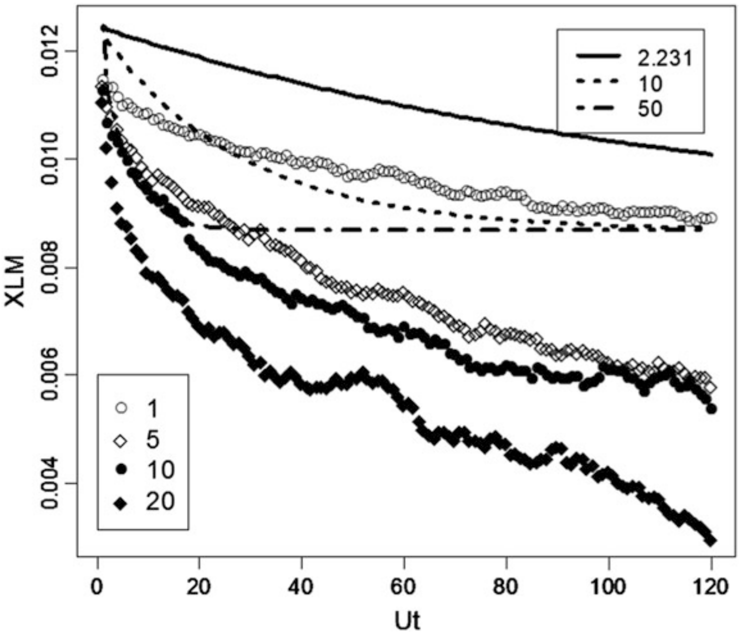

Fig. 7.10 Full Intelligence Model

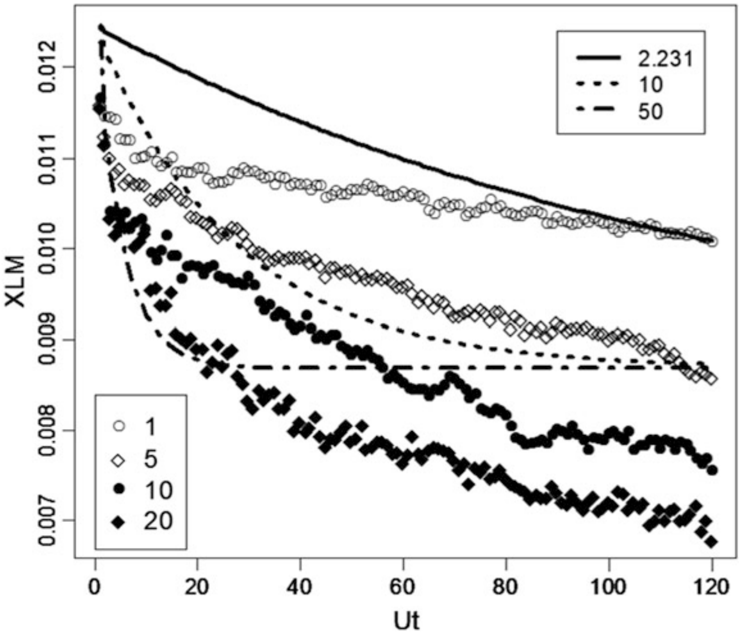

Fig. 7.11 Low Intelligence Model

XLM transitions at the initial point. These results show that the optimal investment strategy with $\rho = 2.231$, which always invests 25 % of the total investment volume at both the beginning and the end of the investment period, could not be optimal. The next section confirms this through simulation.

7.4 Analysis of Optimal Investment Strategies Based on the U-Mart System

This section describes the artificial-market-based simulation on models embedded with resilience, from the viewpoint of the role of resilience in optimal investment strategy, which is the theme of this study.

7.4.1 Simulation Overview

As agents that form an artificial market, one agent of either the Bertsimas and Lo (BL) model or the Obishaeva and Wang (OW) model was introduced to the market as a heavy trader with a market impact. In contrast, as resilience models, in the FI and LI models, 1–20 traders were brought into the market as market participants. As the pricing mechanism, the limit order board trading system, which is adopted by the Tokyo Stock Exchange [30], is the default for the U-Mart system Ver. 4.0.

By default, ordering is conducted based on the Itayose method before the morning session, between the morning and afternoon sessions, and after the afternoon session. In our simulation, which is configured such that orders are not placed, we examined the market dynamism based on the pricing mechanism that simply uses the continuous double auction method.

With regard to the optimum investment strategy taken by heavy traders, as described in Sect. 7.3, the BL model invests equally in a number of dividing investments and the OW model always invests 25 % at the beginning and end of the investment period while the remainder of the investment sum is invested equally across each of the transactions into which the investment is divided. The total investment volume was 1,500, the board depth was 5, and the permanent impact was the investment volume * 0.5; namely, the fundamental price was raised only half of the investment volume.

Setting the number of transactions into which an investment is divided (10, 25, 50, 75, and 100) and the number of traders (1, 5, 10, and 20 traders from each of FI and LI) per session, while changing the random seeds per session, 10 simulation sessions were conducted for the FI model and 50 for the LI model.

As for the simulation results, we examined the differences in the total execution cost, which is the objective function of two optimal investment strategies, and examined its relationship with resilience.

7.4.2 Simulation Results

Figures 7.12 through 7.16 show the simulation results based on the FI model, which was organized according to the number of transactions into which the investment was divided (Figs. 7.12, 7.13, 7.14, 7.15, and 7.16).

With respect to all the numbers of transactions into which the investment was divided in these figures, we observe a tendency whereby the total execution cost in both optimal investment strategies decreases with increasing number of FI traders. Additionally, for any of the numbers of transactions into which the investment was divided, compared with the BL model, the OW model displays a tendency for the total execution cost to decrease given few FI traders. Another observed tendency is for the total execution cost of the OW model to become significant given an increase in the numbers of dividing investments and FI traders. Next, let us focus on the absolute price of the total execution cost. When comparing each number of dividing investments under the same number of FI traders, where there are few FI traders, we can see that the total execution cost is controlled as the number of transactions into which an investment is divided increases. However, where there are many FI traders, the total execution cost does not differ significantly due to the different numbers of dividing investments in either case for the optimal investment strategy.

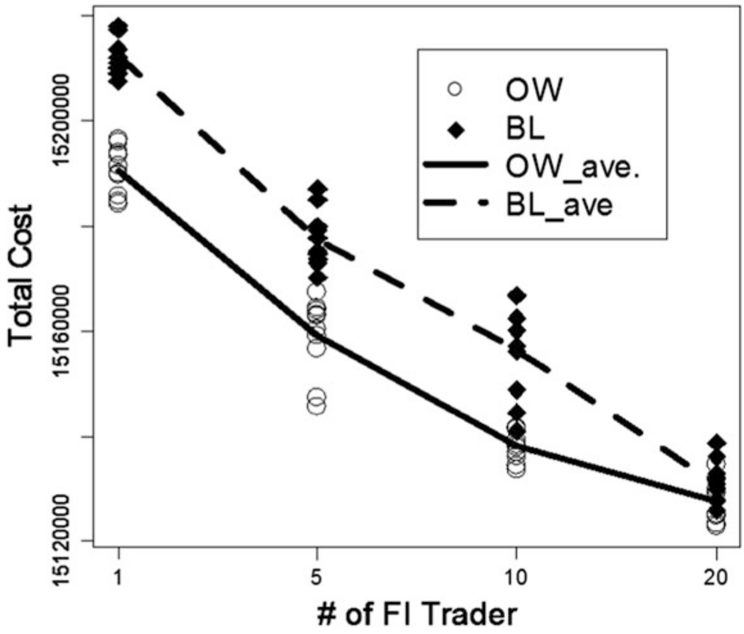

Fig. 7.12 $N = 10$

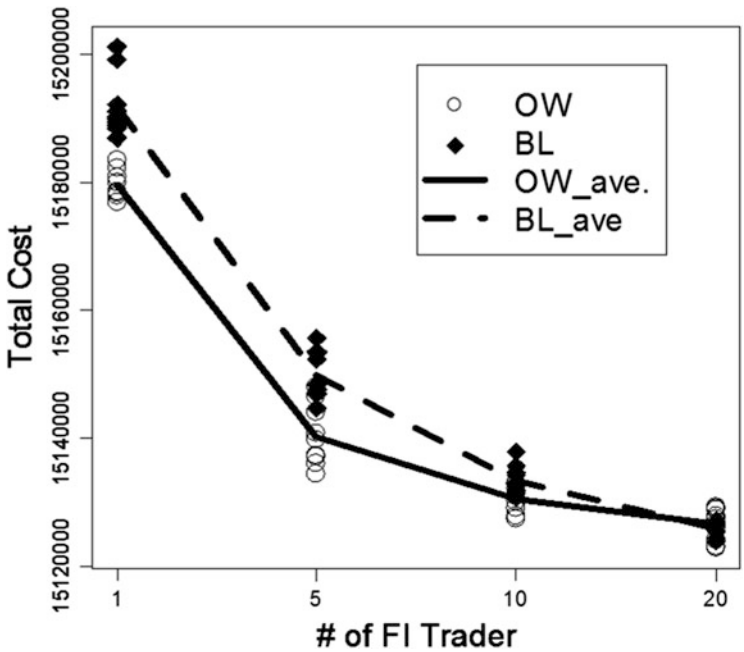

Fig. 7.13 $N = 25$

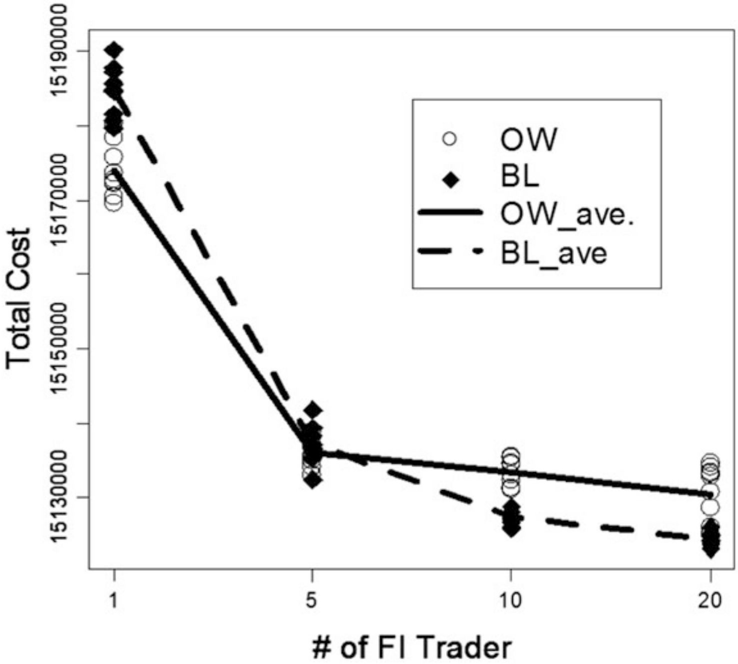

Fig. 7.14 $N = 50$

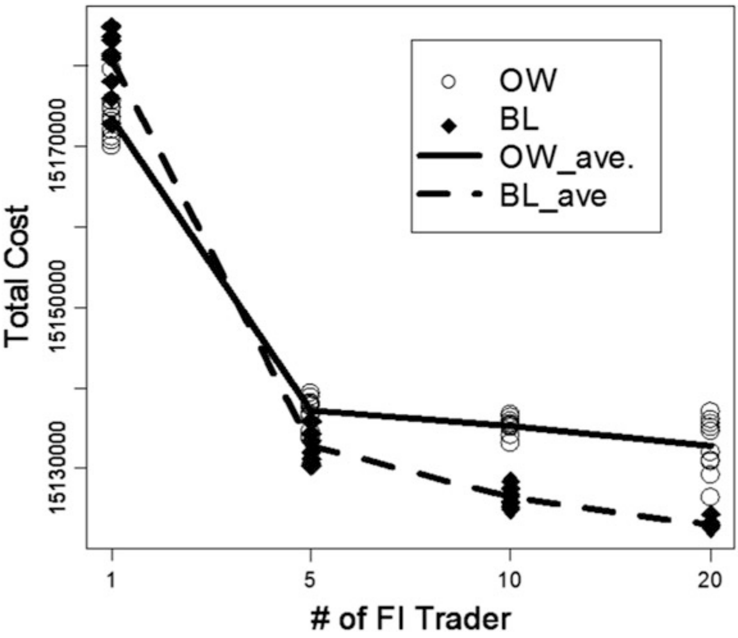

Fig. 7.15 $N = 75$

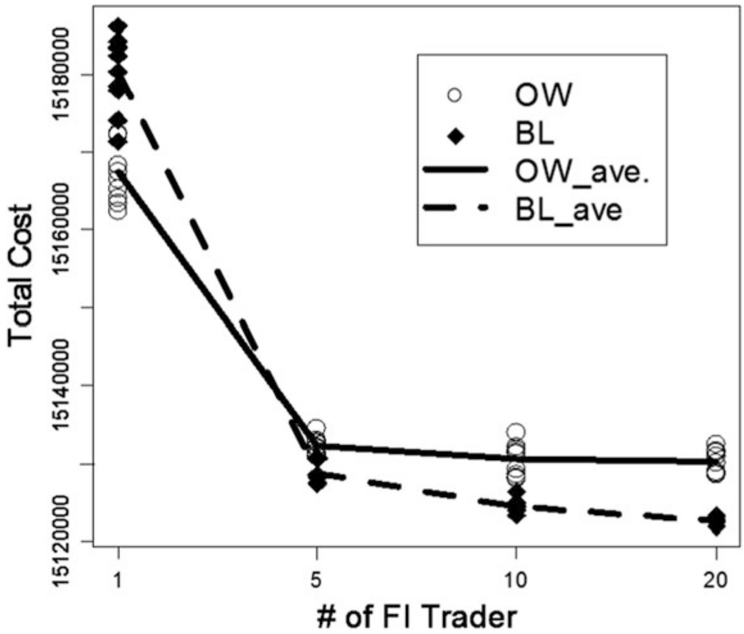

Fig. 7.16 $N = 100$

Next, Figs. 7.17 through 7.21 show the simulation results based on the LI model, which were similarly organized according to the number of transactions into which the investment was divided (Figs. 7.17, 7.18, 7.19, 7.20, and 7.21).

Compared with the FI model, this case shows insignificant differences. As configured in Sect. 7.3.3.4, LI traders invest randomly when spreads are small, and thus market volatility increases. This results in significant dispersal of total execution cost. This result is also confirmed since the total execution cost varies with an increase in the number of LI traders. The evident tendency is that as with the FI model, when LI traders increase, so too does the total execution cost of both of the optimal investment strategies.

Additionally, we can see that where the investment is divided into a small number of transactions and there are few LI traders, execution cost tends to be small for the OW model. In contrast, where investments are divided into a large number of transactions and there are many LI traders, similar to the FI model, the execution cost tends to be significant for the OW model. However, these differences are slight. Fifty simulation sessions are insufficient to clarify these differences.

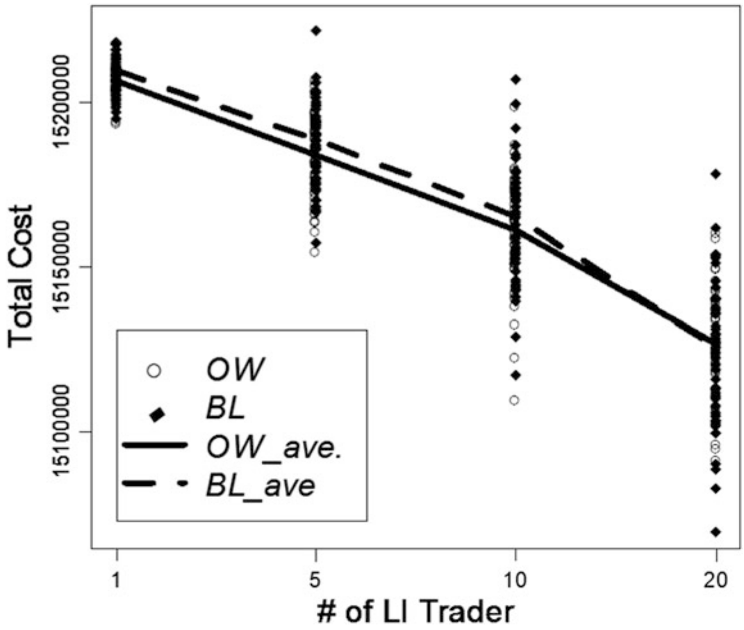

Fig. 7.17 $N = 10$

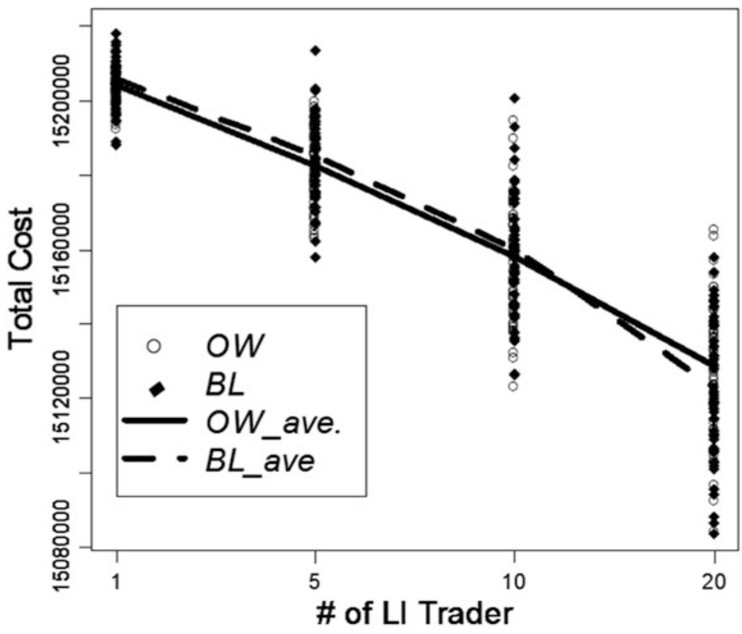

Fig. 7.18 $N = 25$

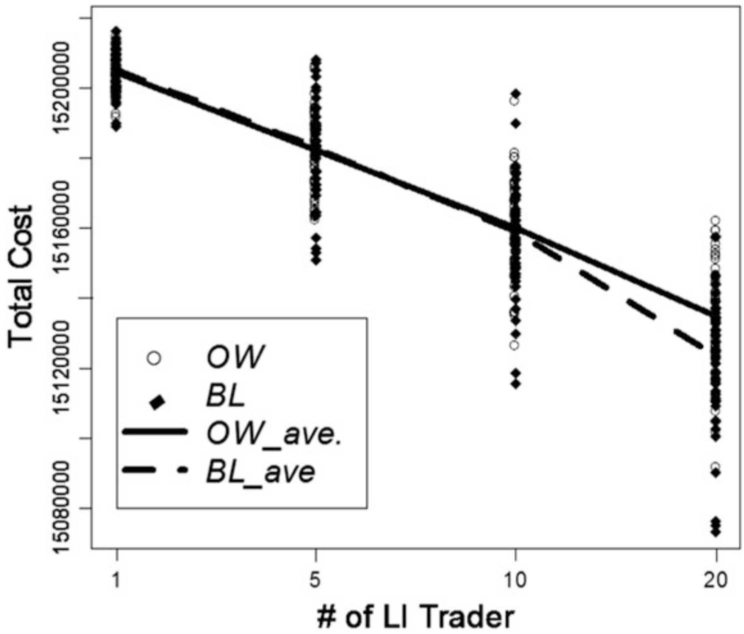

Fig. 7.19 $N = 50$

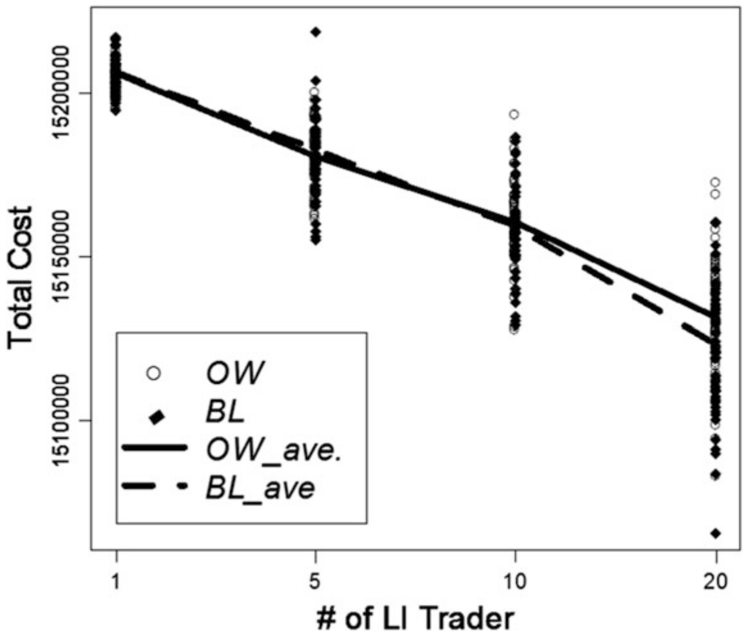

Fig. 7.20 $N = 75$

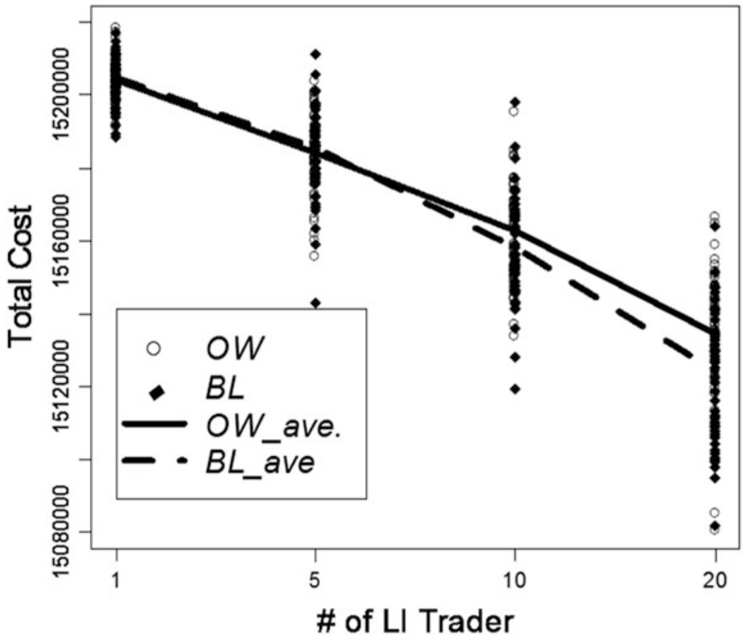

Fig. 7.21 $N = 100$

7.4.3 Consideration

In this section, we consider and discuss the simulation results obtained in the previous section from the perspective of the relationship between the optimal investment strategy and resilience.

First, we focus on the FI model. Regardless of the number of transactions into which an investment is divided, given few FI traders, the OW model tended to maintain a total execution cost lower than the BL model. This result suggested the possibility that the optimal investment strategy was that with very little strong resilience, where 25 % of the total investment sum was always invested at both the beginning and the end of the investment period and there was consistency with the simulation results. In other words, this confirms the validity of adopting the OW-model investment strategy in a market where traders know the fundamental price. However, this strategy could be not optimal under misevaluation of resilience by these traders. This point became apparent in comparison with the BL model under an increase in the number of investment transactions. In the BL model, the volume invested per transaction decreases with increasing number of transactions, while the influence on the fundamental price decreases. In contrast, in the OW model, the volume invested at the first transaction remains unchanged at 25 %, and the size of this transaction continues to affect subsequent investments. This is likely to increase the total execution cost. In the present simulation, with regard to this negative influence, we confirm borderlines exist when the number of investments is around 50 and the number of traders is around 5.

Next, we focus on the LI model. As mentioned in the previous section, the results of simulation based on the LI model were less clear than those based on the FI model. We can say that because total execution cost tended to decrease with increasing number of LI traders, the LI model could play the role of resilience. However, we could not observe clear differences in total execution cost between the optimal investigation strategies in the LI model, unlike in the FI model. These differences suggest that when a model has more intelligence, as for the FI model relative to the LI model, this is assumed to provide resilience in the optimal investment strategy.

7.5 Conclusion

In this study, we focused on the BL model and OW models. These models have different optimal investment strategies due to different market-related hypotheses even though they have the same purpose. It is desirable that the market-related hypotheses be realistic; however, we have no choice but to provide factors that are impossible to observe in certain exogenous forms. If such hypotheses cannot be confirmed theoretically and empirically, the strategies derived also become questionable. One of them is the concept of resilience that we focused on in this study.

If asset price fluctuations in financial markets are caused by trader behaviors, certain trader behaviors should also generate resilience. Based on this assumption, while modeling some traders that could play such a role, we attempted to compare two optimal investment strategies based on simulation. The simulation environment called artificial-market simulation played a significant role in our attempts. Financial markets involve complex, intertwining factors. Clarifying these factors individually can eventually reveal trader investment behavior. An artificial market can serve as an effective tool for reproducing the micro-macro loop.

In this study, we simulated traders with modeled resilience on the artificial market, while verifying the validity of those with resilience using the index, XLM. Our simulation confirmed that two models, the FI and LI models, could probably serve as the principles of resilience. Furthermore, we discovered that the number of traders indicates the strength of resilience. Finally, we simulated two optimal investment strategies based on the two types of resilience models to consider the relationship between the optimal investment strategy and resilience.

As a result, Obizhaeva and Wang [23] assumed weaker resilience that was provided as numerical samples when compared with the models of this study. Provided this assumption is correct, the optimal investment strategy of the Obizhaeva and Wang [23] model can be valid. In contrast, where resilience in the market is not evaluated properly, such as where it is underestimated, as considered in this study, there also exists the risk of producing a large total execution cost as the number of dividing investments is increased relative to the Bertsimas and Lo [4] model. Moreover, the two resilience models could be identical from the standpoint of the XLM evaluation. However, in the context of the optimal investment strategy, differences were observed between these two models. These findings suggest that intelligence that exceeds that of the LI model could be assumed in resilience in the optimal investment strategy.

7.5.1 Future Issues

In this study, which focused on the concept of resilience, comparatively neglected by preceding studies, we attempted to find the principles of resilience in the behaviors of traders. Our attempts confirmed that resilience could be modeled as a trader behavior. Future research can take two directions based on the results of this study.

One direction is to build a resilience model that follows the exponential function assumed by Obizhaeva and Wang [23]. In this case, we need to search for models that fit functions by using XLM.

The other direction is to focus on differences between the FI and LI models to propose a resilience model that can be positioned between these two models. This necessitates that we add some strategies to the LI model.

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Chapter 8
Observation of Trading Process, Exchange, and Market

Kazuhisa Taniguchi

Abstract Markets are the economic core and crucial evolutionary phenomena. Execution of the exchange is the premise for markets, and a human society has developed from a primitive colony to the Great Society with markets generated by expansion of the exchange. The act of exchange enhances economic performance. This fact has come to be regarded as buy and sell since the appearance of money. The principle of buy and sell is the key to understanding the market, and the process of the arbitrage which are conducted by buy and sell can clearly be observed through artificial market experiments. Based on the artificial market experimental results, this paper describes environments and processes where trading is conducted and why gain is obtainable by means of arbitrage and contemplates the significant meaning of market from the view of evolutionary economics.

8.1 Introduction

In *Elements of Pure Economics*, Walras showed the transactions observed in the securities market of Paris. The transaction example he explained is the trading of 3 % French Rents. Supposing the market rate is to be 60 francs, he wrote this transaction as follows:

> The brokers with orders to buy can no longer find brokers with order to sell. This is a clear indication that the quantity of three per cents demanded at 60 francs is greater than the quantity offered at that price. Theoretically, trading should come to halt. Brokers who have orders to buy at 60 francs 05 centimes or who have orders to buy at higher prices make bids at 60 francs 05 centimes. They raise market price. Two results follow from this bidding: first those buyers who would have bought at 60 francs but who refuse to buy at 60 francs 05 centimes, withdraw; second, those sellers who are willing to sell at 60 francs 05 centimes but who previously refused to sell at 60 francs, come forward. ⋯⋯. Then, in consequence of a two-sided movement, the difference between effective demand and effective offer is reduced. If equality between effective offer and effective demand is restored, the rise in price ceases. (Walras [14], Translated by W. Jaffé p.85.)

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On the contrary, when supply exceeds demand, the reverse thing occurs to the market. For instance, those sellers who desire to sell at 60 francs withdraw, because they cannot become sellers at 59.95 francs. Buyers who cannot be buyers at the offered price of 60 francs can participate at 59.59 francs in transactions. Walras said that where excess supply or excess demand exist, prices change as a parameter until there exist no such excess supply or demand. As a result, trading is conducted at the point where demand is equal to supply.

About 140 years have passed since Walras wrote *Element of Pure Economics*, has our understanding of the market improved? Could we explain the mechanisms of market more deeply than the explanation by Walras? Hayek denoted that any apparatus of classification must possess a structure of a higher degree of complexity than is possessed by the objects which it classifies.[1] If so, dose our own brain have fully a complexity to be able to explain the market which is complex like the universe or the life? Fortunately, we could build the artificial market system which is able to experiment the trading by means of a computer network. We could acquire the experimental tools which was not able to use in Walras age. Even if our brain does not have fully a complexity to understand real market, we obtained the test bed of market which is understandable by our limited ability of the brain. It is an artificial market system.[2]

This chapter describes the realization process of the transaction and arbitrage trading based on an artificial market observation and contemplates the significant meaning of market from the viewpoints of evolutionary economics. The artificial market based on the U-Mart system which the author has observed is a futures market where stock price indexes are traded. This artificial market is a small-scale market where just a few to tens of traders participate in the market. The number of market participants is extremely few when compared to actual markets. It is such a small market model which can be likened to a miniature garden with a simple but sophisticated system. As it is such a small and simple market system, we are able to observe dynamic market movements with it and understand the meanings and characteristics of the phenomenon that occurs. Through repeated observations, we can come to notice some things which have been invisible. Some things which seem to have been unquestionable then become questionable. For example, as Walras showed, there is a textbook style understanding that the price and quantity are determined when supply and demand correspond in a market. In order to determine

[1]Hayek wrote, "The proposition which we shall attempt to establish is that any apparatus of classification must possess a structure of a higher degree of complexity than is possessed by the objects which it classifies; and that, therefore, the capacity of any explaining agent must be limited to objects with a structure possessing a degree of complexity lower that its own. If this is correct, it means that no explaining agent can ever explain objects of its own kind, or of its own degree of complexity, and, therefore, that the human brain can never fully explain its own operations. This statement possesses, probably, a high degree of *prima facie* plausibility. It is, however, of such importance and far-reaching consequences, that we must attempt a stricter proof." (Hayek [2] 8.69.)

[2]See Kita [3], Ono, et al. [5], Taniguchi [9].

the price and quantity, however, something very important happens at before and after the moment of price-quantity determination. Orders are placed and trading is conducted, and the price and quantity are emerged as a result. Therefore, we cannot understand what is happening in the market unless focusing on the process which occurs and the results followed by the next process. Obviously, there is a market where only single trading is conducted. The representative example is the auction of paintings. However, many markets are opened one after another as time passes. Therefore, we must focus on the processes of the markets that are continuously open.

8.2 Trading Processes in the Stock Market

8.2.1 The Call Auction and the Continuous Double Auction

Before the results of performed experiments are considered, a simple overview of transactions conducted in a securities exchange should be described here. In a representative securities exchange such as the Tokyo Stock Exchange, the call auction method which is called Itayose method in Japanese and the continuous double auction method which is called Zaraba method are used for price determination. The call auction is mainly used to decide opening and closing prices in consideration of the balance between buy and sell orders. The continuous double auction is used to execute orders when orders enter the order book during continuous auction trading. During the call auction trading, order priority is determined based on principle of price priority.[3] Orders are accepted from 08:00, but no transactions take place before the session opens at 09:00 in the Tokyo Stock Exchange. Therefore, there are many sell and buy orders at various prices in the call auction session. In the Walrasian tâtonnement process, a trading auction is repeatedly conducted until the trading volumes between sellers and buyers match. Those market participants who cannot conduct trading have to withdraw from the market. However, there exist those sellers who could not sell and buyers who could not buy in the call auction trading session. Where considering this session as a one-time tâtonnement process, it can be considered as a quasi tâtonement process.[4]

The continuous double auction method is used in a continual process to match orders during the rest of the trading session. New orders are matched with those already in the order book. After the opening price is determined, trading is executed

[3]Principle of Price Priority:

- The lowest sell order takes precedence over other orders.
- The highest buy order takes precedence over other orders.

See *Guide to TSE Trading Methodology* [13], p.26.

[4]Taniguchi [11], Daniel Friedman [1], p.9.

when the order book is not crossed about prices with others. In addition to the principle of price priority, the principle of time priority is used in the continuous double auction.[5] The continuous double auction method is the process used to match individual incoming orders with orders that remain in the order book at that time. Those orders which were not matched continue to remain on the board unless they are canceled. The principle of time priority is used in the continuous double auction trading session; thus, transactions are conducted continuously. In other words, when orders are placed, they are matched with orders that remain on the board without delay.[6]

8.2.2 Observation of Trading Processes by Artificial Market Experiments

Both human and computer-programmed machine agents (hereinafter, human agents and machine agents) can simultaneously participate in the U-Mart system. This flexibility in participants is one of the noteworthy characters of the U-Mart system. In the experiment conducted by the author between May and July in 2013, 14 human agents and 10 machine agents participated, and between May and July 2014, 9 human agents and 10 machine agents participated.[7]

14 Human agents in 2013 and 9 human agents in 2014 are students enrolled in the author's seminar course. These students preliminarily learned about futures markets and trading methods, performing pilot experiments. They were different students each year. Figures 8.1 and 8.2 show one day of these experiments in each year. Regarding the machine agents, the same type machine agents were used for each year experiments. Here were 10 machine agents that participated, and 5 of those machine agents placed orders around the futures price in a random manner. The remaining 5 agents placed orders around the spot price in a random manner. These machine agents did not try to gain a profit when ordering. This was programmed for the purpose of ensuring market liquidity.

The experiments were performed 6 times (sessions) in 2013 and 12 times (sessions) in 2014. One experiment session was performed for about 23 min, and two experiments were performed for each 90-min lesson a week. The spot price system was given exogenously in this U-Mart experiments, and the futures price market was formed endogenously within the system while this given spot price

[5]principle of time priority:

- Among orders at the same price, the order accepted earliest by the exchange takes precedence.

[6]Taniguchi, et al. [12], Taniguchi [10].

[7]U-Mart system ver. 4 (Zaraba-based market) was used for these experiments. The other human participated experiments by U-Mart Ver.2 (Itayose-based market) were reported in chapter 4 of Shiozawa et al. [8].

Fig. 8.1 Artificial market experiment on 7 June 2013

Fig. 8.2 Artificial market experiment on 23 May 2014

system was referred to. There was no arbitrage trading conducted between the futures markets and the spot markets. Arbitrage trading was conducted between the different points in time of the future markets.

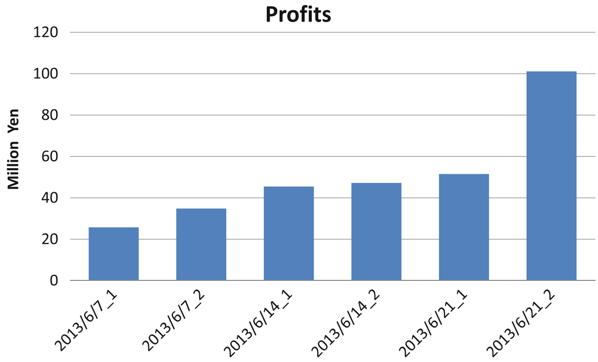


Fig. 8.3 Profits: experiments in June–July 2013

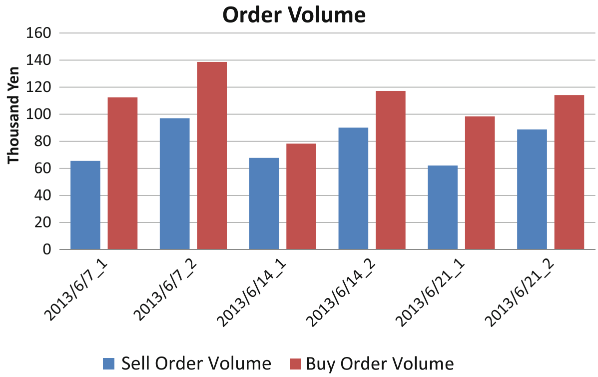


Fig. 8.4 Order volume: experiments in June–July 2013

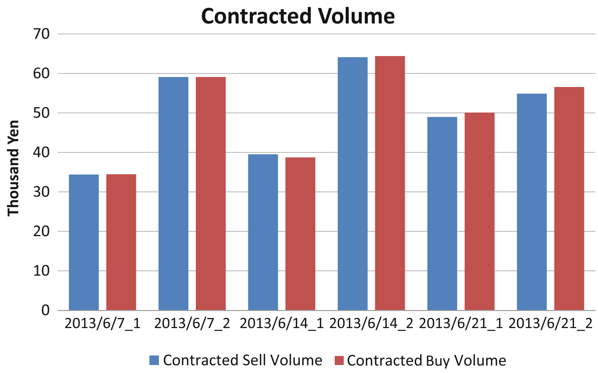


Fig. 8.5 Contracted volume: experiments in June–July 2013

8.2.2.1 Experiments in 2013

In the experiment conducted in 2013, the learning effects clearly appeared in the experimental results. Machine agents were added to this experiment in order to ensure liquidity; therefore, they did not have any particular trading strategy in this experiment. Machine agents were neutral with regard to profit earned by human agents. Figure 8.3 shows profits earned, Fig. 8.4 shows the order volume of each session, Fig. 8.5 shows the contracted volume, and Fig. 8.6 shows the contract

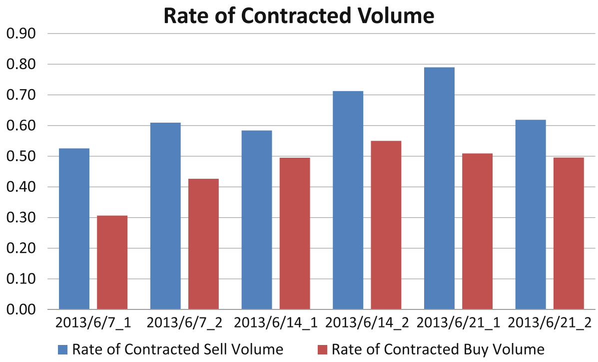


Fig. 8.6 Rate of contracted volume: experiments in June–July 2013

rate. Each value indicates the total volume of orders placed by 14 human agents (except machine agents). As we can see from these figures, gradually, humans became able to certainly earn profits by utilizing the difference between the spot price and the futures price. Experimental participants learned the mechanism of the futures market and the trading rules prior to starting the experiment. Through each experiment session, human agents were also acquired know-how knowledge gradually. The group of human agents came to be able to win against the group of machine agents, comparatively speaking.

8.2.2.2 Experiments in 2014

In order to examine how price change occurred and whether this price change continued or not, clear differences were configured among the experimental participants. Namely, machine agents participated in the first 6 experiment sessions of the entire 12 sessions and did not participated in the second 6 experiments. And the same processed real spot price series was used for the first six experiment sessions and the second six experiment sessions for comparison. With regard to the spot price series, any preliminary knowledge such as characteristics was not given. Unless extra care was taken for the price series, it was difficult for human memory to notice that the price series was the same as the one that had been used for the experiment performed 3 weeks ago. Actually, no one noticed that the same price series was used in this experiment.

Although exactly the same spot price series was given, significant differences arose in the futures price series formed between the cases where machine agents participated in addition to human agents and the case where only human agents participated. As shown by Figs. 8.7 and 8.8, the futures prices followed the spot

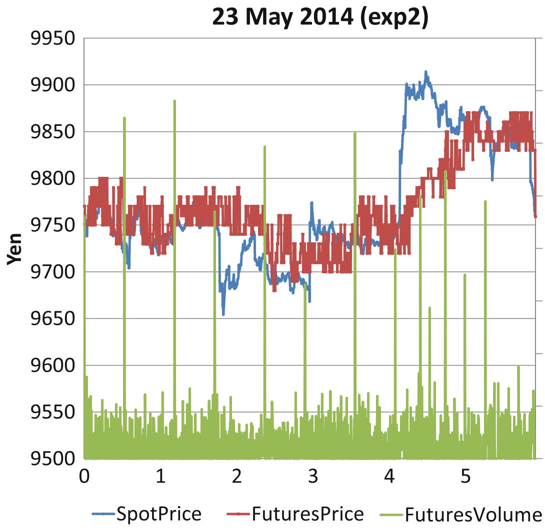


Fig. 8.7 Price and volume: experiment with machine on 23 May 2014

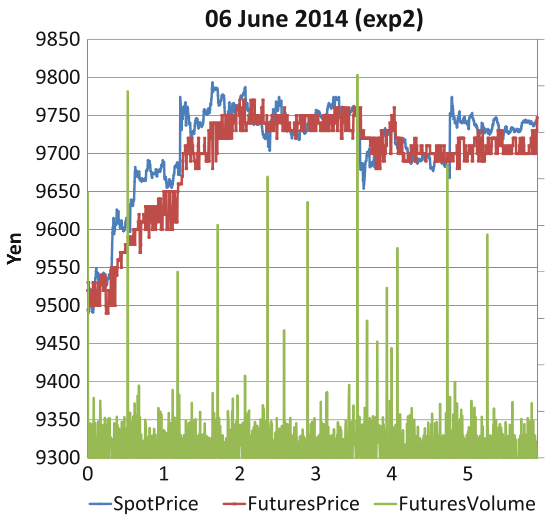


Fig. 8.8 Price and volume: experiment with machine on 06 June 2014

prices in the case where machine agents participated. However, Figs. 8.9 and 8.10 show that the futures prices diverged from and hardly followed the spot prices in the case only human agents participating without machine agents, and the number of executions was reduced. Arbitrage trading between the spot and the futures is conducted in the actual market. The U-Mart system which was used for this experiment is not capable of conducting arbitrage trading between them. However, despite the fact that such arbitrage trading could not be conducted, the spot prices and the futures prices did not diverge significantly in the experiment where machine agents participated.

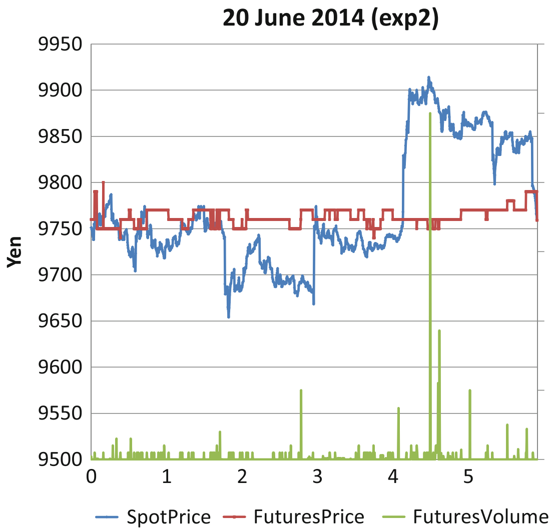


Fig. 8.9 Price and volume: experiment without machine on 20 June 2014

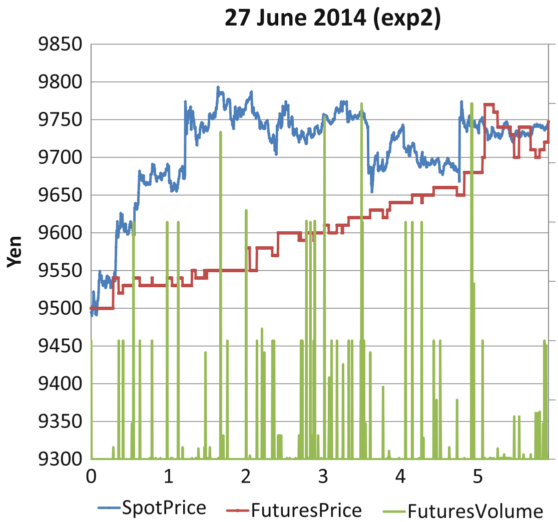


Fig. 8.10 Price and volume: experiment without machine on 27 June 2014

It is not so difficult to suppose the cause of this phenomenon. Machine agents were programmed to simply place orders around the spot or futures prices randomly without trying to gain a profit. Therefore, orders were randomly placed around the spot prices, and those orders placed were executed around the spot prices in the experiments in which machine agents participated. This is because trading participants including human agents react to the prices and place their own orders.

In the case where machine agents did not participate, the spot price series diverged from the futures price series. Humans who participated in trading know many matters by learning about these futures markets. They know that the spot price corresponds with the futures price on the final day of the market, and furthermore, as positions are matched, the residual selling orders are forcefully bought as well as the residual buying orders are forcefully sold by the stock exchange system. Why did the divergence continue? The following two points can be considered as the reasons for this phenomenon. The first point is the predictions made by traders. When the futures price follows the spot price, such a price movement is predictable and orders can more easily be placed. For example, when the futures price is higher than the spot price, traders sell futures, while traders can buy futures when the futures price is lower than the spot price. However, sometimes in spite of a small gap between the futures price and the spot price, the case where both prices did not change was observed. At this time, the spot price is not of much help to the predictions. It is hard for the traders to place orders because they can refer only to the price information formed on the futures board. Given this situation, the futures board is not affected even though the spot price changes. As a result, it becomes more difficult for the traders to make predictions about the change in the futures prices. Furthermore, where there is a long period without any execution, which causes the prices stay totally flat, there are no more price changes. When such a situation arises, the traders observe these situations and stop placing orders. This also stops price changes.

The second point is regarding the mechanism of the futures market and the number of trading participants. Suppose that a trader holds one position in trading at a certain price in the early trading stage. At this time, with expectation for the future fluctuation, he could switch his trading strategy into a long-term operation without dissolving the position he holds. In the futures market, the existence of traders that hold a certain positions means that there should exist the traders who hold the opposite positions. At this time, even if other traders try to respond to a short-term fluctuation which has been formed, there are no trading partners where those partners change their strategy into a long-term operation. In other words, no buying and selling can be done, and as a result, prices stop changing. For example, those traders who bought at a high price do not want to sell it at a low price even though the spot price falls. Hence, they shift their strategy into holding positions for the long term. On the other hand, those traders who sold at a high price want to buy it at a low price. However, no matter how they place buying orders, trading cannot be established since there is no one who sells at a low price. This situation makes high prices continue to exist and vice versa. Afterward, as the spot price fluctuates and gets closer to the futures price, those traders who aim to dissolve their positions can do it along with other traders that consider the same thing.

Price change and trading volume are now focused on next. The vertical axis on the right indicates the volume. In figure, the height of the bar charts indicates the trading volume, and these figures show that several peaks appear in each of experiments. In the experiments with machine agents, the points where significant transactions were conducted appear about more than ten times. Though the trading volume of machine agents is predetermined to be always 50–100 volumes per each trading, peaks of trading volume appear about more than ten times. The trading volume becomes small where the change in the futures price is small, and the peak of intense trading volume sometimes suddenly appears. These facts show that it is more important to consider "how much the price changes" than "how much the price is," in order for trading to be conducted. When prices change, the predictions also change, and this promotes more orders to be placed, and then trading is conducted.

8.3 Contract and the Principal of Exchange

8.3.1 The Importance of Contract

The first step of trading which should be taken by market participants is to contract their orders. It does not make any sense if orders are not contracted. Above all things, orders have to be contracted. Firstly, a trader needs an opposite trader for an order contract. It is assumed that opposite traders already exist in the market, or if they do not exist, they are to come to the market. The guarantee of the existence of opposite traders is an important mission of the market. Secondly, ordering conditions placed by the trader must be accepted by the opposite trader. Trading is not established when you do not deal with the opposite trader's order or if the opposite trader does not deal with your order. There is an ordering method called "market order." It is an order by traders who want to sell or buy at any available price. The traders do not indicate specific prices, but are executed at the available price on the market at the time. Market orders take precedence over another kind of order, for example, "limit order," and its ease of execution is a key merit. However, since no price conditions are set for market orders, it is possible that an order may be executed at an unexpected price. Market orders only guarantee a contract and have a priority over another kind of order. The existence of such an order method that has a priority without any conditions itself indicates that the guarantee and promotion of the contract are very important missions of the market.

Upon ordering, the following three factors should be determined: the ordering type, selling or buying, the order price, and the order volume. Matching the orders already placed increases contract opportunities. If you are already present in the market, disclosing information by placing orders ahead for those other trading partners who are not yet present in the market increases your opportunities for accepting orders. There are only three factors to determine prior to placing orders. However, the following fundamental conditions accompany these three factors in order for orders to be contracted. Namely, orders need to be placed as a result *at a price higher or equal to the market price for buying or at a price lower or equal to the market price for selling*. In other words, disadvantageous orders need to be placed in order for orders to be contracted. However, why then can we place buy orders at prices higher than the market price or sell orders at lower prices? Why can we place disadvantageous orders? Why do such orders, which seem to produce a loss, appear in the market?

8.3.2 The Principle of Exchange

At least two agents need to exist in order to conduct trading, and the trading between two agents (two individuals) has to be done based on the same logic. However, why is it that completely opposite behavioral patterns, namely, buying and selling, are generated for an identical commodity? To answer this question, we need to start by considering the most basic point, why exchange is done. Exchange of commodities, that is, barter, usually comes to mind when the expression "exchange" is heard. If money is considered to be one of the commodities, however, buying and selling can also be regarded as exchange. Money is an abstract commodity, that is, a general medium of exchange. "Selling" is done by an agent to exchange his specific commodity with an abstract commodity (= money); on the other hand, "buying" is done by an agent to exchange an abstract commodity (= money) with a specific commodity. Buying and selling is a particular exchange form. The following explains why exchange is conducted, based on the principle of exchange proposed by Shiozawa.[8] Exchange means only a transaction at a certain point in time; therefore, this principle is used not only in speculative markets but also in product markets.

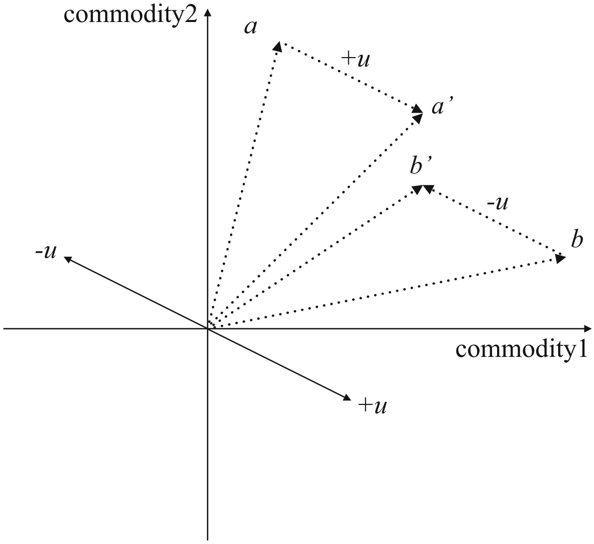
First of all, the price vector p, the exchange vector u, and the valuation vector v are defined. The price is the ratio of exchange and the price vector is the ratio of exchange vector. It is expressed as $p = (p_1, p_2, \cdots, p_n)$. This is referred to as an objective price vector.

Next, the exchange vector u is defined. The exchange vector u indicates trading of commodities between the exchange agent A and agent B. A commodity obtained by agent A from agent B with the exchange vector u is the positive vector u^+, and a commodity given to agent B from agent A is negative vector $-u^-$ (the absolute value is u^-). Therefore, this exchange for agent A is expressed as $u = u^+ - u^-$. When viewed from agent B, the things agent B obtains and gives through exchange are opposite from those of agent A; therefore, the exchange vector for agent B in this case becomes $-u$. As for the commodity of agent B, u^+ is to give and u^- is to be obtained through exchange. In case of two kinds of goods, the exchange can be depicted on a two-dimensional plane as shown by Fig. 8.11.

The valuation vector v is valuation held by each agent, which could be subjective or objective. This is different from the objective executed price, namely, price vector. Suppose the valuation vector of agent A and agent B is v_a and v_b, respectively. The separation theorem is used in order to prove this. Where there is hyperplane including the price vector p, and v_a is separated from v_b (where end-point conditions are appropriate), agent A and agent B can evaluate their own new properties highly by means of exchange defined by the normal line vector u of this hyperplane. Exchange vector u is perpendicular to the objective price vector p, that is, the scalar product is zero; therefore, property value never changes before and after exchange.

[8] Shiozawa [6], Shiozawa [7].

Fig. 8.11 Principal of exchange



However, v_a is separate from v_b by hyperplane that includes price vector p, so that the two scalar products of the normal line vector u of hyperplane are positive and negative, respectively. Namely, both agents can enhance their evaluation by exchange.[9]

8.3.3 Exchange with Money

When money emerges and buying and selling are conducted, the exchange with money, namely, buying and selling, is expressed by using this exchange vector. Suppose there exist agent A as a seller, agent B as a buyer, and two goods to be exchanged, that is to say, one good is bought and sold. Where a particular good is exchanged for money, that is to say when it is bought and sold, let the first good be money and the second good be a commodity which is exchanged for money. As money is an abstract commodity, there exists the price of the commodity which is money. The price of money is generated by measuring money by money, so that the value is 1. Suppose, for instance, this commodity is a scarf which costs 20 dollars each. Therefore, the price vector is $p = (1, 2)$.

Here, one scarf is bought and sold. Where this exchange vector u is $u = u^+ - u^- = +(2, 0) - (0, 1)$, the exchange by seller A is expressed as $u = (+2, -1)$, while that of buyer B is expressed as $-u = -u^+ + u^- = -(2, 0) + (0, 1) = (-2, +1)$. Where the horizontal axis indicates money and the vertical axis indicates the

[9] See mathematical notices in this chapter.

commodity which is exchanged with money in Fig. 8.11, we are able to understand the relationship between both parties intuitively. The scalar product of the price vector p and the exchange vector u is 0; therefore, the value of the good remains unchanged before and after buying and selling. There is a no-win-no-lose situation where sellers and buyers neither suffer losses nor gain profits, depending on the type of buying and selling. It should be noted that losses and profits of the good vector value measured by the price vector are distinguished from profits of the good vector evaluation measured by the evaluation vector.

8.3.4 Quotes and Prices

As stated above, the determination of price does not become grounds for the execution of exchange. Property value which is vaulted based on price never changes before and after exchange. Therefore, the exchange is not conducted because there exists the price vector. Rather, the exchange is conducted because there exist different (unproportional) valuation vectors on both parties, plus exchange vectors for valuation. That is why exchange is conducted. Mises mentioned about valuation as follows:

> Each party attaches a higher value to the good he receives than to that he gives away. The exchange ratio, the price, is not the product of an equality of valuation, but, on the contrary, the product of a discrepancy in valuation. (Mises [4], Vol.2, p.331.)

Mises skillfully describes how exchange is conducted, stating that it is conducted not by an equality of valuation but by a discrepancy in valuation. However, he also stated that the price is a product of a discrepancy in valuation. How can we accept this idea?

In a productive market, an objective price is determined by a full-cost principal, and the objective price vector is clearly presented to both exchange parties. The market which Mises mentioned is a speculative market, not a productive market. The price, which appears after trading, described by Mises is probably the execution price of which Walras also observed at the securities market of Paris. However, this price does not exist before trading. If there is no objective price that serves as a benchmark for the market, there is a need to present the price to the opposite party. According to the author's observation of the U-Mart experiments, it is quotes, namely, bid prices or ask prices on the order book. Those agents that can correspond to such quotes appear in the market as transaction parties and send orders of buying or selling toward those quotes. In product trading, merchants (brokers) intervene between producers and consumers, while sellers and buyers are fixed. Price changes never replace their positions. In security markets, however, the positions of sellers and buyers are instantaneously switched. Quotes which serve as the determination

Table 8.1 Book Sample

Seller	Volume of offer (sell)	Price (Yen)	Volume of bid (buy)	Buyer
A2	1	5		
A1	2	4		
		3		
		2	2	B1
		1	5	B2

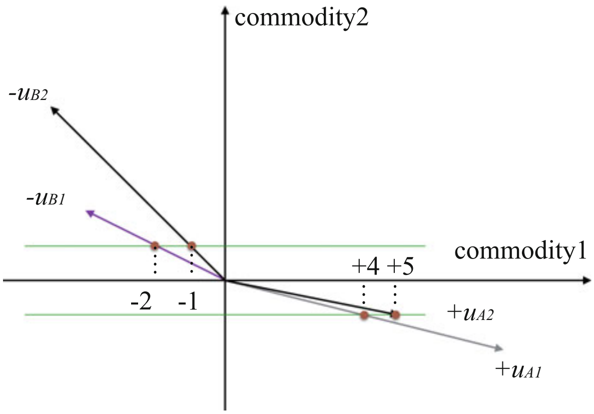


Fig. 8.12 Exchange vector and buy-sell

standard for buying and selling are so strong that they replace the positions of buying and selling.[10]

In order to consider buying and selling at a securities market in detail, let us discuss an order book and the principle of exchange. Suppose the order book in Table 8.1 is generated in financial index futures trading. The "best ask" means the sell order at the lowest price which appears on the book. In Table 8.1, the order placed by A_1 is the best ask. In addition, the "best bid" is the buy order at the highest price, which is placed by B_1. "A quote (price quotation)" means the buying or the selling price desired by the buyer or the seller, and it sometimes indicates the best bid and the best ask.

On the order book in Table 8.1, regardless of the Itayose trading method or the Zaraba trading method, transactions have already been concluded, and no orders that can be executed remain. In Fig. 8.12, which shows the exchange, orders placed by sellers of A_1 and A_2 appearing on the book are indicated with the exchange vectors u_{A1} and u_{A2}. Each asked price is indicated as the intersection of the line in parallel with the horizontal axis (a horizontal line with a distance of 1 from the horizontal

[10]The Tokyo Stock Exchange actually restricts a range of prices when prices are updated in order to prevent violent fluctuation in stock prices. If orders that exceed the price range limit are sent, special quotes are placed so as to control such fluctuations by securing time for determination of buying and selling. Additionally, when the opening price has not been determined, preopening quotes are placed in order to provide the determination standard. Quoted prices come in several different forms, and they are provided to traders as objective standards for valuation.

axis) and the exchange vectors u_{A1} and u_{A2}. The value of each of these intersections is $+4$ and $+5$, respectively. The orders placed by buyers B_1 and B_2 are the exchange vectors u_{B1} and u_{B2}, while each bid price is the intersection of the line in parallel with the horizontal axis. The value of these intersections is -2 and -1, respectively. The amount of the intersection of the line in parallel with the horizontal axis, namely, distance from the vertical axis, generally indicates the quantity of commodity 1 that is exchanged with commodity 2. Here, however, this amount is the quote (price quotation). As the scalar product of the price vector p and the exchange vector u is 0, if only two goods are exchanged, in other words, if only one property is bought and sold, the price vector can be determined when the exchange is determined. As stated by Mises, in a financial market, the price, namely, the exchange rate, is generated, not because the values evaluated are equal but only because there is a discrepancy in values evaluated. In addition, however, the evaluation vector has to be within a certain range, that is, on both sides of the hyperplane which includes the price vector. Additionally, the values evaluated by this discrepancy have to be presented to the parties of buying and selling. If not, the contract price does not appear in the market.

8.4 Arbitrage Trading and Maket

8.4.1 Arbitrage Trading

Suppose trading is established. In order to gain a profit in the trading, you must earn a marginal gain between the current trading session and the next trading session. To achieve this, you need to sell at a price higher than the first contracted price for buying or to buy at a price lower than the contracted price for selling. In the futures market, markets are opened one after another as time passes and trading is conducted. Therefore, you must conduct trading so as to *buy at a low price and sell at a high price or sell at a high price and buy at a low price* through the time. To realize this trading, you need to prepare for the next trading session at the execution of the first trading session while supposing price movements in the market.

Arbitrage trading is a form of trading engaged for the purpose of obtaining a profit, taking advantage of price discrepancies or interest spread generated in spatially or temporally separate markets. In arbitrage trading, traders purchase commodities for the purpose of reselling. Since traders in a futures market can sell commodities they actually do not have, they sell them for the purpose of purchase. Therefore, arbitrage conduct requires buying and selling conducted at least in two different points. In a certain market, for example, a buyer that quoted the highest price can gain predominance over other buyers, and he is able to buy the commodity. At that time, this buyer makes a judgment that there should be a market where the commodity can be sold at higher price. At the same time, a seller that quoted the lowest price can gain predominance over other sellers, and he is able to sell the

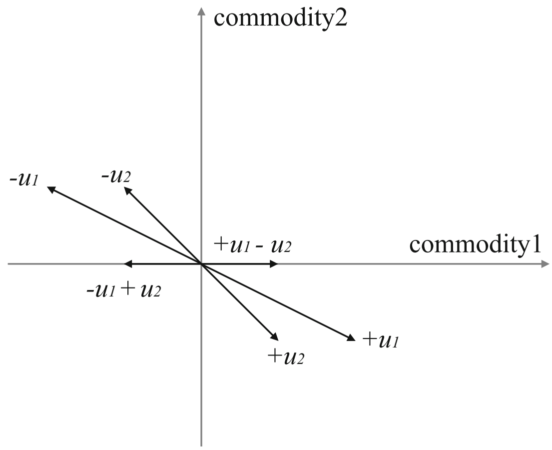


Fig. 8.13 Exchange and arbitrage

commodity. At that time, this seller similarly makes a judgment that there should be a market where the commodity can be bought at lower price. Buyers become sellers in another market. If the commodity can be sold at a price higher than the purchase price, arbitrage trading has successfully been done. Namely, a profit has been gained. The opposite is still the opposite. Arbitrage trading is conducted just because the price differential exists. Or it is conducted because there is a prediction that a price differential would be created.

At this time, what kind of relationship can be observed between the arbitration transaction and exchange (buying and selling)? Figure 8.13 shows arbitrage trading by using a diagram of the principles of exchange. Buying and selling are executed based on different evaluation vectors, while the exchange result is evaluated by the price vector (contract price). Suppose the first exchange (buying and selling) is expressed as u_1, and the second exchange (buying and selling) is expressed as u_2. When exchange u_1 is executed, the scalar product of u_1 and its price vector is 0 where the value itself does not increase nor does it decrease. When the second exchange u_2 is executed, the scalar product of u_2 and its price vector is also 0. If buying and selling are executed twice here, the number of commodity 1 possessed by those traders who executed buying and selling of $+u_1 - u_2$ increases in this transaction, while that of commodity 2 remains the same. The number of commodity 2 possessed remains the same because speculative trading is conducted with respect to commodity 2; however, the number of commodity 1 increases. This means that when commodity 1 is considered to be money, profits are gained. The number of commodity 1 possessed by those traders who executed the opposite trade, $-u_1 + u_2$, decreases, that is, they suffer losses, while that of commodity 2 remains the same.

8.4.2 Different Decisions and Market

After the execution, in the market, those traders who wanted to buy at the price executed already bought at that price, while those traders who wanted to sell at the price executed already sold at that price. Therefore, only sell orders at a high price that buyers cannot buy and buy orders at a low price that sellers cannot sell remain on the board. As a result, a situation continues to exist, where it is neither possible to buy at a price lower than the price expressed by the point of intersection of the demand curve with the supply curve (i.e., the price executed in the market) nor is it possible to sell at a price higher than the executed price. Therefore, if the price does not change or if such a prediction is made, as mentioned earlier, nobody remains in the market. The aim of arbitrage trading is not to obtain objects or services for the purpose of using them; rather, the ultimate aim of this trading is only to gain a profit from price differential. Trading does not make any sense unless there exists some kind of price differential (or a prediction that price differential is going to be created). In a situation of no estimate execution price (expected price) differential, arbitrage trading cannot exist. Arbitrage is enabled because there are different predictions.

Individual market participants make different decisions. There are traders who place orders considering that they can win because of their talent, although it is impossible to exclude the possibility of making a loss. Such traders are able to understand the variation in the market from the instantaneous price change in the market, placing buy orders at a price higher than the executed price in the market or sell orders at a lower price. Trading is done since there remain orders that correspond to such prices in the market, and, at the next moment, a new execution price appears in the market. Or, when the market conditions change, one trader judges the price as rising, while another trader judges the price as falling. Here, completely opposite orders, buy and sell orders, appear during the same situation.

However, how to recognize the change of market conditions? In the artificial market experiments reported on the previous section, change in market conditions is defined as the change in prices. The actual market is not always an organized auction market, where all required information is not necessarily transmitted constantly. For example, when the same price continues to exist, sometimes it could be impossible to understand based only on price scale information whether there has been a newly formed price, which means market conditions are changed, or the past price has continued from the previous price formation, which means market conditions are constant. When the price changes for every price formation, traders can absolutely find that the price formed is new. The information that is transmitted is only the price (scale) itself; in other words, the information of price change is transmitted along only with the information of price scale itself. Market traders can know the market conditions by means of price change. It depends on the price change, not the price scale itself, to begin the trade.

In order for trading to be conducted in this way, it is necessary that the market conditions change, and for such change, individual market participants make different decisions on their own. Different decisions and the change of market conditions are interdependent. The decision-making based on information obtained depends on the subjective view of each individual trader, and each trader has the different subjective view. Trading can be realized and established because each trader makes different decisions. The origin of the market, that is, exchanges, would not exist, if all traders have the same subjective view and make the same decisions. Because prices in the market change, predictions of market participants change. This causes participants to make different judgements. These different judgements change, and then prices in the market also change again. Macro change produces micro change, and this produces macro change again. This is referred to as a micro-macro loop. Prices generated as a result of microscopic decision-making of individuals produce the entire movements. Furthermore, a shift in these prices brings about changes in microscopic decision-making of individuals.

What makes entities make diverse decisions based on a different subjective view of each entity? Or, we could ask, why is the subjective view different depending on each entity? The answer is that humans can live only in the present, understanding nothing about tomorrow. Humans are unknowable (ignorant) about the future, or there exists pure uncertainty. Given that, a huge variety of predictions appear, and different actions are produced out of such predictions. The fact of being unaware of the future is the fact that there exist diverse subjective views. Although decision-making is caused due to exogenous events, the decision made itself depends on each entity. The human limitation of being unable to know about the future underlies the base layer of the market. This plain common fact generates prices and establishes the market.

As described above, the main premise in order for the market to exist is that all traders cannot make the same predictions. The agnostic future actually ensures the fact that the traders make different predictions and diversification of traders is also ensured. Diversification of market participants and knowledge dispersion are critical factors for the market. The predictions made by all market participants are not correct, but at the same time, they do not fall short in the same direction. Therefore, there should be no winning formula for conducting transactions in financial markets. If such a formula was available, no one could make a profit. There would be no one to participate in transactions, which would result in the disappearance of the market itself. An approach of modeling using one representative entity lacks the fundamental viewpoint that market trading can be available only because numerous entities with different strategies exist in the market.

8.5 Conclusions

Research using artificial markets has actively been done as a new study approach of economic research; however, it is hard to find any artificial market research other than the U-Mart system in which human agents participate in collaboration with machine agents. For more than 10 years, the author has conducted artificial market experiments by using the U-Mart system in which human agents participate. The artificial market research in which humans participate takes cost. Experiments in which only machine agents participate can end comparatively in a short period, and this feature makes it possible to perform a wide variety of experiments. However, experiments in which human agents participate require the securing of human participants first, and practical experiments can be performed only after those human participants have learned about securities exchanges and the mechanism of the futures market. When human agents without stock trading experience participate in trading at a stock exchange for the first time, some of them are so perplexed that they can hardly execute their orders. Their orders may be executed if they place incoherent orders. When participating in a market with the goal of obtaining a profit, however, they find how difficult it is to execute their orders. Execution of orders may be difficult even though they place orders while referring to charts that show changes in stock prices. Moreover, obtaining a profit is extremely difficult. In order to execute their orders, they need to learn how to utilize order book information. They need to consider how to realize a profit afterward. Realizing a profit is far more difficult than execution of orders, which needs to be comprehended through ranges of time. Market participants might be able to execute their orders if they can understand the order book (photo) of one moment. In regard to arbitrage, however, market participants must be able to observe the market that moves with time (movie). They probably do not even understand that they face such learning problems at first. Upon conducting trading, they need to become adept at the operation of the U-Mart system to a certain level.

Sometimes an experiment itself could not be performed due to the sicknesses or accidents that occur because they are humans. These factors restrict the number of experiments that can be performed in a year. If the characteristics of a group of humans are reflected on the experimental results, it must be necessary to prepare a number of groups of human participants which certainly requires a considerable time to perform a series of experiments. It is undeniable that this article has insufficient persuasive experimental data. For this reason, it is necessary that experimental data of this sort must be accumulated and we need to continue to watch for the future experimental results.

In the beginning, this chapter introduced Walras's observation of the stock exchange. Observing the actual securities exchange, Walras described the execution of trading at the time point when the price (exchange ratio) is determined along with the trading results. On the other hand, Mises indicated that a discrepancy in valuation held by both parties of buying and selling is necessary for execution of buying and selling. However, it is difficult to find how to emerge the discrepancy in valuation in his description. Based on observation of trading in artificial markets, this chapter considered how traders place their orders, how their orders are executed, how part of traders can realize a profit, and how other traders suffer a loss. When beginning arbitrage, every arbitrage trader buys and sells while aiming at realizing a profit. In a futures market, however, not all traders can realize a profit. The properties of both parties are highly evaluated by exchange. That is why exchange is conducted. The point in that receiving high evaluation marks by exchange is the same with product markets as well as financial markets. In product markets, prices do not change on a short-term basis. In production economy, industrial products whose production volume can be adjusted are produced by an amount that those who want to buy at the determined price can buy. Exchange is conducted only with those who can satisfy the conditions of that exchange ratio. On the other hand, almost all commodities transacted in financial markets are commodities that are not produced. Their volume is not changed, so that it is impossible to adjust production volume. Therefore, a price change serves as an important economic variable. The important thing for sellers and buyers is to realize a profit by arbitrage trading, and only valuation where quotes are referred to (predictions whether the price goes up or down) is available. Prices and a system that surrounds prices were generated from the world of production economy that utilizes differences in valuation vectors that are subjective to economic agents. As a result, this system has evolved to a financial asset market. The balances of financial assets of the world were almost equal around 1980 at share of gross domestic product (GDP). However, they tripled over 30 years. Markets where money and financial systems evolve and expanded further will be emerged in the future.

8.6 Mathematical Notices

Shiozawa [6] gave the proof in a general formula in which exchange is conducted by owners of nonnegative n commodities. Here, for the purpose of intuitive understanding of the theorem, all commodities owned are positive.

At first, the commodity vector owned by agent A is $a(>0)$, and the commodity vector owned by agent B is $b(>0)$. The exchange vector u indicates trading of commodities between the exchange agent A and agent B. A commodity which is obtained by agent A from agent B with the exchange vector u is the positive vector u^+, and a commodity which is given to agent B from agent A is negative vector $-u^-$ (the absolute value is u^-). This exchange for agent A is expressed as $u = u^+ - u^-$. When viewed from agent B, the things agent B obtains and gives through exchange become opposite from those of agent A; therefore, the exchange vector in this case becomes $-u$. As for the commodity of agent B, u^+ is to give and u^- is to be obtained instead through exchange.

If it is impossible to give more than what each agent has, the commodities owned by each agent after exchange a', b' respectively can be expressed as follows:

$$a' = a + u = (a + u^+) - u^- \geq 0$$

$$b' = b - u = (b + u^-) - u^+ \geq 0$$

Where the valuation vector of agent A and agent B, v_a and v_b, is different (disproportional), respectively, and they are separated with hyperplane that includes the price vector p, and where the scalar product of the normal line vector u of this hyperplane is taken, the formula below is derived:

$$\langle u, v_b\rangle < 0 < \langle u, v_a\rangle$$

Where $\langle , \rangle$ means the scalar product. The valuation of the commodities owned by each agent before exchange is expressed as the scalar product $\langle a, v_a\rangle$ and $\langle b, v_b\rangle$, respectively. After exchange, they are expressed as follows:

$$\langle a', v_a\rangle = \langle a, v_a\rangle + \langle u, v_a\rangle > \langle a, v_a\rangle$$
$$\langle b', v_b\rangle = \langle b, v_b\rangle - \langle u, v_b\rangle > \langle b, v_b\rangle$$

Here, $\langle a + u, v_a\rangle > \langle a, v_a\rangle$ and $\langle b - u, v_b\rangle > \langle b, v_b\rangle$, both agents can enhance evaluations of their vectors by means of exchange that is defined by the vector u.

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Index

ABCE, 3, 34
ABS, 3, 34, 38, 42, 46, 51
  trouble with —, 40
ABS-gaming hybrid, 56
abstract commodity, 182
abstract model, 55
agent-based modeling toward new social system sciences , 88
agent-based simulation, 51
Alchian, Armen, 14
AM, 51
arbitrage, 172, 175, 178, 186–188, 190
Archimedes, 39
artificial market, 51, 57, 172, 188, 189

batch-auction market, 121
bounded rationality, 22, 43, 54
breakthrough, 35

call auction, 173
capital controversy, 5, 7
cell automata, 52
CGE model, 30
classifier system, 22
Cohen, Ruth, 9
complex world, 36, 42
complexity, 36
computer simulation, 39
computing time, 22
consistency, 15
continuous double auction, 173, 174
continuous-auction market, 118, 121

data exploration, 39
demand function, 16, 20, 21
DSGE, 9, 31

effective demand, 17
equilibrium, 43
Euclid, 38
evolution, 44
evolutionary economics, 22, 44
exchange vector, 182, 191
execution price, 184, 188
exhaustion theorem, 8
experiments, 38

facsimile model, 55
fidelity, 61
functional cycle, 42
futures market, 172, 180, 186, 190
futures price, 174, 177, 179, 180

GA, 44
Galilei, Galileo, 38
gaming simulation, 56
general equilibrium, 16
GET, 19, 26, 30

H. Kita et al. (eds.), *Realistic Simulation of Financial Markets*, Evolutionary Economics and Social Complexity Science 4, DOI 10.1007/978-4-431-55057-0

good model, 37
good simulation, 43

Hicks, J. R., 32
high fidelity, 60
human agent, 135
human behavior, 42
hybrid players, 56

if-then directives, 43
ignorant, 189
increasing returns, 15, 16, 23, 26
    — revolution, 29
    — to scale, 27
input substitution, 27
Itayose, 173
itayose, 61

keep it simple, stupid, 55
KISS, 55
knapsack problem, 20

Lakatos, Imre, 41
Langton, Christopher, 22
learning, 44
learning agents, 54
Li-Yorke theorem, 42
limit order, 181
liquidity, 117–121, 134, 135

machine agent, 135
marginalist controversy, 11
market order, 181
Marshall, Alfred, 16, 26
mathematics
    bounds of —, 36
maximization, 20
methodology, 46
methods
    mathematical —, 4
    seescientific research, 4
micro-macro loop, 45, 46, 189
microsimulation, 52
middle range model, 55
Mill, John S., 32
mode
    seescientific research, 38

new worldview, 36

observation, 39
order book, 119, 120
order-driven market, 121

Popper, Karl, 15
price vector, 182–184, 191
principle of exchange, 182
principle of price priority, 173, 174
principle of time priority, 174
process analysis, 33, 34, 41–43
production function, 8

$q_1 S_1 S_2 q_2$, 43
queuing model, 52
quote-driven market, 121
quotes, 184, 185, 191

random trader, 128
rationality, 54
RBC theory, 9, 10
reproducibility, 61
reswitching, 9
Rethinking Economics Network, 11
routine agents, 54
routine behavior, 22, 43
rules of conduct, 22, 44

scalar product, 182, 191, 192
scientific research
    first mode of —, 38
    fourth mode of —, 39
    second mode of —, 38
    third mode of —, 39
scientific reserach
    third mode of —, 47
sequential analysis, 41
shifting equilibrium, 32
SMD theorem, 25
social simulation, 51
Soros, George, 10
spot price, 174, 177, 179, 180
Sraffa's principle, 17, 40, 46
Stockholm school, 41
supply function, 16
system dynamics, 51

theoretical necessity, 6, 15
theory, 38

Tokyo Stock Exchange, 173, 185
traceability, 61
transparency, 61

uncertainty, 189
unknowable, 189
usability, 61

valuation vector, 182, 191
voluntary trading, 27

Zaraba, 173