ABSTRACT

Title of dissertation: EXPLORING AND MODELING OF BIDDING BEHAVIOR AND STRATEGIES OF ONLINE AUCTIONS

Wei Guo, Doctor of Philosophy, 2013

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Internet auctions, as an exemplar of the recent boom in e-commerce, are growing faster than ever in the last decade. Understanding the reasons why bidders behave a certain way allows invaluable insight into the auction process. This research focuses on methods for modeling, testing and estimation of bidders' behavior and strategies.

I start my discussion with bid shading, which is a common strategy bidders believe obtains the lowest possible price. While almost all bidders shade their bids, at least to some degree, it is impossible to infer the degree and volume of shaded bids directly from observed bidding data. In fact, most bidding data only allows researchers to observe the resulting price process, i.e. whether prices increase fast

(due to little shading) or whether they slow down (when all bidders shade their bids). In this work, I propose an agent-based model that simulates bidders with different bidding strategies and their interaction with one another. The model is calibrated (and hence properties about the propensity and degree of shaded bids are estimated) by matching the emerging simulated price process with that of the observed auction data using genetic algorithms. From a statistical point of view, this is challenging because it requires matching functional draws from simulated and real price processes. I propose several competing fitness functions and explore how the choice alters the resulting ABM calibration. The method is applied to the context of eBay auctions for digital cameras and show that a balanced fitness function yields the best results.

Furthermore, in light of the discrepancy find from the model in bidders' behavior and optimal strategies proposed from online auction literature. I extract empirical bidding strategies from auction winners and utilize the agent-based model to simulate and test the performance of twenty-four different empirical and theoretical strategies. The experiment results suggest that some empirical strategies perform robustly when compared to theoretical strategies and taking into account other bidders' ability to learn.

In addition, I expended the online auction framework from single auction to multiple auction simulation, which acts as a platform for investigating and testing more complicated situations that involves the competition among concurrent auctions. This framework facilitates my investigation of bidders' switching behavior and enables me to answer a series questions. For example, is it beneficial for auction website to promote bidders' switching behavior? Will bidders and even sellers get any advantage from bidders' switching? What is the best auction recommendation strategy for online auction website to obtain higher profit and/or a better customer experience? Through careful experiment design, it has been showed that higher switching frequency leads to higher profit for auction website and reduces the price dispersion, which leads to reduced risk for both bidders and sellers. In addition, the best auction recommendation strategy is providing the five earliest closing auctions so that bidders can choose the lowest price auction.

EXPLORING AND MODELING OF BIDDING BEHAVIOR AND STRATEGIES OF ONLINE AUCTIONS

by

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To my parents and my husband Changhui. Your love means everything to me.

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Chapter 1

Introduction

Internet auctions, as an exemplar of the recent boom in e-commerce, are growing faster than ever in the last decade. For example, eBay, the world's largest online auction website, reported revenues of $14.1 billion for 2012 [1], compared with $6.0 billion for 2006 [2] and $0.7 billion for 2001 [3]. In 2012, eBay had more than 123 million registered users and served as a market for more than $175 billion of commerce. Considering the large amount of online auctions and their users, understanding the relationship between auction price process and bidders' behavior and strategies becomes an important growth area for statistics, marketing and economic research.

The growing popularity of online auctions provides many interesting topics to study. Unlike traditional auctions, online auctions generate a large volume of data, which enables researchers to analyze real time bidders' behavior. Also, the good data quality facilitates researchers to identify users across auctions and even auction platforms. This data structure provides the opportunity to study the interactions and competitions between bidders, sellers and auctions.

With the existence of competition, the study of strategies is always an interesting area that attracts lots of researchers. From the bidders' point of view, what is the optimal strategy that will lead to a good chance of winning with fair price?

Do theoretical strategies from mathematical deduction with restricted assumptions work better than empirical strategies learned from real auction winners or the other way around? Do bidders really shade their bids to avoid "winner's curse" (i.e., winners bear the risk of overpaying for the item)? If so, to what degree do bidders shade their bids? From another point of view, the online platform managers might want to ask, what bidding strategies should we recommend to bidders to increase the profit of the website? Should we enhance our website to recommend additional auctions to bidders? If so, is there any optimal strategy in choosing the auctions to recommend? In this thesis, I am dedicated to provide some insights about these questions.

1.1 Introduction to Online Auctions

In this section, I will cover some of the basic concepts and relevant literature of online auctions and then discuss the structure of eBay data.

1.1.1 Online Auctions and Literature Review

There has been intensive investigation of bidders' behavior and various proposed strategies for Internet auctions. For example, the following studies explored bidders' behavior patterns and their impact. Bapna et al.[4] developed a taxonomy of bidding behavior in online auctions, in which early bidders and snipers are identified through empirical data of online auctions. Roth and Ockenfels [5] and Easley and Tenorio [6] focus their studies on sniping behavior and jump bidding respectively. Haruvy and Leszczyc [7] discussed bidders' search and choice in simultaneous online auctions and their impact on price dispersion. Ariely and Simonson [8] talked about bidders' value assessment and decision dynamics in online auctions.

Furthermore, many different methodologies are used to investigate and construct optimal bidding strategies. Zeithammer [9] proposed forward-looking strategy through theoretical models and concluded that with perception of future auctions, bidders would strategically shade their bids down comparing to the single auction setting. Jank and Zhang [10] proposed a functional forecast model of auction price to assist bidders' bidding decision. Chu and Shen [11] concluded that the best strategy is bidding one's maximum willingness to pay (WTP) derived from theory of game mechanism design. Gray and Reiley [12] discussed whether there is any benefit of early bidding and sniping through real-world experiments.

In addition, modeling of bidders' behavior is another growing field of online auction literature. Shmueli, Russo and Jank [13] proposed a BARISTA model for bid arrivals in online auction, which capture the deadline and earliness effects. Bradlow and Park [14] modeled the bid amount and timing of bidders through Bayesian estimation of a record-breaking model. In this dissertation, my work includes modeling of online auction by agent-based modeling (ABM), investigation and comparison of winners' bidding behavior and strategies, study of hte impact for bidders switching behavior, which are a combination of the three fields of online auction literature.

1.1.2 eBay Data Structure

The auction mechanism used on eBay is an ascending second price auction in which the highest bidder wins and pays the amount of the second highest bid plus a minimum required bid increment.[1] In addition, eBay features a proxy bidding system, which helps bidders to raise their bids incrementally. For example, if a bidder A places a bid that is higher than the current minimum required bid[2], the system only shows the minimum required bid as the current price and bidder A as the winner. If another bidder B comes and places another bid lower than bidder A's actual bid[3], then the system will raise the auction price automatically to outbid bidder B and bidder A will stay as the winner. The eBay system will continue to outbid any following bidders for A, until some bidder X places a bid amount higher than A's, in which case bidder A gets outbid and the bidder X becomes the current winner of the auction. Thus there are two kinds of bidding history in eBay, one of which is the record of actual bids submitted by bidders and the other is the proxy bidding price history generated by the system. Both of these records are important, because the actual bids provide information on bidders' behavior while the proxy price is the one available to bidders when they make their bidding decisions.

The eBay data used in this dissertation contain the actual bidding records and I generate the proxy price processes according to the proxy bidding rule from eBay.

[1]The minimum bid increment is predetermined based on the current price by eBay according to the incremental amount table available at http://pages.ebay.com/help/buy/bid-increments.html, which has also been adopted in the online auction model I proposed.

[2]Current minimum required bid = current price + minimum bid increment.

[3]eBay allows bidder to place any bid amount higher than the current minimum required bid, so the coming bid could be lower than the current winner's bid amount.

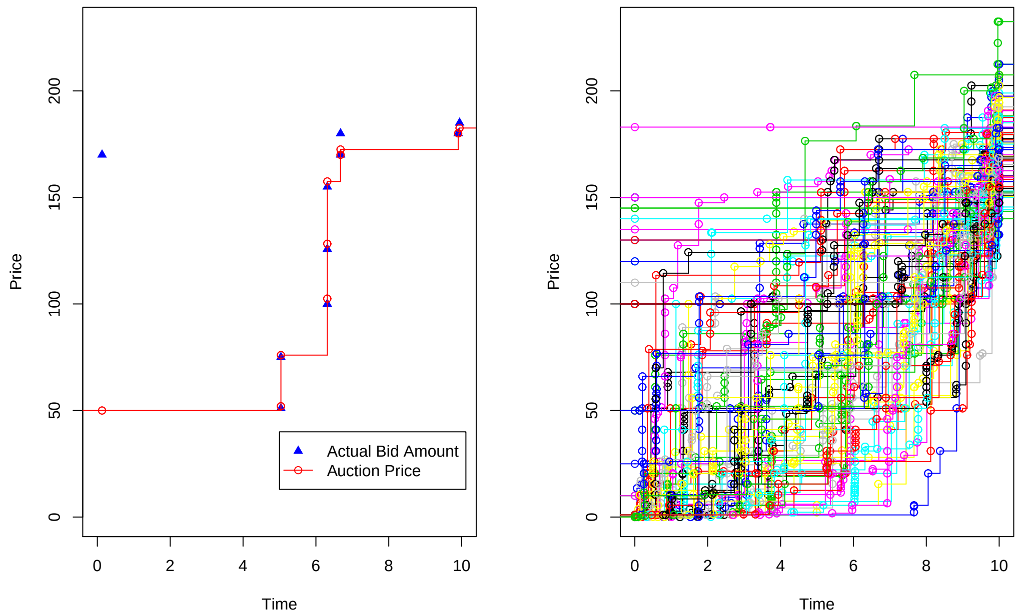

Figure 1.1: Price curves of Canon SD1000 camera auction on eBay.

The left panel of Figure 1.1 illustrates an auction price process for Canon SD1000 digital camera. The solid blue triangles represent bidders' actual bid amounts included in the eBay data. The red line and dots represent prices generated from eBay proxy bidding mechanism. For this auction, the first bid ($170.00) is higher than the auction starting price ($50.00), but the auction price is still shown as $50.00.[4] The auction price stays the same until the second bid ($51.00) placed by another bidder, then the price goes up to $52.00, which equals to the second bid plus the minimum required bid. The same thing happened to the third through seventh bids, they are all automatically outbid by the eBay system based on behave of the first bidder. One thing worth mentioning is that the seventh bid is $170.00 which equals the first bid.

[4]For the first bid in an eBay auction, the required minimum increment is $0. In other words, the initial bidder can bid the starting price. The online auction model follows the same rule.

Because the first bid has time priority, the temporary winner is still the first bidder and the auction price is \$170.00. Then the first bidder gets outbid by the eighth bid (\$180.00) and the auction price becomes \$170.00 + \$2.50 = \$172.50, where \$2.50 is the required minimum increment, when auction price is between \$100 and \$249.99. Finally, the last two bids are \$180.07 and \$185.00 and the auction closing price is \$180.07 + \$2.50 = \$182.57. In addition, the right panel of Figure 1.1 shows 100 auctions price process. It is clear that despite the homogeneity of the auction goods and formats, price processes vary drastically. Some curves move very slowly initially and only speed up toward the end, while some other curves climb quickly during the early stages of the auction and level off later. In this work, I apply agent-based modeling (ABM) to simulate price dynamic of online auctions and assist our study of bidders' behavior and strategies as discussed in next section

1.2 Contribution of the Dissertation

This section gives an overview of the main contributions I made in this dissertation.

1.2.1 Calibration of Functional Agent-Based Models

In this dissertation, I propose a method for calibrating agent-based models to *functional data*. I focus specifically on functional data [15], because agent-based models are often used to model processes where emerging phenomena are measured over time. For example, the results of the online auction model are the price processes, which can be interpreted as functional observations. Therefore, I propose the use of a genetic algorithm (GA) [16] in a functional data analysis framework to calibrate a complex agent-based model.

In particular, I am interested in quantifying bidders' propensity to shade their bids, that is, their aversion to risk. Bid shading is related to the "winner's curse" [17], that is, bidders, recognizing that winning an auction is conditional on being the most optimistic bidder about an item's worth, respond strategically by lowering their actual bids below their WTP [18]. In an auction setting, bid shading cannot be directly observed and I thus propose the use of ABMs to infer it from observable data.

To that end, I design an agent-based modeling framework with each bidder represented as an agent who has to make several repeated decisions: whether to place a bid, when to place a bid, how much to bid and whether the bidding process should be repeated once another bidder places a higher bid. In a real auction setting, the cause for each of these decisions cannot be observed directly. I hypothesize that the reasons are linked (among other things) to a bidder's willingness to take on risks and hence "equip" the bidding agents with varying levels of bid shading. Using the proposed methodology, I identify the model parameters which most closely match real auction data using several different fitness functions and find that most of the bidders are averse to the risk of overpaying (i.e., they prefer to make conservative bids despite a high willingness to pay).

1.2.2 Comparison of Winners' Bidding Strategies

As in offline auctions, the winner of an online auction is the bidder who places the highest bid. So an outstanding high bid will guarantee winning. However, for a common value item auction, this is not considered a wise strategy, because it bears the risk of overpaying for an item that could be bought cheaper somewhere else. The second main component of my work is a close investigation of winners' behavioral pattern, which has been left out from the growing body of internet auction literature. Because online auctions have been a popular exchange mechanism for more than a decade, it is fair to assume that the auction winners gained experiences through participation and developed empirical strategies to win auctions with fair price. Therefore in this analysis, I analyze winners' behavior and extract empirical strategies from digital camera auction winners on eBay and test their performance through the online auction model. For comparison purposes, I also test bidding strategies that have been deemed important in previous work, such as maximum WTP bidding [11], early bidding [4] and sniping [5] etc.. In total, I test 24 different combinations of both bid increment and bid timing strategies and the test result of each strategy is summarized from 2000 simulated auctions.

When a bidder decides in which auction to bid, there are two crucial aspects involved in the strategy: when and how much to bid [19]. In this work, I analyze the winners' strategies that consist of both bid amount and bid timing strategies. More specifically, I try to identify the factors that influence winners decision of bid increment and timing. The main findings are that some easily observable factors, such as current price and number of bids, are related to winners' bid increment, while some other informative factors of closing price [20], such as price dynamic and competitive auction information are not. In addition, I find that winners' bid timing is not significantly related to any of the auction features and dynamics, which leads to the assumption that winners bid timing is a pre-determined strategy rather than temporal decision evolving with the development of the auctions.

1.2.3 Investigation of Influence of Bidders' Switching Behavior

Price dispersion of online auctions exists even among auctions selling the exact same item. In Chapter 4, I discuss one of the possible causes of this phenomena – bidders' inertia to switch auctions. One hypothesis of the reason behind bidders' inertia of switching auctions is associated with searching cost [7], i.e., the information of similar auctions readily available to bidders is limited which requires bidders to put in more time to search for next auction matches their needs.

In Chapter 4, I design a multiple auction agent-based model to examine the influence of bidders' switching behavior on price dispersion and discuss how to facilitate similarity of auction prices by providing bidders with information of contemporary auctions. This study is important for online auction managers for two main reasons. First, by reducing the price difference of the same item, the risk for both auction bidders and sellers are reduced, which will lead to an increase of customers' satisfaction for both bidders and sellers using online auction platform. Second, by successfully promoting bidders' switching behavior, it has been shown from my experiments that the average closing price also increase, which leads to increasing profits of sellers and online auction websites. The reason behind this phenomena is that participating in a new auction acts as an incentive for bidders to stay in the auction platform and increase the competitive level of bidders

1.2.4 Summary of Dissertation Contribution

To summarize, the contributions of this dissertation are in the following explorations:

1. Proposing a calibration method for a functional agent-based model, and appling this method to the context of online auction simulation (Chapter 2).

2. Investigating winners' bidding strategies and comparing their performance to previously proposed bidding strategies in the literature (Chapter 3).

3. Constructing multiple online auction agent-based model and investigating the influence of bidders' switching behavior on auction price dispersion (Chapter 4).

In Chapter 5, I summarize the contributions and explore future work based on this dissertation.

Chapter 2

Agent-Based Model of Online Auctions

In this chapter, I describe my work in designing and calibrating of the online auction agent-based model.

2.1 Introduction

An agent-based model [21] is a framework that consists of computational, autonomous decision-making entities, which often represent individuals, who interact repetitively within the framework [40]. Each individual, called an agent, evaluates the information they have about the environment and makes decisions based on rules set by the modeler. The goal of using ABM is to experiment and observe the phenomena or consequences generated from the collective behavior of agents. In the last few years, agent-based modeling has become a useful and popular tool to carry out experiments in social science studies.

One of the main reasons for the recent increase in the popularity of agent-based models is that it enlarges the set of questions researchers can explore [21]. In contrast to classical statistical models which rely on restrictive – and at times unrealistic – assumptions (such as linearity, homogeneity, normality and stationarity) which are often imposed for mathematical analysis and proof rather than realistic applicability, agent-based models operate within a framework of minimal, simple and realistic rules. As a result, agent-based modeling (ABM) allows researchers to examine issues that have been avoided previously in theoretical disciplines and for which mathematical and analytical derivation is impossible [22].

In this work, I apply the ABM framework to the context of online auctions. The spectacular growth of internet auctions and the availability of massive amounts of auction data has lead to new insights into bidder-seller behavior [4, 23, 6, 24], the impact of the auction format [25], the auction process [26, 27, 17, 28, 29, 30] and its dynamics [19, 14]. However, while most of the extant literature focuses on behavior that is directly measurable from observed data (such as the timing and the magnitude of individual bids), I am exploring bidders' behavior that is *unobservable* in this work. In particular, I am interested in bidders' propensity to shade their bids, that is, the extent to which bidders bid below their true willingness to pay. In an auction setting, bid shading can not be directly observed but it is reflected in the amount of their *bid increment*. For instance, a risk averse bidder, who is afraid of overpaying for an item, will bid closer to the minimum required bid amount (despite having a much higher willingness to pay). On the other hand, an aggressive bidder, who cares more about winning than the final price, will bid higher (i.e., closer to her true willingness to pay) to deter other bidders and thus to increase her own chances of winning. The difference between a bidder's willingness to pay and her actual bid is often referred to as the amount of the *shaded bid* and can be viewed as a measure of a bidder's riskiness. In this work, I will infer the distribution of shaded bids using online auction agent based model.

I propose to calibrate the online auction model via a genetic algorithm (GA)

Table 2.1: Bidder characteristics of the digital camera auctions. A high bid increment is defined as an increment of at least 100% over the previous bid. A low bid increment is defined as an increment of less than 5% increment over the previous bid.

	Mean	Std. dev.
Number of bidders per auction	8.2	4.0
Number of repeat bids per bidder	0.97	3.63
Prop. of early bidders	15.9%	
Prop. of last-minute bidders	10.8%	
Prop. of high bid increments	13.8%	
Prop. of low bid increments	37.8%	
Prop. of bidders with more than 1 bid	26.6%	

[31, 16] that searches for the degree and volume (i.e., the distribution) of bid shading that best matches the observed data. Weinberg [32] proposed one of the earliest applications of GAs to characterize the parameters of a cell simulation. Later, Miller [33] proposed the use of nonlinear optimization techniques for a variety of model-exploration and -testing tasks, dubbed "Active nonlinear testing" or ANT [33]. In recent years, GA has been used for several parameter search tasks in the context of ABMs in a variety of domains including: ant food foraging [34], consumer retail environments [35] and viral marketing strategies [36].

2.2 Online Auction Data

The dataset used for this study is based on 1104 new Canon SD1000 digital camera auctions sold on eBay.com. The dataset used in this dissertation is obtained directly from eBay contains the real bid of each bidders. Because all the auctions sell the identical product, heterogeneity due to product differences is minimized.

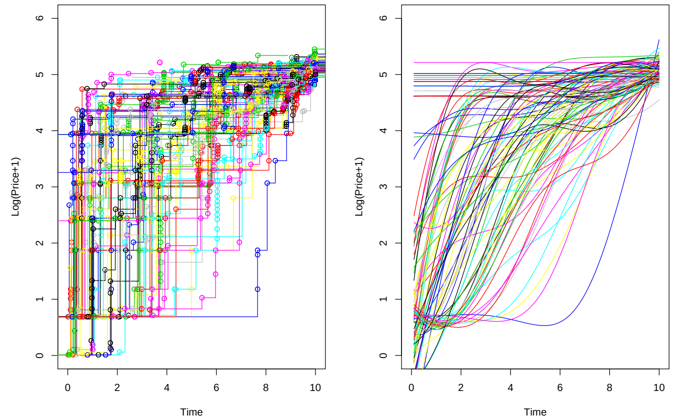

Figure 2.1: Price Curves of observed eBay auction data.

In addition, all the auctions share the same auction format, since auctions with reserve price and "buy it now" features are not included in the data. Thus, most of the variability observed from this dataset is due to the bidders and their different strategies, which is summarized in Table 2.1.

Table 2.1 shows that, despite a very homogeneous auction setting (i.e., same product, similar bidder and similar auction format), bidders' behavior ranges vastly. For instance, while only 15.9% of all bidders place bids early (within the first 10% duration of the auction), even fewer (10.8%) place them within the last minute[1]. Moreover, while 13.8% place bids higher than 100% over the previous bid ("high bid increment"), many more bid more conservatively (i.e., 37.8% with a low bid increment). This shows that bidders' strategies vary enormously. In fact, differences in timing and magnitude of bidders' bids suggest that there exist enormous variety in bidders' willingness to assume risk; in other words, the data suggests that some bidders shade their bids much more than others.

[1]Last-minute bidding is often regarded as one of the most popular bidding strategies [18].

While Table 2.1 suggests that there are differences in bidder's strategies, simple summary statistics cannot capture the *interaction* of bidders' behavior. Bidders compete against one another [23] and they react to each others' moves. In fact, a bidder's strategy might adjust as a result of other bidders' actions. Measuring the reaction of one bidder to another bidder's action is impossible using this data. However, what I *am* able to measure is the emerging phenomenon, that is, the resulting price and the rate at which price changes. Take a look at Figure 2.1 which shows prices curves for 100 auctions in the data. It is clear that, despite the homogeneity of the products and the auction formats, price curves vary drastically, with some curves moving very slow initially, only to speed up towards the end. In contrast, other price curves climb fast during the early stages of the auction and level-off later. This change in dynamics (fast price increase vs. price deceleration) is a result of different bidders and their interaction with one another. In other words, if the model can match the price curves to actual eBay data, that is evidence that the model is capturing the action and reaction of bidders to one another and the change in their behavior. By focusing on the shape of the price curves (and their dynamics), I adopt a point of view that borrows ideas from the field of *Functional Data Analysis* [15, 37, 26, 27].

One special aspect of the online auction environment is dynamic bid density, which means the time intervals between bids are time dependent and thus unequal [10]. So the traditional time series model requiring equally spaced observations is inadequate in analyzing online auction price process. One way to capture the price process of online auctions would be to use a functional data analysis approach

[15, 42]. The main idea of functional data analysis is that the data points are observed from a continuous smooth function. Then by recovering the function, the velocity and acceleration information of the price process could be obtained by taking derivatives. In this dissertation, I utilize three steps to get the price velocity and acceleration. First, we regenerate the proxy bidding price processes from the actual bidding record of each auction, which are step functions as in the left panel of Figure 2.1. Then for each step function, I take 100 equally spaced sample points and use the polynomial smoothing method to estimate the underlying smooth function, as shown in the right panel of Figure 2.1. At last, by taking derivatives of the polynomial functions on the time points, price velocity and acceleration can be calculated. For more details on the smoothing process and functional data analysis of online auctions, please see [27, 43].

2.3 Functional Agent-Based Model for Online Auctions

As mentioned earlier, one of the objectives of this work is to understand bidders' propensity to shade their bids, which is unobservable. To that end, I develop a model which simulates different levels of bid shading. Bidders' actions (including their willingness to assume risk) are interconnected in the sense that the timing and magnitude of one bidder's bid will influence the reaction of all remaining bidders. As pointed out above, the interplay between action and reaction is observable only in the price curve and its shape. Therefore, the output of the agent based model is treated as a *functional object*, and compared with the observed price curves. In what follows, I explain how to model this price curve by making assumptions only about the individual bidder-level interactions. In the subsequent section, I will then propose ways for matching this simulated price curve to observed price histories from real auctions data.

2.3.1 Model Parameters

An online auction (such as on eBay.com) consists of several key components: an item to be sold, a seller selling that item, an auction format that describes the rules of the transaction and a set of bidders. In the following, I describe each of these components separately.

2.3.1.1 Bidders' Evaluation of the Item

Most bidders evaluate the item separately and hence may possess different valuation of the item. The price information of an item could be gathered from a variety of sources, including internet search, in store prices and advertisements. As a result, bidders' evaluations tend to fluctuate randomly around the average market value. The distribution of bidders' evaluation could have a variety of different shapes, while there is no reason to assume anything different but a symmetric shape. In fact, it is quite plausible that some bidders value an item above the average retail price while it is below market value for others. Theoretical modeling (e.g. [38]) often assumes a uniform distribution, typically out of mathematical convenience. I generalize this assumption by allowing for a Normal fluctuation around the item's market value, i.e., I assume a Normal distribution for bidders evaluation of the item:

$$w_{k,i} \sim \text{Normal}(\mu_w, \sigma_w^2).$$

As pointed out earlier, bidders' actual bids might be different from their evaluations, i.e., bidders shade bids. The modeling of bid shading is explicitly discussed further below.

2.3.1.2 The Seller and the Auction

As pointed out above, the auction data used in this work is homogeneous in terms of the seller characteristics and the auction format. I will hence only allow variation in the starting price and assume other auction parameters are constant in my simulations. In this model, the variation in starting prices is simulated by a re-scaled Beta distribution because Beta distribution provides the best fit to the observed variation in starting prices. Also, the length of auctions are standardized to 10 days.

2.3.1.3 The Bidders

Most of the dynamics of the auction model are focused on bidders and their interactions with one another. Bidders' strategies are determined by three key elements: (1) the number of competing bidders, (2) the bid timing and (3) the magnitude of the bid.

A) The Number of Bidders

The number of bidders determines the overall level of competition in an auction and more bidders competing for the same item usually results in an increase of the final price. This model distinguishes between the number of *potential* bidders and *actual* bidders. A potential bidder might be interested in the auction, and she might monitor the auction progress, but she might never decide to place a bid because the current price might be higher than her own evaluation of the item. Thus, the number of *actual* bidders is a subset of the total number of *potential* bidders. I model the number of potential bidders according to a Poisson distribution, which is a common assumption for bidders' arrival rate [13, 27]. The number of potential bidders of each auction is generated in the beginning of the simulation and this number will not change thereafter.

B) The Bid-Timing

In this model, a price dependent method is used to simulate bidders' timing of bids. It starts with generating bidders' decision times $d_1, d_2, d_3, ..., d_N$ from a carefully designed process discussed in the next paragraph. Then, at each decision time, the corresponding bidder place a bid only when current price is lower than her evaluation of the item. Therefore the actual bidding times $t_1, t_2, t_3, ..., t_M$ are a subset of decision times $d_1, d_2, d_3, ..., d_N$ (i.e., $M \leq N$), because some bidders might decide not to place bids. By implementing this approach, the simulated bid timing is a stochastic process that dependents on auction price dynamic and differs considerably from an independent sample from an empirical distribution. Let P_t denotes the auction price at time t and w_t denotes the arriving bidder's evaluation, the next bidding time t_l is determined by the following function.

$$t_l = \min_{t \in d_j, \ldots, d_N} \{t : w_t \geq P_{t_{l-1}} + \text{Min.incr}(P_{t_{l-1}})\}, \tag{2.1}$$

where $t_{l-1} = d_{j-1}$ is the last bidding time, and $\text{Min.incr}(P_{t_{l-1}})$ is the minimum required bid increment for the current price $P_{t_{l-1}}$. From Equation 2.1, it is clear that bid timing depends on both current price and bidders decision times. When the price is low, the coming bidder is likely to have an evaluation higher than the current price and the waiting time for the next bid is short; when the price is high, it is less likely that the next bidder has a higher evaluation than the current price and the waiting time for the next bid might be longer. However, most bidders tends to decide their bids close to the end of the auction, i.e., the intensity of bidders' number of decision is much higher towards the end of the auction, so the waiting time for next bid might be shorter during the last minutes of auctions, even though the price is higher.

To generate the general bidders' decision time sequence, there are two components involved: each bidder's number of decisions and corresponding decision times. According to researches of eBay auctions [11] some bidders only place one bid and some bidders place several bids as reactions to other bidders' bidding behavior. Each bidder's number of subsequent decision times is simulated using a Poisson process and the average rate is estimated from the empirical eBay data. To simulate bidders' first decision times and subsequent decision times, a beta distribution and a uniform distribution are used respectively. While it is an intuitive choice to use the

Poisson process to simulate first decision times, empirical research of online auctions has shown that the Poisson process is not a suitable choice [13], because bidders' activity is much more intense toward the end of the auction and thus the distribution is far away from a uniform distribution. Each bidder's first decision time is modeled by a rescaled beta distribution across the duration of the auction. Figure 2.2 illustrates some probability density functions of beta distribution. As can be seen from the density functions, beta distributions could represent various shapes, including a uniform distribution (Beta (1,1) in top left corner), a bell shape distribution as Beta (5,5), and different skewed shapes: left skewed as Beta (5,1) and right skewed as in the second row. This flexible character of Beta distribution enables us to closely capture bidders' first arrival time from eBay data by estimating just two parameters. At the time of a bidder's first decision time, she decides how often to check back and decide future bids. Because bidders' first decision times are different, each bidders' revisite (i.e., subsequent decision) times is simulated separately by a Poisson process. For a Poisson process, if the given number of arrivals in $[t_1, t_2]$ is n, then the n unordered arrival times are independently uniformly distributed on $[t_1, t_2]$. Following this theorem, each bidder's revisit times are simulated as follows. Bidder i's number of revisits n_i are drawn from a Poisson distribution. Then, the n_i revisit times $t_{i,j}$'s, $(j \geq 2)$ are generated using uniform distribution $[t_{i,1}, 10]$. I separate bidders' first decision times and revisit times, because the waiting time for a bidder's first decision time, which is just $t_{i,1}$, could be substantially different from waiting time for subsequent decisions, $t_{i,j} - t_{i,j-1}, j \geq 2$. For instance, a bidder may participate in the auction at an early stage, but never come back; or a bidder

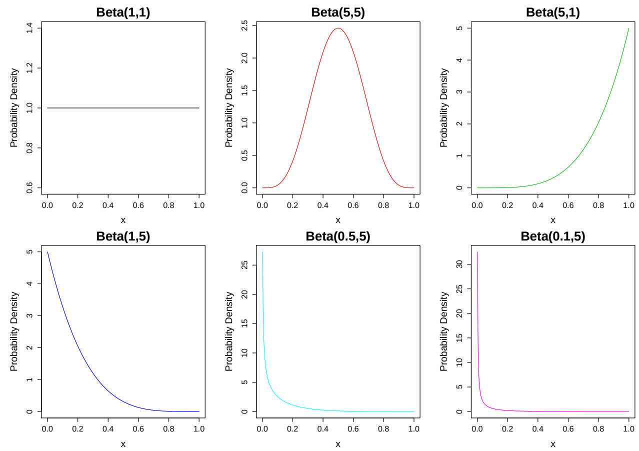

Figure 2.2: Probability Density Function of Bid Shading based on the Beta distribution

might notice an auction very late, but she is very interested in the auction and revisits it frequently. Both situations will results in very different pattern between first decision time and subsequent decision times.

C) The Bid-Amount

In this auction model, bidders' bid amount is determined by three factors: (1) the current auction price, (2) the bidder's own evaluation and (3) the bidder's sensitivity to risk (i.e., the amount of bid shading). Let $\rho_{k,i}$, $0 < \rho_{k,i} < 1$, denote bidder i's bid shading character, where $\rho_{k,i}$ is drawn from a Beta distribution, $\rho_{k,i} \sim \text{Beta}(\alpha_\rho, \beta_\rho)$. The Beta distribution allows for flexibility in capturing different volume and the degree of bid shading. For instance, Figure 2.2 shows examples of the Beta distribution for six different parameter pairs $(\alpha_\rho, \beta_\rho)$. From the graphs, $(\alpha_\rho, \beta_\rho) = (1, 1)$ (top left corner) results in a uniform distribution; the implication of that distribution is a pool of bidders with very diverse amounts of bid shading, with some bidders shading their bids almost entirely while others do not shade their bids at all. The bottom right $(\alpha_\rho, \beta_\rho) = (0.1, 5)$ shows an example of a very right-skewed bid shading distribution; in that case, most bidders would shade their bids almost entirely and bid close to the current price, while only few bidders bid close to their evaluations of the item; this scenario represent a group of very conservative bidders. In contrast, the top right distribution $(\alpha_\rho, \beta_\rho) = (5, 1)$ is highly left-skewed and represents bidders who bid very aggressively (i.e., close to their evaluations of the item).

Let $P_{k,m}$ denote the current price, and $Inc(P_{k,m})$ denote the minimum bid increment; recall that $w_{k,i}$ denotes the bidder's evaluation of the item and $\rho_{k,i}$ is her bid shading character. Then the bidder i's mth bid in auction k equals to the minimum required bid amount, i.e., $P_{k,m} + Inc(P_{k,m})$, plus the shaded difference between the evaluation of the item and the minimum required bid amount:

$$B_{k,m} = P_{k,m} + Inc(P_{k,m}) + (w_{k,i} - P_{k,m} - Inc(P_{k,m})) \times \rho_{k,i}. \tag{2.2}$$

2.3.2 Simulation Implementation

I complete the description of the online auction model by presenting the simulation process. The agent-based model is initiated by generating all the random variables as listed in Table 2.2. For auction k, all the decision events (both first decision event and revisit decision events) are ordered by their corresponding times $t_{k,i,j}$'s. Starting with the first decision event, the coming bidder i observes the auction price $P_{k,t=0}$ and compares it with her own valuation $w_{k,i}$. If her valuation is higher, she will make a bidding decision according to Equation (2.2) and might revisit the auction if $n_{k,i} > 0$; otherwise she will leave the auction and will not revisit. For the first bidder who makes a bid, the current price of the auction still equals the starting price with a latent price equal to this bidder's bid amount, and this bidder becomes the temporary winner. The subsequent decision events are carried out in the same manner, except there are two possible scenarios after the first bidder places a bid: the coming bidder could be the new temporary winner or automatically get overbid by the system on behalf of the temporary winner. Because the current price of an auction is only the second highest bid plus a small increment, the new entered bid could be lower than the latent highest bid. If this happens then the online auction system will automatically overbid the new bidder on behalf of the winner, who remains as the temporary winner of the auction. The new auction price equals the new bid plus a small increment or the highest bid of the auction, whichever is lower. If the new bid is higher than the previous highest bid, then the new bidder becomes the new temporary winner and the auction price equals the previous highest bid plus a small increment or the new bid, whichever is lower. After the update of temporary winner and auction price, the simulation goes to the next decision event. In the situation where a bidder revisits an auction and discovers she is still the winner, she will not make a bid but might revisit later. After all the decision events have been processed, the simulated auction ends at the current price with the winner who places the highest bid. The model kept records of the price process, the identification of the winner and other relevant variables for further investigations.

Table 2.2: List of Variables in the ABM.

Notation	Definition	Distribution
N_k	Number of bidders	Poisson(λ_N)
P_k	Starting price	180·Beta(α_p, β_p)
$w_{k,i}$	Evaluation of the item	Normal(μ_w, σ_w^2)
$\rho_{k,i}$	Bid shading	Beta$(\alpha_\rho, \beta_\rho)$
$n_{k,i}$	Number of revisits	Poisson(λ_{re})
$t_{k,i,1}$	First decision time	10·Beta(α_t, β_t)
$t_{k,i,j}$	Revisit times $j \geq 2$	Uniform$[t_{k,i,1}, 10]$

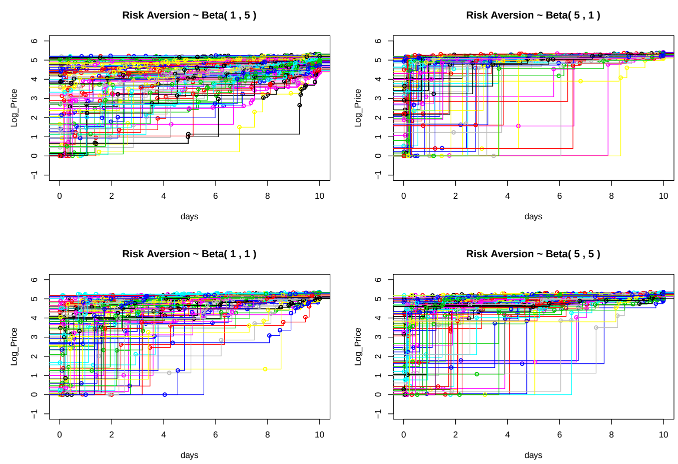

Figure 2.3: Simulated Price Paths for different levels of bid shading.

2.3.3 Visual Parameter Estimation

In order to implement this online auction agent-based model, all the parameters of the simulation variables need to be calibrated from actual eBay data. Table 2.2 lists all the 7 simulation variables and their associated 10 parameters. Most of these variables are directly observable from data, thus the corresponding parameters can estimated using maximum likelihood estimation method. However, bid shading is unobservable.

Before diving into parameter estimation, a visual examination is helpful in understanding the big picture of identifiability of bid shading using price processes. Figure 2.3 illustrates the price path of 100 simulated auctions with four different distributional assumptions of the bid shading parameter $\rho_{k,i}$ (see Figure 2.2). The top row represents situations in which bidders bid conservatively (left panel) or aggressively (right panel) and the bottom row shows symmetric situations (uniform bid shading in the left panel and bell-shaped bid shading in the right panel). It is clear that for conservative bidding, price increases very slowly and there is large variation in the closing price (upper left panel). On the other hand, with mostly aggressive bidders, price increases quickly, the average closing price is higher and exhibits less variation (upper right panel). Finally, in the case of symmetric bid shading, there is more variation in the price paths. It is interesting that, at least from a pure visual inspection, the simulated price curves pertaining to the conservative bidders (upper left panel in Figure 2.3) best resembles the observed data in Figure 2.1. In other words, it suggests that the degree and volume of bid shading in real eBay auctions might be roughly characterized by a Beta distribution with parameters 1 and 5. While such a visual matching provides some initial insight, it is not precise. To that end, I propose a parameter estimation method for functional agent based model via the genetic algorithm.

2.4 Parameter Estimation via Genetic Algorithm

In this section, I first introduce the parameter estimation method and then discuss simulation tests of the method and the estimation results.

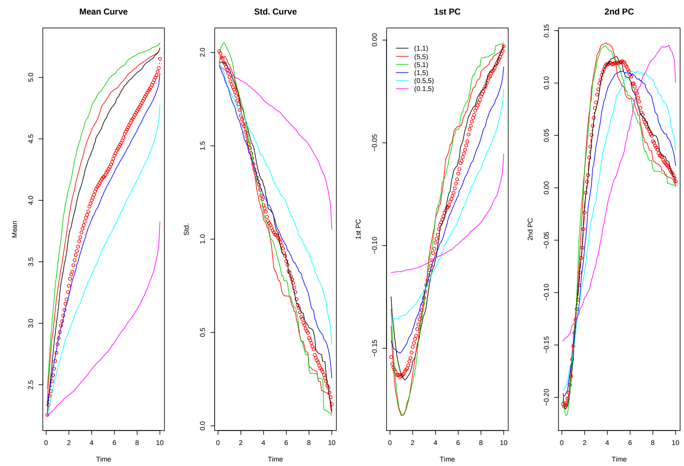

Figure 2.4: Visual Comparison of Summary Curves

2.4.1 Estimation Method

In order to use a genetic algorithm (GA) to calibrate the online auction agent-based model, the first step is to define a proper fitness function. Note that my task involves matching simulated price curves (Figure 2.3) to actual price curves (Figure 2.1). Under the assumption that the price curves are realizations of the same stochastic process, I propose to match *summary curves* of simulated price processes to corresponding *summary curves* of actual price processes. That is, matching the mean curve of the simulated data $\mu_{\text{sim}}(t)$ to the mean curve of the actual eBay data $\mu_{\text{eBay}}(t)$. Similarly, in order to capture variation in the actual eBay price curves, I also match the corresponding standard deviation curves $\sigma_{\text{sim}}(t)$ and $\sigma_{\text{eBay}}(t)$. And finally, since the *shape* of the price curve is of particular importance, I also match the corresponding first and second *principal component curves* $PC1_{\text{sim}}(t)$, $PC1_{\text{eBay}}(t)$ and $PC2_{\text{sim}}(t)$, $PC2_{\text{eBay}}(t)$ respectively[2].

[2] The first and second principal component curves capture trends (e.g. up/down) or curvature (e.g. concave/convex) of functional objects; see e.g. [37].

Figure 2.4 illustrates the four summary curves for the actual eBay price (red circles) and simulated data (thin colored lines). The graphs shows some interesting and profound relationship between simulated and actual eBay price curves. For example, in the leftmost panel, the mean of the simulated curves $\mu_{\text{sim}}(t)$ pertaining to Beta(1,5) (blue line) best tracks the mean of the actual eBay price curves $\mu_{\text{eBay}}(t)$. On the other hand, the standard deviation curve $\sigma_{\text{sim}}(t)$ pertaining to Beta(0.1, 5) (pink line) is most dissimilar compared to the corresponding $\sigma_{\text{eBay}}(t)$ in the second panel. Overall, while these summary curves allow some comparison between simulated and observed data, detecting the best match is hard, at least visually.

To that end, I define a fitness function across all four summary curves. In fact, I propose a weighted root means squared error (RMSE) criterion of the following form:

$$\begin{aligned} F_{\mathbf{y}}(\mathbf{x}) &= w_1 \cdot |\mu_{\text{sim}}(t) - \mu_{\text{eBay}}(t)|_{\text{RMSE}} \\ &+ w_2 \cdot |\sigma_{\text{sim}}(t) - \sigma_{\text{eBay}}(t)|_{\text{RMSE}} \\ &+ w_3 \cdot |PC1_{\text{sim}}(t) - PC1_{\text{eBay}}(t)|_{\text{RMSE}} \\ &+ w_4 \cdot |PC2_{\text{sim}}(t) - PC2_{\text{eBay}}(t)|_{\text{RMSE}}, \end{aligned}$$

where the RMSE of two functions is defined as

$$|f(t) - g(t)|_{\text{RMSE}} = \sqrt{\frac{\sum_{j=1}^{100}(f(t_i) - g(t_i))^2}{n}}.$$

Both the online auction model and GA selection of parameters are implemented in the freely available software R. In this work, the GA program is based on the "genalg" package in R, with a few modifications to better measure the results and increase efficiency. The GA is used to optimize 6 parameters of the online auction model. Each parameter is specified by a real number, so each individual in the GA is composed of 6 genes that represent a potential parameter set of the online auction model. To evaluate the fitness function of each individual (a set of parameters), the corresponding set of summary curves are calculated from 1000 simulated auctions. The population size of the GA is 100 and the number of iterations is 100. So, in total there are 1000 simulations $\times$ 100 individuals $\times$ 100 generations $= 10,000,000$ simulated auctions used in the estimation process. In each iteration, the 20 best individuals are kept for the next generation (elitism), while the other 80 pairs of parents are randomly selected (each pair of parents only have one offspring). The crossover rate is 60% and the mutation rate is 5% per gene. The range of each parameter are based on inference from maximum likelihood estimation, visual inspection and simulation experiments.

2.4.2 Fitness Function Weighting

Before estimating model parameters using GA, I investigate the impact of the weights w_i on the fitness function. To that end, I experiment with three different scenarios: In Scenario 1, $w_1 = 0.75$, $w_2 = 0.25$, and $w_3 = w_4 = 0$; this scenario only uses the mean and standard deviation curves and hence ignores the shape of the price curves via PC1 and PC2. Scenario 2 is reversed and puts all weight on

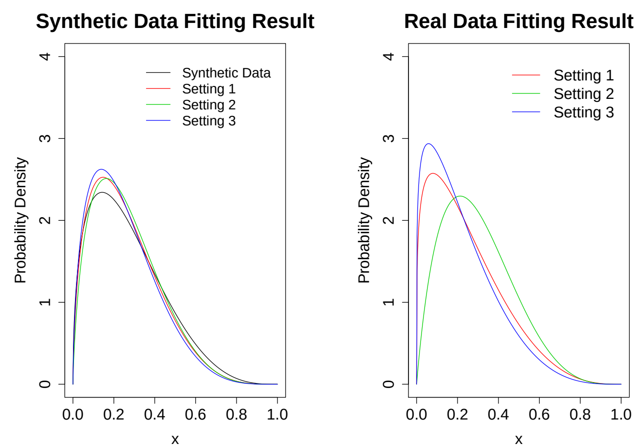

Figure 2.5: Different Fitness Function Settings and Resulting Probability Density Function of Beta Distributions of Synthetic and Real Data

the shapes PC1 and PC2 and no weight on the mean and standard deviation curves (i.e., $w_1 = w_2 = 0$, $w_3 = 0.75$ and $w_4 = 0.25$). And finally Scenario 3 uses all four components in a balanced form via $w_1 = 0.35$, $w_2 = 0.15$, $w_3 = 0.35$ and $w_4 = 0.15$.

I first examine these three scenarios on a synthetic data set. That is, I generate data with a known set of parameters and then use the GA to extract the original underlying bid shading parameters. The results of this experiment is given in the left panel of Figure 2.5. I can see that the results are very robust to the choice of the weights on the synthetic data. In other words, regardless of the choice of the weights, the algorithm produces almost identical result.

I repeat the same experiment on the observed data and find that the outcome is more sensitive to the choice of the weights (right panel of Figure 2.5). While there is more variability in the outcome, it is still clear that regardless of the choice of the weights, all the scenarios estimate right-skewed distributions for bid shading. Thus I can conclude that while the choice of the weights matters, it does not impact the

Table 2.3: RMSE

weighting	μ	σ	PC1	PC2
Setting 1	0.03696	0.07417	0.00746	0.01451
Setting 2	0.25209	0.06321	0.00488	0.01146
Setting 3	0.03765	0.05276	0.00505	0.00671

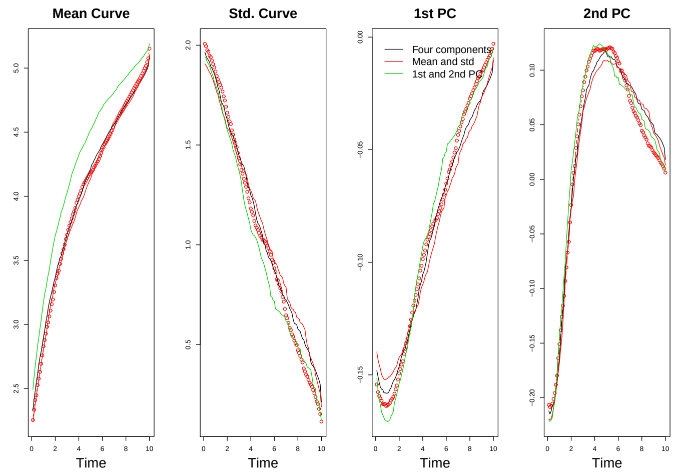

Figure 2.6: Visual Comparison of Different Fitness Function Settings' Effect on Price Curves.

results too much, in that, qualitatively, my overall conclusions remain the same.

Finally, in order to evaluate the difference between the different fitness function weighs, I examine the RMSE of the resultant components of the price curves, i.e, μ, σ, PC1 & PC2 for the three different settings and the real data. The hypothesis is that if one of the three fit the data better on all four components that would be the best choice for the weighting. Table 2.3 and Figure 2.6 shows the results. It is clear that Scenario 3, which uses all four curves, provides the best results, or nearly best results (RMSE of PC1 is a little greater than Scenario 2), for all four RMSE values. Therefore, I will use the settings from Scenario 3 for the rest of this dissertation.

Table 2.4: Estimation Results

Variable	Parameter	Method	Estimation
Number of bidders	λ_N	MLE&GA	12.35
Starting price	α_p, β_p	MLE	0.17, 0.59
Evaluation of the item	μ_w, σ_w^2	MLE&GA	174.4, 21.0
Bid shading	α_ρ, β_ρ	GA	1.2,4.2
Number of revisits	λ_{re}	MLE&GA	0.97
First decision time	α_t, β_t	MLE	0.58, 0.34

2.4.3 Estimation Result

The GA algorithm is applied to the eBay auction data in the following way. As pointed out earlier, some of the ABM parameters are estimated directly from the data using maximum likelihood estimation (e.g. starting price and each bidder's first visit time). For other parameters, I use maximum likelihood estimates as starting values and then update these values using the GA. The reason I combine these two method together is that it provides for a better way of estimating parameter values than MLE alone. For example, the average number of different bidders in each auction is a good initial value for the arrival rate of bidders, but I would expect the true parameter is greater then the observed average, because there are potential bidders that checked the auction status but did not bid [14]. Similarly, by just using MLE from observed data, the inference of bidders' revisit rate λ_{re} and evaluation of the item $w_{k,i}$ would be biased. So both MLE and GA are used in estimation of parameters. The parameters for the bid shading distribution are estimated entirely from the GA. Table 2.4 shows the estimation results and the estimation methods.

2.4.4 Computational Error Analysis

Finally, I examine the convergence rate of my algorithm. For simplicity, I focus the investigation only on the bid shading parameters and hold all other parameters constant. The left panel in Figure 2.7 shows the fitness performance of GA over 100 populations. I can see that the fitness function improves rapidly over the first 20 iterations and slows down subsequently. In the right panel of Figure 2.7, I fit a linear regression line to the log-transformed fitness (Y) and log-transformed number of iterations (X). This model fits the data very well ($R^2 = 0.88$) and both the intercept and slope are significant with values of -1.79 and -0.35, respectively. Let F denote the fitness and n the number of iterations, then the relationship between fitness and number of iterations can be approximated by

$$F = 0.179n^{-0.35}.$$

From the regression equation, it is clear that the mean fitness converges toward 0. Thus, the fitness of the best individual also converges to 0, since mean fitness is an upper bound of it. Also, from the regression function, it is easy to calculate that from 50 iterations to 100 iterations, the weighted RMSE drops about $22\% = 1 - 100^{-0.35}/50^{-0.35}$. While for an additional step, after 100 iterations, the weighted RMSE drops only $.3\% = 1 - 101^{-0.35}/100^{-0.35}$, which indicates that 100 iterations is a good stop point for the algoritm used in my model.

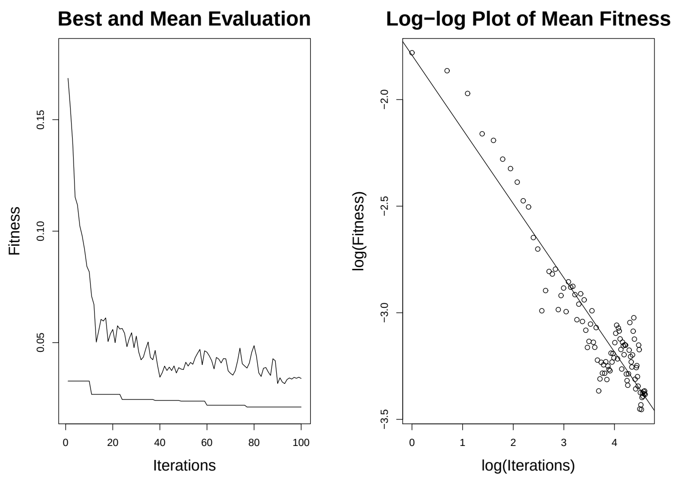

Figure 2.7: GA performance

2.5 Conclusions

Understanding the reason why bidders behave a certain way allows invaluable insight into the auction process. In this work, I shed some light on the amount by which bidders shade their bids, i.e., their aversion to taking risks. I do so by combining novel tools from functional data analysis, agent based modeling and genetic algorithm. One obvious benefit of the genetic algorithm is computational simplicity, in this case I save substantial computation time by not having to fully iterate through the whole search space.

I find that bidders tend to bid rather conservatively, with a bid shading distribution that is right-skewed. This indicates the auction price might not give sufficient information on bidders' evaluation of item. So, if a bidder places a bid early with a bid amount close to the current price, it triggers other bidders to overbid her, since the required overbid price tends to stay in the range of their willingness to pay. So sniping (placing a bid in last minute) an auction might be a good strategy for bidders in internet auctions to avoid competition from other bidders. In the next chapter, I utilize this online auction model to test performance of sniping strategy as well as some other theoretical and empirical strategies.

Chapter 3

Bidding Strategy Investigation and Comparison

3.1 Introduction

In this chapter, I study the performance of bidding strategies. I first derive empirical winners' strategies from actual eBay data and then test and compare the performance of both theoretical and empirical strategies, by embedding them into the online auction agent-based model. As discussed in Chapter 2, by utilizing agent-based modeling (ABM) approach, I constructed an online auction simulation model. The model is a close representation of the online auction bidders' behavior and the auction price processes, of which parameters are estimated from eBay data. By equipping chosen bidders with certain strategies and tracking their performance through the auction process, this online auction model provides a flexible platform for testing bidding strategies. There are several advantages of using ABM to carry on simulation experiments. First, it allows us to explore scenarios that hard to conduct in empirical tests in real online auctions. For example, we can test scenarios that a particular kind of bidding strategy used by one bidder or any fixed number of bidders, or even a random number of bidders in an auction, which is not under control of experimenters in empirical studies. In addition, ABM simulation enables us to collect results with a large sample size, which plays a very important role in getting reliable test results because of the large variance in the price dynamics, even within auctions selling the same item . This ABM simulation experiment design can serve as an testing mechanism for bidding strategies in future online auction studies, which is not easily generated within other modeling approaches.

The first main component of this chapter is a close investigation of winners' behavioral pattern. As in offline auctions, the winner of an online auction is the bidder who places the highest valid bid. To get a better chance of winning, one might want to bid the highest price she can afford. However, in a common value item auction, this is not considered as a wise strategy, because it bears the risk of overpaying for an item, which could be bought cheaper somewhere else. Because online auctions have been a popular exchange mechanism for more than a decade, it is fair to assume that the auction winners gained experiences through participation in auctions and developed empirical strategies to win auctions with a fair price. Therefore in this analysis, I analyze winners' behavior and extract empirical strategies from digital camera auction winners on eBay.

When a bidder decides to bid in a auction, there are two crucial aspects involved in the bidding strategy: (1) when to bid, and (2) how much to bid [19]. In this work, the winners' strategies are investigated on both aspects. More specifically, I try to identify the factors that influence a winner's decision with respect to bid increment and timing. Through data analysis, I show that some easily observable factors, such as current price and number of bids, are related to winners' bid increments; while some other factors which influence closing price [20], such as price dynamic and competitive auction information are not related to winners' bid increments. In addition, I find that winners' bid timing is not significantly related to any of the auction features and dynamics, which leads to the assumption that winners' bid timing decisions are pre-determined rather than temporal decisions evolving with the development of the auctions.

In the second component of this chapter, I test the performance of bidding strategies through the online auction model. I begin with a discussion on how to incorporate different strategies in the simulation model for testing. Then, I present and discuss the simulation results from different simulation settings. For comparison purposes, I test both empirical winners' strategies and bidding strategies that have been deemed important in previous work, such as willingness to pay (WTP) bidding [11] (i.e., bid the highest price that one is willing to pay for the item), early bidding [4] and sniping [5]. In total, there are 24 different combinations of bid increment and bid timing strategies tested in this work and the test result of each strategy is summarized from 2000 simulated auctions.

3.2 Winners' Bidding Strategies

In this section, I derive empirical winners' bidding rules from the actual eBay data. This section includes two parts: the first part investigates winners' bid increment strategies (i.e., how the winners decide to what degree they raise their bids). The second part focuses on the bid timing (i.e., when the winners place their bids). To get better prediction power, different methods are used to model bid increment and bid timing. Modeling details are described below in Section 3.2.2 and 3.2.3

3.2.1 Data Description

In this study, I use the same dataset from eBay in Chapter 2. The auction closing prices in the data range from \$89 to \$232.5, with the mean at \$172.3 and standard deviation \$19.58. Because all the auctions are selling the exact same item, the winning price of a winners is a good indicator of whether she made a good decision in bidding. For comparison purpose, the auction winners are divided into three even groups according to their winning prices. The first group includes the top 33.3% *smart* winners, (i.e., winning with the lowest prices), the second group comprises the *average* winners and the third group includes the *bottom* 33.3% winners with the highest winning prices. An uneven grouping method with the cut-off as average winning price plus and minus one standard deviation was also investigated. I found that the captured strategies of each winner categories are similar from both grouping methods, i.e., the smart winners' strategy from the even group is similar to smart winners' strategy from one standard deviation group. So in this chapter, I only present results from the even grouping method.

When a bidder tries to make a bidding decision, there are all kinds of information available on eBay, including information on the chosen auction and of its concurrent auctions. Table 3.1 lists the candidate predictors used in this study and their summary statistics. Some of the predictors are static variable, i.e., not changing over time, such as starting price and duration of the chosen auction; while some of the predictors are evolving over time, such as current price and time left of the chosen auction. Another major component of our candidate predictors is

Table 3.1: Descriptive statistics of predictors for winners' bidding strategy.

Variable	Mean	Std. dev.	Median	Min	Max
Chosen Auction					
Static features					
Duration	3.53	2.42	3	1	10
Starting Price	48.16	68.40	1.00	0.01	219.99
Evolving Features					
Current Price	162.7	23.9	162.5	18.5	230.0
Time Left (days)	0.109	0.360	0.007	0.000	6.454
Number of Bidders	7.41	4.09	8	0	19
Number of Bids	14.8	9.85	15	0	79
Number of the Winner's Bids	1.06	1.88	0	0	15
Price Dynamic					
Price Velocity	0.18	0.27	0.11	-0.07	4.03
Price Acceleration	0.0000	0.0005	0.0000	-0.0031	0.0020
Dummy Variable	0's	1's			
If Chosen Auction Ends First	270	853			
Concurrent Auction Features					
Number of Concurrent Auctions	23.2	9.7	21	1	48
Average Price	90.0	21.9	87.8	43.1	149.5
Average Number of Bidders	3.00	0.82	2.96	0.57	10.00
Average Number of Bids	5.84	1.93	5.71	0.57	25.00
Average Time Left	2.500	0.594	2.550	0.221	4.210

the information from concurrent auctions. Once a bidder searches for an item on eBay, there will be several to hundreds of auctions available on the website selling the same item. The price of all these auctions could be quiet different and some auctions might end soon and some last for days. All this information might provide some reference for bidders. In this study, I include five variables representing the information from concurrent auctions as listed in the concurrent auction feature of Table 3.1. In addition, since eBay provides the option to sort the search result by ending time, and it is believed that users frequently use this option, we kept track of a dummy variable that indicates whether the chosen auction is the one ending soonest among all the auctions that sell the same item. As the frequency table shows, 76% of winners make their winning bid when the chosen auction is the one ending first among all auctions selling the same item. In addition, since price dynamics of an online auction have been shown to be powerful in predicting internet auction prices [26, 10], we also investigate whether auction winners utilize price dynamics their decision making.

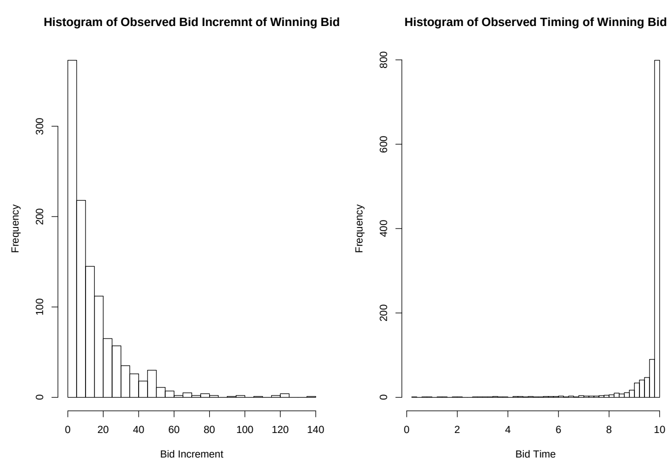

Figure 3.1: Histograms of bid increment and bid time of winning Bid.

One major focus of my analysis of winners' behavior is how the winners choose their bid increments under different auction scenarios, because how much more to bid is the key decision a potential bidder needs to make [14]. The left graph of Figure 3.1 shows the distribution of bidders' bid increment. The heavily right-skewed shape indicates that most winners tend to bid with relatively small increments. About 50% of bid increments are less than $10, and 75% are less than $20, while only 0.7% of bid increments are more than $100. In addition, the bid timing is another important aspect of bidding strategies. From the observed data in Figure 3.1, we can see that most winning bids are placed near the end of the auction. About 90% of the bids are placed in the last day, 53.8% in the last hour, and 17.6% in the last minute.

3.2.2 Modeling of Winners' Bid Increments

To extract empirical bid increment strategies from winners, I focus on the winners' winning bid, which is the most crucial bid leading to their victory. It is important to stress that there are two possible kinds of winner's winning bids. It could be the only bid placed by the winner, or it could be one of the series bids placed by the winner. For the single bid scenario, it is clear that the winning bid includes the complete information of the winner's bidding behavior and hence a proper choice for my investigation. For the series bids scenario, I chose to rule out the previous bids and only focus on the winning bid by considering eBay's auction mechanism. In an eBay auction, once a bidder gets outbid by others, his/her bidding information, including the original bid time and actual bid amount, is available to

Table 3.2: Correlation table of winners' bid increments and predictors.

Variable	Smart	Average	Bottom	Losing
Chosen Auction				
Static features				
Duration	-0.05	0.07	0.01	-0.05
Starting Price	-0.11	-0.20	-0.13	-0.14
Evolving Features				
Current Price	-0.82	-0.79	-0.72	-0.27
Time Left (days)	0.38	0.44	0.28	0.09
Number of Bidders	-0.14	-0.01	-0.11	-0.19
Number of Bids	-0.13	-0.01	-0.08	-0.17
Number of the Winner's Bids	-0.12	-0.10	-0.19	-0.22
Price Dynamic				
Price Velocity	0.04	0.31	0.11	0.18
Price Acceleration	-0.02	0.02	-0.03	-0.11
Dummy Variable				
If Chosen Auction Ends First	-0.34	-0.25	-0.29	-0.23
Concurrent Auctions Features				
Number of Concurrent Auctions	0.08	0.00	0.02	-0.005
Average Price	-0.06	-0.04	-0.09	-0.002
Average Number of Bidders	-0.03	0.00	-0.04	-0.02
Average Number of Bids	-0.03	-0.01	-0.03	-0.02
Average Time Left	-0.02	-0.03	0.11	-0.02

others. So, the information available to make the current bidding decision is the same for the first time bidders and returning bidders. In addition, what I am interested in this research is how winners utilize the available auction information to make their victory decision. Thus I chose to focus on the winning bids for my investigation of empirical bidding strategies from winners. Besides the 1123 winners in the 1123 auctions, there are 8333 losing bidders. I also investigate the losing bidders' bidding strategies for comparison purpose. To keep my investigation consistent, only the last bid of each losing bidder in each auction are kept for strategy investigation.

The goal of this work is to understand winners' strategies. To capture how winners make decisions about their bidding magnitude, both bid amount and bid increment are suitable dependent variables. I first tried to build separate models for these two dependent variables and found that by using bid increments as a dependent variable, the modeling results and prediction power are more significant. Therefore bid increment is chosen as the dependent variable. As mentioned earlier, winners are separated into three different groups according to their winning price. The correlations of bid increment and the predictors are shown in Table 3.2. From the table, it is clear that evolving features have the strongest correlation to bid increment. It is interesting that current price, number of bidders and number of bids have the strongest negative correlations with *smart* winners' bid increment, which indicates that *smart* winners reduce their bid increment most significantly, when the price or competition level rises. The other predictors, especially the price dynamic and concurrent auctions groups have low correlations with winners' bid increments, which indicate these characters might not be taken into consideration, when winner decide their bids.

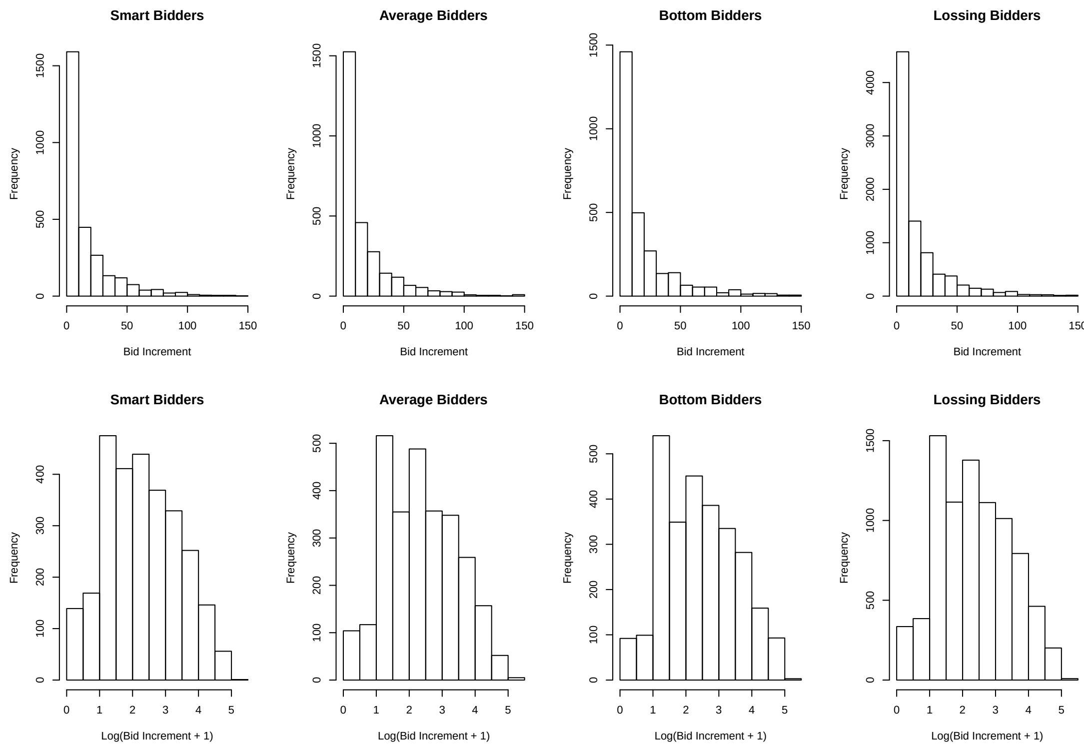

Figure 3.2: Histogram of winners' bid increment before and after transformation.

The bid increment variable is highly right-skewed as shown in the first panel of Figure 3.1 and the skewness is kept into each subgroup of winners as shown in Figure 3.2. Taking logarithm transformation helps ease the skewness and large variance of bid increment as shown in the lower row of Figure 3.2. The summary statistics of transformed bid increments are shown in Table 3.3. It is interesting that the distribution of bid increments for these three groups (smart, average, bottom and losing) of winners are similar in both shape and magnitude, which indicates that the lower closing price achieved by smart winners is not simply due to conservative bids. In the following sections, I will show that the smart winners' bidding decision helps them avoid intense competition and their strategy outperforms other bidding

Table 3.3: Descriptive statistics of transformed winners' bid increment.

Group	Mean	Std. dev.	Median	Min	Max
Smart	2.36	0.91	2.40	0.00	4.94
Average	2.27	0.99	2.27	0.00	4.83
Bottom	2.41	0.98	2.40	0.00	4.82

strategies in multiple simulation tests.

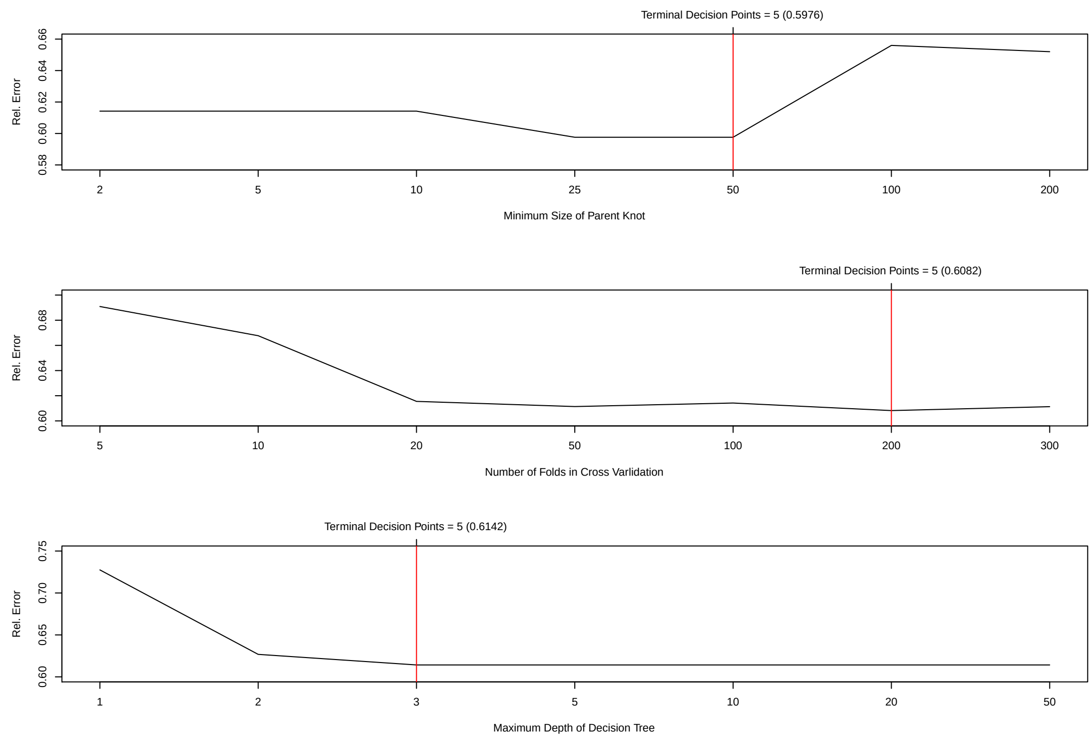

Figure 3.3: Error portfolio of regression tree for smart bidders' increment.

The regression decision tree (CART) [44] method is used to capture the bidding strategy of each winner group. A decision tree is a tree-like model made up with various decision points, where each point is optimized to closely represent the observed bidding behaviors. There are several reasons that I choose regression decision tree method. First, a decision tree regression is easy to interpret and im-

Table 3.4: Variable selection results and cross-validation error.

Winner Type	Smart	Average	Bottom
Summary Statistics			
Sample Size	375	374	374
Winning Price Range	[$89.00,$160.50]	($160.50,$182.00]	($182.00,$232.50]
Decision Tree			
Cross-Validation MSE	0.451	0.374	0.355
Variable Selected	current price	current price	current price
	number of bids	number of bids	starting price
Linear Regression			
Cross-Validation MSE	0.528	0.888	0.925
Variable Selected	current price	current price	current price
	number of bidders	Starting Price	Starting Price
	If End First	Num. Own Bids	Num. Own Bids
		Concur. Avg. Num. Bids	Std. Bid TIme

plement. Especially in this analysis, the bidding strategies derived have only three to five final decision points, as shown in Figure 3.4 to 3.7. Second, the decision tree method utilizes fewer variables and performs better (i.e., less testing error) when compared with linear regression models; this indicates that decision trees have a better leverage in utilizing information from predictors. The variable selection results and cross-validation results are shown in Table 3.4. The testing errors are calculated from exhaustive cross-validation – specifically, the error of each winning bid increment is calculated from a model (decision tree/linear regression) generated without that particular winning bid. Finally and most importantly, the three decision trees of winners' strategies are robust to the choice of modeling parameters, including minimum data size in parent decision points, maximum depth of the tree, and number of folds in cross-validation for pruning purposes. Figure 3.3 shows the relative error graph with changing parameters for the *smart* winners' dataset. As marked on the graph, all the optimal trees have five final decision points and are actually all the same model. The standard errors in the three charts exhibit a little difference, because the default number of fold in cross-validation is 100 and the default minimum data size in parent decision points is 10. Here I utilize a one standard deviation rule to select the best tree [45], that is, I choose the tree that is within one standard deviation of the minimum error and with the least layers. The same robustness is also seen in decision trees of *average* and *bottom* winners.

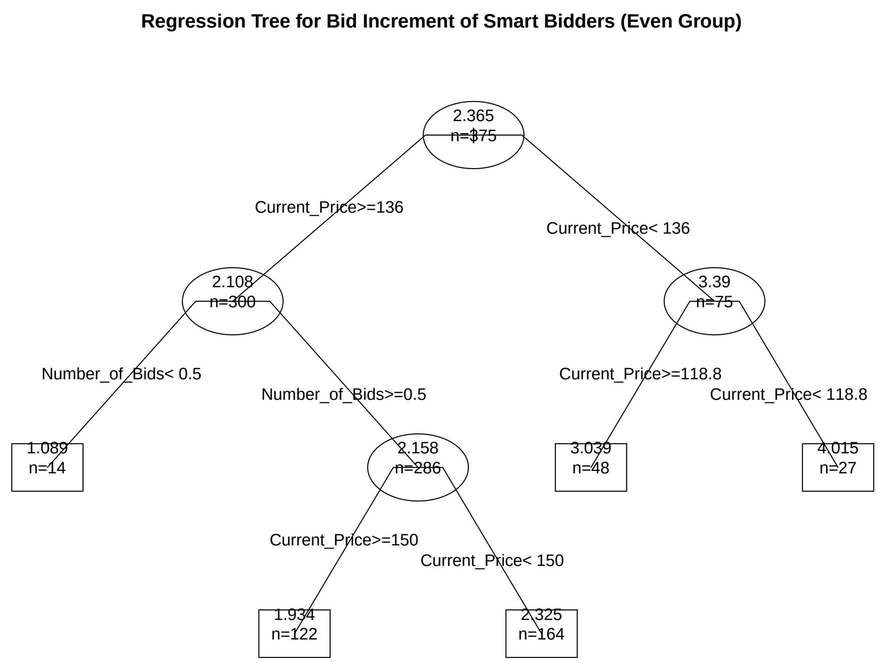

Figure 3.4: Regression decision tree of smart winners' bid increment.

There are several interesting results in the bid increment decision trees, shown in Figure 3.4 to 3.7. First, all the decision trees showed a similar pattern that bidders tend to add more bid increment when the price is low, and add less bid increment

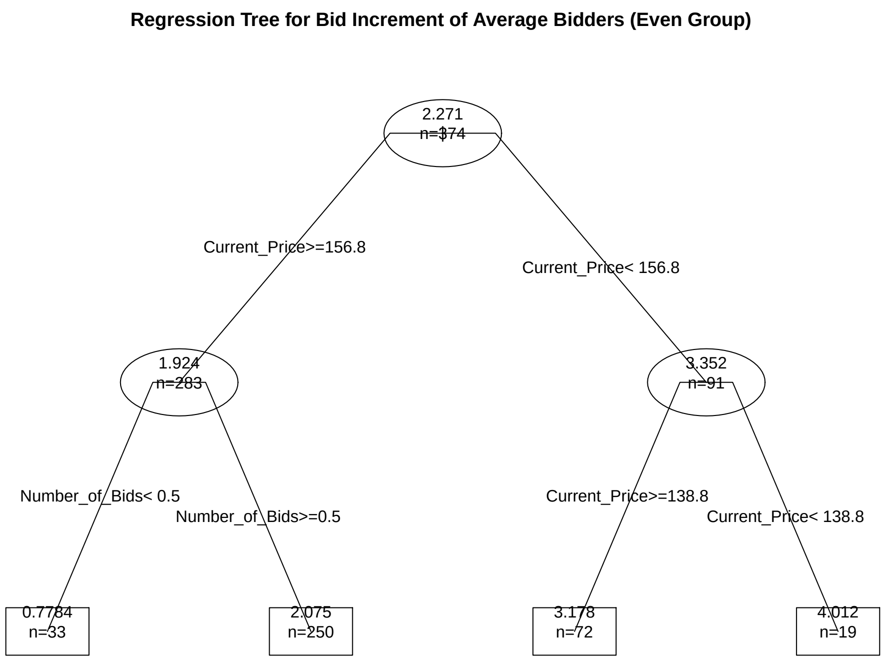

Figure 3.5: Regression decision tree of average winners' bid increment.

when the price is high. This phenomenon indicates that when bidders make decision about bid magnitude, they reference both the current price and their evaluation of the product. So when the gap between the two is large, they might consider to adding more bid increment. This observation is coincident with the assumption and results in our online auction model in Chapter 2 and [39]. Second, in addition to the major split factor current price, the split points for different groups of bidders are different. Take the first splits as an example. The losing bidders have the lowest split point $129.5 (Figure 3.7), then smart winners have the second lowest split point $136 (Figure 3.4), average winners have a higher split point $150.1 (Figure 3.5), and bottom winners have the highest split point $180 (Figure 3.6). This phenomena show that the smart winners are more conservative and begin to add small increments at

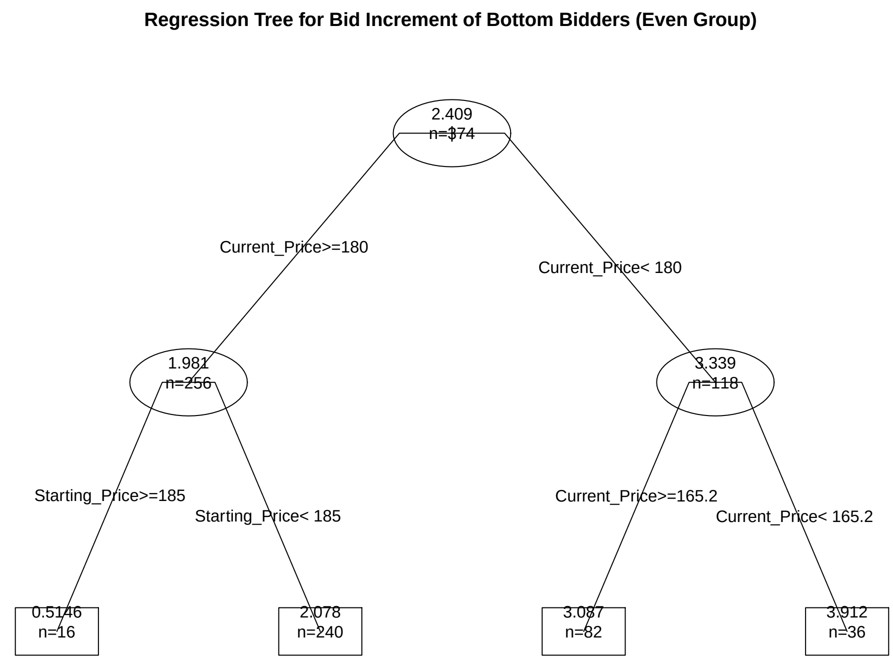

Figure 3.6: Regression decision tree of bottom winners' bid increment.

a relatively low price, while bottom winners are still adding large increments when the price is high. While losing bidders are the most conservative and therefore loss in the auctions. Thirdly, the magnitude of bid increments for losing bidders is much less than winners. For all three group of winners, the magnitude of bid increment are around 3 and 4 after logarithm transformation, when the price is lower than the threshold mentioned earlier. While, losing bidders bid increments are all less than 3 after logarithm transformation. In addition, bidders also consider some other factors, such as whether they are the first bidder in the auction (Figure 3.4 and Figure 3.5). One interesting thing worth mentioning is that concurrent auctions information is not selected into the decision trees, which indicates that winners are making their decisions based on simple facts that they can easily observe from the

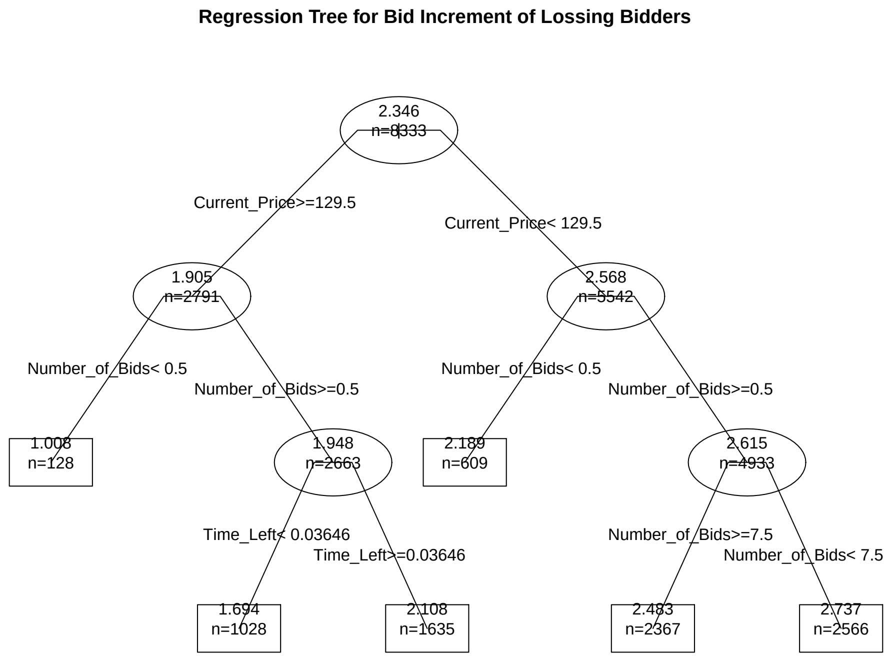

Figure 3.7: Regression decision tree of losing bidders' bid increment.

auction rather than complicated factors derived from multiple auctions.

3.2.3 Modeling of Winners' Bid Timing

There are two main difficulties in building a predictive model for winners' bid timing strategy. First, there is some evidence that bidders' bid timing might not be directly relevant to static or dynamic features of auctions. For example, sniping behavior is wildly observed in online auctions, which do not show dependence on auction price or competition intensity. If bidders' bid timing decisions are not based on their observation of auction characteristics, then it would be hard to build a reliable predictive model for bid timing. To answer this question, I build predictive models for bid timing to see if there is significant evidence to support that bid-timing

Table 3.5: Distribution of winning time.

Auction Day (Standardized)	1	2	3	4	5	6	7	8	9	10
Count of Winning Bids	5	4	4	6	7	8	12	18	53	1038

decisions are based on auction characteristics. Second, assuming bidders bid timing decisions are based on their observation of auction characters, the eBay data do not include the information of bidders observation time, because the data only contain bidders' actual bid information without their search and click history. Therefore I have little information on the dynamic (time dependent) features of the auction when the winners observed the auction and decided their bid timing. To overcome this difficulty, I make assumptions about winners' observation time T_{obs}. Table 3.5 shows the frequency count of winning bid in each day.[1] In total, there are only 26 winning bids happened in the first 5 days of auctions, 64 winning bids in the first 8 days and 117 winning bids winning bids in the first 9 days. So as long as the hypothetical observation time T_{obs} is before the last day of the auction, I will not lose many data points. To find the "optimal" observation time T_{obs} that produces the most powerful predictive model, a series of observation points are tested out, including the end of 5, 6, 7, 8 and 9 days.

The intuitive choice to model the bid timing is treating the response variable, bid timing, as a continuous variable. However, after investigating the scatter plots (Figure 3.8), correlations and initial regression modeling ($R^2 < 0.1$), the relationship between predictors and the response variable are not very strong. My second

[1]The auction length in eBay data are different (1, 3, 5, 7, 10 days). To make the bid timing and price dynamic comparable, all the auction length are standardized to 10 days.

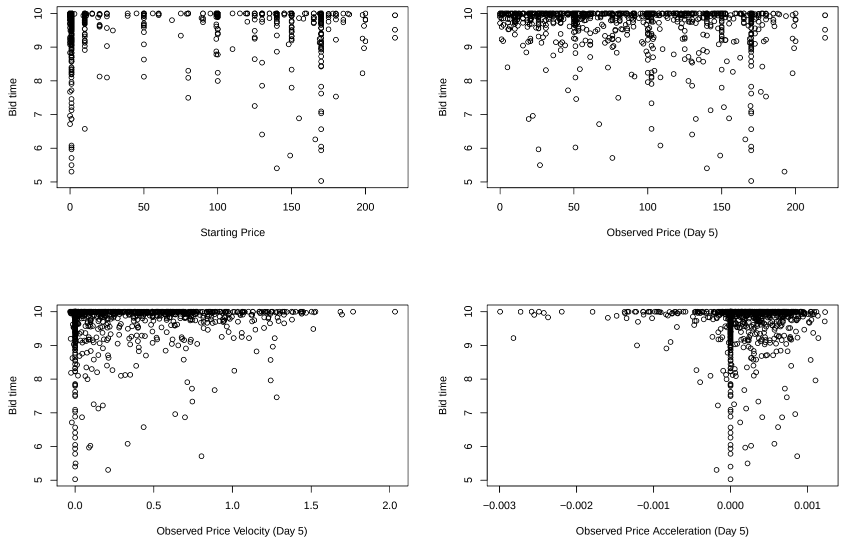

Figure 3.8: Scatter plots of bid time v.s. auction characters.

modeling attempt is to segment the bid timing and build a classification predictive model. Thus the next question is how to segment the winning times. To get an idea about whether a classification model will work for winners' bid timing, I started with two segments: *early* and *late* bid timing. Following similar ideas of observation time T_{obs}, the cut-off point for *early* and *late* bid timing is not pre-determined but searched on the interval $[T_{\text{obs}} + 1, 9.999]$ (unit: day). The reason that the cut-off points start on $T_{\text{obs}} + 1$ is that there are very few winning bids between T_{obs} and T_{obs} + 1 (for $T_{\text{obs}} \leq 9$) and hence there will be too few data points for *early* timing class within the first day. To search for the optimal cut-off point, the prediction accuracy of different points is evaluated on the interval $[T_{\text{obs}} + 1, 9.5]$ by .1 increments and on the interval (9.5, 10) by .001 increments. For example, if $T_{\text{obs}} = 5$, on the interval $[T_{\text{obs}} + 1, 9.5]$ the potential cut-off points include 6, 6.1, 6.2, ... , 9.5 and on the interval [9.501, 9.999] the cut-off points include 9.501, 9.502, 9.503, ... , 9.999. So

Table 3.6: Results of performance test for observation time T_{obs} and cut-off points of *early* and *late* timing.

Observation Time T_{obs}	Day 5	Day 6	Day 7	Day 8	Day 9
Optimal cut-off on $[T_{\text{obs}} + 1, 9.5]$	6.6	7.3	8.0	9.0	NA
Area under ROC	0.722	0.775	0.776	0.688	NA
Optimal cut-off on [9.501, 9.999]	9.517	9.517	9.517	9.517	9.518
Area under ROC	0.639	0.658	0.662	0.659	0.646

totally, the model tests 535 potential cut-off points for *early* and *late* timing when $T_{\text{obs}} = 5$.

A logistic regression model is used to build the class prediction model of bid timing[2]. To access the model fitting, the area under ROC curve[3] is calculated to access the prediction performance. Table 3.6 lists the optimal cut-off points for different observation points. It is clear that the cut-off points on the first interval $[T_{\text{obs}}+1, 9.5]$ generates a binary response variable that is easier to predict. However, with the cut-off points this early, there are only around 20 observations in the early bidding category and more than 1000 observations in the late bidding category. In this situation, the coefficient estimation results might not be robust and the model will bear high false negative rate. In addition, it is interesting that for the second interval [9.501, 9.999], the optimal cut-off points for different observation time are almost the same at 9.517 (day). Furthermore, for both cut-off intervals, observation time at day 7 has the best performance than other observation times.

[2]The decision tree method was also considered and a test run showed that the resulting decision tree is unstable with different number of cross-validation. Therefore, the result is nor reliable and not reported here.

[3]A rough guide for classifying the accuracy of a diagnostic test is the traditional academic point system: .6 to .7: poor, .7 to .8: fair, .8 to .9: good, .9 to 1: excellent. http://gim.unmc.edu/dxtests/roc3.htm

However, from the area under ROC curve, it is clear that the prediction accuracy is poor. This is not unexpected, because the histogram of winning times in Figure 3.1 shows a clear pattern that most winning bids concentrate on the closing period despites the diversity in price dynamic as shown in Figure 2.1. So in this study, I chose to use a simulation method to represent winners' timing strategy, rather than predictive modeling. Similar to bidders' bid timing discussed in Section 2.3.1.3, I use the empirical distribution to model the winners' decision times $d_1, d_2, d_3, ..., d_N$ and derive winners' bidding times $t_1, t_2, t_3, ..., t_N$ according to auction price process as in Equation 2.1 in Chapter 2.

3.3 Experimental Set-Up and Results

In this section, I first discuss how to carry on simulation experiments for different bidding strategies and then discuss the findings from experiment results.

3.3.1 Simulation Framework and Experiment Testbed

The online auction model discussed in Chapter 2 can serve as an simulation experiment platform for bidding strategies. The model simulates bidders' bidding behavior and generates the corresponding auction price process. The simulation parameters for bidders' behavior are estimated from actual eBay data as listed in Table 3.7. By changing the distributions to another distribution or even another rule/function, the model allows researchers to explore various questions. For example, if a research is interested in testing the influence of starting price on the auction

Table 3.7: List of variables in the online auction model.

Level	Variable	Distribution & Parameters	Apply to
Auction	$P_{t=0}$: Starting price	$180{\cdot}\text{Beta}(\alpha_p = 0.17, \beta_p = 0.59)$	All bidders
	N: Number of bidders	$\text{Poisson}(\lambda_N = 12.35)$	All bidders
Bidder i	w_i: Evaluation of the item	$\text{Normal}(\mu_w = 174.4, \sigma_w^2 = 21.0)$	All bidders
	ρ_i: Bid increment/shading	$\text{Beta}(\alpha_\rho = 1.2, \beta_\rho = 4.2)$	General bidders
	$t_{i,1}$: First decision time	$10{\cdot}\text{Beta}(\alpha_t = 0.58, \beta_t = 0.34)$	General bidders
	n_i: Number of revisits	$\text{Poisson}(\lambda_{\text{re}} = 12.35)$	General bidders
	$t_{i,j}$: Revisit times $j \geq 2$	$\text{Uniform}[t_{i,1}, 10]$	General bidders

price process, she can experiment with different parameters and distributions for starting price. In this work, I focus on bidding strategies including both bidding increment and timing strategy. So the last four distributions shown in Table 3.7 will be substituted with different strategies/distributions from the testbed.

Bidders' bidding strategies can be changed, by varying the way bidders decide their bid increment, that is, changing the expressions in Equation (2.2). For example, I can include previous number of bidders, price velocity, and the like. The only difference compared to the general model is that there is a step to decide if the coming bidder is a special bidder. If the bidder is a special bidder, then she will follow a special rule to decide bid increment (e.g. decision trees in Figure 3.4 to 3.7), instead of Equation (2.2). Similarly, I can also change some bidders' decision time to a special rule. Simulation test for the performance of different bidding strategies can be carried on by assigning the strategies to bidders in the agent-base model.

In addition to the empirical strategies discussed in Section 3.2, I also include several famous theoretical bidding strategies in the experiment testbed for comparison purpose. *Early* bidding and *sniping* are the two most famous timing strategies in Internet auction literature [4]. The early bidders place their bids early with a high price to ensure a time advantage and to intimidate other bidders with their high bid amount. Although eBay does not reveal the highest bid in an auction and instead only shows the second highest price, bidders could still be intimidated and give up on a particular auction, if their bids are automatically overbid several times because of a not-shown high bid. In my model, early bid timing is simulated by a continuous uniform distribution on the first day of the auction, i.e., $t_l \sim \text{Uniform}(0, 1)$, where bidder l is an *early* bidder. The terms "snipers" or "last minute bidders" refer to those who bid near the end of the auction, to avoid competition, i.e., lower the chance of being overbid by others. This bid timing strategy is well observed in Internet auctions and its effectiveness is quiet controversial. Some researchers have claimed the benefit is not significant and the reason that bidders keep sniping in eBay auctions is due to a lack of understanding of the second price auction mechanism [12]. However, in this study, the simulation experiment results show that *sniping* combined with some suitable bid increment strategy outperforms other strategies. In the simulation experiments, the *sniping* bid is uniformly distributed in the last minute of the auction, i.e., $t_l \sim \text{Uniform}(10 - 1/1440, 10)$, where bidder l is a *sniper*. To make my investigation more thorough, I also included a *carefree* timing, which refers to bidders who do not make careful choice in the bid timing and place their bids when they check on the auction. Thus, it is simulated by a uniform distribution over the whole auction duration, i.e., $t_l \sim \text{Uniform}(0, 10)$, where bidder l is a *carefree* bidder. Furthermore, I also investigated two theoretical bid increment

Table 3.8: Test-bed of bidding strategies

Timing Strategy	Arrival Time Distribution[4]
Early Timing	Uniform distribution on first day
Carefree Timing	Uniform distribution on entire auction
Winners' Timing	Empirical distribution from winners' timing
Sniping	Uniform distribution on the last minute

Bid Increment Strategy	Description
Maximum	bid amount = evaluation
Minimum	bid amount = minimum require bid
Smart Winner	decision tree as in Figure 3.4
Average Winner	decision tree as in Figure 3.5
Bottom Winner	decision tree as in Figure 3.6
Losing Bidder	decision tree as in Figure 3.7

strategies: *maximum* bidding and *minimum* bidding. The eBay website suggests bidders to bid the maximum amount that they are willing to pay for an item, and let the eBay platform automatically place incremental bids on their behalf. eBay indicates that bidders will benefit from this strategy by having a greater chance of winning and still only needing to pay the second highest price. In contrast with eBay's suggestion, there are also bidders who only bid the *minimum* required bid to try their luck, which I name *minimum* bidding and also test in the study. The testbed consists of 4 timing strategies and 6 bid increment strategies as shown in Table 3.8. Because each special bidder needs both timing and bid increment strategies, there are 24 pairs of strategies tested in this study.

3.3.2 Single Special Bidder Experiments

The online auction agent-based model is used to carry on simulation experiments for the performance of 24 different bidding strategies. To get the performance evaluation, each strategy was tested in 2000 simulated auctions. In each auction, one bidder/agent is equipped with a special strategy for testing and other agents (general bidders) keep the same behavior rule as in Table 3.7, which are calibrated in Chapter 2. The rules marked as "applied to all bidders", are applied to both special and general bidders. To get a meaningful result, I drop the very rare (.006%) situation in which there are auctions with no bidder or only one interested bidder, because there is no competition and the auction will end with the starting price, no matter what the bidder's strategy is.

When evaluating the performance of each strategy, I focus on two main factors, the winning price and the probability of winning. These two aspects are both important, since the winning price represents bidders' monetary cost and the probability of winning relates to bidders' time cost. Different bidders might put different emphasis on these two aspects. But with both kinds of information available, they would be able to choose the strategy that best suits their needs. Furthermore, if there exists a single strategy that outperforms others in both aspects, this strategy would be the optimal strategy among the 24 strategies we investigated.

Table 3.9 shows the probability of winning by using each bidding strategy and Table 3.10 shows the average winning price of each strategy with 95% confidence half length. From Table 3.9, it is clear that the first two timing strategies result

Table 3.9: Winning probability (by percentage) for single special bidder.

Timing	Early	Carefree	Winners'	Sniping
Smart	0.2	2.1	22.6	39.5
Average	0.2	3.3	29.5	43.9
Bottom	1.2	6.4	33.7	48.6
Maximum	22.0	27.8	42.3	50.6
Minimum	0.1	0.6	11.1	24.5
Losing	0.2	0.8	17.8	36.8

Table 3.10: Average winning price for single special bidder.

Timing	Early	Carefree	Winners'	Sniping
Smart	120.05±91.85	154.68±10.96	157.29±2.74	158.11±1.90
Average	132.54±69.89	165.55±5.28	158.63±2.15	158.16±2.15
Bottom	186.99±3.28	174.90±3.87	163.67±1.87	161.10±1.62
Maximum	182.20±1.87	177.19±1.85	165.10±1.80	159.98±1.70
Minimum	166.61±133.31	174.82±6.94	165.04±2.88	166.73±1.88
Losing	182.23±8.08	179.80±15.38	163.87±2.54	162.18±1.86

in very low probability of winning (less than 10%) when combined with most of the bid amount strategies except the *maximum* strategy, which means that the bidder submits the maximum price she is willing to offer and lets the system do proxy bidding on her behalf. The interesting thing is that this strategy is what eBay's website advises bidders to do. In addition, it is clear that by carefully choosing the bid timing (e.g. *winners'* timing or *sniping*) the probability of winning is significantly raised with all bid amount strategies. The highest probability of winning is from the combination of *sniping* and *maximum* bidding, which is in accord with common intuition, because this combination minimizes the chance of overbidding by both maximizing bid amount and minimizing time left in the auction. In Table 3.10, I focus the discussion on the strategies with a reasonable winning chance (above 10%), among which the lowest average winning price results from the combination of *winners'* timing and *smart* bidders' bid increment strategy. In addition, by considering the confidence interval, there are several strategies perform as well as this pair, including *winners* timing combined with *average* bid increment, and *sniping* timing combined with *smart*, *average*, *bottom* and *maximum* bidding. From both tables, it is clear that *sniping* combined with *maximum* bidding results in the highest winning probability and one of the lowest winning prices. In addition, this strategy requires almost none consideration and computation in bid amount. So, the *maximum* bid strategy suggested by eBay seems to be an optimal strategy in this observed bidding environment.

As can be imagined, if a bidding strategy leads to higher winning probability and lower winning price than other strategies, this strategy would gain popularity among bidders. Then there would be more than one bidder to adopt this strategy in auctions. The next question I am trying to answer is what will happen if more than one bidder adopts the same special strategy. Will *sniping* combined with *maximum* bidding still be the optimal strategy after it gains popularity? If so, why we did not observe its popularity in eBay data? If not, which strategy would lead to a robust return, even if more bidders adopted the same strategy? These questions are answered in the next section.

Table 3.11: Winning probability (by percentage) with 20% special bidders.

Timing	Early	Carefree	Winners'	Sniping
Smart	0.4	3.1	25.5	41.1
Average	0.5	4.4	31.1	45.1
Bottom	2.1	8.7	36.4	51.1
Maximum	18.6	24.1	43.6	51.4
Minimum	0.1	1.1	15.6	26.3
Losing	0.2	1.4	20.5	38.3

3.3.3 Multiple Special Bidders Experiments

In this section, I test strategy performance in the scenario that a particular bidding strategy gains popularity among bidders. The flexibility of the agent-based modeling method enables us to equip a random number of bidders with the same strategy in one auction. In particular, I test the scenarios with 20%, 30% ... to 100% bidders adopting the same strategy. More specifically, for each percentage of popularity, the number of special bidders is drawn from a truncated binomial distribution with the given percentage. To ensure the simulation is meaningful in testing the performance of strategy, the number of special bidders is at least one instead of zero in binomial distribution. I still test the same set of 24 strategies as described in the previous section. The probability of winning is calculated as in Equation (3.1), where $I_i(\text{win})$ is the indicator function of whether auction i is won by a strategy bidder, n_i represents the number of strategy bidders participating in the auction and N represents total number of auctions simulated.

$$P(\text{win}) = \frac{\sum_{i=1}^{N}(I_i/n_i)}{N} \tag{3.1}$$

Table 3.12: Average winning price with 20% special bidders.

Timing	Early	Carefree	Winners'	Sniping
Smart	154.19±36.33	161.92±7.06	164.14±2.10	165.03±1.51
Average	178.89±5.26	168.94±5.47	169.96±1.59	169.42±1.37
Bottom	184.76±7.26	179.97±2.64	172.59±1.75	171.88±1.45
Maximum	192.57±1.43	189.18±1.58	178.75±1.48	176.40±1.36
Minimum	181.51±12.82	179.57±10.56	163.45±2.72	163.24±2.02
Losing	165.22±78.9	164.98±14.75	162.66±2.63	162.48±1.95

Table 3.11 and Table 3.12 show the simulation results with 20% strategy bidders participating in the auctions. As we can see from the tables, the probability of winning presents a similar pattern as in the single strategy bidder scenario. Especially with the *early* and *carefree* timing, most of the winning probabilities are less than 10%, except when combined with *maximum* bid increment. The average winning prices of *smart* or *minimum* bid amount strategy combined with *winners'* timing or *sniping* are significantly lower than any other strategies. Another thing worth mentioning is that the *maximum* bidding results in a significantly higher winning price when there are same-strategy competitors. In this 20% same-strategy bidder scenario, considering both the winning probability and winning price, *smart* strategy combined with *sniping* seems to be superior than other strategies with one of the lowest average winning prices and a 41.1 % chance of winning.

We list the test results for the scenario where there are 50% special bidders in Tables 3.13 and 3.14. In addition, the results of the extreme case with 100% special bidders using the same strategy are listed in Table 3.15 and 3.16. There are several interesting facts we can observe from the simulation results. For timing strategies, excluding the cases of *maximum* bid amount strategy, for the *early* and *carefree*

Table 3.13: Winning probability (by percentage) with 50% special bidders

Timing	Early	Carefree	Winners'	Sniping
Smart	1.2	3.9	20.8	25.9
Average	2.3	7.3	23.5	30.2
Bottom	5.4	10.9	26.1	34.9
Maximum	19.2	23.2	33.8	37.1
Minimum	0.3	1.3	12.1	17.5
Losing	0.6	2.7	18.5	25.1

Table 3.14: Average winning price with 50% special bidders

Timing	Early	Carefree	Winners'	Sniping
Smart	162.74±9.89	168.36±4.59	169.95±1.55	168.68±1.35
Average	175.30±4.66	176.74±2.92	176.27±1.45	176.19±1.18
Bottom	185.44±3.20	181.60±2.53	180.90±1.55	180.99±1.37
Maximum	196.74±1.17	195.84±1.02	191.07±1.12	188.51±1.09
Minimum	144.97±76.38	161.05±13.77	148.91±4.46	149.81±3.59
Losing	166.95±26.47	155.06±10.97	152.81±3.45	155.32±2.85

timing, the probability of winning an auction increases as the percentage of same strategy bidders increases. However, with the *winners'* timing and *sniping* strategy, the winning probability decreases when there are more same-strategy bidders. To understand the reason behind this phenomenon, look back to Table 3.9 and 3.11, which show that the first two timing strategies are less competitive (very low winning probability) than the observed general bidding behavior from eBay data. So with more bidders adopting these strategies, the competition level in the auction goes down and the chance of winning using these strategies goes up. In contrast, with more bidders adopting the *winners'* timing or *sniping* strategies the competition becomes intense, therefore the winning probability decreases and the winning price increases.

Second, for the extreme case with 100% bidders using the same strategy, it is interesting to see that the bid amount strategy controls the outcome. In both Tables 3.15 and 3.16, the results in the same row basically match each other. With all the bidders using the same bid increment strategy, the auction results directly relate to how aggressive the strategy is. Thus with all the bidders being conservative using *minimum* increment strategy, the auctions end with amazingly low prices around $49. I want to note that in a fair competition bidding environment with the average bidders' evaluation around $174, this situation would induce bidders to change their strategy, because being more aggressive would significantly increase the winning chance and still make a big profit. In contrast, with all bidders adopting the *maximum* increment strategy, the average winning prices are much higher, even outside one standard deviation of average bidders' valuation of the item, which means that if all bidders followed the suggestion from eBay, most auction winners would suffer winner's curse – overpaying for the item. Furthermore, it is clear that for bid increment strategies extracted from data, the *smart* strategy leads to an average winning price close to average bidder's evaluation, so this strategy successfully avoids the winner's curse even in this extreme situations. In addition, with the extreme case that all bidders use the same strategy, the winning probability of each strategy simply equals the multiplicative inverse of number of active bidders. In my simulation, the arrival rate of potential bidders is the same and the difference in the probability of winning results from the fact that some bidders did not participate in bidding due to the high price they observed. Thus, the winning probabilities are related to the aggressiveness of each bid increment strategy.

Table 3.15: Winning probability (by percentage) with 100% special bidders.

Timing	Early	Carefree	Winners	Sniping
Smart	12.3	12.6	12.5	12.6
Average	13.4	13.5	13.5	13.6
Bottom	14.5	14.9	14.8	14.4
Maximum	24.7	24.4	24.6	24.2
Minimum	10.4	10.3	10.2	10.4
Losing	10.2	10.8	10.7	10.4

Table 3.16: Average winning price with 100% special bidders.

Timing	Early	Carefree	Winners	Sniping
Smart	174.98±1.52	175.17±1.45	174.57±1.56	174.93±1.51
Average	180.90±1.31	180.28±1.24	180.79±1.35	180.55±1.37
Bottom	186.23±1.76	187.26±1.65	186.42±1.86	186.85±1.79
Maximum	199.46±0.91	199.15±0.93	199.24±0.92	199.19±0.92
Minimum	45.48±8.48	49.57±8.80	49.57±8.80	45.64±8.46
Losing	111.48±5.84	112.11±5.85	113.25±5.95	109.72±5.64

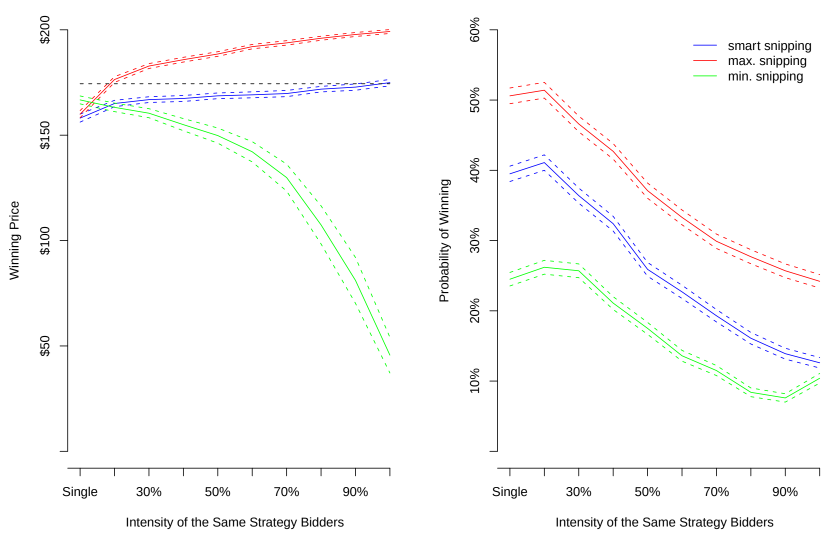

Figure 3.9: Strategy performance with different popularity.

Third, to assess and select the "optimal" performance of the combination of strategies, I refer back to Tables 3.11, 3.12, 3.13 and 3.14, which involve moderate (20%) to considerably excessive (50%) competition from same–strategy bidders. For the moderate (20%) case, as I mentioned earlier the *sniping* with *smart* increment strategy outperforms other strategies by retaining a high winning chance (41.1%) and a significantly low average closing price (\$165.03 $\pm$ \$1.51). For the case where there are 50% bidders adopting the same bidding strategy, it is clear that the winning prices in each row of Table 3.14 tend to converge, which indicates the bid increment strategy has a strong influence on winning prices. But for the winning probabilities in Table 3.13, the timing strategies play more important roles. When each bid increment strategy combines with *sniping,* the winning probabilities increase from 3.3% to 29.5%, while the winning price stays at the same level. Thus it is easy to pick sniping as an optimal timing strategy, but it is hard to pick which combination of bid increment strategy with *sniping* timing is the optimal strategy, because for lower average winning price there is always a trade off for lower winning probability, and vice versa. In the situation where it is a personal choice for bidders to give priority to either aspect, I can give some simple pointers: (1) *sniping* with *minimum* increment results in a low average winning price with a low but reasonable winning probability 17.5%; (2) *sniping* with *maximum* leads to a high winning chance with also a high price; (3) *sniping* with *smart* increment results in a balanced case with an average price still lower than bidders' average evaluation and a higher winning chance compared with *minimum* bid increment. In sum, the optimal strategy shifts among *sniping* with *maximum*, *minimum* and *smart* increment strategies depending on the competition level.

To get a more thorough comparison, I plotted the performance of these three strategies in Figure 3.9. Each color represents one pair of strategies as noted in the legend, and the colored dashed lines represent the corresponding 95% confidence interval. In addition, the black horizontal dashed line represents bidders' average evaluation of the item, which is a good criterion to measure whether adopting a particular strategy bears the risk of winner's curse. The x-axis represents the percentage of bidders who adopt the focal strategy. If a particular strategy gains popularity among bidders for a certain level (30%), the winning probability of adopting this strategy goes down due to the increase of same-strategy competitors. For both *smart* and *maximum* strategies, the average winning prices also increase due to competition. But *maximum* increment strategy results in a more dramatic increase and leaves the winners suffering winner's curse. Although there is a huge drop in the winning price curve of *sniping* with *minimum* increment strategy – which seems ideal for the special bidders, this situation is unlikely to happen because free competition will induce the emergence of more aggressive strategies due to the large potential profit. In sum, *sniping* with *smart* bid increment strategy is one of the best strategies when other bidders are not aware of this special strategy. In addition, it has a robust performance in protecting bidders from winner's curse when this strategy gains its popularity among bidders.

Table 3.17: Sample size of different strategy.

Special Bidder Bidding Strategy	Single Sample Size	Multiple 20%	50%	100%
Early	501	778	2103	9999
Carefree	799	1533	3371	9996
Winners'	2840	4950	7407	9998
Sniping	4085	6528	8623	9996
Smart	1286	2309	3732	7998
Average	1548	2618	4265	7998
Bottom	1865	3083	4974	7998
Maximum	2831	4310	6196	7997
Minimum	695	1469	2337	7998

3.3.4 Further Investigation

In this section, I perform regressions on the simulated data to answer a series of questions about the influential factors of the performance of different strategies. The questions I try to answer here include the following. How does non-special bidders' bid increments affect the winning price and winning probability of strategy bidders? Does the number of all bidders participating in the auction affect the winning probability of the special bidders? How do all bidders' bid timing and evaluation affect the bidding outcome of special bidders? Would the effects of these factors fade out, if the same-strategy bidders increase?

Similar to the previous discussion, I start my investigation with only one special strategy bidder participating in each auction and then I increase the number of special bidders up to 100%. To investigate the winning price of special strategy bidders, I use the simulated dataset that only contains auctions won by special bidders. Table 3.17 shows the sample size of each strategy. The data I used here are

Table 3.18: Regression results for different scenarios.

Special Bidder Predictors	Single	Multiple 20%	50%	100%
Intercept	-91.78	-67.46	-30.10	43.01
Start Price	0.29	0.17	0.12	0.25
Num. Bids	4.33	3.25	2.33	1.41
Avg. Evaluation	0.94	0.97	0.88	0.61
Avg. Bid Time	-0.54	-1.59	-1.37	-1.16
Avg. Bid Increment	205.46	62.64	24.94	NA
Carefree	-11.67	0.46	3.10	4.18
Winners'	-25.70	-4.58	4.08	10.08
Sniping	-29.08	-5.21	4.19	10.95
Average	1.30	4.58	7.80	6.08
Bottom	2.47	8.03	13.56	12.65
Maximum	6.06	16.48	26.34	25.90
Minimum	1.72	-7.20	-23.72	-129.18

unbalanced, because different strategies have different winning chance. Table 3.18 presents the results of regression analysis for different scenarios with single, 20%, 50% and 100% special strategy bidders in each auction. In this regression analysis, timing strategies and bid amount strategies are treated as categorical variables and the baseline variables are *early* timing strategy and *smart* bid amount strategy.

It is interesting to see that while competition from same-strategy bidders increases, the effect of different timing strategies changes accordingly. For the single special strategy bidder situation, adopting *carefree* timing will lower the winning price by $12 compared with *early* timing, and adopting *winners'* or *sniping* timing will lower the winning price even more. When the same-strategy bidders increased in the auction, the beneficial effect diminished and the winning price is even raised when the competition from same-strategy bidders become intense. For the bid increment strategies, it is clear that *smart* bidding, which is the default category, results in lower winning price compared with *average*, *bottom* and *maximum* bidding. Particularly when the same-strategy bidders increase in the auction, the winning prices of *smart* bidders are much lower than the other three, which is consistent with the observations from previous discussion. When the results for *minimum* bidding go in the other direction, there is also a straightforward explanation. When more bidders only bid the minimum required bid amount, the price curve flattens out and results in low closing price. Although bidders would love to have such a bidding environment, this situation is unstable because it will easily attract snipers, who bid late with high amounts, to break the balance. From the regression analysis, a high volume of bids results in high closing prices, which is consistent with common intuition that the number of bids is an indicator of competition level, and high competition levels result in high winning prices. However, the influence of number of bids becomes weaker when the same-strategy bidders increased in the auction. (The number of bidders in each auction is not presented here in the regression, because it is highly correlated to number of bids. I expect similar effects and patterns for the influence of number of bidders.) Similarly, average bid shading (ranges from 0 to 1) of non-special strategy bidders has a significant positive effect on the closing price, while its effect drops quickly when the same strategy bidders increase. When the percentage of special bidders increase, the percentage of non-special strategy bidders decrease and thus their effect drops and the competition is more from same-strategy bidders. It is quite interesting to see that the effect of average evaluation on closing price is almost 1, i.e., for each \$1 increase in bidders' evaluation of the item, the price also increases about \$1. The effect drops when the same-strategy bidders increase to 100%. Also, the starting price has a positive effect on the closing price and average bid timing has a negative effect on closing price.

3.4 Conclusion

In this chapter, I extracted winners' strategies from eBay data and tested the performance of twenty-four bidding strategies in my agent-based model. From the test, I observed the following results. First, the *maximum* bid increment strategy, suggested by eBay, bears a high risk of overpaying when adopted by more than 20% of bidders. It is to eBay's advantage to encourage people to use the eBay strategy, i.e., *maximum* bidding strategy, because the more bidders adopts this strategy, the higher closing price of the auction and eBay charges "commission" from sellers according to the closing price. If all bidders adopt this strategy, the overpaying amount is around 6% to 14% of the item value, comparing to the empirical strategies I observed from eBay winners (Table 3.16). Second, although the *minimum* bid increment strategy might results in winning with low price, the chance of winning is less than 1%, even when half of the bidders adopt this strategy. The only exception happens, when all the bidders adopt *minimum* bid increment strategy. However, this scenario is not stable and one aggressive bidder will lower the winning chance of all other *minimum* bidders. Therefore, the *minimum* bid increment strategy is not a wise choice. In addition, the performance of losing bidders' bid increment strategy is most similar to *minimum* strategy. Thirdly, in my simulation experiment, *sniping* timing really pays off when other bidders are not sniping. Also, the performance of winners' timing is most closely to *sniping* timing. Last, but most importantly, from my study *smart* bid increment strategy combined with *sniping* timing has a robust and optimal performance no matter how many bidders adopts this strategy, which proves that winners' bidding empirical wisdom has a leverage for the bidding result.

I would like to note a number of limitations and future directions of our research. First, all of the discussion of the bidding strategy in this work is contingent upon the fact that bidders have already chosen a particular auction for bidding. There is a separate question about which auction to chose. This question is beyond the scope of this work and I leave this to the future work. Second, the data I used are common value auctions with a value of the item around $174. It is possible that bidders' behavior involved in collectables or in very low common value auctions is different from what I observed from this set of data. Correspondingly, the optimal strategy for those auctions might be different – the *smart* bid incremental rule could be different. We hope to generalize my conclusions for more general value auctions in my future research efforts. I hope my model provides a framework for further tests on multi-bid strategy and empirical exploration. Third, my agent-based model focused on a single auction and thus my strategy investigation does not involve auction selection. The strategy and benefit associated with auction selection could be an interesting future research area due to its great importance in bidders' decision making processes.

Chapter 4

Multi-Auction Agent-Based Model and Influence of Bidders' Switching Behavior

4.1 Introduction

Price dispersion of online auctions exists even among auctions selling the exact same item. In this research, I discuss one of the possible cause of this phenomena – bidders' inertia to switch auctions. The reason behind bidders' inertia of switching auctions are associated with search cost [7], i.e., the information about similar auctions that is readily available to bidders is limited, which requires bidders to put in more time to search for the next auction matches their needs.

In this research, I design a multiple auction agent-based model to examine the influence of bidders' switching behavior on price dispersion and discuss how to facilitate consensus of auctions prices by providing bidders' with information of contemporary auctions. This study is important for online auction managers for three main reasons. First, by reducing the price difference of the same item, the risk for both auction bidders and sellers are reduced, which will lead to an increase of customers' satisfaction for both kinds of users of online auction platform. Second, the website will have better customer retention, by successfully promoting bidders' switching behavior. Because participating in a new auction serves as an incitement

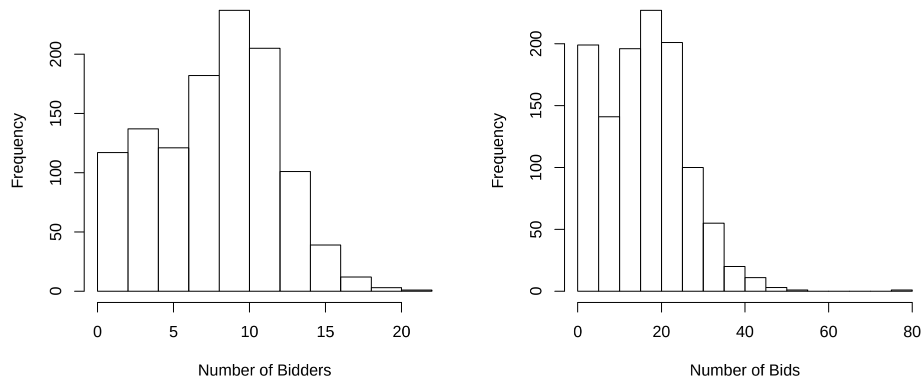

Figure 4.1: Histograms of Number of Bidders and Number of Bids per Auction

for bidders to check back and stay in the platform. Therefore, the auction platform is seen in the long run as a dominant contender. Third, the average closing price will also increase. More bidders stay in the auction platform will increase o the competition level, which leads to increasing profits of sellers and online auction websites.

The remainder of this chapter is organized as follows. In section 4.2, we give an overview of the data and describes exploratory analyses. Section 4.3 describes the simulation model of multiple online auctions used to test the effect of bidders' switching behavior. In Section 4.4, I present the simulation experiment test results. Section 4.5 presents conclusions.

4.2 Data Description

I use the same database of digital camera auction data from eBay.com, all of which were selling brand new Canon SD1000 digital cameras without accessories.

Table 4.1: Frequency table of bidders' number of auction participated.

Num of Auctions	1	2	3	4	5	6	7	8	9	10	11	12
Frequency	4295	865	311	142	79	48	32	8	17	3	7	10
Num of Auctions	13	14	15	16	18	19	22	27	28	35	43	53
Frequency	6	4	3	4	4	2	3	1	1	1	2	1

There are 1155 auctions and 19007 bidding records. Figure 4.1 shows the histograms of number of bidders and number of bids per auction. On average, there are 8 different bidders and 16 bids per auction. In total, there are 5849 bidders participated in the auctions and only 1554 (26.6%) of them participate in more than one auction. Also, about 40% (2428) of bidders only placed 1 bid while the other 60% (3421) of bidders placed all other 16579 bids. Table 4.1 shows the frequency with which bidders' participated in auctions. From the table, about 73% of all the bidders left the platform after participating in just one auction. However, there are some enthusiastic bidders who participated in more than 10 auctions.

In this chapter, I am particularly focused on bidders' switching behavior. If a bidder bids on another auction before her previous auction ends, then this bid is considered as a switching bid. There are 1320 bidders who placed returning bids before the previous auctions ended, which means they were facing the option of continuing to bid on the same auction or switching to another auction. The proportion of switching bids for each bidder is calculated as in equation (4.1). The histogram of p.switch is shown in upper left plot of Graph 4.2. From the histogram, there are three modes at 0, 0.5 and 1. For bidders with only 1 returning bid, the proportion could only be 0 or 1. If these bidders are excluded, the frequency counts

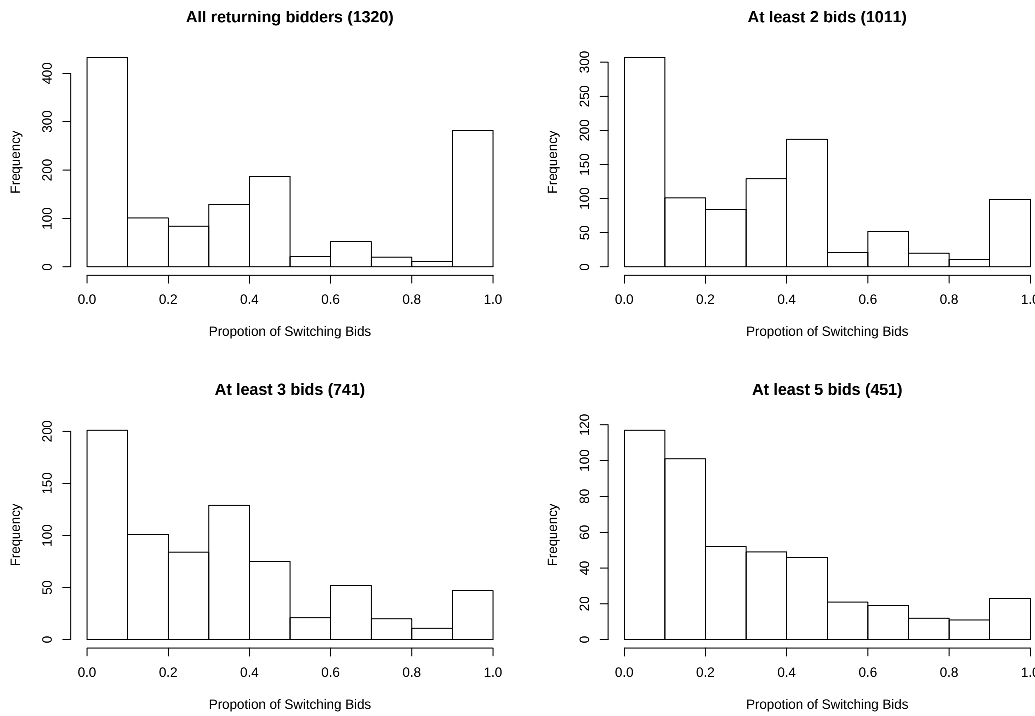

Figure 4.2: Histograms of Proportion of Switching Bids

of 0 and 1 drops as shown in the upper right histogram. In addition, for bidders with 2 returning bids, the proportion could only be 0, 0.5 or 1. If bidders with only 1 or 2 returning bids are excluded, then the tri-mode shape fades as shown in the lower left plot. Furthermore, the shape is more like a right skewed shape, when only considering bidders with at least 5 returning bids. However these bidders only accounts for 1/3 of all the returning bidders. These phenomena leads to the question, which distribution should I choose for the simulation tests? In section 4.4, I will investigate and answer this question.

$$\text{p.switch} = \frac{\text{Num. switching bids}}{\text{Num. staying bids} + \text{Num. switching bid}} \tag{4.1}$$

4.3 Multi-Auction Model Description

4.3.1 Switching Design

The multi-auction model is designed based upon the single online auction model as described in Chapter 2 [39]. The bidders' arrival process to an auction is kept the same in the multi-auction setting. And each coming bidder has a designated auction, when they arrived in the multi-auction system. Different from the single auction model, upon each arrival, the bidder could switch to other auctions. For each visit to an auction, a bidder will first check if she is still the current winner of the auction. If so, he/she will not take any action, except coming back at the next scheduled time. If she is not the current winner, she will make decisions according to the following rules. Let P_{D} denote the price of the designated auction, P_i's denote price of other auctions and w denote the arrival bidder's willingness to pay for the item.

1. If $P_{\mathrm{D}} \leq \min(P_i)$, i.e., the bidder's designated auction has the lowest price, then the bidder won't switch.

   (a) If in addition $w > P_{\mathrm{D}}$, the bidder will place a bid and come back on scheduled revisit time.

   (b) If in addition $w \leq P_{\mathrm{D}}$, the bidder will leave the system and won't come back.

2. If $P_{\mathrm{D}} > \min(P_i)$, i.e., there is at least one auction j with $P_j < P_{\mathrm{D}}$, then the bidder might switch.

(a) If in addition $w > P_{\mathrm{D}}$, the bidder will switch with probability q_1 to another auction and with probability $1 - q_1$ stay in the same auction.

(b) If in addition $w \leq P_{\mathrm{D}}$, the bidder will switch with a probability q_2 to another auction and with probability $1 - q_2$ leave the system.

If a bidder decides to switch to another auction, the bidder's number of revisit will be updated and the revisits will be scheduled at new times according to the new auctions' closing time. In addition, there are several switching strategies I test in this model. Each switching strategy is corresponding to an auction recommendation strategy of the online auction website. The switching strategies list below are conditional on two things: 1. the bidder has decided to switch based on the switching in decision discussed above; 2. only the auction with price P_j lower than price of the bidder's designated auction P_D and the bidder's willingness to pay w are considered in the following rules.

1. **MinPrice**: The bidder could switch to the one with lowest price.

2. **Earliest**: The bidder could switch to the one with earliest closing time.

3. **Random of MinPrice**: The bidder could randomly switch to one of the n auctions with lowest price. n can be consider as the recommendation limit of the auction platform. When $n = 1$, this switching rule degenerates to the first rule.

4. **Random of Earliest**: The bidder could randomly switch to one of the n auctions with earlest ending times. When $n = 1$, this switching rule degenerate

Table 4.2: List of variables in of multi-auction model.

Level	Notation	Definition	Distribution & Parameters
Auction	$P_{t=0}$	Starting price	180·Beta($\alpha_p = 0.17, \beta_p = 0.59$)
	N_b	Number of bidders	Poisson($\lambda_b = 12.35$)
	T_s	Start Time	Poisson Process($\lambda_a = 6.08$)
Bidder i	w_i	Evaluation of the good	Normal($\mu_w = 180, \sigma_w^2 = 21$)
	ρ_i	Bid increment	Beta($\alpha_\rho = 1.2, \beta_\rho = 4.2$)
	$t_{i,1}$	First decision time	10·Beta($\alpha_t = 0.58, \beta_t = 0.34$)
	n_i	Number of revisits	Poisson($\lambda_{\text{re}} = 0.97$)
	$t_{i,j}$	Revisit times $j \geq 2$	Uniform$[t_{i,1}, 10]$
	$p_{\text{switch}i}$	Probability of Switching	Empirical distribution
			Normal distribution
			Constant value

to the second rule.

5. **Earliest of MinPrice**: The bidder could switch to the auction with earliest time among the n auctions with lowest price.

6. **MinPrice of Earliest**: The bidder could switch to the auction with lowest price among the earlest ending n auctions.

4.3.2 Simulation Framework

I complete the model description section by presenting the simulation process of the multi-auction model. Similar to the single auction model discussed in Chapter 2 and 3, the multi-auction model simulation starts with generating all the random variables as listed in Table 4.2. The main differences between Table 4.2 and the single auction model presented in Table 4.2 are that there are two new variables: auction starting time and bidders' switching probability. Auction starting time

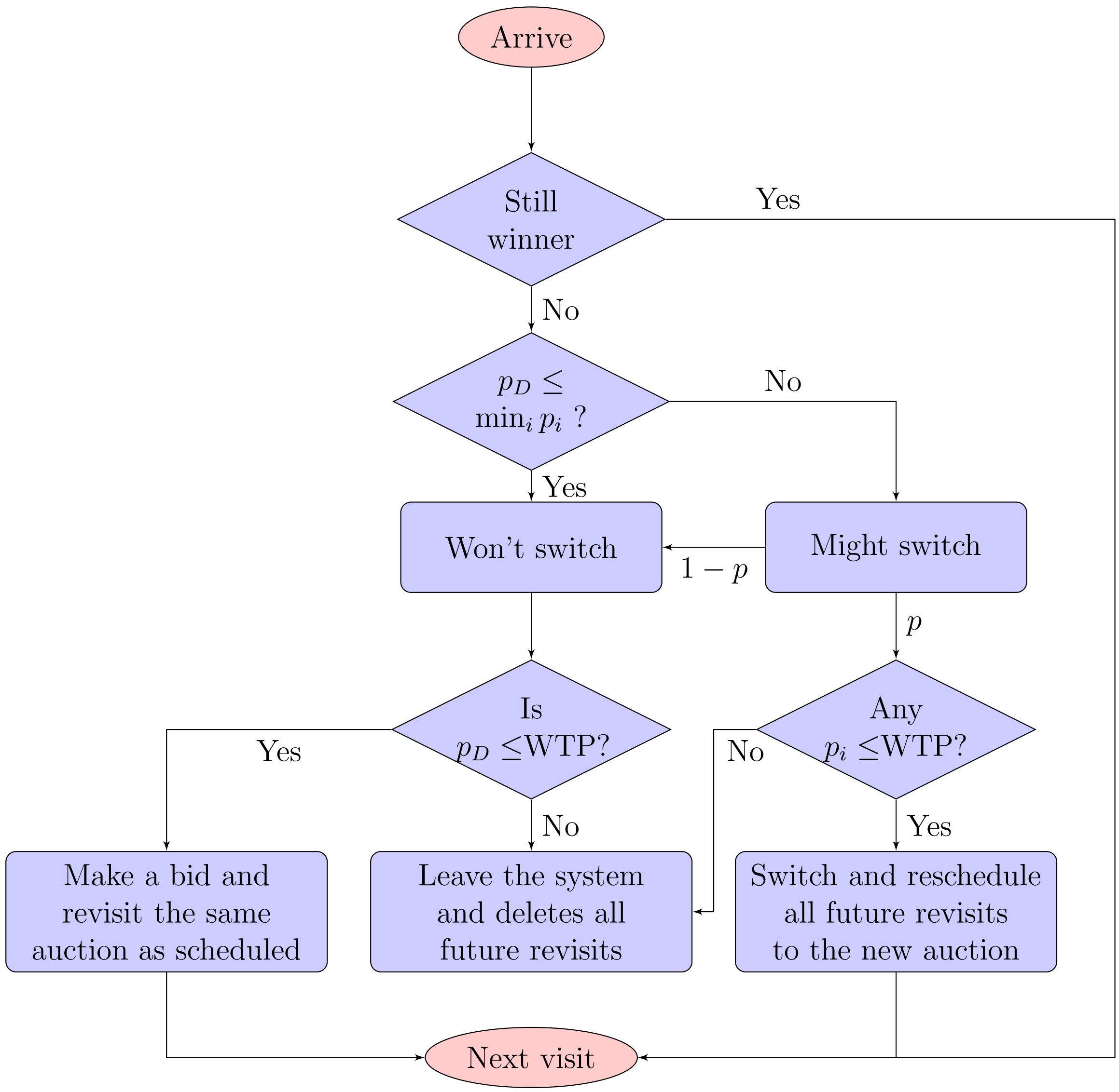

Figure 4.3: Flow Chart of One Bidder's Bidding Decision Process

is simulated by a Poisson process with parameter λ_a matched to eBay data. As discussed in Section 4.2, different distributions of bidders' switching probability are tested in this chapter to see if the shape of the distribution has significant influence on the closing price (both the average and standard deviation). For the second step of the simulation, all the auctions starting and ending events, bidders' visit and revisit events are ordered according to the event times. Then the online auction model begins with the earliest event and continues one by one till the ending time of the simulation. When it comes to auction starting and ending events, the indicator of auction status will change to "open" or "close" according to the event type. Therefore, when a bidder visits the auction platform, it is clear which auctions are available for the bidder to choose from. When a bidder places a bid to an auction, the auction's price will change according to eBay price as well as the current winner and underlying highest bid of the auction. If a bidder decides to switch auction, his/her number of future revisits and corresponding revisit times to the new auction will be regenerated and the event queue of the whole simulation will be updated accordingly. Also, if a bidder decides to leave the auction platform, his/her future revisits will be deleted fromt the event queue of the simulation. Figure 4.3 illustrates a bidder's bidding decision process of one visit.

4.4 Experiment Tests and Results

In this chapter, I endeavor to investigate and answer several interesting questions. The first question is whether promoting switching behavior will increase the

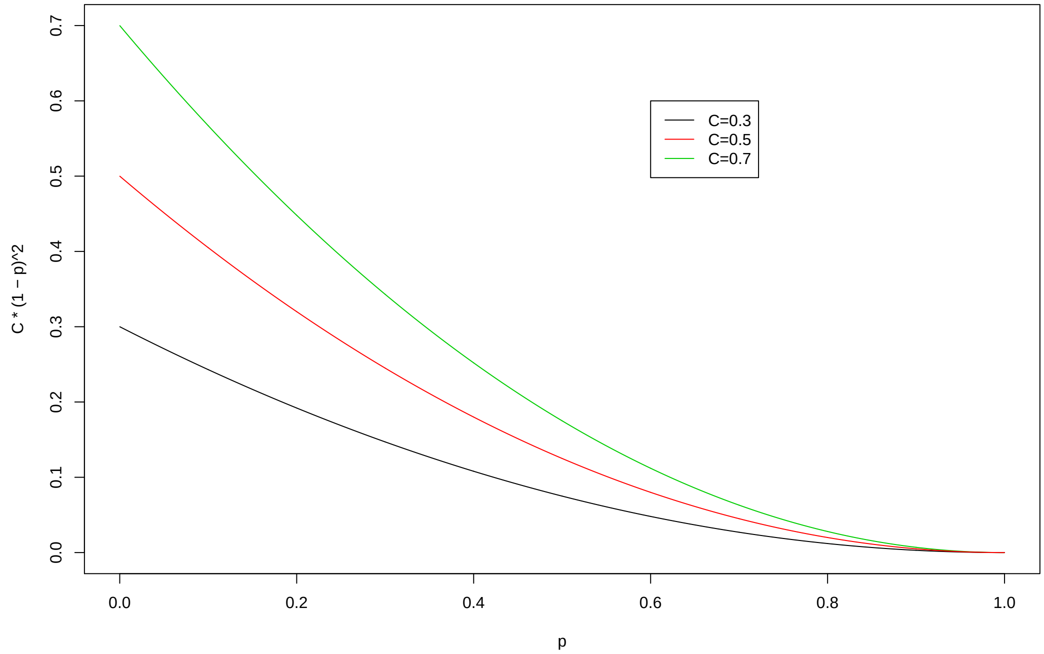

Figure 4.4: Illustration of Non-linear Increments of Switching Probability

profit of online auction website and decrease price dispersion. If so, does any switching rule have a more significant effects than others? In other words, which auctions should the website recommend to the bidders? Also, as discussed earlier, I want to test if the distribution of switching probability affects the modeling results or only the average switching probability affects the auction prices. In this chapter, I answer these questions through agent-based model simulation experiments.

4.4.1 Effects of Distribution of Switching Probability

To answer the question whether there is any benefit by promoting switching for online auction website. I experiment with the model by increasing the switching probability. Here I use a non-linear increment on empirical distribution: $\Delta p_i =$

Table 4.3: Mean and Standard Deviation of Switching Probability with Non-linear Increments on Empirical Distribution

C Value	Increment	Mean	Std.
0	$\Delta p_i = 0$	.40	.38
0.1	$\Delta p_i = 0.1(1-p_i)^2$	.45	.34
0.2	$\Delta p_i = 0.2(1-p_i)^2$	.50	.30
0.3	$\Delta p_i = 0.3(1-p_i)^2$	.55	.26
0.4	$\Delta p_i = 0.4(1-p_i)^2$	.60	.23
0.5	$\Delta p_i = 0.5(1-p_i)^2$	.65	.19
0.6	$\Delta p_i = 0.6(1-p_i)^2$	.70	.16
0.7	$\Delta p_i = 0.7(1-p_i)^2$	.75	.13
0.8	$\Delta p_i = 0.8(1-p_i)^2$	.80	.11
0.9	$\Delta p_i = 0.9(1-p_i)^2$	.85	.10
1.0	$\Delta p_i = (1-p_i)^2$	.90	.11

$C(1-p_i)^2$, where C represents the maximum increment and varies from 0.1 to 1.0 by 0.1 in the experiments. Figure 4.4 illustrates the increment curves, when $C = 0.3, 0.5, 0.7$. In addition, Table 4.3 shows the mean and standard deviation of the switching probability corresponding to different increments added to the empirical distribution. It can be seen from the table that the mean of switching probability increases linearly and standard deviation decreases, when the C value increases.

Before investigating the benefit of promoting switching behavior, we need to answer the preliminary question, whether the distribution of switching probability makes any difference to the simulation results of the average and standard deviation of auction closing price. We test three distinct distributions: the empirical distribution from eBay data, a normal distribution and a constant value. As discussed in the data description section, the empirical distribution has a tri-mode shape, with the three modes at 0, 0.5 and 1, which is very different from a normal distribution and a constant value. To test the effect of distributions, the three distributions are

Table 4.4: Experiment 1: Switching Probability Experiment – 99 Settings

3 Switching Rules	3 Probability Distribution	11 Probability Increments
1. Minimum price 2. Earliest ending 3. Radom switching	1. Empirical distribution 2. Noraml distribution 3 . Constant Value	All 11 increments as in Table 4.3

scaled to have the same mean and the same standard deviation for empirical and normal distributions.

In the Experiment 1, I experiment on 3 switching distributions with 11 increments (as listed in Table 4.3), under 3 switching rules. The 3 rules in this experiment represent three extreme situations (deterministic for minimum price, earliest ending time and random switch) and serve as illustrations for the influence of switching probability and its distribution. All the switching rules discussed below are conditional on the bidder deciding to switch and will only switch to the available auctions for him/her. The available auctions for each bidder is defined as the auctions that have price less than the price of bidder's current auction and the bidders willingness to pay.

1. Choose the auction with the minimum price (Minimum rule in Section 4.3)

2. Choose the auction with the earliest closing time (Earliest rule in Section 4.3)

3. Randomly choose all the available auctions (3rd/4th rule with $n = \infty$)

In sum, there are 99 settings in the Experiment 1 as shown in Table 4.4. For each setting, 200 days of auctions are simulated and approximately 1200 auctions occur during this period, because the auction start rate is around 6. I exclude ex-

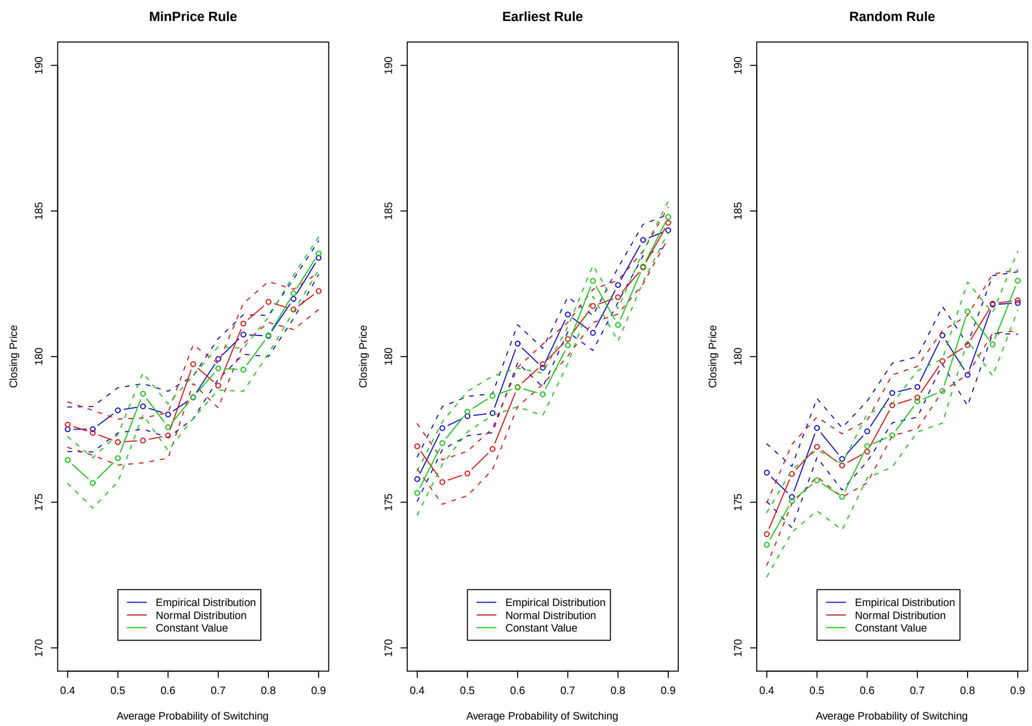

Figure 4.5: Average Closing Price in the Experiment 1

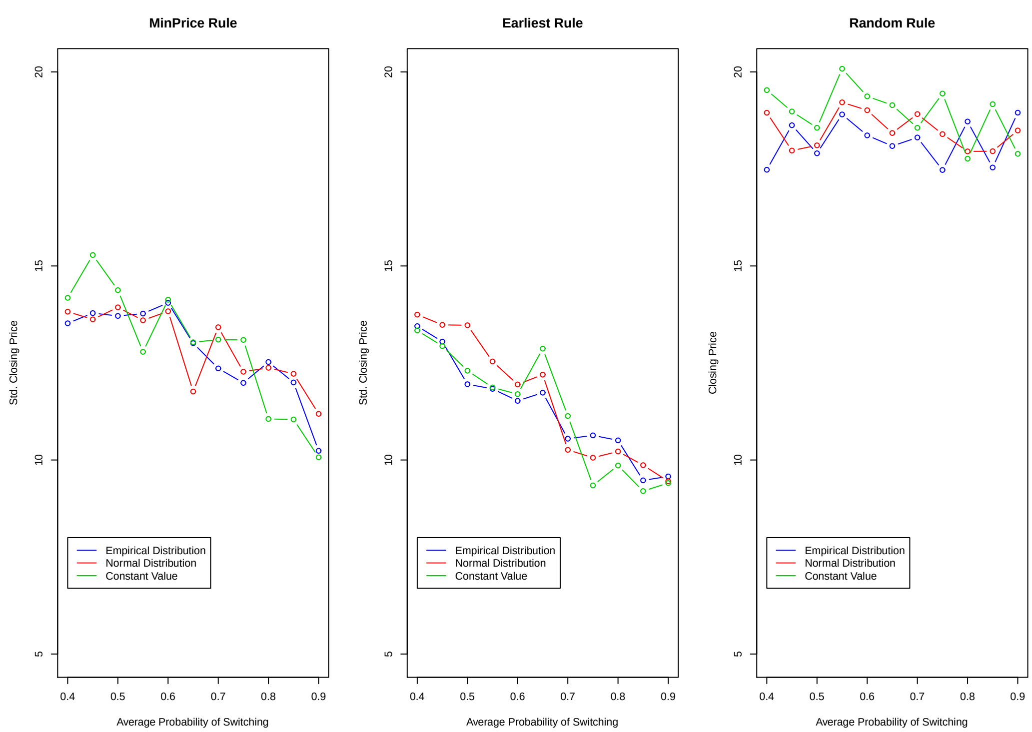

Figure 4.6: Standard Deviation of Closing Price in the Experiment 1

treme values and keep track of the trend for both mean and standard deviation of closing price. Experiment 1 provides insights on both the effect of the switching distribution and the influence of promoting switching behavior. Figures 4.5 and 4.6 shows the experiment results of average and standard deviation of closing price for each setting. In Figure 4.5, the solid lines represent the average value and the dashed lines represent a 95% confidence interval of average. Each color represents one distribution of switching probability. In all the graphs, the three colored lines are essentially overlapping with each other and share the same trend. Therefore without losing generality, I use the empirical distribution with non-linear increment for the future experiment. In both figures, each graph represents one switching rule: minimum price, earliest ending and random switching. From Figure 4.5, it is clear that increasing switching probability will increase average closing price with all the three switching rules, while the random switching rule results in lower price comparing to the other two rules. In addition, by increasing switching probability with minimum price and earliest ending rule, the price dispersion is reduced, while with random switching rule there is barely any effect on price dispersion. In the next section, I investigate further the effect of each switching rule and explore to answer the questions, what is the optimal recommendation strategy for online auction website?

4.4.2 Effects of Switching Rule

In this section, I investigate which switching rule has the most significant effect on the closing price, i.e., what kind of auctions should the website recommend

Table 4.5: Experiment 2: Switching Rule Experiment – 154 Settings

14 Switching Rules	11 Probability Increments
1. Random of MinPrice ($n = 1, 3, 5, 10$) 2. Random of Earliest ($n = 1, 3, 5, 10$) 3. Earliest of MinPrice ($n = (1), 3, 5, 10$) 4. MinPrice of Earliest($n = (1), 3, 5, 10$)	All 11 increments on Empirical distribution as in Table 4.3

to bidders. To answer this question, I test the last 4 switching rules (Random of MinPrice, Random of Earliest, Earliest of MinPrice and MinPrice of Earliest), with recommendation limit $n = 1, 3, 5, 10$. When $n = 1$, Random of MinPrice and Earliest of MinPrice degenerates to the first rule MinPrice; and Random of Earliest and MinPrice of Earliest degenerates to the second rule Earliest. Therefore, I only need to test the first 2 rules and the last 4 rules with $n = 3, 5, 10$. As listed in Table 4.5, Experiment 2 contains 14 different switching rules with 11 increments on empirical distribution and 154 settings are implemented, with each setting simulating 200 days of auctions.

Figures 4.7 and 4.8 demonstrate the experiment results of average and standard deviation of closing price for each setting. Each graph represents one family of switching rule (Random of MinPrice, Random of Earliest, Earliest of MinPrice and MinPrice of Earliest), and each color represents a value of the recommendation limit n. It worth noting that the black lines in the first and third graphs are the same and the second and fourth are the same, because the switching strategies in the first and the third graph degenerate to the same rule when $n = 1$ and so do the second and the fourth ones. With the increase of probability of switching, the increasing trend of average closing price is clear in Figure 4.7. By careful comparison, the lowest curve

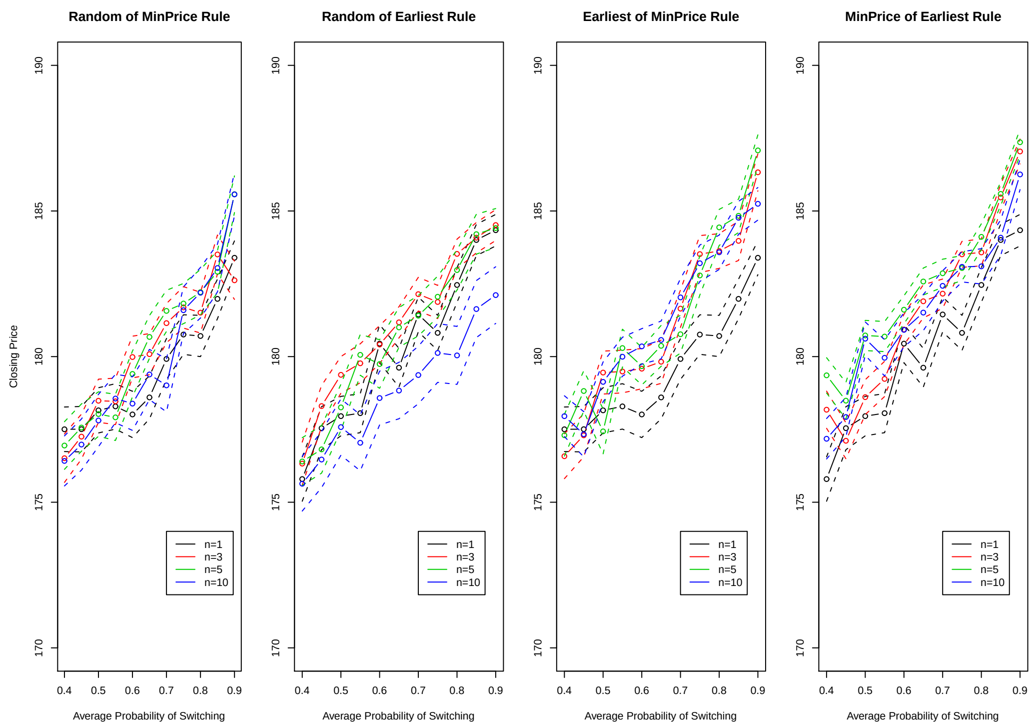

Figure 4.7: Average Closing Price in the Experiment 2

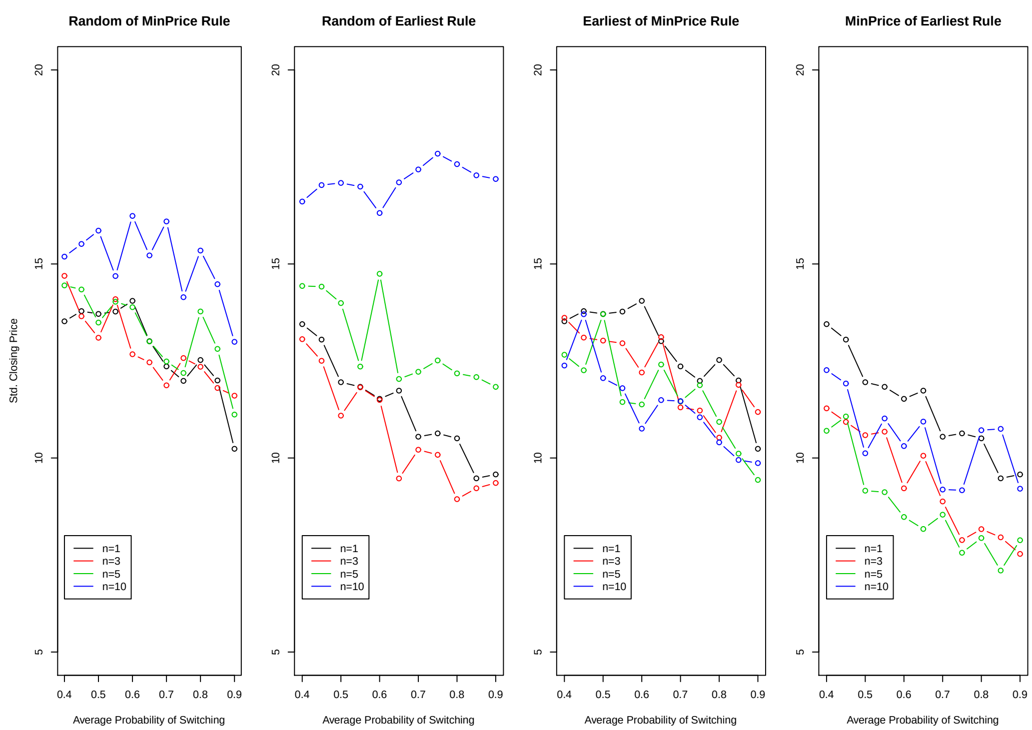

Figure 4.8: Standard Deviation of Closing Price in the Experiment 2

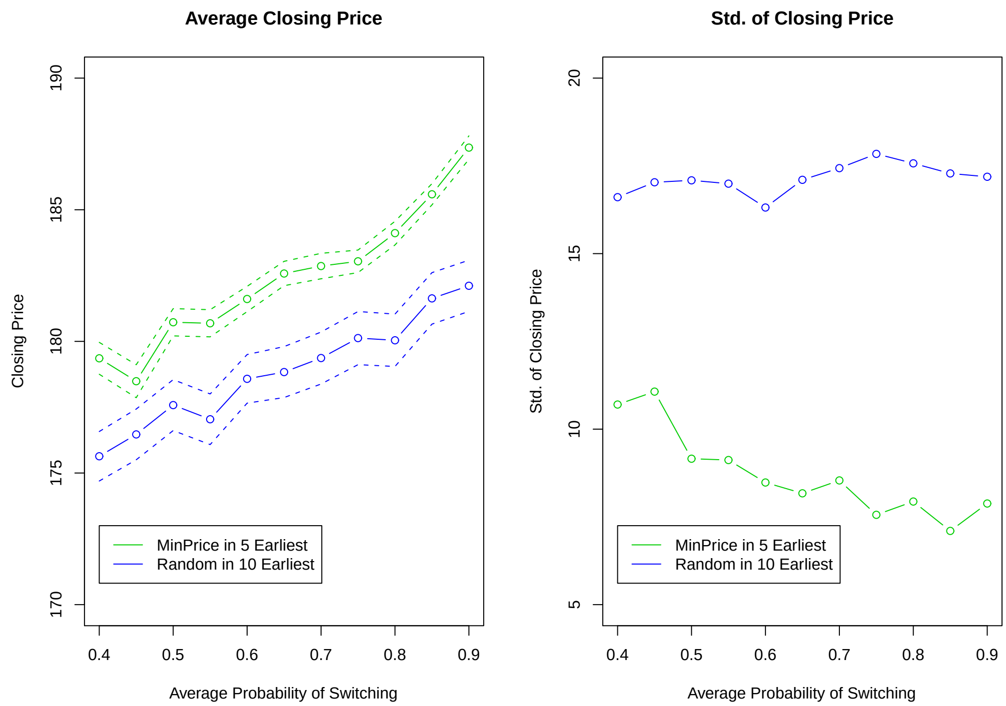

Figure 4.9: The Most Distinct two Settings in the Experiment 2

of all 14 curves is the blue line ($n = 10$) in the second graph (Random of Earliest rule) and the highest line is the green line ($n = 5$) in the fourth graph (MinPrice in Earliest rule). The confidence intervals of the lowest and highest curves of average closing price have no overlap as shown in the left graph of Figure 4.9. This indicates that the there is a significant difference among auction recommendation strategies. If the website intends to increase auction closing price, then the highest curves of average closing price should be preferred, i.e., the green line in the left graph of Figure 4.9 is the best for website, while the blue line is the least favorable one. In addition, the decreasing of price dispersion is clear in most of the experiment settings as in Figure 4.8. One thing interesting is that the lowest standard deviation curve is the blue line ($n = 10$) in the second graph (Random of Earliest rule) and the highest

Table 4.6: Experiment 3: Auction Start Rate Experiment – 90 Settings

3 Auction Start Rate	5 Switching Rules	6 Probability Increments
$\lambda_a = 6, 12, 18$	MinPrice of Earliest with $n = 1, 5, 10, 15, 20$	$C = 0, 0.2, 0.4, 0.6, 0.8, 1$ as in Table 4.3

standard deviation curve is the green line ($n = 5$) in the fourth graph (MinPrice in Earliest rule), which are the same two most distinct settings identified for average closing price. For comparison purposes, the two standard deviation curves are plot in the right graph of Figure 4.9. As discussed earlier, having lower price dispersion will decrease the risk for both bidders and sellers, thus will leads to better customer satisfaction. Therefore, the most beneficial auction recommendation system would increase the average closing price while at the same time reduce price dispersion, so the *MinPrice in 5 Earliest* Rule is the most ideal strategy among the 14 settings.

Experiment 3 is focused on the optimal switching rule *MinPrice of Earliest* from Experiment 2. This switching rule means choose the auction with minimum price among n earliest closing auctions. When $n = 1$, this switching rule degenerates to the *Earliest* rule, i.e., choose the earliest closing auction among all available auctions. When n increases to (or is greater than) the number of available auctions, this switching rule becomes the *MinPrice* rule, i.e., choose the auction with minimum price among all auctions. When n is between 1 and the number of available auctions, this rule can be consider as a conditional *MinPrice* rule, i.e., conditional on the auction is one of the n earliest closing auction, the one with minimum price will be chosen. This scenario is close to the actual online auction situation. When a

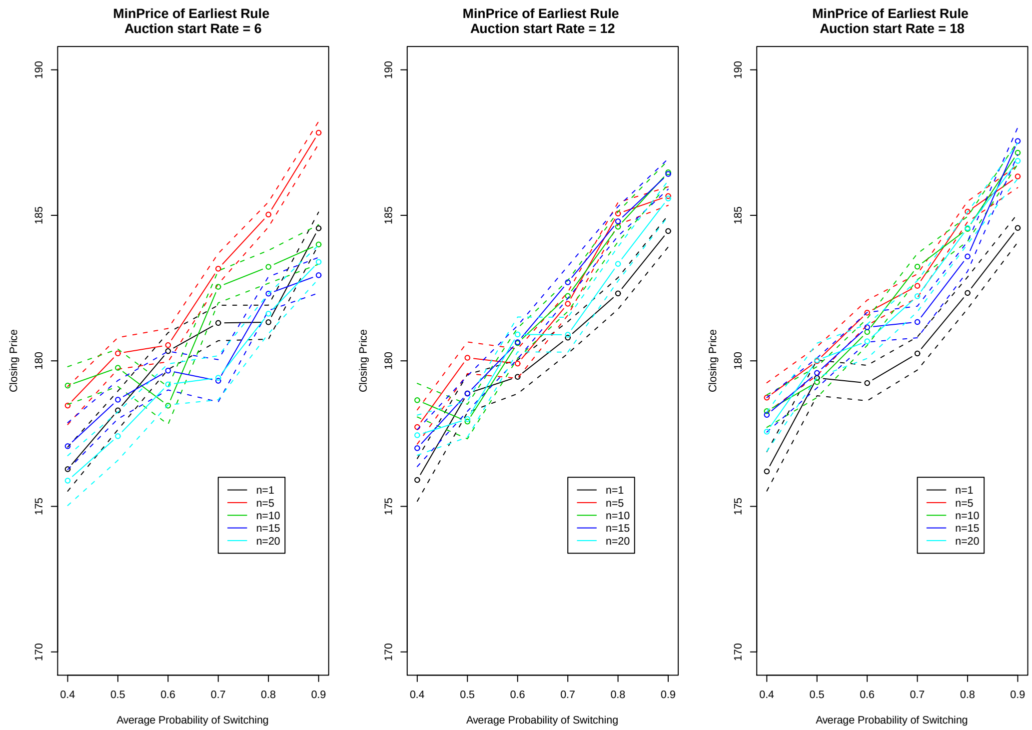

Figure 4.10: Average Closing Price in the Experiment 3

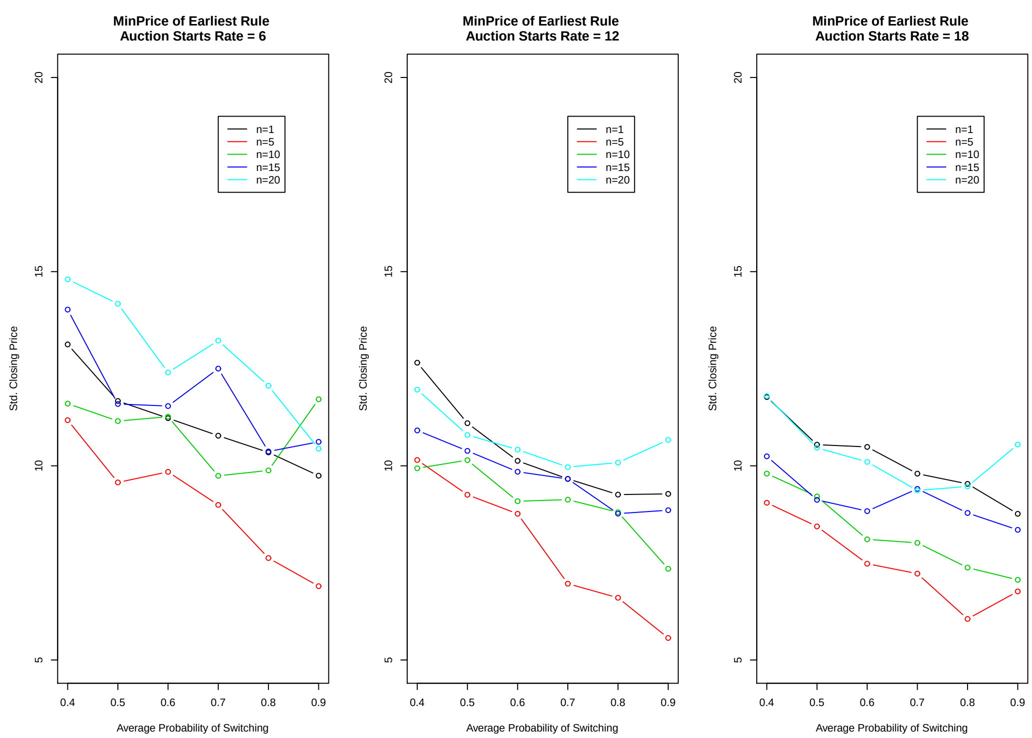

Figure 4.11: Standard Deviation of Closing Price in the Experiment 3

bidder sees a list of auctions selling the exact same items, the first thing catch his/her attention might be the price, especially when the closing times are also similar. From Experiment 2, the optimal n of the *MinPrice of Earliest* rule is 5. In this Experiment 3, we test if the optimal n stays the same, when the number of available auctions varies. In the simulation experiment, the auction start rate is directly related to the number of available auctions. In this experiment, I test 5 recommendation limits $n = 1, 5, 10, 15, 20$ and 3 different auction start rates $\lambda_a = 6, 12, 18$, which are the start rate calculated from data and its two to three times that value. For each combination of auction recommendation limit and auction start rate, 6 increments on the distribution of switching probability are tested with $C = 0, 0.2, 0.4, 0.6, 0.8, 1$. To get approximately 1200 closed auctions per setting, the simulated durations are set to 200, 100 and 70 days according to the auction start rates $\lambda_a = 6, 12, 18$. As listed in Table 4.6, there are 90 settings tested in Experiment 3.

The simulation results of Experiment 3 are shown in Figure 4.10 and 4.11. From both figures, the performance of $n = 5$ (red lines) is robust. In the average closing price graphs, the red line remains one of highest curves across all three graphs. And in the price dispersion curves the red lines are clearly the lowest line in each graph. It is quiet interesting to see that when n increases, the price dispersion first decreases and then increase again. According to the discussion earlier, it is beneficial for the online auction website, when average closing increases and the price dispersion decreases. Therefore, from Experiment 3, I have the same conclusion as in the Experiment 2 that the *MinPrice in 5 Earliest* Rule is the best strategy for online auction website.

4.5 Conclusion

In this research, I designed and utilized a multiple auction agent-based model to examine the influence of bidders' switching behavior on auction prices. This study is important for online auction managers for three main reasons. First, by reducing the price difference of the same item, the risk for both auction bidders and sellers are reduced, which will lead to an increase of customers' satisfaction for both kinds of users of online auction platform. Second, the website will have better customer retention, by successfully promoting bidders' switching behavior. Because participating in a new auction serves as an incitement for bidders to check back and stay in the platform. Therefore, the auction platform is seen in the long run as a dominant contender. Third, the average closing price will also increase. More bidders stay in the auction platform will increase o the competition level, which leads to increasing profits of sellers and online auction websites. In addition, I discuss how to design the recommendation system to best facilitate the price increasing and reduce price dispersion. Through simulation experiments, the optimal recommendation strategy is providing the five earliest closing auctions so that bidders can choose the lowest price auction. This strategy has the best performance in lowering the auction price dispersion and the most robust performance in increasing average auction price.

Chapter 5

Conclusions and Future Research

The overall goal of my work is to better understand bidders' behavior and price dynamic of online auctions and therefore to propose and to test optimal strategies for bidders and website managers. Although various researchers have investigated online auctions on these aspects, my contribution is to construct an online auction simulation framework, which simulates bidders' behavior and interaction and generates price dynamic of online auctions. This framework allows researchers to test various bidding strategies by equipping certain special strategies to some bidders and observing their bidding results. Also, by varying bidders' behavior rules, the simulation framework provides insights about the outcome of nudging bidders to behave in certain ways and provides advice for online auction managers about website design and marketing champions. The main challenge of building this simulation model is how to calibrate the parameters, so that the model is a close representation of actual online auctions. Part of my work is dedicated to solving this parameter estimation problem. I propose to use functional summary curves as criteria to match the simulated price dynamic to actual online auction price data, by genetic algorithm. Also I conduct simulation studies to validate and confirm the performance of the estimation method.

In addition, I investigate empirical strategies from online auction winners and conduct a series of simulation experiments to compare both empirical strategies and theoretical strategies. The experiment results confirm the merits of winners' empirical strategies gained from actual bidding experience over theoretical strategies that derived from restricted assumptions. Moreover, the smart winners' empirical strategies proved to have a robust capability to avoid the "winners' curse" even when the strategies gain popularity among bidders. These experiments require control of the exact proportion of bidders, which is not easy to conduct in actual online auction, but could be implemented with ease in the simulation framework.

Furthermore, I expended the online auction framework from single auction to multiple auction simulation, which acts as a platform for investigating and testing more complicated situations that involves the competition among concurrent auctions. This framework facilitates my investigation of bidders' switching behavior and enables me to answer a series questions. For example, is it beneficial for auction website to promote bidders' switching behavior? Will bidders and even sellers get any advantage from bidders' switching? What is the best auction recommendation strategy for online auction website to obtain higher profit and/or a better customer experience? Through careful experiment design, it has been showed that higher switching frequency leads to higher profit for auction website and reduces the price dispersion, which leads to reduced risk for both bidders and sellers. In addition, the best auction recommendation strategy is providing the five earliest closing auctions so that bidders can choose the lowest price auction.

In conclusion, my contributions in this dissertation consist of three major parts.

1. I construct an online auction simulation framework to test and validate possible theories and assumptions of online auction strategies for bidders, sellers and website managers.

2. I propose and validate a general parameter estimation method for agent based model with functional outputs.

3. I investigate and design experiments for several online auction related strategies and provide insights for online auction participants and managers.

The studies presented here serve as a basis for a continuing investigation of bidders' behavior and their impacts through carefully designed simulation experiments. The first step in extending the flexibility of the simulation framework is to utilize diversified data sources. In this work, we use eBay auction data and its corresponding second price proxy bidding mechanism to construct the simulation framework. It is important to extend the study to other formats of online auction. Also, this framework is built without consideration of auctions that do not sell the same but just similar items. If a bidder is still debating on what product to buy and is switching back and forth between different but similar items. This kind of behavior is not captured by the current framework. By including similar item auctions, the scope of the framework will be extended and wil allow researcher to address further questions. In sum, this study is just the first step to address auction strategy questions by simulation experiments and serves as an illustration on how to tackle questions in model design and experiment implementation for future researchers.

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