

# Strategic Bidder Behavior of Consumers in Open-Ascending Internet Auctions

Economics

Master's thesis

Kalle Pekkonen

2014

## ABSTRACT

In this paper I study the equilibrium bidding strategies in open-ascending Internet auctions. Having approximately 20 years of history, Internet auctions are no longer new to anyone. In spite of that, I dedicate some time to presenting the most significant characteristics that differentiate Internet auctions from their offline counterparts. This will add some valuable insight in analyzing the empirical evidence of the observed bidding behavior in completed auctions.

This thesis aims at finding strategic reasoning for the common practice of last-minute bidding, i.e. *sniping*, in online auctions. Open-ascending Internet auctions with proxy bidding mechanism have been generally viewed as close equivalents to second-price sealed-bid auctions due to the property that the payoff of the winning bidder  $i$  is not directly affected by bidder  $i$ 's own bid amount. Further, during the course of the auction the highest prevailing proxy bid is never explicitly revealed in the bidding history. Given these properties, we would not expect as significant concentration of bids near the end of the auction as we find in the empirical studies.

The focus of this thesis is on the results derived in the independent private values model with proxy bidding. In this model, assuming a single-item framework the symmetric equilibrium - where every bidder uses the same strategy - has bidders bidding early and up to their reservation prices. We find some empirical evidence supporting this equilibrium: experienced bidders tend to bid either near the beginning or near the end of an auction.

Standard independent private values model alone is not able to sufficiently explain last-minute bidding. Therefore, in order to better capture the essential features of Internet auctions we discuss the following value models as well: repeated auctions, interdependent auctions and common value auctions. These models introduce uncertainty into bidder  $i$ 's value formation: bidding decisions can be affected e.g. by sequential auctions offering similar items, or there may be liquid resale markets for the auctioned item.

In practice, not all the bidders seem to follow any rational bidding strategy. Some may derive utility not only from the acquisition of the item but also from the competitive aspect of bidding. The effects of the existence of such bidders on the optimal bidding strategies are to be briefly discussed.

**Keywords:** Open-ascending, Internet Auctions, proxy bidding, last-minute bidding, independent private values, repeated auctions, interdependent values, common values

# TABLE OF CONTENTS

<b>ABSTRACT.....</b>	<b>i</b>
<b>LIST OF FIGURES.....</b>	<b>iv</b>
<b>LIST OF TABLES.....</b>	<b>iv</b>
<b>1 INTRODUCTION.....</b>	<b>1</b>
1.1 Early development of Internet auctions.....	1
1.2 Increase in online commerce - decline in Internet auctions.....	4
1.3 Market for auctions in the future.....	7
1.4 Purpose and structure of the study.....	9
<b>2 BIDDING DYNAMICS IN INTERNET AUCTIONS.....</b>	<b>11</b>
2.1 Network effects.....	11
2.2 Inspection problems associated with the lack of physical presence.....	13
2.3 Matching of buyers to sellers.....	16
2.4 Proxy bidding system.....	17
2.5 Basics of auction process on eBay.....	19
<b>3 AUCTION FORMAT.....</b>	<b>22</b>
3.1 Auction formats employed in the Internet.....	22
3.2 Open-ascending English auction on eBay.....	23
<b>4 THE INDEPENDENT PRIVATE VALUES MODEL (IPV).....</b>	<b>25</b>
4.1 Basic assumptions.....	25
4.2 IPV strategies in online auctions.....	26
4.2.1 The symmetric equilibrium.....	26
4.2.2 Other equilibria.....	30
<b>5 BEYOND STANDARD ASSUMPTIONS.....</b>	<b>31</b>
5.1 Repeated eBay auctions.....	32
5.2 Search frictions.....	35
5.3 Interdependent values model.....	37
5.4 Common values model.....	38

<b>6</b>	<b>EMPIRICAL RESULTS</b> .....	<b>41</b>
6.1	Introduction to last-minute bidding.....	41
6.2	Data on last-minute bidding.....	46
6.3	Rational reasoning for last-minute bidding behavior.....	49
6.4	The incentives of winning.....	52
<b>7</b>	<b>DISCUSSION AND</b>	
	<b>CONCLUSIONS</b> .....	<b>53</b>
	<b>REFERENCES</b> .....	<b>56</b>

## **LIST OF FIGURES**

Figure 1. Auction Share on eBay over Time.....	5
Figure 2. Empirical cumulative distribution of the timing of last bids for all bidders.....	47

## **LIST OF TABLES**

Table 1. Bidding Increments in eBay Auctions.....	19
Table 2. Bidding History of a Completed Baseball Card Auction.....	42
Table 3. Bidding History of a Completed Desktop Auction.....	45

# 1 INTRODUCTION

In the year 2000 *The Economist* was convinced that the Internet had introduced us a marketplace where no prices would remain fixed for long, all information would be readily available, and buyers and sellers would constantly haggle to get the best deals (Einav et al. 2013b). Internet auctions, in particular, had attracted a lot of interest from consumers. The dominant auction platform in the field of consumer auctions at that time and ever since, eBay, was in fact the third-ranked website measured by consumer attention in August 2001<sup>1</sup>.

Einav et al. (2013b) reported that the annual transaction volume of eBay in 2001 had already come close to 10 billion dollars, consisting of both sales between consumer sellers and buyers as well as including the supply of large corporations. At that time auctions had established a stage where they comprised a big portion of ecommerce, but a lot has changed in the last decade or so: auctions are no longer at the core of eBay's *business model*<sup>2</sup>. On the contrary, the majority of auctioned items are now sold utilizing a Buy It Now option<sup>3</sup>. It seems that buyers have become to prefer fixed priced offers over auctions. To be able to find some reasons for this development, we will first examine the foundation of Internet auctions.

## 1.1 Early development of Internet auctions

Development path of online auctions has been far from smooth since their introduction to the audience at the beginning of 1990s. At first low transaction costs offered by the Internet led to a boom in the popularity of auctions in general. Internet auction houses such as eBay, Amazon and Yahoo! made it possible for consumers from all corners of the world to participate in an auction in a simultaneous manner. Internet also made it possible for a savvy bidder to consider other relevant auctions and/or posted price listings at the same time when contemplating his participation or bidding decisions in any single auction. Furthermore,

---

<sup>1</sup> Source: <http://blog.compete.com/2007/10/01/top-ranked-web-sites-popularity-2001/>

<sup>2</sup> In the beginning eBay connected consumer sellers and buyers together. Transaction fees based on a percentage of sales were utilized. eBay collected the fees whether or not the buyer and seller were able to complete the transaction or not. As of now, it is the retailers that dominate the sales on eBay.

<sup>3</sup> Seller is able to add a Buy It Now option in his auction listings. When it is used, a buyer can purchase the item straight away at an announced price. However, the Buy It Now option will disappear when the first bid is made. If the seller has set a reserve price (minimum selling price) for the auction, the bid has to meet the reserve price in order to exclude the BIN option.

finding up-to-date price guides for a desired item appeared to be much more convenient online than what it ever was in the offline environment.

Earliest web-paged auctions took place in 1995, though some auctions had already been running on some text-based Internet newsgroups and email discussion lists before that. In these earliest auctions bidding happened via email in an ascending-bid format, and daily updates of bidders' high bids were posted by the seller (Lucking-Reiley, 2000). Auctioned items were mostly used and distinctive items offered by consumer sellers who may well have thought that the competitive environment provided by an auction would ensure the best profits.

As a matter of fact, it has been studied that auctions sometimes lead to competitive arousal where a bidder may shift his focus from making the best decision to winning the auction - no matter what (Malhotra & Murnighan, 2000). Time pressure and competition are the key elements in creating this competitive arousal: by observing the regression results of Chicago Cow Auctions<sup>4</sup>, Malhotra and Murnighan (2000) found out that the number of other bidders had all the more effect on one's bidding decisions as the auction was about to come to a close. As opposed to eBay auctions and Internet auctions in general, bidders had the information of the current high bid at hand which most likely emphasized the competitive nature of bidding.

According to Ariely and Simonson (2003), auctions can also lead to an escalation of commitment. They conducted a survey answered by 200 bidders from a large auction site and found out that a large majority of bidders (76.8 % of respondents) view other bidders as "competitors". In addition, auction outcomes were referred to as "winning" or "losing". As Malmendier and Lee (2011) also point out, some bidders either bid beyond their valuation or their valuation might increase as the auction progresses if they derive utility from gambling or competitiveness.

As depicted above, there are usually some complex psychological aspects affecting the bidding process along with pure economic considerations. We will have some consideration for these issues in this introductory chapter, but in the further analysis of bidding strategies in this thesis the psychological aspect of bidding is more or less excluded since it would complicate our analysis too much.

---

<sup>4</sup> In Chicago Cow Auctions bidders had the ability to bid on multiple items, so these results can't be generalized to single-unit auctions.

Turning back to the establishment of web-paged auctions, we notice that the first two platforms opening their operations were OnSale and eBay<sup>5</sup>. They utilized technologies offered by the web, allowing for the use of automated bids as well as search engines and clickable categories that made it convenient for bidders to browse through the items of their interest (Lucking-Reiley, 2000). Researchers were provided a solid natural testing ground for existing theories and market design<sup>6</sup>. Sellers could experiment with different parameters, ranging from the minimum bid level<sup>7</sup> to the number of days the auction would run. Yahoo! even offered sellers an option to choose whether to assign fixed or flexible ending time in any given auction. Flexible ending time meant that bidders didn't have - at least in theory - that much motivation for bidding late: in case there was a late bid, the auction was automatically extended for a few more minutes (Stryszowska, 2005).

If we were to briefly speculate the implications of the ending time rule, it would not be that straightforward to state whether it is the flexible or the fixed ending time that would generate higher revenues for the seller. On the one hand, given the flexible ending time rule *incremental bidders*<sup>8</sup>, i.e. bidders engaging in multiple counter bidding - don't have the same kind of pressure to learn to bid up to their values over auctions. On the other hand, flexible ending time enables both incremental and sophisticated bidders to react to being outbid (Ariely et al. 2005).

What does the evidence tell us? By collecting data from Amazon auctions with flexible ending times and eBay auctions with fixed ending times, Roth and Ockenfels (2002) found that bidding in eBay was much more concentrated near the end of the auction. They also noted that more experienced bidders<sup>9</sup> were more likely to bid late on eBay and reversely less likely to bid late on Amazon. A laboratory experiment conducted by Ariely et al. (2005) concluded that efficiency and revenue wise Amazon had it better; given the flexible ending time it was difficult to find any strategic reasoning for delaying one's bids. At least the commonly stated advantage of last-minute bidding, to prevent other bidders from reacting to

---

<sup>5</sup> OnSale opened its auction platform in May, 1995 and eBay in September, 1995 (Lucking-Reiley, 2000).

<sup>6</sup> eBay archives detailed records of completed auctions.

<sup>7</sup> Minimum bid level is set by the seller, and it is the lowest bid that the seller accepts. Once some bidder bids this amount or more, the current high bid of an open-ascending auction is set to the minimum bid level.

<sup>8</sup> There are various definitions for incremental bidders. Roth and Ockenfels (2002) define an incremental bidder as one who starts by bidding well below his maximum willingness to pay, and updates his proxy bid whenever he is outbid by another bidder. As opposed to a view that these bidders are naïve, we note that some type of incremental bidding can also arise if bidders were to switch between auctions.

<sup>9</sup> Feedback ratings were used as proxies to experience.



one's bid, was mitigated. On top of that, the opportunity for a bidder to learn his valuation over time was better.

## **1.2 Increase in online commerce - decline in Internet auctions**

Online commerce has grown vastly during the past decade or so. It seems that Internet auctions, however, have not benefited from this large expansion of interactive channels the World Wide Web has delivered; while only at the beginning of the 2000s online auctions were regarded as one of the most successful forms of ecommerce, the commercial significance of auctions has begun to diminish rapidly already since the late 2000s. It is now the posted retail prices that are commonly preferred over arranging auctions.

Although the change in the decreasing interest in conducting auctions has been more rapid than anyone could have expected there are economic reasons that have led to this experienced decrease in auction popularity. We will first specify some intuitive explanations that actually seem not to have contributed to the observed change.

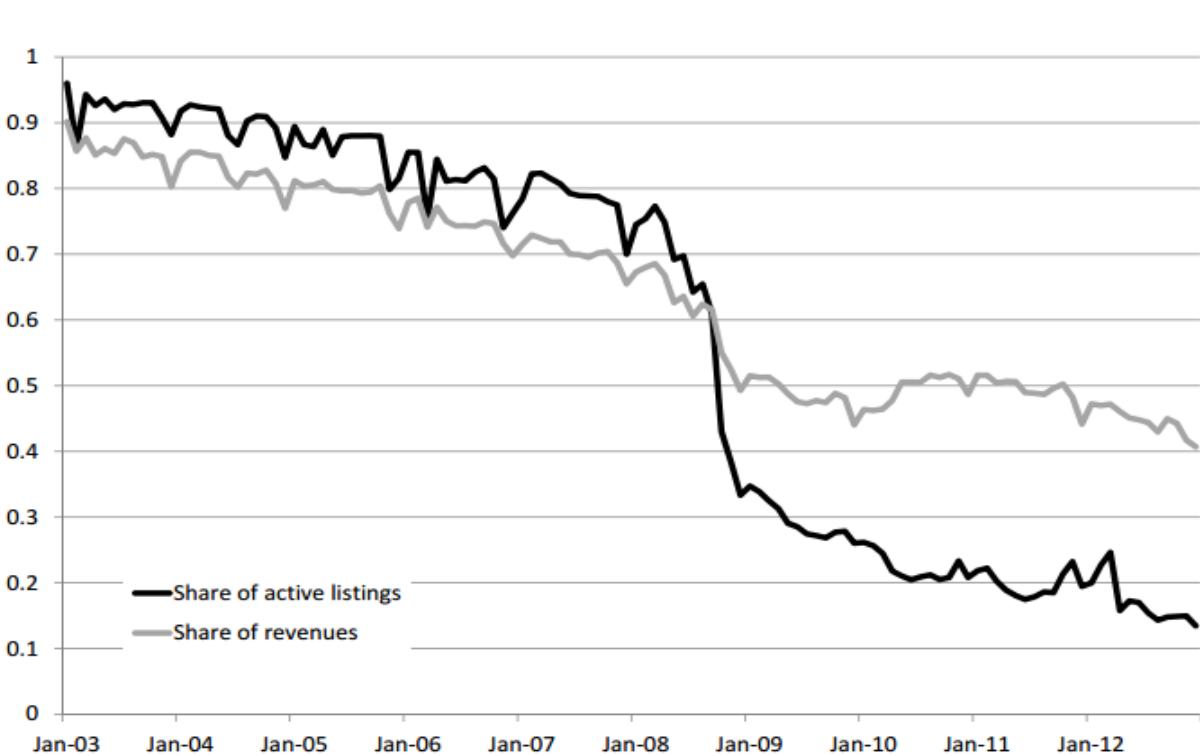
According to data from eBay, compositional shifts in the items being sold or the sellers offering these items are not sufficient to explain the decrease in the relative demand for auctions (Einav et al. 2013b). Einav et al. (2013b) also found that the reason didn't appear to lie in any compositional changes in the set of buyers either. They made a remark, though, that due to the vast heterogeneity in the pool of buyers in the Internet, there is always room for customer segmentation. This could help in explaining the fact that auctions are still used along with posted prices even among items that are not rather unique, and therefore have pretty good reference prices to compare auction prices with.

What explains the decrease in auction popularity then? Well, the evidence shows that the auction revenues have been diminishing during the last decade or so. Einav et al. (2013b) found that while auction revenues in 2003 were on average within 5 % of the corresponding posted price sales, there was a 16 % difference in 2009. However, if the seller would have valued the probability of sale more than the sale price, the same data shows that in 2009 auction listings still had somewhat higher possibility of sale than the corresponding posted

price listings: the success rate of auctions was 49 %, while only 42 % of posted price listings in the sample resulted in a sale.

In order to analyze the above returns to auction and posted price listings, Einav et al. (2013b) constructed a large dataset of matched listings from 2003 to 2009. By these matched listings the authors referred to the same items that the sellers in the sample were listing either simultaneously or over time using a different format of sale. In Figure 1 below we'll see that in the beginning of 2009 posted price listings surpassed auctions with regard to the share of listings and transaction revenues. In September, 2008 eBay allowed posted price listings an automatic extension after 30 days. This policy change may help in explaining the sharp rise (in relation to auctions) in active posted price listings at that time (Einav et al. 2013b).

**Figure 1. Auction share on eBay over time**



**Source:** Einav, Liran & Farronato, Chiara & Levin, Jonathan & Sundaresan, Neel 2013b

In economic sense it is highly plausible that the observed decrease in auction returns could have related very closely to the decrease in auction sales in general. But what are the possible factors that may have contributed to the decrease in auction returns then? Einav et al. (2013b) suggest that it is the relative demand for auctions that has diminished. Indeed, a lot has changed in the buyer side since the early 2000s. In these early days of Internet auctions the experience of bidding online had value in itself, i.e. these auctions offered hedonic benefits for the bidders (Surowiecki, 2011). As argued before, for some bidders it may not have been solely about acquiring the item of interest but maybe more about winning the auction. Consequently, it may well be that changes in online attitudes and competition account for a lot of this observed change.

Although Einav et al. (2013b) proposed that the reason for the decrease in the relative demand for auctions wasn't likely due to compositional changes in regard to the set of buyers, we could contemplate if there has been a meaningful evolution in the buyers' incentives leading to a decrease in auction returns. Maybe the bidding strategies of buyers are now more closely set towards maximizing the expected revenues rather than towards competing with other bidders.

What about the aspect of entertainment then? Some bidders may well attach some entertainment value to bidding in auctions. It can be easily observed that the entertainment potential of Internet auctions have been decreasing over time due to the emergence of other interactive channels like YouTube and Facebook. Moreover, people have become more familiar with the use of Internet and its ever expanding spectrum of channels. This has led to decreasing price discovery benefits of auctions: price comparing through online search has become easier and increased competition has had its impact on seller margins (Einav et al. 2013b). It may be that there is now less room for bidders to find good bargains, given that more and more bidders account for concurrent auctions and/or posted price listing when making their bidding decisions.

Related to the issue of entertainment value, there have been series concerns over the phenomenon of bidding at the last minutes of the auction, i.e. *sniping*. It has been proposed that the entertainment value would have possibly suffered significantly from this habit: is there any reason for a bidder to make a bid and wait for the closing time several days, only to see someone outbid him at the last moment (Surowiecki, 2011).

In their research, Backus et al. (2013) explored the effects of losing an auction to a late bidder. They found out that sniping indeed had a negative effect on the likelihood of a sniped inexperienced bidder bidding again. They suggest that some bidders are upset of the fact that they don't get to submit a counter-bid. Some bidders may even develop an attachment to the item, leading to a *quasi-endowment effect*: a bidder maintaining the high bidder position for a long time may think the item is already his. In fact, Backus et al. (2013) found out that the probability of not participating in future auctions was increasing in the amount of time the bidder was the highest bidder in the auction.

How would a rational bidder react to being sniped? Assuming the bidder has bid up to his valuation, there should be no reason for being upset. Furthermore, if a rational bidder would expect there to be other bidders (mainly) interested in maintaining the position of the highest bidder - i.e. bidding only when being outbid - it has been suggested that a rational bidder would engage in sniping himself (Roth & Ockenfels, 2002). Roth and Ockenfels (2002) also claim that sniping is a best response in the presence of naïve incremental bidders. We will assess if there is any logic in this claim later on in this thesis.

### **1.3 Markets for auctions in the future**

For what types of goods does an auction seem most likely to be used? Well, since the basic idea of an auction is to find a market-clearing price, we would expect that the more the seller is unknown of the actual demand the more likely he will choose to run an auction. Already Lucking-Reiley (2000) hypothesized that the benefits of a flexible, market-determined price are probably highest when the supply of the item is limited and its demand unknown. And as previously discussed, the seller is likely to increase his probability of sale by conducting an auction rather than relying on a posted price listing.

Einav et al. (2013b) find in their research that used and distinctive items are the ones that still encourage the use of auctions. In their work, they model the key trade-off between the price discovery benefits of auctions and the convenience of posted price listings. Not surprisingly, the model suggests that in the presence of greater retail competition, greater demand for convenience and reduced uncertainty about an item's value seller is better of using posted prices.

According to Einav et al. (2013b), auctions were clearly favored over posted prices on eBay in 2009 when it came to used items. New items, on the contrary, were more likely offered by posted prices. They suggest that this is what we would expect since finding comparable prices for new goods is relatively easy these days. Then again, bidders in real world auctions are a heterogeneous pool, some of whom have bigger opportunity costs than others. Those who are willing to wait for a good bargain across many auctions will probably continue favoring auctions for some time to come. Einav et al. (2013b) also found in their data that it was very common for sellers to use both posted prices and auctions side by side, even if they were to favor one format. However, their general view was that this phenomenon was most likely a consequence of seller experimentation.

A brief look at evidence shows us that, at least among consumer sellers, collectibles (with limited supply) represent the major share of goods auctioned online. In fact, collectibles may be the only category in which auctions in the Internet will have a major share of markets in the future. Finding an accurate reference price for a collectible is not an easy task since e.g. sports cards and other consumable collectibles come in many shapes. There are of course grading services available for the seller that help in determining the possible price range for a collectible. Although these grading services are a costly activity, seller is advised to utilize them due to the fact that bidders heavily discount the value of ungraded collectibles.

As an example of how difficult it is to assign a right price to a collectible, a grade-10 Ken Giffrey Jr's 1989 Upper Deck Card had an average eBay price of \$1,450 according to Jin and Kato (2002; see Bajari & Hortacs, 2004). That same card with a self-claim of 10 only yielded an average of \$94.26. What explains this difference? To make things short, some of the things that will drop a card from being gem mint (i.e. 10/10) are not visible for an untrained eye. Grading baseball cards is based on the following four characteristics: centering, corners, creases and surface. In the most renowned standards, PSA Card Grading Standards that is, a grade 5 is still called "excellent"<sup>10</sup>.

There are also certain types of goods, such as plane and hotel reservations or web-page advertising, where auctions can vastly help in allocating last-minute inventory (Levin, 2013). In these cases seller's opportunity cost of selling will fall in time, and buyers anticipating the price declines can time their purchases in a strategic manner. It can be shown that assuming forward-looking buyers, the perishable good seller is best off by adjusting the price

---

<sup>10</sup> <http://www.psacard.com/Services/PSAGradingStandards>

dynamically as time advances and arranging a last-minute auction in case there is some inventory left (Levin, 2013).

Some could say that auctions on the Internet are nowadays only a niche service. Then again, we could argue that even if only 10 % of eBay's current customer base<sup>11</sup> would actively take part in some auctions, auctions would still be of high significance to us. Regardless, in an economic sense the importance of auctions is now as existent as ever. The competitiveness of online pricing mechanisms has risen to a whole new level. Dynamic pricing, the possibility of bargains and competition are now characteristics describing trading even in its more traditional sense. There was a time when these characteristics were distinct to auctions. (Surowiecki, 2011).

#### **1.4 Purpose and structure of the study**

Let us now turn to the main purpose of this thesis. I have chosen to examine the online bidding process and its dynamics with a concentration on the buyer side. First, I will formulate the necessary theoretical models in order to find the plausible bidding strategies in open-ascending Internet auctions utilizing the proxy bidding mechanism. Then, I will compare these findings with some data on completed real life auctions.

There is one main research question that I try to answer in this thesis. That is, I aim at finding adequate reasoning for the prevailing phenomenon in Internet auctions, last-minute bidding. In addition, I will briefly discuss if the incentives of winning some specific auction are static or change over time. Intuitively, if we were to allow for changes in preferences during the auction process, bidding in the later stages would be strategically valid. Just to speculate, a bidder might for instance begin his bidding process by evaluating different auctions in order to find the one that will maximize his expected profits. However, given that this bidder has made a bid in some given auction and finds himself outbid in the last hour, he may end up giving more attention to this specific auction than needed.

---

<sup>11</sup> 128.1 million active registered users in the fourth quarter of 2013  
(<http://www.statista.com/statistics/242235/number-of-ebays-total-active-users/>)

Turning to the structure of this thesis, I will start Chapter 2 by familiarizing us with the characteristic features that differentiate online auctions from their offline counterparts. The ones that I have chosen to be extremely pivotal are network effects, inspection problems, proxy bidding system and matching of buyers to sellers. Of these features, we would expect that the presence of network effects clearly contribute to the popularity of online bidding. Inspection problems, originating from the anonymity in online bidding process, may have an effect of bidders discounting their valuations. On the other hand, anonymity may help in encouraging the participation. Participation is further encouraged by the proxy bidding system that will bid on bidder's behalf up to the value the bidder has set to the proxy, effectively reducing the time constraints of individual bidders.

In Chapter 3 I will introduce the auction formats employed in the Internet, particularly the open-ascending English auction. The argument for having the focus on this format stems from the fact that the one dominant consumer auction platform in the Internet these days, eBay, utilizes this format. Hence, the whole emphasis of this thesis is on the strategies of open-ascending English auctions with proxy bidding. In Chapter 3, I will first examine the similarities of this format with a traditional second-price sealed-bid auction format. Then, I will present the properties that differentiate these two formats from one another.

The standard independent private values model of bidding will be introduced and explained in Chapter 4. We will consider single-unit auctions only. In Chapter 5 we will go beyond the standard assumptions in order to better explain the last-minute bidding phenomenon. The following three models are to be presented in the 5<sup>th</sup> Chapter: repeated auctions, interdependent values, and common values. In addition, we will introduce search frictions that account for some of the price difference we see between more or less identical goods.

In the 6<sup>th</sup> Chapter we will gather some empirical evidence on last-minute bidding in Internet auctions. We will discuss how well our data is in line with the strategies suggested by the models presented before. It is also briefly discussed in this chapter whether or not the incentives of winning an auction stay constant during the course of the auction or not.

Chapter 7 concludes our work by combining the strategically valid bidding strategies proposed by the different models of value formation presented in the core of this study. We will also suggest some ideas for future research related to our thesis topic.

## 2 BIDDING DYNAMICS IN INTERNET AUCTIONS

As already mentioned in the introduction part, the innovation of Internet led to a huge increase in the amount of auctions arranged. Of course Internet in itself has evolved a lot since the days of its introduction, now offering a vast range of options for price comparing. For most items, it has become easier for sellers to find reasonable reference prices. As a result, we have observed a gradual shift in favor of posted prices. In addition, the share of individual sellers as opposed to large retailers has also had a shift in favor of the retailers.

In this Chapter I will present how vastly Internet auctions differ from conventional *brick and mortar*<sup>12</sup> auctions. The issues presented here are: network effects, inspection problems, matching of buyers to sellers, and the presence of proxy bidding system. We will also go briefly through the basics of eBay auction process as a means of explaining some preliminary things for the chapters that follow. We will show that while Internet makes many things easier to facilitate, there are problems as well that the participants would like to mitigate.

### 2.1 Network effects

Internet auction houses offer participants a platform where different types of users - buyers and sellers, consumers and advertisers etc. - are able to engage in economic or social interaction. Gathering these users together involves network effects.

Network effects span from external demand side scale economies. What this means is that the users of a certain auction platform benefit and thus assign greater value to that platform as the set of users expand (Levin, 2013). In other words, whenever a new user decides to subscribe to a platform, other users will benefit along with the new user. Respectively, the highest number of potential buyers is likely to generate the highest number of sellers. eBay has always benefited from these network economies of scale: the auction market gradually tipped in favor of eBay, having the biggest rivals Yahoo! and Amazon ceasing from the auction business in the US altogether in 2007 (Hasker & Sickles, 2010). Yahoo! is still operating in Asia and other areas though. In the US practically the only competition comes from some niche auctioneers or companies offering auctions as a service.

---

<sup>12</sup> Traditional business dealing face-to-face with customers, i.e. offline.



Buyers benefit from a bigger auction platform for instance in form of reduced search costs. A bigger platform also provides them with a wider variety of items not only to choose from but also to compare prices with. These network effects give us the reason why the global consumer auction activity has become so concentrated on one platform, eBay. Due to its large existing customer base, even innovative new platforms boasting better technology and applications will have it difficult to gain market share (Levin, 2013).

What is the relevance of network effects when we think of competition and the actual sales prices? In their study, Brown and Morgan (2009) auctioned identical coins in both eBay and Yahoo! auctions<sup>13</sup>. At the time the field study was made, eBay dominated the consumer auction market with an 80 % market share. As expected, eBay auctions had on average 50 % more bidders. As not such an obvious finding, Brown and Morgan (2009) found that eBay buyers paid from 20% to 70 % more than Yahoo! buyers for identical items. This is certainly striking, since the price difference is far from negligible. One could ask why the bidders did not arbitrage the prices. It may be that some of the bidders considered only the options offered in one of these platforms, giving little or no time to the offers that were for sale in the other platform (see Ch. 5.2). Or it may be that the competition was fiercer, given that eBay auctions had approximately two additional buyers per seller.

One may speculate that in the case presented above, there could be some lock-in phenomenon at hand, caused by the transaction cost of logging on to an auction site. However, we could argue that these days it should be relatively easy for bidders to use multiple platforms at the same time if needed, given that Internet auctions as a market have matured a lot since the early days. Nevertheless, it still may be that some users are committed to using a certain platform due to reputational reasons for instance. We will cover this in more depth next.

---

<sup>13</sup> Experiments were conducted between August, 2003 and November, 2004.

## **2.2 Inspection problems associated with the lack of physical presence**

As an exchange mechanism, Internet auctions make matters relatively easy for both consumers as well as for sellers. In order to be able to participate in an Internet auction one can be located almost anywhere in the world, the only requirement being that one has a working Internet connection and the required wealth to raise the winning bid. Since costs of organizing an Internet auction (commission fees charged by the auction house) are also nearly negligible we can assume that there are practically no other transaction costs than sending the item from the seller to the buyer, i.e. shipping fees. Bidders may of course place some cost in the activities of searching for the right auction or attentively watching the bidding come to a close. These costs, however, are nothing but a fraction of the costs experienced in offline auctions. Consequently, a higher number of items can be profitably sold which means that Internet auction platforms have it a lot easier (than the offline counterparts) to attract sellers and buyers to participate in some auction activity.

Convenience advantage in relation to traditional auctions, both geographic and temporal, makes it easier for bidders to take part in an Internet auction. By temporal difference we refer to the fact that where traditional auctions call for synchronous bidding, Internet auctions lasting several days or weeks give bidders the opportunity to submit their bids to the computerized system at any time, and as long as the predetermined ending time of the auction is not met (Lucking-Reiley, 2000). Therefore, bidders don't have to worry about their time constraints as much, even though the ending time of an auction may have its consequences on how an experienced bidder will divide his time between auctions. In the Internet, multiple similar objects are constantly being auctioned, thus the bidder may find it profitable to shade his bid in an ongoing auction based on some concurrent auctions. The bidder may even find it profitable not to bid at all even though a non-negative payoff could be achieved, given there is another auction possibly leading to a better payoff. In Chapter 5.1 we present the repeated auctions model that is set to address these issues.

The fact that there are no geographic barriers to bidding in the online world - and hence physical presence is not required - creates some major challenges as well. First, how well is the bidder able to inspect the goods before bidding? Of course, the seller has the opportunity to post pictures of the item and the buyers can ask further descriptions of the auctioned item via email if needed. But as we all know, there is the potential problem of fraud and thus it is up to the bidder to decide whether to believe in the claims of the seller or not. This inspection

problem is even more pronounced in the field of collectibles, say cards of superstar baseball players with values largely dependent on the condition of these cards. Seller can improve his trustworthiness in the eyes of possible buyers by getting his cards graded by a company specialized in grading cards, and furthermore by sealing the cards. Nevertheless, there can never be full guarantee that the seller will actually deliver the items after the payment has been made.

In their study, Kazumori and McMillan (2003) acknowledge the problem of fraudulent behavior. They go as far as suggest that the biggest problem limiting the growth of online auctions may well be the problem of information asymmetry. Indeed, in the global trading environment it is difficult for a buyer to inspect the item directly before making his bidding decisions. Hence, by assumption fraudulent behavior by sellers may limit the trade volume of online auctions. And as Jin and Kato (2007; see Levin, 2013) found in their study, there is considerably more misrepresentation in online than offline transactions. They got this result buying baseball cards both online and offline and getting them graded by a professional grading service.

In some cases the informational asymmetry between the seller and possible buyers could lead to a winner's curse problem. Take common values for instance where bidders make independent estimates of the common value  $V$ , which is not directly observed by the bidders. Common value  $V$  could be for instance the resale value of a collectible. Suppose bidder with the highest estimate makes the highest bid. Then, even when all the bidders would have made unbiased estimates, the winner would have overestimated (on average) the value (Milgrom & Weber, 1982). In the Internet auctions, in which the winner doesn't pay his own bid but the second-highest one, the winner's curse is somewhat alleviated. Still, as Bajari and Hortacsu (2004) point out, a strategic response to the winner's curse problem would be to lower one's bids. It is also true that if a bidder would assign some probability either for the possibility of the item not being in the promised condition or for the possibility that the seller would not deliver the item, a rational response would be to discount one's bids.

Feedback mechanisms have been created to alleviate the winner's curse and other problems related to asymmetric information. Through aggregate user feedback buyers can better review the quality of sellers or products. Feedback ratings of sellers could possibly differentiate the auctions of otherwise similar items from their counterparts, offering some explanation to the observed price difference across auctions of similar items.

On the eBay platform users are able to give three types of feedback: positive, negative or neutral. Users are also given the ability to give an additional message assessing the transaction. Levin (2013) has pointed out that many studies starting with Resnick et al. (2001) have argued this feedback system was vital for eBay's success. In addition, Levin states that according to substantial empirical literature higher seller feedback scores amount to higher prices and sales rates.

A natural question of the feedback systems is if they actually succeed in providing sufficient information. By taking a closer look at it, we see that the mean overall feedback rate of a seller on eBay appears to be over 99 % (Fu, 2011). What this practically means is that the negative rating is quite possibly a better indicator of a seller's reliability than the overall rating (Bajari and Hortacsu, 2003).

The most intuitive explanation for mostly positive seller feedback would be the fear for retaliation: sellers receiving negative feedback might be urged to give the buyer negative feedback in return. Consequently, buyers expecting the retaliation from a seller would abstain from giving feedback altogether. The elimination of sequential feedback would help to alleviate this problem, and actually during the past few years eBay has allowed sellers only the possibility to react to any buyer feedback with merely a positive rating if any. Still, keeping in mind that feedback provision is a costly activity (and completely voluntary) many of the buyers don't find it worthwhile to provide reviews about their sellers (Bajari & Hortacsu, 2004).

In order to further highlight the possibility of fraudulent behavior, I briefly present a type of behavior a bidder may face in Internet auctions. This behavior is called *shill bidding*. A seller that engages in shill bidding is bidding in his own auction as a means of driving the final price artificially high. Needless to say, the behavior of this sort is against the auction rules, but the new technology creates a possibility for Internet savvy users to create multiple usernames as a means of bending the rules.

Does shill bidding complicate our analysis of rational bidding strategies in open-ascending Internet auctions? As we will show in Chapter 4, given the most simple independent private values case, in which other bidders' valuations have no effect on one's own valuation, shill bidding has zero impact. Shill bidding should not have any impact on other generalizations of the model either, since shill bidders are quite easily spotted by an attentive bidder. For instance, the feedback scores of shill bidders are usually empty because they don't follow through with transactions. Further, we would expect that a rational bidder would switch to another auction if the price of a particular auction seems to rise out of proportion. Therefore, even in the common values setting, a shill bidder doesn't possess any valuable information to buyers.

### **2.3 Matching of buyers to sellers**

The potential market for an item in the Internet is infinite: approximately close to three billion people have Internet connections these days. Therefore, we can confidently assume that Internet auctions are a good way to find a price for an item with uncertain demand. As a matter of fact, the largest e-commerce platform eBay acts as a primary sales channel for tens of thousands of retailers (Einav et al. 2013a).

Online auctions undoubtedly offer a less-costly way of trading items that have locally thin markets, such as specialized collectibles (Bajari & Hortacsu, 2004). Collectibles are and have always been sort of a cash-cow for online auctions; stuffed dolls called Beanie Babies for instance were the ones that really made eBay popular in the first place, totaling 6.6 percent of overall eBay sales in May, 1997. Not only can bidders find what they are looking for but in most product categories they are continuously faced with more or less multiple similar items at the same time.

When we come to think of it, online auction sites actually work as a substitute for more traditional market intermediaries, say specialty dealers in antiques for instance. Extensive listings and powerful search technologies make it convenient for buyers to browse through the items of their interest with negligible transaction costs (Bajari & Hortacsu, 2004). It is true in e-commerce marketplaces that more often than not buyers have comparable prices at hand, meaning that there is not much room for sellers to exploit their market power. Therefore, it is

only natural that many traditional intermediaries have found it unprofitable to continue their businesses in the global trading environment.

Powerful search engines and clickable hierarchies of categories in today's auction platforms make it particularly easy for bidders to find what they are looking for and compare prices with similar items. Decisions to enter an auction need very limited pre-planning; hence, assuming a small minimum reserve price set by the seller, many buyers can be attracted to bidding in the early stages of a given auction. In practice, auctions also reduce the feel of commitment (Ariely & Simonson, 2003). A bidder can for instance make a small early bid, in which case he supposedly doesn't regret whether his bidding leads to winning or losing. Having more bidders per auction, we would assume that there is more pressure for bidders to bid up to their valuation. This in turn would lead to a more efficient outcome. As a means of providing the efficient outcome eBay utilizes the proxy bidding system, which we will shortly introduce next.

## **2.4 Proxy bidding system**

In traditional offline auctions there is no computerized system for bidders to utilize. Most auction platforms today offer bidders a chance to use automatic bidding, i.e. proxy bidding system to bid for them. The organization running the auction may also allow straight bids, and if we hypothesize that a particular straight bid would be the winning bid, one would have to pay up to this sum. In other words, the highest bidder would have to pay a price equal to his bid. If the highest bidder would have bid the same sum through proxy, the price paid would have been the second highest bid plus a bidding increment. In this thesis we will not examine *straight bidding*<sup>14</sup>, since it is more closely related to charity reasons than actual utility considerations.

---

<sup>14</sup> A bidder decides to bid a specified amount outside proxy bidding. Yahoo!, once a prominent platform in Internet auctions, allowed straight bids.

Auction platforms have their own guidelines for using the automated proxy bidding system. eBay for instance informs that a bidder must first decide his maximum willingness to pay and tell this to proxy. Then, the proxy will keep on placing bids on one's behalf using the automatic bid increment amount. For instance, suppose bidder A's proxy bid is \$20, the predetermined bid increment \$1 and bidder A currently has a *standing high bid*<sup>15</sup> of \$10. If bidder B would then enter a bid of \$15, proxy would raise bidder A's bid to \$16 - i.e. minimum bid increment above the second highest bid. In this scenario, other bidders would only observe bidder B's participation, although due to the observed change in the standing high bid they would know that some other bidder has entered the auction.

Proxy bidding system will update the current leader's bid as long as this bidder's valuation in the proxy is enough to maintain the position of the highest bidder. The valuation need not be the bidder's maximum willingness to pay for the item, i.e. bidder's reserve price. Auction platforms of course advise bidders to reveal their reservation prices to proxy early, most likely due to efficiency considerations.

The highest proxy bid is never directly revealed during the course of the auction. Most of the time, other bidders only see an amount of the second highest bid plus a predetermined bidding increment<sup>16</sup>. Let there be an outbid, proxy notifies the bidder and the bidder may revise his bid. In order for any bidder's bids to be accepted, they must at least exceed the current standing bid by the minimum bid increment. The minimum increment rule applies only on the standing high bid, and hence it is sometimes possible to submit a proxy bid that is in very close vicinity with the highest (hidden) proxy bid.

As can be derived from the earlier paragraph, what proxy bidding does is that it makes the fixed-length English Internet auction resemble the Vickrey second-price sealed-bid auction (Lucking-Reiley, 2000). What these two auction formats have in common is that the bidder surplus is not directly affected by one's own bidding amount, given that the bidder pays the second highest bid plus the bidding increment. As opposed to traditional Vickrey auction, however, an open-ascending English auction is a continuous auction. By this we mean that bids arrive randomly and every bidder is given the ability to update their bids without any upper limit during the course of the auction.

---

<sup>15</sup> Standing high bid is the bid amount every bidder sees in the auction history. Only the current leader knows the highest bid in the proxy system.

<sup>16</sup> It is possible that a new proxy bid is made in the vicinity of the highest proxy bid, not exceeding it though (the two bids closer than the increment). In this case, the standing high bid is adjusted equal to the highest proxy bid.

Due to the nature of proxy bidding, no bidder will know for certain how many bidders there actually are actively bidding for the item at stake. If the first bidder happens to bid an amount that no other bidder is willing to exceed by at least the increment, then the bidding history will show only this bidder. Bidders do not see the complete bidding path until the auction has ended. It should also be noted that in the empirical study we can never know if the winner, or any of the other players for that matter, have submitted their true willingness to pay.

**2.5 Basics of auction process on eBay**

Before turning to auction theory and its implications, I think it is justifiable to describe the regular sequence of events that take place in an online auction. First, the seller determines the duration and the starting bid of the auction. The starting bid is the seller’s reserve price, i.e. the lowest price the seller is willing to accept<sup>17</sup>. When some buyer makes a bid at least equal to this amount, the current price of the auction is set to this starting bid. As described earlier, any following bids must exceed the current price (or the current standing bid) by at least the amount of the minimum bid increment. We will show the current bid increments (mainly) used in eBay auctions in Table 1 below.

**Table 1. Bidding Increments in eBay Auctions**

<b>Current price</b>	<b>Bid increment</b>
\$ 0.01 - \$ 0.99	\$ 0.05
\$ 1.00 - \$ 4.99	\$ 0.25
\$ 5.00 - \$ 24.99	\$ 0.50
\$ 25.00 - \$ 99.99	\$ 1.00
\$ 100.00 - \$ 249.99	\$ 2.50
\$ 250.00 - \$ 499.99	\$ 5.00
\$ 500.00 - \$ 999.99	\$ 10.00
\$ 1000.00 - \$ 2499.99	\$ 25.00
\$ 2500.00 - \$ 4999.99	\$ 50.00
\$ 5000.00 and up	\$ 100.00

**Source:** eBay, bid increments <http://pages.ebay.com/help/buy/bid-increments.html>

---

<sup>17</sup> As a side-note, the seller also has an option to set a secret reserve price for an item, and in case this secret reserve price is not reached the item remains unsold.



Direct bidding is not enabled on eBay; proxy bidding system is to be used instead. At the fixed closing time of the auction, the winner is the bidder who has successfully entered the highest valuation to the proxy bidding system<sup>18</sup>. If two bidders have bid the same amount, the earlier bidder wins. This quality combined with the existence of bid increments is somewhat peculiar. According to the auction rules the price can never exceed the highest bid submitted, and hence theoretically if the valuations that determine the two highest proxy bids would be closer together than the bidding increment  $s$ , the winner of the auction wouldn't actually have to pay the second highest valuation plus the increment. Rather, the winner would pay his own bid, effectively making the auction a first-price one. However, as can be seen from Table 1, the increments amount only to a fraction of the current price. Hence, the small probability of an increased payoff resulting from the avoidance of the whole bid increment shouldn't virtually have any effect on any bidder's bidding strategies.

As explained in the previous paragraph, an eBay auction can sometimes end up being conceptually a first-price one. According to standard auction theory, it would be in the bidders' best interests to shade their bids in that setting. Nevertheless, given that in the online environment the arrival of bidders is random, and no bidder can make even closely accurate estimates of the number of bidders either actively or passively participating in an auction, there is actually no room for bid shading in a single-item setting.

Rogers et al. (2007) suggest in their research that when several bidders engage in last-minute bidding, i.e. sniping, bidders should aim at "sniping before the snipers". It is notable, though, that they advise this strategy only in if there are some real life phenomena at stake, such as incremental bidders, or if the auction has some *common value*<sup>19</sup> component in it. As already explained, due to the presence of bidding increment a bidder having the highest valuation (but who hasn't bid yet) may not sometimes be able to enter his bid in a later stage of the auction if his bid doesn't exceed the current standing bid by the minimum increment. Therefore, a rational bidder would bid at a time when there is no time for others to update their bids, but still not too late to avoid being excluded by similar bids made by competing bidders.

---

<sup>18</sup> It is important to note that even if every bidder will enter their values truthfully to proxy, the bidder with the highest value may not always win. This is due to the fact that subsequent proxy bids exceeding the highest prevailing proxy bid have to also exceed the highest standing bid by the minimum increment in order to be accepted.

<sup>19</sup> In common value setting bidders can update their valuation of an item in response to other's bids.

Given that the bidder with the highest valuation may not always win, the outcome of the auction may in some cases be inefficient revenue wise. Then, what should the bid increment be in order to achieve the best attainable efficiency? There is no clear answer. While increasing a small bid increment directly increases the closing price of a given auction (and the expected auction revenue), an increase in the increment will also increase the probability of some bidders being excluded from the auction.

### 3 AUCTION FORMAT

An inherent feature of auctions is the uncertainty of the values the participants have for the auctioned object. Auctions are a multi-stage process where bidders make sequential decisions, such as whether to enter an auction or not, how much to bid and whether to revise one's bid/bids (Ariely & Simonson, 2003). Seller knowing the precise valuations of the buyers could simply offer the item to the bidder with the highest valuation at or just below the bidder's willingness to pay (Krishna, 2002). Of course, in regular circumstances this information is private, and this is where auctions come to play.

#### 3.1 Auction formats employed in the Internet

Lucking-Reiley (2000) found in their survey of different auction sites in the Internet that basic auction formats utilized were English, Dutch, sealed-bid and double auctions. The dominant auction format was English ascending-price auction, used by over 80 % of the sites in the survey. There were some sites that offered the possibility to choose from more than one auction format. We note that the Dutch auction in the Internet is not the same as the traditional Dutch auction in the economic literature. Instead, here multi-unit auctions in which bidders bid a number of units and a price per unit are referred to as Dutch auctions (Haskey & Sickles, 2010).

Why the open-ascending auctions are so popular compared to other auction formats?

Lucking-Reiley (2000) suggests that assuming there are similar items auctioned at the same time, open-ascending format makes it easier for bidders to choose which auction to bid on. Given that a bidder tries to maximize his utility, it is intuitive to think that bidder  $i$  will prefer an auction that maximizes his expected revenue, which is the difference between his valuation  $v_i$  of the item and the price  $p$  to be paid.

Traditional open-ascending English auction and its rules are probably familiar to anyone that has ever participated in an auction. However, Internet auctions have several non-standard features differentiating them from the traditional English auctions described in the literature. In this thesis and in this chapter we will concentrate on describing the eBay auction format and its characteristics.

### 3.2 Open-ascending English auction on eBay

In an open-ascending English auction with proxy bidding mechanism the bidder sees the current standing bid and can decide whether or not to raise it. If a bidder submits a bid, he is readily told if he became the high bidder or not. It is up to the bidder to check on his status during the auction, if needed. The proxy bidding system will send instant notifications when a bidder is outbid, and then a bidder can revise his bid.

William Vickrey (1961) has demonstrated that the English auction and the second-price sealed-bid auction are strategically equivalent in the private values case. By strategic equivalence we mean that the dominant strategy for a bidder is the same in these two auction types: to bid one's own valuation. It also follows that the expected revenue for the auctioneer is the same in each auction type whenever the equivalence holds.

English auctions are conventionally modeled as *button auctions*, in which an auctioneer announces prices, and bidders indicate whether they stay in or not by “pressing on a button”. When a bidder decides to drop out, he will let go of the button. Drop-out decisions are irrevocable and they are observed immediately. The auction ends when there is only one bidder standing. The remaining bidder, the winner, pays the current price equaling the price when its last rival dropped out. Thus, the price to be paid is approximately the second highest valuation<sup>20</sup>. As we will show in Chapter 4, this is also the symmetric equilibrium of a single-item open-ascending Internet auction with private values. (Wang, 2006).

Single-item open-ascending English auctions have a close resemblance to *second-price sealed-bid auctions*<sup>21</sup>. First, proxy bidding system creates a feel of a closed auction in an open-ascending English format since the exact bid amounts are not visible. Bidders can only guess what the number of bidders is and what their bidding strategies are. In other words, we don't observe “drop-outs” but bidders' out-cry bids (Wang, 2006). Evidently, a regular strategy employed in eBay auctions has bidders indicating their participation only in the last minute. This is equivalent to “almost always staying out” in the button auctions.

---

<sup>20</sup> It is expected that bidders follow the equilibrium bidding strategy of bidding up to one's valuation.

<sup>21</sup> In second-price sealed-bid auctions each bidder submits a sealed bid to the seller. Winner is the highest bidder and he has to pay the second-highest bid.

As explained in Chapter 2.4, the winner and hence the highest bidder on eBay auctions usually pays the amount of the second highest bid plus an increment - not his own bid. In other words, it is true in most circumstances that a bidder's own bid does not directly affect his payoff even if he wins the auction.

Proxy bidding eliminates the possibility of jump-bidding since the current standing bid can only increase up to the rival bid plus the increment. The high bidder is always the bidder who has successfully submitted the highest proxy bid. We have also learned that, in order to be successfully submitted, the later proxy bids must exceed the current standing bid by the minimum bid increment.

As opposed to button auctions which will end when all but one bidder has dropped out, eBay auctions have a fixed-time ending rule (Wang, 2006). It makes no difference if some bidder would be willing to continue bidding or not, the auction always ends at a predetermined time. At the fixed ending time, the bidder with the highest standing bid is declared the winner.

Since there are many identical items sold repeatedly on eBay, Wang (2006) suggests that we should treat these Internet auctions as more like a multi-unit, market like structure where the auction house will repeat the same single-unit auction  $M$  times. This quality would lead bidders to consider the prices in the future auctions as well, not only their private values in a single auction. We should add that, realistically, not only the future auctions but also the concurrent one's affect the bidding decisions of an individual bidder.

In the next chapter we will familiarize us with the standard independent private values model in a single-unit framework in which the future auctions are excluded. Later in Chapter 5 we will make our approach more realistic by considering e.g. the repeated auctions setting as well as interdependent values on eBay auctions. As we will show, we may have to relax the strict assumptions of private values in order to enhance our understanding of the last-minute bidding behavior in online auctions.

## 4 THE INDEPENDENT PRIVATE VALUES MODEL (IPV)

Private values model is a good starting point for analyzing the online bidding process. In this model we suggest that at the time of bidding each bidder knows the value of the object to himself. Theoretically, all bids exceeding this private value are weakly dominated (Ariely et al. 2005). By bidding above one's own value, the bidder will of course increase his probability of winning, but more importantly this region responsible for increasing the winning potential lies above the bidder's reservation value. The reference used here were Krishna (2002) and Levin (2004).

### 4.1 Basic assumptions

In order to analyze the IPV model, we need to make some assumptions. First of all we assume that we have a risk-neutral seller selling an indivisible item, and there are  $N$  potential bidders bidding to claim the item. Bidders observe signals  $S_i \sim F(\cdot)$  with typical realization  $s_i \in [\underline{s}, \bar{s}]$ , and they assume that  $F$  is continuous. Bidders' signals  $S_1, \dots, S_n$  are independent, and bidder  $i$ 's value is  $v_i(s_i) = s_i$ .

We must note that bidder  $i$ 's information as well as his value are *independent* of bidder  $j$ 's information. Hence, bidder  $j$ 's information is *private*: it has no effect on anyone else's valuation.

At the fixed ending time of the auction, the auctioned item will be given to the highest bidder with a price  $p$ . Hence, the payoff of the winning bidder will be the difference between his value  $v_i(s_i) = s_i$  and the price  $p$  he has to pay. Payoff will be zero for all the other bidders.

We assume that bidders have no liquidity or budget constraints. Hence, they can pay their respective bids in case of winning. Bidders are also assumed to be risk neutral, thus they try to maximize their expected profits.

## 4.2 IPV strategies in online auctions

As pointed out in the previous chapter, the bidding strategies of open-ascending Internet auctions resemble the strategies of second-price sealed-bid auctions. However, there are the following main differences:

- 1) There is a minimum increment that the winner will usually have to pay on top of the second highest bid<sup>22</sup>.
- 2) The bidding is dynamic, i.e. bids arrive randomly and price rises continuously from zero.

Open-ascending English auctions in the traditional sense can be modeled in a way that the price will rise continuously from zero and bidders can push a button to drop out of the bidding (Levin, 2004). The setting here is somewhat more complex since any bidder has the possibility to follow the auction any time they see fit. Most notably, the participation of bidders bidding only in the last minutes of the auction can't be observed until the end of the auction.

### 4.2.1 The symmetric equilibrium

Bidding behavior in an IPV auction is a non-cooperative game among the bidders, i.e. bidders are assumed to behave competitively. Bidder's strategy is a function  $\beta_i : [0, \omega] \rightarrow \mathbb{R}_+$  that will determine the bid for any value. Bidders search for the bidding function leading to the best outcome, given that all the other bidders form their bids according to the same bidding function.

According to Levin (2004), the unique symmetric equilibrium in a traditional open-ascending English auction is for each bidder to drop out when the price has reached his value. Consequently, in this *symmetric equilibrium*<sup>23</sup> the highest bidder ends up paying the valuation of the second highest bidder. We will show next that bidding up to valuation is also weakly dominant in a single-item eBay auction with private values.

---

<sup>22</sup> If the two highest values are within the increment, the highest bidder has to pay his own bid.

<sup>23</sup> In symmetric equilibrium all bidders follow the same strategy.

We will consider the usual case here where the price the winner pays is the second-highest bid plus the increment  $s$ . Therefore, the price to be paid is independent of the winner's own bid amount.

First, we will determine the outcome of a second-price sealed-bid auction without the bidding increment. Given the private value environment and the property that the winner pays the second-highest bid, this is enough to prove that the bidder maximizes his expected payoff by bidding up to his valuation. Next, we will show that on eBay or any other online auction platform utilizing proxy bidding mechanism it is best to bid early in a single-item framework.

We will propose that it is a weakly dominant strategy in a second-price auction to bid one's value  $b_i(s_i) = s_i$ . In the following presentation we will prove that this is true.

First, by bidding over one's valuation the bidder runs the risk of winning the auction with a payment above his value. Let's assume we have a bidder  $i$  with a valuation  $s_i$ . We also assume that the highest competing bid is  $p_1 = \max b_j, j \neq i$ . The outcome of bidding the valuation  $b_i = s_i$ ; bidder  $i$  will win if  $b_i > p_1$  and does not win if  $b_i < p_1$ .

If bidder  $i$  bids higher than his valuation ( $b_i > s_i$ ), there are three possible outcomes. First, in case  $b_i > s_i \geq p_1$  bidder  $i$  will win and obtain a payoff  $s_i - p_1$ . The payoff would have been the same if he had bid his valuation. Second, in case  $p_1 > b_i \geq s_i$ , bidder  $i$  loses but the same outcome would have followed by bidding the valuation. Third, if  $b_i > p_1 > s_i$ , bidder  $i$  wins but makes a loss  $s_i - p_1$ . This loss could have easily been avoided by bidding the valuation  $s_i$ . To conclude, the bidder's profit never increases (but can decrease) if he bids above his own valuation. Hence, it is better to bid  $s_i$  than  $b_i > s_i$ .

Now we have proven that overbidding one's valuation is never plausible. Next we consider the case in which the bidder bids under his valuation ( $b_i < s_i$ ). In that case, and given that  $s_i > b_i \geq p_1$ , bidder  $i$  wins with a payoff  $s_i - p_1$ . The same payoff could have been achieved through bidding the valuation  $s_i$ . If  $s_i > p_1 > b_i$ , bidder  $i$  loses but bidding up to valuation would have resulted in a win. As a conclusion, bidding under one's own valuation may decrease the profit. It is better to bid  $s_i$  rather than  $b_i < s_i$ .



Having every bidder bid their valuation results in a truth-telling equilibrium. It is the unique symmetric Bayesian Nash equilibrium of the second-price sealed-bid auction. Truth-telling is weakly dominant: bidding one's valuation weakly increases one's payoff. In the following presentation we will show that in a continuous second-price auction, like the one on eBay, the timing of the bid is also of utmost importance.

Given that Internet auctions are continuous, we will have to include the bidding increment in our following considerations to find the results for optimal bid timing. The following presentation shows that, in a single-item eBay auction, not only is it a weakly dominant strategy to bid up to one's valuation but also to bid early. Notation  $v_i$  is used for bidder's true valuation,  $s$  indicates the bidding increment and there is the time factor  $t$ . Bidding starts from  $t = 0$  and ends at  $T$ .

First, suppose bidder  $i$  has a strategy of submitting several proxy bids, and that the bidder ceases to bid after  $t_n \leq T$ . In this case, the final proxy bid must be in the interval  $(v_i - s, v_i]$ . Otherwise, adding a proxy bid equal to one's valuation  $v_i$  at time  $t_{n+1} \geq t_n$  would dominate the proposed strategy. Since  $t_n \leq T$ , there exists  $t_{n+1}$  between  $t_n$  and  $T$ , the ending period of the auction. To conclude, not bidding up to valuation is dominated. (Wang, 2006).

Submitting a proxy bid of  $v_i$  at time  $t = 0$  yields the same outcome as bidding  $v_i$  at any other time during the course of the auction, with one exception. If there are other bidders (at least two) with valuations in the interval  $(v_i - s, v_i]$ , one strictly gains by submitting a proxy bid equal to one's reservation price before the others do. Suppose bidder  $i$  let's two other bidders make early bids in the interval  $(v_i - s, v_i]$ . Then, since the standing high bid would now be strictly above  $v_i - s$ , bidder  $i$  would have to bid over his valuation  $v_i$  in order to become the highest bidder. This is never an option for a rational bidder. Hence, submitting a proxy bid  $b_i = v_i$  at time  $t = 0$  weakly dominates a strategy of bidding one's valuation at any other time. To conclude, all bidders end up bidding at time  $t = 0$ . (Wang, 2006).

We have now achieved that bid timing does matter. The bidder with the highest valuation maximizes his expected payoff by bidding early. Respectively, the bidder with the second highest valuation can increase his payoff by bidding early: in case being the first to bid there is a finite chance for this bidder to win the auction (Rogers et al. 2007). It is true for any bidder that delaying one's bidding decisions increases the probability that the current standing bid will rise to a point where they are not able to submit their bids anymore.

What are the real world implications of the results derived here? Should buyers bid as soon as they see an auction they like to bid in? By taking a quick look at some evidence, we see that the bidding in Internet auctions is concentrated near the beginning and near the end of the auction (Jank & Shmueli, 2010). Thus, we could argue that some bidders may view the auction as a private values one and bid according to the above theory predictions. Then again, early bidding can simply be the result of some time constraints: if a bidder is not able to place any subsequent bids after  $t = 0$  (i.e. revise his proxy bid) in the remainder of the auction, the bidder has to bid his valuation early or not bid at all (Hossain, 2008).

The results we have derived here in a single-item framework should be interpreted with caution. It is likely that almost any given bidder in the real world will actually consider more than one auction at a time. Since it is not possible (in general circumstances) to retract or cancel one's bids, it is not that easy for a current leader of some auction to switch between auctions given that he has demand for one item only. Therefore, we can assume that in a more generalized setting with  $N$  auctions bidders may find it profitable to delay their bids, if there are some price differences between the auctions.

We will now briefly consider the situation where the winner has bid only slightly above the opponent's highest bid, effectively avoiding the payment of the whole minimum increment. In this case, as noted earlier in this thesis, the winner would have to pay his own bid and hence, bidding one's value would not seem to be a dominant strategy anymore. However, as Ariely et al. (2005) point out, the price can never be pushed down by more than one increment by bidding less than the valuation. Consequently, they call the strategy of bidding one's valuation an  $s$ -dominant strategy since it never yields a payoff more than the minimum increment below what could be achieved by any other strategy. The result holds regardless of the strategies employed by the other bidders.

### 4.2.2 Other equilibria

In the preceding subchapter of independent private values we introduced the symmetric equilibrium, where every bidder bid their true values. There are also asymmetric equilibria in which some bidders use weakly dominated strategies (Levin 2004, Wang 2006). For instance, having bidder  $i$  bidding his valuation and other bidders bidding zero would be an asymmetric equilibrium. In the following subchapter we will show that in continuous-time sealed-bid auctions, where some bidders apply weakly dominated strategies, a rational bidder would sometimes be better off by making his bid in the last seconds of an auction.

Let's denote the minimum initial bid (that the seller sets) by  $m$  and the smallest increment by  $s$ . If we consider the case with two bidders, it is sufficient to show that no strategy of bidder  $j$  with value  $v_j > m + s$  is a best response to every strategy of the other bidder  $i$ . Suppose  $i$  has a strategy of bidding the minimum bid  $m$  early on and not to bid further given he remains the high bidder, but to bid  $B > v_j + s$  whenever his information set tells him he is not the high bidder. Bidder  $j$ 's best reply in this case is to bid  $v_j$  at the last seconds of the auction, avoiding a counterbid of  $B$ . This way bidder  $j$  leaves no time for bidder  $i$  to learn that he is not the high bidder anymore.

The payoff to bidder  $j$  from the preceding strategy will be  $p(v_j - m - s) > 0$ . No deviation from this strategy increases this payoff. However, other bids than  $v_j$  at the last seconds would still yield the same payoff for bidder  $j$ , but they are weakly dominated by the strategy of submitting the valuation.

Now, let's suppose bidder  $i$  would decide to refrain from bidding altogether. Then, allowing for the possibility that some of the late bids may not be successfully transmitted, bidding at the last seconds would not be the best strategy for bidder  $j$ . In this case, bidding early would lead to a payoff  $v_j - m$ , which would be greater than that of last-minute bidding  $p(v_j - m)$ .

Asymmetric equilibria in private values give us some further insight in understanding the last-minute bidding phenomena. Even if all bidders have their own private values, it is only plausible that not all the bidders in typical Internet auctions follow the same strategy. There are different types of bidders, some of who maximize the expected payoffs and some of who might derive utility simply from participating or competing.

## 5 BEYOND STANDARD ASSUMPTIONS

In the previous chapter we examined the standard independent private values model in a single-item framework. The purpose of this chapter is to go further and analyze some attributes that may have a significant effect on the strategic validity of bidder's choices. Most importantly, we present a model in which we add another identical auction to the private value setting with a proxy bidding system.

Most literature on empirical auctions has had their focus on the single auction model only. However, due to the fact that an abundance of similar auctions are conducted repeatedly in the Internet and more specifically on eBay, we should examine repeated auctions setting here. Einav et al. (2013a) describe in their study that it is extremely common for sellers to post almost identical listings varying in prices, fees and sales mechanisms at the same time or over time. In early 2008, for instance, a search of "Wii console" brought forth around 6000 auctions on eBay alone (Fu, 2011).

It should also be noted that not only auctions but concurrent retail price offerings can have a significant impact on one's bidding decisions. Accounting for these outside opportunities, it may be optimal for a bidder to not bid at all or to bid below his true valuation in some real life situation. There may be a better achievable bargain for a bidder somewhere else, e.g. an auction including bidders with lower high bids or an auction with more irrational bidders. In this case, an early bid up to valuation that no bidder challenges takes away the chance of switching to another auction, given that the bidder only has a demand for one item.

Here, allowing for the presence of multiple competing auctions, optimal bid will still be a function of the bidder's private valuation and the optimal strategies of the bidder type dependent. As Hossain (2008) points out, however, given there are concurrent auctions running bidders might end up in multiple bidding as they update their information about their outside opportunities. And as evidence by Bajari & Hortacsu (2003) shows, an average amount of proxy bids observed by a bidder is approximately two. It is usually alleged, though, that experienced bidders are not likely to engage in multiple bidding. Rather than making a bold assumption that multiple bidding is always irrational, we could see this as an indication that the most experienced bidders are the ones with the most rigorous time constraints and therefore abstain from multiple bidding.

## 5.1 Repeated eBay auctions

Wang (2006) demonstrates that last-minute bidding strategies can be rationalized in the private values setting when we add another identical auction to the picture. Assuming there were two identical auctions conducted in a row, bidders expecting to win the second auction at a lower price wouldn't have to bid up to their true valuation in the first one. On the contrary, their maximum willingness to pay in the current auction would equal the expected winning price of the next auction. This, in turn, is the expectation of the highest loser's valuation in the next auction. Bidders' expectations are correlated with other bidders' valuations, and hence Wang (2006) makes a remark that there is a common value component included in the repeated auctions framework.

In his work, Wang (2006) focuses on a symmetric sequential equilibrium. Weakly dominated strategies that we mentioned in Chapter 4 when going through asymmetric equilibria in private value single-item auctions are not considered here.

We will not introduce all the complexities related to eBay auctions in the next example by Wang (2006). The result derived can however be generalized to  $N$  bidders as well as other distributions than uniform, assuming we have an independent private values framework at hand.

It is assumed that there are three bidders with unit demand bidding on two identical items that are sold sequentially by two sellers. The sequential second-price auction is divided into two stages with one seller auctioning off one item in each stage. The sellers value the items at zero. Bidders have a demand for one item only and have valuations  $v_i$ , which are called their types. Types are private and they are independently drawn from the distribution uniform  $[0,1]$ .

Winner of the first stage as well as the current price (the second highest bid) are revealed before the second stage takes place. In the second stage we have the standard case in which the remaining bidders will bid their valuation  $\beta_2 = v_i$ . Bidding any other sum would be a dominated strategy. There are two bidders left, thus item is sold at a price equaling the valuation of the second highest bidder in the second stage. Knowing this, we assume that all three bidders can calculate the expected winning price of the second auction, which is also the maximum amount bidder  $i$  is willing to pay in the first one. If the expected winning price in the first stage happens to be larger than that of the second stage, bidders rather wait and bid in the second one.

In his model, Wang (2006) considers  $v_i = v_1$ . In the first auction, bidder with valuation  $v_1$  is willing to bid up to the price that he expects to be the payment of the winning bidder in the second auction. It is assumed here that this bidder is the tied winner of the first auction. By independence we have

$$E[V_{(3)}|V_{(1)} = v_1, V_{(2)} = v_1] = E[V_{(3)}|V_{(2)} = v_1]$$

First, we calculate  $E[V_{(3)}|V_{(2)} = v]$ . We note that  $g(v_{(3)}|V_{(2)} = v)$ . Then, since

$$\begin{aligned} G(y) &= Pr(V_{(3)} < y | V_{(2)} = v) \\ &= \frac{2 \int_0^y dv_2 \int_v^1 dv_3}{2 \int_0^v dv_2 \int_v^1 dv_3} = \frac{y}{v} \end{aligned}$$

we have

$$g(y|V_{(2)} = v) = \frac{1}{v} \text{ for } 0 \leq y \leq v.$$

Thus,

$$E[V_{(3)}|V_{(2)} = v_1] = \int_0^{v_1} \frac{y}{v_1} dy = \frac{v_1}{2}$$

However, seeing bidder 2 bid  $b$  in earlier rounds, and inferring she has  $V_2 \geq b$  for  $b$  causes a revision of  $G(y|v)$ . Given  $b \leq v$ , the revision is:

$$\begin{aligned} G(y|v) &= Pr(V_{(3)} < y | V_{(2)} = v_1, V_2 \geq b) \\ &= \frac{\int_b^y dv_2 \int_v^1 dv_3 + \int_0^y dv_3 \int_v^1 dv_2}{\int_b^v dv_2 \int_v^1 dv_3 + \int_0^v dv_3 \int_v^1 dv_2} \\ &= \begin{cases} \frac{2y - b}{2v - b}, & \text{if } b \leq y \leq v \\ \frac{y}{2v - b}, & \text{if } 0 \leq y \leq b. \end{cases} \end{aligned}$$

Thus, we have

$$g(y|v) = \begin{cases} \frac{2}{2v-b}, & \text{if } b \leq y \leq v, \\ \frac{y}{2v-b}, & \text{if } 0 \leq y \leq b \leq v. \end{cases}$$

Hence, for  $b \leq v_1$ ,

$$\begin{aligned} & E[V_{(3)}|V_{(2)} = v_1, V_2 \geq b] \\ &= \int_0^b \frac{y}{2v_1-b} dy + \int_b^{v_1} \frac{2y}{2v_1-b} dy \\ &= \frac{v_1 - \frac{b^2}{2v_1}}{2 - \frac{b}{v_1}} \geq \frac{v_1}{2}. \end{aligned}$$

According to the above presentation by Wang (2006), we see that early bidding has an effect of raising high valuation opponents' conditional expectation of the next auction's price. As a consequence, these opponents will raise their bids in the first auction, decreasing the payoff of the winning bidder in the first auction. Respectively, rational bidders will only bid in the last possible moment causing the phenomena of last-minute bidding in the first auction. In the second auction bidding one's valuation would still be the dominant strategy.

In his work, Wang (2006) shows that in the repeated eBay auctions where two items are sold in a sequence and the bidding increment  $s \geq 0$ , there exists a symmetric last minute bidding equilibrium, where

$$\beta_1 = \begin{cases} \emptyset & t < T \\ E[V_{(3)}|V_{(1)} = v_i, V_{(2)} = v_i] & t = T \end{cases}$$

$$\beta_2 = \begin{cases} v_i & t = 0 \\ \emptyset & t > 0. \end{cases}$$

We should note that in the above case there are only two auctions completed in a sequence. If the bidder would be willing to wait for the acquisition of the item for an infinitely long time, he would always bid at the last seconds of any auction since there would be no last auction in which it would be in his best interest to reveal his true valuation.

Wang emphasizes that private values and common values are difficult to distinguish in the repeated auctions case, since bidding always depends on other bidders' information in early auctions. In other words, bidders' valuations are affiliated in a way that revealing information effectively increases other bidders' expectations and induces them to raise their bids.

Stryzowska (2006) hypothesizes that a weak bidder has no chance to win the good in the second auction; hence, this bidder would weakly prefer to increase his bid in the first auction given that he learns that he has no chance of winning the good in the second auction. Other bidders would then abstain from revealing this information to the weak bidder. This would strongly support the last-minute bidding equilibrium.

## **5.2 Search frictions**

In the early days of ecommerce it was commonly hypothesized that competition would be intensified and price dispersion reduced due to reductions in search costs (Levin, 2013). Indeed, it is easily observed that physical costs of search are vastly lower in online commerce. E-commerce marketplaces and price search engines are a convenient and an efficient way to compare prices between products of one's interest. However, even though these platforms aim at limiting search frictions, non-negligible price dispersion between homogeneous goods still exist. This may be partly due to retailers' incentives on keeping the price high: sellers may try to differentiate or obfuscate their offerings as a means of limiting price competition (Levin, 2013). On the other hand, results of Malmendier and Lee (2011) suggest that identical items on the same website are paid insufficient attention to by a subset of bidders. This would suggest that there may be some good bargains somewhere for a rational bidder: it has been argued that a bidder who is able to bid across different auctions ends up paying lower prices (Fu, 2011).



Internet data enables us to track the way the consumer searches. Evidently, even with many competing sellers buyer's only come across a few. Consumers have a certain *consideration set*, a set of products they actually make their choices of. The smaller the actual consideration sets are, the weaker the competition and the lower the possibility for a seller to enter the consideration set. If the bidders would actually bid across several auctions, we should expect concurrent auctions having closely the same final prices.

Based on their evidence of overbidding in Internet auctions, Malmendier and Lee (2011) actually suggest that bidders may at first realize the lower-price outside option but being faced with eBay's outbid notification they fail to account for it. Some bidders may address some value to the competitive aspect of bidding. Nevertheless, overbidding is not a phenomenon that can be explained by standard rational models of bidding behavior. Neither is it confirmed by Einav et al. (2013a): they show that on average auction prices are actually well below posted prices<sup>24</sup>. Still, 20 % of auction prices in their sample exceeded the reference price but not by much. Their sample, however, tells us that there is some substantial variation, by around 10-15 %, in auction prices for identical objects sold by the same seller.

Ariely and Simonson (2003) claim that bidders may have their focus primarily on the set of options presented to them (local context), while at the same time having little attention to a wider range of auctions or fixed price offerings of similar products. Moreover, Simonsohn and Ariely (2008) have shown that eBay bidders tend to be more likely to participate in auctions that have already attracted existing bids. This is a peculiar phenomenon, given that following this logic, bidders end up paying higher prices in these auctions. However, the eBay platform is designed in a way that it shows the auctions ending soonest on top of the search results. We could assume that this at least partly affects the timing of the bids we observe.

Study by Pownal and Wolk (2013) confirms that the final price of an auction is significantly increased by the early bids. However, it should be noted that they studied antique auctions that most probably have some common value component in them. However, Einav et al. (2013a) also find some patterns in their data that low start prices may attract more bidder attention which in turn might ultimately lead to higher final prices.

---

<sup>24</sup> In their study, Einav et al. (2013a) have the same seller offering the same item through different mechanisms. Existing studies, like the one by Malmendier and Lee (2011), had compared prices across retailers. Einav et al. (2013a) made a remark, though, that in the mid 00's auction prices above posted price were much more common than today.

### 5.3 Interdependent values model

When there are interdependent valuations at stake, bidders are uncertain of their valuation and other bidders' valuations may have an impact on their willingness to pay for an item. In the interdependent values model it is assumed that every bidder has some private information in form of a signal. However, no bidder has an exact value of the object. To be more precise, it is assumed that bidders only have partial information such as a noisy signal. (Krishna, 2002).

Bidder  $i$ 's private information is the realization of the random variable  $X_i \in [0, w_i]$ . This is  $i$ 's signal. Krishna (2002) writes the bidder  $i$ 's valuation for the object as follows:

$$V_i = v_i(X_1, X_2, \dots, X_N)$$

Bidder  $i$ 's valuation is assumed to be non-decreasing in all its variables and twice continuously differentiable. It is assumed that  $v_i$  is strictly increasing in  $X_i$ . In the preceding specification the value is completely determined by the signals.

Let's suppose for a moment that a bidder in an online auction is facing interdependent values. Since the exact value of the auctioned item is unknown and dependent on other bidders' signals, a bidder may need to revise his bid. In the single-item private values setting, which we introduced in the previous chapter, bidder had a weakly dominant strategy to bid his valuation (that the bidder knew when bidding). But in the interdependent valuations setting revising one's *a priori* estimate of the value may take place even after the auction (Krishna, 2002). We would then assume that as a bidder gains more experience in certain product categories, he will gradually be better at estimating the value of auctioned items to himself.

In their study, Ariely and Simonson (2003) point out that by relying on the bids made by other bidders a bidder may end up overestimating the value of the auctioned item. Explanation for this is that active bidders only account for a sub-segment: some bidders may have considered the item without submitting a bid. As the auction process goes on, this sample bias is only expected to increase, as only the bidders with the highest valuations continue to bid.

Allowing for interdependent values the bidding in online auctions becomes more complex. As bidders constantly learn during the auction and between auctions, we could suppose that the more experienced bidders we have, the less likely they would reveal information (signals) they possess. At the same time, we could argue that experienced bidders in certain categories would have learned well the valuations of frequently traded items, and thus wouldn't have to

wait for other bidders to reveal their signals in a single auction. With this logic we could claim that even in interdependent values case rational bidders would only bid once. But it is not clear whether they would bid early or late.

According to Krishna (2002) the specification of interdependent values is well suited for such cases where the auctioned item could be resold after the auction. In the next sub chapter we introduce the common values model which is a special case of interdependent values. While in interdependent values the value a bidder assigns to an object is dependent on other bidders' values, in common values the bidders have the same value for the object - only the signals they get vary.

#### **5.4 Common values model**

In the common values case the value of the object is the same for every bidder, but the information they have of the actual value differs. To be more precise, bidders have the same true value of the item *ex post* since this true value is determined for instance through resale prices and such. The bidders don't know for certain the true value *ex ante* (Wilcox, 2000). Knowing that it is now the large retailers dominating the Internet auction market, we would expect that for many items the resale prices are of utmost importance.

In the common value setting, bidders may get different signals regarding the item's condition or its authenticity. This being the case, bidders' estimates keep on changing as they get information in form of signals from their competitors (Ariely et al. 2005). The information of bidders is not independent. Therefore, given that a bidder  $j$  has a high estimate of the value of the item,  $i$ 's estimate is also likely to be high.

The possibility of a liquid resale market for an item strengthens the proposition that there are common values at stake. Given there are common values at hand, a bidder learning about other bidders' assessments of an item's resale value may end up improving his forecast of the value of the item (Bajari & Hortacsu, 2003). Due to inspection problems associated to online auctions, assessing the right valuation of an item is difficult to anyone. However, as earlier introduced in this thesis, collectors' valuations are highly affected by any scratches or blemishes in an item. If we would assume that some experts are better at identifying collectibles with higher value, we would also expect that common values matter.

Roth and Ockenfels (2002) argue late bidding is only rational in the common values setting. They claim that e.g. in an antique auction some dealers or experts may be better in identifying antiques of high value. We could reason that already their participation in a specific auction would act as a signal for other bidders that the item is worth competing for (assumptions of experience can be made e.g. with the help of feedback numbers). According to field data, there is much more late bidding in eBay antique auctions than in auctions selling computers (Bajari & Hortacsu, 2003). Hence, the information conveyed by bids can have a major impact in increasing late bidding; bidders don't want to reveal their information to other bidders.

In their study, Bajari and Hortacsu (2003) demonstrate that waiting until the end of an auction to bid is an equilibrium phenomenon in a common value framework. We will now present their model of common values in eBay auctions. In this model, bidders can update their proxy bids anytime before the auction ends; hence there is no possibility to observe one's dropout decisions as in the traditional English auctions.

Bidders are assumed to be risk-neutral, i.e. they maximize their expected utility. They are also assumed to be *ex ante* symmetric. Cross-auction considerations are not present.  $V_i$  is the utility bidder  $i$  gains from winning and  $x_i$  is his private information on the value of the item.  $V_i = v$  is a random variable, realization of which will not be observed until after the auction is completed. Private information of bidder  $i$  is  $x_i = v + \varepsilon_i$ , where  $\varepsilon_i$  are identically and independently distributed. Minimum bid is zero.

In the model of Bajari & Hortacsu (2003), eBay auction is viewed as a two-stage auction, where the total auction time is  $T$ . The first-stage auction is an open-exit ascending auction played until  $T - \varepsilon$ , where  $\varepsilon \ll T$  is the time frame in which no bidder is able to update their bids in response to others. All bidders observe the dropout points of bidders in this stage, though it should be noted that every bidder has the option to continue bidding in stage two. Bidders will be ordered by their dropout points in the first-stage auction,  $\theta_1 \leq \theta_2 \leq \dots \leq \theta_n$ . We must note that  $\theta_n$  as the highest bid in the first-stage is unobservable. This is due to the fact that in Internet auctions, as previously mentioned, the highest standing bid visible to bidders is the second highest bid plus the increment. It can be argued that not all the other bids submitted to the proxy system will be visible either<sup>25</sup>.

---

<sup>25</sup> Proxy bids that fail to meet the current highest bid are revealed only after the auction is completed.

The second stage of the auction, conducted as a sealed-bid second-price one, occurs from  $T - \varepsilon$  to  $T$ . Every bidder, including the first-stage dropouts, has the option to submit a bid  $b$ . The object goes to the highest bidder in this stage.

Given this setup, Bajari and Hortacsu (2003), make the following claims:

*Proposition 1.* Symmetric Nash equilibrium of the eBay auction is to bid zero in the first stage and participate only in the second stage of the auction, making the auction equivalent to a sealed-bid second-price auction. This result is based on the following lemma:

*Lemma 1.* Dropout points in the first stage  $\theta_i, i = 1, \dots, n$  cannot be of the form  $\theta(x_i)$ , a monotonic function in signal of bidder  $i$ . This lemma leads to the conclusion that less information revelation is generated during the auction than in the Milgrom and Weber (1982) model of ascending auctions.

In the extreme case where everybody bids zero in the first stage, we have a sealed-bid second-price auction in the second stage, each bidder knowing only his own signal. The symmetric equilibrium bid function, as derived by Milgrom and Weber, will be  $b(x) = v(x, x)$ , where  $v(x, y) = E\{v|x_i = x, y_i = y\}$ , with  $y_i = \max_{j \in \{1, \dots, n\} \setminus i} \{x_j\}$ . If a bidder  $j$  were to unilaterally deviate from this equilibrium (of not bidding in the first stage), proxy bidding system would indicate this bidder's signal  $x_j$  to be greater than zero and not much else. Bidder's entry decision would therefore not work as a means of driving away competition; the entry would only work against the bidder since signals are affiliated:

$$E\{v|x_i = x, y_i = x, x_j > 0\} \geq E\{v|x_i = x, y_i = y\}.$$

Hence, a deviating bidder would unilaterally decrease his probability of winning the auction.

## 6 EMPIRICAL RESULTS

In this Section I will first introduce how the bidding process has been going in some actual completed auctions. The purpose of this is to show that the real life bidding process has some intriguing phenomena that are difficult to explain by the standard private values model alone. What we see is that there are different types of bidders present these auctions. For some bidders the entertainment value or the aspect of competing may be more important than playing their truth valuation. Some bidders may even be completely oblivious of the proxy bidding system and its purpose. But most importantly, we'll notice that there are frequently some bidders bidding only in the last few minutes in the auction. In the literature the bidders submitting bids in the last ten minutes are called snipers. This phenomenon is specifically discussed in Section 6.3. With the help of the results derived in the models introduced in this thesis, I will collect together the possible explanations for this behavior.

### 6.1 Introduction to last-minute bidding

Already since the early days of Internet auctions there have been programs like eSnipe that will place the late bids on behalf of the bidder only a couple of seconds before the auction is about to end. However, these programs can't offer a full guarantee that a bid will be successfully submitted: in September 2000 eSnipe reported that on average 4.5 % of bids through eSnipe failed to be transmitted (Roth & Ockenfels, 2005). This is the inherent risk in late bidding, whether the late bid is placed manually or by using software.

Let's see through an example how rational bidders actually are when they participate in an auction. This auction is of a highly valuable baseball trading card that still creates a good amount of interest. Due to the high valuation of the object, we could expect more experienced bidders bidding in this auction. Collectibles are generally considered to be common value items, thus we would expect to see last-minute bidding.

The card traded in this auction was 1915 Cracker Jack #68 Honus Wagner with a condition Near mint-Mint 8<sup>26</sup>. In the next page we have the complete bidding history for this item<sup>27</sup>.

---

<sup>26</sup> PSA card grading standards <http://www.psacard.com/Services/PSAGradingStandards>

<sup>27</sup> Source:

[http://offer.ebay.com/ws/eBayISAPI.dll?ViewBids&item=371030478798&rt=nc&\\_trksid=p2047675.l2565](http://offer.ebay.com/ws/eBayISAPI.dll?ViewBids&item=371030478798&rt=nc&_trksid=p2047675.l2565)

**Table 2. Bidding History of a Completed Baseball Card Auction**

Bidder	Bid Amount	Bid time
<b>k***y( 250)</b>	<b>US \$8,629.00</b>	<b>Apr-03-14 20:58:45 PDT</b>
a***a( 1949)	US \$8,529.00	Apr-03-14 20:58:55 PDT
m***a( 516)	US \$8,105.00	Apr-03-14 20:58:52 PDT
e***a( 796)	US \$7,800.00	Apr-03-14 20:53:40 PDT
o***l( 228)	US \$7,700.00	Apr-03-14 20:50:37 PDT
g***g( 821)	US \$7,600.00	Apr-03-14 17:10:15 PDT
o***l( 228)	US \$7,600.00	Apr-03-14 20:50:32 PDT
o***l( 228)	US \$7,400.00	Apr-03-14 20:50:27 PDT
o***l( 228)	US \$7,200.00	Apr-03-14 20:50:22 PDT
g***g( 821)	US \$7,100.00	Apr-03-14 16:54:39 PDT
o***l( 228)	US \$7,100.00	Apr-03-14 19:29:36 PDT
o***l( 228)	US \$6,900.00	Apr-03-14 19:29:06 PDT
o***l( 228)	US \$6,700.00	Apr-03-14 19:29:01 PDT
o***l( 228)	US \$6,500.00	Mar-30-14 08:25:04 PDT
e***a( 796)	US \$6,300.00	Mar-30-14 22:14:25 PDT
e***a( 796)	US \$6,000.00	Mar-28-14 21:30:03 PDT
c***c( 1077)	US \$6,000.00	Mar-29-14 05:28:47 PDT
c***c( 1077)	US \$5,800.00	Mar-27-14 17:08:51 PDT
e***a( 796)	US \$5,500.00	Mar-28-14 21:29:51 PDT
o***l( 228)	US \$4,600.00	Mar-27-14 07:49:25 PDT
e***c( 583)	US \$4,500.00	Mar-25-14 19:15:31 PDT
o***l( 228)	US \$4,350.00	Mar-27-14 06:21:01 PDT
o***l( 228)	US \$4,100.00	Mar-27-14 06:20:50 PDT
o***l( 228)	US \$3,900.00	Mar-27-14 05:19:27 PDT
o***l( 228)	US \$3,700.00	Mar-25-14 18:10:04 PDT
d***f( 862)	US \$3,500.01	Mar-25-14 15:02:04 PDT
o***l( 228)	US \$3,500.00	Mar-25-14 15:45:21 PDT
o***l( 228)	US \$2,800.00	Mar-25-14 12:48:57 PDT
a***a( 406)	US \$2,500.00	Mar-25-14 11:06:55 PDT
o***l( 228)	US \$2,500.00	Mar-25-14 12:06:04 PDT
o***l( 228)	US \$2,000.00	Mar-25-14 08:44:17 PDT
a***a( 406)	US \$2,000.00	Mar-25-14 11:06:33 PDT
1***x( 1198)	US \$1,749.21	Mar-25-14 09:16:59 PDT
4***c( 933)	US \$1,555.55	Mar-25-14 08:39:23 PDT
d***f( 862)	US \$1,000.01	Mar-25-14 07:06:00 PDT
n***a( 6231)	US \$998.00	Mar-25-14 04:32:20 PDT
z***t( 1593)	US \$835.21	Mar-25-14 06:23:13 PDT
1***x( 1198)	US \$815.21	Mar-25-14 04:28:03 PDT
r***h( 7521)	US \$666.00	Mar-25-14 04:04:22 PDT
4***c( 933)	US \$511.55	Mar-25-14 03:43:12 PDT
o***o( 1162)	US \$222.00	Mar-24-14 22:38:46 PDT
c***y( 81)	US \$88.00	Mar-24-14 23:11:46 PDT
6***h( 933)	US \$1.00	Mar-24-14 21:07:54 PDT
Starting Price	US \$0.99	Mar-24-14 20:58:58 PDT

First, we notice that the bids are displayed as ascending in bid amounts rather than chronologically. However, the process of bidding is not that gradual as it may seem at first glance. For instance, bidder o\*\*\*1 (228) is the one bidding extremely many times in this auction, possibly trying to “search” for the prevailing highest bid. Updating the bids in such a rapid fashion is not explained by concurrent auctions and their effect on one’s information set. To be more precise, at the last minutes of this auction bidder 0\*\*\*1 (228) made multiple bids within seconds. Therefore, we can be certain that Hossain’s (2008) hypothesis that outside opportunities may lead to multiple bidding as bidder initially bids under his valuation, doesn’t explain the behavior of this bidder here. Furthermore, the auctioned card here was not a usual one, which would lead us to think that similar items may not be offered at a regular basis.

We could make an assumption that o\*\*\*1 (228) didn’t quite understand the principles of proxy bidding, given that he bid 17 times. It seems plausible that for this bidder it was important to maintain the status of the highest bidder.

As introduced in Chapter 2.5 on eBay’s bidding process, if there are two people who have bid the same amount, the bidder who has made this bid earlier will be the one leading the auction. In this auction there are many occasions where two bidders have bid the same amount at different times. On these occasions the earlier bid is displayed higher. We can also observe that some people have bid odd amounts: for instance d\*\*\*f (862) bid two times using this strategy. By bidding odd amounts the bidder increases the probability that his bids don’t coincide with some other bidder.

As can be seen from the table, the auction had a strong start: during the first 24 hours the price rose from \$0.99 to \$3.700. Given that the auction lasted for ten days and the price after 24 hours was almost half from the final price, we see that the auction followed the regular pattern that auction intensity is high in the first day (Jank & Shmueli, 2010). There were also a few days with no activity, as well as last-minute bidding at the end.

In the independent private values single-unit framework we found that the bidder should only make one bid amounting to his reservation price early in the auction. There is of course no way for us to know the reservation prices here, but we can observe that there were few early bidders that submitted only one bid in the auction. Therefore, we could suggest that there were possibly some bidders treating the auction as a private values one. Some bidders were active both during the early moments and the last hour of the auction. This would lead us to think that there may have been some interdependence between bidders’ valuations as well. Of



course, it is also possible that these bidders first bid below their reservation values, waiting for a better bargain in some concurrent auction.

There were three bidders who submitted their bid in the last seconds of the auction. These bidders bid only once in the auction and by taking a closer look at their bidding histories we find that the two highest bidders were experienced in the field of baseball cards<sup>28</sup>. Their decision to refrain from bidding until the last possible moment is consistent with the common values model: they most likely didn't want to reveal their information of the item's value until it was too late for others to react.

Now we have seen one example of a complex real life bidding process that had a seller with 100 % positive feedback (there were few negative votes, but they didn't add up to one per cent). Judging by the volume of trades the seller had engaged in, we could assume that the buyers didn't need to put much weight for possible fraudulent behavior when making their bidding decisions. Nevertheless, as noted previously in this thesis, inspection problems in terms of the quality of the item are always a problem especially in collectibles like sports cards.

Let us now take another example. The auctioned item is an Acer Aspire AX3950 Desktop with Windows 8. First of all, we would assume that being a desktop auction the bidders will have a reasonable base for making their estimate of the true value of the item. Second, given that computer technology is characterized with rapid innovation, we would expect the resale value of this item to be very low. Based on this, we can make an assumption that there are no common values present. On the other hand, computers are usually sold based on rather incomplete descriptions, creating uncertainty about their value (Haskey & Sickles, 2010).

---

<sup>28</sup> Based on their recent bidding activity in this field. Their bidding histories also show a regular pattern of mostly bidding only once per auction.

**Table 3. Bidding History of a Completed Desktop Auction**

Bidders: 14	Bids: 24	
Time ended: May-27-14 01:43:01 PDT		
Duration: 3 days		
Bidder	Bid amount	Bid time
3***2( 53)	EUR 197.00	May-26-14 13:30:18 PDT
k***k( 186)	EUR 196.00	May-27-14 01:43:00 PDT
4***1( 192)	EUR 190.00	May-27-14 01:42:56 PDT
g***y( 52)	EUR 185.00	May-27-14 01:35:00 PDT
d***m( 257)	EUR 183.00	May-26-14 14:37:58 PDT
d***m( 257)	EUR 177.00	May-26-14 14:37:34 PDT
n***h( 112)	EUR 150.00	May-26-14 12:10:15 PDT
i***t( 1362)	EUR 121.00	May-26-14 13:07:10 PDT
i***t( 1362)	EUR 118.00	May-26-14 13:07:03 PDT
i***t( 1362)	EUR 115.00	May-26-14 13:06:53 PDT
i***t( 1362)	EUR 111.00	May-26-14 13:06:43 PDT
g***s( 723)	EUR 108.00	May-26-14 12:30:50 PDT
g***y( 52)	EUR 100.00	May-26-14 00:56:03 PDT
l***s( 578)	EUR 99.00	May-25-14 14:12:00 PDT
g***y( 52)	EUR 85.00	May-26-14 00:55:52 PDT
i***t( 1362)	EUR 83.00	May-25-14 12:37:34 PDT
i***t( 1362)	EUR 77.00	May-25-14 12:37:20 PDT
l***a( 773)	EUR 76.65	May-25-14 12:14:11 PDT
i***t( 1362)	EUR 66.00	May-25-14 12:14:01 PDT
i***t( 1362)	EUR 44.00	May-25-14 04:26:36 PDT
r***e( 324)	EUR 41.10	May-25-14 03:55:10 PDT
i***t( 1362)	EUR 33.00	May-25-14 04:26:29 PDT
y***i( 553)	EUR 22.22	May-24-14 22:48:58 PDT
e***e( 397)	EUR 20.00	May-24-14 10:16:32 PDT
_***v( 1368)	EUR 20.00	May-24-14 20:59:05 PDT
Starting Price	EUR 18.98	May-24-14 01:43:01 PDT

**Source:**

[http://offer.ebay.com/ws/eBayISAPI.dll?ViewBids&item=291154195790&rt=nc&\\_trksid=p2047675.12565](http://offer.ebay.com/ws/eBayISAPI.dll?ViewBids&item=291154195790&rt=nc&_trksid=p2047675.12565)

In this auction, we observe three late bidders. However, none of them wins the auction. The winner made his only bid well before the auction was about to end. The information the winner had when bidding was a bid amount of EUR 122.00, which is of course the EUR 1.00 increment above the second highest bid at the time. Given that the winning bidder's only bid was well above this value, we can assume that at least the winner perceived the item as a private values one.

In this auction there is one bidder, i\*\*\*t (1362), who engaged in the same kind of behavior of placing multiple bids in rapid fashion as o\*\*\*l (228) in the baseball card auction. We could infer that not all the bidders follow any of the rational strategies presented in this thesis, but rather engage in incremental bidding. If an incremental bidder would be the one having the second highest valuation, a rational strategy for the highest bidder would be to snipe. However, this is only speculation, since incremental bidders clearly don't have any exact valuation in mind. It seems that they rather decide on some discrete moments that they are willing to bid more.

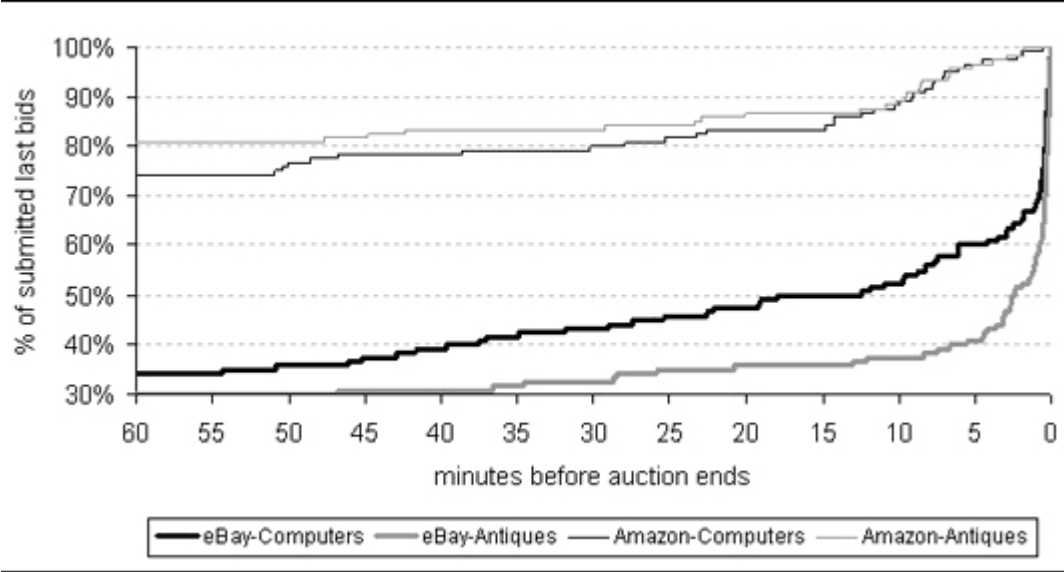
## 6.2 Data on last-minute bidding

In his study, Hossain (2008) reports some stylized facts of Internet auctions. In the light of our evidence from Chapter 6.1, it is sufficient to note the following:

- 1) More than two thirds of late bidders on eBay bid only in the last few minutes of an auction.
- 2) Many bidders bid repeatedly below the highest standing bid, i.e. *self-nibble*. In addition, many bidders place a new bid every time they drop from being the highest bidder.
- 3) More experienced bidders are more likely to engage in sniping.

Roth and Ockenfels (2002) found in their study that in over two-thirds of their samples from eBay auctions there had been some bidding activity in the last hour of an auction. Further, more than 50 per cent of the auctions had bidding in the last ten minutes. The figure below highlights the fact that in eBay auctions with a fixed deadline last-minute bidding is very common.

**Figure 2. Empirical cumulative distribution of the timing of last bids for all bidders**



**Source:** Roth and Ockenfels (2002)

The results by Roth and Ockenfels (2002) are in line with the first stylized fact above. In their study of Internet antique auctions, Pownal and Wolk (2013) found that the proportion of bids arriving in the last ten minutes was somewhat smaller, 30 %. Nevertheless, the main point is clear: data shows that not just few but many bidders find it worthwhile to submit late bids.

Bajari and Hortacsu (2003) found in their data that the median winning bid arrives as late as after 98.3 % of the auction time has elapsed. In a three-day auction this corresponds to the last 73 minutes of the auction. In the set of auctions they considered, two proxy bids were placed by an average bidder. In a more recent study, Fu (2011) found out that on his sample of 4256 auctions close to 30 % had last-minute bidders as winners<sup>29</sup>. Several other strategies were used, most notably a mixed strategy of first submitting proxy bids exceeding the current standing bid by more than the minimum increment and later engaging in incremental bidding.

<sup>29</sup> Last-minute bidding was defined as bidding in the last ten minutes.

Borle et al. (2006) investigated over 10,000 auctions across 15 consumer product categories on the eBay auctions website while investigating the extent of late bidding in different product categories and the impact of bidder experience on both the timing of bids and the extent of multiple bids. Their main findings were that experienced bidders are less likely to place multiple bids than inexperienced ones, and that they either bid at the beginning or at the close of the auction.

Before Borle et al. a study of Wilcox (2000) dealt with more or less the same issues. One of his main findings was that the likelihood of placing bids in the final minute of the auction increased with experience: of the most experienced bidders 8.2 % bid in the last minute while only 1.2 % of the least experienced did<sup>30</sup>. Moreover, last-minute bidding among experienced bidders was even more prevalent with auctioned items having a common value component.

More recent work by Pownall and Wolk (2013) finds that bidders do adapt their within-auction bidding strategies as they gain more experience<sup>31</sup>. Apparently, bidders learn to bid earlier in the auction as well as revise their bids less often. An interesting finding is that their evidence suggests that inexperienced bidders learn extremely quickly to reduce their bids, and that learning will in fact disappear within five to seven auctions. Consequently, we could argue that rational bidders should not give too much emphasis on inexperienced bidders and their respective bidding decisions as they form their own bids.

The fact is that in pure private value setting - excluding the repeated auctions case - experience should have no correlation with bids. This holds true whenever bidders estimate and know their valuations accurately. However, Malmendier and Lee (2011) find, surprisingly, in their study that the final auction price in the majority of auctions (72 %) is higher than a fixed price for the same good available simultaneously on the same webpage. According to them, not many bidders systematically overbid but a small number of biased bidders are sufficient for generating the overbidding phenomenon, which they call the bidder's curse - auctions are won by bidders most likely to overbid.

---

<sup>30</sup> Percentages significantly different at the  $p = .01$  level.

<sup>31</sup> Instead of feedback scores, the actual number of auctions participated was used as a proxy for experience here.

### **6.3 Rational reasoning for last-minute bidding behavior**

As the data clearly shows, bidding in the last minute (or in the last seconds) of an auction, i.e. sniping, is a peculiar and persistent phenomenon in online auctions, although the auction guidelines advice bidders to submit their maximum willingness to pay early on in the auction. In this subchapter we will combine the explanations for the last-minute bidding behavior, offered by the value models studied in this thesis. We will also comment on some of the claims made by various authors studying the Internet auctions.

We showed in Chapter 4.1 that, assuming symmetric strategies, we should not expect last-minute bidding in the private values single-item setting with proxy bidding. In this setting, bidders are better off bidding early, due to the presence of the minimum bid increment rule. As we learned, it is possible that some of the bidders have valuations within the increment, and as we know the auction rules state that in case of a tie the earliest bidder bidding the high valuation wins. Furthermore, a new bid must always exceed the current standing bid by at least an increment. Hence, the order in which the bids arrive may have its impact on the final price, due to the excluding effect.

As presented in Chapter 5.3, allowing for the presence of interdependent values the bidding decisions in open-ascending Internet auctions are more complex. If we assume that the participation of an informed (and experienced) bidder reveals information to other bidders that the item is of high value, we would expect last-minute bidding from the informed bidder. On the other hand, the need for an informed bidder to gather further information and revise his bid during the course of the auction is much lower than that of an average bidder, and thus we could also see early bids in this setting.

Related to the interdependent valuations case, in the model of Rasmusen (2006) it is assumed that there are some uninformed bidders that don't initially know their private valuation, and there is a cost of finding out this valuation. In this case, an uninformed bidder facing an informed bidder knowing his own value could save the cost of finding out if the informed bidder has a high valuation or not. Rasmusen assumes that the uninformed bidder can learn his private valuation during the auction by paying a cost. In this setting, there is an equilibrium in which a bidder may use a mixed strategy of first making an early bid below his true valuation, and later bidding up to the valuation. The setting of Rasmusen is rather specific and special though, but it still adds some possible reasoning for last-minute bidding.

Roth & Ockenfels (2002) have studied late bidding in their research. They succeeded in finding a few possible explanations why we see so much late bidding in the Internet. First, an auction may have inexperienced bidders who are not familiar with the proxy bidding system. These bidders, call them incremental bidders, may make consecutive bids with an aim of maintaining the status of the highest bidder. Roth and Ockenfels (2002) suggest that if we expect this kind of behavior, we would not want to submit our valuation at first, encouraging these bidders to raise the second highest bid. Accordingly, by bidding strategically late against these incremental bidders, we could possibly obtain the item with a price below the private values of these incremental bidders. In this scenario late bidding would be the best response to out-of-equilibrium bidders.

The incremental bidder hypothesis of Roth and Ockenfels (2002) requires an asymmetric equilibrium in which bidders update their values only in response to being outbid. We briefly explained this possibility through an example with two bidders in Chapter 4.2.2. However, assuming that an auction has even a few rational bidders bidding their valuation, it is plausible to think that the presence of few incremental bidders will have no effect on the winner's payoff at all. At least, we can claim that the possibility of few irrational bidders should not affect the formation of one's bids.

Another case where late bidding, according to Roth and Ockenfels, would prove its point would be a situation where a fraudulent seller uses *shill bidders*<sup>32</sup> against an honest proxy bidder. A party or alternative identity engaging in shill bidding has no intention to acquire the auctioned item. Its aim is to only drive the price up through increasing the second highest bid that the winner has to pay. Shill bidders may bid strange amounts in order to reveal the highest bid. However, as pointed out earlier in this thesis, it may be easy to engage in shill bidding given the technology of today but detecting this activity is not difficult either: shill bidders have no intention to acquire any items.

As shown in Chapter 5.1, late bidding is not unusual in the repeated auctions setting. We found out that when similar items are auctioned in a sequence, early bidding has an effect of raising high valuation opponents' conditional expectations of the prices in following auctions, which induces these opponents to raise their bids in the current auction. Given that early

---

<sup>32</sup> <http://www.ebay.com/gds/SHILL-BIDDING-5-Ways-To-Detect-Shill-Bidders-On-Ebay-/1000000002559018/g.html>

bidding in this model decreases the winner's expected profits, we should in fact expect that at least experienced bidders bid as late as possible.

Roth and Ockenfels (2002) suggest that late bidding could be rational in private value single-item case also due to the probability of late bids not being successfully submitted. They introduce an idea of implicit collusion against the seller, where the probability of late bids not being registered would have an effect of probabilistically suppressing some bids.

In an implicit collusion equilibrium bidders will not bid their true values until the last moment  $T$ , at which time the probability of a successfully transmitted bid is  $p < 1$ . There is little intuition to this kind of "collusive equilibrium": a bidder bids at the last minute hoping for the small probability of gaining a lot when others' bids are lost (Wang, 2006). We could argue the plausibility of all bidders colluding, given that there are numerous bidders who never knew each other. Roth and Ockenfels (2002) only provided an example with two bidders having identical values as a proof for the possibility of a collusive equilibrium. To further question the plausibility of their idea, we point out that according to the laboratory experiment by Ariely et al. (2005) sniping actually increases if the last-minute bids are submitted with certainty.

Roth and Ockenfels (2002) also conducted a bidder survey to find answers to the last-minute bidding behavior. 91 percent of respondents claimed last-minute bidding to be their strategic choice. Some bidders admitted that the bidding activity of others sometimes had an impact on their own bids. Experience was also of significance: some antique bidders explicitly stated that they bid late as a means of not sharing valuable information with competing bidders.

As presented earlier in Chapter 5.1, Wang (2006) makes a good argument that in the repeated auctions setting bidding always depends on the information of other bidders in early auctions, and therefore it is difficult to distinguish whether the bidder valuations are formed according to private or common values. Repeated auctions setting may in fact be the best fit for explaining the bidding behavior in Internet auctions, since at all times there are near similar items offered repeatedly through either auctions or posted prices.



## **6.4 The incentives of winning**

In the standard model of independent private values in a second-price sealed-bid auction it is assumed that bidders have static reservation prices for the item at sale. However, if we allow for interdependent valuations or learning effects, some of the bidders may find it useful to revise one's value estimations.

In his article Hossain (2008) suggests that bidders may not always know their private valuations in a precise manner. He introduces a dynamic-second price auction comprising both informed and uninformed bidders. The former know their private valuations while the latter have the possibility to learn if their valuations are above the current price in the auction or not. As a conclusion, Hossain (2008) finds that common patterns on eBay auction like sniping and nibbling (e.g. placing multiple bids in a rapid fashion) are to be found in any equilibrium of this auction.

The main point of the model by Hossain (2008) is that it suggests that preferences can and do change as the auction progresses, either through bidders getting new information about their own preferences or other bidders' preferences. In the model, the current price (standing bid) of the auction works as a benchmark for bidders to learn their own preferences. In addition to affecting the incentives of winning during the course of the auction, this would also imply that bidders with more experience should snipe.

In short, whenever we assume that the bidder's payoff is potentially increased through acquiring additional information of the auctioned item, the incentives of winning will not stay constant along the whole auction process. Moreover, allowing for outside options or sequential auctions of the same item, the bidders interest from an auction to another or from an auction to a posted price listing may happen at an instant. By this logic, rather than being a signal of a bidder reaching his valuation, the decision to drop out from an auction could as well stem from the bidder finding a better outside option.

## 7 DISCUSSION AND CONCLUSIONS

In this thesis the main emphasis has been in the strategic bidding decisions of bidders in open-ascending Internet auctions with proxy bidding mechanism. However, I have also covered the general Internet auction environment and its development during the past two decades to some extent, with a purpose of validating the necessity of this research.

The open-ascending auction format studied here has a close resemblance to Vickrey second-price sealed-bid auctions. First, during the course of the auction bidders (with the exception of the current leader) never directly observe the prevailing highest proxy bid. Second, winning bidder usually pays the price of the second highest bid, although in the Internet auctions a predetermined increment is also assigned on top of that. We have, however, noted that in some circumstances where the highest prices are within the increment the winner actually ends up paying his own bid.

The standard independent private values model served as a baseline model for us, but in order to fully understand the empirical phenomenon of last-minute bidding and the empirical results in general, we addressed the model of repeated auctions. Due to the abundant volume of similar items simultaneously or sequentially offered either by auctions or posted prices in the Internet, determining one's true valuation or reservation price for an item is not as obvious as the baseline model would suggest. At the same time, we find that even though Internet has decreased the barriers to find comparable prices for a product, search frictions still prevail and even in the presence of many competing seller offerings buyers only consider or come across few of them.

In addition to independent private values and repeated auctions we also discussed in some detail the interdependent values model as well as the special case of interdependent valuations, the common values model. While in the independent private values model the bidder is assumed to know his valuation for an item when entering the auction, in the interdependent values setting bidders have only imperfect information of the value of the item to themselves. Therefore, some bidders may refrain from bidding until they have acquired enough information. Correspondingly, bidders with more information or experience have the motivation to delay their bids until the last minutes of the auction as a means of concealing their information and limiting the expected competition. This logic is further strengthened by the fact that the highest bid other than the current leader ever notice is usually the second

highest bid plus an increment, practically excluding the possibility for entry deterrence through high early bids.

The bidding strategies proposed by our models vary. First, given the pure private values single-item case, the bidders are advised to bid only once in the auction. Due to the continuous nature of Internet auctions and the random arrival of bids, the timing of the bid is of importance as well. Assuming bidders were to follow the same strategy, the equilibrium strategy for any bidder would be to bid his valuation early. We would only expect last-minute bidding in the private values single-item case if other bidders were to follow weakly dominated strategies. However, given that the market for Internet auctions has matured a lot since the early 2000s, it is not convincing to think that not but a few would end up applying these dominated strategies.

Probably the main support for last-minute bidding comes from the fact that eBay as the dominant consumer auction platform is a marketplace where there is in many categories a constant supply of almost identical items listed in any given day. Therefore, even bidders assigning pure private values to certain items may end up delaying their bids as they search for the best bargain. As a means of further enhancing our understanding of the last-minute bidding phenomenon, we included the repeated auctions model in this thesis. According to the most simple repeated auctions model with two identical auctions conducted in a row, a bidder need not bid his true valuation in the first auction if he expects to win the second auction at a lower price. Rather, the expected winning price in the second auction acts as a reference for a maximum bid in the first auction. The expectations of the price in the second auction are correlated with the valuations of other bidders; hence it is in the bidder's best interest not to reveal his information early in the first auction.

The conclusion of this paper is that, despite the proxy bidding system, there are many circumstances in which the last-minute bidding is in fact the bidding strategy that should be preferred to any other strategy. Despite some close similarities between the two, open-ascending eBay auctions are not strategically equivalent to second-price sealed-bid auctions. Internet auctions are theoretically challenging since while not being pure common value goods, many of the auctioned items have some common value component in them.

Further empirical research could study the role of repeated auctions on eBay in more depth, since the model of repeated auctions likely fits best with the data we observe in the Internet auction markets. One could also study the evolution of buyer types in the Internet auctions or in e-commerce in general. For instance, we would like to know if the bidders have become more able in estimating their values as they are confronted with all the more information in which to base their reserve prices on. We would also be interested in knowing whether or not this additional information encourages them to utilize it by searching for bargains in auctions or whether they will favor the convenience of posted prices.

## REFERENCES

- Ariely, Dan & Ockenfels, Axel & Roth, Alvin E. 2005. An Experimental Analysis of Ending Rules in Internet Auctions. *RAND Journal of Economics*, Vol. 36, No. 4.
- Ariely, Dan & Simonson, Itamar 2003. Buying, Bidding, Playing, or Competing? Value Assessment and Decision Dynamics in Online Auctions. *Journal of Consumer Psychology*, 13.
- Backus, Matt & Blake, Tom & Masterov, Dimitryi V. & Tadelis, Steve 2013. Is Sniping a Problem for Online Auction Markets? eBay Research Labs, work in progress.
- Bajari, Patrick & Hortacsu, Ali 2003. The Winner's Curse, Reserve Prices and Endogenous Entry: Empirical Insights from eBay Auctions. *RAND Journal of Economics*, Vol. 34, No. 2.
- Bajari, Patrick & Hortacsu, Ali 2004. Economic Insights from Internet Auctions. *Journal of Economic Literature*, Vol. 42, Issue 2.
- Borle, Sharad & Boatwright, Peter & Kadane, Joseph B. 2006. The Timing of Bid Placement and Extent of Multiple Bidding: an Empirical Investigation Using eBay Online Auctions. *Statistical Science*, Vol. 21, Issue 2.
- Brown, Jennifer & Morgan, John 2009. How Much is a Dollar Worth? Tipping Versus Equilibrium Coexistence on Competing Online Auction Sites. *Journal of Political Economy*, Vol. 117, No.4.
- Compete pulse* 2007. Internet All Stars '01: Where are They Now? <https://blog.compete.com/2007/10/01/top-ranked-web-sites-popularity-2001>. 9.10.2014.
- Dinerstein, Michael & Einav, Liran & Levin, Jonathan & Sundaresan, Neel 2014. Consumer Price Search and Platform Design in Internet Commerce. National Bureau of Economic Research Working Paper.
- eBay Bid Increments. <http://pages.ebay.com/help/buy/bid-increments.html>. 9.10.2014.
- Einav, Liran & Kuchler, Theresa & Levin, Jonathan & Sundaresan, Neel 2013a. Learning from Seller Experiments in Online Markets. National Bureau of Economic Research Working Paper.
- Einav, Liran & Farronato, Chiara & Levin, Jonathan & Sundaresan, Neel 2013b. Sales Mechanisms in Online Markets: What Happened to Internet Auctions? National Bureau of Economic Research Working Paper.
- Fu, Rao 2011. Essays on Multi-item Auctions: Theoretical and Empirical Investigations. Dissertation, The University of Texas at Austin.
- Hasker, Kevin & Sickles, Robin 2010. eBay in the Economic Literature: Analysis of an Auction Marketplace. *Review of Industrial Organization*, Vol. 37, Issue 1.

- Hossain, Tanjim 2008. Learning by Bidding. *The RAND Journal of Economics*. Vol. 39, Issue 2.
- Houser, Daniel & Wooders, John 2006. Reputation in Auctions: Theory and Evidence from eBay. *Journal of Economics and Management Strategy*, Vol. 15, No.2.
- Jank, Wolfgang & Shmueli, Galit 2010. *Modeling Online Auctions*. Wiley, New Jersey.
- Kazumori, Eiichiro & McMillan, John 2003. Selling Online Versus Offline: Theory and Evidence from Sotheby's. Levine's Working Paper Archive.
- Krishna, Vijay 2002. *Auction Theory*. Second Edition. Academic Press, Massachusetts.
- Levin, Jonathan 2004. *Auction Theory*. Stanford University.
- Levin, Jonathan 2013. The Economics of Internet Markets. *Advances in Economics and Econometrics*. Edited by D. Acemoglu & M. Arellano & E. Dekel, 2013.
- Lucking-Reiley, David 2000. Auctions on the Internet. What's Being Auctioned, and How? *The Journal of Industrial Economics*, Vol. 48, No. 3.
- Lucking-Reiley, David & Bryan, Doug & Prasad, Naghi & Reeves, Daniel 2007. Pennies from the eBay: The Determinants of Price in Online Auctions. *The RAND Journal of Economics*, Vol. 34, No. 2.
- Malhotra, Deepak & Murnighan, J. Keith 2000. Milked for All their Worth: Competitive Arousal and Escalation in the Chicago Cow Auctions. Kellogg Graduate School of Management.
- Malmendier, Ulrike & Lee, Young Han 2011. The Bidder's Curse. *American Economic Review*, Vol. 101, Issue 2.
- Milgrom, Paul R. & Weber, Robert J. 1982. A Theory of Auctions and Competitive Bidding. *Econometrica*, Vol. 50, No. 5.
- Pownall, Rachel A.J. & Wolk, Leonard 2013. Bidding Behavior and Experience in Internet Auctions. *European Economic Review*, Vol. 61.
- Rasmusen, Eric 2006. Strategic Implications of Uncertainty over One's Own Private Value in Auctions. *Advances in Theoretical Economics*, Vol. 6, Issue 1.
- Rogers, Alex & Asther, David & Jennings, Nicholas R. 2007. The Effects of Proxy Bidding and Minimum Bid Increments within eBay Auctions. *ACM Transactions on the Web*, Vol. 1, No. 2.

Roth, Alvin E. & Ockenfels, Axel 2002. Last-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet. *American Economic Review*, Vol. 92, No. 4.

PSA Card Grading Standards. <http://www.psacard.com/Services/PSAGradingStandards>. 9.10.2014.

Statista 2014. EBay's total active buyers. <http://www.statista.com/statistics/242235/number-of-ebays-total-active-users/>. 9.10.2014.

Simonsohn, Uri & Ariely, Dan 2008. When Rational Sellers Face Nonrational Buyers: Evidence from Herding on eBay. *Management Science*, Vol. 54, No. 9.

Stryzowska, Marta 2005. On the Ending Rule in Sequential Internet Auctions. Tilburg University, 2005.

Surowiecki, James 2011. Going, Going, Gone: Who Killed the Internet Auction? *Wired Magazine*. [http://www.wired.com/2011/05/ff\\_endofauction/](http://www.wired.com/2011/05/ff_endofauction/). 9.10.2014.

Vickrey, William 1961. Counterspeculation, Auctions and Competitive Sealed Tenders. *The Journal of Finance*, Vol. 16, No. 1.

Wang, Joseph Tao-yi 2006. Is Last Minute Bidding Bad? Humanities and Social Sciences, Caltech.

Wilcox, Ronald T. 2000. Experts and Amateurs: The Role of Experience in Internet Auctions. *Marketing Letters*, 11.