Universität Karlsruhe (TH)
Forschungsuniversität • gegründet 1825

Information Management
and Market Engineering

Competition Between Electronic Auction Marketplaces

– An Analysis Based On Computer Simulations –

Zur Erlangung des akademischen Grades eines
Doktors der Wirtschaftswissenschaften

(Dr. rer. pol.)

von der Fakultät für
Wirtschaftswissenschaften
der Universität Fridericiana zu Karlsruhe

genehmigte
DISSERTATION
von

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Tag der mündlichen Prüfung: 9. Dezember 2008
Referent: Prof. Dr. Christof Weinhardt
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Karlsruhe, 2008

To my parents — Bian, Chengxia and Chen, Baosheng.

Acknowledgement

First and foremost, I would like to thank Prof. Dr. Christof Weinhardt, who, as my supervisor, has supported my work in many folds. His spirit of innovation, broad vision and systematic guidance have motivated and helped me throughout my research.

I also gratefully acknowledge the support of my co-supervisor Prof. Dr. Berninghaus, who provided valuable advices and new perspectives for an interdisciplinary research. In addition, Prof. Dr. Svetlozar Rachev and Prof. Dr. Bruno Neibecker have been very kind to serve in the examination committee.

Special thanks go to Jun.-Prof. Dr. Stefan Seifert. He spent much time discussing with me the details of my work. His insightful and constructive feedbacks helped in great extent to ensure the progress in the right direction. Dr. Clemens van Dinter, PD Dr. Dirk Neumann and Dr. Carsten Holtmann also provided constructive suggestions regarding research approaches and methodologies.

I would also thank all my colleagues at the Institute of Information Systems and Management (IISM) and from the Graduate School "Information Management and Market Engineering" at the Universität Karlsruhe (TH). They gave useful feedbacks as well as a friendly and open research atmosphere. I also thank the proofreaders, especially Stefan Seifert, Junzhi Lin and Hinnerk Gnutzmann for their time and their valuable suggestions for improvement.

Last but not least, I thank my parents for everything they have done for me. This work would not been possible without their supports.

Contents

List of Notations

R	Simulation round
t	Time
M_A, M_B	Marketplace A, marketplace B
n	Total number of agents
a	Agent
s	Total number of sellers
s_j	A seller. j=1,2,...s.
b	Total number of buyers
b_k	A buyer. k =1,2,...b.
$\bar{v}_b$	Upper bound of a buyer's valuation
X	Decision space of an agent
x	Decision of an agent in a simulation round
M_a	Marketplace which an agent participates in
$M_{\widehat{a}}$	Marketplace which an agent does not participate in
p	Winning price of the auction in a marketplace
v	Valuation of a buyer on the demanded item
π	Payoff of an agent
ψ	Preference indicator
θ	Payoff difference indicator
μ	Scaling coefficient of payoff difference
f	Discount factor

d	Probability of switching to the other marketplace
l	Listing fee charged by a marketplace
z	Number of repeated rounds in a simulation run
γ	Aggregate Seller-buyer ratio
$\gamma(M_A)$	Seller-buyer ratio of the marketplace A
$\gamma(M_B)$	Seller-buyer ratio of the marketplace B
$\dot{\Delta}p$	Average price difference before the steady state is reached
$\widetilde{\Delta p}$	Average price difference during the steady state
$\widehat{\pi}^s$	Average payoff of the sellers in a marketplace

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Chapter 1

Introduction

A marketplace, as an historically-evolved institution, allows customers and suppliers to meet at a certain place and a certain time in order to announce buying or selling intentions which eventually match and may be settled. However, in recent years, the developments in computer technology, electronic information processing, and the Internet have pushed the transformation of traditional trading mechanisms into the electronic world, and thereby transformed traditional markets into *electronic markets*.

1.1 Electronic Marketplace

The electronic market enables interactions between suppliers and consumers directly via the Internet medium. The feature of electronic trading includes instantaneous global search, geographical independence, decreased transaction costs, rapid spread of information, control over participant identities and anonymity, and so on. Online trading usually takes place in an *electronic marketplace*. It is provided by a *marketplace operator*, who provides the necessary hardware and software environment for the electronic trading platform.

Among the many trading mechanisms applied in electronic marketplace, auction is undoubtedly one of the prevailing protocols for efficient allocation of goods and determination of prices. *Electronic auctions (e-auction)* offer electronic implementations of the traditional bidding mechanisms, and are often integrated with contracting, payments, and delivery of the goods being traded in electronic markets.

The advantages of using e-auction are manifold. Sellers can use e-auctions to reduce surplus stock, to lower sales overhead, and to have a better utilization of production capacity. Because of the lower cost it becomes feasible for sellers to offer for sale small quantities of low value goods, such as used items. Buyers can use e-auctions to reduce the search cost and the purchasing overhead cost. Besides, e-auctions can increase efficiency and time-savings for both sellers and buyers.

As a result, many e-auction marketplaces were built in the last few years for sellers and buyers to trade via auctions on the Internet. The Internet auction company eBay[1] may serve as an example of hundreds of such marketplaces. Those marketplaces provide similar auction services, such as search engine, item listing and description, electronic transaction, etc., which they charge for. Clearly, the profits from those services depend not only on the prices of the services, but also on the number of traders who use them. Therefore, marketplace operators who provide similar auction services must compete with each other in attracting potential *participants* (i.e., buyers and sellers) to trade.

1.2 Motivation

In this section, a short case study is conducted regarding the ongoing competition in the Chinese e-auction market. Two marketplaces, eBay (China)[2] and Taobao[3], are the main players in the market. eBay was a de facto monopolist, with over 80% share of the Chinese e-auction market in 2002. However, its leading position has been greatly challenged by Taobao. Taobao is a relative new marketplace which started business operation in May 2003, but it successfully achieved 57.10% of the market share in a

[1]http://www.ebay.com

[2]http://www.ebay.com.cn

[3]http://www.taobao.com

short two years by September 2005, while eBay's market share was reduced to 34.19%.[4] Taobao's market share kept increasing in 2006, and forced eBay to stop its marketplace service in China mainland as an independent provider in December 2006.[5]

Although the market share does not directly equal the market leadership of a firm in a competitive market, it does reflect the competitive position of the firm. The success of Taobao, as pointed out by many commentators, is that it is able to quickly attract many users to participate and trade in Taobao. Besides, the *listing fee* policy of Taobao seems to play an important role in attracting participants from its rival eBay.

The listing fee (also referred to as an "insertation fee" in eBay[6]), is the price that a marketplace charges for listing an item or items for sale. This fee is charged only to sellers at the time of listing. It is charged independently from auction transactions, meaning that it is not refundable no matter whether the offered items are sold or not. eBay used to charge listing fees to sellers for years, while Taobao announced from its start that it would charge no listing fees at all. Commentators point out that the zero listing fee policy let Taobao successfully attract many sellers from eBay, and the increased number of sellers on Taobao helps it to attract buyers to join Taobao, too. The significant gain in participants hence leads to a significant increase of the market share for Taobao.

1.3 Research Questions

The analysis of the competition between eBay and Taobao through the commentaries is interesting, but is lacking scientific support. Moreover, it is also not clear about the future evolution of the market structure in the Chinese e-auction market. Will the market structure evolve into a monopoly state, in which only one marketplace

[4]See http://news.analysys.com.cn/tjnews.php?id=1981.

[5]Rather, eBay decided to merge its service with another Internet service provider *Tom.com*. See http://www2.ebay.com/aw/cn/200612.shtml#2006-12-2 for details.

[6]See http://pages.ebay.com/help/sell/insertion-fee.html.

survives as the winner? Or, will it evolve into a state of market duopoly, in which both marketplaces coexist and the participants always "loyally" trade in their current marketplaces?

Rather than carry the case study of eBay and Taobao into a deeper level, this work generalized the problem, and studies the competition between two similar e-auction marketplaces, which compete with each other to attract as many participants as possible. The research questions are formally described below.

Q1. *If all the institutions in the two marketplaces are the same, how does the market evolve in respect to the dynamics of the winning prices of the auctions and the selections of the participants?*

Q2. *Does a convergence of such evolution exist? If yes, does the evolution converge to market duopoly or monopoly?*

Q3. *Does the market evolve differently if the institutional control of the listing fee exists? What is the influence of the listing fee on the selections of the participants?*

Q4. *How can this study contribute to marketplace operators' strategic operations in a competitive e-auction market environment?*

1.4 A Simple Scenario

This section describes a simple scenario of competing marketplaces and explores the selection problem of the traders, in order to obtain a first impression of the competition.

Suppose in the electronic auction market there are two marketplaces (named as M_1 and M_2), that provide similar e-auction services. Both marketplaces have the same objective to attract as many participants as possible.

Each participant is assumed to pursue payoff maximization via auctions and can freely but exclusively choose one marketplace for this purpose. Intuitively, a seller prefers the *winning price of an auction* to be as high as possible, in order to maximize his payoff.[7] Contrarily, a buyer always looks for a marketplace, in which the winning price is as low as possible.

Suppose that at one time, one seller, s_1, and four buyers, b_1, b_2, b_3 and b_4, participate in M_1. The buyers' bids for the single item provided by s_1 are $v_{b_1} = 12.0$, $v_{b_2} = 9.0$, $v_{b_3} = 5.0$ and $v_{b_4} = 3.0$, respectively. Meanwhile, M_2 contains also some sellers and buyers, but the number of sellers and buyers in M_2 is unknown to participants in M_1. Suppose that the winning price of the auction in M_1 (denoted by $p(M_1)$) is the highest rejected bid from the buyers. Thus, $p(M_1)$ equals 9.0. Suppose also that the price in M_2 (denoted by $p(M_2)$) is 7.0.

Obviously, the buyer b_1 wins the auction in M_1, and his payoff $\pi_{b_1} = v_{b_1} - p(M_1) = 12.0 - 9.0 = 3.0$. However, by observing the price in M_2, the buyer b_1 may think: if I had participated in M_2, then my payoff would be higher. Therefore, b_1 would prefer to move to M_2 for a possibly higher payoff, although he has won the auction in M_1.

For the buyer b_2, given a bid of 8.0, he fails to win the auction in M_1. But if he has participated in M_2, he might have won the auction and received a positive payoff. Therefore, b_2 also prefers to move to M_2. For the buyers b_3 and b_4, their valuations are lower than both the auction prices. Therefore, they are not motivated to leave their current marketplace M_1, since they cannot win the auction in M_2, either.

On the seller side, sellers would contrarily prefer M_1 than M_2, because the price is higher in M_1. Now assume that one seller, s_2, moves from M_2 to M_1. M_1 contains now more sellers but the same number of buyers. If each buyer repeats his old bid in M_1, it is expected that $p(M_1)$ decreases. Assume, on the other hand, that no seller moves to M_1 but the buyer b_1 leaves M_1 and joins M_2. Because there are fewer buyers in M_1, it can also be said that M_1 contains relatively more sellers. If all the other buyers in M_1 insist on their former bids, $p(M_1)$ then decreases to 5.0, which is consistent with the former expectation that $p(M_1)$ should decrease.

The above analysis shows that the winning prices in e-auction marketplaces are

[7] In the rest of this book, the winning price of an auction is shorted to the *winning price*, or simply the *price*.

dynamic, and they are influenced by the movements of sellers and buyers. However, an increase or decrease of the price is not determined by the movement of a single buyer or seller, but is rather an aggregate result of all buyers' and sellers' decisions. Therefore, it is necessary to study the movements of participants on a macro level.

Now suppose that altogether there are n participants trading in two marketplaces, M_1 and M_2, in which s participants are sellers and the rest b participants are buyers. Denote the number of sellers and the number of buyers in a marketplace M_i by $s(M_i)$ and $b(M_i)$ respectively, $i = 1, 2$. This scenario can be simply presented by Equation 1.1.

$$\begin{aligned} n &= s + b \\ &= \sum_{i=1}^{2} s(M_i) + \sum_{i=1}^{2} b(M_i) \end{aligned} \tag{1.1}$$

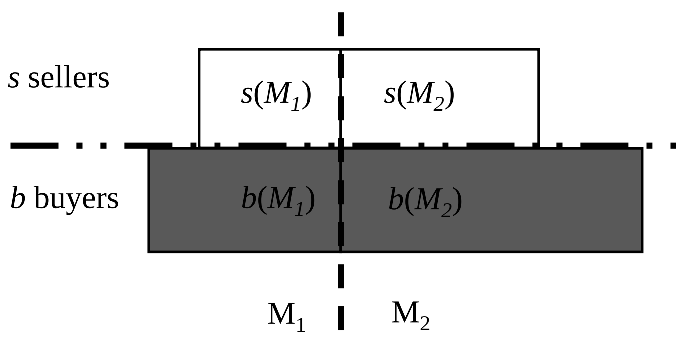

Figure 1.1: Distribution of participants in two marketplaces.

At any given time, if one seller leaves M_1 and joins M_2, $s(M_1)$ then decreases by one and $s(M_2)$ increases by one. Similarly, a buyer's movement also leads to changes in the number of buyers in both marketplaces. In other words, the movements of the participants can be reflected in the change of the distribution of participants in the marketplaces. Figure 1.1 gives a direct impression of that. Thus, the study of the dynamics of the market can be conducted in an easy way, by studying the dynamics of the distribution of participants.

1.5 Organization of the Book

The presented work is organized in seven chapters, and the overall structure of it is shown in Figure 1.2.

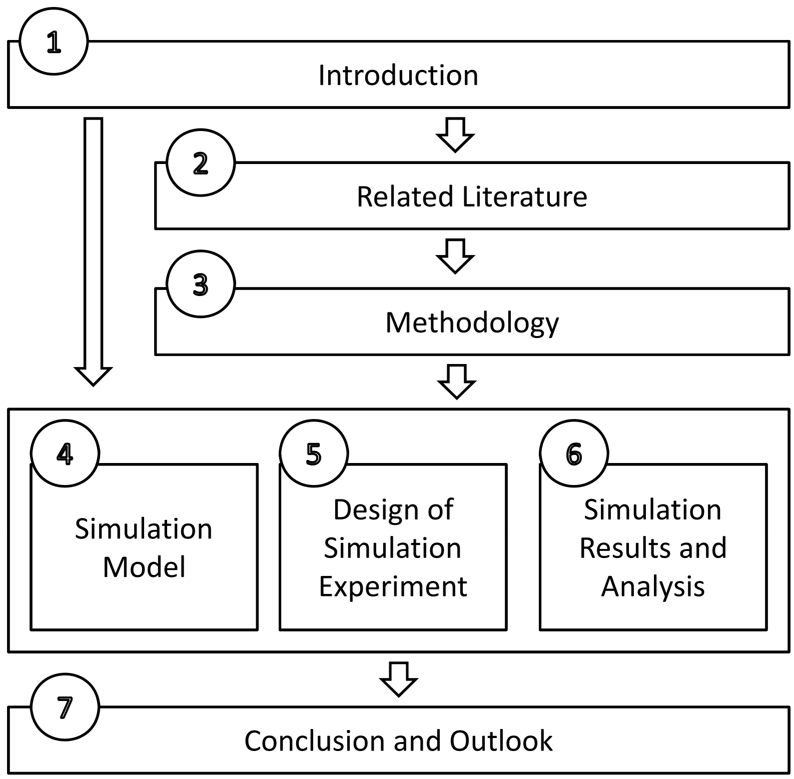

Figure 1.2: Organization of the book.

Chapter 2 provides a guide to related works around the topic of competition between markets. Chapter 3 discusses the methodology problem and explains why computer-based simulation is an appropriate method for the purpose of this study. This chapter also briefly introduces the general framework of a simulation study.

In Chapter 4, a simulation model is proposed which formally describes the competition between two e-auction marketplaces. Series of simulation settings are designed in Chapter 5 for experimentation. Chapter 6 analyzes in detail the data obtained from the simulations. The findings are summarized and compared with results from related literature. The final part of this book, Chapter 7, provides a concluding discussion of the limitations as well as the contributions of the presented study. In the end, an outlook about further research is given.

Chapter 2

Related Literature

The general existence of competition in our daily lives makes it a vivid field of research in economics. Economists are used to the notion of competition within a market. Typically, research works address the competition only within one market, such as the competition among sellers to attract buyers (see, for example, McAfee (1993), Peters and Severinov (1997), and Burguet and Sakovics (1999)).

However, competition also exists between markets, for example, between market operators or between the market rule-regulators. Some researchers study the competition under different market environment scenarios; some investigate several factors or factor combinations; and some others use various performance measures in analysis. Literature of this category is closely related to the presented work, and this chapter mainly introduces the research works of this category.

This chapter is organized as follows. Section 2.1 introduces the research works that study the competition between conventional marketplaces, which generally include all the marketplaces that do not operate on Internet. Section 2.2 deals with the studies on competitions between conventional and electronic marketplaces, and that between electronic marketplaces as well. Section 2.3 presents several papers which investigate competitions empirically. Section 2.4 summarizes this chapter.

2.1 Competition between Conventional Markets

This section introduces the papers that study the competition between conventional marketplaces, which include direct exchange markets and intermediaries. In direct exchange markets, buyers and sellers are matched by the market directly, or they seek each other out by costly search, and then negotiate on prices.

Intermediaries often compete with decentralized direct exchanges in attracting potential buyers and sellers. Market intermediaries provide a central place of exchange. They buy items from sellers and sell the items to buyers. The intermediated exchange can have advantages over direct exchange for many reasons. These include lowering the costs of transacting through centralization of exchange, reducing costs of searching and bargaining, etc. (Spulber, 1999, p. ix).

2.1.1 Between Search Market and Intermediary

Gehrig studies the competition between a search market and a monopolistic intermediary (Gehrig, 1993). In the search market, individual agents who are buyers or sellers are randomly matched and the prices at which the exchanges take place are set bilaterally. Because matching is random, the search market does not exhaust all possible gains from trade.

The intermediary sets a publicly observable bid price at which he is willing to buy from the sellers, and a publicly observable ask price, at which he is willing to sell what he has previously bought. The intermediary trades simultaneously with both buyers and sellers. Agents face three options: to join the search market, to trade with the intermediary, or simply remain inactive.

Gehrig shows that there is an equilibrium in which the search market and the market of the monopolistic intermediary are simultaneously open, and the intermediary makes positive profits because he trades at a positive ask-bid spread.

Loertscher studies a scenario similar to Gehrig's work above, in which buyers and sellers choose to join one of the several intermediaries, to join a search market, or remain inactive (Loertscher, 2004). Loertscher's model extends the model of Gehrig in three aspects. Firstly, in his model there is a finite number of market-making intermediaries rather than only one. Secondly, a sequential structure is imposed, by requiring that the intermediaries first have to buy the goods from the sellers (buy in the input market) before they can be sold to buyers (sell in the output market). Thirdly, a physical capacity constraint of the tradable items is introduced for the intermediaries in competition.

Based on this model, Loertscher shows that the intermediaries endowed with Cournot capacities (or with smaller than Cournot capacities) set the same market clearing price on the input and output markets, and trade the same quantity on the subgame perfect equilibrium path of the game as would be set and traded if input and output markets were organized by a Walrasian auctioneer.[8] As a corollary, when the number of intermediaries with Cournot capacities becomes large, the equilibrium in this model coincides with the Walrasian perfect competition outcome.

2.1.2 Between Location Differentiated Markets

In the competition between conventional markets, the location of a marketplace is often an important issue. This issue is studied by Gehrig (1998), in which a two-dimensional spatial competition between two places of market is analyzed. One dimension is the geographical distance, and the other dimension investigated is the product characteristics (such as maturity of a futures contract). The scenario is modeled as a multi-stage game. In the first stage, each firm (seller) selects a location of market to offer products to sell. Each firm offers precisely one kind of product in exactly one market, but the markets may contain products of different varieties. In the second stage, fiscal authorities (market makers) define the transaction taxes on the basis of the relative

[8]The Walrasian auctioneer is the presumed auctioneer that matches supply and demand in a market of perfect competition.

attractiveness of their markets. The structure of the markets, i.e. the number of varieties and the vectors of prices on offer, are known by the customers (buyers). Based on this information, the customers decide which market to enter in the last stage, without knowing their own demands.

The competition in the aspects of the price and the transaction tax in a multi-stage game is investigated. The paper reveals that if the market externalities are strong, a firm with a lower price not only increases its market share at the expense of its closest rivals, but also makes the marketplace in which he participates become more attractive to outside consumers, which benefits all firms in this marketplace. The attractiveness of a marketplace to customers is also increased when the number of the participating firms in the marketplace increases, although this leads to increasing competitiveness for the firms in the marketplace at the same time.

This paper also points out the innate conflict of domestic fiscal authorities in taxing domestic firms. If authorities plan to participate in industry profits by means of a transactions tax, they have to limit the ability of domestic firms to attract foreign (and domestic) customers. The tax hence reduces the ability of domestic firms to compete internationally.

The fiscal authorities can afford high tax rates when their domestic markets are very attractive, as measured by the number of firms. Despite the fact that transaction taxes reduce the agglomeration advantage, in equilibrium they do not completely annihilate this advantage.

2.1.3 Between Financial Intermediaries

Market makers include not only price-making firms but also other market institutions such as organized exchanges for securities, options, futures, and other financial assets. Competition between markets typically exists in financial areas, such as between stock exchanges or between credit card firms.

Santos and Scheinkman (2001) study the competition among financial intermediaries. The motivation of their work arises from an often-heard assertion that competitions among financial intermediaries force them to sign contracts with customers with lower standards (i.e., with fewer contractual guarantees), in order to increase trading volume. An analytical model is constructed to describe the competition, taking into consideration that traders differ in credit quality and may default (fail to fulfill the obligation).

The authors find that the competition does not necessarily lead to low standards, and the intermediaries demand rather appropriate amounts of guarantees, when the credit quality is observable. Moreover, the private information about credit quality has an ambiguous effect in a competitive environment. When the cost of default is large (small), the private information leads to higher (lower) standards.

2.2 Competition between Electronic Markets

The presence of electronic markets provides an alternative for trading within a new market environment. The markets that apply information technologies in traditional businesses, for example the retail sector, inevitably compete with the existing marketplaces. Besides, with the growth of e-commerce, the providers of Internet marketplaces begin to compete with each other, too. This calls for a better understanding of the electronic market as well as the competition.

This section closely investigates the studies which focus on the competitions between electronic markets, such as the competitions between institution designers, between the operators of electronic marketplaces, or between electronic intermediaries.

2.2.1 Between Online- and Conventional Channels

Technology-driven online commerce channels, such as the Web, possess several unique features that differentiate them from conventional channels — channel flexibility, positive network externalities, and market lock-in (switching costs). These channels have become a significantly differentiated choice for consumers, and provide firms with new opportunities to rethink the way business is conducted.

Viswanathan (2005) studies the competition between technology-differentiated channels. A stylized spatial-differentiation model is set up to examine how the three key parameters, that is, the channel flexibility, the positive network externalities, and market lock-in (switching costs), affect competition between online, conventional, and hybrid firms (namely firms that operate across multiple channels).

Network externalities, especially positive network externalities, are often noticed in the study of two-sided markets: an increase in the size of one side of the market (namely the number of firms) helps to attract the other side of the market (namely the customers). The analysis in this paper indicates that while network externalities as well as switching costs lead to the tipping of markets,[9] such tipping occurs primarily due to the moderating effects of the competing channels. Moreover, with network externalities an increased market share does not translate into higher profits.

An interesting result from this paper is that in a static market, consumers rather than firms benefit from increasing network externalities, with competitive effects outweighing the surplus-extraction abilities of firms. Viswanathan's results highlight the importance of alternative revenue streams and provide insights for firms grappling with issues of channel choice as well as integration and divestiture.

2.2.2 Between e-Intermediaries

In the traditional economy, intermediaries often buy and resell goods. Now the development of new technologies for information and communication has brought informational intermediation to the forefront of the "new economy." Intermediation in this new economy consists of services such as search, certification, advertising, and price discovery,

[9] Tipping is a set of activities that helps a firm "tip" a market toward its own platform rather than some other one.

as opposed to storage, showrooms, or delivery in the traditional intermediation.

Caillaud and Jullien (2003) propose a model to analyze the imperfect competition between two informational intermediation service providers. The model considers the presence of indirect network externalities, the possibility of using the non-exclusive services of several intermediaries, and the widespread existence of price discrimination based on the identities and usage of buyers and sellers. Matchmakers (intermediaries) rely on two pricing strategies to attract buyers and sellers: the registration fee, which is user-specific and paid ex ante; and the transaction fee, which is an ex post payment after a transaction takes place between two matched parties.

Their study contributes to the literature in two aspects. First, it determines the equilibrium market structure that is likely to emerge and characterizes the efficiency property of the market in equilibrium.

Under the assumption that any generated matching surplus is efficiently shared, they prove that, equilibria with the efficient market structure always exist. An efficient market structure may involve only one intermediary serving all users or, with non-exclusive technologies and low costs of matching, both intermediaries serving all users, a situation they call "global multi-homing." Intermediaries have incentives to propose non-exclusive services so as to allow users to turn to several intermediaries simultaneously, because this moderates competition and reinforces market power as well as intermediation profits. But inefficient equilibria also exist, especially when the matching technology is effective or the ability to rely on transaction fees is limited.

Second, it provides a precise description and analysis of the pricing strategies that allow intermediation service providers to protect their businesses or to gain new business. With exclusive services, matchmakers use transaction fees as an additional instrument to extract profit. In cases where multi-homing is efficient, transaction fees are able to differentiate the intermediaries, with one offering low registration but high transaction fees while the other adopts the mirror-pricing strategy.

Another study related to the price competition of e-intermediaries focuses on the

B2B field (Suelzle, 2005). The competition is between two B2B intermediaries who differ with each other regarding their ownership structures. One intermediary is an independent marketplace operated by a third-party incumbent, while the other one is a collaborative buy-side consortium intermediary, who challenges and competes with the former in terms of attracting firms in buying and selling. The background of the competing scenario is the decline of independent B2B marketplaces, which were highly valued at the advent of B2B e-commerce some years ago during the formation of the industry, and the formation of industry consortiums for establishing B2B electronic marketplaces, which account for the recent developments in B2B e-commerce.

Suelzle's study considers also indirect network externalities and the exclusivity of registration. He finds that when firms can register exclusively with at most one intermediary, the independent intermediary is able to deter the entry of the challenger only if the number of firms taking ownership in the consortium is sufficiently small. Otherwise, the consortium can successfully enter and monopolize the market. When firms can multi-home, i.e., they register simultaneously with both intermediaries, the consortium can always enter while both intermediaries stay in the market with positive profits.

One other work that also focuses on competition in the B2B field is from Yu and Chaturvedi (2001). They build a two-stage game theoretic model, and investigate the industrial structure in the dynamics of the competitions between B2B electronic marketplaces. In the model, business traders who use different IT infrastructures (e.g., different information processing system) are modeled as being on different islands and are not able to trade with each other directly. B2B marketplaces invest to build networks that connect the islands and provide services to bring buyers and sellers together. In the first stage, the marketplaces simultaneously and independently choose the IT infrastructures they want to support, which thereby determines the liquidity of the marketplaces. In the second stage, the marketplaces compete over the prices of their services, whose qualities are differentiated in terms of liquidity.

Their analytical results show that price competition between B2B exchanges does not lead to a perfect competitive outcome, as in markets of vertically differentiated products. Moreover, the industrial structure of B2B exchanges exhibits a natural oligopoly. The number of active B2B exchanges in a market is bound, regardless of how large the market is. If the user preferences are not highly diversified, only three marketplaces can survive. Since, in many cases, electronic marketplaces provide their services for free in order to gain liquidity in their marketplaces, it would then be risky for the marketplaces to base their revenue models solely on transaction fees. The authors suggest that the marketplaces find additional means, such as advertisements, to generate revenue.

2.2.3 Between e-Auction Marketplaces

The IT technology helps to put the conventional auction market on the Internet. The booming of electronic auction marketplaces naturally leads to the competitions between them for attracting buyers and sellers.

Ellison et al. notice that the battles between several of the biggest e-auction marketplace operators often end with a single overwhelming winner. They wonder why auction activity is concentrated, and build a game-theoretic model on competing auction markets for this purpose (Ellison et al., 2004). In the first stage, each buyer and each seller simultaneously selects an auction site (marketplace) in order to trade. Each seller offers a single unit of goods and sets a reservation price of zero. In the second stage, buyers learn their private values for the goods, and a uniform-price auction is held at each auction site.

They use the model to show that a larger auction marketplace typically provides a greater expected surplus per participant (which they name as the scale effect, or the efficiency effect); this scale effect pushes the market toward concentration. However, since buyers and sellers have opposite preferences in respect to the winning price of an auction, two competing auction marketplaces can still coexist in equilibrium despite the scale effect, and in equilibrium the marketplaces may be of quite different sizes (i.e., may contain quite a different number of buyers and sellers).

However, there is a critical mass of buyers that a marketplace must attract to survive, and such mass of buyers increases proportionally with the total buyer population. They also find that the range of the sizes of the marketplaces in equilibrium depends on the aggregate buyer-seller ratio, and also whether the marketplaces are especially thin (i.e., whether there are only a very small amount of buyers and sellers).

The competition between e-auction marketplaces is also studied via numerical approaches, for example in the research for the Trading Agent Competition (TAC).[10] People in this research community are interested in studying the competition problem via simulated agents. One of their activities is a game called TAC Market Design Competition (shortened to *reverse TAC*, or simply *CAT*), which especially addresses the competition between market makers.

A CAT competition game consists of buyers, sellers, and brokers (i.e., marketplace operators). The buyers and sellers are software agents, whose behavior is simulated according to a common protocol. The brokers are also simulated agents, but their behavior is determined by several different human researcher groups (known as entrants) that participate in the CAT game. Each broker operates a single exchange market with a double auction. Each broker also sets the rules for his auction marketplace, and for the buyers and sellers that participate in his marketplace as well. One of the rules is the charging policy. The brokers are allowed to charge buyers and sellers a fee for registering to trade. The brokers aim to attract potential buyers and sellers and then to match the two parties, and they compete with one another in doing this. The performance measure of the brokers is based on the profit, the market share, and the rate of successful transactions.

Niu and his colleagues study the brokers and their behavior from the 2007 CAT competition (Niu et al., 2008). They find that increasing fees will boost the profit

[10] See http://www.sics.se/tac/page.php?id=1.

of a broker but gradually leads to loss of the market share. Moreover, if the market share falls too low, the profit return cannot be sustained. In contrast, low charges help a broker gain market share but hampers his profit. However, if a charging policy is properly designed, it may keep both measures (namely the profit and the market share) at suitably high levels.

The two papers introduced in this subsection both focus on the competition between electronic auction marketplaces, which is also the problem field that the presented work is interested in. Because of the close relevance, some of the results of these works are revisited and compared with the results of the presented work in Section 6.4.

2.3 Empirical Studies

Many works analyze the competition between markets analytically. Besides, there are also some works which investigate the competition between marketplaces empirically. This section introduces two papers in this regard.

Kollmann (2000) conducts a case study of online German trading websites for used cars. He aims to analyze the competitive situations of the operators of those marketplaces, especially their strategies for increasing transactions. The operators compete at two levels — the information level and the transaction level. There are two strategy options at the information level — to generate a wide selection of search results from the information matching (the selection strategy), or to create accurate search results (the assignment strategy). The operators have also two strategy options at the transaction level — to emphasize the quality of the intermediated transactions, or to emphasize the number of intermediated transactions. Those strategy options of the two levels form, as named by the author, a competition matrix, and it is used in the paper as a method for comparing the marketplaces.

Kollmann finds that at the information level, although both selection strategies and assignment strategies can be observed, most operators are still trying to become assignment leaders. In regard to the transaction level, all marketplaces have much higher information matching rates than transaction rates, which indicates that all the marketplaces have difficulties in moving from the information level to the transaction level. However, the author points out that the cooperation of those online marketplaces with real car dealers helps to achieve higher transaction rates, and can be seen as an emphasis of quality at the transaction level.

Compared to Kollmann's case study, the study by Lin and Li (2005) is more related to the presented work, because they conducted an empirical study of competing electronic auction marketplaces. They analyze the competition between two main e-auction marketplace operators in China – eBay and Taobao, with a focus on their reputation systems.

Both marketplaces use positive, negative, and neutral scores as the indicators of traders' reputations. Lin and Li collect the reputation scores of sellers in both marketplaces, and use these as the basis of analysis. They find that the sellers on Taobao receive reputation feedbacks less often than the sellers on eBay, therefore, they have on average much lower overall reputation scores.[11] However, the overall six-month positive feedback rates on Taobao and eBay are about the same. In respect to the neutral and negative scores, the eBay sellers tend to have higher negative feedback rates, while Taobao sellers are likely to have higher neutral feedback rates. This, as argued by the authors, indicates the cultural differences in the traders' populations. Taobao has all its service built in China, and most of the traders are Chinese. By comparison, eBay involves much more trading between Chinese and international traders, because eBay is a well-known international marketplace service provider.

2.4 Summary

Although there is plenty of research about competition within a market, this chapter confines itself to introducing only the research works focusing on the competition

[11] The overall reputation score of a seller is simply the sum of his positive, negative, and neutral reputation scores.

between markets.

The related literature is categorized in this chapter by whether the focus is on the conventional markets or on the electronic markets. Section 2.1 and Section 2.2 introduce the related works in these two categories separately. What is worth mentioning is that part of the literature studies the competition between conventional and electronic markets; this part of the literature is included in Section 2.2. The papers introduced in this chapter differ in many aspects, e.g., the application field of the marketplaces studied, the factors investigated, the measures of the analysis, and the methodology used.

The next chapter deals with the methodological problems. The analytical methods will be discussed as well as the numerical methods. It is also determined in the next chapter which method is applied as the main research method of the presented study.

Chapter 3

Methodology

For the research questions proposed in Chapter 1, there is more than one method that can be applied. This chapter discusses some possible approaches in the problem field, and then one methodology is selected as the main approach for the presented work.

3.1 Analytical Solutions

Generally, in order to study a problem of an economic system, it is necessary to first build a model that represents the problem, and then "solve" the model. There are analytical and numerical ways to do this. An analytical study of an economic system usually follows a four-stage procedure (Naylor, 1971, p. 7):

(1) the observation of the system;

(2) the formulation of a mathematical model that attempts to explain the observation of the system;

(3) the prediction of the behavior of the system on the basis of the model by using mathematical or logical deduction, that is, by obtaining solutions to the model; and

(4) the performance of experiments to test the validity of the model.

Usually, analytical models are built upon preference-based individual decision theories. Three characteristics are noteworthy. First, the core of such a model is equilibrium. The equilibrium provides a convenient tool for organizing the information contained in the model. Second, the usefulness of the model generally lies in its ability to yield comparative static results showing how this equilibrium changes as parameters of the model change. Finally, behind this equilibrium analysis lie implicit assumptions about out-of-equilibrium behavior, designed to address the questions of how an equilibrium is reached or why the equilibrium is interesting (Samuelson, 1998, p. 2).

There are several cases in which analytical analysis may not be the most feasible method. First, it is frequently found in economics that to observe the actual behavior of an economic system is either impossible or extremely costly. Such difficulty also lies in this study, because tracing and recording the behavior of each individual participant in the marketplaces across a long span of time is hard to achieve.

Secondly, for such real-world economic problems, complex and large dimensional models are usually necessary. It is often hard or not attainable to find an analytical solution. As a matter of fact, analytical solutions are often based on highly abstract models of the real-world problems.

For example, perfect rationality is often assumed in an analytic model. The type of rationality assumed in neoclassical economics — perfect, logical, deductive rationality — is extremely useful in generating solutions to theoretical problems. But it demands much of human behavior, much more in fact than it can usually deliver. There are two reasons for perfect or deductive rationality to break down under complications. The obvious one is that human logical capacity ceases to cope with problems beyond a certain level of complexity — human rationality is bounded.

The other is that in interactive and complex situations, agents cannot rely upon other agents they are dealing with to behave perfectly rational, and so they are forced to guess their behavior. Therefore, it has been argued in recent decades that economic models with bounded rational agents should be included (see Arthur (1994) and Arthur (1991), for example).

The evolutionary game approach appears to be fruitful in the field of economics and business studies. There is a particular reason why economists should now be interested in evolutionary models. Non-cooperative game theory, as applied in economics, is facing two difficulties: first, in many economic problems, it is not entirely clear how Nash Equilibrium can be finally reached by the players and, second, when there are many equilibria with different implications, it is important to understand how a particular equilibrium will eventually be selected. It happens that the dynamic adjustments described by evolutionary models may give interesting answers to both questions. So, even though economic applications are still rare and some progress is still to be made in order to adapt the modeling, the path seems to be a very promising one to follow.

Learning models for game situations and evolutionary games have become an active field of research since 1990. While the traditional approach treats a game in isolation, with the modeler attempting only to infer the restrictions that players' rationality imposes on the outcome, the evolutionary approach treats a game as a model designed to explain some observed regularity when decision makers interact repeatedly in real time. That is why this approach sometimes is also called the "steady-state" interpretation of an equilibrium (Osborne and Rubinstein, 1994).

Economic analysis has largely avoided questions about the way in which economic agents make choices when confronted by a perpetually novel and evolving world. There is a growing amount of economic literature using models of learning and adaptive behavior and a number of searchers are using various evolutionary algorithms, ranging from replication dynamics (see Van Damme (1991) and Binmore (1992), for example) to genetic programming (see Arifovic (1994) and Kaebling et al. (1996), for example), to specify the dynamics of the situation.

3.2 Numerical Solutions

Many economic systems can be classified as complex adaptive systems. Such a system is complex in a special sense: (i) it consists of a network of interacting agents (processes, elements); (ii) it exhibits a dynamic, aggregate behavior that emerges from the individual activities of the agents; and (iii) its aggregate behavior can be described without a detailed knowledge of the behavior of the individual agents (Holland and Miller, 1991). The resulting complex adaptive systems can be examined both numerically and analytically, offering new ways of experimenting with and theorizing about adaptive economic agents.

Typically, a numerical solution substitutes numbers for the independent variables and parameters of a model and manipulates these numbers. Many numerical techniques are iterative, i.e., each step in the solution gives a better solution using the results from previous steps (examples are linear programming and Newton's method from approximating the roots of an equation). Two special numerical techniques are the Monte Carlo method and simulation method.[12]

The Monte Carlo method, defined in a broad sense, is any technique for the solution of a model using random numbers or pseudo random numbers. Simulation is defined in a broad sense as "experimenting with a model over time" (Kleijnen, 1974, p. 12). This definition emphasizes that simulation implies experimentation. However, instead of experimenting with the real-world objects, the experiments are executed by means of a model of virtual objects and the behavior of the modeled objects are followed over time.

Kleijnen further defines simulation in a narrow sense as experimenting with an (abstract) model over time, and this experimentation involves the sampling of values of stochastic variables from their distributions. This type of simulation is called stochastic simulation. Since random numbers are used, this type of simulation is also known as Monte Carlo simulations.

There are many reasons why simulation is an advantageous method (see Adkins and Pooch (1977) and Gilbert and Troitzsch (1999), for example). Some of the advantages that are most important for the research problem in the presented work are listed in the following.

[12]Notice that the various methods can be combined for the solution of a complicated model.

- Simulation permits controlled experimentation. A simulation experiment can be run a number of times with varying input variables to test the behaviors of the system under a variety of situations and conditions. Thus, it is convenient for sensitivity analysis by manipulation of input variables.

- Through simulation, one can study the effects of certain informational, organizational, and environmental changes on the operation of a system by making alterations in the model of the system and by observing the effects of these alterations on the system's behavior. This may lead to a better understanding of the system and to suggestions for improving it.

- Simulation can be used to experiment with new situations, about which we have little or no information, so as to prepare for what may happen. Because simulation does not disturb the real system, it can serve as a "pre-service test" to try out new policies and decision rules for operating a system, rather than taking the risk of experimenting directly on the real system. This advantage, as mentioned by many authors (Schriber, 1991; Pegden et al., 1995; Banks et al., 1996), especially benefits companies in providing a look into the future.

The simulation method has also some disadvantages, as listed in the following.

- Model-building requires special training.

- Simulation results may be difficult to interpret.

- Simulation modeling and analysis can be time consuming and expensive.

- Simulation may be used inappropriately, especially when an analytical solution is preferable.

However, these four disadvantages are not unavoidable. Professional simulation software and the development of computer technology have facilitated the modeling and the analysis of simulation. In respect to the last disadvantage, Naylor points out that simulation is considered as a relevant tool for analyzing economic systems when it is not clear whether carrying out a study using analytic techniques is plausible (Naylor, 1971, pp. 299-300).

3.3 Computational Economics

Computational economics is a methodology for solving economic problems with the help of computing machinery (Amman, 1997). Computational economics explores the intersection of economics and computation. Applications of computational methods are not restricted to a specific branch of economics, but rather widespread throughout the major subject fields in economics.

Areas encompassed under computational economics include agent-based computational modeling, computational econometrics and statistics, computational finance, computational modeling of dynamic macroeconomic systems, of transaction costs, computational tools for the design of automated Internet markets, programming tools specifically designed for computational economics, and pedagogical tools for the teaching of computational economics. Any line of economic research that uses the methodology fits the definition of computational economics. The only restriction is that the methodology has a value added in terms of (economic) problem solving (Lakatos, 1970).

Broadly, the computational methods can be classified into two categories, depending on their application context. The first encompasses the use of numerical methods to solve "high-rationality" models that are too difficult or cumbersome to handle analytically. The second approach is known as agent-based computational economics (ACE). In this approach, agents are programmed to use simple rules of behavior to respond to their environment. Here "agent" refers broadly to a bundle of data and behavioral methods representing an entity constituting part of a computationally constructed world. The computation model is then used to study the aggregate patterns that emerge when such simple rules interact.

3.4 The Applied Approach: Computer-based Simulation

In the presented work, *computer-based simulation* is used as the main research method. It is explained in the following why simulation is necessary and appropriate for the presented work.

This study is interested in the competition between online auction marketplaces, in which each marketplace may contain a large population of participants. The research problem investigated has the property of quantitative uncertainty. The outcome of competition can be influenced by various factors in continuous time periods. In such a context, conducting computational experiments via simulation is recommended (Kydland and Prescott, 1996), that is, to model the phenomenon as faithfully as possible and then to rely on a computer-based simulation study to analyze it. Computer-based simulations are able to present the abstraction of the real system and ideally characterize the essential properties of the system. Simulation can also greatly expand the set of models that can be evaluated and estimated for reasonable computer costs (Stern, 1997).

Besides, the simulation technique can also be utilized for the study of the dynamic behavior of a system. For dynamic structural problems, surveys already provide prominent roles for simulation methods (see (Parkes, 1994) and (Rust, 1994)).

Howrey and Kleijnen point out that in many cases, it is not obvious whether simulation or an analytical solution would be more appropriate for a particular model. However, there are some cases in which it would be questioned as to whether it would be worth the time and effort to find an analytical solution if such a solution existed in the first place. But it is quite possible that a numerical solution or the simulation of a model provides the analyst with much of the information that is needed regarding the behavior of the particular system. Even if an analytical solution exists, results from simulations can also work as a validation of the analytic results (Howrey and Kleijnen, 1971). Naylor also points out that in many cases, this simulated data may prove to be completely adequate, particularly if the model of the economic system under study is sensitive only to large changes in the values of the simulated input data (Naylor, 1971, p. 7).

Another advantage of using the simulation approach in the presented work is that competition can be studied in marketplaces comprised of boundedly rational agents.

As pointed out in Section 3.1, many analytical works are based on an unrealistic picture of human decision making. Economic agents are portrayed as fully rational Bayesian maximizers of subjective utility. In fact, there is overwhelming experimental evidence for substantial deviations from Bayesian rationality (Kahnemann et al., 1982): people do not obey Bayes' rule, their probability judgments fail to satisfy basic requirements like monotonicity with respect to set inclusion, and they do not have consistent preferences, even in situations involving no risk or uncertainty (see (Selten, 1991) for a more detailed discussion).

H. A. Simon created the beginnings of a theory of bounded rationally (Simon, 1957). Bounded rationality is not irrationality; rather, it refers to the rational principles that underlie non-optimizing adaptive behavior of real people. Boundedly rational decision making necessarily involves non-optimizing procedures. Sometimes the term is also used in connection with theories about optimization under some cognitive bounds.

Computational approaches are often used to investigate problems with boundedly rational agents (Carley and Prietula, 1994; Feldman, 1962). It is relatively easy to model agents by simulations, who are cognitively restricted, task oriented, and socially situated. Section 4.5 returns to this issue, and describes the principles of decision-making in the presented work under the assumption of bounded rationality.

Due to the above reasons, computer-based simulation is used as the research methodology in the presented study.

3.5 Terminology

This section gives the definitions of the most important terms in simulations. Besides the simulation concept proposed by Kleijnen in Section 3.2, Shannon also gives a complete definition of simulation.

Definition 3.1 (Simulation)**.** *Simulation is a process of designing a computerized model of a system (or process) and conducting experiments with this model for the purpose either of understanding the behavior of the system or of evaluating various strategies of the operation of the system. (Shannon, 1975, pp. 289-301)*

Naylor's definition of simulation emphasizes the use of computer technology in conducting simulations.

Definition 3.2 (Computer-based Simulation)**.** *Simulation is a numerical technique for conducting experiments with certain types of mathematical models which describe the behavior of a complex system on a digital computer over extended periods of time. (Naylor, 1971, p. 2)*

Definition 3.3 (Simulation Model)**.** *A model can be defined in general as a simplified representation of the original object or system in the real world. Simulation models consist of building a virtual world out of small components. The important characteristic of simulation model is that it enables an experimental approach. The experimenter is able to change parts of the model and to observe the resulting behavior. (Brooks et al., 2001, pp. 4-5)*

A simulation model contains various elements, as defined in (Graybeal and Pooch, 1980, p. 12) and (Brooks et al., 2001, p. 13). A real-world object modeled in a simulation model is called an *entity*. Characteristics or properties of entities are called *attributes*. Any process that causes changes in a system is called an *activity*. A description of all the entities, attributes, and activities, as they exist at some point in time, is called the *state of the system*. The *simulation executive* is the part of the simulation that provides overall control. It is the architecture that carries out the simulation run.

Simulation models can be categorized depending on how the time is represented and whether they include any randomness. Simulation models that do not include the time at all are called *static models*. However, most simulation models do include the time because it is the changes of the system over time that are of interest. Such models are called *dynamic models*.

In dynamic models, the variations over time can be simulated in two different ways. *Continuous models* represent continual changes and often use differential equations, so that the behavior in the model is always altering. A simulation system based on a continuous model is then a *continuous system*, and is characterized by smooth changes in the system state.

On the other hand, in a *discrete model*, behavior only changes at a particular instance of an event (or time), with constant behavior between the events. A simulation system based on a discrete model is then a *discrete system*, and is characterized by discontinuous changes in the system state.

Random numbers are used in simulation to simulate variable, unpredictable behavior such as the time at which the next customer will arrive at a bank or the time at which a machine will break down. A great advantage of simulation is its ability to model variable behavior in this way. Models that include random numbers are called *stochastic models*, whereas those which not are called *deterministic models*. In a system based on a deterministic model, the response of the system is completely determined by its initial state and input. Compared to that, the response of a stochastic system may take a range of values, given the initial system state.

What is worth mentioning is that in business systems, it is usually unnecessary to model changes continuously and so a discrete model provides a simpler and more appropriate representation. Besides, most Operational Research simulation models are dynamic, discrete, and stochastic.

3.6 A Typical Simulation Study

Computer simulation experiments with models of economic systems usually involve a procedure that consists of the following six steps. Note that a simulation study is not a simple sequential process; it may be necessary to go back to a previous step in conducting the study.

1. Formulation of the problem

   At the start of a simulation study there is some real-world problem that needs to be tackled. This might be a shortcoming with an existing system, or a need to investigate the workings of a proposed system. The task of the modeler is to understand the system, to extract the essence of the system without including unnecessary details, and to extract and formulate the questions that are to be answered.

2. Formulation of a mathematical model

   For the questions proposed, a mathematical model should be developed to formally describe the system. The mathematical model should be suitable for tackling the questions; however, it is worth mentioning that modeling is considered a creative activity and there are no established, published principles (Banks, 1998, p. 32).

3. Development of a computer program

   Based on the design of the conceptual model, a computer model is developed. The computer model is used to develop solutions to the real world problem and/or to obtain a better understanding of the real world.

4. Verification and validation of the model

   Verification refers to the proof that the simulation program is a faithful representation of the system model. Validation refers to the proof that the model is a correct representation of the real system. It is worth mentioning that the process of verification and validation should not be seen as a stage within a simulation study, but as a process that continues throughout the whole simulation study.

5. Experimental Design

   Because a simulation model cannot directly determine the best procedure, but simply predicts the outcome of specific policies and procedures, a great many experiments may be required to obtain a good understanding. Experimental design refers to a sequence of simulation runs in which parameters are varied, with both economic and statistical methods considered in achieving some specified goals.

6. Data analysis

   Data analysis is the process of looking at and summarizing data with the intent to extract useful information and develop conclusions. Since a simulation is in many cases a computer-based statistical sampling experiment, in a sound simulation study, statistical techniques must be used to analyze the output of the simulated system.

The above procedure is also shown in Figure 3.1. Once satisfactory solutions or better understandings of the real-world problem have been found, these can then be published to add to the existing scientific knowledge, or be implemented in order to effect improvement in the real world.

3.7 Summary

Traditional theories of the oligopoly and duopoly are often based on fairly strong (and frequently unrealistic) assumptions, since otherwise it may lead to models of such a complex nature that they would be impossible to solve or to interpret. Nevertheless, there has not been a very high degree of correlation between the behavior of actual business firms and the behavior of the hypothetical firms described by the mathematical constructs of classical oligopoly and duopoly theory.

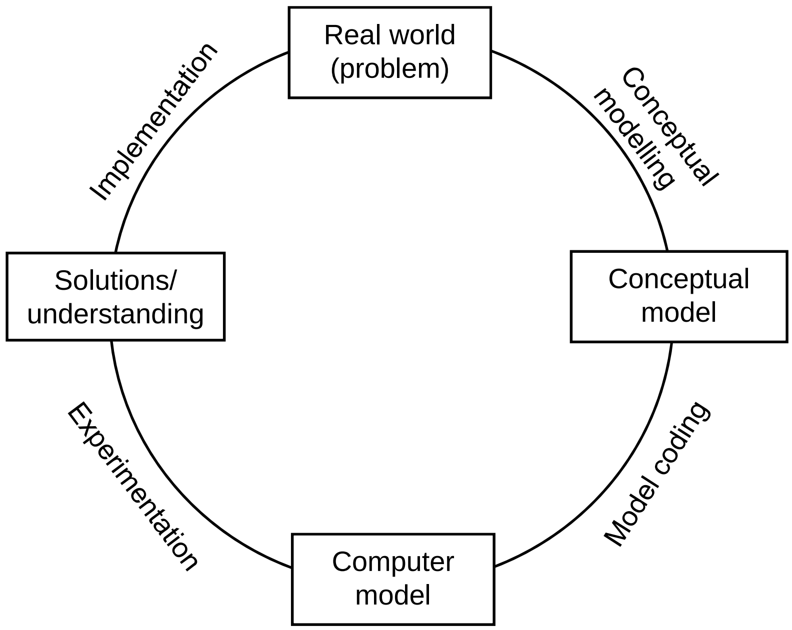

Figure 3.1: The procedures of a simulation study.

The arrival of computer techniques enables studies of oligopoly and duopoly problems with a set of highly detailed assumptions, which can be more compatible with the real world than those in analytical solutions. The presented work uses a numerical solution, or, to be more precise, uses computer-based simulation to study the competition between two e-auction marketplaces.

Chapter 4

Simulation Model

This chapter introduces the simulation model. Section 4.1 describes the economic environment where the competition takes place. Afterward, the auction mechanism, the agents, and the decision space are introduced separately in Sections 4.2, 4.3 and 4.4. Section 4.5 introduces the concept of bounded rationality, which is an important assumption in the model. The payoff calculations of the agents are specified in Section 4.6. This is the basis for the decision-making of agents, which are described in Section 4.7. A short summary is given at the end of this chapter.

4.1 Economic Environment

The simulation model considers two e-auction marketplaces, denoted by M_A and M_B. The marketplaces provide homogeneous auction services. It is assumed that in each marketplace, only one auction is being conducted. There is a large population of sellers and buyers, and each of them chooses one of the two marketplaces and participates in the auction hosted by that marketplace. One can only participate in one of the marketplaces at a time.

In the simulation model, each participant is considered as an agent. Let the size of the population be n, and any agent of the population be either a seller or a buyer. The

n agents consist of s sellers and b buyers, and the number of sellers is smaller than the number of buyers.

The simulation consists of multiple simulation rounds. In every round, each agent takes part in one auction. Sellers offer their items and buyers bid for the items. The buyers who win the items and the winning prices of the items are determined by the auctions. Based on those auction outcomes, each agent independently decides which marketplace to join in the next round — whether to stay in his current marketplace or switch to the other marketplace.

To put it more clearly, a simulation round consists of the following four steps.

Step 1: Each agent makes a decision about which marketplace to join.

Step 2: Each seller offers his item. All items are homogeneous goods. Each buyer receives his private valuation for one of the items and submits a bid.

Step 3: Auctions are conducted simultaneously in the two marketplaces.

Step 4: All agents are informed about the auction results. Each seller knows at what price he sold his item. Each buyer is informed of the winning price and whether he acquired an item. Moreover, the winning prices in both marketplaces are publicly known.

A simulation round, as described above, is conducted repeatedly in a simulation. Denote the simulation round that is repeated for the t-th time by R^t. At time $t = 1$, that is, in the first simulation round, each agent randomly decides which marketplace to join. In the following simulation rounds, each agent makes decisions in order to maximize his payoff. The decision-making process is described in Section 4.6 and Section 4.7.

4.2 Auction Mechanism

A uniform-price auction is used in the simulation model. It is a multi-unit sealed-bid auction, in which units offered by the sellers are sold at the same winning price. The winning price in this model is determined by the highest rejected bid among the buyers. Sellers are assumed to be the price takers, and have a reserve price of zero for the items to offer.

For example, consider an auction with three sellers (each of which has one unit to offer) and five buyers (with single-unit demands). Suppose the buyers' bids are 1.0, 3.0, 5.0, 7.0, and 9.0, respectively. The three buyers whose bids are 5.0, 7.0, and 9.0 respectively, are the winners. Each of them obtains one unit with a price of 3.0, which is the fourth highest bid among the buyers. Moreover, if the number of sellers is equal to or larger than the number of buyers, the winning price is set to zero.

Similar mechanisms are often applied in electronic markets. For example, one of the auction mechanisms used by eBay is the "dutch auction."[13] Despite its name, this auction is not what is generally called a "dutch auction" in auction theory. It is rather a multiple item auction, in which one seller offers multiple, identical items for sale, and many buyers bid for those items. This type of auction can have several winners, who pay the same price.

From buyers' points of view, eBay's mechanism is similar to the uniform auction used in this study, because in both cases the winners pay the same price. The only difference is that a buyer in a dutch auction on eBay can bid for several identical items, while in this model a buyer can only bid for one item. On the seller side, in an eBay dutch auction, only one seller, who offers multiple identical items, is involved. In this model, the uniform auction may contain many sellers, and each seller offers only one item. However, a seller on eBay can be considered as a group of sellers, each selling a single item. The decision of an eBay seller represents the joint decision of the group of sellers. From this point of view, the two mechanisms are also similar to sellers.

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[13] See http://pages.ebay.com/help/buy/buyer-multiple.html.

4.3 Agents

Every agent in the simulation model is either a seller or a buyer. Throughout the simulation, an agent never changes his role. This means that, for example, if an agent is designated as a buyer, he will be a buyer in all simulation rounds. If not particularly mentioned as a seller or buyer, an agent is generally denoted by a.

Sellers Among all n agents there are s sellers, and an individual seller is denoted by s_j, $j = 1, 2, ..., s$. A seller offers one item in each simulation round, and in each round he offers his item in exactly one of the two marketplaces. He receives the price which is determined by the auction. Sellers are assumed to be price-takers, and to have a reserve price of zero for the item to sell. The items offered by sellers are assumed to be identical.

Buyers Among all n agents there are b buyers, and an individual buyer is denoted by b_k, $k = 1, 2, ..., b$. In every simulation round, each buyer seeks to acquire one item. Buyers have private valuations for the items, and the valuations are independently drawn from a uniform distribution over the interval of $[0, \bar{v_b}]$, $\bar{v_b} > 0$. In order to obtain one item, each buyer submits a bid in the auction held at the marketplace that he currently participates in.

It is a well-known result of auction theory that in a second-price auction with private valuations, it is a weakly dominant strategy for each buyer to bid true valuation (Krishna, 2002, p. 15). In a uniform-price auction as in this model, it can be easily proved that bidding their true valuations is a weakly dominant strategy for buyers as well (see proof in Appendix A).

Each buyer receives a new valuation in each round. The valuation is only valid in the current round. Moreover, buyers neither know the identity of their trading partners, nor do they have any preference with whom to trade.

4.4 Decision Space

In the model, agents make decisions on which of the two marketplaces to join. In each round, a seller takes one of the following two actions:

1. participate in marketplace M_A.

2. participate in marketplace M_B.

As pointed out in Section 4.3, it is a weakly dominant strategy for buyers to bid their true valuation. Thus, the decision on how much to bid is not explicitly modeled, and a buyer's decision in a simulation round is to participate in either M_A or M_B, too. In a word, sellers and buyers have the same decision space.

Denote the decision space of an agent by X. $X = \{M_A, M_B\}$. The decision space remains the same throughout the simulation. Given a simulation round R^t, the decision of a seller s_j in this round is then $x^t_{s_j}$, it should be either M_A or M_B. Similarly, the decision of a buyer b_k in round R^t is denoted by $x^t_{b_k}$.

4.5 Bounded Rationality

The neoclassical economic theory assumes that agents are rational. This means that the agents know the utility function of other agents (or the probability that other agents have these utility functions), they calculate the possible actions of their own as well as other agents, and make decisions that maximize their payoffs. However, this assumption is rather demanding and implausible for the problem studied in the presented work.

In this model, agents are assumed to be "bounded rational." The originator of the phrase, Herbert Simon, defines a choice with bounded rationality as "a rational choice that takes into account the cognitive limitations of the decision-maker — limitations of both knowledge and computational capacity" (Simon, 1987). In contrast to the rational scenario, agents are endowed with more or less limited cognitive and computational capacities, but such weak rationality is compensated by repetitions in the simulation. As time goes, agents summarize their experiences in actions by their payoffs received in the past. They find optimal actions by applying ameliorating rules which reinforce good actions and weaken bad actions.

Derived from the assumption of bounded rationality, agents in this model are assumed to take the following principles in decision-making.

- Agents are not able to calculate other agents' possible payoffs and actions. Therefore, they consider only their own choices and calculate only their own payoffs.

- Once an action turns out to have maximized an agent's payoff, the agent believes "what worked well in the past may also work well in the future," and then just sticks to this action in the next round.

4.6 Payoff Specification

In a simulation round, agents first participate in a marketplace, and then calculate their payoffs upon receiving the winning prices of the auctions. This section defines how an agent's payoff is determined. According to the assumptions in Section 4.5, agents calculate their own payoffs, without considering the choices and payoffs of other agents.

4.6.1 Payoff of a Buyer

In each simulation round, different agents may join different marketplaces. An agent may also join different marketplaces in different simulation rounds. Given a simulation round, the marketplace that an agent a currently participates in is referred to by M_a, and the other marketplace by $M_{\widehat{a}}$. Correspondingly, the winning prices in the marketplaces are $p(M_a)$ and $p(M_{\widehat{a}})$, respectively.

Denote the valuation that a buyer b_k receives in round R^t by $v^t_{b_k}$. As pointed out in Section 4.3, it is a (weakly) dominant bidding strategy for each buyer to bid his true valuation, thus the bid by buyer b_k in R^t is simply $v^t_{b_k}$.

The payoff of a buyer b_k, who participates in market M_{b_k} in round R^t, is defined in the following equation.

$$\pi^t_{b_k}(M_{b_k}) = \begin{cases} v^t_{b_k} - p^t(M_{b_k}) & , \text{ if } \quad v^t_{b_k} > p^t(M_{b_k}) \\ 0 & , \text{ otherwise} \end{cases} \tag{4.1}$$

Since a buyer participates only in one marketplace, strictly speaking, a buyer has no payoff with respect to the other marketplace. However, this model proposes a "presumed payoff" concept, which follows an intuitive way of thinking by individuals. The following example explains this in detail.

Example 1. *Consider a buyer who currently participates in marketplace M_A with a private valuation of* 12.0*. The winning prices in the two marketplaces are* $p(M_A) = 10.0$ *and* $p(M_B) = 8.0$ *respectively. The buyer's payoff in M_A, according to Equation 4.1, is simply* $12.0 - 10.0 = 2.0$*. Although this buyer has not participated in M_B, observing a winning price of* 8.0 *in M_B, he might think: if I had been in that marketplace, I would have won in that auction as well, but with a price of* 8.0 *— choosing marketplace M_B seems to be more profitable for me.*

To conclude from the above example, an agent always calculates his payoff in his current marketplace (named as his *real payoff* in the following). Besides, the agent also calculates his *presumed payoff*, which refers to a payoff that the agent subjectively thinks he would have received, if he had participated in the other marketplace. It is calculated in the same way as his real payoff, except that the price of the current marketplace is substituted by the price in the other marketplace (see Equation 4.2).

$$\pi^t_{b_k}(M_{\widehat{b_k}}) = \begin{cases} v^t_{b_k} - p^t(M_{\widehat{b_k}}) & , \text{ if } \quad v^t_{b_k} > p^t(M_{\widehat{b_k}}) \\ 0 & , \text{ otherwise} \end{cases} \tag{4.2}$$

4.6.2 Payoff of a Seller

In Section 4.3 it is assumed that all sellers' valuations of their offered items are zero. Thus, the real payoff of a seller s_j in marketplace M_{s_j} simply equals the winning price in that marketplace.

$$\pi^t_{s_j}(M_{s_j}) = p^t(M_{s_j}) \tag{4.3}$$

Analogously to the presumed payoff of a buyer, a seller's presumed payoff in the other marketplace $M_{\hat{i}}$ is given in Equation 4.4

$$\pi^t_{s_j}(M_{\hat{s_j}}) = p^t(M_{\hat{s_j}}) \tag{4.4}$$

4.6.3 Preference Generation

After calculating his real and presumed payoff, each agent derives his preference for one marketplace according to his real payoff and presumed payoff. The principle is rather simple: the marketplace that yields a higher payoff is preferred.

If, in a simulation round R^t, an agent a's current marketplace provides a higher or equal payoff compared to the other marketplace, then the agent prefers the current marketplace. Let $\psi^t_a = 0$ stand for this case. Otherwise, the agent prefers to switch to the other marketplace, and in this case ψ^t_a takes the value of 1. Equation 4.5 presents the function ψ^t_a in formula.

$$\psi^t_a = \begin{cases} 0 & , \quad \text{if} \quad \pi^t_a(M_a) \geq \pi^t_a(M_{\hat{a}}) \\ 1 & , \quad \text{otherwise} \end{cases} \tag{4.5}$$

4.7 Heuristics in Decision Making

This section describes the decision-making process, that is, how an agent finally derives a decision regarding which marketplace to join. The following information is known for an agent a, when he is about to decide which marketplace to join in the simulation round R^{t+1}.

1. The agent's choice in round R^t
   The choice of a seller s_j is $x^t_{s_j}$, and it is $x^t_{b_k}$ for a buyer b_k.

2. The agent's real payoff and presumed payoff in R^t
   The real payoff and presumed payoff of a seller s_j are $\pi^t_{s_j}(M_{s_j})$ and $\pi^t_{s_j}(M_{\widehat{s_j}})$ respectively, and for a buyer b_k they are $\pi^t_{b_k}(M_{b_k})$ and $\pi^t_{b_k}(M_{\widehat{b_k}})$ accordingly.

3. The agent's preference for one marketplace
   The preference is generated based on the agent's real and presumed payoff, and it is denoted by $\psi^t_{s_j}$ for a seller s_j, and $\psi^t_{b_k}$ for a buyer b_k.

The decision-making process of an agent is differentiated according to an agent's preference, that is, is differentiated in the following two cases.

Case I: An agent prefers the current marketplace.

Case II: An agent prefers the other marketplace.

Section 4.7.1 and Section 4.7.2 define the decision-making process under these two cases, respectively.

4.7.1 Case I: Preference for the Current Marketplace

According to the assumption of bounded rationality in Section 4.5, an agent follows the principle "what worked well in the past may also work well in the future." If, for an agent a, ψ^t_a equals zero, which means that his current marketplace has "worked well," the agent simply sticks to his choice. Equation 4.6 and 4.7 show this in formulae.

$$x^{t+1}_{s_j} = x^t_{s_j} \quad , \quad \text{if} \quad \psi^t_{s_j} = 0 \tag{4.6}$$

$$x^{t+1}_{b_k} = x^t_{b_k} \quad , \quad \text{if} \quad \psi^t_{b_k} = 0 \tag{4.7}$$

4.7.2 Case II: Preference for the Other Marketplace

If, for an agent a, ψ_a^t equals one, which means that the other marketplace is preferred, simply following this preference may not ensure a maximal payoff. There are several reasons for this.

- The presumed payoff is calculated in a subjective way. If an agent had joined the other marketplace, this might have changed the winning price. Therefore, the preference that is generated based on the real and presumed payoff may not precisely reflect the decision problem. Therefore, although an agent clearly knows his preference, he does not know the actual accurate payoffs.

- Agents are not able to forecast the future actions of other agents. Again, due to limitations in information and computation abilities, agents can not calculate probabilities over their decision spaces which take into account every other agent's probabilities in taking certain actions. When an agent switches to the other marketplace in a new simulation round, other agents may also adapt their decisions at the same time. This naturally leads to changes of the winning prices and consequently changes of the agents' payoffs.

- Agents' valuations are randomly generated in each simulation round. In each round, buyers' valuations for the items are redrawn. Thus, even if the number of buyers and the number of sellers are fixed in one marketplace, the winning price in this marketplace may still vary from round to round. Consequently, the payoffs and preferences of the agents may vary.

Due to the above reasons, when an agent prefers the other marketplace, he may not simply take an action that follows his preference. Rather, each agent may generate a probability in which he follows his preference and moves to the other marketplace. Let d_a^{t+1} represent the probability that the agent a joins the other marketplace in the simulation round R^{t+1}. It is determined by two parameters: 1) the indicator of the difference between the real and presumed payoff; and 2) the discount factor.

4.7.2.1 The Payoff Difference Indicator

It is intuitive and reasonable for an agent to consider the difference between his real payoff and presumed payoff. For example, consider that a seller's real payoff is 6.5, and his presumed payoff is 8.5, that is, his presumed payoff is higher than his real payoff with a difference of 2.0. The seller prefers to switch to the other marketplace. Now suppose that his presumed payoff is 12.5, and thus the payoff difference is as high as 6.0. Compared to the former case, it is natural that the seller be subjectively more motivated to join the other marketplace. Therefore, in this model, a payoff difference indicator θ is introduced to present an agent's "eagerness," or in other words, the "degree of motivation," to switch to the other marketplace. The payoff difference indicator of an agent a (denoted by θ_a^t), is determined by Equation 4.8.

$$\theta_a^t = \mu * \frac{\pi_a^t(M_{\hat{a}}) - \pi_a^t(M_a)}{\pi_a^t(M_{\hat{a}}) + \pi_a^t(M_a)} \tag{4.8}$$

Given an agent's real payoff $\pi_a^t(M_a)$, it is clear from Equation 4.8 that the larger his presumed payoff $\pi_a^t(M_{\hat{a}})$, the larger the payoff difference indicator θ_a^t. μ is a scaling coefficient that lies in the interval of $[0, 1]$.

4.7.2.2 The Discount Factor

The discount factor is used to present an agent's "sensitiveness" of the payoff difference. The underlying principle of the discount factor is that the longer an agent stays in a marketplace, the less he is influenced by the payoff difference. This principle actually reflects several considerations when agents trade via auctions in reality. For example, the longer an agent stays and trades in a marketplace, the higher his reputation might be, and therefore the less he is motivated to switch when the other marketplace occasionally yields a higher payoff. Another example could be that an agent has switching costs, such as learning how to use the services provided by the marketplace that the agent switched to.

On the other hand, after an agent has switched to the other marketplace, his discount factor should change in a way that the agent is more influenced by the payoff difference. One possible motivation from the real world is that an agent often pays more attention to his payoff than his reputation, when he first joins a marketplace. The agent does not attain much of a reputation in the new marketplace in a short time; in the meantime, his reputation in the former marketplace is much less important after the switch. Therefore, the agent is more sensitive to the variations of his payoffs. Another possible argument is that agents are uncertain about the expectations due to the reasons mentioned in the beginning of Section 4.7.2. Because of this, an agent is likely to be quite sensitive to the dynamics of the payoffs immediately after a switch.

The value of the discount factor is always updated after a decision is made. An agent a in the simulation round R^t compares his decision in round (x_a^t) with his decision in the former round (x_a^{t-1}). If the decisions are the same, that is, the agent has stayed in the same marketplace, then the value of f_a^t decreases. Contrarily, f_a^t increases if the decisions are different. Equation 4.9 defines the calculation of f_a^t in a formula. The initial value of the discount factor is set to 1.0, that is, $f_a^1 = 1.0$.

$$f_a^t = \begin{cases} \frac{1}{2} * [f_a^{t-1} + 1] & , \quad \text{if} \quad t \geq 2 \quad \text{and} \quad x_a^t \neq x_a^{t-1} \\ \frac{1}{2} * f_a^{t-1} & , \quad \text{if} \quad t \geq 2 \quad \text{and} \quad x_a^t = x_a^{t-1} \\ 1 & , \quad \text{if} \quad t = 1 \end{cases} \tag{4.9}$$

Although the value of the discount factor is determined only by its formal value and the agent's decisions in two successive rounds, by iteration f_a^t is able to take into account all former decisions. An example is given in the following, showing how the value of the discount factor varies according to a series of decisions over time.

Example 2. *Consider a simulation that runs eight simulation rounds. That is, the value of t increases from one to eight (see the first row of Table 4.1). Assume that the decisions of an agent a in those rounds are observed as listed in the second row of*

Table 4.1. The discount factor is calculated in each round according to Equation 4.9, and the values are listed in the third row of the table.

t	1	2	3	4	5	6	7	8
x_a^t	M_A	M_B	M_B	M_B	M_A	M_A	M_B	M_A
f_a^t	1	1	0.5	0.25	0.625	0.313	0.657	0.829

Table 4.1: An example of the discount factor.

From Example 2 one can see that the discount factor has the following features:

- The value of f_a^t decreases if an agent sticks to his former decision and stays in the same marketplace.
- The value of f_a^t increases if an agent switches to a different marketplace.
- The value f_a^t varies in the range of $(0, 1]$.
- $f_a^t = 1$ holds as long as an agent keeps switching between the two marketplaces.

The first two features show that the calculation of the discount factor reflects the changes of an agent's sensitiveness of payoff in the correct way. The latter two features make sure that the value of the discount factor can be used as a discounting coefficient to the payoff difference.

After an agent a in the simulation round R^t has calculated the payoff difference indicator and updated the discount factor, he is then able to calculate his probability of switching to the other marketplace in the next round, denoted by d_a^{t+1}. Equation 4.10 and 4.11 present the function with respect to sellers and buyers respectively.

$$d_{s_j}^{t+1} = \theta_{s_j}^t * f_{s_j}^t \tag{4.10}$$

$$d_{b_k}^{t+1} = \theta_{b_k}^t * f_{b_k}^t \tag{4.11}$$

After the agent a has calculated the probability, he makes a decision in the next round R^{t+1} based on this probability, and then acts following the decision, which is either to stay in the same marketplace as in round R^t, or to switch to the other marketplace in round R^{t+1}.

An example is given at the end of this subsection, showing the decision-making of an agent in Case II — the case that an agent does not prefer the current marketplace.

Example 3. *Suppose that in a simulation round* R^4*, a buyer* b_{18} *joins the marketplace* M_A*, that is,* $x^4_{b_{18}} = M_A$*. He calculates the payoffs after the two auctions are executed, and it turns out that his real payoff* $\pi^4_{b_{18}}(M_A)$ *is* 2.01 *and his presumed payoff* $\pi^4_{b_{18}}(M_B)$ *is* 8.818*. Clearly,* M_B *is more preferred than the buyer's current marketplace* M_A*.*

Suppose the scaling coefficient $\mu = 0.8$*. According to Equation 4.8 the payoff difference indicator* $\theta^4_{b_{18}} = 0.8 * (8.818 - 2.01)/(8.818 + 2.01) = 0.503$*. Suppose that the discount factor* $f^4_{b_{18}}$ *is updated with a value of* 0.5*. Thus, the buyer's probability of switching to* M_B *in the next round* R^5*, according to Equation 4.11, is* $d^5_{b_{18}} = \theta^4_{b_{18}} * f^4_{b_{18}} = 0.252$*. The buyer then draws a decision.*[14] *With a probability of* 0.252*, the decision will be* M_B*, and then the buyer joins* M_B *in round* R^5*, that is,* $x^5_{b_{18}} = M_B$*. With a probability of* 0.748 *the buyer decides to stay in* M_A*, and* $x^5_{b_{18}} = M_A$*.*

4.7.3 Decision-making Considering Listing Fees

One objective of the presented work is to study how the market evolves when the marketplaces impose listing fees on the sellers. So far, the simulation model has not included the parameter of the listing fee. In this subsection, the simulation model is

[14]The implementation of probability in computer algorithm is done as follows. Suppose that the probability is 0.5. Draw a random number q in the range of [0,1]. Obviously, the probability that $q \leq 0.5$ is 0.5, and the probability that $q > 0.5$ is also 0.5. Similarly, given any probability p, we just draw a random number q, and compare q with p. The probability that $q \leq p$ is p, and the probability that $q > p$ is $1 - p$. Therefore, the probability p can be implemented by drawing a random number q and then judging whether $q \leq p$.

extended, so that it considers the listing fee as a further parameter.

A listing fee is a price that a marketplace charges for listing an item or items for sale. Only sellers are charged a listing fee at the time of listing. Moreover, this fee is charged independently of any transaction, meaning that it is not refundable, no matter whether the offered item is sold or not. A marketplace usually charges the same listing fee to all participating sellers.

Intuitively, a seller prefers a marketplace with a higher price but he also has to consider the amount of the listing fee. His payoff in a marketplace is simply the price he receives minus the listing fee he must pay. In the case that the listing fee equals or is even higher than the price, a seller simply receives a payoff of zero. Let $l(M_{s_j})$ represent the amount of the listing fee that a seller s_j is charged by his current marketplace M_{s_j}, and let $l(M_{\widehat{s_j}})$ represent the listing fee charged in the other marketplace. The calculation of the real payoff and the presumed payoff is then modified, as shown in Equation 4.12 and 4.13, respectively.

$$\pi^t_{s_j}(M_{s_j}) = \begin{cases} p^t(M_{s_j}) - l^t(M_{s_j}) & , \text{ if } \quad p^t(M_{s_j}) > l^t(M_{s_j}) \\ 0 & , \text{ otherwise} \end{cases} \tag{4.12}$$

$$\pi^t_{s_j}(M_{\widehat{s_j}}) = \begin{cases} p^t(M_{\widehat{s_j}}) - l^t(M_{\widehat{s_j}}) & , \text{ if } \quad p^t(M_{\widehat{s_j}}) > l^t(M_{\widehat{s_j}}) \\ 0 & , \text{ otherwise} \end{cases} \tag{4.13}$$

Buyers are not charged with the listing fee, therefore their payoff functions need not be changed. However, they are indirectly influenced by the listing fees, because they consider the prices in their payoff functions, and the prices are actually determined by the buyers' bids as well as the number of sellers and buyers in the marketplaces.

No further change of the simulation model is necessary, because the variables of listing fees are already modeled within the payoff functions, and the payoff calculations are the basis of all further calculations in the decision-making process. From this point of view, the model has its advantage in extension.

4.8 Summary

This chapter proposes a simulation model of the competition between two e-auction marketplaces. The model defines the competition scenario, the agents who participate in the marketplaces, the agents' decision spaces as well as their decision-making processes. The simulation model is further extended to the case where the two marketplaces impose listing fees. In the next chapter, the simulation experiment based on the simulation model is designed.

Chapter 5

Design of the Simulation Experiment

In Chapter 4, a simulation model of two competing e-auction marketplaces is proposed. The model is implemented as a computer program so that the competition can be simulated(Chen and Maekioe, 2006). This chapter describes how the computer simulations should be conducted for the purpose of this study.

In a computer simulation experiment, as in any experiment, careful attention should be devoted to the experimental design. Law and Kelton point out that "carefully designed experiments are much more efficient than a 'hit-or-miss' sequence of runs in which we simply try a number of alternative configurations unsystematically to see what happens," (Law and Kelton, 1999, p. 623).

In order to design a simulation experiment, two elements — *factor* and *response* — need to be defined first. Both terms refer to variables. The input parameters are called factors, and the output performance measures are called responses (Law and Kelton, 1999, p. 622). Section 5.1 defines the factors and responses in this study.

Factors include fixed factors and experimental factors. It depends on the goals of the study rather than on the inherent form of the model as to which input parameters should be considered as the fixed factors of the simulation, and which should be considered as the experimental factors. Section 5.2 introduces the three fixed factors in the presented work, and a pre-stage simulation study is conducted in order to determine the appropriate values of those fixed factors.

Based on the research questions and the pre-stage simulation, several treatments are designed, each of which consists of several different simulation settings. The treatments and the settings are introduced in detail in Section 5.3.

5.1 Factors and Responses

5.1.1 Factors

Table 5.1 lists the factors included in the simulation model.[15] Kleijnen has suggested that for a standard design of experiment, a simulation system should not deal with more than about fifteen factors (Kleijnen, 1998, p. 175). Therefore, the number of factors in this work is appropriate.

Parameter	**Definition**
n	Total number of agents (including sellers and buyers)
s	Total number of sellers
b	Total number of buyers
$s^1(M_A)$	Number of sellers in M_A at simulation initialization
$b^1(M_A)$	Number of buyers in M_A at simulation initialization
$s^1(M_B)$	Number of sellers in M_B at simulation initialization
$b^1(M_B)$	Number of buyers in M_B at simulation initialization
$l(M_A)$	Listing fee charged to sellers in M_A
$l(M_B)$	Listing fee charged to sellers in M_B
$\bar{v_b}$	Upper bound of a buyer's valuation (the lower bound is zero by default)
μ	Scaling coefficient used in payoff calculation
z	Number of repeated rounds in a simulation run

Table 5.1: Input factors.

[15]Refer to Chapter 4 to see how these factors are incorporated into the simulation model.

The last three factors from Table 5.1, i.e., the upper bound of a buyer's valuation ($\bar{v}_b$), the scaling coefficient of the payoff difference (μ), and the number of repeated rounds in a simulation run (z), are set as fixed factors in the simulation experiment. The other factors are the experimental factors.

Since each factor can be set with many different values, the combination of the factors generates a huge factor space. Clearly, it is neither computationally feasible nor necessary to simulate every factor combination. Rather, multiple simulation settings should be defined which on the one hand meet the interests of the study, and on the other hand have the discriminatory power that facilitates easy analysis of the simulation data. Section 5.3 defines how the experimental factors are combined in various simulation settings.

5.1.2 Responses

A simulation can be considered as a mechanism that turns input parameters into output measures. In a discrete event simulation, two types of variables are often used for output data analysis — the *counter* variable and the *system state* variable (Ross, 1997). A counter variable counts the number of times that a certain event has occurred by a certain time. A system state variable describes the "state of the system" at a certain time. Whenever an "event" occurs, i.e., the values of the above variables change or are updated, the relevant data that is of interest is collected as the output. In this way, the evolution of the simulated system can be monitored.

Type	**Response Variable**
Counter	t: a counter of the number of simulated rounds
System state	$p^t(M_A)$, $p^t(M_B)$: the prices of the auctions in round R^t; $s^t(M_A)$, $b^t(M_A)$, $s^t(M_B)$, $b^t(M_B)$: the distribution of agents in the marketplaces in round R^t.

Table 5.2: Response variables.

Table 5.2 lists the response variables used in this work. The counter t is a discrete variable, which refers to the number of simulated rounds. The counter increases by one in each simulation round, and a simulation run terminates in the simulation round in which the counter equals the maximum limit z. There are two types of system state variables — the winning prices of the auctions and the distribution of agents in the two marketplaces M_A and M_B in a simulation round.

5.2 Simulation Trials

Before finalizing the design of the simulation settings, several trial simulations are conducted and analyzed in this section. The purpose of the trials is to get a first impression of the simulation dynamics and to verify whether the output is reasonable.

5.2.1 A Trial Run

The first trial simulation uses the settings shown in Table 5.3. Twenty agents are simulated. At the beginning of the simulation, two sellers and five buyers join the marketplace M_A, while the remaining four sellers and nine buyers join the marketplace M_B. The valuations of the buyers are independently drawn from a uniform distribution over the interval of $[0, 10.0]$. The coefficient μ is set to 0.1. The simulation runs for fifty rounds.

n	s	b	$s^1(M_A)$	$b^1(M_A)$	$s^1(M_B)$	$b^1(M_B)$	μ	$\bar{v}_b$	z
20	6	14	2	5	4	9	0.1	10.0	50

Table 5.3: Simulation setting used in the trial simulation.

To give an overview of how agents select between the two marketplaces, Figure 5.1 shows the number of sellers and the number of buyers of each marketplace in each round. In the first several rounds, one can see that agents switch between the marketplaces quite frequently. However, in later rounds, the number of agents in each marketplace remains more or less constant. Such stableness may occur in two situations. One is that no agent changes his location, and consequently there is no movement. The other situation is that the movements from M_A to M_B exactly offset the movements from M_B to M_A. The detailed simulation data shows that the stableness is observed because the former is the case.

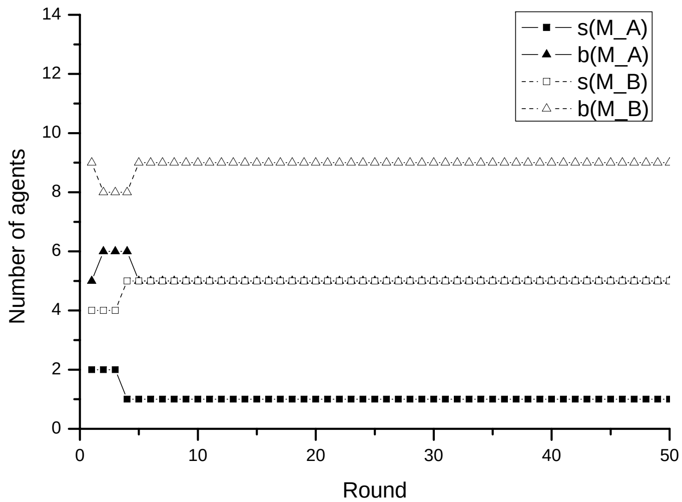


Figure 5.1: Dynamics of the movements of agents in the trial simulation.

Table 5.4 lists the winning prices as well as the distribution of agents in each round. In the first simulation round, the prices in the marketplaces turn out to be 4.402 and 5.958 respectively. The price difference is 1.556, and one buyer switches from M_B to M_A in the second round.

This agent had randomly joined M_B in the first round and receives a valuation of 6.324. Thus, as a buyer his real payoff is 0.366 and his presumed payoff in the other marketplace, M_A, is 1.922. Thus, he prefers to move to M_A, and after calculation he moves to M_A with a probability 0.068. By drawing a random number, which turns out to be 0.0327 and is smaller than 0.068, the agent follows his preference and joins M_A in the second round.[16]

Actually, there are several other buyers, who also prefer to switch from M_B to M_A in the second round. However, according to the decision-making rules, they compute

[16]Refer to Section 4.6 and Section 4.7 for the decision-making process. See also Example 3 in Section 4.7.2.

R^t	$s^t(M_A)$	$b^t(M_A)$	$s^t(M_B)$	$b^t(M_B)$	$p^t(M_A)$	$p^t(M_B)$
1	2	5	4	9	4.402	5.958
2	2	6	4	8	5.998	5.341
3	2	6	4	8	1.305	4.431
4	1	6	5	8	7.234	1.418
5	1	5	5	9	2.097	2.641
6	1	5	5	9	7.582	4.693
7	1	5	5	9	5.958	7.582
8	1	5	5	9	6.469	5.958
9	1	5	5	9	6.469	4.657
10	1	5	5	9	6.469	5.843
11	1	5	5	9	3.09	5.839
12	1	5	5	9	5.325	5.365
13	1	5	5	9	3.078	2.427
14	1	5	5	9	5.843	2.097
15	1	5	5	9	4.559	5.626
16	1	5	5	9	6.631	4.955
17	1	5	5	9	5.958	3.676
18	1	5	5	9	5.154	2.812
19	1	5	5	9	6.324	4.548
20	1	5	5	9	5.551	3.078
21	1	5	5	9	6.695	0.521
22	1	5	5	9	5.341	1.305
23	1	5	5	9	6.469	1.305
24	1	5	5	9	5.998	4.402
25	1	5	5	9	6.762	5.573
26	1	5	5	9	1.531	6.580
27	1	5	5	9	3.09	2.641
28	1	5	5	9	5.573	3.090
29	1	5	5	9	9.665	5.573
30	1	5	5	9	7.582	5.573
31	1	5	5	9	6.58	3.104
32	1	5	5	9	5.551	4.402
33	1	5	5	9	5.365	2.812
34	1	5	5	9	5.431	5.084
35	1	5	5	9	7.693	1.844
36	1	5	5	9	6.631	3.104
37	1	5	5	9	6.909	5.154
38	1	5	5	9	4.955	1.769
39	1	5	5	9	9.84	5.084
40	1	5	5	9	4.402	2.812
41	1	5	5	9	8.607	4.839
42	1	5	5	9	5.551	4.955
43	1	5	5	9	5.839	5.843
44	1	5	5	9	4.839	2.812
45	1	5	5	9	5.341	3.700
46	1	5	5	9	3.078	1.531
47	1	5	5	9	3.676	4.402
48	1	5	5	9	7.649	5.154
49	1	5	5	9	5.958	2.423
50	1	5	5	9	6.631	5.365

Table 5.4: Dynamics of the prices and the distribution of agents in the trial simulation.

their probabilities of moving, and it turns out that those buyers stay in M_B in the second round.

This simulation run uses a setting with only twenty agents. Because the agents are distributed in the two marketplaces, the number of sellers and the number of buyers in each single marketplace are even smaller. Thus, the movement of a single agent may easily lead to large changes in the winning prices. This explains why in the third round, one seller moves from M_A to M_B, and then the winning price in M_A rises to 7.234 (which is much higher than its former value of 1.305 in R^3), while the price in M_B decreases to 1.418 (which is much lower than its former value of 4.431 in R^3). Due to this great change in the winning prices, it is observed that a buyer leaves M_A and joins M_B in R^5.

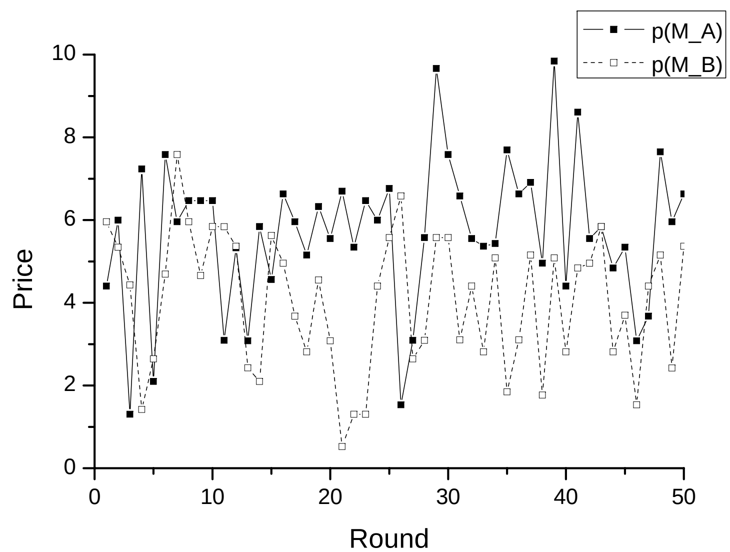


Figure 5.2: Dynamics of the winning prices in the trial simulation.

In fact, the prices are very sensitive throughout the simulation. Figure 5.2 shows the dynamics of the winning prices in the two marketplaces. One can see that the prices often vary significantly between two successive rounds, and this can be observed throughout the simulation. For example, the price in M_B is around 6.5 in round 26, but it decreases to around 2.5 in the next round, R^{27}. For another example, the price in M_A jumps from around 5.0 in R^{38} to almost 10.0 in the following round, R^{39}, but the value decreases again to a even lower value that is around 4.5 in R^{40}.

One reason for this, as pointed out in the above, is that within a small population, a single agent's movement may cause big changes in the winning prices. However, it does not explain why the prices still vary greatly after the round R^5, in which every agent chooses to stay in his marketplace, and the distribution of agents remains at a state of $s(M_A) = 1, b(M_A) = 5, s(M_B) = 5, b(M_B) = 9$. Clearly, the demand-offer relationship is not in balance in the two marketplaces, with M_A containing one seller but five buyers, while there are five times as many sellers but only two times as many buyers in M_B. Correspondingly, the price in M_A is often much higher than in M_B. It seems unreasonable for the buyers in M_A to stick to the high price and sellers in M_B to stick to the relatively low price.

There are three issues that jointly account for the phenomenon. One of the issues is that the buyers' valuations for the items are redrawn in each round. A buyer's new valuation is independent from his valuation in the former round. The buyers' valuations are also independent from each other in each round. Therefore, even if the number of buyers and the number of sellers is fixed in one marketplace, the winning price in this marketplace may still vary from round to round.[17]

The second contributing parameter is the discount factor f. For example, compare the two rounds R^3 and R^{26}. In round 3, the price difference is 3.126, and in the next round one seller chooses to move. In round R^{26}, the winning prices are $p^{26}(M_A) = 1.531$ and $p^{26}(M_B) = 6.58$ respectively. However, no seller in M_A moves, although the price difference is as large as 5.049.[18]

This example shows the influence of the discount factor f. According to the simulation model, the longer an agent stays in a marketplace, the lower is his incentive to

[17]It is shown in Section 6.1.2 that the prices vary less intensely during the stable state in the simulation with a larger population of 300 agents.

[18]In this example, sellers are simply assumed as price-takers, therefore in each round the price difference simply equals payoff difference for each seller.

move, and this leads to the agent's probability of moving being discounted. Table 5.4 shows that by round 26, each seller has continuously stayed in the same marketplace for 22 rounds. Thus, the payoff difference 5.049 is greatly discounted by f, so that the probability of moving is close to zero. In such a case, even a great change in the prices might not be sufficient to make any agent change his choice of a marketplace.

Last but not least, the payoff indicator μ also partly leads to a distribution of agents with an unbalanced demand-offer relationship. To see this, compare the two rounds R^6 and R^{26}. In round 6, the price difference is 2.889 for sellers. This is almost double compared to that of the first round, and the discount factor is not as small as in round 26. However, no seller chooses to move.

One reason for this is that the value of the coefficient μ, which is set to 0.1 in this simulation run, might be too small. Remember that μ is a coefficient that lies in the interval between 0 and 1.0. While the discount factor represents an agent's opinion as to how important payoff differences are, the value of μ represents a common opinion of all agents, regarding the extent to which a payoff difference is important, and this opinion is not changed throughout the simulation.

If μ is very small, according to Equation 4.8, no matter how big the payoff difference is, it will be greatly scaled down, and the value of θ should be very small, too. This means that even a big payoff difference might not be taken into great account. In the extreme case where $\mu = 0$, agents simply disregard their payoff differences and they always stay in their current marketplaces. In another extreme case where $\mu = 1$, agents are then very sensitive to the payoff differences. In those two extreme cases, the influence of μ on the decision is so large that it directly determines the system's state in the simulation.

5.2.2 Appropriate Values of the Fixed Factors

The analysis of the trial simulation shows that the simulation dynamics can be strongly influenced by some fixed factors, rather than determined by the prices and the according payoff differences. In order to avoid this, it is necessary to find out the appropriate values of the fixed factors.

5.2.2.1 The Upper Bound of Buyers' Valuations

In the simulation model, each buyer's valuation is drawn from a uniform distribution over the interval from 0 to $\bar{v_b}$. So far, the simulations have set the interval as $[0, 10.0]$. It naturally comes to the question: Is this interval appropriate? How large should $\bar{v_b}$ be? Does the upper bound influence the dynamics of the agent movements? In this subsection, simulation trials aim to answer these questions.

n	s	b	$s^1(M_A)$	$b^1(M_A)$	$s^1(M_B)$	$b^1(M_B)$	μ	$\bar{v_b}$	z
20	6	14	2	5	4	9	0.5	10.0	50
20	6	14	2	5	4	9	0.5	50.0	50
20	6	14	2	5	4	9	0.5	100.0	50

Table 5.5: Simulation settings in the pre-study of $\bar{v_b}$.

The simulation trials use the same settings, as listed in Table 5.5, except that $\bar{v_b}$ is set at different values. The three simulation trials evolve in a similar manner, and they end in the same stable state of half-split of agents — three sellers and seven buyers join M_A, while the remaining three sellers and seven buyers participate in M_B.

The average price difference is calculated for each simulation run. Since the buyers' valuations are generated based on different scales of intervals among the three runs, the prices of the three runs are expected to be significantly different from each other, and so are the average price differences. For an easy comparison between the runs, the *relative price difference* is introduced, which is calculated as shown in Equation 5.1.

$$\text{relative price difference} \quad = \quad \frac{\text{average price difference}}{\bar{v_b}} \tag{5.1}$$

Table 5.6 shows the average price differences in the three runs as well as the corresponding relative price differences. From this table one can see that the average

$\bar{v}_b$	Distribution of agents				Average price difference	Relative price difference
	$s^{50}(M_A)$	$b^{50}(M_A)$	$s^{50}(M_B)$	$b^{50}(M_B)$		
10.0	3	7	3	7	1.546	0.155
50.0	3	7	3	7	9.419	0.188
100.0	3	7	3	7	19.617	0.173

Table 5.6: Average- and relative price difference of the simulations in the pre-study of $\bar{v}_b$.

price difference is significantly larger, when buyers' valuations are drawn from a larger field, which is a rather intuitive result. However, the relative price differences of the three runs are very close to each other in value. This means that changing the support interval of the distribution does not significantly change the dynamics of the simulations. In other words, how large $\bar{v}_b$ should be set is not the crucial issue in the design of the simulation experiment. Therefore, in the following simulations, $\bar{v}_b$ is commonly set to 10.0. That is, the buyers' valuations are always drawn from the same uniform distribution over the interval of $[0, 10.0]$.

5.2.2.2 The Payoff Scaling Coefficient

Simulations in this subsection aim to find out an appropriate value of μ, so that the agents' decisions are mainly determined by payoff differences they receive, rather than influenced by the value of μ.

In this subsection, there are ten simulation runs studied, each using one setting. The ten settings are almost the same, as shown in Table 5.7, except that the value of μ in those settings is set to 0.1, 0.2 up to 1.0 respectively.

The simulation run in which μ equals 0.1 has already been studied in Section 5.2.1. The dynamics of the agents' movements in the remaining nine simulation runs are all similar to this trial simulation run. Each of the simulation runs evolves to a stable state, in which every agent sticks with his current marketplace. Table 5.8 shows the distribution of agents at the end of the simulation run in those ten settings.

It is known from the analysis in Section 5.2.1 that 0.1 is too small to be an appropri-

n	s	b	$s^1(M_A)$	$b^1(M_A)$	$s^1(M_B)$	$b^1(M_B)$	μ	$\bar{v}_b$	z
20	6	14	2	5	4	9	0.1	10.0	50
20	6	14	2	5	4	9	0.2	10.0	50
20	6	14	2	5	4	9	0.3	10.0	50
20	6	14	2	5	4	9	0.4	10.0	50
20	6	14	2	5	4	9	0.5	10.0	50
20	6	14	2	5	4	9	0.6	10.0	50
20	6	14	2	5	4	9	0.7	10.0	50
20	6	14	2	5	4	9	0.8	10.0	50
20	6	14	2	5	4	9	0.9	10.0	50
20	6	14	2	5	4	9	1.0	10.0	50

Table 5.7: Simulation settings in the pre-study of μ.

Value of μ	Distribution of agents			
	$s^{50}(M_A)$	$b^{50}(M_A)$	$s^{50}(M_B)$	$b^{50}(M_B)$
0.1	1	5	5	9
0.2	2	5	4	9
0.3	2	6	4	8
0.4	3	7	3	7
0.5	3	7	3	7
0.6	2	5	4	9
0.7	2	4	4	10
0.8	3	7	3	7
0.9	2	5	4	9
1.0	4	10	2	4

Table 5.8: Distribution of agents at the end of the simulation runs. Simulations in the pre-study of μ.

ate value for μ, because agents would rather be "locked" in their current marketplaces than make decisions based on their payoff differences. As one can see from Figure 5.1, frequent switches of agents between the marketplaces are not observed, even in the beginning of the simulation. Since the demand-offer situations are not balanced due to the lock effect, it is not surprising to see that a large price difference still exists at the end of the simulation, similar to that at simulation initialization. In other words, if the agents are not locked due to too small a value, small price differences between the marketplaces can be expected, especially in the stable state.

Table 5.9 lists the average price differences in the ten runs, in which μ takes the value of 0.1, 0.2, ..., 1.0 respectively. The average price difference is given by calculating the price difference in each simulation round, and then calculating the average for fifty consecutive rounds in a simulation run. The table shows that the average price difference is relatively small when μ lies between 0.2 and 0.5; the smallest average price difference occurs when $\mu = 0.5$. Therefore, 0.5 appears to be an appropriate value for μ.

Value of μ	Average price difference
0.1	2.320
0.2	1.717
0.3	1.911
0.4	1.712
0.5	1.546
0.6	2.220
0.7	2.461
0.8	2.057
0.9	2.069
1.0	2.293

Table 5.9: Average price differences of the simulations in the pre-study of μ.

5.2.2.3 The Number of the Repeated Rounds

This work aims to study the system dynamics and the behavior of agents in the "long run." Samuelson (1998) suggests that the long-run concept that one should be interested in is some period of time long enough for the process to have converged to a stable pattern of behavior. It is then necessary to find out the appropriate simulation-run length z, which satisfies the long-run concept.

In the trial simulations so far, z is always set to 50, and it seems that the evolution to a stable state can always be observed within the fifty rounds, in which no agent seeks to leave the current marketplace. Thus, a simulation length of fifty rounds seems to be long enough to deliver a distinguishable stable pattern for analysis. Therefore, in the following simulations, the fixed factor z is commonly set to 50.

5.2.2.4 Summery of the Section

As a short summary of the above pre-studies in Sections 5.2.2.1, 5.2.2.2, and 5.2.2.3, Table 5.10 lists the values of the three fixed factors, which are commonly set in all the simulations hereinafter.

Fixed factor	Value used in simulation
μ	0.5
$\bar{v}_b$	10.0
z	50

Table 5.10: Values of the fixed factors used in the simulation experiment.

5.3 Treatment Design

In this section, the research questions proposed in the first chapter of this work are converted into simulation settings, so that they can be conducted by computer simulations.

According to the research questions, the simulation experiments mainly investigate the influence of the following three aspects on the system dynamics: the *population size*, the *aggregate seller-buyer ratio*, and the *listing fee*.

The population size refers to the number of all agents in the whole economy. Its value is the sum of the number of sellers and buyers in both marketplaces. Obviously, the factor n corresponds to the aspect population. The aggregate seller-buyer ratio is defined by the number of sellers in both marketplaces divided by the number of buyers in both marketplaces. The factors $s^1(M_A)$, $b^1(M_A)$, $s^1(M_B)$, and $b^1(M_B)$ together implicitly define the aggregate seller-buyer ratio. The listing fee corresponds to the factors $l(M_A)$ and $l(M_B)$. For each aspect, the factors could be designated with many different values. Thus, the combinations of the factors form a huge parameter space. Figure 5.3 depicts the parameter space used in this work.

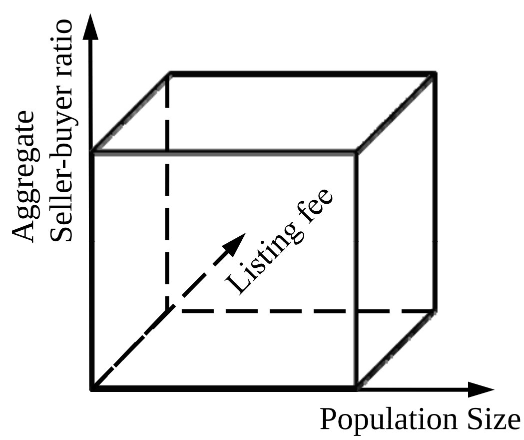


Figure 5.3: The experimental factor space.

According to the parameter space, the simulation experiments are designed according to two categories: experiments without listing fees, and experiments with listing fees. The first category considers the aspect of the population size and the seller-buyer ratio, and the aspect of the listing fee is added in the latter category of experiments. Sections 5.3.1 and 5.3.2 present the treatments in those two categories, respectively.

5.3.1 Treatments without Listing Fees

In this section, several treatments are designed, with each treatment consisting of several simulation settings drawn from the factor space. On the one hand, a setting investigates a certain combination of the factors. On the other hand, if the simulation results from different settings or treatments are compared, a comprehensive understanding of the simulation over the factor space can be obtained.

5.3.1.1 Treatment A

Treatment A is intended to simulate a small population. It comprises two settings. As one can easily see, the initial distribution of the agents in setting A1 is the same as that of the trial simulations. In setting A2, the initial distribution of sellers and buyers is generated randomly. The random generation method is also applied to determine the initial distributions in most of the simulation settings afterwards.

The trial experiments in Section 5.2 simulate an economy with twenty agents. This is a rather small population. Treatment A continues to simulate on this scale with two simulation settings, as shown in Table 5.11.

Setting	n	s	b	$s^1(M_A)$	$b^1(M_A)$	$s^1(M_B)$	$b^1(M_B)$
A1	20	6	14	2	5	4	9
A2		4	16	1	10	3	6

Table 5.11: Simulation settings in Treatment A.

5.3.1.2 Treatments B and C

This subsection introduces two treatments, Treatment B and Treatment C, both of which are intended to run simulations within a medium-sized population. Three hundred agents are used in both treatments. Tables 5.12 and 5.13 list the simulation settings in these two treatments, respectively.

Setting	n	s	b	$s^1(M_A)$	$b^1(M_A)$	$s^1(M_B)$	$b^1(M_B)$
B1	300	100	200	29	108	71	92
B2				25	50	75	150
B3				18	96	82	104
B4				7	80	93	120

Table 5.12: Simulation settings in Treatment B.

Setting	n	s	b	$s^1(M_A)$	$b^1(M_A)$	$s^1(M_B)$	$b^1(M_B)$
C1	300	60	240	11	20	49	220
C2				35	48	25	192
C3				40	120	20	120
C4				45	80	15	160

Table 5.13: Simulation settings in Treatment C.

These two treatments are designed to study how the simulation dynamics change if the demand-supply relationship significantly changes. Therefore, the largest difference between the two treatments is the aggregate seller-buyer ratio. The ratio in every setting of Treatment B is 0.5, which means that the three hundred agents consist of one hundred sellers and two hundred buyers. In comparison, the ratio in Treatment C is only 0.25. For each of these treatments, fours settings are investigated, which differ in the initial distribution of the agents.

5.3.1.3 Treatments D and E

Compared to Treatment B and Treatment C, Treatments D and E are intended to study the simulation dynamics within a relatively large population. In both treatments there are 4500 agents. Similarly, the largest difference between Treatment D and E is also the aggregate seller-buyer ratio. The ratio in Treatment D is 0.5, while in Treatment E it is 0.25. Simulations under these two treatments aim to find out whether the simulation dynamics share some common characteristics with those settings in Treatment B and Treatment C within a smaller population.

Setting	n	s	b	$s^1(M_A)$	$b^1(M_A)$	$s^1(M_B)$	$b^1(M_B)$
D1	4500	1500	3000	4	447	1496	2553
D2				49	492	1451	2508
D3				364	642	1136	2358
D4				336	1834	1164	1166

Table 5.14: Simulation settings in Treatment D.

Setting	n	s	b	$s^1(M_A)$	$b^1(M_A)$	$s^1(M_B)$	$b^1(M_B)$
E1	4500	900	3600	82	541	818	3059
E2				162	2717	738	883
E3				270	857	630	2743
E4				322	2505	578	1095

Table 5.15: Simulation settings in Treatment E.

5.3.1.4 Summary of the Section

To give an overview of the above treatment settings, Figure 5.4 locates the treatments in the experimental factor space. The domain has only two dimensions, because listing fees are not considered in these treatments. The population size is segmented into three levels along the horizontal axis. A simulation setting with twenty agents is used for the low level; a setting with three hundreds agents is of the middle level; and a setting with 4500 agents is used for the large population level. Similarly, the axis of the aggregate seller-buyer ratio is divided into a low ratio part and a high ratio part. In this study, a setting with an aggregate seller-buyer ratio of 0.25 is classified as a low ratio, and a ratio of 0.5 is then the high one. Note that the aggregate seller-buyer ratios are different between the settings in Treatment A, thus Treatment A is located somewhere between a high ratio and a low ratio.

5.3.2 Treatments with Listing Fees

One of the research questions proposed in the first chapter of this work is about two marketplaces' competition with listing fees. So far, the simulation experiments have

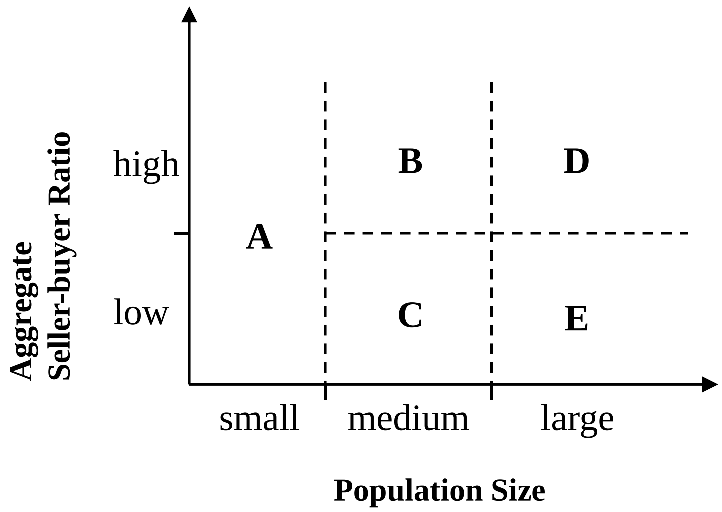


Figure 5.4: Location of the treatments without listing fees in the experimental factor space.

been considered under the case without listing fees. In this section, several treatments are designed, so that the dynamics of simulations with listing fees can also be studied.

Basically, there are two cases. One case is that both marketplaces charge the same listing fee, abbreviated as the *symmetric listing fee* case. The other case is that the two marketplaces charge different listing fees, abbreviated as the *asymmetric listing fee* case. Sections 5.3.2.1 and 5.3.2.2 introduce the treatments under those two cases, respectively.

5.3.2.1 Symmetric Listing Fees

A special case of the symmetric listing fee scenario is the case in which both marketplaces charge no listing fee. Clearly, simulations under this case should have the same characteristics with other simulations without listing fees. It is interesting to compare this scenario with cases in which both marketplaces charge a positive listing fee. Do the simulation dynamics still share the same characteristics with those under treatments without listing fees?

Treatment F defines the simulation settings in the symmetric listing fee case, as

Setting	n	s	b	$s^1(M_A)$	$b^1(M_A)$	$s^1(M_B)$	$b^1(M_B)$	$l(M_A)$	$l(M_B)$
F1(B1)	300	100	200	29	108	71	92	0.0	0.0
F2								3.0	3.0
F3								6.0	6.0
F4(D4)	4500	1500	3000	336	1834	1164	1166	0.0	0.0
F5								3.0	3.0
F6								6.0	6.0
F7(E1)	4500	900	3600	82	541	818	3059	0.0	0.0
F8								3.0	3.0
F9								6.0	6.0

Table 5.16: Simulation settings in Treatment F.

listed in Table 5.16. The treatment contains three groups of settings. Settings F1, F2, and F3 are in the first group. In setting F1, both marketplaces charge the same listing fee of zero. This setting is actually the same as setting B1. In setting F2 and F3, the listing fees charged by the marketplaces are still equal, but the value increases to 3.0 and 6.0 respectively.[19] Simulations under these three settings are intended to investigate whether symmetric listing fees may significantly affect the simulation dynamics.

The remaining two groups of settings are similarly designed. Each group contains three settings, and the listing fees of the settings within a group increase from 0.0 to 6.0.

It shall be mentioned that the design is intended to facilitate comparisons between the groups. In the first two groups, the aggregate seller-buyer ratios are both equal to 0.5. In the latter two groups, the population is set to 4500 agents. Thus, by comparing the simulation data between two groups, it is feasible to determine whether the simulation is dependent on a certain aspect (i.e., the population or the aggregate seller-buyer ratio) or not.

[19] The highest possible valuation of a buyer is 10.0. Although it is possible to set the listing fees as high as 10.0, it does not make sense to study this scenario, since no seller could receive a positive payoff in any of the marketplaces.

5.3.2.2 Asymmetric Listing Fees

This subsection defines the treatments for the case where the two marketplaces charge different listing fees. Table 5.17 lists all the treatment settings in this case.

Treatment G corresponds to the case that one marketplace charges a listing fee, while the other marketplace does not. The initial distribution of agents in Treatment G is a half-split situation. In setting G1, both marketplaces charge zero listing fees. Simulations under G1 are intended to show whether the simulation system that starts from a possible steady state can stay at this state.[20]

Setting	n	s	b	$s^1(M_A)$	$b^1(M_A)$	$s^1(M_B)$	$b^1(M_B)$	$l(M_A)$	$l(M_B)$
G1	300	100	200	50	100	50	100	0.0	0.0
G2								0.0	3.0
G3								0.0	6.0
G4								0.0	8.0
H1	300	100	200	25	50	75	150	1.0	3.0
H2								1.0	6.0
H3								3.0	1.0
H4								6.0	1.0
I1	4500	1500	3000	364	642	1130	2358	1.0	3.0
I2								1.0	6.0
I3								3.0	1.0
I4								6.0	1.0
J1	4500	900	3600	270	857	630	2743	1.0	3.0
J2								1.0	6.0
J3								3.0	1.0
J4								6.0	1.0

Table 5.17: Simulation settings in Treatments G, H, I, and J.

Compared to setting G1, M_A still charges no listing fee in setting G2, whereas M_B charges a fee of 3.0. Simulation runs under those two settings need to be compared, to see whether the listing fee is a factor that independently discriminates the simulation dynamics or not.

[20] The trial simulations in Section 5.2 have shown that simulation may evolve to a stable state with a half-split of buyers and sellers between the marketplaces.

Treatment H aims to study how the amount of the listing fee influences the simulation dynamics. In both H1 and H2, the marketplace M_A charges a low fee of 1.0, while M_B charges a higher fee. Compared to H1, M_B charges a higher fee of 6.0 in H2. In contrast to H1 and H2, M_A charges a higher listing fee than M_B in setting H3 and H4. And the fee charged by M_A in H4 is even higher than in H3.

Treatments I and J are designed in a similar way as Treatment H. Now those treatments under asymmetric listing fees are compared. Treatments G and H share the same population of 300 agents. The aggregate seller-buyer ratio in Treatments G, H and I are all 0.5, and in Treatment J the ratio is only 0.25. Treatments I and J share the same population of 4500 agents. The initial distributions of the agents in those treatments are also randomly generated. The significant difference between Treatment H, I, and J is the population. Besides, in both Treatments H and I, the aggregate seller-buyer ratio is 0.5, while in Treatment J the ratio is only 0.25. In this way, the treatments are able to cover most of the factor space.

5.4 Summary

This chapter deals with the design of the simulation experiment based on the simulation model given in Chapter 4. Firstly, the factors and responses are defined in Section 5.1. The factors consist of fixed factors and experimental factors.

The analysis and design of an experiment can be distinguished but usually cannot be easily and completely separated. In practice, the analysis of the simulation output is usually performed after several observations have been obtained, and this is called a multi-stage approach.

The multi-stage approach is used in this study. In Section 5.2, the simulation program is run for trials. The trial simulations are used to validate the computer algorithms which implement the simulation model, as well as to get a first impression of the simulation dynamics. Section 5.2.2 continues to run trial simulations, in order to find out the appropriate values of the fixed factors.

Based on the above work and according to the research questions, a series of simulation experiments are defined in Section 5.3. Simulation data from each treatment will be analyzed in the next chapter.

Chapter 6

Simulation Results and Analysis

This chapter analyzes the simulation data derived from the simulation experiments. The experiments are conducted according to the treatment settings designed in Chapter 5. Section 6.1 defines the concept of the steady state in this work, and then studies the dynamics of the system towards a steady state and the dynamics after mutating from that state. Section 6.2 analyzes the characteristics of the steady states, based on the simulations without listing fees. Statistical analysis is used to test observations for significance. In Section 6.3 the simulation experiments conducted with listing fees are analyzed. This section aims to find out whether the characteristics of the steady states still hold true in treatments without listing fees, and whether there are new characteristics in treatments with listing fees. Section 6.4 discusses the simulation results, and compares the results with those in the related literature. The findings are summarized at the end of the chapter.

6.1 The Steady State

A problem commonly encountered in simulation systems is that the performance measures observed during the initial part of a simulation run are different from the long-run outcomes. It normally takes some time for the effect of the starting conditions to become insignificant and for the simulation model to stabilize, or to reach the *steady state* (Graybeal and Pooch, 1980, p. 145). The analysis of the simulation results under steady-state conditions is then desirable, since it is normally under these conditions that the simulated system's true characteristics are shown.

The presented work aims to investigate the steady-state performance of the simulated system. First of all, it is important to know how to determine whether a steady state has been achieved. Section 6.1.1 deals with this question.

6.1.1 Determination of the Steady State

The methods of determining the steady state of a simulation are not unique. Kleinjnen defines a system as being in its steady state if the probability of being in one of its states is governed by a fixed probability distribution (Kleijnen, 1974, p. 69). Graybeal and Pooch point out that one of the simplest methods for the determination of the steady state is to compute a moving average of the performance measure (Graybeal and Pooch, 1980, p. 145). The steady state is assumed to be reached when the successive computations of the system state variables no longer vary significantly. In this study, the method recommended by Graybeal and Pooch is applied.

The trial simulations conducted in Chapter 5 show that the system seems to converge to a stable state by the end of the simulations, in which no agent seeks to move away from his current marketplace. Based on this observation, in this work, the simulation system is considered to reach a steady state if, from a certain simulation round onward, the number of sellers and the number of buyers in each marketplace does not vary, and meanwhile the number of agents' movements between any two successive rounds equals zero.

6.1.2 Dynamics Towards the Steady State

Before analyzing the data from many simulation settings, it is illustrative to study the simulation dynamics under one simulation setting in detail. One simulation run under

Setting B1 is studied here.

The dynamics of the winning prices and the distribution of agents in the two marketplaces are shown in Figure 6.1 and Figure 6.2 respectively. In both figures, the X-axis is the simulation round. The Y-axis in Figure 6.1 represents the winning price of the auctions; in Figure 6.2 the Y-axis stands for the number of agents in a marketplace.

In this simulation there are 100 sellers and 200 buyers, that is, 300 agents in total. By random designation in the first simulation round, 29 out of 100 sellers and 108 out of 200 buyers join marketplace A, while the remaining 71 sellers and 92 buyers join marketplace B. Obviously, M_A contains relatively more buyers than M_B, and there are relatively fewer sellers in M_A.

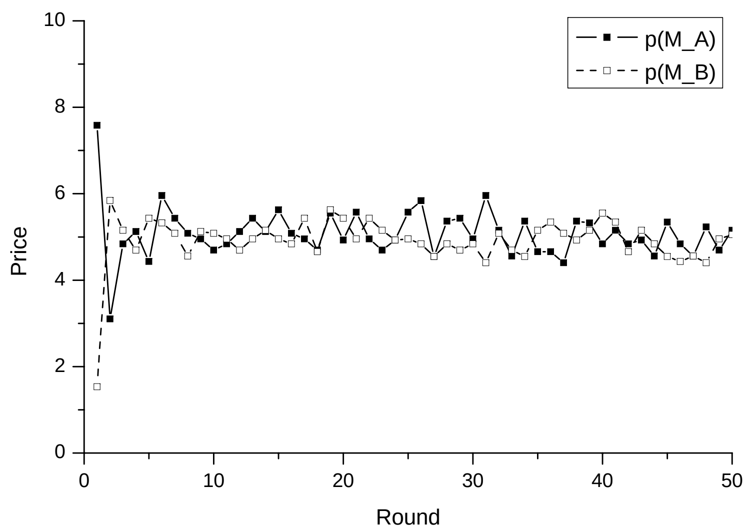


Figure 6.1: Dynamics of the winning prices: one simulation run under Setting B1.

Given this initial distribution, the winning prices of the auctions in the first round turn out to be $p(M_A) = 7.582$ and $p(M_B) = 1.531$, respectively. Observing these prices, each agent calculates his real payoff and compares it with his presumed payoff in the other marketplace. Sellers always prefer the marketplace with the higher price, and on observing a price difference of 6.051, 14 sellers leave M_B and participate in M_A in the second round (R^2). Buyers prefer M_B because of the lower winning price, and as a result 49 buyers leave M_A and join M_B in R^2. These movements trigger significant

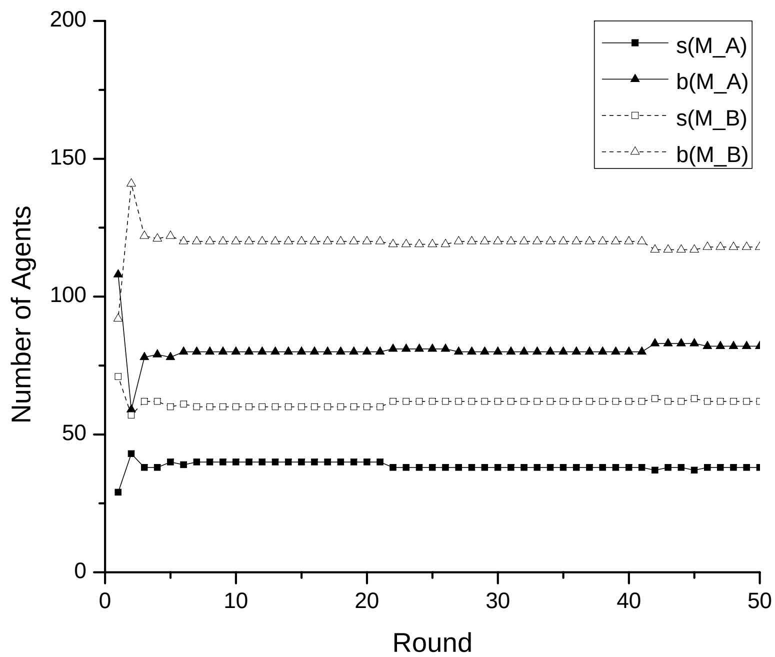


Figure 6.2: Dynamics of the movements of agents: one simulation run under Setting B1.

changes in the demand-offer relationship in the second round — M_A now contains 43 sellers and 59 buyers, while 57 sellers and 141 buyers participate in M_B.

Consequently, the winning price in M_A, which was much higher in M_B in the first round, turns out to be only 3.104 in the second round. In comparison, $p(M_B)$ in the second round is now as high as 5.843. The simulation dynamics show that on the one hand, agents calculate payoffs according to the prices and then make their decisions; on the other hand, the agents' decisions influence the prices.

Now the dynamics of the price difference is analyzed. The price difference in the first round is 6.051. The movement of agents in the second round leads to the price difference being reduced to 2.739. As the simulation continues, it can be seen that the price difference varies within a relative narrow range in the simulation rounds afterward. The average price difference between the two marketplaces for the remaining 48 rounds is as small as 0.45.

The movements of agents are also reduced in the meantime. Figure 6.2 shows that from round R^7 onward, the distribution of agents is stable, with M_A containing

40 sellers and 80 buyers while M_B contains 60 sellers and 120 buyers. The detailed simulation data shows that the stableness in the distribution of agents is due to the number of movements being reduced to zero in these rounds. This means that in these rounds, each agent chooses to stay in his current marketplace.

R^t	$s^t(M_A)$	$b^t(M_A)$	$s^t(M_B)$	$b^t(M_B)$	$\gamma^t(M_A)$	$\gamma^t(M_B)$
1	29	108	71	92	0.27	0.77
50	40	80	60	120	0.5	0.5

Table 6.1: Distribution of agents at simulation initialization and termination: one simulation run under Setting B1.

Table 6.1 compares the distribution of agents at simulation initialization and termination. To see how the distribution has changed, the table includes the seller-buyer ratios of the two marketplaces. The seller-buyer ratio in M_A is given by $\gamma(M_A) = s(M_A)/b(M_A)$ and similarly $\gamma(M_B) = s(M_B)/b(M_B)$.

One can see from Table 6.1 that at the beginning of the simulation, the seller-buyer ratio in M_A is much smaller than in M_B. However, at simulation termination the seller-buyer ratios in the marketplaces equal each other — $\gamma(M_A) = \gamma(M_B) = 0.5$. Notice that the aggregate seller-buyer ratio γ (defined in Section 5.3) is also 0.5. Is this a contingent observation or a typical result?

According to the design of the simulation experiment, the simulation under Setting B1 is repeated thirty times. It is found that these simulation runs all share similar dynamics. The price difference between the marketplaces is reduced at the beginning of the simulation; meanwhile the number of agent movements is reduced, too. As the simulation continues, the number of agents who leave their current marketplaces and switch to their rivals' marketplaces follows the trend of falling, till it decreases to zero in some round. From that round onward, each agent sticks to his current marketplace, and the prices vary within a relative small range. In each of the thirty runs, the simulated system is observed to evolve into a steady state within fifty rounds.

Figure 6.3 displays the distribution of agents at simulation termination in all thirty simulation runs under Setting B1. The X-axis stands for the number of sellers in a marketplace, and the Y-axis stands for the number of buyers in a marketplace. Thus, the number of sellers and buyers that a marketplace contains can be presented by a point in the graph. The rectangle points stand for the status of agents' participance in M_A, while the circular points stand for the status in M_B. For convenience, the initial distribution of agents is also plotted in the graph, but in a larger point size.

It can be easily seen from Figure 6.3 that in the steady states, the number of agents in the marketplaces differs from run to run. In other words, there are many steady states with different distributions of agents, rather than a unique steady state with a deterministic distribution of agents.

Interestingly, the distributions of the agents in the steady states appear to lie along a line where the seller-buyer ratio is 0.5. This means that the seller-buyer ratios in the two marketplaces seem to be similar with each other in all the steady states, and their values are around 0.5, which equals the aggregate seller-buyer ratio. Section 6.2.2 will analyze this in detail.

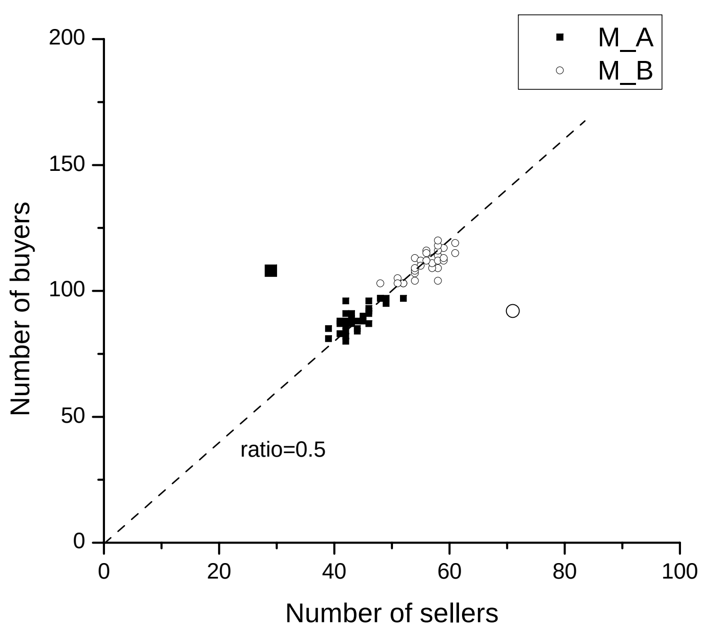


Figure 6.3: Distributions of agents at the end of simulations: thirty simulation runs under Setting B1.

As a short summary of this subsection, the following observations can be concluded from the analysis of the simulation runs under Setting B1.

1. A simulation run under Setting B1 generally evolves into a steady state of market duopoly, in which no agent seeks to move away from his current marketplace.

2. In the evolution process towards a steady state, the price difference between the two marketplaces falls; in the steady state, the price difference varies within a relatively narrow range.

3. The steady state is neither unique nor deterministic. Several simulation runs under the same setting may evolve into multiple steady states, in which the distributions of agents are different from each other.

4. In the steady states reached under Setting B1, the seller-buyer ratios in the two marketplaces are quite close to each other, and close to the aggregate seller-buyer ratio as well. Reflected in the graph, the distributions of agents in the steady states appear to lie along a line where the seller-buyer ratio is 0.5.

The above observations are only based on simulation data under Setting B1. In Section 6.2, simulation data from several other treatment settings will be analyzed, to see whether the above observations still hold true.

6.1.3 Mutation on Steady State

From the analysis in Section 6.1.2 we know that a simulation run under Setting B1 typically evolves into a stable state of market duopoly, in which every agent with bounded rationality sticks with his current marketplace. In this section, the "stability" of the steady state is examined. What happens if some agents become totally irrational, and select marketplaces contrary to their decisions? More interestingly, what happens if the mutation of some agents takes place after a steady state is reached? Will the simulated system evolve into another steady state?

In order to answer the above questions, it is necessary to study a simulation run that allows mutation and then compare it with a simulation run without mutation. In the following, the run without mutation is referred to as the "the original run" and the run with mutation as the "the mutation run."

The simulation run under Setting B1, which is studied in detail in Section 6.1.2, is taken directly as the original run. In order to make a simple comparison, the mutation run first copies the simulation dynamics from the original run, and then allows mutation after the steady state has been reached. The mutation is triggered when the system is in the steady state for ten rounds continuously. Twenty out of three hundred agents are randomly chosen from the two marketplaces, and they mutate by behaving contrary to their original decisions.[21] The mutation of agents is triggered only once throughout a simulation run.

Figure 6.4 shows the dynamics of the movements of agents in the mutation run. The steady state is reached in round R^7. Ten rounds afterwards, i.e., in round R^{16}, the mutation is triggered. Twenty agents are chosen randomly from the marketplaces, and the detailed simulation data manifest that the twenty agents consist of thirteen sellers and seven buyers. Nine out of these thirteen sellers have stayed in M_A since the steady state is reached; they mutate and join M_B in round R^{17}. The other four sellers leave M_B and join M_A in round R^{17}. On the buyer side, six out of the seven buyers leave M_A and join M_B, while the remaining buyer, who participates in M_B in R^{16}, joins M_A in R^{17}. These mutations lead to a situation where M_A contains five less sellers and five less buyers. Correspondingly, M_B contains five more sellers and five more buyers.

Figure 6.4 shows that the distribution of agents appears to be static from round 23 onward, which is the seventh round after the mutation, and the simulated system seems to have reached another steady state. Now the simulation dynamics between

[21] It is also possible to study the simulation dynamics within the case where all the agents who mutate are from the same marketplace. However, such "group mutation" needs some special reasons in reality, such as a group disclaimer or an organized demonstration. It is not the main focus of the presented work to include these additional factors.

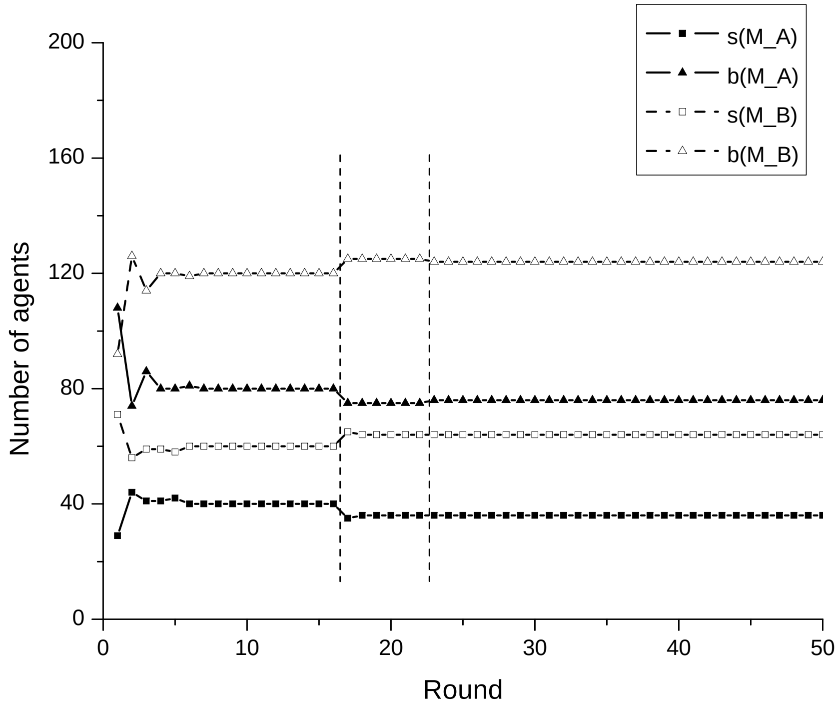


Figure 6.4: Dynamics of the movements of agents in the mutation run.

rounds R^{17} and R^{23} are analyzed in detail.

Table 6.2 shows the distribution of agents and the winning prices in the rounds between R^{16} and R^{24}. The mutation of the twenty agents causes the winning price in M_A to increase from 5.084 to 5.839 in R^{17}, while in M_B the price decreases from 4.839 to 4.431. Compared to R^{16}, the price difference in R^{17} rises almost tenfold from 0.145 to 1.408. Consequently, one seller switches from M_B to M_A in round R^{18}.

The detailed simulation data shows that this seller is one of the agents who mutates and switches from M_A to M_B in R^{17}. However, due to the changes of the prices after the mutation, the seller prefers to switch back to M_A in round R^{18}. The other sellers, who also participate in M_B in R^{17}, prefer to switch to M_A in R^{18}, too. However, it turns out that only this seller switches in R^{18}. Two reasons jointly account for this.

One is that the probability of moving for most of the sellers in M_B in R^{17} is not as high as with this seller. The discount factor of this seller increases because of

R^t	$s^t(M_A)$	$b^t(M_A)$	$s^t(M_B)$	$b^t(M_B)$	$p^t(M_A)$	$p^t(M_B)$
16	40	80	60	120	5.084	4.839
17	35	75	65	125	5.839	4.431
18	36	75	64	125	5.573	5.124
19	36	75	64	125	4.955	5.084
20	36	75	64	125	5.341	4.657
21	36	75	64	125	5.089	4.929
22	36	75	64	125	3.793	4.955
23	36	76	64	124	5.365	4.929
24	36	76	64	124	4.559	5.084

Table 6.2: Simulation dynamics between R^{16} and R^{25} in the mutation run.

the mutation,[22] while most of the sellers in M_B never mutate. Therefore, the price difference of 1.408 in R^{17} is less discounted by this seller than by most of the other sellers, and consequently this seller has a relative higher probability of moving.

There are eight sellers who mutate together with this seller and join M_B in R^{17}. The probabilities of moving by these sellers are relatively higher than with most of the sellers who never mutate. However, they may be not so "lucky" in drawing a decision based on their probabilities of moving — as a result, they all decide to stay.

From round R^{18} till round R^{22}, the distribution of agents is rather stable. The price difference varies in a narrow range between R^{18} and R^{22}, with a mean value of 0.356 and a standard deviation of 0.206. However, the price difference jumps up to 1.162 in round R^{22}. According to the simulation model, buyers' valuations are randomly generated in each round. Therefore, it is possible that in a round a larger price difference occurs.

Due to the changes of the prices in R^{22}, the simulation data shows that several buyers prefer to switch to M_A in R^{23}. Similar to the seller side, the buyers who mutate and join M_A in R^{17} are relatively more sensitive to the larger price difference, compared to other buyers who never mutate. After computing the probabilities of moving and drawing a decision according to the probabilities, it turns out that one buyer switched back to M_A in round R^{23}.

[22] To see why the switch of an agent increases his discount factor, refer to Section 4.7.2.2 in Chapter 4.

From round R^{23} till the end of the mutation run, the distribution of the agents remains the same. Thus, the simulation has evolved into another steady state, in which 36 sellers and 76 buyers participate in M_A, while 64 sellers and 124 buyers join M_B.

The above analysis manifests that the simulated system is able to sustain the mutation of a small proportion of agents, and can quickly converge to another steady state. In the evolution towards a new steady state, it is observed that the agents who have mutated are more sensitive to the variations of the prices. The agents who never mutate have stayed in their current marketplaces for a long enough time, therefore they do not necessarily react to the mutation of other agents.

6.2 Results of the Treatments without Listing Fees

The observations in Section 6.1.2 show the existence of steady states. In this section, the general existence of steady states is examined by simulations under multiple heterogeneous treatment settings, in which listing fees are not considered.

At the same time, this section studies the characteristics of the steady state, whenever it is observed. The analysis focuses on the following three issues in the steady state: a) the average price difference between the marketplaces; b) the seller-buyer ratios in the marketplaces; and c) the distribution of agents.

6.2.1 The Price Difference

The simulations under Setting B1 show that the price difference between the marketplaces follows a trend of decreasing in the dynamics toward a steady state. In the steady state, since the changes of the prices caused by the movements of agents have been eliminated, the prices vary only due to the randomly generated buyers' valuations. The price difference between the marketplaces is therefore relatively small, and seems to vary only within a small range during the steady state. This section examines whether the above observations hold true statistically, and whether they are independent of the setting used.

The thirty simulation runs under the Setting B1 are examined first. For each run, the price differences between the marketplaces in each round are calculated. Take the simulation rounds, during which the system is in the steady state. The average of the price differences in those rounds is defined as the *average price difference during the steady state* (denoted by $\widetilde{\Delta p}$). In contrast, the *average price difference before the steady state* (denoted by $\dot{\Delta p}$) is the average from the first round till the round in which the steady state is reached.

Run	$\dot{\Delta p}$	$\widetilde{\Delta p}$	Run	$\dot{\Delta p}$	$\widetilde{\Delta p}$
1	1.261	0.408	16	1.565	0.555
2	1.478	0.511	17	1.175	0.523
3	1.332	0.429	18	1.265	0.448
4	1.121	0.559	19	1.530	0.456
5	0.994	0.398	20	1.481	0.436
6	1.842	0.541	21	1.422	0.459
7	1.224	0.554	22	1.286	0.416
8	1.340	0.61	23	1.261	0.619
9	1.365	0.528	24	0.971	0.555
10	0.964	0.539	25	1.761	0.639
11	1.521	0.491	26	1.018	0.529
12	0.996	0.327	27	1.791	0.537
13	1.483	0.495	28	1.626	0.515
14	1.408	0.41	29	1.247	0.386
15	1.020	0.393	30	1.138	0.382

Table 6.3: Average price difference before and during the steady state: thirty simulation runs under Setting B1.

For the thirty runs under Setting B1, there are thirty $\dot{\Delta p}$s and thirty $\widetilde{\Delta p}$s correspondingly, as listed in Table 6.3. One can see that for each run $\dot{\Delta p}$ is larger than $\widetilde{\Delta p}$, and the value of $\widetilde{\Delta p}$ seems to be always around 0.5 in those runs. Statistical measurements further show that the mean value of those $\widetilde{\Delta p}$s is 0.488 and the standard deviation is only 0.078 (see Table 6.4).[23] This confirms that the average price difference is small and varies only within a small range during the steady state under Setting B1.

Similar analysis has been conducted for all the other settings in Treatments B, C, D, and E. For each setting, the values of $\widetilde{\Delta p}$ in all the thirty simulation runs are calculated and listed in a table; the corresponding tables are shown in Appendix B. To give an overview, Table 6.4 gives the statistics on $\widetilde{\Delta p}$ in those treatment settings.

In all four settings of Treatment B, the mean values of $\widetilde{\Delta p}$ lie around 0.5, and the deviations are not more than 0.138. This means that given a population of 100 sellers and 200 buyers, a small $\widetilde{\Delta p}$ is always observable in the steady state, independently of the initial distribution of these sellers and buyers.

Such small $\widetilde{\Delta p}$s can also be observed for all simulations under settings in Treatment C. Note that the aggregate seller-buyer ratio in Treatment B is 0.5 while in Treatment C it is only 0.25. Similarly, Treatments D and E are different to each other also in the aggregate seller-buyer ratio, but the $\widetilde{\Delta p}$s in both settings are always around 0.2. This shows that $\widetilde{\Delta p}$ is generally small, independent of the aggregate seller-buyer ratio.

Furthermore, the mean value of $\widetilde{\Delta p}$ is larger in Treatments B and C (in which there are 300 agents) than in Treatments D and E (in which 4500 agents are simulated). The reason for this will be given later in Section 6.2.2, since it would be more explicit to be explained after the characteristic of the seller-buyer ratios in the steady states is studied.

6.2.2 The Seller-buyer Ratios

The simulation runs studied in Section 6.1.2 show that in the steady state the seller-buyer ratios seem to be quite close to each other, and are close to the aggregate seller-buyer ratio as well. In this subsection, more simulations conducted under different

[23]In the presented work, all the statistical measurements are obtained by using the scientific computing and analysis software *OriginPro 7.5*. Refer to http://www.originlab.com/www/helponline/orgin/Origin_Reference_Version_75.htm for more details about the statistical techniques used in the measurements.

Setting	Average price difference during the steady state ($\widetilde{\Delta p}$)				
	Min	Max	Mean	StDev	90% confidence interval
B1	0.327	0.639	0.488	0.078	[0.382, 0.619]
B2	0.357	0.974	0.537	0.138	[0.359, 0.779]
B3	0.372	0.726	0.486	0.082	[0.376, 0.667]
B4	0.304	0.744	0.486	0.102	[0.354, 0.715]
C1	0.401	0.766	0.562	0.089	[0.441, 0.730]
C2	0.291	0.668	0.496	0.097	[0.366, 0.655]
C3	0.334	0.630	0.495	0.073	[0.355, 0.622]
C4	0.298	0.858	0.522	0.134	[0.329, 0.845]
D1	0.116	0.543	0.294	0.124	[0.136, 0.507]
D2	0.124	0.467	0.247	0.090	[0.126, 0.432]
D3	0.078	0.247	0.130	0.037	[0.089, 0.238]
D4	0.074	0.207	0.110	0.029	[0.076, 0.183]
E1	0.132	0.408	0.216	0.065	[0.132, 0.323]
E2	0.103	0.284	0.168	0.042	[0.119, 0.237]
E3	0.108	0.261	0.170	0.039	[0.127, 0.256]
E4	0.080	0.319	0.184	0.054	[0.132, 0.283]

Table 6.4: Statistics on the average price difference during the steady state: simulations under Treatments B, C, D, and E.

settings are analyzed, in order to see whether this is a contingent observation or a typical characteristic.

Ratio	Min	Max	Mean	StDev	90% confidence interval
$\gamma(M_A)$	0.4375	0.5361	0.4944	0.0227	[0.4588,0.5250]
$\gamma(M_B)$	0.4660	0.5577	0.5048	0.0189	[0.4779,0.5321]

Table 6.5: Statistics on the seller-buyer ratios in the steady states: simulations under Setting B1.

Again, the thirty simulation runs conducted under Setting B1 are examined first. For each run, the seller-buyer ratios of the marketplaces ($\gamma(M_A)$ and $\gamma(M_B)$) in the steady state are calculated. Table 6.5 gives the statistical properties of these two ratios. The mean value of $\gamma(M_A)$ out of the thirty runs is 0.4944, with a standard deviation as small as 0.0227. Similarly, the seller-buyer ratio in M_B has a mean value of 0.5048, with a standard deviation of 0.0189. The difference between 0.5 and the mean of $\gamma(M_A)$ is 0.0056, and the difference is 0.0048 between 0.5 and $\gamma(M_B)$. The 90% percentile confidence interval of $\gamma(M_A)$ lies in $[0.4588, 0.5250]$, and for $\gamma(M_B)$ it lies in $[0.4779, 0.5321]$. Given these statistical values, it is reasonable to argue that the two ratios are both close to 0.5, and at the mean time similar to each other.

Table 6.6 lists the statistical measurements of the simulations under Treatment B and D. Simulations under these two settings have the same aggregate seller-buyer ratio of 0.5. One can see that under Treatment B, the mean values of the two ratios are always close to 0.5, and the largest standard deviation is only 0.0343. For simulations under Treatment D, the mean values of the two ratios are also close to 0.5. The aggregate seller-buyer ratio in Treatments C and E is 0.25, and the mean values of $\gamma(M_A)$ and $\gamma(M_B)$ in these two treatments are observed to be both close to 0.25, too (see Table 6.7).

Further, the statistic values between the treatments are compared. Table 6.6 and Table 6.7 show that the standard deviations under Treatment D are generally smaller than those under Treatment B, and those under Treatment E are generally smaller than those under Treatment C.

Setting	Ratio	Mean	StDev	90% confidence interval
B1	$\gamma(M_A)$	0.4944	0.0227	$[0.4588, 0.5250]$
	$\gamma(M_B)$	0.5048	0.0189	$[0.4779, 0.5321]$
B2	$\gamma(M_A)$	0.4843	0.0343	$[0.4238, 0.5469]$
	$\gamma(M_B)$	0.5067	0.0143	$[0.4834, 0.5320]$
B3	$\gamma(M_A)$	0.5018	0.0224	$[0.4605, 0.5385]$
	$\gamma(M_B)$	0.4993	0.0142	$[0.4797, 0.5242]$
B4	$\gamma(M_A)$	0.4867	0.0229	$[0.4429, 0.5156]$
	$\gamma(M_B)$	0.5079	0.0143	$[0.4921, 0.5349]$
D1	$\gamma(M_A)$	0.4685	0.0153	$[0.4435, 0.4921]$
	$\gamma(M_B)$	0.5097	0.0047	$[0.5024, 0.5175]$
D2	$\gamma(M_A)$	0.4742	0.0108	$[0.4508, 0.4893]$
	$\gamma(M_B)$	0.5080	0.0035	$[0.5033, 0.5153]$
D3	$\gamma(M_A)$	0.5004	0.0089	$[0.4885, 0.5183]$
	$\gamma(M_B)$	0.4999	0.0033	$[0.4931, 0.5044]$
D4	$\gamma(M_A)$	0.4979	0.0049	$[0.4908, 0.5054]$
	$\gamma(M_B)$	0.5019	0.0043	$[0.4953, 0.5076]$

Table 6.6: Statistics on the seller-buyer ratios in the steady states: simulations under Treatments B and D.

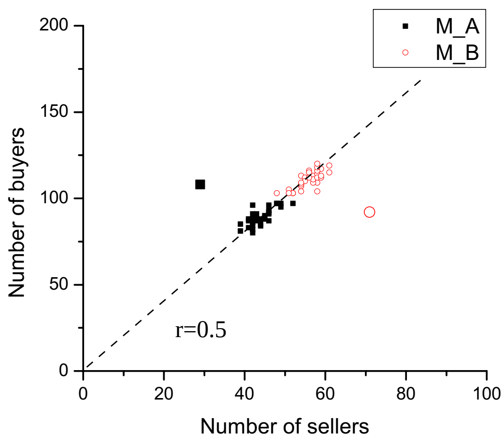
This is due to the different population sizes used in the simulations. The movement of a single agent can lead to greater changes in the prices and in the seller-buyer ratios in a smaller population than in a larger population. Therefore, it may happen in the case of a small population size that an agent switches due to a price difference, but this movement leads to an even larger price difference. Large populations, on the other hand, are robust to these effects. The movement of an agent in a larger population is more likely to "fine tune" the price difference as well as the difference between the seller-buyer ratios down to a lower level than in a smaller population. This also explains why the average price difference in the steady states is relatively lower in Treatment D and E (with 4500 agents) than in Treatment B and C (with 300 agents).

Setting	Ratio	Mean	StDev	90% confidence interval
C1	$\gamma(M_A)$	0.2309	0.0270	$[0.1818, 0.2766]$
	$\gamma(M_B)$	0.2577	0.0099	$[0.2432, 0.2759]$
C2	$\gamma(M_A)$	0.2478	0.0146	$[0.2222, 0.2736]$
	$\gamma(M_B)$	0.2517	0.0126	$[0.2313, 0.2783]$
C3	$\gamma(M_A)$	0.2563	0.0150	$[0.2345, 0.2910]$
	$\gamma(M_B)$	0.2421	0.0198	$[0.2000, 0.2727]$
C4	$\gamma(M_A)$	0.2626	0.0173	$[0.2326, 0.2910]$
	$\gamma(M_B)$	0.2349	0.0202	$[0.1981, 0.2703]$
E1	$\gamma(M_A)$	0.2530	0.0105	$[0.2356, 0.2757]$
	$\gamma(M_B)$	0.2495	0.0019	$[0.2456, 0.2525]$
E2	$\gamma(M_A)$	0.2504	0.0041	$[0.2413, 0.2591]$
	$\gamma(M_B)$	0.2496	0.0037	$[0.2419, 0.2575]$
E3	$\gamma(M_A)$	0.2540	0.0057	$[0.2468, 0.2652]$
	$\gamma(M_B)$	0.2483	0.0024	$[0.2436, 0.2514]$
E4	$\gamma(M_A)$	0.2455	0.0037	$[0.2389, 0.2512]$
	$\gamma(M_B)$	0.2546	0.0037	$[0.2487, 0.2612]$

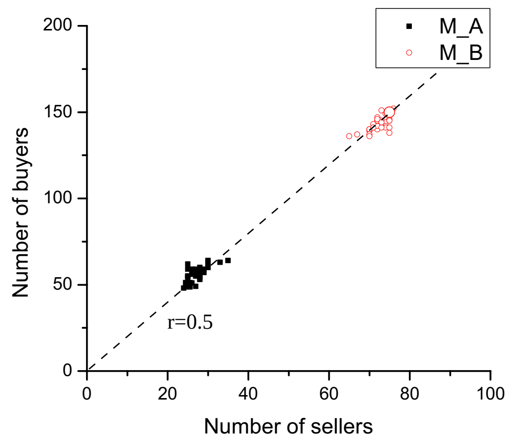
Table 6.7: Statistics on the seller-buyer ratios in the steady states: simulations under Treatments C and E.

6.2.3 The Distribution of Agents

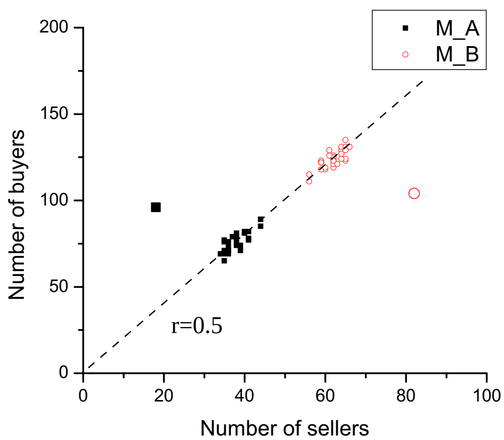
The analysis in Section 6.2.2 shows that the seller-buyer ratios of the marketplaces are generally similar to each other in the steady states. If displayed in a graph, the distributions of the agents under the same Setting B1 seem to form a straight line in the steady states rather than randomly scattering (see Figure 6.3, for example).



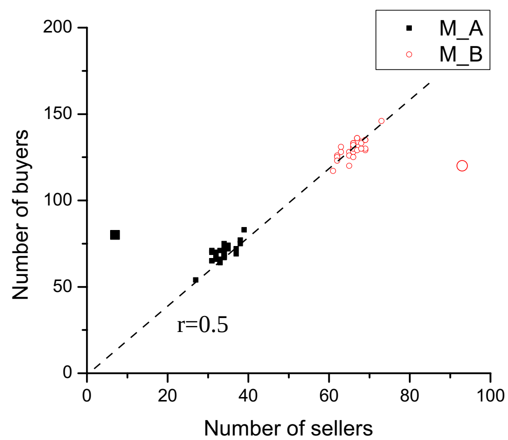
(a) Thirty simulation runs under Setting B1



(b) Thirty simulation runs under Setting B2



(c) Thirty simulation runs under Setting B3



(d) Thirty simulation runs under Setting B4

Figure 6.5: Distributions of agents in the steady states: simulations under Treatment B.

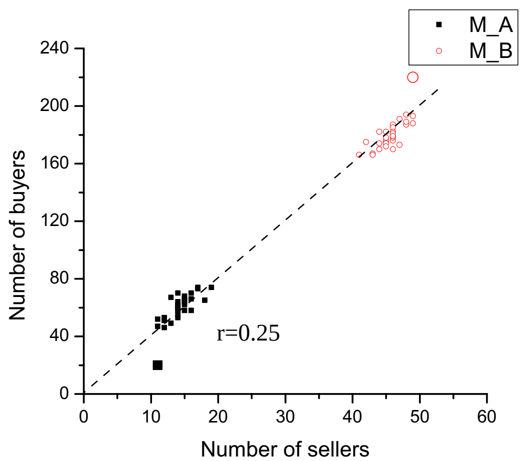
In this section, the distribution of agents in more simulations under different settings is examined. The objective of the analysis is to find out a) whether a broad range of possible distributions along a straight line is a general result; and b) what the relationship is between the number of sellers and the number of buyers.

Figure 6.5 depicts the distribution of agents in the four settings of Treatment B. Although the thirty simulation runs under each setting all start from the same initial distribution, the distributions of agents always lie across a broad range in the steady states. Moreover, the range of the distribution of agents is different from setting to setting. This is because the distributions of agents already differ from one another at simulation initialization. Besides, the distributions under Setting B2 appear special in comparison with the other three settings, in that the distributions of agents in the steady states are quite similar to the initial distribution. This is because the demand-offer relationship is already in a balance status at the beginning of the simulations. This makes the winning prices in the marketplaces already close to each other at simulation initialization; thus not many agents are motivated to move. Consequently, a simulation ends with a similar distribution.

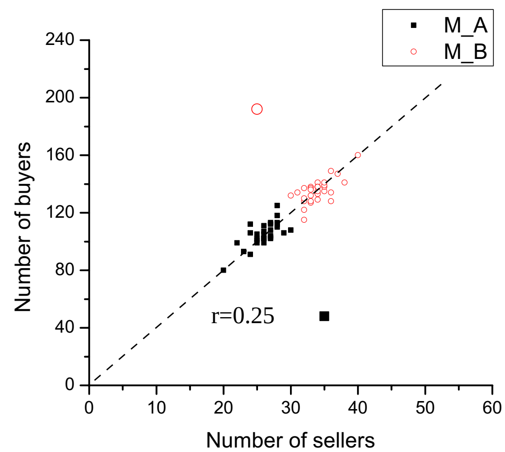
The broad range of the distributions of agents in the steady states, as observed under Treatment B, can also be observed under Treatments C, D, and E. Figures 6.6, 6.7, and 6.8 display the distributions of agents under these three treatments, respectively.

These figures also give an impression that for a marketplace in a steady state, the more sellers there are, the more buyers there are, and vice versa. Recall that the seller-buyer ratios of the marketplaces are similar to each other. It is then expected that the correlation between the number of sellers and the number of buyers in the steady states is strong. Note that there are only two marketplaces available for agents to switch, and that the total number of sellers the total number of buyers are both constants in a simulation run. Thus, the correlation between the number of sellers and the number of buyers in one marketplace must equal the correlation in the other marketplace. Therefore, it is enough to calculate the correlation in one of the marketplaces.

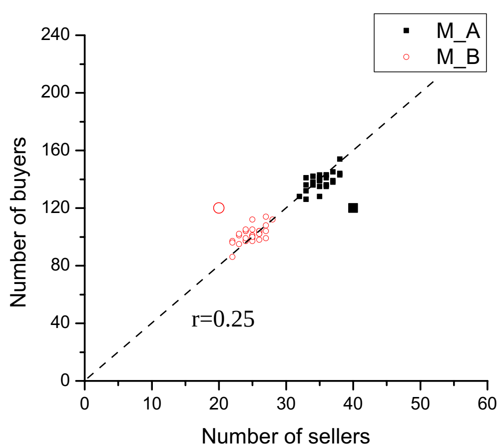
In this study, the Pearson's correlation coefficient is used to measure the correlation. Table 6.8 lists the values of the correlation coefficient of simulations under settings in Treatments B, C, D, and E. One can see that in all these settings, the coefficient is



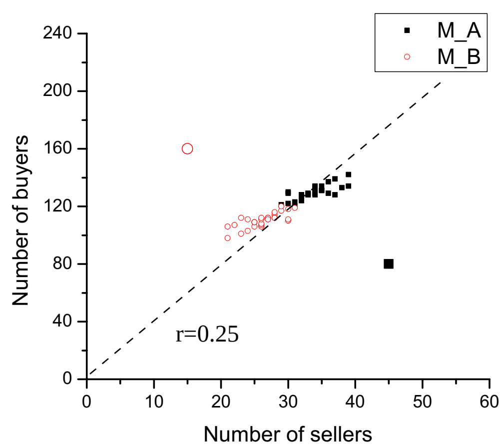
(a) Thirty simulation runs under Setting C1



(b) Thirty simulation runs under Setting C2

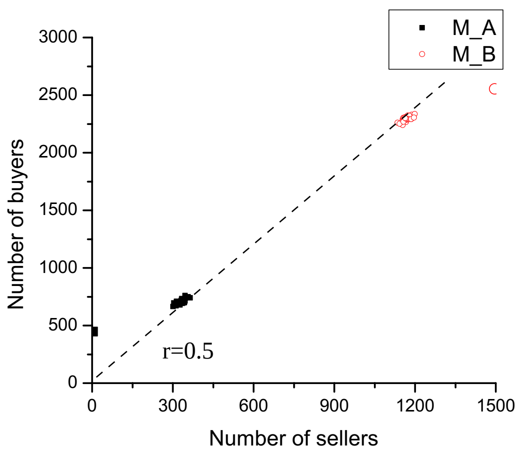


(c) Thirty simulation runs under Setting C3

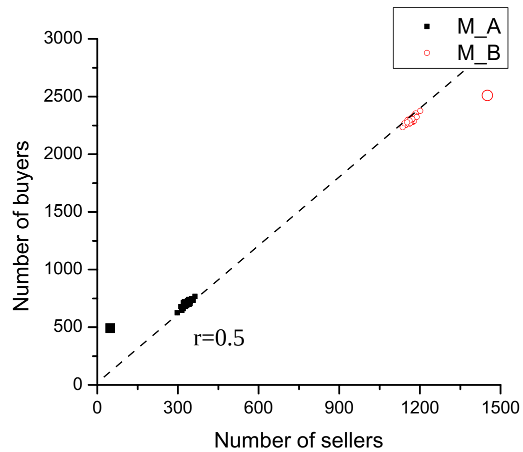


(d) Thirty simulation runs under Setting C4

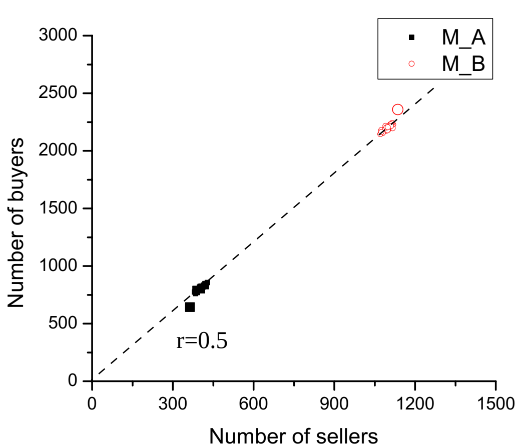
Figure 6.6: Distributions of agents in the steady states: simulations under Treatment C.



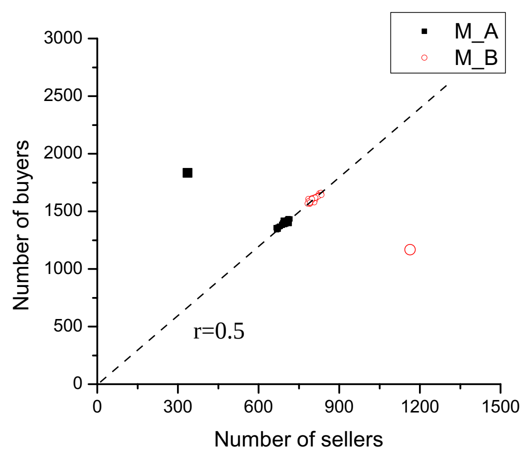
(a) Thirty simulation runs under Setting D1



(b) Thirty simulation runs under Setting D2

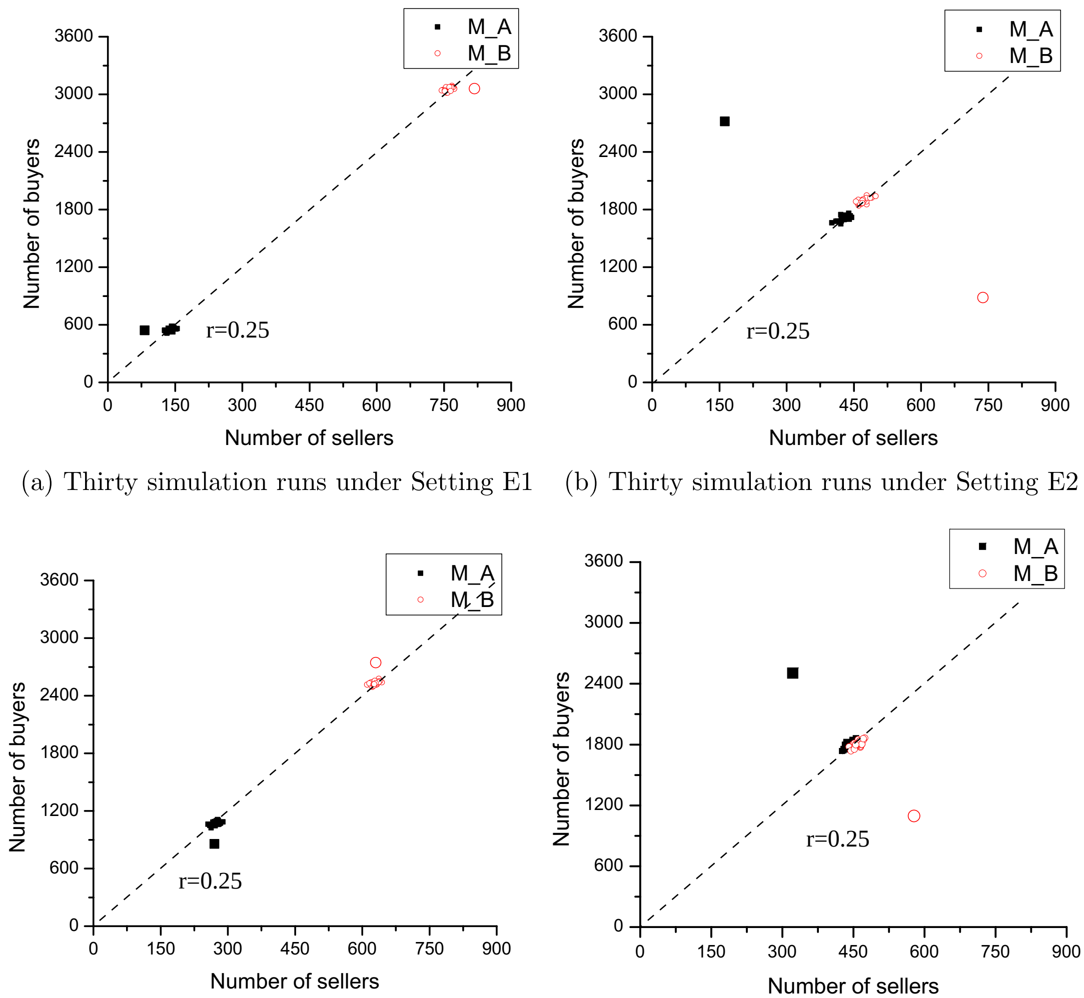


(c) Thirty simulation runs under Setting D3



(d) Thirty simulation runs under Setting D4

Figure 6.7: Distributions of agents in the steady states: simulations under Treatment D.



(a) Thirty simulation runs under Setting E1

(b) Thirty simulation runs under Setting E2

(c) Thirty simulation runs under Setting E3

(d) Thirty simulation runs under Setting E4

Figure 6.8: Distributions of agents in the steady states: simulations under Treatment E.

Setting	Pearson's correlation coefficient
B1	0.751
B2	0.618
B3	0.780
B4	0.794
C1	0.781
C2	0.715
C3	0.637
C4	0.770
D1	0.680
D2	0.866
D3	0.826
D4	0.881
E1	0.643
E2	0.656
E3	0.674
E4	0.717

Table 6.8: Pearson's correlation coefficient in simulations under Treatments B, C, D, and E.

always higher than 0.6.[24]

Correlation	**Negative**	**Positive**
Small	-0.3 to -0.1	0.1 to 0.3
Medium	-0.5 to -0.3	0.3 to 0.5
Large	-0.5 to 1.0	0.5 to 1.0

Table 6.9: Interpretation of correlations in social science research.

The interpretation of the correlation coefficient depends on the context and purpose. Cohen suggests an interpretation for correlations in social science research, as shown in Table 6.9 (Cohen, 1988). According to the table, the correlation coefficient is large in the simulations. This indicates that the strength of a linear relationship between the number of sellers and the number of buyers in a marketplace is strong.[25]

[24]What is worth mentioning is that the value of the Pearson correlation coefficient alone may not be sufficient to evaluate this relationship, especially in the case where the assumption of normality is incorrect. Therefore, the correlation coefficient, as a summary statistic, cannot replace the individual examination of the data.

[25]One may argue that numerical simulations are different from social science researches such as

6.2.4 A Special Case: Small Population

So far, the analysis has focused on the medium and the large population. This section analyzes the simulations within a small population of only twenty agents (i.e., under Treatment A). As one will later see, the characteristics of the steady states under Treatment A are not similar to those within the medium and the large population, and the main reason is the size of the population.

Run	$\dot{\Delta}p$	$\widetilde{\Delta p}$	Run	$\dot{\Delta}p$	$\widetilde{\Delta p}$
1	1.799	3.397	16	2.258	2.1
2	3.279	2.281	17	1.65	2.042
3	4.014	2.374	18	2.742	2.194
4	3.264	1.806	19	6.96	3.349
5	3.609	1.94	20	2.34	2.064
6	3.09	4.366	21	2.933	1.621
7	2.913	2.029	22	0.316	1.95
8	2.656	1.734	23	1.546	2.219
9	1.672	1.566	24	2.488	2.663
10	4.521	1.588	25	3.21	2.112
11	3.233	2.513	26	1.99	2.328
12	3.697	2.419	27	2.409	1.768
13	3.2	3.302	28	4.135	2.457
14	2.609	2.703	29	2.181	2.02
15	1.133	2.148	30	3.579	4.59

Table 6.10: Average price difference before and during the steady state: thirty simulation runs under Setting A1.

Firstly, the aspect of the price difference is examined. For the thirty simulation runs under A1, Table 6.10 gives the average price difference before and during the steady states. In 11 out of 30 runs (i.e., 36.7% of all runs), $\dot{\Delta}p$ is smaller than $\widetilde{\Delta p}$. This indicates that the price difference between the marketplaces does not significantly drop when the system reaches a steady state. In comparison, the values of $\dot{\Delta}p$ are always larger than $\widetilde{\Delta p}$s in the simulations under Treatments B, C, D, and E (see

psychological studies, and a larger correlation might be necessary to claim a strong linear relationship. Clearly, there is no strict standard about this, and Cohen's suggest is presented here as a reference.

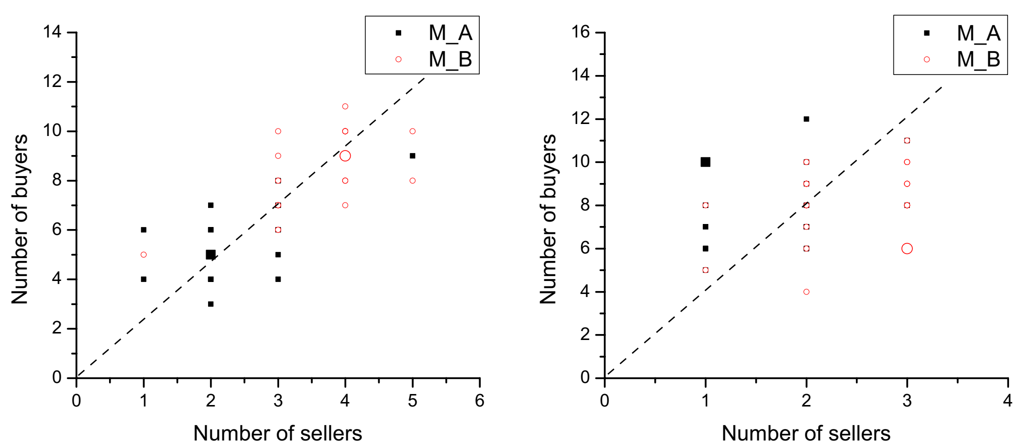
Table 6.3, for example).

The statistical properties of the $\widetilde{\Delta p}$s are calculated for the simulations under both settings in Treatment A, and are listed in Table 6.11. Compared to the statistical measurements under Treatment B, C, D and E (see Tables 6.11 and 6.4), the mean value and the standard deviation of $\widetilde{\Delta p}$s are significantly greater.

Setting	Average price difference during the steady state ($\widetilde{\Delta p}$)				
	Min	Max	Mean	StDev	90% confidence interval
A1	1.566	4.590	2.388	0.742	[1.588, 4.366]
A2	1.316	3.508	1.857	0.458	[1.408, 2.950]

Table 6.11: Statistics on the average price difference during the steady state: simulations under Treatment A.

Secondly, the distributions of agents in the steady states under A1 and A2 are examined. One can see from Figure 6.9 that under neither of the settings does the distribution of agents appear to lie along a straight line, which indicates the aggregate seller-buyer ratio. Rather, the distributions are spread wildly across the graph.



(a) Thirty simulation runs under Setting A1 (b) Thirty simulation runs under Setting A2

Figure 6.9: Distributions of agents in the steady states: simulations under Treatment A.

This is because the above observations are obtained with a very limited number of agents in the simulation. In a marketplace that contains a small population, the difference between the $k - th$ and the $(k + 1) - th$ highest valuations of the buyers is generally greater than that in a marketplace with a larger population. Moreover, the movement of a single agent in a smaller population may lead to a larger variance in the prices than in a larger one, given that the other agents do not move. In a word, both the price difference and the variance of the prices tend to be greater in a small population. It is then easy to understand why both the mean value and the standard deviation of the price difference are significantly greater in simulations with twenty agents than that with 300 agents or 4500 agents.

The above analysis also explains the wide spread of the distribution of agents within the small population. The endogenous principle of the agents' decision-making is that the winning price in a marketplace indicates the demand-offer relationship in that marketplace. However, if a marketplace contains only a few agents, the connection between the price and the demand-offer situation is weakened.

To see this, consider a marketplace with only one seller and two buyers. Clearly, the winning price is the lowest valuation of the buyers. Assume that the price is 2.5 in a simulation round. Then assume that the valuations of the buyers turn out to be 4.3 and 6.0 respectively in the next round. Now the price is 4.3, which is significantly higher than in the former round. However, this is not necessarily related to more demands or fewer offers in the marketplace, but rather to the higher variance of the winning bids.

From the above example, one can see that the decision-making of agents may work less accurately in payoff maximization, when the population size in the economy is very small. It is then not surprising to see that even though the simulations still evolve into steady states, the distributions of agents are actually erratic.

6.2.5 Summary of the Section

As a short summary of Section 6.2, the following observations are concluded.

1. Simulations under treatments without listing fees generally converge to steady states of market duopoly, in which all agents always stick to their current marketplaces.

2. Although the simulations converge to many steady states with different distributions of agents, they share several common characteristics, which include:

a) the winning prices of the two marketplaces vary in a narrow range during the steady states, and the difference between the prices are small.

b) the seller-buyer ratios of the two marketplaces are both close to the aggregate seller-buyer ratio;

c) a strong linear relationship between the number of sellers and the number of buyers in a marketplace exists;

3. However, the above characteristics do not necessarily hold true, in the steady states observed within a small population size (such as twenty agents). This is because both the discrepancy between the buyers' valuations and the variance of the valuations tend to be larger in a small population, which leads to (to some extent) erratic decision-makings by agents in payoff maximization.

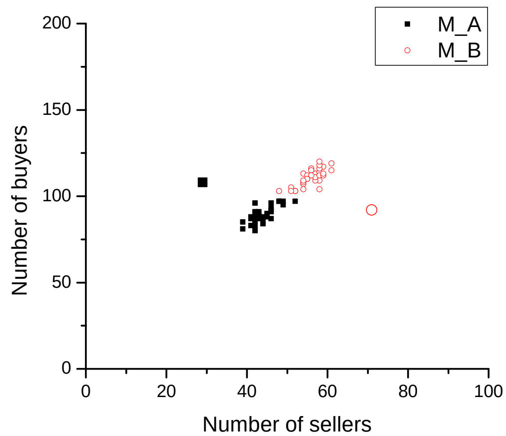
6.3 Results of the Treatments with Listing Fees

According to the design of the simulation experiment in Section 5.3.2, the simulations including listing fees are conducted under two cases: the symmetric case and the asymmetric case. This section analyzes these two cases.

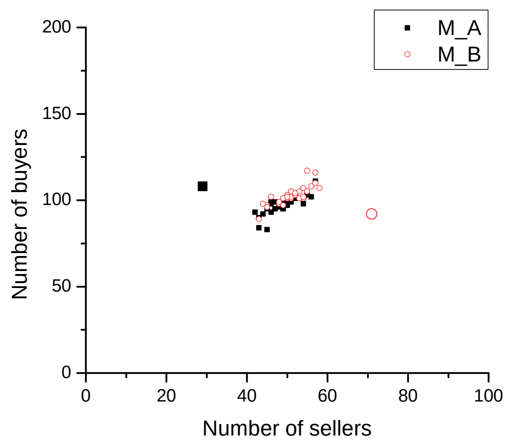
6.3.1 Symmetric Listing Fees

The analysis starts with the simulation data under Settings F1, F2, and F3. In each of these three settings, the two marketplaces charge the same listing fee, but the amount of the listing fee varies from setting to setting. Note that the amount in Setting F1 is zero, which makes Setting F1 actually identical to Setting B1.

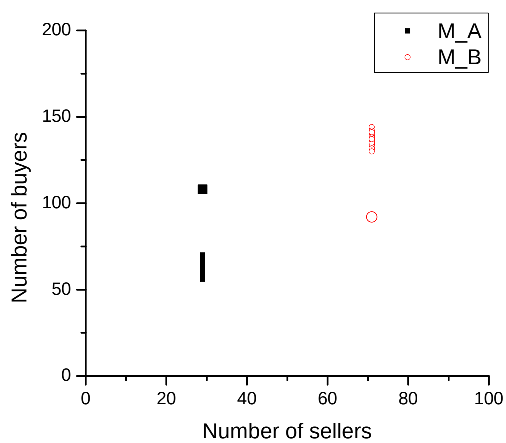
The detailed simulation data shows that steady states are observed in all the simulations under the above three settings. Figure 6.10 depicts the distribution of agents in the steady state under those three settings respectively. The figure shows that the



(a) Thirty simulation runs under Setting F1



(b) Thirty simulation runs under Setting F2



(c) Thirty simulation runs under Setting F3

Figure 6.10: Distributions of agents in the steady states: simulations under Settings F1, F2, and F3.

distributions under Settings F1 and F2 are widely spread and appear to lie along the line that presents a seller-buyer ratio of 0.5 — these characteristics appears to be quite similar to those in simulations without listing fees.

Setting	Ratio	Mean	StDev	90% confidence interval
F1	$\gamma(M_A)$	0.4944	0.0227	$[0.4588, 0.5250]$
	$\gamma(M_B)$	0.5048	0.0189	$[0.4779, 0.5321]$
F2	$\gamma(M_A)$	0.5031	0.0244	$[0.4647, 0.5490]$
	$\gamma(M_B)$	0.4967	0.0230	$[0.4510, 0.5346]$

Table 6.12: Statistics on the seller-buyer ratios in the steady states: simulations under Settings F1 and F2.

In order to confirm this impression, the statistical properties of the seller-buyer ratios are calculated, as listed in Table 6.12. Moreover, Table 6.13 gives the values of the correlation coefficient in these two settings. It is clear that no significant difference is observed between the two settings and the settings under Treatment B, in which listing fees are not included.

Setting	Pearson's correlation coefficient
F1	0.751
F2	0.811

Table 6.13: Pearson's correlation coefficient of simulations under Settings F1 and F2.

Further, the aspect of the price difference is analyzed. Table 6.14 lists the average price differences for each run under F2.[26] Moreover, Table 6.15 gives the statistical properties of the $\widetilde{\Delta p}$s in both settings. Not surprisingly, the average price differences in the steady states are always small under both settings. Although the standard deviation under F2 is larger than in F1, it is not significantly larger, if compared to that under other settings such as B2 and B4.

Compared to the distributions of the agents under F1 and F2, the distributions under F3 appear obviously different. To investigate the details, one simulation run is

[26] See Table 6.3 for the average price differences under Setting F1.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.561	11	0.673	21	0.498
2	0.46	12	0.519	22	0.428
3	0.448	13	0.446	23	0.346
4	0.673	14	0.656	24	0.78
5	0.861	15	0.596	25	0.558
6	0.49	16	0.564	26	0.386
7	0.527	17	0.368	27	0.548
8	0.59	18	0.728	28	0.384
9	0.393	19	0.432	29	0.428
10	0.339	20	0.589	30	0.338

Table 6.14: Average price difference during the steady state: thirty simulation runs under Setting F2.

Setting	Average price difference during the steady state ($\widetilde{\Delta p}$)				
	Min	Max	Mean	StDev	90% confidence interval
F1	0.327	0.639	0.488	0.078	[0.382, 0.619]
F2	0.338	0.861	0.520	0.135	[0.339, 0.780]

Table 6.15: Statistics on the average price differences in the steady states under Settings F1 and F2.

randomly selected out of the thirty runs under F3 and analyzed.

Table 6.16 shows the dynamics of the distribution of agents as well as the dynamics of the winning prices in all fifty rounds. The number of sellers has not changed in either of the marketplaces throughout the simulation run. The detailed simulation data shows that there is no switch by any seller.

The reason for this is that the listing fee, which is 6.0 in both marketplaces in Setting F3, is too high. Note that the winning prices in both marketplaces are often between 4.0 to 6.0. Thus, no matter which marketplace a seller participates in, his real and presumed payoff, according to the simulation model, is often as low as zero. In other words, neither marketplace is able to realize a positive payoff for the sellers, simply because the listing fees for both are too high. Therefore, sellers passively stay in their original marketplaces. The same behavior of sellers can be observed for all thirty simulation runs under F3, the details of which are omitted due to space limitation.

On the buyers' side, the payoffs are not directly determined by the listing fees, but they may switch due to the variations of payoffs, which are influenced by the listing fees. Since the number of the items being offered is "fixed" in each marketplace because of the sellers behavior, it is easy to understand that the buyers' movements quickly balance the demand-offer relationship, and the simulation soon converges to a steady state.

It is noteworthy to mention that the random generation of buyer's valuations in each simulation round makes the prices vary despite there being no change in demand or offer. Thus, the decisions of buyers are not exactly the same in different simulation runs, although the sellers always passively stay in their current marketplaces. This explains why the distributions of buyers in the thirty simulation runs are slightly different from each other, while the distributions of sellers are the same. Reflected in the graph, the distributions of agents in the two marketplaces form two vertical lines, as shown in Figure 6.10c.

This part of the analysis shows that when both marketplaces charge equal listing

R^t	$s^t(M_A)$	$b^t(M_A)$	$s^t(M_B)$	$b^t(M_B)$	$p^t(M_A)$	$p^t(M_B)$
1	29	108	71	92	6.695	1.783
2	29	63	71	137	5.431	4.693
3	29	58	71	142	5.124	4.693
4	29	55	71	145	4.402	5.154
5	29	58	71	142	5.626	5.124
6	29	56	71	144	5.431	5.551
7	29	56	71	144	4.693	5.325
8	29	56	71	144	4.657	4.955
9	29	56	71	144	4.955	5.124
10	29	56	71	144	4.955	5.084
11	29	56	71	144	5.124	4.339
12	29	56	71	144	5.124	4.693
13	29	56	71	144	4.657	5.365
14	29	56	71	144	3.38	5.573
15	29	56	71	144	4.929	5.325
16	29	56	71	144	4.693	5.084
17	29	56	71	144	5.843	4.955
18	29	56	71	144	4.929	5.084
19	29	56	71	144	4.929	5.325
20	29	56	71	144	5.573	4.693
21	29	56	71	144	5.573	5.154
22	29	56	71	144	4.339	5.831
23	29	56	71	144	4.339	5.084
24	29	56	71	144	3.078	5.124
25	29	56	71	144	4.839	5.365
26	29	56	71	144	4.693	5.084
27	29	56	71	144	5.325	5.124
28	29	56	71	144	5.124	4.929
29	29	56	71	144	3.38	4.929
30	29	56	71	144	5.365	4.839
31	29	56	71	144	4.839	5.124
32	29	56	71	144	5.084	5.084
33	29	56	71	144	5.573	5.154
34	29	56	71	144	5.998	5.084
35	29	56	71	144	4.402	4.929
36	29	56	71	144	3.104	5.084
37	29	56	71	144	5.958	5.626
38	29	56	71	144	4.657	4.431
39	29	56	71	144	4.955	4.955
40	29	56	71	144	4.955	4.929
41	29	56	71	144	5.084	5.341
42	29	56	71	144	4.929	4.693
43	29	56	71	144	4.657	5.325
44	29	56	71	144	4.955	5.124
45	29	56	71	144	4.929	4.955
46	29	56	71	144	4.657	5.084
47	29	56	71	144	5.341	4.929
48	29	56	71	144	4.559	4.839
49	29	56	71	144	4.339	4.657
50	29	56	71	144	4.431	4.955

Table 6.16: Dynamics of the prices and the distribution of agents: one simulation run under Setting F3.

fees, a steady-state duopoly still exists, and the value of a listing fee does not significantly affect the distribution of agents by the stable-state duopoly. Only, if both marketplaces charge the same but very high listing fees, sellers do not switch because it is not possible to pursue a higher payoff in either of the marketplaces.

6.3.2 Asymmetric Listing Fees

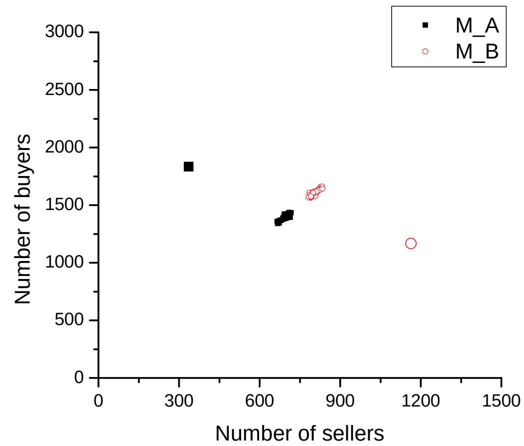
It has been shown that without listing fees, the simulation generally evolves into a steady state of duopoly. This result also applies when both marketplaces charge the same listing fee, which is not too high. Simulations in this section aim to find out whether the above results still hold true with asymmetric listing fee settings; and if yes, how and to what extent the listing fee influences the distribution of agents in the steady state.

6.3.2.1 Simulations under Treatment G

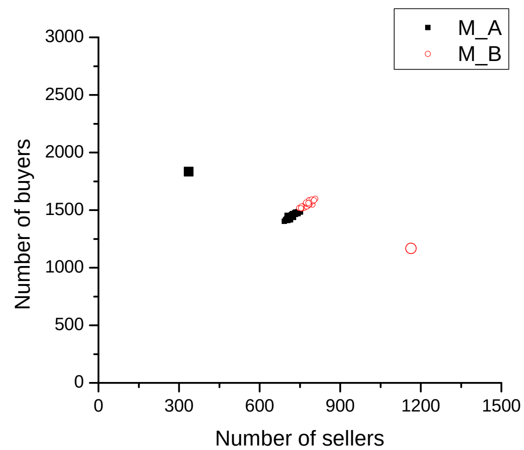
In Treatment G, simulations start from a "half-split" state, in which an equal number of sellers and buyers participate in each marketplace. In Setting G1, both marketplaces charge zero listing fees. Thus, it is expected to see only small price differences between the marketplaces, and to see only few movements of agents. As one can see from Figure 6.13a, the distributions of agents in the steady states are very similar to the distribution in the initial state of the simulations — this is consistent with the above expectation.

In the other three settings in Treatment G, M_A always charges a zero listing fee, while the listing fee in M_B is set as 3.0, 6.0, and 8.0, respectively. Thus, if significantly different observations are obtained by comparing the simulation data under those settings with those under G1, it should be due to the difference in the amount of the listing fees.

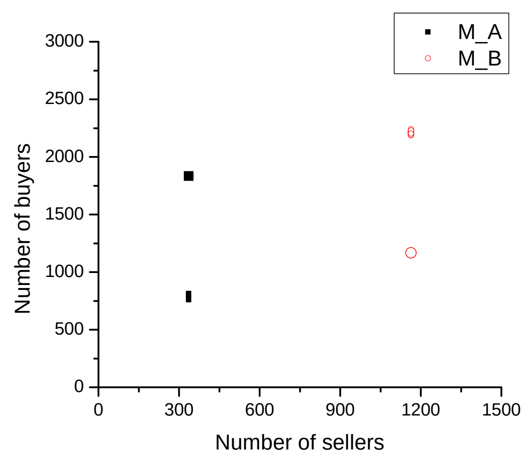
Figure 6.13b shows that in the steady states that have been reached under Setting G2, M_B contains around 35 sellers and 75 buyers, and both numbers are lower than



(a) Thirty simulation runs under Setting F4

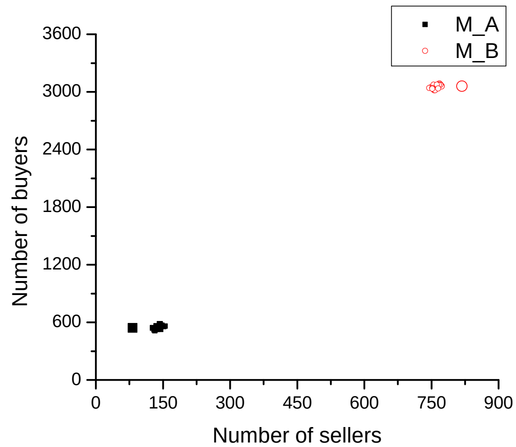


(b) Thirty simulation runs under Setting F5

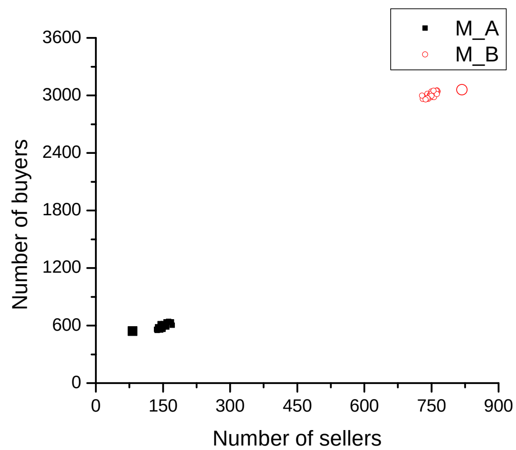


(c) Thirty simulation runs under Setting F6

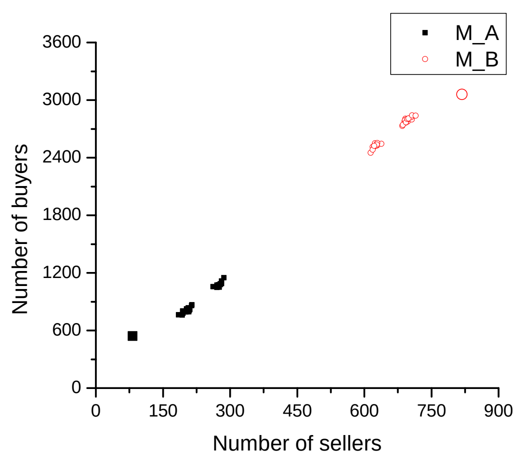
Figure 6.11: Distributions of agents in the steady states: simulations under Settings F4, F5, and F6.



(a) Thirty simulation runs under Setting F7

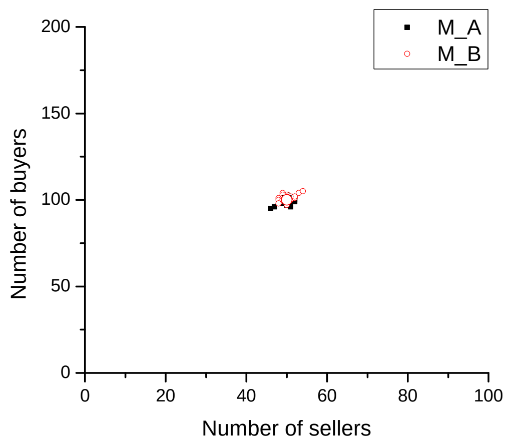


(b) Thirty simulation runs under Setting F8

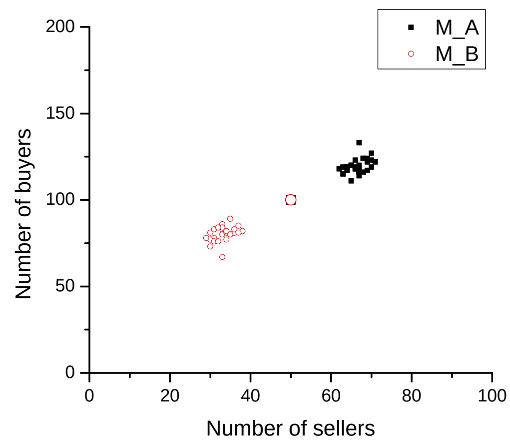


(c) Thirty simulation runs under Setting F9

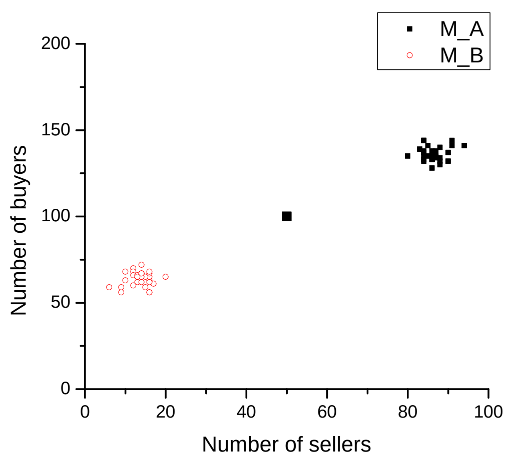
Figure 6.12: Distributions of agents in the steady states: simulations under Settings F7, F8, and F9.



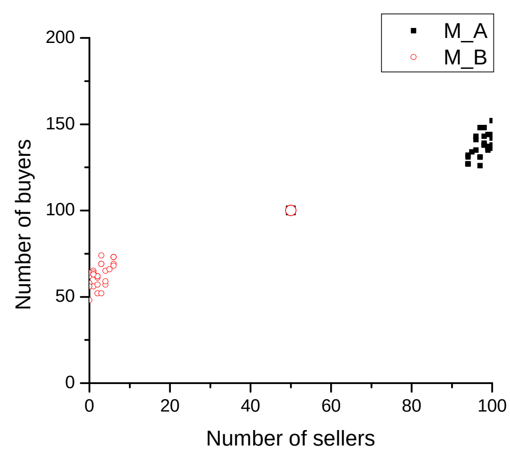
(a) Thirty simulation runs under Setting G1



(b) Thirty simulation runs under Setting G2



(c) Thirty simulation runs under Setting G3



(d) Thirty simulation runs under Setting G4

Figure 6.13: Distributions of agents in the steady states: simulations under Treatment G.

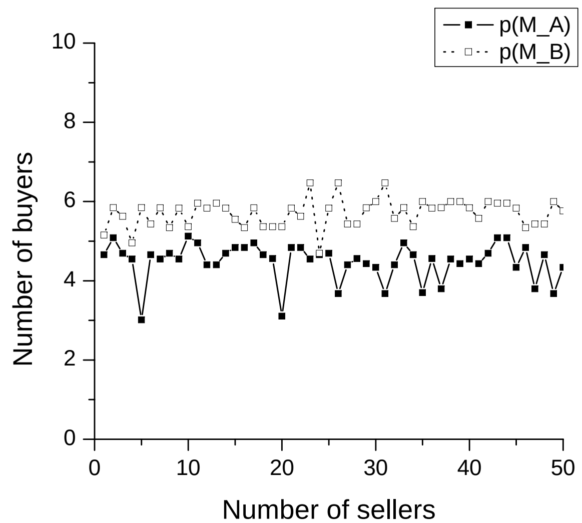
those in the initial state. Correspondingly, M_A contains more sellers and buyers. Figure 6.14 gives the simulation dynamics of one simulation run, which is typical among all thirty runs under G2. In the early period of the simulation, a few sellers switched from M_B to M_A due to a lower listing fee in M_A. The relatively lower amount of sellers in M_B naturally led to a higher price, and consequently some buyers in M_B to switch to M_A. Thus, when the simulation evolves into a steady state, the marketplace M_B, which charges a higher listing fee, loses both a few sellers *and* a few buyers. Similar observations are also obtained in simulations under Settings G3 and G4 (see Figures 6.13c and 6.13d), in that M_A is always able to attract some sellers as well as some buyers from M_B.

Comparing the distributions of agents between the settings in Treatment G, one can see that the higher the listing fee in M_B is, the more buyers and sellers leave M_B. Despite this, simulations under Settings G2 and G3 still converge to steady states of market duopoly. However, when M_B charges a listing fee as high as 8.0 (as in Setting G4), Figure 6.13d shows that in some of the runs, M_A is able to attract all the sellers in the steady states. In the following, one of the simulation runs under Setting G4 is analyzed in detail.

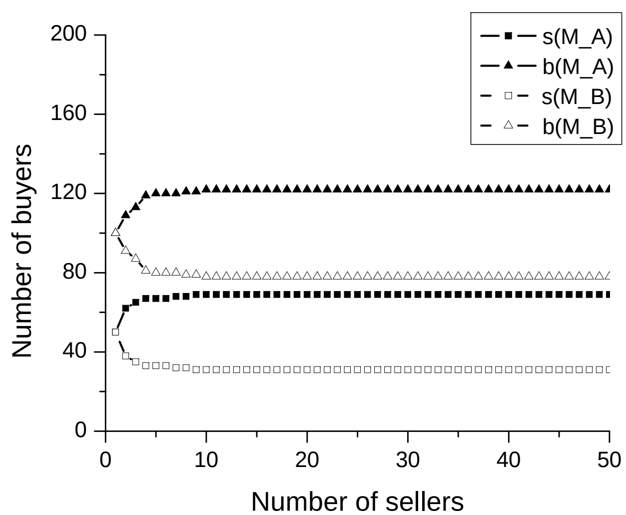
Table 6.17 shows the dynamics of the prices and the distribution of agents in this simulation run. The very high listing fee of 8.0 in M_B leads to zero-payoffs of all sellers in this marketplace in the first round. As a result, all sellers in M_B switch to M_A in the second round. This makes the price in M_B jump up to 9.929,[27] while in M_A the price decreases to zero because the number of sellers exceeds the number of buyers. In such a situation, M_B seems to be more profitable than M_A, despite the high listing fee. Therefore, 37 sellers switch from M_A back to M_B in round R^3.

However, thirty-seven sellers are too many to keep the sellers in M_B still profitable. As a result, these sellers all switch back to M_A in round R^4 and stay in M_A for the

[27] According to the simulation model, the winning price is the highest rejected bid. If there is no seller but some buyers, the price is simply the highest bid from the buyers, although no transaction actually takes place.



(a) Dynamics of the prices



(b) Dynamics of the distribution of agents

Figure 6.14: Dynamics of one simulation run under Setting G2.

remaining rounds. In several other simulation runs under Setting G4, M_B attracts some sellers in the steady states (see Figure 6.13d), but the number of the sellers is very small. This shows that M_B can “afford” only several sellers in making them profitable despite the high listing fee.

On the buyers’ side, Table 6.17 shows that the number of buyers in M_B follows a trend of decreasing, until the simulated system converges to a steady state. Since there is no seller in M_B, which leads to a very high price in M_B, buyers in M_B gradually switch to M_A, too.

However, not all the buyers in M_B choose to switch to M_A, and fifty-eight buyers still stay in M_Bs during the steady state. This reflects the influence of path dependency. According to the simulation model, a decision to “stay” is made under two cases. In the first case, an agent prefers to switch to the other marketplace. However, due to bounded rationality there is only a probability that he might move, and it turns out the decision is to stay. In the second case, a buyer’s valuation is lower than both of the prices in the marketplace. The buyer receives a payoff of zero in both marketplaces, and thus does not prefer to switch. No matter which of the cases holds, the decision is the same. Therefore, it is possible that a buyer chooses to stay in his current marketplace successively in the early period of a simulation run. This leads to the payoff difference having less influence on the buyer’s decisions, and the time is so long that he rather “ignores” the payoff difference, and simply sticks to the current marketplace in the remaining simulation rounds.

As a short summary of Section 6.3.2.1, simulations under Treatment G show that the simulation system may converge to steady states of market duopoly, in the case where the two marketplaces charge different listing fees. In such a steady state, the marketplace that charges a lower listing fee attracts both a few sellers and a few buyers from the other marketplace with a higher listing fee. Meanwhile, the latter one does not lose all its participants and still attracts some sellers and buyers. However, such a steady state of market duopoly cannot be observed, if one of the marketplaces charges

R^t	$s^t(M_A)$	$b^t(M_A)$	$s^t(M_B)$	$b^t(M_B)$	$p^t(M_A)$	$p^t(M_B)$
1	50	100	50	100	5.365	4.955
2	100	89	0	111	0	9.929
3	63	133	37	67	5.365	4.839
4	100	128	0	72	2.427	9.929
5	100	135	0	65	2.423	9.929
6	100	138	0	62	2.427	9.929
7	100	139	0	61	1.844	9.929
8	100	140	0	60	3.09	9.929
9	100	142	0	58	3.078	9.929
10	100	142	0	58	1.844	9.929
11	100	142	0	58	2.466	9.86
12	100	142	0	58	3.078	9.929
13	100	142	0	58	3.676	9.929
14	100	142	0	58	2.427	9.929
15	100	142	0	58	2.466	9.929
16	100	142	0	58	2.423	9.86
17	100	142	0	58	2.495	9.929
18	100	142	0	58	2.862	9.86
19	100	142	0	58	2.423	9.86
20	100	142	0	58	2.641	9.86
21	100	142	0	58	2.495	9.84
22	100	142	0	58	2.812	9.86
23	100	142	0	58	3.7	9.929
24	100	142	0	58	2.423	9.929
25	100	142	0	58	2.812	9.929
26	100	142	0	58	3.09	9.929
27	100	142	0	58	3.09	9.929
28	100	142	0	58	2.641	9.929
29	100	142	0	58	2.812	9.846
30	100	142	0	58	2.495	9.86
31	100	142	0	58	2.862	9.84
32	100	142	0	58	2.641	9.846
33	100	142	0	58	2.423	9.846
34	100	142	0	58	3.011	9.929
35	100	142	0	58	3.078	9.929
36	100	142	0	58	3.011	9.929
37	100	142	0	58	2.495	9.86
38	100	142	0	58	2.495	9.846
39	100	142	0	58	2.466	9.846
40	100	142	0	58	2.01	9.929
41	100	142	0	58	2.641	9.689
42	100	142	0	58	2.812	9.929
43	100	142	0	58	3.078	9.929
44	100	142	0	58	2.862	9.86
45	100	142	0	58	3.011	9.929
46	100	142	0	58	2.641	9.846
47	100	142	0	58	2.495	9.929
48	100	142	0	58	2.423	9.846
49	100	142	0	58	2.097	9.846
50	100	142	0	58	3.011	9.805

Table 6.17: Dynamics of the prices and the distribution of agents: one simulation run under Setting G4.

an extremely high listing fee.

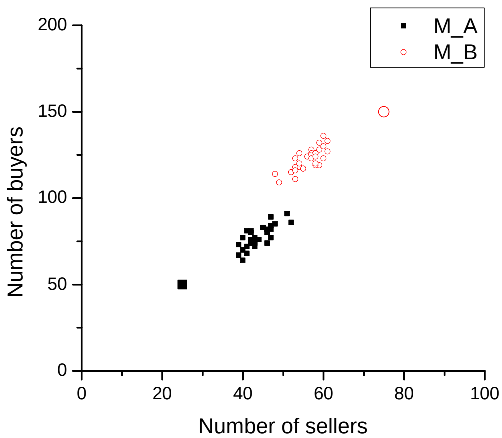
6.3.2.2 Simulations under Treatments H, I, and J

Simulations under Treatment G study the influence of asymmetric listing fees within a population of 100 sellers and 200 buyers, with an aggregate seller-buyer ratio of 0.5. This subsection analyzes the simulations under Treatments H, I, and J, which examine the influence of asymmetric listing fees under other input parameter combinations. The objective is to see whether the observations under Treatment G still hold true.

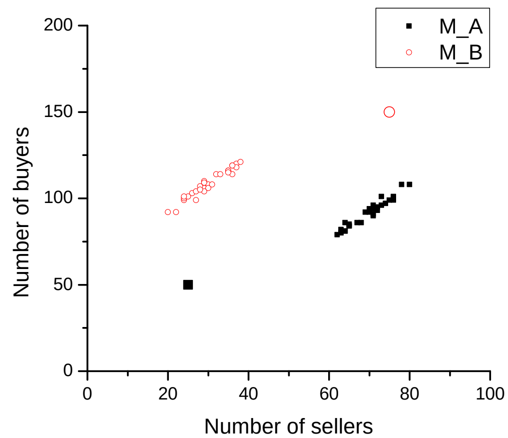
In Treatment H, the aggregate seller-buyer ratio is still 0.5, but the initial distribution of agents is different between Settings H1, H2, H3, and H4. In both H1 and H2, M_A charges a lower fee of 1.0, while M_B charges a higher fee, and the fee charged by M_B in Setting H2 is even higher than in H1. Compared to that, M_B charges a relatively low fee of 1.0 in H3 and H4, but the listing fee in M_A is higher in Setting H4 than in H3.

Steady states are observed in simulations under all those settings. To give an overview of the simulation results, Figure 6.15 depicts the distributions of agents under these four settings in the steady states. Denote the number of agents in a marketplace as the *size of a marketplace*. We see from Figures 6.15a and 6.15b that if the marketplace with a larger size charges a higher listing fee, it loses some sellers as well as some buyers, and consequently its size is reduced in the steady state. In fact, it is even possible that the marketplace with a larger size loses so many agents that it becomes the marketplace with a smaller size, as shown in Figure 6.15b. In contrast, if the smaller-sized marketplace charges a higher listing fee, it loses even more agents and its size becomes even smaller, as one can see from Figures 6.15c and 6.15d. These observations are consistent with those under TG.

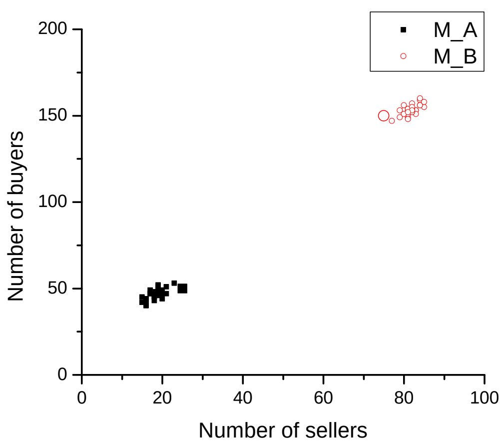
Now the influence of the listing fees on the sellers' side is analyzed. According to the simulation model, sellers who participate in the same marketplace always receive the same payoff in a simulation round. Therefore, it is easy to compare the sellers' payoffs



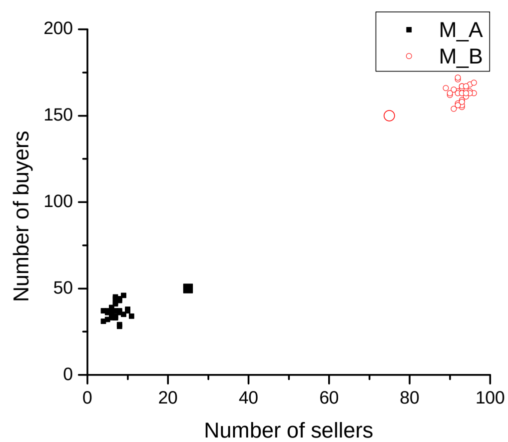
(a) Thirty simulation runs under Setting H1



(b) Thirty simulation runs under Setting H2



(c) Thirty simulation runs under Setting H3



(d) Thirty simulation runs under Setting H4

Figure 6.15: Distributions of agents in the steady states: simulations under Treatment H.

between the marketplaces. For each simulation run, an *average payoff of the sellers* in a marketplace during the steady state is calculated, and compared to the average payoff in the other marketplace. Table 6.18 lists the average payoffs of the sellers in M_A and M_B (denoted by $\widehat{\pi^s(M_A)}$ and $\widehat{\pi^s(M_B)}$ respectively) in the thirty simulation runs under Setting H1. Similarly, Table 6.19 lists the average payoffs of the sellers in simulations under Setting H2.

In each of the two tables, one can see that the average payoffs of the sellers in the two marketplaces are at the same level. However, the payoff levels are different between the two tables. The payoffs in both marketplaces under H1 are roughly in the range from 2.0 to 4.0, while under Setting H2 the payoffs are roughly in the range from 0.5 to 1.5. This is because the value of $l(M_B)$ is set higher in Setting H2 than in H1, which drives more agents from M_B to M_A under Setting H2 than under H1. This results in M_A containing relatively more sellers under H2, and consequently the sellers' payoffs in M_A are generally lower than under H1. For the marketplace M_B, although the prices in M_B under Setting H2 are generally higher than under H1 due to a greater loss of sellers, it is discounted by the higher value of $l(M_B)$. As a result, in both marketplaces, the average payoff of sellers is lower under Setting H2 than under H1.

If M_A charges a higher listing fee than M_B, as simulated in H3 and H4, similar observations are obtained in respect to the average payoff of sellers. The detailed data that support this are listed in Table 6.20 and Table 6.21.

The simulations under Treatment I and Treatment J have also converged to multiple steady states. Figure 6.16 and Figure 6.17 depict the distribution of agents in the steady states in each of those settings. It is clear from the graphs that the observations under those settings are all consistent with the observations in Treatment G, with respect to the distribution of agents in the steady states. The observations with respect to the average payoff of sellers during the steady state are also consistent among the treatment settings among asymmetric listing fees.[28]

[28]Due to space limitation, the detail is omitted.

Run	$\widehat{\pi^s(M_A)}$	$\widehat{\pi^s(M_B)}$	Run	$\widehat{\pi^s(M_A)}$	$\widehat{\pi^s(M_B)}$
1	3.159	2.458	16	3.067	2.386
2	3.625	2.249	17	3.323	2.225
3	2.895	2.589	18	3.453	2.397
4	3.247	2.368	19	3.864	2.198
5	3.373	2.338	20	3.373	2.336
6	2.668	2.568	21	2.935	2.482
7	3.805	2.272	22	3.937	2.087
8	2.962	2.433	23	3.500	2.337
9	3.193	2.414	24	3.519	2.308
10	3.747	2.098	25	3.903	2.178
11	2.918	2.530	26	3.203	2.332
12	3.271	2.436	27	3.231	2.365
13	3.355	2.456	28	3.584	2.232
14	3.293	2.251	29	3.698	2.266
15	4.034	2.097	30	3.650	2.278

Table 6.18: Average payoff of sellers during the steady state: thirty simulation runs under Setting H1.

Run	$\widehat{\pi^s(M_A)}$	$\widehat{\pi^s(M_B)}$	Run	$\widehat{\pi^s(M_A)}$	$\widehat{\pi^s(M_B)}$
1	0.993	0.845	16	1.148	1.023
2	1.462	0.889	17	0.930	0.825
3	0.784	0.419	18	1.160	0.504
4	1.231	0.728	19	0.813	0.726
5	1.382	1.275	20	1.386	0.978
6	1.438	0.730	21	1.264	0.921
7	0.893	0.597	22	1.392	0.753
8	0.971	0.554	23	0.969	0.628
9	1.050	0.504	24	1.576	0.848
10	1.571	1.108	25	1.660	0.806
11	1.198	1.003	26	1.277	0.921
12	0.780	0.592	27	1.207	0.750
13	1.290	0.720	28	1.186	1.112
14	0.935	0.859	29	0.929	0.644
15	1.016	0.588	30	0.882	0.526

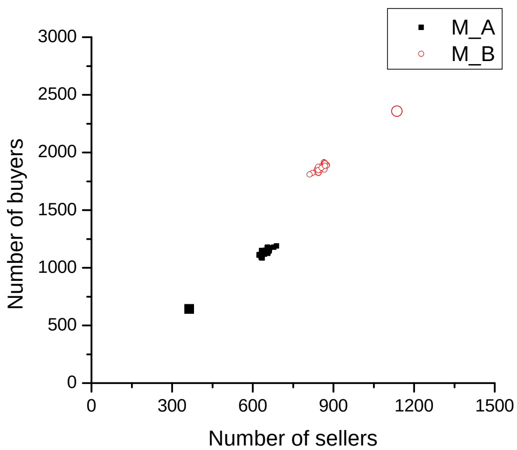
Table 6.19: Average payoff of sellers during the steady state: thirty simulation runs under Setting H2.

Run	$\widehat{\pi^s(M_A)}$	$\widehat{\pi^s(M_B)}$	Run	$\widehat{\pi^s(M_A)}$	$\widehat{\pi^s(M_B)}$
1	2.631	3.936	16	2.850	3.725
2	3.039	3.779	17	2.383	3.848
3	2.646	3.910	18	2.356	3.952
4	2.966	3.720	19	2.486	3.913
5	2.781	3.923	20	2.635	3.843
6	2.446	3.894	21	2.954	3.764
7	2.836	3.791	22	2.488	3.865
8	2.958	3.580	23	2.774	3.759
9	3.170	3.627	24	2.775	3.840
10	3.391	3.640	25	3.094	3.755
11	3.112	3.723	26	2.773	3.855
12	3.217	3.557	27	2.813	3.712
13	2.782	3.828	28	2.598	3.777
14	2.693	3.838	29	2.720	3.927
15	2.438	3.860	30	3.341	3.576

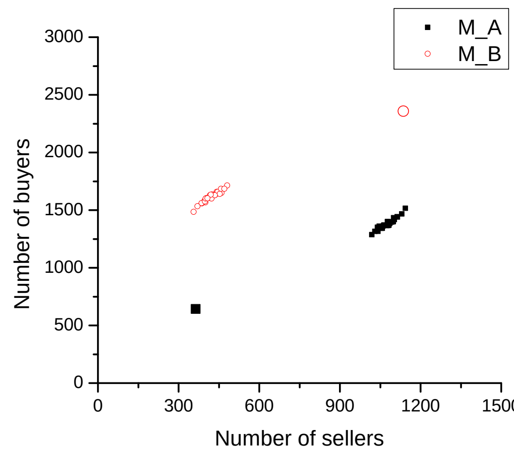
Table 6.20: Average payoff of sellers during the steady state: thirty simulation runs under Setting H3.

Run	$\widehat{\pi^s(M_A)}$	$\widehat{\pi^s(M_B)}$	Run	$\widehat{\pi^s(M_A)}$	$\widehat{\pi^s(M_B)}$
1	1.984	3.487	16	2.989	3.347
2	2.633	3.200	17	1.410	3.672
3	2.798	3.304	18	2.756	3.062
4	2.961	3.574	19	3.288	3.411
5	1.477	3.778	20	1.952	3.671
6	2.589	3.349	21	2.785	3.307
7	0.974	3.805	22	2.294	3.465
8	2.735	3.072	23	2.373	3.292
9	1.712	3.391	24	2.845	3.217
10	2.328	3.433	25	2.368	3.516
11	1.453	3.566	26	2.352	3.486
12	2.890	3.392	27	2.662	3.354
13	1.912	3.570	28	2.544	3.309
14	1.883	3.493	29	1.472	3.823
15	2.970	3.409	30	2.368	3.116

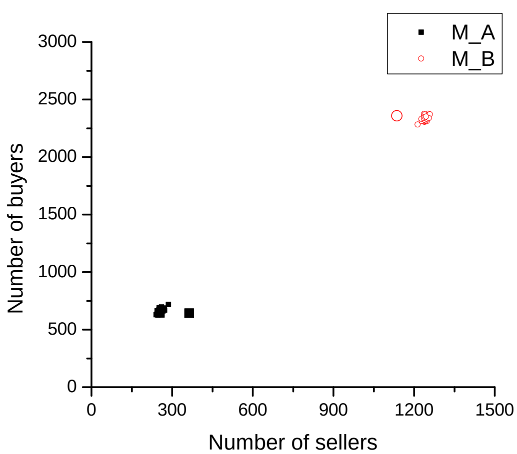
Table 6.21: Average payoff of sellers during the steady state: thirty simulation runs under setting H4.



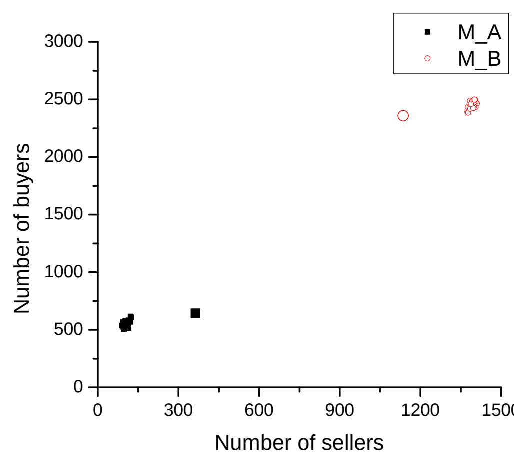
(a) Thirty simulation runs under Setting I1



(b) Thirty simulation runs under Setting I2

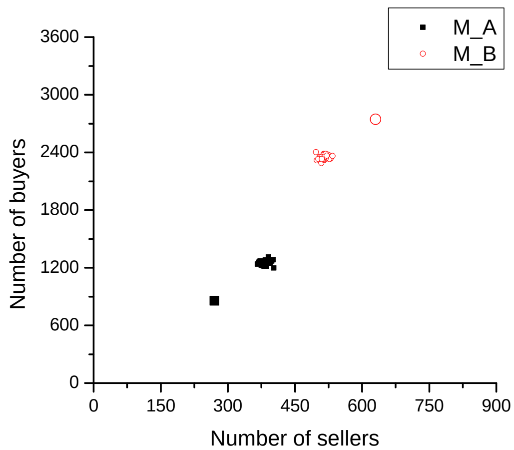


(c) Thirty simulation runs under Setting I3

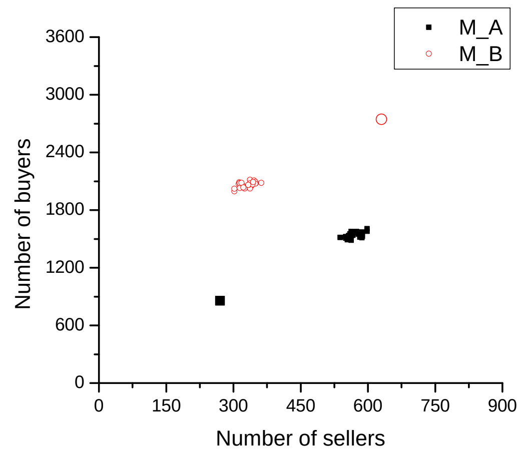


(d) Thirty simulation runs under Setting I4

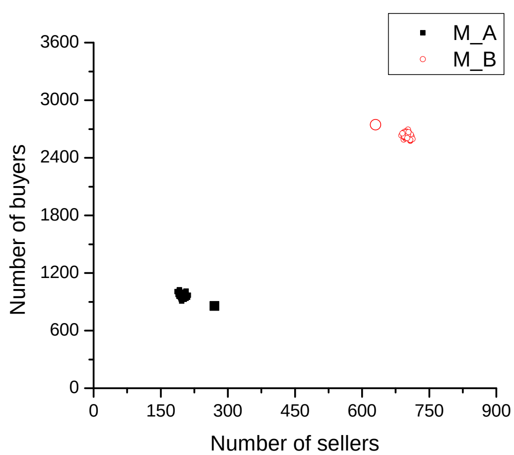
Figure 6.16: Distributions of agents in the steady states: simulations under Treatment I.



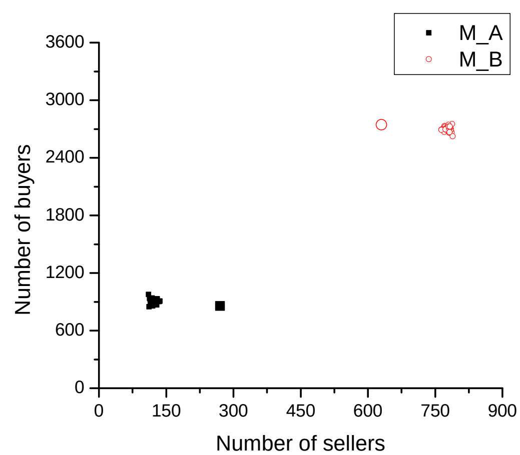
(a) Thirty simulation runs under Setting J1



(b) Thirty simulation runs under Setting J2



(c) Thirty simulation runs under Setting J3



(d) Thirty simulation runs under Setting J4

Figure 6.17: Distributions of agents in the steady states: simulations under Treatment J.

As a short summary of Section 6.3.2.2, simulations under Treatments H, I and, J confirm the observations in Treatment G: the higher the listing fee charged in a marketplace (compared to the other marketplace), the more agents the marketplace loses. Furthermore, the analysis in this subsection shows that the average payoff of sellers in the two marketplaces is on the same level, despite the fact that sellers are charged different listing fees in the marketplaces.

6.4 Discussion and Summary of Results

This section is intended to give an overview of the observations obtained from the simulations, and compares the results with those in the related literature.

In this chapter, simulations of the competition for participants between two similar e-auction marketplaces consist of two parts of experiments. The first part simulates two competing markets without listing fees. With respect to this part, the following observations are made.

1. The simulated system generally converges to a steady state of a market duopoly, in which no participant is willing to leave his current marketplace and join the other one.

2. The simulated system in a steady state can quickly converge to a similar steady state, despite the mutation of some agents (i.e., agents irrationally leaving their current marketplace).

3. The difference of the winning prices between the marketplaces is generally small during the steady state, if compared to those before the steady state is reached.

4. The steady state is not unique but rather exists across a broad range. Simulations that start from the same initial distribution of agents may converge to steady states with different distributions of agents. An equal split of buyers and sellers

between the marketplaces can be observed, but steady states with quite different numbers of buyers and sellers in the two marketplaces also exist.

5. For the simulation runs under the same setting, the distributions of agents in the steady states share certain characteristics. Statistical analysis shows that the seller-buyer ratios of the two marketplaces almost equal each other, and also equal the aggregate seller-buyer ratio. Moreover, the strength of a linear relationship between the number of sellers and the number of buyers in each marketplace is strong.

6. The existence of the steady state is not dependent on a certain size of the population, a certain initial distribution of agents, or a certain aggregate seller-buyer ratio of the whole economy. The above observations hold generally, with the exception of an extremely small population.

The above five findings are consistent with the conclusions from an analytical model by Ellison et al. (2004). They find that two competing and otherwise identical market platforms or auction sites of different sizes can coexist in equilibrium. Moreover, there is a broad range of "quasi-equilibria".[29]

With respect to small populations, they analyze a "thin" market scenario, in which the number of sellers is extremely small. They consider an economy with many buyers but only three sellers, each of whom has one item to sell. They point out that equilibrium on market duopoly exists, when $S_1 = 1$, $S_2 = 2$, $B_1 = (2B-1)/5$, $B_2 = (3B+1)/5$, and $B1$ and $B2$ are both integers. Here S_1 and B_1 represent the number of sellers and buyers in one marketplace M_1, while S_2 and B_2 represent the corresponding numbers in its rival marketplace M_2. B is the total number of buyers in the whole economy.

Simulations within a small population in this work (i.e., Treatment A) find some steady states that are consistent with the above proposition. For example, out of thirty

[29] "Quasi-equilibria" is the term created in the paper. The difference between quasi-equilibria and the commonly used concept of equilibria is that the number of sellers and the number of buyers in a marketplace must be integers.

runs under Setting $A1$, the steady state with the distribution of $s(M_A) = 3, b(M_A) = 7, s(M_B) = 3, b(M_B) = 7$ is observed for three times. Out of the thirty runs under Setting $A2$, it is also observed that the simulation converges to a distribution of $s(M_A) = 2$, $b(M_A) = 8$, $s(M_B) = 2$, $b(M_B) = 8$ for two times. However, the distribution of agents are rather erratic in other steady states observed. Therefore, the steady states that are consistent with the above proposition by Ellison et al. could be only a coincidence. From another point of view, the fact that a general analytical solution is not given in their paper supports, to some extent, the finding in this work that a steady state in the sense of equilibrium on market duopoly may not occur within an extremely small population.

The second part of the simulation experiment analyzes the dynamics of the system regarding two competing marketplaces which charge listing fees. Firstly, two marketplaces that charge the same listing fee are simulated. Simulations in this case lead to the following observations.

7. The simulated system generally converges to a steady state of market duopoly, if both marketplaces charge the same listing fee.
8. The characteristics of the steady states in the symmetric listing fee case are the same as that in the case without listing fees.
9. An exception to the above two findings is that when both marketplace charge a listing fee that is unreasonably high, all sellers simply stay in their current marketplace.

Secondly, the case that two marketplaces charge different listing fees is also simulated. This part of study leads to the following observations.

10. For two marketplaces with an equal split of sellers and buyers, a steady-state duopoly exists, in which one marketplace does not charge a listing fee, while the other marketplace does. In the steady state, the marketplace that does not charge

a listing fee acquires participants, including sellers as well as buyers. Despite that, the marketplace that charges a listing fee does not lose all its participants.

11. If both marketplaces charge listing fees but of different amounts, a steady-state duopoly can still be observed. In such a case, the higher the discrepancy between the two listing fees, the more participants acquired by the lower-fee marketplace.

12. It is possible that a marketplace that starts initially with a smaller size and a lower listing fee acquires so many participants from the other one that it becomes the larger marketplace. Contrarily, if the smaller-sized marketplace charges a higher listing fee, it loses many participants and its size becomes even smaller.

13. The characteristics of the steady states in the simulations without listing fees, are not observed in the steady states that are converged to in simulations with listing fees.

14. Sellers receive similar payoffs, independent of which marketplace they participate in.

15. A monopoly state occurs if the discrepancy between the amounts of the listing fees is very high.

16. The above findings with respect to the asymmetric listing fee case are not dependent on a certain population size, a certain initial distribution of agents, or a certain aggregate seller-buyer ratio of the economy.

To the author's knowledge, the influence of listing fees on competing marketplaces has only been studied by Ellison et al. (2004). They show that equilibrium of monopoly may exist, in which only one marketplace charges a listing fee. They also show that equilibrium on market duopoly may exist when both marketplaces charge the same listing fee. These conclusions are consistent with the findings in the presented work, as listed in the above.

However, the above mentioned authors do not deal with asymmetric listing fees. To the author's knowledge, the presented work is the only one that studies asymmetric listing fees in competing marketplaces.

Based on the above findings, the next chapter discusses how these findings contribute to the existing theories, and what are the implications of these findings on the strategic operation of marketplace operators. The limitations of the study will also be discussed, as well as the possible extensions.

Chapter 7

Conclusion and Outlook

A market has endogenous characteristics of potential competition and dynamics. When an economy consists of more than one marketplace, the competition and dynamics may exist not only within a marketplace, but also between the marketplaces. Real-world examples of such competition can be observed in conventional markets, such as between Christie's and Sotheby's, as well as in online markets, such as between eBay and Taobao.[30]

The presented study introduces a simulation model of competing auction marketplaces. In the model, buyers and sellers are modeled as agents, who select marketplaces to maximize their own payoffs. Simulation experiments are designed, to investigate the dynamics of the market evolvement and the possible steady-state features. The analysis is more on the macro level, rather than on some single agent's behavior. The analysis focuses on the market structure in the steady state, that is, whether the steady state presents a market duopoly or monopoly. Moreover, the presented work is also interested in studying how the variation of the listing fee influences such evolvement and the steady-state features.

[30] The competition between eBay and Taobao is briefly introduced in Section 1.2.

7.1 Summary of the Main Contributions

Many simulations under heterogeneous settings are conducted in this work and the analysis of the simulation data has led to many findings. A direct summary of these findings has been given in Section 6.4. This section summarizes the findings from a more comprehensive perspective and points out the main contributions of the presented study.

1. Verification of existing theory

One of the main results of this study is that two competing marketplaces with the same institution may coexist as a steady state. This result directly supports the analytical work by Ellison et al. (2004), which concludes that auction sites of quite different sizes can coexist in equilibria.

Another important finding of this study is the existence of market duopoly in a competition which includes listing fees. The marketplace that charges a lower listing fee can attract both some sellers and some buyers from the other marketplace with a higher listing fee; however, both marketplaces survive in the competition. Such movements from the high-fee market toward the low-fee market, which happen to both sellers and buyers, can also be seen in a recent simulation experiment by Cai et al. (2008). They show that the movements are sharpened by starting charging fees, because this tends to reduce profits and further discourages agents from remaining in markets that are unprofitable for them.

2. Provision of system dynamics

Most related literatures on the competition between markets use game-theoretic methods and investigate the existence of equilibrium on some aspects they are interested in. Typically, a two-stage game theoretic model is built. In the first stage, traders select a marketplace to trade, according to their information about the marketplace and its institutional structure. In the second stage, transactions take place and it is analyzed whether certain equilibrium exists in this stage.

Compared to the analytical solutions, the presented work uses a computer-based approach. The simulations conducted not only reveal the existence of steady states, but also show how the simulation system converges to the steady states. The simulation method also permits sensitivity analysis by manipulation of the input variables. This advantage on one hand makes it easy to find the appropriate values of some of the input parameters, and on the other hand facilitates the confirmation of the generality of the observations.

3. Understanding the impact of the listing fee

Almost every e-auction marketplace has its own policy about how the sellers are charged listing fees. However, this institution is seldom investigated. The presented work studies this issue and shows that sellers tend to move towards the marketplace with a relatively low listing fee for better payoffs. More interestingly, simulations also show that some buyers, whose payoffs are not directly determined by the listing fees, also move towards the low-fee marketplace. Moreover, if the discrepancy between the listing fees charged in the two marketplaces is large enough, it is possible for the marketplace of a smaller size to attract enough sellers and buyers and consequently become the larger-sized marketplace.

4. Contributions for strategic operations

The findings regarding the impact of listing fees lead to some suggestions for the marketplace operators in a competitive market environment. Since listing fees can influence traders' decisions on selecting a marketplace, the marketplace operators can use this institution as a tool to attract participants. There are two advantages. One is that a listing fee is public information for all current participants as well as potential participants. The other advantage is that a marketplace needs not to make efforts in attracting both sellers and buyers at the same time. Rather, a marketplace can first attract many sellers by setting a more favorable listing fee than it is charged by its rival. Then, the increased number of sellers may help the marketplace in attracting more buyers from its rival. This strategy is especially important for a marketplace which has a relatively small share of participants.

The impact of listing fees also pushes the e-marketplace operators to realize that they should always be aware of the influence of the institutional change on the market structure, and be creative in finding a set of institutions that generates a positive influence on their market shares.

7.2 Limitations of the Study

This section discusses the limitations of the study. The disadvantages of the simulation approach itself are addressed first, and then several limitations in the presented study are discussed.

General disadvantages of using the simulation approach

Despite simulations often producing valuable results, there are also some limitations of the approach. Generally, there are four disadvantages to using the simulation approach in problem solving, as listed in the following (Adkins and Pooch, 1977).

1. A simulation model may become expensive in terms of manpower and computer time.

2. Extensive development time may be encountered.

3. Hidden critical assumptions may cause the model to diverge from reality.

4. Model parameters may be difficult to initialize. These may require extensive time in collection, analysis, and interpretation.

With the development of computer technologies, conducting simulations has become less expensive. However, the other three disadvantages still exist. Although simulation might be the easiest tool for management science to use, as pointed out by Phillips et al. (1976), it is also probably one of the hardest to apply properly and perhaps the most difficult to draw accurate conclusions. They further state that the skills required to develop and operate an effective simulation models are substantial. The variability or dispersion of simulation results is a significant problem in itself and may require long and complex simulation analysis in order to draw meaningful conclusions from the simulation.

Limitations in the presented study

Although the simulation results of the presented work meet well with the relevant theoretical results, the simulation model used is rather simple and may not reflect the reality in the best way. In the extension of this simulation model, it has some particular limitations.

This model is particularly limited to the competition between two marketplaces. To extend the model to describe the scenario of three or more competing marketplaces, part of the model needs to be modified, for example in the decision-making part. This is not a trivial issue, because if an agent does not prefer the current marketplace, additional modeling is then necessary, regarding how to determine which of the other marketplaces is most preferred.

It would be a valuable effort if a laboratory experiment or an empirical study is conducted to study the real behavior of human participants on selecting marketplaces, and compare the findings with the results from the simulation experiment. This may give evidence whether the conclusions from this presented work hold true in reality. Moreover, a laboratory experiment or an empirical study may investigate factors that are difficult to be captured by simulations, such as the risk attitude in switching to another marketplace, the habit of multi-homing, etc.

However, it can be difficult to obtain the real data. First, a huge amount of data regarding participants' decisions in a continuous time space is necessary for analysis. Second, the decisions of the participants can be comprehensive ones that combine so many factors that are too complex for analysis. Moreover, real-world business operators might be reluctant to reveal private data of their individual participants.[31]

[31] Especially, it is necessary to obtain data from not only one marketplace operator, but at least two operators who are rivals to each other. This makes the collection of data more difficult.

7.3 Outlook

This work studies the competition between two e-auction marketplaces, in which the marketplaces compete to attract sellers and buyers. Computer-based simulation is used as the main methodology. The results of the conduced simulations are promising for further research. In the following, some ideas for future research are presented.

Firstly, it is possible to improve and to extend the simulation model. Although in Section 7.2 some limitations of the model have been pointed out, the model is still advantageous for many extensions, which demand only trivial modification of the model in addition.

For example, the decision-making process can be easily extended to include other monetary factors. This is because preference is always based on payoff calculations. Monetary factors, such as transaction cost and reserve price, can be conveniently incorporated into the payoff calculation function in the same way that the listing fee is incorporated.

Another possible modification of the model is to consider the competition not under a static population but a dynamic one. This modification enables us to study the impact of a dynamic population (for example, an increasing population) on the market structure in the steady state. The motivation of this extension is that more and more people have started to trade on the Internet in recent years, which has led to a significant increase of the population in the whole e-auction economy.

Secondly, it is also interesting to introduce more complex methods in modeling the agents. The approaches from Computational Economics can be considered, such as genetic algorithms. As it is widely used in artificial intelligence, it may also be applied in the learning process of agents in finding the best strategy for payoff maximization.

Last but not least, the application field, which is confined to the electronic auction market in the presented study, can also be extended to other fields, such as the stock exchange markets, the energy trading markets, etc. The marketplace operators in those electronic markets are generally facing the problem of attracting potential participants, because most of the marketplaces base their business models (where the main profit comes from) on the scale of customers (the amount of participants). Simulation under the framework of this study can help the operators achieve a better understanding of the market dynamics and may also support them in strategic operations.

There are certainly many more open questions in the understanding of markets and competition. The author hopes that this study contributes to the existing work and the simulation approach is accepted as a promising approach for similar research problems.

Appendix A

Mathematical Proof

Consider a uniform-price sealed-bid auction. There are x sellers and y buyers, who participate in the auction. $y > x \geq 1$. Each seller has one unit to offer and each buyer has single-unit demand. The winning price is determined by the highest rejected bid.

Suppose that the winning price is p. Denote the valuation of a buyer i by v_i and his bid by b_i. His payoff in this auction is:

$$\pi_i = \begin{cases} v_i - p & , \quad \text{if} \quad b_i > p \\ 0 & , \quad \text{otherwise} \end{cases}$$

Proposition A.1. *In a uniform-price sealed-bid auction with multiple single-unit-offer sellers and single-unit-demand buyers, it is a weakly dominant strategy for each buyer to bid his valuation.*

Proof. Suppose that the bid b_i by buyer i does not equal his valuation v_i. First consider the case that $b_i > p$. In this case the buyer wins the auction. If, in this case, $v_i > p$, then the buyer receives a positive payoff of $v_i - p$, no matter whether $b_i > v_i > p$ or $v_i > b_i > p$. If, otherwise, $v_i \leq p$, then the buyer's payoff $v_i - p$ is a negative value. But if he has bid his true valuation, he would have made a better payoff, although it will be only zero.

Then, we consider the case that $b_i \leq p$. In this case the buyer loses the auction,

Case		if $v_i > p$	if $v_i \leq p$
if $b_i = v_i$		$\pi = v_i - p > 0$	$\pi = 0$
if $b_i \neq v_i$	if $b_i > p$	$\pi = v_i - p > 0$	$\pi = v_i - p < 0$
	if $b_i \leq p$	$\pi = 0$	$\pi = 0$

Table A.1: Payoff of a buyer.

and his payoff is zero anyway. However, if $v_i > p$, then the buyer might have won the auction by bidding true valuation and received a positive payoff of $v_i - p$. This happens when v_i is higher than the current lowest accepted bid, otherwise the buyer still loses and receives a payoff of zero. If, otherwise, that is, $v_i \leq p$, then the buyer loses and his payoff is always zero, no matter $p > v_i > b_i$ or $p > b_i > v_i$.

To make it more clear, Table A.1 shows the payoff of a buyer i in all cases. From the table, one can see that a buyer is not better off, if his bid does not equal his valuation. Therefore, bidding the true valuation is a weakly dominant strategy.

$\square$

Appendix B

Simulation Data and Measurements

This appendix shows the average price difference between the two marketplaces, M_A and M_B, during the steady states. Each of the following tables lists the average price differences in thirty simulation runs under one simulation setting.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.599	11	0.466	21	0.529
2	0.446	12	0.779	22	0.437
3	0.470	13	0.588	23	0.414
4	0.531	14	0.357	24	0.359
5	0.571	15	0.726	25	0.607
6	0.395	16	0.474	26	0.408
7	0.365	17	0.524	27	0.545
8	0.753	18	0.581	28	0.521
9	0.974	19	0.585	29	0.574
10	0.630	20	0.417	30	0.490

Table B.1: Average price difference during the steady state: thirty simulation runs under Setting B2.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.460	11	0.408	21	0.423
2	0.476	12	0.450	22	0.376
3	0.474	13	0.547	23	0.482
4	0.553	14	0.372	24	0.468
5	0.726	15	0.584	25	0.396
6	0.577	16	0.538	26	0.667
7	0.387	17	0.496	27	0.491
8	0.531	18	0.488	28	0.466
9	0.398	19	0.467	29	0.497
10	0.528	20	0.401	30	0.466

Table B.2: Average price difference during the steady state: thirty simulation runs under Setting B3.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.460	11	0.408	21	0.423
2	0.476	12	0.450	22	0.376
3	0.474	13	0.547	23	0.482
4	0.553	14	0.372	24	0.468
5	0.726	15	0.584	25	0.396
6	0.577	16	0.538	26	0.667
7	0.387	17	0.496	27	0.491
8	0.531	18	0.488	28	0.466
9	0.398	19	0.467	29	0.497
10	0.528	20	0.401	30	0.466

Table B.3: Average price difference during the steady state: thirty simulation runs under Setting B4.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.766	11	0.524	21	0.615
2	0.567	12	0.508	22	0.680
3	0.496	13	0.730	23	0.698
4	0.559	14	0.525	24	0.681
5	0.441	15	0.561	25	0.659
6	0.477	16	0.491	26	0.490
7	0.558	17	0.543	27	0.401
8	0.552	18	0.469	28	0.623
9	0.466	19	0.485	29	0.620
10	0.535	20	0.568	30	0.572

Table B.4: Average price difference during the steady state: thirty simulation runs under Setting C1.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.655	11	0.577	21	0.385
2	0.466	12	0.461	22	0.456
3	0.598	13	0.519	23	0.596
4	0.413	14	0.461	24	0.600
5	0.407	15	0.632	25	0.404
6	0.474	16	0.447	26	0.366
7	0.410	17	0.545	27	0.396
8	0.668	18	0.413	28	0.525
9	0.634	19	0.520	29	0.449
10	0.579	20	0.519	30	0.291

Table B.5: Average price difference during the steady state: thirty simulation runs under Setting C2.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.467	11	0.449	21	0.491
2	0.486	12	0.475	22	0.485
3	0.485	13	0.581	23	0.591
4	0.480	14	0.558	24	0.622
5	0.334	15	0.564	25	0.425
6	0.541	16	0.457	26	0.485
7	0.506	17	0.587	27	0.355
8	0.473	18	0.564	28	0.555
9	0.482	19	0.433	29	0.437
10	0.436	20	0.630	30	0.407

Table B.6: Average price difference during the steady state: thirty simulation runs under Setting C3.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.516	11	0.536	21	0.329
2	0.425	12	0.858	22	0.476
3	0.482	13	0.449	23	0.488
4	0.584	14	0.470	24	0.573
5	0.521	15	0.363	25	0.577
6	0.434	16	0.479	26	0.725
7	0.760	17	0.641	27	0.514
8	0.845	18	0.358	28	0.440
9	0.494	19	0.545	29	0.466
10	0.522	20	0.298	30	0.489

Table B.7: Average price difference during the steady state: thirty simulation runs under Setting C4.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.305	11	0.159	21	0.434
2	0.193	12	0.388	22	0.258
3	0.379	13	0.194	23	0.262
4	0.432	14	0.367	24	0.213
5	0.507	15	0.116	25	0.312
6	0.139	16	0.339	26	0.327
7	0.138	17	0.136	27	0.484
8	0.262	18	0.476	28	0.266
9	0.263	19	0.386	29	0.185
10	0.172	20	0.198	30	0.543

Table B.8: Average price difference during the steady state: thirty simulation runs under Setting D1.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.210	11	0.282	21	0.372
2	0.187	12	0.343	22	0.161
3	0.127	13	0.214	23	0.212
4	0.432	14	0.467	24	0.241
5	0.167	15	0.124	25	0.126
6	0.271	16	0.296	26	0.400
7	0.166	17	0.168	27	0.337
8	0.259	18	0.271	28	0.279
9	0.253	19	0.232	29	0.210
10	0.246	20	0.171	30	0.192

Table B.9: Average price difference during the steady state: thirty simulation runs under Setting D2.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.162	11	0.121	21	0.138
2	0.139	12	0.133	22	0.116
3	0.129	13	0.130	23	0.097
4	0.108	14	0.149	24	0.108
5	0.098	15	0.089	25	0.130
6	0.111	16	0.129	26	0.238
7	0.130	17	0.112	27	0.095
8	0.104	18	0.078	28	0.137
9	0.247	19	0.090	29	0.156
10	0.151	20	0.140	30	0.124

Table B.10: Average price difference during the steady state: thirty simulation runs under Setting D3.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.131	11	0.107	21	0.207
2	0.102	12	0.105	22	0.095
3	0.109	13	0.084	23	0.100
4	0.183	14	0.076	24	0.112
5	0.101	15	0.113	25	0.081
6	0.106	16	0.074	26	0.136
7	0.130	17	0.104	27	0.078
8	0.139	18	0.130	28	0.116
9	0.100	19	0.084	29	0.102
10	0.105	20	0.090	30	0.102

Table B.11: Average price difference during the steady state: thirty simulation runs under Setting D4.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.132	11	0.172	21	0.202
2	0.243	12	0.187	22	0.291
3	0.199	13	0.191	23	0.262
4	0.206	14	0.174	24	0.250
5	0.254	15	0.323	25	0.136
6	0.196	16	0.408	26	0.165
7	0.166	17	0.205	27	0.170
8	0.277	18	0.150	28	0.293
9	0.227	19	0.132	29	0.300
10	0.180	20	0.239	30	0.152

Table B.12: Average price difference during the steady state: thirty simulation runs under Setting E1.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.133	11	0.186	21	0.156
2	0.175	12	0.219	22	0.185
3	0.184	13	0.178	23	0.177
4	0.139	14	0.122	24	0.151
5	0.130	15	0.186	25	0.231
6	0.140	16	0.123	26	0.284
7	0.133	17	0.174	27	0.132
8	0.141	18	0.207	28	0.131
9	0.237	19	0.103	29	0.161
10	0.206	20	0.119	30	0.194

Table B.13: Average price difference during the steady state: thirty simulation runs under Setting E2.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.256	11	0.140	21	0.219
2	0.138	12	0.261	22	0.152
3	0.182	13	0.127	23	0.190
4	0.239	14	0.156	24	0.142
5	0.199	15	0.136	25	0.135
6	0.147	16	0.140	26	0.138
7	0.216	17	0.188	27	0.200
8	0.152	18	0.150	28	0.148
9	0.155	19	0.201	29	0.152
10	0.145	20	0.108	30	0.170

Table B.14: Average price difference during the steady state: thirty simulation runs under Setting E3.

Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$	Run	$\widetilde{\Delta p}$
1	0.319	11	0.132	21	0.182
2	0.170	12	0.200	22	0.147
3	0.164	13	0.205	23	0.176
4	0.219	14	0.280	24	0.157
5	0.283	15	0.154	25	0.216
6	0.147	16	0.134	26	0.253
7	0.146	17	0.140	27	0.221
8	0.152	18	0.159	28	0.230
9	0.244	19	0.199	29	0.141
10	0.140	20	0.143	30	0.080

Table B.15: Average price difference during the steady state: thirty simulation runs under Setting E4.

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