The Dissertation Committee for Ilke Onur
Certifies that this is the approved version of the following dissertation:

ESSAYS ON INTERNET AUCTIONS

Committee:

Kenneth Hendricks, Supervisor

Stephen G. Donald

Thomas E. Wiseman

Randal B. Watson

Kerem Tomak

ESSAYS ON INTERNET AUCTIONS

by

Ilke Onur, B.A., B.S., M.S.

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ESSAYS ON INTERNET AUCTIONS

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Ilke Onur, Ph.D.
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Supervisor: Kenneth Hendricks

This dissertation examines the online auction markets and focuses on eBay in particular. EBay provides an environment in which losers can bid again and we study the effects of this dynamic feature on the bidding behavior of buyers. Chapter 1 presents the introduction for the dissertation. In Chapter 2 we first introduce the eBay market and the data we have collected. Then we focus on the bidding behavior of bidders and empirically analyze the importance of the dynamics while modeling eBay auctions. In Chapter 3 we develop a theoretical model and show that the option to bid again leads to last-minute bidding for bidders. We also examine some empirical predictions of the model. Chapter 4 analyzes the impact of a particular eBay feature called Buy-It-Now on bidding behavior of bidders. This feature is a choice for the seller that enables participants to preempt and end the auction early without competing with other bidders. Chapter 5 summarizes main conclusions of the dissertation and proposes directions for future research.

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Chapter 1

Introduction

Historically, auctions have been one of the most prominent and popular selling mechanisms. In recent years, the pervasive spread of high-speed internet has led to a significant spurt in online trading; internet auctions are a popular manifestation of this trend. Buyers and sellers can meet in this virtual market place to buy and sell a varied range of products without leaving the comfort of their home. The historic development of this low-cost trading mechanism thus created an entirely new market. Key players in this market are internet auction sites such as eBay, Yahoo and Amazon. In the United States eBay has become the dominant player in this market with expected sales as high as $4.4 billion in 2005. As of June 2005, its customer base has grown to 147 million and earnings climbed 53 percent relative to the corresponding figure the year before.[1]

It is therefore not surprising that eBay is one of the most commonly studied online auction mechanisms by academicians. EBay provides an environment in which losers can bid again and the objective of my dissertation is to analyze the effects of this dynamic feature on the bidding behavior of buyers. Initially, I introduce the dataset I have collected from eBay's website and then utilize it to empirically present how crucial the dynamic environment is for modeling eBay auctions. This research adds to the online auction literature by explaining last-minute bidding and the existence of the Buy-It-Now

[1] This information and more about eBay is available at www.forbes.com.

feature using eBay's multi-auction environment. Subsequently, I again use the dataset I have collected from eBay's website to show that the majority of the theoretical predictions are satisfied.

In the second chapter of my dissertation, 'An Empirical Study of EBay's Dynamic Feature', I study the importance of considering a dynamic environment rather than a static one by analyzing the bidding behavior in eBay auctions. Due to high-speed internet and practically costless search possibilities, bidding on an auction is no longer only a function of characteristics of a single auction but it also depends on auctions running simultaneously, completed auctions, available Buy-It-Now prices as well as some outside options. I show how the dynamic market affects a bidder's probability of participating in an auction or leaving eBay. In order to perform this analysis, I study Texas Instruments (TI-83) Graphing Calculator auctions featured on eBay. I utilize a probit regression to study the effects of eBay's dynamic marketplace over bidders' probability of staying in eBay. The results suggest that variables containing information from other auctions significantly affect bidders' decision, thus emphasizing the importance of the dynamic, multi-auction environment in eBay marketplace for potential buyers.

In the third chapter of my dissertation, 'Gone in 60 Seconds: Last-Minute Bidding on EBay Auctions' (joint with Ken Hendricks and Tom Wiseman), we study the delay of bid submission due to strategic last-minute bidding in eBay. We consider a two-period model in which two identical items are auctioned sequentially by different sellers. We show that there is a symmetric equilibrium in which the bidders wait until the last minute to submit their bids in the first auction. The last-minute bidding arises from the sequential structure of the sale and not, as in Roth and Ockenfels (2002, 2005), because last minute bids may not be recorded. Additionally, we prove that the last-minute bidding equilibrium yields the same expected revenue for both auctions. We test the predictions of the theory and confirm the existence of last-minute bidding using eBay bid data from 1,817 auctions of Texas Instruments TI-83 Graphing Calculators. Furthermore, we introduce a new and informative approach of studying bid submission times. We arrange the auctions consecutively according to their closing times and focus on the intervals in between. This method provides us with an accurate measure of LMB in eBay.

In the fourth chapter of my dissertation, 'Preemption in EBay Auctions' (joint with Ken Hendricks and Tom Wiseman), we analyze the Buy-It-Now (BIN) option in eBay auctions. The BIN feature gives sellers the opportunity to provide bidders with the possibility of buying the item forthwith by paying the BIN price. We study the bidders' strategic incentive to execute the BIN feature as well as the timing of the execution. To start with, we build our theoretical model that is motivated by the facts obtained from our dataset. We present a two-period model in which two identical items are auctioned sequentially by different sellers and the first seller offers a BIN price. As a result, bidders have a strategic incentive to execute the BIN option and they tend to act early on in order to purchase the item without competing against other bidders. The main result of our theoretical model is that it is rational for the early seller to set a BIN price and an equivalent reserve price. Moreover, we analyze our TI-83 Graphing Calculator auctions and offer empirical support to the results from our theory section. Lastly, we perform a statistical test to show that conditional on sale, the revenue for executed BIN auctions are higher than the revenue for no reserve, no BIN price case.

Chapter 2

An Empirical Study of EBay's Dynamic Feature

2.1 INTRODUCTION

EBay is an ever growing online auction market with millions of participants and hundreds of different categories. For countless items there are multiple auctions running simultaneously and in most cases ending sequentially. This huge marketplace offers various alternatives to the bidders. A potential buyer planning on participating in an eBay auction first performs a search for the item she wants to buy. EBay lists current auctions with the early closing ones on top of the screen. For instance, for a specific item, on the first page of the search result a potential buyer can observe 50 auctions closing in next 6 hours at a single glance.[2] These are overlapping auctions that are closing sequentially in a short period of time. Hence, it is appropriate to think of the eBay marketplace as a dynamic environment.

However, most of the studies in the online auction literature have focused on stand-alone auctions. These papers explain the bidders' bidding strategies, last-minute bidding (LMB) phenomenon and the presence of Buy-It-Now (BIN) prices by mainly focusing on single auctions. Last-minute bidding is when bidders wait until the very end

[2] This number holds for Texas Instruments (TI-83) calculator auctions in the afternoon for a weekday. It might vary depending on the item, day and time.

of the auction to submit their bids and the Buy-It-Now option gives sellers the opportunity to provide bidders with the possibility of buying the item forthwith by paying the BIN price before serious bidding starts in an auction. Researchers formulate these explanations by making some reasonable yet limiting assumptions that may not always hold in real life.

Ockenfels and Roth (2002, 2005) argue that late bidding could be due to network congestion that might prevent some of the submitted bids from being recorded. When bids are submitted at the last minutes of the auction, an increase in the network activity decreases the probability of each bid getting recorded. As a result, bidders, under certain conditions, prefer to submit their bids at the last seconds of the auction hoping to win the auction for a lower price. In another paper, Reynolds and Wooders (2004) compare the buy prices for two online auction houses, eBay and Yahoo.[3] Their results show that when bidders are risk-neutral, both buy prices are equivalent to the standard English ascending bid auction in terms of revenue. However, with risk-averse bidders, the sellers in both auction houses can raise more revenue by using the buy price feature than with ascending bid auctions.

Only recently researchers have been paying more attention to the dynamic feature of eBay to offer alternative explanations to the BIN price and LMB that are free of the assumptions mentioned above. In Chapter 3 we show that when multiple auctions are present, there is an equilibrium in which the bidders wait until the last minute to submit their bids in the early closing auctions. Wang (2003) also uses a similar dynamic setting to study last-minute bidding. In these papers, the last-minute bidding equilibrium arises from the sequentially ending multi-auction structure of the online marketplace. In

[3] *Buy price* is a common term for the feature mentioned above. Buy-It-Now is the name of the eBay version of a buy price. Yahoo also has a similar buy price feature which is called Buy-Now option.

Chapter 4 we study Buy-It-Now prices on eBay while taking the existence of multiple auctions into account. Kirkergaard and Overgaard (2004) is another recent paper following a similar approach for studying BIN prices. These papers rationalize the existence of BIN prices by showing that due to the multiple-auction setting, the first seller is better off setting a BIN price even when the buyers and sellers are risk-neutral.

Here are some ways how a dynamic environment affects the behavior of potential buyers in eBay: 1) losing an auction does not mean zero payoffs for the bidder. Since there are more auctions she can participate in future, her expected payoff is greater than zero; 2) due to possibility of future competition, bidders are more strategic about when to submit their bids and reveal their valuations; 3) the existence of many sellers offering auctions with and without BIN prices increases the bidders' choice set. In summary, there is an information linkage across eBay auctions which we analyze in this study.

There are two goals of this paper. First we introduce the eBay market and the data we have collected. Then we focus on the bidders and gather some crucial facts about their bidding behavior. We utilize these facts both in this Chapter and in the rest of this dissertation. Secondly, we empirically analyze the importance of the dynamics for modeling eBay auctions. Our objective is to explore the extent eBay auctions should be modeled as a dynamic game. For this purpose, we demonstrate the existence of information linkage and the effect of the dynamics on the behavior of bidders.

The studies in the literature show that most of the bidding activity takes place in the last couple of hours of eBay auctions. Moreover, they show that substantial amount of bids are submitted in the closing minutes of an auction. For instance, Roth and Ockenfels (2005) find that 13 percent of all bids come in the last five minutes of antique auctions on eBay. Hence, the last hours and minutes are crucial for the resulting transaction price for an auction. Alternatively, Buy-It-Now options are widely utilized and they also play a critical role on bidders' decisions. Reynolds and Wooders (2003) show that a BIN price is offered in roughly 40 percent of the eBay auctions they have studied. Thus, in our study, we assume that a bidder bidding on eBay either submits a proxy bid at the closing hours of an auction or executes a BIN price.

Alternatively, with the existence of high speed internet, finding an outside option is costless for the bidders. A potential buyer who does not prefer to use eBay, can search for an item using one of the many search engines and find an online store selling the same good. Thus we believe that the potential buyer faces two main choices; 1) submit a proxy bid in an auction or pay the Buy-It-Now price (eBay); 2) purchase the item from an outside option or bid on eBay later on (leave eBay). We treat all potential buyers as rational bidders and study the extent that they make their choices depending on the dynamic state of eBay market.

Our dataset comprises 2,526 auctions of Texas Instruments TI-83 Graphing Calculators and the bids submitted in those auctions. We follow the bidders and derive some facts about their bidding behavior. Then, using the raw data, we create some new variables, which we use in our empirical section. In our analysis we use a probit model to estimate the effect of parameters from eBay's dynamic online auction market on the two choices mentioned above. The focus is on actions of bidders after they fail to succeed in an auction since data on non-active potential bidders and the auctions they monitor is not available.

Our results show that losers of an auction are less likely to stay in eBay when the competition among potential bidders is higher. They are more likely to leave eBay when their willingness-to-pay and ranking is higher in the auction they lose. On the other hand, these losers are more likely to stay in eBay when more BIN options are available. We show that variables containing information from other auctions significantly affect bidders' decision after they fail to win an auction. As a result, we empirically demonstrate the importance of the dynamic eBay marketplace for potential buyers.

The rest of the paper is organized as follows. In section two we summarize the eBay auction market. Section three introduces the dataset we have collected from eBay along with the summary statistics. In section four we study the bidders in our dataset and state several facts that are crucial for Chapters 3 and 4. Furthermore, in section five we create some new variables from the raw data, which we use in our econometric analysis. In section six we briefly introduce the empirical method used and then we present our estimation results. Finally, in section seven, we present our conclusion and suggest future research ideas.

2.2 EBAY AUCTION

EBay attracts numerous bidders and sellers to its online market. As a result, there are countless items that are listed in many different categories and subcategories such as antiques, cars, coins and all kinds of electronics. Bidders can search for an item by using keywords and then narrow down the results using specific criteria related to the goods like price range or location.

EBay auctions are ascending bid auctions. The seller determines the length of the auction which can last for 1, 3, 5, 7 or 10 days.[4] The starting bid is also set by the seller

[4] While the data were collected, 1-day auctions were not an option for the sellers in eBay.

before the auction commences. Any amount below the starting bid is not sufficient for the transaction to go through. The starting bid acts like a posted reserve price for an auction since it is observed by all the potential buyers. EBay also offers sellers an option to set a secret reserve price that is not observable to the bidders. The reserve price is the lowest amount that the seller is willing to accept. Potential buyers are informed by eBay via email and a posting on the website whether the reserve price is met or not. Moreover, eBay charges the seller a certain fee for choosing this option. The amount varies with the amount of the reserve price she sets. However, the fee is fully refunded if the auction ends with a successful transaction.

In eBay, potential buyers bid by means of proxy bidding. By submitting a proxy bid, the bidder assigns an amount that she is willing to pay for a particular item and eBay's computer runs the bidding on her behalf. If the submitted proxy bid is the highest, then the highest-standing bid is the second highest proxy bid plus the bid increment.[5] As higher bids get submitted, eBay's computer keeps increasing the highest-standing bid on the bidder's behalf until she is outbid and is no longer the highest bidder. This bidding process continues until the auction ends. The winner is the buyer who submitted the highest proxy bid and pays the second-highest proxy bid plus the bid increment. Hence, we regard eBay as an ascending second-price auction. However, since a bidder can learn about others' proxy bids by increasing her own proxy bid, it is not precisely a sealed-bid auction. Therefore, it qualifies as a partially "sealed" bid ascending second-price auction.

At any point in the bidding, the bidders can observe the following information: the highest standing bid, time left for the auction to close, starting and ending time of the

[5] Bid increment is the lowest amount by which a bidder can raise the highest-standing bid. This number is predetermined by eBay and it depends on the highest-standing bid.

auction, ID of the high bidder including his/her feedback, ID of the seller including his/her feedback along with the percentage of positive feedback, location of the item, shipping and payment details, item specifics including a detailed description with one or more pictures of the item, starting bid, number of bids, quantity being sold and, in most cases, a counter showing how many prospective bidders have visited the auction site. Moreover, information on the bid history can be obtained with a single click on the "history" link. In this new page, the potential buyer observes all submitted bids, the IDs of the bidders along with the dates and times of the bid submissions.

EBay also offers a special Buy-it-now (BIN) option to sellers. The BIN option gives sellers the opportunity to provide bidders with the possibility of buying the item forthwith by paying the BIN price. The advantages paying the BIN price to the bidder are that she is certain to win the item, she does not have to compete with other potential buyers, and she does not have to wait for the auction to end. However, to execute the BIN option the bidder may have to act quickly since the opportunity disappears once a proxy bid that is equal to or higher than the reserve price is submitted. When this occurs, the BIN option is removed from the auction web site by eBay. Of course, the seller can prevent this from happening by setting the reserve price equal to the BIN price. The inclusion of the BIN option costs the seller a fixed fee of five cents.

2.3 THE DATA

Our dataset consists of information collected for Texas Instruments TI-83 Graphing Calculator auctions featured on eBay. The data includes every auction that took place between June 15th, 2003 and July 30th, 2003. We chose this item due to the availability of many data points as well as the homogeneous nature of the good itself. Dutch auctions, in which bidders compete for multiple quantities of an item, and private auctions, in which information about the bidders are not available, are excluded from our dataset. In auctions without a BIN price, the information about the final transaction of the item is not revealed by eBay. Therefore, we cannot distinguish between auctions ending with a successful sale and auctions ending without any sale. We assume that all auctions that attracted a bid ended with a sale and the winner was the buyer with the highest standing bid. On the other hand, we have sale information for auctions in which the BIN price is offered. In these auctions either the transaction took place with the execution of the BIN feature, or the reserve price is met and the BIN option is wiped out. In both cases we know that the sale was successful.

The sale prices for TI-83 calculators in retail stores are between 80 and 100 dollars for new items and between 40 and 60 dollars for used ones. The final prices of the auctions we have in our dataset show substantial variance. The reasons for the variation are the used and new items as well as additional features like the case or the manual of the calculator. However, the dataset also contains auctions offering just the accessories without the calculator, or more quantities of the calculator bundled together. In order to keep the items reasonably homogeneous, we decide to keep only the auctions which have a transaction price greater than or equal to 20 dollars and less than or equal to 110 dollars. We are only dropping extremely low and high valued auctions in order not to lose crucial information.

There are 2,526 unique auctions that were completed in the 6-week period. We observe 4,907 bidders who have participated in these auctions and submitted 14,720 bids in total. Moreover, we observe 53 auctions that were cancelled by the seller before the pre-determined ending time. Some reasons for the sellers to cancel the auction are an error in the starting price or the reserve price, an error in the listing or simply unavailability of the item. We exclude the cancelled auctions from our dataset. We also notice 139 auctions that did not attract any bids. For this study we do not include no-bid auctions in our dataset.

We collected the following information for each TI-83 auction in the 6-week period: Winning bid, Buy-It-Now price, Starting Bid, Auction length, Number of bids, Number of bidders, Seller and Bidder ratings. Table 1 presents a brief description of the variables in our dataset. Additionally, we provide the descriptive statistics of these variables in Table 2. More information on the variables along with discussion of the summary statistics is provided below.

The Winning bid is the price that the winner pays at the end of the auction. Remember that this price is the willingness-to-pay of the second-highest bidder plus the bid increment. Our dataset shows that the TI-83 calculators on eBay sell for a bit less than $59 on average. They also have a standard deviation around $18 which is mainly due to the existence of used and new items.

The average BIN price is $62.55 and it is slightly higher than the mean for the Winning bid. These variables are correlated; for executed BIN options the Winning bid is the BIN price itself. Thus, it is intuitive to observe a higher average for the BIN price since for most auctions the BIN price acts like an upper bound of the support for the bids submitted.

Using the starting bid variable, the seller sets the amount her auction will start from. Any bid that is submitted has to be equal to or greater than this amount. The average starting bid is $25.71 and we observe quite a bit variation. In Chapter 4 we show that the sellers set the Starting bids high enough to prevent from the BIN option getting wiped away early. Thus, the reason for the high variance is the existence of auctions with a BIN option. There is evidence of reasonable interest by potential buyers in eBay's TI-83 auctions. On average, these auctions last a bit less than 5 days with about 6 bidders showing up and submitting more than 10 bids per auction.

Another important feature of eBay is the feedback score that both sellers and bidders receive. EBay users can leave feedback for each other anytime up to 90 days after the completion of a transaction and the feedback assigned is permanent. A positive comment earns the user a +1 point, a neutral one 0 points and a negative comment corresponds to -1 point. The feedback score is the sum of all the points that the user receives from other parties. In our sample, the mean seller and bidder ratings are 590.88 and 49.03 respectively. The sellers are more experienced than the bidders for TI-83 auctions on eBay. The median seller has a feedback point of 63 and the same number is only 6 for the bidders.[6]

2.4 The Bidders

In this section, the focus is on the buyers and their bidding behavior. We follow the bidders for two consecutive auctions that they participate in. We establish facts that motivate the assumptions of our theoretical model utilized in Chapters 3 and 4.

[6] In 22 auctions we do not observe the seller ratings. However, the data points we observe are enough to conclude that the sellers are fairly experienced. Therefore, it is a reasonable assumption to think that they follow revenue maximizing strategies in their auctions.

For this purpose, we first identify the bidders and track their bidding activities in eBay over time. We also record how many auctions they win and lose. This method provides us with the opportunity to capture the bidders' decisions given the outcomes of the auctions they previously participated in. Note that in auctions without a BIN option we do not observe if the sale is successful or not. We assume that all the non-BIN auctions that attracted a bid ended with a sale and the winner is the buyer with the highest standing bid.

There are 4,907 unique bidders submitting one or more bids in the 6-week period. 2,163 bidders were the winners of the 2,526 auctions we have in our dataset. This suggests that some bidders were successful in more than one auction. Subsequently, we focus on all potential buyers and the number of auctions they won. We report our findings in Table 3. There were 2,744 bidders who were not successful in winning an auction. Among the 2,163 winners, we observe 2,001 bidders winning only a single auction, which corresponds to almost 93 percent of total winners. Only 162 bidders were successful in winning multiple auctions. This suggests that most bidders have only a single-unit demand for the item, with only a small percentage of bidders having a multi-unit demand.

In order to analyze how the bidders behave after they win or lose an auction, we monitor all 4,907 bidders up to two consecutive auctions they participate in. In Figure 1, we summarize our findings and display the existing number of bidders at nodes of a tree. For each auction we report the number of bidders who are successful (W) and unsuccessful (L). Subsequently, we study how bidders behave after participating in both auctions. Some prefer to keep on bidding in another auction (B) and others choose to leave eBay's website (E).

The great majority of the winners tend to leave the auction site, whereas most of the losers choose to stay and keep bidding. The same trend continues with the second auction. This finding is also in accord with our earlier observation of single-unit demand. In summary, we witness that winners tend to exit but the bidders who lose tend to stay and keep bidding in order to win an auction.

Thus, both in this Chapter and the rest of this dissertation, in view of the bidder facts from the data, we make the assumption that bidders have a single-unit demand for TI-83 on eBay. This assumption suggests that when bidders win an auction, they do not bid in another auction anymore. However, when they lose, they move onto another auction offering the same item. This fact also suggests that the expected payoff for the bidders from losing an auction is greater than zero.

2.5 EMPIRICAL ANALYSIS

In this section we create some new variables from the raw data, which we use in our econometric analysis. We explain the relevance of these variables and present summary statistics below.

Obtaining data on all potential bidders and the auctions they monitor is not possible. We observe the bidders only when they submit a bid in an auction. Thus, we introduce the dependent variable for our estimation, Next Action, as the action a bidder takes after she loses an auction. This is the only way we can identify bidders in our dataset, be sure that they are online, observing other auctions and making a choice as a result of their observations.[7] Next Action consists of the following two choices; 1) submit a proxy bid in an auction or pay the Buy-It-Now price (eBay); 2) purchase the item from an outside option or bid on eBay later on (leave eBay).

In order to study the state of the eBay market we introduce a time window extending both into the future and the past. With this method we record upcoming opportunities by new auctions ending soon, together with, potential competition due to unsuccessful bidders from completed auctions. In our empirical part we use 3 hours as the length of the window. We assume that all the bidders are identical. A bidder makes her decision depending on the observations in this window. If she chooses to wait and bid later than 3 hours, then we assume that this bidder exits the auction website (leave eBay). When she returns to eBay later on, she faces a brand new choice set and carries no information from her previous attempt.

Following are the modifications we perform on our dataset in order to observe some determinants of the Next Action choice for the bidders. Table 4 presents brief descriptions of the created variables we introduce below. First, we identify the proxy bids submitted by the bidders and keep the highest proxy bid submitted by each bidder. These bids correspond to the willingness-to-pay for each bidder except for the winner. (The winner pays the second highest proxy bid thus we cannot identify her willingness-to-pay). We utilize the highest proxy bid a buyer submits in the auction which she loses, as one of the predictors for her Next Action.

We create a variable to use as a proxy measuring the competition a potential buyer faces in the market after bidding and losing in an auction. For this purpose, the

[7] We are aware that this limits our results to bidders who have lost at least once rather than all the potential buyers. Moreover, we are aware of the exclusion of bidders who choose to execute the BIN option right away without submitting a bid.

number of sellers and bidders in the market matter and a potential buyer takes these into consideration while deciding on her Next Action. For instance, existence of many bidders and less sellers in the market might make an outside option more attractive for a bidder than staying in eBay. We record the number of bidders who have lost in the completed auctions. This number represents the amount of potential competition for an upcoming auction. Then, we monitor the number of auctions that will be closing in the future. As a result, we realize the potential demand and supply for an item. We assume that the bidder studies the information available for the time window specified, extending both into the future and the past. By dividing these two numbers with each other, we create the ratio of potential buyers over sellers (Ratio BOS) which we use to measure the competition in the market.

We have shown that most of the serious bids come during the last couple of hours in eBay auctions. Thus, the ending part of an eBay auction is informative for the bidding activity. Auctions ending during the day time and the ones ending later in the evening have different number of bidders and maybe bidders with different strategies. By using four dummy variables, Time 1, Time 2, Time 3, and Time 4, we capture the effects of the ending time of each auction in our dataset. Time 1 equals to one if the auction ends between 12am and 6am and zero otherwise. The rest follows similarly with 6 hour ending windows.

Available BIN options in future auctions might also affect a bidder's Next Action choice. We report the number of upcoming Buy-It-Now auctions that are available in our time window using Number of BIN sellers. Existence of more or less BIN options would have a decisive impact on the choice of the bidders. In addition to the number of the BIN options available, we believe the average price of these options might have a significant effect. Thus we also present the variable called Average BIN price. This is the average value of the upcoming Buy-It-Now options that are available during the time window.

As for individual bidder data, we count the number of previous losses for every bidder. This number might affect the bidders' decisions. We use three dummy variables, Losses 1, Losses 2 and Losses 3, to identify the number of times every bidder has lost. First two are binary variables that are equal to one if the number of previous losses for a bidder equals to the number specified and zero otherwise. Losses 3 is equal to one if the number of previous losses equals to 3 or more and zero otherwise. Note that due to the selection criteria of the bidders we monitor, every bidder in our dataset has at least one loss.

As mentioned earlier, in our analysis we utilize the highest proxy bid that every bidder submits in the auction that they have just lost. Additionally, we calculate how these proxy bids rank among the other bids for each auction. Then, we create the variable Previous ranking which represents the position of a loser's bid in the previous auction. Next, we record the winning bid for each auction that a bidder loses. This number is an approximation for the sale price of the next auction the bidder considers to join in. These bidder and auction specific records might considerably affect the bidder's decision for Next Action.

We make couple of assumptions while running the empirical estimation. As shown earlier, we assume that the bidders have unit-demand and they leave the website after winning an auction. Thus, for the regression, we do not consider actions of bidders after they win. We are only interested in the decisions of bidders who have just lost. Similarly, we do not consider bidders who win multiple auctions. They account for 3 percent of all bidders we have in our dataset. These bidders differ from the rest of our dataset. In general, they buy the calculator in order to sell it later on for a higher price. They are not mere users like the majority of the bidders in our dataset. We believe the incentives and actions of multiple winners might bias our results.

As the last modification, we truncate some of our data both from the beginning and end of our 6 week period. We do not consider the actions of bidders if the auction they just participated starts in the first 1 day and ends in the last 1 day of our 6-week period. The reason for this truncation is to have all the information bidders consider while making their decisions, included in our estimation.

After truncating some of the dataset for our analysis, we are left with 2,412 unique auctions. We observe 4,652 bidders who have participated in these auctions and submitted 14,003 bids in total. We provide the summary statistics of our modified dataset in Table 5.

The average Proxy bid is \$44.39 with \$42.29 as the median. As expected the number of observations for Proxy bids is less than number of bids we observe since we do not observe the Proxy bids submitted by the winners. The Previous ranking informs us that on average the bids submitted in the previous auction rank fifth compared to the rest. It is not surprising to see that only 4 percent of all the auctions end very early in the morning (Time 1). Other times of the day have similar amount of auctions ending with the highest being afternoon hours (Time 3). The measure for competition, Ratio BOS, is 5.37 on average. This means that on average for each auction starting up there are close to 6 bidders who have lost in the past. They are likely to be potential competitors in future auctions for the time window we have introduced earlier. This number is significantly high enough for us to believe that bidders consider the existence of potential competition while choosing their Next Action. Similarly, average Number of BIN Sellers in the future time window is a bit more than 2. This is a substantial number for the bidders to consider the BIN option prior to deciding on their Next Action. Next, we study the average price of these options. The mean for Average BIN price is $60 which is a little more than the average Winning bid for all auctions. Number of previous losses might also be a good indicator for bidders' Next Actions; existence of several losses might considerably affect a bidder's decision. Additionally, in more than 50 percent of the cases we study, the number of losses that a bidder has before making a decision is equal to or greater than 3. This demonstrates that bidders with multiple losses keep coming back to the eBay marketplace as we have demonstrated in section 2.4.

2.6 ECONOMETRIC SPECIFICATION

In this study we use a probit model to show how the dynamic variables in eBay affect the probability that a bidder stays in eBay.[8] Next Action is the dependent variable for the probit regression performed. Next Action represents the probability of staying in eBay for a bidder who has just lost an auction. Remember that staying in eBay for a bidder stands for either submitting a bid or executing a BIN price in the 3 hour window. We use a set of variables describing the bidder and the eBay marketplace consisting of multiple auctions. The explanatory variables we utilize for this regression are Time 1-3,

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[8] We study the following binary response model

$$\Pr\left(y=1\middle|x\right)=\Phi\left(x\beta\right)$$

where Φ is the cumulative standard normal distribution. We want to explain the effects of the explanatory variables on the response probability. The log-likelihood function for probit is

$$\ln L=\sum y_j \ln\Phi\left(x_j\beta\right)+\sum y_j \ln\left(1-\Phi\left(x_j\beta\right)\right)$$

where $y_j=0,1$.

Ratio BOS, Number of BIN sellers, Proxy bid, Winning bid, Previous ranking, Losses 2, Losses 3 and the constant. Time 4 and Losses 1 are the omitted dummy variables.

The estimation results are presented in Table 6. We report the coefficients in one column and the marginal effects in another one. The marginal effects report the variation in probability of staying in eBay for a marginal change in each independent variable. For binary choice variables, the change is the difference in probability when the dummy variable is 1 and when it is 0. The marginal change is calculated by holding all other variables at their mean. The marginal effects help us with the interpretation of the results since they inform us about the magnitude of the probit estimates.

The results are mostly consistent with our expectations. Except for two of the Time variables, the rest are all statistically significant. Ratio BOS, which is the proxy for the competition in the market, has a negative sign as we have anticipated. Presence of more bidders and less sellers decreases the probability of a loser staying in eBay. Similarly, Proxy bid, Winning bid and Previous ranking have also negative signs. Alternatively, probability of staying in eBay rises with the Number of BIN sellers and the Average BIN price. Thus, we see that variables connected with other auctions significantly affect bidders' decisions on their next action.

Time 2 and Time 3 do not have a significant effect on the Next Action. These variables are relative to the omitted dummy variable of Time 4. Thus, compared to the auctions ending between 6pm and midnight, only auctions ending in the early hours of the day significantly decrease the probability of staying in eBay. This is intuitive since bidders might be more willing to end their day or purchase the item from an outside option (leave eBay) when the auction they have just lost ends after midnight.

The Losses variable has a negative effect on the probability of a bidder choosing another action to submit a proxy bid or to execute the BIN option. However, as the number of losses increase, although the sign of the marginal effect stays the same, there is a considerable decrease in the magnitude. Bidders with more losses are less likely to leave eBay. Note that all these results are relative to a bidder with only one loss. Additionally, we report and compare the observed probability with the predicted probability for Next Action. These probabilities are almost identical and they inform us that around one third of the case the losers choose to stay in eBay.

Overall, we see that our results conform to the dynamic structure of eBay marketplace. All the variables that are connected to other auctions are statistically significant informing us that they play a major role in a bidder's decision to stay in eBay or leave.

2.7 CONCLUSION

In this study, our main focus is on empirical analysis of the importance of dynamics for eBay auctions. For this purpose we study the bidders in eBay and their behavior regarding multiple auctions using a probit regression. With our results we demonstrate the existence of information linkage across auctions and the effect of the dynamics on the behavior of bidders. The results of our study inform the researchers on the importance of modeling the theory in a dynamic framework. We also follow this result and use a multi-auction structure while setting up our theoretical model in next Chapters.

We perform the empirical regression by utilizing the data we have collected from eBay auctions. Our dataset comprises 2,526 auctions of Texas Instruments TI-83 Graphing Calculators and the bids submitted in those auctions. Then, using the raw data, we create some new variables, which we use in our econometric analysis. We focus on actions of bidders after they are not successful in an auction since data on all potential bidders and the auctions they monitor is not available.

Our results show that losers of an auction are less likely to stay in eBay when the competition among potential bidders is higher. They are more likely to leave eBay when their willingness-to-pay and ranking is higher in the auction they lose. On the other hand, these losers are more likely to stay in eBay when more BIN options are available. With these results we show that variables containing information from other auctions significantly affect bidders' decisions on their next action.

An extension of this research would be to extend the time interval in our model and compare the results to our findings. It would be interesting to observe if the bidders' consideration of multi-auctions is contingent on the length of the time interval we use. We believe that since eBay is a thick market with many auctions available, changing the time window would have little effect on our earlier results.

For further extensions we can consider various items with thicker and thinner markets. The comparison of those results with ours would reveal the connection of multiple auctions and bidders' choices more precisely. Another way to extend our research is to analyze the Yahoo online auction site. Yahoo is a thinner market relative to eBay, both in terms of variety of products available and in terms of the volume of trading. Yahoo also has many features in common with eBay but differs in some very interesting aspects. It would be interesting to study how these distinctions affect players' decisions.

Chapter 3

Gone in 60 Seconds:
Last-Minute Bidding on EBay Auctions

3.1 INTRODUCTION

EBay allocates the item through an auction with proxy bidding, which is a mechanism that bids on behalf of the bidder up to a reservation price specified by her. At the end of the auction, the bidder with the highest reservation price wins the item by a price equal to the second highest reservation price submitted. The auction thus resembles an ascending second-price auction. The auction lasts for a number of days that is chosen by the seller. By choosing the starting date and length of the auction, the seller also chooses the precise day and time it closes. There is no extension of auction length at the end of eBay auctions. This "hard-close" rule gives bidders an opportunity to delay their bid submissions and place their bids in the last minutes of the auctions. In a second-price setting with private values[9] Vickrey (1961) shows that bidders have a weakly dominant strategy to bid their valuations at any time during the auction. In practice, though, observation of bid submission times shows that bidders tend to wait until the very end of

[9] In a private value environment potential buyers know their own valuation of the item. All these individual valuations are independent of each other.

the auction to submit their bids. This delay in submission time until the end of the auction is called “Last-Minute Bidding” or “Sniping”.

Researchers offer various explanations for the incidence of Last-Minute Bidding (LMB). Ockenfels and Roth (2002, 2005) argue that late bidding could be due to network congestion that might prevent some of the submitted bids from being recorded. This explanation seems plausible due to the firm ending rule of eBay auctions. When bids are submitted at the last minutes of the auction, an increase in the network activity decreases the probability of each bid getting recorded. As a result, bidders, under certain conditions, prefer to submit their bids at the last seconds of the auction hoping to win the auction for a lower price. Ockenfels and Roth show that there are two possible equilibrium outcomes of their model: (1) all bidders submit their valuations at the last seconds of the auction; or (2) everyone bids their valuations at any instance during the auction. However, we believe there is more to explain since it is commonly observed in eBay that both last-minute bids and earlier bids are present in same auctions. This co-existence cannot be explained with Roth and Ockenfels’ model.

Bajari and Hortacsu (2003) offer another explanation. They show that LMB can arise in a common value environment.[10] In such an auction, bidders might be revealing some information about the true value of the item by bidding early in the auction. This would cause other bidders to bid more aggressively and the winner might end up paying more than she would otherwise. Although this explanation is reasonable, it is valid in a common value environment and does not apply to private value auctions.

An alternative explanation for LMB has been recently proposed by Barbaro and Bracht (2005). They present LMB as a best response to dishonest actions by the sellers

[10] In a common value environment every potential buyer values the object the same. They differ in their own estimates of this common value.

or sellers' accomplices. Shill bidding and squeezing are examples for such actions.[11] These actions might cause some bidders to wait until the last minutes of the auction to submit their bids. However, we believe the numbers of bidders who actually snipe because of these reasons are insignificantly small.

The common feature of most of these papers is their focus on stand-alone auctions. However, on eBay, many auctions overlap and they close one after another. For instance, while studying auctions on Texas Instruments Calculator (TI-83), we observe that on average 33 minutes elapse between closing times of two consecutive auctions. This number is much smaller during peak hours of the day when more users are actively bidding.

We show that capturing the sequential nature of eBay auctions is crucial in understanding LMB. We consider a two-period model in which two identical items are auctioned sequentially by different sellers. We show that there is a symmetric equilibrium in which low value bidders bid at any time and high value bidders wait until the last minute to submit their bids in the first auction. Thus, our model can explain the incidence of bids prior to closing time and last-minute bidding. The latter arises endogenously from the sequential structure of our model. The existence of the second auction creates a common value component in the first auction. Observing other bidders' valuations affect a buyer's expected payoff from the second auction, and thus his willingness-to-pay in the first one. For a high-valuation buyer, revealing her valuation lowers the expected payoff for the other bidders from the second auction, hence they are willing to bid more aggressively in the current one. Thus, bidders are willing to reveal

[11] *Shill bid* is the name given to a high bid the seller submits in her own auction using another account (or a friend does it for her). She learns the willingness to pay of the highest bidder. Then, the shill bid is canceled by the seller and replaced by the amount that is equal to the willingness to pay for the highest bidder. Thus, any potential gain for the bidder is *squeezed* from him by the seller.

their valuations for the item only at the end of the first auction, when there is not enough time for other bidders to respond. Additionally, we derive the expected revenues for the sellers and show that they are equivalent for both auctions.

A similar argument has been proposed by Wang (2003). He also uses the sequential auctions setting to show that the unique symmetric perfect Bayesian equilibrium of the first auction that survives the deletion of weakly-dominated strategies features last-minute bidding.

In order to observe sequential bidding, we study the temporal distribution of bids on Texas Instruments Calculator (TI-83) auctions that we have collected. We order the auctions by their closing times. This enables us to differentiate between LMB and "bid in next-to-close auction" strategy. More precisely, we demonstrate that some of the late bidding is due to losers from previous auctions moving onto the next-to-close auctions. Nevertheless, as our theory predicts, majority of the late bids are due to the strategic waiting of bidders until the last minutes of the auction.

The rest of the paper is organized as follows. In section two we present the model and our theoretical results. Section three briefly introduces the dataset. In section four we use the eBay data to statistically confirm our theoretical findings and study LMB in the closing intervals of the auctions. Finally, we present our conclusions in section five.

3.2 THE MODEL

We study the following simplified version of the eBay auction setting. There are two potential sellers and three potential buyers of a good. All agents are risk-neutral, their preferences are presented by a utility function that is quasilinear in wealth, and they do not discount the future. There are two possible types of buyer; a buyer is a low type with probability $q \in (0,1)$, and with the complementary probability she is a high type. The three buyers' types are independent. Each type of buyer wants at most one unit of the good, and values that one unit at V_L if she is a low type and at V_H if she is a high type, where $V_H > V_L > 0$. Each seller has one unit of the good to sell, and values the good at zero. This structure is common knowledge, although the buyers' realized types are private information.

The sellers run consecutive auctions. Each auction is a continuous-time, first-price auction with proxy bidding (described below). Seller 1's auction runs from time t_1 to time T_1, and the second auction runs from t_2 to T_2, where $t_1 < T_1 < t_2 < T_2$. The assumption that the auctions do not overlap is not important. However, it is crucial that one auction ends before the other.

The auctions use a proxy-bidding program. A buyer who chooses to participate enters a proxy bid *b*, and the program bids on his behalf up to that level. If *b* exceeds *h*, the maximum of the previous high proxy bid and the reserve price, then the program automatically enters a bid of *h* plus a small, discrete increment ε. If two or more buyers enter the same proxy bid $b > h$ at the same time, then the tie is broken randomly with equal probabilities – the program records a bid of *b* for one of the buyers and no bid for the other(s). If a buyer with proxy bid *b* has the current high bid *h*, and another buyer enters a proxy bid b' between *h* and *b*, then the program automatically enters a new bid of b' for the first buyer and no bid for the second. Having entered a proxy bid, a buyer can neither retract it nor revise it downward, although he can increase it at any time before the end of the auction. When the auction ends, the item is awarded to the buyer with the highest proxy bid at a price equal to the second-highest proxy bid. That outcome is publicly observed.

Throughout, we distinguish between a buyer's proxy bid (the price that he gives the program) and his bid (which the program makes on his behalf as a function of the proxy bids of all bidders and the order in which they were entered). Bids are publicly observed, but proxy bids are private information until they are outbid. Thus, the auction is first-price in bids, but it resembles a second-price auction in proxy bids.

We assume that the minimum bid increment ε is vanishingly small. In particular, we assume that a buyer with valuation V is indifferent between paying p for the good and paying $p + \varepsilon$, as long as $p < V$, but is unwilling to pay $V + \varepsilon$.

Buyers arrive at the first auction in random order. An arriving buyer knows whether he is the first, second, or third to arrive; early buyers observe the arrival of subsequent buyers. That assumption is consistent with the fact that most eBay auction sites have counters that display the number of visitors to the site. All buyers are present at the start of the second auction (although one may have already obtained an item, and thus will not participate).

A pure strategy for a buyer is whether to enter a proxy bid and if so, in what amount to enter the proxy bid, as a function of time, his own previous actions, the history of bids and (during the second auction) the outcome of the first auction. A buyer cannot enter a proxy bid in the first auction before it begins and he arrives, or in the second auction before it begins. Mixed strategies are defined straightforwardly.

We look for symmetric sequential equilibria. As an equilibrium selection device, we make the following assumption:

Assumption 1: With vanishingly small probability, any proxy bid submitted by a buyer is rejected by the eBay mechanism at the end of the auction. That probability is independent of when the proxy bid was submitted and of whether or not the other buyers' proxy bids are rejected.

In the second auction, therefore, each remaining buyer (that is, those who did not obtain the item in the first auction) will play his conditionally weakly dominant strategy to enter a proxy bid equal to his valuation at the end of the auction at time T_2, if he has not previously entered a proxy bid that high. Consequently, the outcome of the second auction is as follows:[12]

Proposition 1: The outcome of the second auction is the same as that of a second-price, sealed-bid auction.

Assumption 1, together with the result of Proposition 1, implies that in equilibrium a low-type buyer will enter a proxy bid of V_L at some time during the first auction. Expecting no surplus in the second auction, he is willing to pay up to his valuation in the first auction, hoping that other buyers' proxy bids will be rejected.

The behavior of high-type buyers in the first auction is more complicated. A high type's continuation value (the surplus from participating in the second auction) depends on the type(s) of the other participants in that auction. If a high type is matched with only low types, then he will win the item at a price $V_L + (\varepsilon)$, yielding surplus $V_H - V_L$. If two or more high types participate, then the winning bid is V_H, and no buyer gets any surplus.

[12] Proofs for the propositions in this chapter are presented in the appendix.

(Note that the surplus to a low-type buyer in the second auction is zero in any case.) There is thus a common-value component in the first auction – other buyers' valuations affect a high-type buyer's continuation payoff, and thus his willingness to pay.

That effect means that a high-valuation buyer is unwilling to reveal his type. Doing so reduces any other high type's expected continuation payoff: the probability that at least one opponent is a low type, so that there will be positive surplus from the second auction, falls from $1-(1-q)^2$ to $q\left(=q(2-q)>q\right)$. Consequently, Buyer i's high-type opponents are willing to bid more aggressively if he reveals himself to be a high type. In particular, another high type will outbid Buyer i unless he enters a proxy bid of at least $(1-q)V_H + qV_L$ (the price that yields surplus $q(V_H - V_L)$). In addition, Assumption 1 implies that another high type's best response to Buyer i's proxy bid $b \geq (1-q)V_H + qV_L$ is a proxy bid of $b - \varepsilon$: if Buyer i's proxy bid is rejected, then Buyer i will participate in the second auction, and there will be no surplus for the other high type if he loses the first auction. By revealing himself as a high type, then, Buyer i will get an expected surplus lower than what he would derive from the equilibrium calculated below, where types are not revealed until the end of the auction, when it is too late for buyers to respond to the information.

Thus, at most one high-valuation buyer will enter a proxy bid greater than V_L before the end of the first auction at time T_1. Otherwise, the publicly-observed high bid would exceed V_L and reveal the bidder as a high type. Whenever there is more than one high-type buyer, therefore, there must be proxy bids submitted at time T_1 – last-minute bidding. (There may also be proxy bids not exceeding V_L submitted earlier in the auction.) We can therefore analyze the first auction as though it were a second-price, sealed-bid auction (with respect to the proxy bids). As described above, a low-type buyer will enter his weakly dominant proxy bid, V_L. A high type, in choosing a proxy bid, must balance two factors. On the one hand, entering a high proxy bid creates the risk of needlessly competing with a single other high type – whichever of them loses will win the second auction at price V_L. On the other hand, when both opponents have high valuations, then there will be no surplus in the second auction – the buyer's only chance for positive surplus is to win the first auction at a price up to V_H.

In fact, the sealed-bid auction does not have a symmetric equilibrium in pure strategies. The intuition is as follows: Suppose that each high type enters a proxy bid equal to $b^* > V_L$. Relative to sitting out the first auction and waiting for the second, proxy bidding b^* benefits the buyer when the other two bidders are also high types – but the buyer gets the benefit in that case only with probability one-third. In contrast, a proxy bid of b^* hurts the buyer with conditional probability one-half when only one of his opponents is a high type. (If both competitors have low valuations, then the buyer gets the same payoff, $V_H - V_L$, from entering b^* as from waiting.) If a high type deviates by bidding $b^* + \varepsilon$, he wins the first auction for sure. By doing so, he doubles his chances of incurring the cost, but triples the probability of gaining the benefit. Thus, if the buyer is willing to enter a proxy bid of b^* rather than wait, then he must strictly prefer to enter $b^* + \varepsilon$ instead, so there is no symmetric, pure-strategy equilibrium. A similar argument shows that in equilibrium, a high type's mixed proxy-bidding strategy cannot have any mass points.

Thus, the only symmetric sequential equilibria of the first auction have the following characteristics:

Proposition 2: Given Assumption 1, the only symmetric sequential equilibria of the first auction call for low-type buyers to enter a proxy bid of V_L and for high-type buyers to randomize over the interval

$$\left[V_L, (1-q)V_H + qV_L\right]$$

according to the cumulative distribution function

$$F^*(b) = \frac{q(b - V_L)}{(1-q)(V_H - b)}.$$

No more than one high type enters that proxy bid before the end of the auction at time T_1. Low types may enter their proxy bids at any time during the auction, and both types may enter other, lower proxy bids before time T_1.

At the end of the auction, the buyers with high valuations are indifferent between submitting a proxy bid anywhere in the support of the *cdf F**, entering a proxy bid above it, or not entering a proxy bid at all and waiting until the second auction, as long as the other buyers follow the equilibrium strategies. The expected payment for a high-type who submits proxy bid $(1-q)V_H + qV_L$ and thus wins for sure is

$$(1-q)^2 V_H + \left[1-(1-q)^2\right]V_L,$$

yielding surplus

$$\left[1-(1-q)^2\right](V_H - V_L).$$

That value is the same expected surplus as waiting until the second auction and, by construction, the same expected surplus from a proxy bid anywhere in the support of *F**.

The expected revenue for the first seller is calculated as the probability $(1-q)^3$ that all three buyers are high types times the expectation under *F** of the second-highest of three proxy bids, plus the probability $3q(1-q)^2$ that two buyers are high types times the expectation of the lower of two proxy bids, plus the complementary probability that at most one buyer is a high type times V_L. That expected revenue is equal to

$$(1-q)^3 V_H + \left[1-(1-q)^3\right] V_L,$$

which is the same as the second seller's expected revenue. The winning bid in the second auction is V_L unless all three buyers are high types – one wins the first auction, and the other two compete up the price in the second to V_H.

As a result we have the following three qualitative results; 1) low types submit their valuations as proxy bid while the high types randomize over a certain interval according to a cumulative distribution function; 2) low types submit their proxy bids at any time during the auction but the high types (all except one) perform last-minute bidding (sniping); 3) expected revenues from the two auctions are equal.

3.3 THE DATA

Our dataset consists of information collected for Texas Instruments TI-83 Graphing Calculator auctions featured on eBay. The data includes every auction that took place between June 15th, 2003 and July 30th, 2003. We chose this item due to the availability of many data points as well as the relatively homogeneous nature of the good itself. Dutch auctions, in which bidders compete for multiple quantities of an item, and private auctions, in which information about the bidders are not available, are excluded from our dataset. For this purpose in this Chapter, we have also excluded Buy-It-Now auctions from our dataset.[13] The information about the final transaction of the item is not revealed by eBay. Therefore, we cannot distinguish between auctions ending with a successful sale and auctions ending without any sale. We assume that all auctions that attracted a bid ended with a sale and the winner was the buyer with the highest standing bid.

There are 1,817 unique auctions that were completed in the 6-week period. We observe 4,289 bidders who participated in these auctions and submitted 13,241 bids in total.[14] Moreover, we observe 192 unique auctions that did not receive any bids or were cancelled. For this study we do not include no-bid auctions in our data set. We provide the descriptive statistics of the variables in Table 7. More information on the variables along with discussion of the summary statistics is provided below.

The winning bid is the price that the winner pays at the end of the auction. Remember that this price is the willingness-to-pay of the second-highest bidder plus the

[13] Nevertheless, our dataset includes some wiped-out Buy-It-Now auctions which we are not able to exclude since we do not observe them. This is due to the impossibility of detecting those auctions after the BIN option disappears with a bid meeting the reserve price.
[14] We detected 229 bids without any bidder ID. Fortunately, most of these bids do not affect the outcomes of the particular auctions.

bid increment. Our dataset shows that the TI-83 calculators on eBay sell for a bit more than $58 on average. They also have a standard deviation around $17 which is mainly due to the presence of used and new items.

Using the starting bid variable, the seller sets the amount her auction will start from. Any bid that is submitted has to be equal to or greater than this amount. A closely related variable is the minimum bid, which is the lowest submitted bid that we observe in our dataset. Minimum bids are, on average, a little higher than the average starting bids set by the sellers. This is due to some inconsistency in eBay's method of recording the first submitted bid. In some auctions the minimum bid and the starting bid are identical however in some others the minimum bid is above the starting bid. This discrepancy does not have any effect on our results. Additionally, there is evidence of reasonable interest by potential buyers in eBay's TI-83 auctions. On average, these auctions last more than 5 days with about 7 bidders showing up and submitting more than 13 bids per auction.

Another important feature of eBay is the feedback score that both sellers and bidders receive. EBay users can provide feedback on each other anytime up to 90 days after the completion of a transaction and the feedback assigned is permanent. A positive comment earns the user a +1 point, a neutral one 0 points and a negative comment corresponds to -1 point. The feedback score is the sum of all the points that the user receives from other parties. In our sample, the mean seller and bidder ratings are 663 and 49 respectively. The sellers are more experienced than the bidders for TI-83 auctions on eBay. The median seller has a feedback point of 50 and the same number is only 6 for the bidders.[15]

3.4 ANALYSIS OF EBAY DATA

We cannot distinguish among the bidder types in our dataset thus we cannot test our first prediction of low types bidding V_L and high types randomizing over a certain interval. However, we study the bid submission times to confirm the main result of our theoretical section; the existence of last-minute bidding. Additionally, we compare and statistically test sellers' revenues for auctions in which late-bidding exists against the ones in which the winning bid is submitted prior to the last-minutes of the auction. One of the implications of our theoretical results is that when there is no LMB in the first auction, it means that at most one bidder is a high-type or all bidders are low-types. As a result, conditional on sale, the revenue from this auction should be lower than the revenue from an auction with LMB.

First we analyze the TI-83 calculator data in eBay and study the last-minute bidding (LMB) phenomenon. We introduce a new and informative approach to studying bid submission times. Many auctions on eBay run around the same time and, as a result, their ending times are fairly close to each other. Analogous to the strategy in our theory model, we believe that a potential buyer would always bid on the early closing auctions. In case she fails to win, then she moves on to one of the next closing auctions. Thus, we

[15] In 22 auctions we do not observe the seller ratings. However, the data points we observe are enough to conclude that the sellers are fairly experienced. Therefore, it is reasonable to think that they follow revenue maximizing strategies in their auctions.

see a trend of bidders preferring to bid on soon-to-end auctions. This trend is strengthened by the order in which eBay displays the auctions after a search for an item has been performed. The auctions are listed according to their closing times with the early closing ones at the top of the list. As a result, when the interval between closing auctions is short enough, it is hard to differentiate among two types of bidders. First type consists of bidders strategically waiting until the end of the auction to snipe. The second type of bidders are the ones just moving onto the next closing auction because they were not successful winning the previous one. Thus, we believe that the existence of short intervals between consecutive closing auctions might incorrectly add to the appearance of last-minute bidding on eBay.

For instance, consider an auction that closes two minutes after the previous one has ended. Some bidders may be strategically waiting until the last minute of the auction to submit their bids, but others may have lost in the previous auction and are moving on to bid in the next-to-close auction. In some previous studies in the literature these two types of submissions would both be categorized as last-minute bids although they actually are not. However, we show that even after controlling for previous losers' bids, significant volume of strategic last-minute bidding exists in eBay.

In order to observe if these intervals are indeed small, we arrange the auctions sequentially by their closing times. In Table 8 we report the summary statistics of the minutes between the closing times of consecutive auctions. We refer to the period that is between the closing times of auctions as the 'Closing Interval'. The table reveals that, on average, the closing times for auctions are 33 minutes apart while having a very low minimum (0) and a relatively high maximum (714). The median for the closing intervals is 14 minutes. We infer that these intervals are highly skewed with most of them lasting only for very short periods of time. This means many of the auctions in our dataset close soon after the previous one ends. Table 9 presents us a closer look at the distribution of the closing intervals. We observe that in more than 6 percent of the time, the closing interval is equal to zero. Moreover, almost one third of the consecutive auctions have 5 minutes or less between their closing times.

As mentioned earlier, the existence of very short closing intervals might lead to an uncertainty about the amount of LMB among bidders. Thus, an accurate way of measuring the extent of LMB is by studying the distribution of bid times relative to the length of the closing interval. Histograms in Figure 2 compose of bins representing 2 percent of the length of the respective closing interval. Our focus is on the submission times of the highest proxy bids submitted by bidders. In the figure, we omit from sample auctions with short closing intervals in order to distinctly observe their effect on the bid submission times. First histogram contains all closing intervals in our dataset. For the second graph we exclude auctions with closing times less than or equal to a single minute. Similarly, for the third and fourth histograms we leave out less than equal to 3 and 5 minute closing intervals respectively.

The existence of some spikes prior to the end of the auctions is apparent in the first figure. For instance, in the first graph we observe that 5 percent of the bids are submitted before 2 percent of the closing interval has elapsed (first 17 seconds of a 14 minutes interval which is the median length in our dataset). However they fade away as we drop the closing intervals and the final histogram becomes almost smooth. This is due to the existence of quite short intervals and when we only consider longer ones, we observe a much smoother distribution.

In addition to that, the big spike in the first bin represents existence of last-minute bidding. In all four cases we see that between 20-25 percent of the proxy bids are submitted after the 98 percent of the closing interval has elapsed (last 12 seconds of a 10 minute interval). This number confirms the existence of strategic bidders waiting until the last minute to submit their bids. The magnitude of the first bin is closer to 25 percent in the first graph but falls down to 22 percent when we leave out some short closing intervals. As we have mentioned earlier, the reason for this drop is the omission of short intervals that are responsible for the slightly overestimated appearance of LMB.

Our data confirms the existence of last-minute bidding on eBay but also draws attention to the bidders from previous auctions submitting their bids without strategically waiting for the last minutes of an auction. We believe that other researchers should also pay attention to these bidders and should not consider them as a part of the last-minute bidding activity.

Next, we focus on sellers' revenues depending on the winning bid being submitted in the closing minutes of an auction or earlier. Our theory suggests that conditional on sale, the revenue for auctions with winning bids submitted in the last minutes should be higher than the revenue for auctions in which the winning bid is submitted early on in the auction. However, prior to testing our theoretical prediction, we correct for some of the heterogeneity in our dataset that is due to the existence of both new and used items. The variation among the winning bids for these auctions is substantial. We identify auctions in which the winning bid is greater than or equal to $80 as new. This is the lowest price any potential buyer can purchase a new TI-83 calculator from a retail store. We classify the rest of the auctions in our dataset as used. Next, we run two-sample t-tests for both categories.

We perform two-sample t-tests for both categories and test if the winning bids submitted in the closing minutes of the auction are on average higher than the ones submitted earlier. The summary statistics and the results for the t-tests are reported for new items in Table 10 and for used items in Table 11.[16] In both cases the average last-minute winning bid is larger than the average early winning bid. However, the difference is statistically significant only for used items. This might be due to scarcity of observations in the new item category. We observe only 292 auctions with new items while there are 1525 auctions offering used calculators. Nevertheless, we illustrate that our theoretical prediction is satisfied for the most part of our dataset. The revenue for auctions with winning bids submitted in the last minutes is higher than the revenue for auctions in which the winning bid is submitted early on in the auction.

3.5 CONCLUSION

In this study, our main focus is on the incidences of the delay of proxy bid submission due to last-minute bidding. We specify a two-period, three-bidder model in which two identical items are auctioned sequentially by different sellers. Our results show that high-value types wait until the end of the auction to reveal their types by submitting proxy bids, while low-value types may submit a proxy bid at any time. The intuition is as follows: revealing one's type early decreases the opponent's expected utility from winning the subsequent auction, causing her to bid more aggressively in the current one. Additionally, we show that expected revenues for the sellers in both

[16] Detailed information about the tests is presented in the appendix.

auctions are equivalent. The existence of LMB does not alter the expected revenue of the first seller.

Then, we analyze the data we have collected from eBay auctions to test our theoretical predictions. Our dataset comprises 1,817 auctions of Texas Instruments TI-83 Graphing Calculators and the bids submitted in those auctions. We arrange the auctions by their closing times. As a result, we confirm the existence of strategic last-minute bidding as our theoretical model predicts. Additionally, we draw attention to the bids of losers' from previous auctions that might appear as strategic last-minute bidding when the interval between closing auctions is short enough.

Lastly, we compare and statistically test sellers' revenues for auctions in which late-bidding exists versus auctions with early submitted winning bids. We perform two t-tests using the data for new and used items. The average revenue for auctions with late-bidding is indeed higher than the others but the difference is statistically significant only for used items, which represent the majority of the auctions in our dataset.

Our theoretical specification of the sequential structure of sale describes the actual eBay setting more precisely compared to other studies in the auction literature. In our model last-minute bidding arises endogenously as a result of the sequential structure. An extension of this framework would be to incorporate simultaneous, overlapping and sequential auctions that can capture the complexity of trading in online markets.

Another way to extend our research is to analyze the Yahoo online auction site. Yahoo has many features in common with eBay but differs in some very interesting aspects. Yahoo is a thinner market relative to eBay, both in terms of variety of products traded and in terms of the volume of trading. Moreover, it offers different ending rules for auctions and has a distinctive buy-now feature. These variations can potentially affect the strategies of buyers and sellers quite differently, compared to eBay. It would be interesting to study how these distinctions affect players' strategies and auction outcomes in these two markets.

Chapter 4

Preemption in EBay Auctions

4.1 INTRODUCTION

EBay allocates the item through an auction with proxy bidding, which is a mechanism that bids on behalf of the bidder up to a reservation price specified by her. At the end of the auction, the bidder with the highest reservation price wins the item by paying an amount equal to the second highest reservation price submitted. The auction thus resembles an ascending, second-price auction. Additionally, the auction lasts for a number of days that is chosen by the seller. Thus, by choosing the starting date and length of the auction, the seller also chooses the precise day and time it closes.

However, it is possible for bidders to preempt and end the auction early by executing the Buy-It-Now (BIN) option if it is offered. The BIN feature gives sellers the opportunity to provide bidders with the possibility of buying the item forthwith by paying the BIN price. The advantages of paying the BIN price to the bidder are that she is certain to win the item, she does not have to compete with other potential buyers, and she does not have to wait for the auction to end. However, to execute the BIN option the bidder has to act quickly since the opportunity disappears once a proxy bid that is equal to or higher than the reserve price is submitted. When this occurs, the BIN option is removed from the auction web site by eBay. Of course, the seller can prevent this from happening by setting the reserve price equal to the BIN price. When the reserve price is equal to BIN price, the auction actually becomes a posted price mechanism.

On the surface it seems like the BIN price puts a limit on the bids which also restricts sellers' expected revenue in an ascending auction setting like eBay. However, sellers regularly offer this option. In this paper we answer the puzzling question about the existence of this preemption feature in eBay auctions. We analyze the Buy-It-Now option in a dynamic eBay environment to explain the rationale behind the existence of this feature. We show the conditions under which the bidders prefer to preempt the auction by paying the BIN price. Accordingly, we compare the expected revenues for the sellers to demonstrate when sellers are better off offering a Buy-It-Now option.

Most of the studies about the BIN option in the literature have focused on stand-alone auctions. Existence of the BIN feature has been explained with the presence of risk-aversion and impatience among bidders and/or sellers. Instead, in our study we focus on multiple auctions free of any assumptions on the agents' preferences. We have a two-period model in which two identical items are auctioned sequentially by different sellers. The first seller offers a BIN option. We show that there is a symmetric equilibrium in which the first auction either ends quickly with a buyer exercising the BIN or it ends with no sale and bidders move on to the next auction. The outcome depends not only on the valuation of the bidders but also on the sequence of their arrival. Consequently, we characterize the conditions under which a seller can increase her revenue using the BIN option.

There is couple of theory papers in the literature that focuses on the Buy price options both in eBay and Yahoo. Buy price is the term used in the literature for all types of options that let bidders preempt and end the auction early. One of the earlier studies, Budish and Takeyama (2001), considers the Buy-Now price offered by Yahoo and study whether utilizing this option makes sense for the sellers. Unlike its eBay counterpart Buy-It-Now, Yahoo's Buy-Now option does not disappear once bidding starts. In this study, they show that sellers can increase expected revenue by using Buy prices when bidders are risk averse. The Buy price enables the seller to extract a premium by reducing risk for high-value bidders.

In another paper, Reynolds and Wooders (2004) compare the Buy prices for two online auction houses, eBay and Yahoo. Their results show that when bidders are risk-neutral, both Buy prices are equivalent to the standard English ascending bid auction in terms of revenue. However, with risk-averse bidders, the sellers in both auction houses can raise more revenue by using the Buy price feature than with ascending bid auctions.

Recent studies by Timothy Mathews also pay a good deal of attention to the online Buy price topic. In his work, Mathews (2005) compares the welfare of bidders in a Buy price auction and a regular one. He shows that the effect of the Buy price on the bidder welfare depends on the distribution from which bidder valuations are drawn. In another work, Mathews (2004) shows that discounting is crucial for the seller's choice of Buy price option. If there is discounting by the seller or the bidders, then the seller can choose a Buy price which has a positive probability of being exercised. Moreover, in a joint work, Mathews and Katzman (2004) use a model composed of risk-neutral bidder and risk-averse sellers. They show that the seller can increase her expected utility compared to a sealed bid second price auction by offering a Buy price that is low enough to get exercised.

Similar to our research, Kirkergaard and Overgaard (2004) study Buy prices on eBay taking the presence of multiple auctions into account. They show that the first seller is better off setting a Buy price even when the buyers and sellers are risk-neutral. Their study differs from our research since they assume that the bidders have multi-unit demands and they do not take reserve prices into consideration. In contrast, we assume that buyers have single-unit demands and sellers utilize the reserve price by setting it as high as the Buy-It-Now price. We build our theoretical model using these modeling assumptions which are motivated by the facts obtained from our eBay dataset. Despite the differences in these two studies, the results are similar which is due to the dynamic nature of both models.

Subsequently, we test the predictions of our theory using eBay data from 709 auctions of Texas Instruments TI-83 Graphing Calculators. We study how the execution times are distributed and show that most of them are executed early on in the auction. Then, we statistically test and show the validity of one of our theoretical predictions that conditional on sale, the revenue for executed BIN auctions should be higher than the revenue for No-BIN auctions with no reserve price. This result is motivated by the trade-off between lower probability of sale and higher revenues as a result of offering a BIN option.

The rest of the paper is organized as follows. In section two we present the model and our theoretical results. Section three briefly introduces the dataset. In section four, we analyze the eBay data to statistically confirm our theoretical findings and empirically study the timing of the execution of BIN. Finally, in section five, we present our conclusion and suggest future research ideas.

4.2 THE MODEL

The main structure of the model is the same as the one we have introduced in Chapter 3. Nonetheless, we repeat some key parts of our theoretical model as a reminder. We study the following simplified version of the eBay auction setting. There are two potential sellers and three potential buyers of a good. All agents are risk-neutral, their utility is quasilinear in wealth, and they do not discount the future. There are two possible types of buyer; with probability $q \in (0,1)$, a buyer is a low type, and with the complementary probability he is a high type. The three buyers' types are independent. Each type of buyer wants at most one unit of the good, and values that one unit at V_L if he is a low type and at V_H if he is a high type, where $V_H > V_L > 0$. The unit-demand assumption for the bidders is motivated by the facts from our dataset, which we present in the next section. Each seller has one unit of the good to sell, and values the good at zero. This structure is common knowledge, although the buyers' realized types are private information.

The sellers run consecutive auctions. Each auction is a continuous-time, second-price auction with proxy bidding.[17] Seller 1's auction runs from time t_1 to time T_1, and the second auction runs from t_2 to T_2, where $t_1 < T_1 < t_2 < T_2$. The assumption that the auctions do not overlap is not important. However, it is crucial that one auction ends before the other. Sellers choose whether and at what level to set their (publicly observed) reserve price[18] and Buy-It-Now price. Both sellers must make their choices before the beginning of the first auction, and their choices are observed by buyers at that time.

[17] A detailed description of the proxy-bidding program is introduced in Chapter 2.
[18] Actual eBay auctions have both a public "starting bid" and a hidden "reserve price," as described in Chapter 2.

A seller has the option of specifying a Buy-It-Now (BIN) price *B*. By exercising the BIN option, a buyer can pre-empt the auction and acquire the good for the price *B*, as long as *i)* the BIN option has not been previously exercised, and *ii)* no buyer has entered a proxy bid greater than or equal to the reserve price. That is, buyers can "wipe out" the BIN option by entering a proxy bid above the reserve. In that case, the auction proceeds as above. If two or more buyers attempt to execute the BIN option simultaneously, then the winner is determined randomly. Execution of the BIN option is publicly observed.

We assume that the minimum bid increment ε is vanishingly small.[19] In particular, we assume that a buyer with valuation V is indifferent between paying p for the good and paying $p + \varepsilon$, as long as $p < V$, but is unwilling to pay $V + \varepsilon$.

Buyers arrive at the first auction in random order. An arriving buyer knows whether he is the first, second, or third to arrive. That assumption is consistent with the fact that most eBay auction sites have counters that display the number of visitors to the site. All buyers are present at the start of the second auction (although one may have already obtained an item, and thus will not participate).

We analyze the case in which the first seller offers a BIN price and the second seller does not. We assume that the seller sets the reserve price equal to the BIN price. The motivation for this assumption originates from the facts we gather using our dataset. These facts are presented in the next section. We suppose that the second auction has no reserve and no BIN option. In our model, a pure strategy for the first seller is the choice at what level to set a BIN price B which equals to a reserve price R. A pure strategy for a buyer tells him whether and at what amount to enter a proxy bid, and whether to execute the BIN option, as a function of time, his own previous actions, the history of bids and

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[19] Bid increment is the lowest amount by which a bidder can raise the highest-standing bid. This number is predetermined by eBay and it depends on the highest-standing bid.

BIN executions, the order of arrival at the first auction (including which buyers, if any, have yet to arrive), and (during the second auction) the outcome of the first auction. A buyer cannot execute the BIN option in the first auction before it begins and he arrives, or enter a proxy bid in the second auction before it begins. Mixed strategies are defined straightforwardly.

We look for symmetric sequential equilibria. As an equilibrium selection device, we utilize Assumption 1 which we have introduced in Chapter 3. In the second auction, therefore, each remaining buyer (that is, those who did not obtain the item in the first auction) will play his conditionally weakly dominant strategy to enter a proxy bid equal to his valuation at the end of the auction at time T_2, if he has not previously entered a proxy bid that high, and the auction has not been pre-empted by the execution of the BIN option (if there is a BIN option available). Consequently, the outcome of the second auction is as follows:

Proposition 3: In the absence of a BIN price, the outcome of the second auction is the same as that of a second-price, sealed-bid auction.

Proof: Low types will not enter a proxy bid greater than V_L, because they might get negative surplus. If they enter a bid less than V_L, then a low type can deviate to V_L and increase his surplus in the case where the other buyer or buyers are low types, or where only the proxy bids of low types are not rejected. By a similar argument, high-type buyers will enter a proxy bid equal to V_H. Thus, the outcome will be the same as that of a second-price, sealed-bid auction. *Q.E.D.*

Our main interest is in the outcome of the first auction. Recall that we have already analyzed the case of no-BIN and no reserve price in Chapter 3. Now, we consider bidder behavior in the first auction in presence of a BIN price equal to the reserve price.

If the equal reserve price and BIN prices (*R* = *B)* are greater than $\left(1-q^2\right)V_H + q^2V_L$, then in equilibrium no buyer executes the BIN option. The reserve/BIN price is greater than the low types' valuation, and the high types expect to do better by waiting for the second auction: with probability q^2, both opponents are low types and the high type buyer can win the second auction at price V_L. If the reserve/BIN price is below V_L, then the first buyer to arrive at the first auction will execute the BIN option, regardless of his type. The interesting scenario is when $R = B$ lies between V_L and $\left(1-q^2\right)V_H + q^2V_L$.

With a BIN option available, dynamics and learning come into play. For example, if the second buyer arrives at the auction and observes that the BIN option is still available, he can conclude that the first buyer to arrive chose not to execute it, and may be able to infer the first buyer's type from that choice.

We define p(r) as

$$p\left(r\right) = \left(1-q^r\right)V_H + q^rV_L ,$$

so that a high-type buyer who obtains the item for price $p\left(r\right)$ gets the same surplus that he would expect from participating in the second auction, if he is to be faced by *r* potential competitors in the second auction. These *r* potential competitors are buyers who are low types with probability *q*. Buyers known to be low types do not count as potential competitors. Note that $p(2)$ is the bound above which the BIN option will not be executed, and that $p(0)=V_L$. Proposition 4 describes an equilibrium of the first auction with equal reserve and BIN prices.

Proposition 4: Given Assumption 1, the following strategies constitute a symmetric sequential equilibrium of the first auction when it has a reserve price $R \in (p(r-1), p(r))$ for $r \in \{1,2\}$ and a BIN price equal to *R*, and the second auction has neither a reserve price nor a BIN option: Low-type buyers neither execute the BIN option nor enter a proxy bid. A high-type buyer who is among the first *3 – r* buyers to arrive at the auction executes the BIN option upon arrival, if it is still available. A high-type buyer who is among the last *r* buyers to arrive neither executes the BIN option nor enters a proxy bid.

Proof: Not bidding is a best response for the low types, because the reserve/BIN price *R* exceeds their valuation. The strategies for the high types are also best responses. If Buyer *i* is one of the first *3 – r* buyers to arrive, then he knows that the second auction will include at least *r* other buyers, each of whom are low types with probability *q*: the last *r* buyers wait until the second auction regardless of their types. Therefore, if Buyer *i* is a high type, then he gets a greater expected surplus from executing the BIN option than from waiting, because the BIN price *R* is less than $p(r)$. If Buyer *i* is one of the last *r* buyers to arrive, and the BIN option is still available, then he knows that the first *3 – r* buyers are low types, which means that he will face at most *r – 1* potential competitors in the second auction. Since $R > p(r-1)$, he does better to wait for the second auction and not to execute the BIN option or enter a proxy bid. *Q.E.D.*

The analysis in the previous paragraph assumes that the strategy space for each buyer is a once-and-for-all decision whether or not to execute the BIN option when he arrives. That assumption is without loss of generality. Potentially, a buyer might want to wait and observe the actions of subsequent arrivers before deciding. However if he waits, either he will observe subsequent buyers passing on the option (which weakly lowers the attractiveness of the BIN option, since it weakly increases his belief that the passers are low types), or another buyer will execute the BIN option (in which case he must wait until the second auction). So deciding to wait is the same as deciding not to execute the option at all.

The first seller's expected revenue from setting a reserve/BIN price between $p(r-1)$ and $p(r)$ is the probability $1-q^3-r$ that at least one of the first 3 – r buyers to arrive is a high type and thus willing to execute the BIN option times the BIN price *B*. To maximize revenue, the seller would set *B* equal to ε less than $p(1)$, which yields expected revenue

$$\left(1-q^2\right)\left[(1-q)V_H+qV_L\right]$$

Recall that in Chapter 3 we have established the expected revenue for sellers offering no reserve or BIN price is equal to

$$(1-q)^3 V_H+\left[1-(1-q)^3\right]V_L$$

After comparing the two expected revenues and performing some simple algebra, we note that the first seller can increase his expected revenue if

$$V_H - V_L > V_L \left[\frac{q}{2(1-q)^2} \right]$$

There are two reasons why the BIN option may give the seller higher revenue. First, in the mixed strategy equilibrium of the first auction with no reserve or BIN price, high-type buyers are indifferent between high and low proxy bids within the support of F*, while the seller prefers that they enter high proxy bids. The BIN price limits them to a relatively high price. Second and more importantly, with the BIN option, late-arriving high types, if the BIN option is still available, conclude that many of the other buyers are low types and therefore wait until the second auction. That decision reduces the expected surplus from the second auction for early-arriving high types, because they are more likely to face other high types there, and so increases their willingness-to-pay in the first auction.

As the main result of our theoretical model we establish that it is rational for the first seller to set a BIN price and an equivalent reserve price when there are multiple auctions in eBay. More precisely, there is a trade-off for sale for the first seller when deciding on introducing the BIN option. Starting the auction with a BIN option lowers the probability of sale. Thus, one of the results is that, conditional on sale, the revenue for executed BIN auctions are higher than the revenue for no-BIN auctions with no reserve price.

We realize the following three qualitative results; 1) low-type buyers neither execute the BIN option nor enter a proxy bid; 2) a high-type buyer who arrives early executes the BIN option but if she arrives late, she neither executes the BIN option nor submits a proxy bid. Thus, the probability of the BIN option getting executed is decreasing with the number of arrivals; 3) conditional on sale, the revenue for executed BIN auctions are higher than the revenue for no reserve or BIN price case.

4.3 THE DATA

Our dataset consists of information collected for Texas Instruments TI-83 Graphing Calculator auctions featured on eBay. The data includes auctions with the Buy-It-Now option that took place between June 15th, 2003 and July 30th, 2003. We chose this item due to the availability of many data points as well as the relatively homogeneous nature of the good itself. Dutch auctions, in which bidders compete for multiple quantities of an item, and private auctions, in which information about the bidders are not available, are excluded from our dataset.

We observe 709 unique auctions with a BIN option that were completed in the 6-week period. We recognize that this number is not fully accurate; the actual number is probably greater than 709. The imprecision is due to the difficulty of data collection regarding the BIN option since it disappears when the reserve price is met. Among the 709 BIN auctions that we observe, in 553 of them the BIN option is exercised by 511 bidders. 156 of them had the BIN option wiped out by a bidder submitting a bid that meets the reserve price set by the seller. We have collected several variables that reflect the features of the TI-83 auctions in the 6-week period. Table 12 provides descriptive statistics for our dataset.

One of the options that the sellers decide while designing their auctions is to set a secret reserve price. Due to the secret nature of this feature, we are not able to observe when the reserve price option is implemented in any of the auctions in our dataset. Instead, we treat the *Starting bid* as the posted reserve price that is set by the sellers. Using the *Starting bid* variable, the seller sets the amount that her auction will start from. In our dataset, this variable has a mean of $51.02. In Table 13 we study the *Starting bids* for all the BIN auctions. We expect to see high *Starting bids* set by the seller in order to protect the BIN option being wiped out. Table 13 shows that almost 74 percent of the auctions have the *Starting bid* equal to the *BIN price*. Furthermore, a careful study shows that 30 percent of the rest set the *Starting bid* more than half of the *BIN price*. Thus, a big majority of the sellers who utilize the *BIN price* also set the *Starting bid* exceptionally high, and in most cases as high as the *BIN price* itself.

Next, we analyze the bidding behavior of TI-83 buyers on eBay. We have performed a similar study using our whole dataset in Chapter 2 and concluded that the bidders in general have single-unit demand. However, in Table 14, we specifically focus on the bidders who win an auction by utilizing the BIN option. We are interested in their decision after executing the BIN option: Do they keep bidding in another auction (*Stay*) or leave the auction site (*Leave*)? If we do not observe them bidding again in any TI-83 auction in our dataset, we conclude that they have left. Our findings show that 93 percent of the bidders just leave the auction site after they win. There are only a small percentage of them who stay and keep bidding. We utilize this fact by building our theoretical model accordingly, in which the winners do not participate in upcoming auctions.

The final transaction price of the auction is the *Winning bid* which has a mean of \$60.06, while the average is slightly higher for the BIN price, \$62.48. These variables are closely related; for executed BIN options the *Winning bid* is the *BIN price* itself. Thus, it is intuitive to observe a higher average for the *BIN price* since for most auctions the *BIN price* acts like an upper bound of the support for the bids submitted.

The main focus of this study is the BIN option and execution of it by the bidders. In addition to the major variables mentioned above, the following ones are also helpful in understanding the bidders' decision of execution: *Starting hour, Monday, Tuesday, Wednesday, Thursday, Friday, Saturday, Sunday, and Seller rating*. We believe that the day of the week and the time of the day BIN auction starts are crucial for its execution. The number of bidders viewing the auction soon after its commencement is correlated with when the auction is posted. As a result, it has a direct effect on the BIN option either being wiped out or executed and how quickly one of these actions takes place. We include dummy variables indicating the day of the week auction starts. They are equal to one if the starting day is the same as the dummy variable and zero otherwise. Starting hour has 24 different values indicating the hour of the day that auction starts. In Table 12 we see that *Thursday, Friday* and *Saturday* are less popular in terms of posting a BIN auction. The mean and median Starting hours are around 2pm in the afternoon. This indicates that more sellers post their auctions on days and times during which they expect to have more potential bidders.

Another important feature of eBay is the feedback score that both sellers and bidders receive. EBay users can leave feedback for each other anytime up to 90 days after the completion of a transaction and the feedback assigned is permanent. A positive comment earns the user a +1 point, a neutral one 0 points and a negative comment corresponds to -1 point. The feedback score is the sum of all the points that the user receives from other parties. In our sample, the mean Seller and Bidder ratings are 403 and 49 respectively. The sellers are more experienced than the bidders for TI-83 auctions on eBay. The median seller has a feedback point of 86 and the same number is only 9 for the bidders.[20]

The variable *Duration of auction* represents the time elapsed until the BIN price is executed and the auction is closed. Alternatively, *Auction length* is the number of days the seller sets the auction for. The latter is available only for auctions in which the BIN option is wiped out. We measure this variable in hours but also report it in days or minutes when necessary. The mean for *Duration of auction* is around 31 hours with a median around 13 hours. The minimum is 0.07 hours which corresponds to slightly less than 2 minutes. This is an example of how quickly the BIN option can be executed. Similar numbers are considerably higher for the variable *Auction length*. On average, the auctions last for more than 5 days in our dataset. Lastly, we report the *Number of bids* and *Number of bidders* observed at the end of the auction. On average, about 2 bidders show up for these calculator auctions and end up submitting around 3 bids per auction.

4.4 EMPIRICAL ANALYSIS OF BIN AUCTIONS ON EBAY

We cannot distinguish among the bidder types in our dataset thus it is not feasible to test our prediction regarding the type of bidder executing the BIN price. We also

[20] In 9 auctions we do not observe the seller ratings. However, the data points we observe are enough to conclude that the sellers are fairly experienced. Therefore, it is reasonable to think that they follow revenue maximizing strategies in their auctions.

cannot test the theoretical result that probability of a successful sale is less than one when the seller offers a BIN price. However, we study the BIN execution times to test another result from the theoretical section; the decline of the probability for execution of the BIN option with the increase in the number of potential buyers arriving. Since we cannot observe the arrival of potential bidders, we use time as a proxy. Lastly, we perform a statistical test to show that conditional on sale, the revenue for executed BIN auctions are higher than the revenue for no reserve or BIN price case.

As we stated in the theory section, the sellers set auctions with a BIN option where the reserve price is equal to the BIN price and the bidders either execute the option at the beginning of the auction, before more buyers arrive, or they wait for the second auction. This depends on the type and the arrival time of the bidder. Since we do not observe the number of potential buyers visiting the auction site, we use time as a proxy. Our implicit assumption is that as time elapses, more potential buyers are visiting the auction site and with a certain probability they are high types.

In Figure 3 we report the distribution of BIN execution times. We measure the number of hours that pass after the auction starts until the BIN option is executed. Most of the BIN options get executed in the early hours of the auctions. Every bin in the histogram represents a time frame of 12 hours. Almost 40 percent of the BIN executions take place in the first 12 hours of the auction (that is 10 percent of the auction length for a 5 day auction). In addition, 10 percent of the executed BIN auctions last for slightly more than a single hour. This suggests that in most cases the BIN price is executed immediately. These findings are consistent with our theoretical result that the BIN option gets executed early on in the auction.

An alternative method of studying BIN execution times is by making use of survival analysis. In accordance with our theoretical results, the hazard rate for execution of the BIN option should be decreasing as more bidders arrive. As mentioned earlier, for this analysis we use time as a proxy for the number of potential buyers visiting the auction site. We define the failure for the hazard function as the execution of the BIN option.[21] We utilize the Kaplan-Meier estimator to graph the hazard function in Figure 4. In the first 6 days of our dataset the hazard function is indeed decreasing. We observe fluctuations on and after the seventh day. One reason might be the difference in our analysis of the time variable. In the theory, we predict that the hazard rate is decreasing as more potential bidders arrive, whereas for our hazard function we consider the number of days.

Alternatively, Figure 4 might be indicating that in addition to the BIN option being executed early on in the auction, some bidders in fact wait until the end of the respective auction to push the Buy-It-Now button. This might be due to the bidders' consideration of overlapping auctions. Potential buyers may be monitoring multiple auctions running around the same time. It is reasonable to think of a bidder who submits a proxy bid at a non-BIN auction and waits until the end to see if she wins. In case she is not successful, she might go for an available BIN option. However, our theoretical model requires modifications in order to explain this fact.

Next, we focus on sellers' revenue depending on the existence and execution of the BIN option. Our theory suggests that conditional on sale, the revenue for executed BIN auctions should be higher than the revenue for No-BIN auctions with no reserve

[21] We are aware that most of the auctions in which the BIN is not executed end before 10 days. There is right censoring in our dataset. We follow the method proposed in Kiefer (1988) to correct for this problem. When the auction is closed, either due to execution or expiration of the auction, it is deducted from the number of observations that are "at risk" for the next day.

price. We use the non-BIN auctions from the dataset we have introduced in Chapter 3 to test our theoretical prediction. We consider auctions with a reserve price of $5 or less and regard them as auctions with such low reserve price that they essentially qualify as a no-reserve auction. We report the summary statistics for winning bids in both types of auctions in Table 15. We observe that when there is neither a reserve price nor a BIN option, the average winning bid is $58.1. Alternatively, when there is a BIN option and a reserve price, the average bid is higher, $59.95. To test if these average winning bids are significantly different, we run a two-sample t-test with unequal variances and report our results in Table 16.[22] Our two samples consist of auctions with executed BIN option and a reserve and No-BIN auctions with low reserve price. From our test statistic, we see that the difference between their average values is significantly different than zero.

4.5 CONCLUSION

In this study, our main focus is on the preemption due to execution of the Buy-It-Now option. We study bidders' strategic incentive to execute the BIN feature as well as the timing of the execution. We build a two-period theoretical model motivated by preliminary observations from our dataset. Two identical items are auctioned sequentially by different sellers. The first seller offers a BIN option. Its execution depends on the valuations of the bidders and their sequence of arrival to the auction site. The buyer learns about other bidders' types depending on the timing of her own arrival to the auction site. When the high-value bidder is among the early ones to arrive, she

[22] Detailed information about this test is presented in the appendix.

executes the BIN option. However, if she arrives later and the option is still available, she deduces that if she proceeds to the next auction, she will be facing low types and can win the item by paying a lower price. Thus, she moves on to the second auction. This result also tells us that the probability of execution for the BIN option is decreasing as more bidders arrive to the auction site. Then, we study the expected revenues for the sellers and conclude that under certain conditions it is more rewarding for the sellers to offer a BIN option. As the main result of our paper we establish that it is rational for the first seller to set a BIN price and an equivalent reserve price when there are multiple auctions in eBay. Unlike most of the studies in the literature we explain the existence of the Buy-It-Now option by multiple auctions rather than risk aversion of agents.

Next, we focus on the execution times of the BIN option for TI-83 auctions on eBay. First, we study how the execution times are distributed and show that most of them are executed early on in the auction. Afterward, we statistically test and show the validity of our theoretical prediction that conditional on sale, the revenue for executed BIN auctions should be higher than the revenue for No-BIN auctions with no reserve price.

We believe an extension of this framework where we incorporate simultaneous, overlapping and sequential auctions would capture the complexity of trading in online markets. Such a model might shed more light on some aspects of the timing of BIN execution times.

One way to extend our research is to analyze the Yahoo online auction site. Yahoo has many features in common with eBay but differs in some very interesting aspects. Yahoo is a thinner market relative to eBay, both in terms of variety of products traded and in terms of the volume of trading. Moreover, it offers different ending rules for auctions and has a distinctive buy-now feature. These variations can potentially affect the strategies of buyers and sellers quite differently, compared to eBay. It would be interesting to study how these distinctions affect players' strategies and auction outcomes in these two markets.

Chapter 5

Conclusion

Since the development of high-speed internet, online commerce has been growing rapidly. Internet auctions constitute an important portion of electronic commerce. The leading company in the United States in this market is eBay with millions of customers. Numerous buyers and sellers meet in this online marketplace to buy and sell virtually anything they consider worth trading. When a potential buyer wants to buy an item, she performs a search for it on eBay's website. Most of the time, the result consists of hundreds of auctions that are currently running. As a result, the bidder faces a choice of which auction to bid at. Additionally, the sellers on eBay also offer Buy-It-Now prices which the bidder might execute right away and decide not to compete in an auction. It is probable that the potential buyer will be considering many of these options while deciding on which auction to bid, the amount of the bid and to execute the BIN option or not.

In my dissertation I study this prominent online auction mechanism and establish the importance of dynamics due to many simultaneously continuing auctions. Chapter 2 introduces the dataset on Texas Instruments TI-83 Graphing Calculator auctions that is collected for a 6-week period from eBay. First, we analyze the bidders in our dataset and study their bidding behavior in a multi-auction environment. Secondly, we establish the importance of considering a dynamic environment while modeling eBay auctions. For this purpose, a probit regression is utilized to show the effects of multiple auctions running simultaneously, completed auctions, available Buy-It-Now prices and some outside options on bidders' choices. The results suggest that variables containing information from other auctions significantly affect bidders' decisions, thus emphasizing the importance of the dynamic, multi-auction environment in eBay marketplace for potential buyers. In summary, Chapter 2 demonstrates the necessity of a dynamic model which we introduce in Chapter 3 and Chapter 4 while analyzing eBay.

Chapter 3 focuses on the bidding behavior for multiple bidders who have two consecutive auctions to participate. The bidders in the first auction strategically delay the submission of their bids by waiting until the closing minutes of the auction. High-value types wait until the end of the auction before revealing their types by submitting proxy bids, while low-value types submit proxy bids at any time. The reason for this behavior is the existence of the subsequent auction in which, bidders who are not successful in the current one, will be meeting again. This strategy results in last-minute bidding (LMB) in the first auction and it is because of the sequential structure of the sale. This explanation for LMB is unlike the one in the literature concerning the existence of congestion at the end of an auction which decreases the probability that a late bid is recorded.

Chapter 4 builds on to the main framework of the model introduced in Chapter 3 and considers the case where first seller offers a Buy-It-Now option. EBay's Buy-It-Now feature puzzled some academicians and they were able to explain the existence of it by assuming the participants of the auction having risk aversion or impatience. However, in Chapter 4, the explanation for a seller to offer the BIN option arises from the multi-auction setting of the model without any assumptions about the participants. The first seller in the model earns higher expected revenue than the no-BIN case by offering a BIN price and by setting the reserve price equal to it.

The theoretical predictions from Chapter 3 and Chapter 4 are tested using the dataset introduced earlier. The majority of the predictions are satisfied that demonstrates the validity of the theoretical model. However, some modification of the model is necessary for a better match of the theory and empirical data.

There are other prominent online auction sites that are essentially similar to eBay with their auction rules. Two of these are Yahoo and Amazon. They possess minor differences in terms of auction features but there is a vast distinction in terms of the number of participants. Yahoo and Amazon are thinner markets relative to eBay, both in variety of products and the volume of trade. The main reason for this contrast is the first-mover advantage of eBay into the online auction market. For future research, it is interesting to consider these thin markets, repeat the empirical analysis using the thin-market data and compare the results.

Table 1: Definitions of Variables

Variables	**Explanation**
Winning bid	Maximum recorded bid of each auction
BIN price	The Buy-It-Now price of the auction
Starting bid	Starting price of the auction that is set by the seller
Auction length (hr)	Length of the auction measured in hours
Number of bids	Total number of bids at the end of the auction
Number of bidders	Total number of bidders at the end of the auction
Seller rating	Number representing the rating of the seller
Bidder rating	Number representing the rating of the bidder

Table 2: Descriptive Statistics for TI-83 Calculators

Variable	**Num. of Obs.**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Winning bid	2526	58.73	54	17.97	20	109.99
BIN price	709	62.55	59	19.31	25	140
Starting bid	2526	25.71	15	25.31	0.01	109.99
Auction length (hr)	2526	112.28	120	62.8	0.07	240
Number of bids	2526	10.77	10	8.05	1	54
Number of bidders	2526	5.83	6	3.68	1	18
Seller rating	2509	590.88	63	1627.66	-1	16832
Bidder rating	4890	49.03	6	172.86	-2	3788

Table 3: Number of Bidders and Number of Auctions They Won

Number of wins	Number of bidders	Percentage (%)
0	2744	55.92
1	2001	40.78
2	127	3.3
3	15	
4	4	
5	3	
6	3	
7	1	
8	2	
9	1	
14	1	
15	1	
23	1	
26	1	
29	1	
38	1	

Figure 1: Bidder Behavior for Two Consecutive Auctions

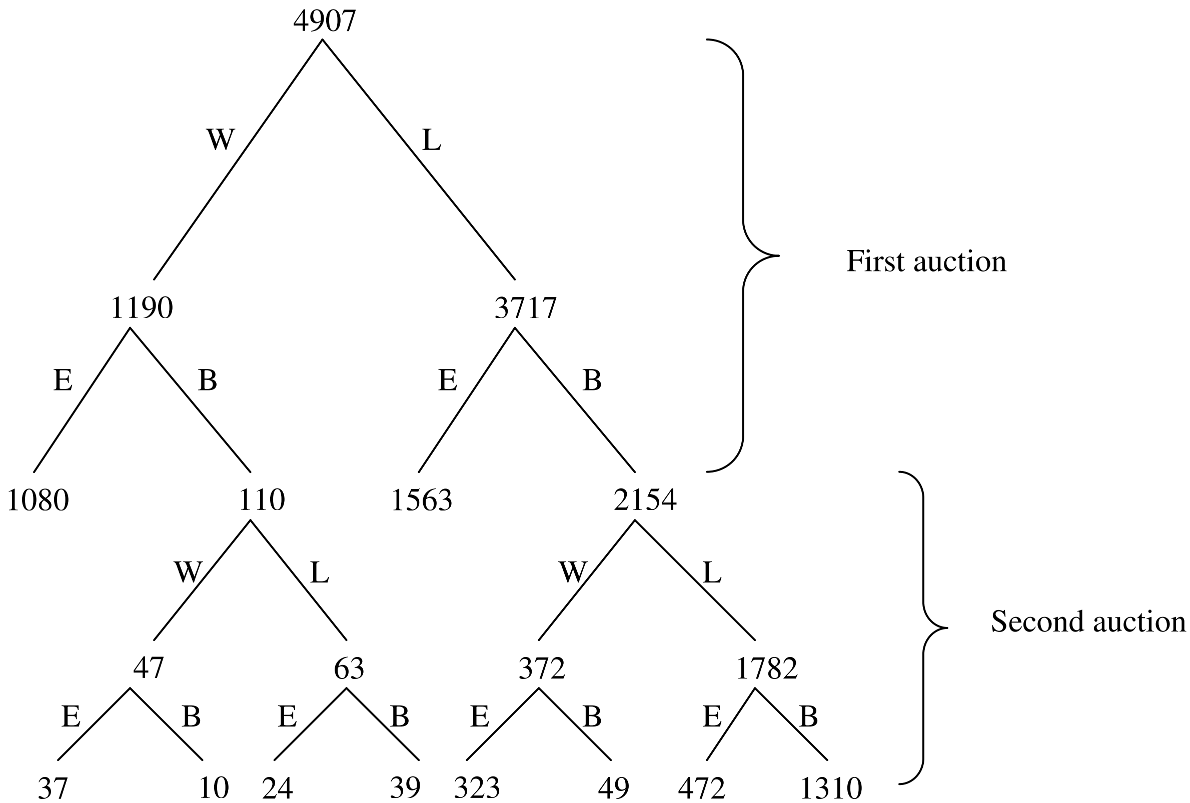

Table 4: Definitions of Created Variables

Variables	**Explanation**
Proxy bid	Highest proxy bid submitted by each bidder for every auction she participates
Previous Ranking	Ranking of the highest proxy bid submitted by each bidder in the previous auction she participates
Time 1	Equals to one if the auction ends between 12am and 6am
Time 2	Equals to one if the auction ends between 6am and 12pm
Time 3	Equals to one if the auction ends between 12pm and 6pm
Time 4	Equals to one if the auction ends between 6pm and 12am
Ratio BOS	Ratio of number of losers from completed auctions over number of new auctions being offered
Num. of BIN Sellers	Number of forthcoming auctions with the BIN option
Average BIN price	Average of the forthcoming BIN prices
Losses 1	Number of previous losses equals to 1
Losses 2	Number of previous losses equals to 2
Losses 3	Number of previous losses greater than or equal to 3
Next Action	$= \begin{cases} 0 & if \quad leave\ eBay \\ 1 & if \quad eBay \end{cases}$

Table 5: Descriptive Statistics for the Created Variables

Variable	**Num. of Obs.**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Proxy bid	11591	44.39	42.29	21.04	0.06	107.52
Previous Ranking	9435	5.04	5	2.78	1	17
Time 1	2412	0.04	0	0.19	0	1
Time 2	2412	0.31	0	0.46	0	1
Time 3	2412	0.39	0	0.49	0	1
Time 4	2412	0.26	0	0.44	0	1
Ratio BOS	2412	5.37	3.74	6.1	0	68
Num. of BIN Sellers	2412	2.11	2	1.89	0	11
Average BIN price	1865	60.05	58.36	14.18	25	179.9
Losses 1	14003	0.33	0	0.47	0	1
Losses 2	14003	0.15	0	0.36	0	1
Losses 3	14003	0.52	1	0.50	0	1
Next Action	11965	2.65	3	0.50	1	3

Table 6: Probit Estimates

Next action	Coefficient	Marginal Effects	Std. Error
Time 1	-0.84***	-0.23	0.17
Time 2	-0.05	-0.02	0.06
Time 3	-0.04	-0.02	0.06
Ratio BOS	-0.05***	-0.02	0.01
Num. of BIN Sellers	0.02*	0.01	0.01
Average BIN price	0.004***	0.001	0.001
Proxy bid	-0.003**	-0.001	0.001
Winning Bid	-0.004***	-0.001	0.001
Previous ranking	-0.02**	-0.01	0.01
Losses 2	-0.66***	-0.21	0.09
Losses 3	-0.31***	-0.12	0.08
Constant	0.39***		0.15
Wald χ^2 *(11)*	217.96		
Prob > χ^2	0.000		
Observations	4731		
Observed probability	0.333		
Predicted probability (at x-bar)	0.323		

Note: *** indicates significance at 1% level. ** indicates significance at 5% level. * indicates significance at 10% level.

Table 7: Descriptive Statistics for TI-83 Auctions with no BIN Option

Variable	**Num. of Obs.**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Winning bid	1817	58.21	53.09	17.7	20	107.52
Starting bid	1817	15.07	9.99	15.96	0.01	99.99
Minimum bid	1817	18.74	12	16.65	0.01	99.99
Auction length (hr)	1817	135.3	168	46.25	72	240
Number of bids	1817	13.7	13	7.04	1	54
Number of bidders	1817	7.29	7	3.02	1	18
Seller rating	1809	663.23	50	1840.44	-1	16832
Bidder rating	4264	48.8	6	174.32	-2	3788

Table 8: Summary Statistics for the Closing Intervals

Variable	**Num. of Obs.**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**
Closing Interval (minutes)	1816	33.59	14	64.92	0	714

Table 9: Distribution of Closing Intervals with Various Lengths

Minutes in the Closing Interval	Frequency	Percent (%)	Cumulative (%)
0	112	6.17	6.17
1	132	7.27	13.44
2	79	4.35	17.79
3	84	4.63	22.41
4	69	3.80	26.21
5	62	3.41	29.63
6-10	238	13.1	42.73
11-30	538	29.63	72.36
>30	502	27.64	100

Figure 2: Bid Submission Times in the Closing Intervals

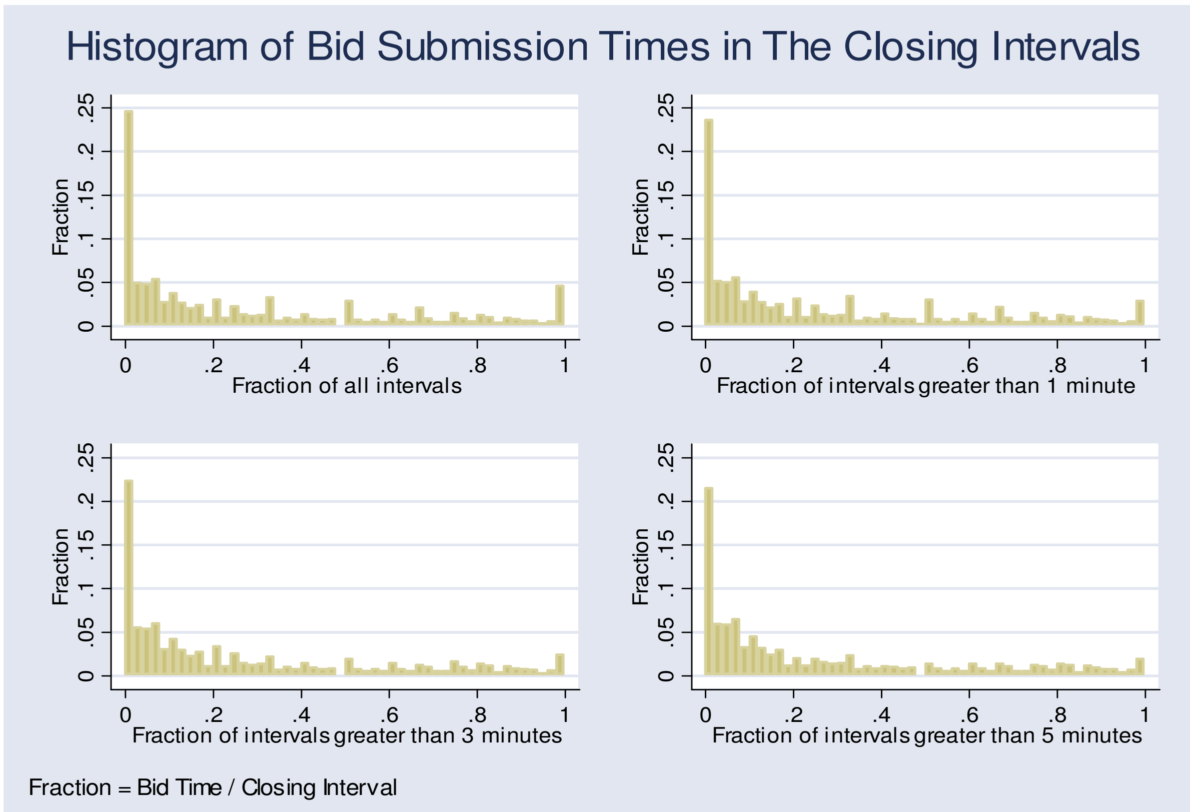

Table 12: Descriptive Statistics for TI-83 Auctions with BIN Option

Variable	Num. of Obs.	Mean	Median	Std. Dev.	Min	Max
Winning bid	709	60.06	55	18.59	20.5	109.99
BIN price	709	62.48	58	19.26	25	140
Starting bid	709	51.02	50	25.12	0.01	109.99
Starting hour	709	14.32	14	5.09	0	23
Monday	709	0.16	0	0.37	0	1
Tuesday	709	0.19	0	0.39	0	1
Wednesday	709	0.18	0	0.38	0	1
Thursday	709	0.12	0	0.32	0	1
Friday	709	0.10	0	0.30	0	1
Saturday	709	0.11	0	0.31	0	1
Sunday	709	0.15	0	0.36	0	1
Seller rating	700	403.74	86	834.1	0	8757
Bidder rating	2500	49.84	9	159.74	-1	3384
Duration of auction	553	31.55	13.37	44.88	0.07	239.5
Auction length	156	130.15	120	47.22	72	240
Number of bids	709	3.27	1	5.07	1	34
Number of bidders	709	2.1	1	2.36	1	14

Table 13: Starting Bid in BIN Auctions

Choice of Starting bid	Frequency	Percent
Starting bid < BIN	188	26.52
Starting bid = BIN	521	73.48
Total	709	100

Table 14: Do Buyers Stay or Leave After Executing the BIN Option?

Choice of Leaving	Frequency	Percent
Leave	479	93.74
Stay	32	6.26
Total	511	100

Figure 3: Distribution of BIN Execution Times

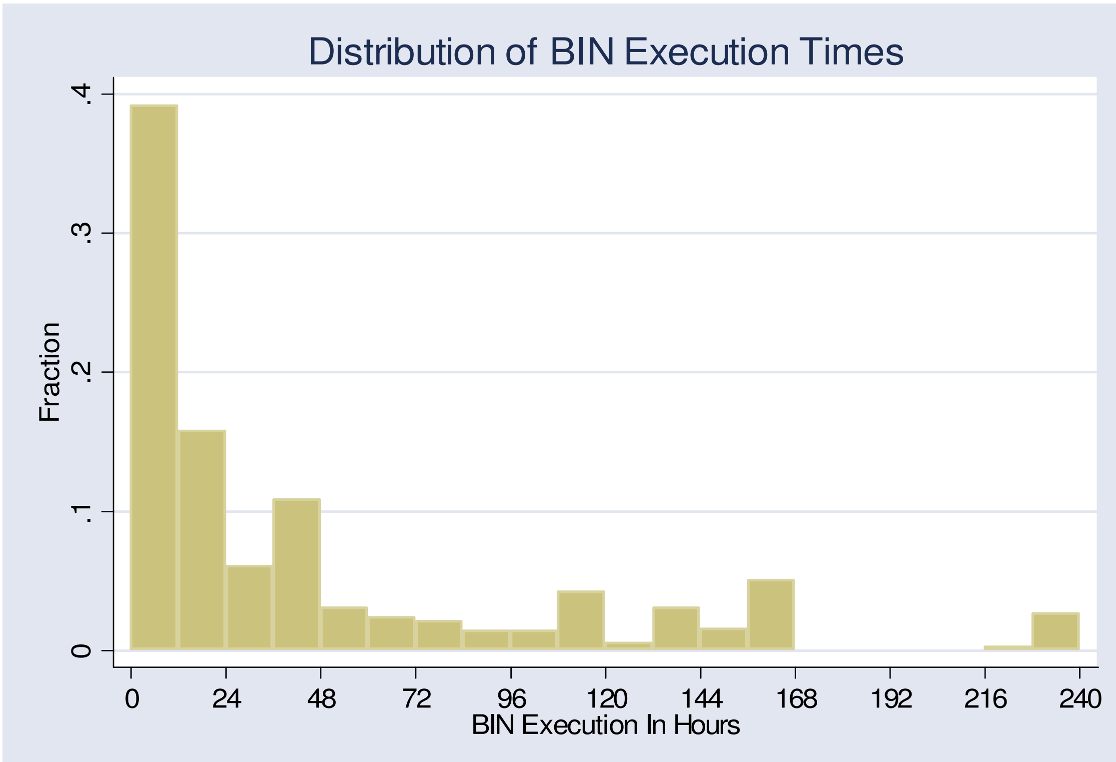

Figure 4: Hazard Function for BIN Execution

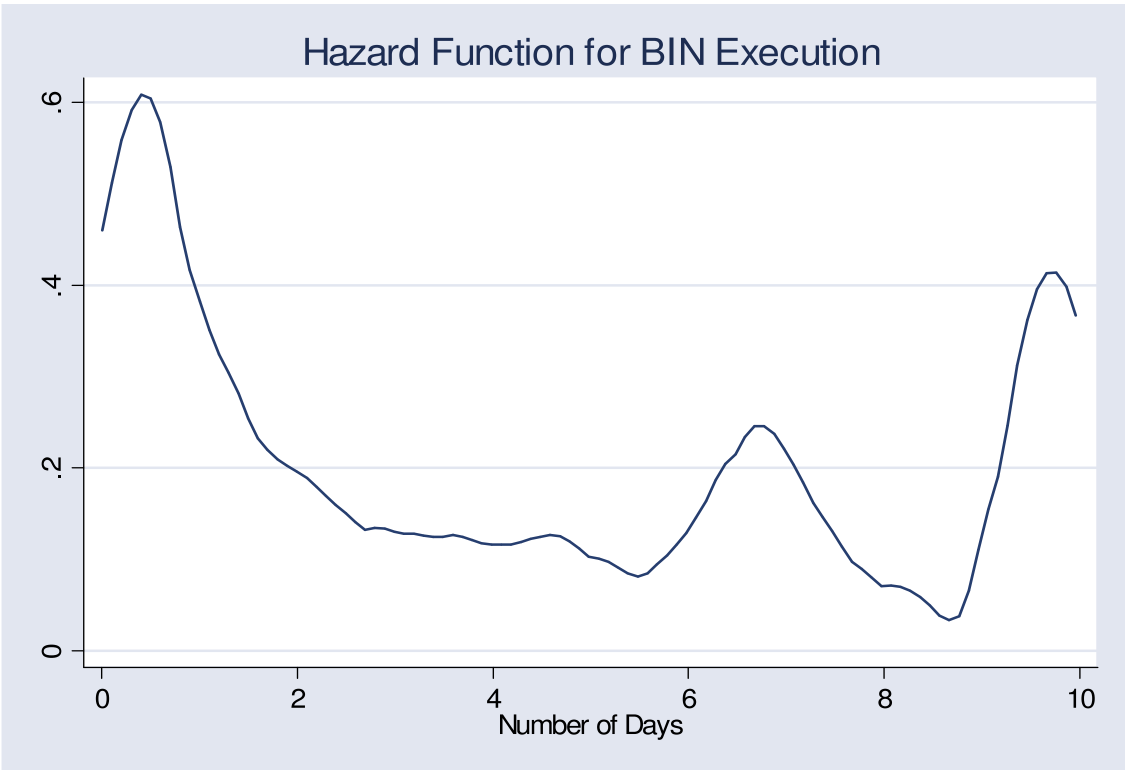

Table 15: Summary Statistics for the Winning Bid in Successful Auctions

Winning bid	No-BIN Auctions with low reserve	Executed BIN Auctions with reserve
Observation	663	543
Mean	58.1	59.95
Median	53.13	55
Std. Dev.	17.51	18.61
Min	21. 5	25
Max	107.5	109.99

Note: Low reserve is defined as the reserve price being less than or equal to $5.

Appendix A

Proofs

Proof of Proposition 1:

Low types will not enter a proxy bid greater than V_L, because they might get negative surplus. If they enter a bid less than V_L, then a low type can deviate to V_L and increase his surplus in the case where the other buyer or buyers are low types, or where only the proxy bids of low types are not rejected.

By a similar argument, high-type buyers will enter a proxy bid equal to V_H. Thus, the outcome will be the same as that of a second-price, sealed-bid auction. *Q.E.D.*

Proof of Proposition 2:

First, an argument similar to the one used in the proof of Proposition 1 shows that low-valuation buyers will enter a proxy bid of V_L. Next, we demonstrate that high types will not reveal their type before the end of the auction. Suppose Buyer *i* is known to be a high type. Then the expected surplus from the second auction for any other high type is $q(V_H - V_L)$, as explained in the text. If another high type can win the first auction with positive probability by bidding $(1 - q)V_H + qV_L$, he will do so, because winning at or below that price yields surplus at least $q(V_H - V_L)$. If, on the other hand, the smallest proxy bid that Buyer *i* might enter, *b*, is greater than $(1 - q)V_H + qV_L$, then any other high type *j* will submit a proxy bid of $b - \varepsilon$, as long as $b \leq V_H$: that bid will win the item only if Buyer *i*'s proxy bid is rejected. In that case, Buyer *i* will participate in the second auction, and there will be no surplus for Buyer *j* if he loses the first auction. In that event, Buyer j is willing to pay up to his valuation to win the first auction. He will not outbid Buyer i, though – he prefers to wait till the second auction and face the third buyer rather than to win the first at price greater than $(1 - q)V_H + qV_L$.

Thus, if there is at least one high type other than Buyer i,, then Buyer i can expect surplus no greater than $q(V_H - V_L)$ in the first auction. If the other two buyers have low valuations, then he get surplus $(V_H - V_L)$. Overall, his expected surplus if he wins the first auction is no greater than $(1 - q^2)q(V_H - V_L) + q^2(V_H - V_L)$, which is strictly less than $[1 - (1- q)^2](V_H - V_L)$, the expected surplus from the equilibrium described below, where types are not revealed until the end of the auction. If he loses the first auction, his expected surplus in the second auction is no greater than $[1 - (1- q)^2](V_H - V_L)$ – he gets no surplus if both opponents have high valuations. His surplus from both auctions, then, does not exceed his surplus from the equilibrium where his type is not revealed, and it is strictly less if he wins the first auction with positive probability. If he loses the first auction for sure after revealing his type, then he might be indifferent, but Assumption 1 breaks the tie in favor of having two chances to win. Thus, a high-valuation buyer will not reveal his type, which implies that no more than one high type will submit a proxy bid before time T_1, as mentioned in the text.

It remains only to show that the mixed strategy over proxy bids F^* is an equilibrium strategy for high types in the second-price, sealed bid auction at time T_1, given that low types enter a proxy bid of V_L, and that that equilibrium is unique.

Suppose that other players follow the equilibrium strategies, and that the equilibrium of the second auction is as described in Proposition 1. If a high type enters a proxy bid b in the support of F^*, then his expected surplus $S(b)$ from both auctions is

$$S(b) = (1-q)^2[F^*(b)]^2\left\{V_H - \frac{1}{[F^*(b)]^2}\int_{V_L}^{b} 2F^*(b')f^*(b')b'\,db'\right\}$$
$$+\,2q(1-q)\left[F^*(b)\left\{V_H - \frac{1}{F^*(b)}\int_{V_L}^{b} f^*(b')b'\,db'\right\} + [1-F^*(b)]\{V_H - V_L\}\right]$$
$$+\,q^2\{V_H - V_L\}.$$

That is, with probability $(1 - q)^2$ he faces two other high types, which means that there will be no surplus in the second auction. Thus, his total expected surplus is the probability that he submits the highest proxy bid in the first auction, $[F^*(b)]^2$, times his surplus if he does win, which is the difference between V_H and the expected value of the higher of two proxy bids drawn from F^* conditional on being less than b. With probability $2q(1 - q)$, he faces one high type and one low type, so if he loses today he will win the second auction for price V_L. If he wins today, his surplus is V_H minus the expected value of a proxy bid drawn from F^* conditional on being less than b. With probability q^2 he faces two low types – he wins the first auction at price V_L.

On the other hand, suppose that he deviates by not entering a proxy bid in the first auction and waiting to the second, or, equivalently, by submitting a proxy bid less than V_L. (The other type of deviation, a proxy bid above the support of F, gives the same payoff as a proxy bid at the top of the support, so it cannot be strictly better.) His surplus from waiting $S(w)$ is

$$S(w) = (1-q)^2 0 + 2q(1-q)\{V_H - V_L\} + q^2\{V_H - V_L\}.$$

That is, if both opponents are high types, he is certain to face one in the second auction and get no surplus. If both are low types, he will win the second auction at price

V_L. He also wins the second auction for V_L if one opponent has high valuation, because that opponent will wins the first auction if he follows the equilibrium strategy. Subtracting $S(w)$ from $S(b)$ yields the difference $D(b)$:

$$D(b) = (1-q)^2[F^*(b)]^2\left\{V_H - \frac{1}{[F^*(b)]^2}\int_{V_L}^{b} 2F^*(b')f^*(b')b'\,db'\right\}$$
$$+2q(1-q)\left[F^*(b)\left\{V_L - \frac{1}{F^*(b)}\int_{V_L}^{b} f^*(b')b'\,db'\right\}\right].$$

Note that $D(V_L) = 0$, implying that a high type is indifferent between waiting and bidding V_L. He must also be indifferent among all proxy bids b in the support of F^*, so we differentiate $D(b)$ and set the derivative equal to 0:

$$D'(b) = 2(1-q)f^*(b)\{F^*(b)(V_H - b)(1-q) + (V_L - b)q\} = 0..$$

Solving yields $F^*(b) = q(b - V_L) / (1 - q)(V_H - b)$, which was to be shown. So F^* is the unique mass-free equilibrium bidding distribution. We note that the equilibrium survives Assumption 1 – introducing a small probability that a proxy bid is rejected causes the equilibrium distribution to be adjusted in a continuous way to compensate.

To show that cannot be a mass point, first we show that there is no pure strategy equilibrium. Suppose that high types enter some proxy bid b with probability one. Then their expected surplus, calculated in the same way as $S(b)$, is

$$(1 - q)^2(1/3)(V_H - b) + 2q(1- q)[(1/2)(V_H - b) + (1/2)(V_H - V_L)] + q^2(V_H - V_L).$$

The surplus from waiting is the same as before. Subtracting yields difference $E(b)$:

$$E(b) = (1-q)^2(1/3)(V_H - b) + 2q(1- q)(1/2)(V_L - b),$$

which must be weakly positive, or else high types would prefer to wait. Now suppose that a high type deviates by entering a proxy bid higher than b. He wins the first auction for sure, at price V_L if both opponents are low types and at price b otherwise. His expected gain relative to submitting proxy bid b is

$$(1-q)^2(2/3)(V_H - b) + 2q(1- q)(1/2)(V_L - b),$$

which is strictly greater than $E(b)$, so he strictly prefers to deviate.

A similar argument shows that in equilibrium there is no mass point at any b: we perform the same exercise conditioning on the other buyers' proxy bids being b or less.

The final step to show uniqueness is to demonstrate that high types must enter a proxy bid with probability one in equilibrium. Suppose that with probability $p > 0$ a high type does not participate in the first auction, and with complementary probability he enters a proxy bid drawn according to some cumulative distribution function G. In that case, a high type has a profitable deviation in the first auction: when his strategy calls for him to wait, he instead submits a proxy bid V_L (+ ε). Then, in the event that his two opponents are high types and they both are waiting until the next auction, he gets positive surplus rather than none. Otherwise, the deviation does not affect his payoff. Thus, high types always enter a proxy bid, and the equilibrium calculated is unique. *Q.E.D.*

Appendix B

Tests

T-TESTS FOR THE WINNING BIDS IN CHAPTER 3: LAST-MINUTE vs. EARLY

For this test, we group the winning bids into two. First group consists of the ones submitted in the last 5 minutes of an auction (*Last-minute*). The second group consists of auctions for which the winning bid is submitted earlier than the last 5 minutes (*Early*). Then, we run t-tests for both new and used items. We want to see if the difference between their average values is significantly different than zero. A two-sample t-test allows us to test the following hypothesis.

H_0 : Mean (*Last-minute winning bid*) - Mean (*Early winning bid*) $=$ Difference $= 0$

H_1 : Difference $\neq 0$

Table 10: T-test for the Winning Bid among New Items

Winning Bid	Obs.	Mean	Std. Err.	Std. Dev.
Last-minute	104	89.95	0.68	6.9
Early	188	89.38	0.43	5.86
Combined	292	89.58	0.37	6.25
Difference		0.57	0.76	
Degrees of freedom: 290				

We get the following result and fail to reject the null hypothesis that the difference among the means is zero.

$$t = 0.7506$$

$$P > |t| = 0.4535$$

The average *Last-minute winning bid* is larger than the average *Early winning bid* but this difference is not statistically significant.

Table 11: T-test for the Winning Bid among Used Items

Winning Bid	Obs.	Mean	Std. Err.	Std. Dev.
Last-minute	591	53.28	0.49	11.96
Early	934	51.52	0.39	11.79
Combined	1525	52.2	0.3	11.88
Difference		1.76	0.62	
Degrees of freedom: 1523				

We get the following result and reject the null hypothesis that the difference among the means is zero.

$$t = 2.8302$$

$$P > |t| = 0.0047$$

The average *Last-minute winning bid* is larger than the average *Early winning bid* and this difference is statistically significant.

T-TEST FOR THE WINNING BID IN CHAPTER 4: BIN vs. NO-BIN

For this test, we consider the winning bids for No-BIN auctions with no reserve price and final price for executed BIN auctions. We want to see if the difference between their average values is significantly different than zero.

A two-sample t-test with unequal variances allows us to test the following hypothesis.

H_0: Mean (Winning bid for No-BIN) – Mean (Winning bid for Executed BIN) =

Difference $= 0$

H_1: Difference $\neq 0$

Table 16: T-test for the Winning Bid

Winning Bid	Obs.	Mean	Std. Err.	Std. Dev.
No-BIN	663	58.1	0.68	17.51
BIN	543	59.95	0.80	18.61
Combined	1206	58.93	0.52	18.03
Difference		-1.85	1.05	
Satterthwaite's degrees of freedom: 1127.7				

We get the following result and reject the null hypothesis that the difference among the means is zero.

$$t = -1.7673$$

$$P > |t| = 0.0774$$

This suggests that the means are significantly different at 10% level. More precisely, we can conclude that the average executed BIN price is significantly larger than the average sale price when there is no BIN option and no reserve price.

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Vita

Ilke Onur was born in Istanbul, Turkey on February 14, 1978. He is the son of Orhan Huseyin Onur and Gulsen Onur. After completing his work in Isik High School, Istanbul, Turkey, in 1995, he attended DePauw University during the fall semester of 1995. He received the Bachelor of Science degree in Mathematics and the Bachelor of Arts degree in Economics in 1999, from Koc University. In August 1999 he entered the Graduate School of The University of Texas at Austin where he obtained his Master of Science degree in Economics in 2001.

Permanent address: 908 E. 56th Street, Austin, Texas 78751

This dissertation was typed by the author.