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BACHELOR THESIS

Sales Design in Online Auctions: Evidence from iPad 2 Sales on eBay

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed resources and literature. This thesis was not used to obtain another academic degree.

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Prague, May 15, 2013

Signature

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Abstract

This thesis studies sales of iPads 2 on eBay. We examine the determinants of the choice of particular sales design among sellers and the effect of this design on probability of sale and price. There is not a difference in prices among fixed price sales and auctions, however posted price sales have lower probability of being sold. BIN option in auctions does not affect their outcome. We also found that higher minimum bids increase price and decrease probability of sale.

JEL Classification D44, D47,

Keywords auction theory, eBay, internet auctions, sales design, price determinants

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Abstrakt

Tato práce studuje prodeje tabletů iPad 2 na eBay. Zkoumáme výběr designu prodeje a jeho efekt na pravděpodobnost prodeje a finální cenu. Nenašli jsme rozdíl v cenách při prodeji v aukci a pomocí prodejů s fixními cenami. Obchody s fixními cenami měly menší pravděpodobnost úspěšného prodeje. Možnost BIN neovlivňuje výsledek aukce. Také jsme zjistili, že větší minimální nabídka zvyžuje konečnou cenu a snižuje pravděpodobnost prodeje.

Klasifikace JEL D44, D47,

lova teorie aukcí, internetové aukce, eBay, design prodeje, determinanty ceny

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Acronyms

2SLS Two Stage Least Squares

AME Average Marginal Effect

BIN Buy It now

IPV Independent Private Value

OLS Ordinary Least Squares

PP Posted Price

Bachelor Thesis Proposal

Author	Bruno Baránek
Supervisor	PhDr. Martin Gregor, Ph.D.
Proposed topic	Sales Design in Online Auctions: Evidence from iPad 2 Sales on eBay

Topic characteristics Auctions are a worldwide used tool for the distribution of goods. The aim of this thesis is to describe how specific determinants affect bidding behaviour and the final prices. The determinants studied in this thesis are divided in two major groups. The first one contains demand factors such as the number of bids or the way of bidding. The second group of interest are the auction rules. The thesis will exploit data from major online auctions.

Methodology Econometric analysis of data from internet auctions

Outline

1. Introduction
2. Survey of Current Literature
3. Empirical Analysis of Data
4. Interpretation of Results
5. Conclusion

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Chapter 1

Introduction

Internet auctions are a rising phenomenon of last two decades. Rapid development of the internet allowed to minimize the transaction costs of trade and so helped creating huge online auction portals. Yahoo!, Amazon.com, eBid, and eBay belong to the largest sales platforms in the world. Our study will focus on the largest online auction portal, on eBay. The gross merchandise volume on this website, which is the total amount of successfully closed sales, was 67 billion dollars in 2012. eBay has around 112 million active users. Goods of total value $2457 are traded every second only on eBay.com.[1]Online portals serve as a huge laboratory where economic behaviour is observed and can be studied. Many economists have already used this opportunity. See Hasker & Sickles (2010) for a recent survey of the economic literature focusing on eBay.

The main topic of this thesis is to study the design of eBay sales using iPad 2 sales data. First part of our model studies determinants of sellers‘ decisions about the design of their sale. The auctioneer can choose between two major formats; auctions and posted price sales. The setting of auctions on eBay is similar to English ones. In the latter case eBay functions as a catalogue. Price demanded by seller is visible and a potential buyer chooses if to buy the product at this price or not.

Many other specifications can be set when selling. Substantial differences in the constitution of an auction can be made by the choice of BIN price and the size of reservation price. BIN price allows any buyer to early end the auction by paying a specific price. Reservation prices secure the seller minimum revenue if the product is sold. These two options will be the most important for our thesis.

[1]http://pages.ebay.in/sellerinformation/index.html

Next we will study how the choices made by the auctioneers when starting a listing influence the outcome of their sale, we will especially examine final price and probability of sale. Formats differ to a large extent. We expect significant differences in outcomes when different settings are used. Posted price sales are much more convenient for a buyer if she sees a product she is interested in, she can immediately purchase it, and she does not need to wait for the end of the auction and compete with other bidders. On the other hand the auction format can attract more interested bidders and most of the eBay auctions receive multiple bids so it is unlikely that an auction with reasonable set initial parameters would not end in a sale. Effects on outcome of both major formats and all specifications of design are studied in our thesis.

We will conduct an econometric analysis of data from eBay.com, which is the largest of the eBay websites. Sales of iPads 2 are observed in order to study determinants of the transaction results. Our thesis is structured as follows: Chapter 2 explains the format of sales on eBay in the first section and the second part offers the survey of relevant literature for differences between auctions and fixed price sales, BIN option, and reservation prices. To the extent of our knowledge we know less about a complex survey of literature focusing on BIN, our thesis contains a list and summary of the relevant literature about this phenomenon. Chapter 3 summarizes the data used for our analysis. Chapter 4 introduces an econometric model and reports results of regressions. Results of our work and their relevance to other literature are discussed in Chapter 5. Chapter 6 concludes our thesis.

Chapter 2

Literature Survey and Rules of Sales on eBay

2.1 Sales Design

In the following lines we summarize the details about selling goods on eBay. This online portal does not sell its own products but intermediates trade between sellers and buyers. The website does secure neither quality of products nor reliability of sellers. Seller on eBay can choose between different formats of sale. There are two basic regimes available for most product categories, auction-style listing and fixed price listing (also called posted price listing). Next paragraphs explain how both of these regimes work.

Fixed Price Sales

Fixed price sales are equivalent to purchases in brick-and-mortar stores. The posted price is also sometimes called Buy It Now price on eBay. The same expression is used for the specific option in auction-style listings. We will use the acronym PP for posted price (Buy It Now option if the auctions mechanism is not present) and BIN for the Buy It Now option in auctions not to confuse it. Fixed price sales work on the take-it-or-leave-it principle. Any buyer can purchase the item immediately by paying this PP and subsequently the sale is being ended. If no buyer is found, the sale will end at a predetermined time. Seller can choose 3, 5, 7, 10, 30 days, or even infinitely long lasting duration.

Selling at a posted price offers a next feature for the seller, Best Offer option. Such a setting allows bargaining between sellers and bidders. If the seller chooses this kind of option, an icon "Make Offer" appears on the website of the offered item. The potential buyer can either buy the product at PP or make an offer by announcing the amount of money she is willing to spend for the product. The seller receives this offer and can accept it, reject it, or make a counter offer. The auctioneer can even set intervals at which the offer will be automatically rejected, respectively accepted by the computer. If the seller accepts the offer the trade is conducted. In the case of refuse, the potential buyer has four more chances to make an offer. When the seller makes a counter offer, the buyer can reject it, accept it, or even again make a next counter offer. It would be interesting to examine this bargaining behaviour but eBay does not show the final prices of the sales that end by successful offers. We can only observe if the item was sold or not.

Auctions

Auction-style listings are formats when every interested buyer bids on the item and the bidder who has submitted the highest bid by the time when the auction ends receives the product at the price which equates to the second highest bid plus minimum bid increment. Bidders do not have to submit each of their bids manually but they can set the maximum bid and eBay will bid for them if their maximum bid is higher than the current winning bid. This system is named proxy bidding. Current winning bid can be outbid by a bid that is at least as high as the current winning bid plus minimum bid increment. The size of bid increment depends on the size of the winning bid; the higher the current winning bid the higher the minimum increment.

Before the auction starts the seller chooses the minimum bid for the bidders, the default option is \$0.01. Seller also selects between five possible durations of the auction: 1, 3, 5, 7, or 10 days. In auction-style listing there are two important options available that virtually change the design of the whole sale; secret reserve price and BIN option.

Secret Reserve Price

This feature can be added for an additional fee. The size of it is known exclusively to the seller and the buyer only sees the note "reserve not met" as long as the current winning bid is lower than the secret reserve price. It is important to stress out that bidders know about the existence of secret reservation price to distinguish eBay auction from ones, where bidders do not know if secret reserve price is present or not. If the highest bid is lower than the secret reserve price after the auctions ends, the product remains unsold.

Buy It Now

BIN allows purchasing a product immediately by paying the specific price set by the auctioneer. The auction ends and additional bids are not possible. BIN is only temporary on eBay, it is present until a bid is placed and disappears after that. It is not possible to recognize if a BIN option was available after the first bid had been placed. The sale after the first bid is equal to a pure auction. There is an exception when the BIN price does not disappear after the first bid; it is if the secret reserve price is set too. Then the BIN is available until the current winning bid exceeds the secret reserve price.

Other Options

In both formats described above there are few common options. The final price for buyers is composed of the winning bid or BIN price plus shipping costs. This allows the seller to further manipulate with the sale by setting the shipping costs. Often these shipping costs are not directly visible on the product‘s webpage and instead of the direct size of shipping costs a direction “contact the seller for details” appears or automatic shipping calculators are used. The seller is also obliged to write a description of the item. A picture of it can be added.

There are also other designs available for a few particular product categories. Classified Ad allows discussing the trade personally or Motors Local Classified Ad sells a vehicle in the area maximum 200 kilometres far from the seller. Such options are not used in most of the sales and neither they are in our data.

Fees

Lastly we will discuss the fees on eBay. They are important because of their direct impact on the revenue of sellers; they create an important incentive for behaviour. Basic fee consists of two components- insertion fee and final value fee. Some additional services are charged, too.[1]

[1] details can be further found on http://pages.ebay.com/help/sell/fees.html

Insertion Fee

The insertion fee is free for 50 auctions posted by a particular seller per month. The fee for an auction-style listing, which is above the 50 free ones, depends on the minimum bid and belongs to the interval from \$0.01 to \$2 . The fee for creating a fixed price listing is constant and equals \$0.50.

Final Value Fee

There are again differences in both mechanisms. For the auction-style listings the fee is 9% of the total amount of the sale up to maximum fee of \$250. Total amount of the sale consists of the final price of the item, shipping, and any other amounts the seller may charge the buyer. The system of computing the final value fee for the fixed price listings is more complicated. Generally the seller is charged a fixed amount per the first x dollars of total amount of the sale and y per cent of the remaining balance up to some cap. Concrete amounts differ per category of products and size of the total amount of the sale. For example for iPads 2 from our dataset the fees are: \$3.50 for the first \$50 plus 5% of the remaining balance up to \$1,000.

Additional Fees

The BIN options for auction-style listings is free if added to the first 50 listings, otherwise the fee is based on the minimum bid. The maximum is \$0.25. Secret reserve prices are also charged additionally. The price is \$2 if the starting price is less than \$200, otherwise it is 1% of the minimum bid. Extending the duration to 10 days costs \$0.4. The standards of calculating fees were notably changed and simplified on April 16, 2013. This was after all our sales have ended, so we describe the former calculation rules.

2.2 Literature Survey

In this section we provide an overview of literature focusing on difference between auction and posted price sales, BIN auctions, and reservation prices. We want to study how changes of these parameters affect the outcome of a sale. We will study the BIN option in auctions more in detail. There has not been a complex survey of literature related to BIN auctions so we will use our thesis to provide one.

How to increase the revenue of a sale? Early literature focused on the search of a dominant sales mechanism. Riley & Samuelson (1981) conclude that in the case of risk-neutral sellers and buyers who arrive one at a time a take-it-or-leave-it price is the best strategy. McAfee & McMillan (1987) show that in a model with many buyers and sellers and more periods, sellers would choose an auction over all other direct mechanisms. Bose & Daripa (2009) point out that an auction with temporary buy price is a part of an optimal sales mechanism consisting of fixed price at a store and an internet auction. First, buyer can buy an item at the store at a posted price. If the item is not sold it is proceeded to the auction with temporary buy price. Now we will look on the literature concentrating on each of these problems separately.

2.2.1 Posted Price Sales versus Auctions

Theoretical literature

Seifert (2006) offers a very simple explanation of dominance of auction mechanism over posted price selling when the values are independent and private. Assume a posted price sale with PP equal to p. Any auction with reservation p can yield higher revenue than posted price sale. If there is no bidder with valuation above p, the item remains unsold and revenue is 0 in both cases. On the other hand if there are bidders with valuation above p, item is sold, the revenue from posted sale is p and revenue from auction is $r \geq p$, because any winning bid has to be at least as high as reservation price in auctions.

Wang incorporated in the analysis costs affiliated with the use of specific formats. Wang (1993) theoretically examines differences between auctions and posted price sales in a more detailed model. The situation with private and independent values is examined. Optimality of mechanism for sellers depends on cost of auctioning and form of the seller‘s marginal-revenue curve. Posted price selling is preferred in the presence of auctioning costs and if, in the same time, the marginal-revenue curve is not sufficiently steep. Next work of Wang (1998) shows that similar results hold under less strict assumption. Correlation of values is allowed. Auctions dominate the posted price selling in the case of nonexistence of auctioning costs. If they are present and at least one of the following conditions holds, auctions are still preferred. The distribution of buyers‘ valuation is sufficiently dispersed or the value of the objects which is being sold is sufficiently high. The same author also compared bargaining and posted price selling in Wang (1995). The costs of both mechanisms again play a major role. When costs of posted price selling are higher than the bargaining ones, bargaining is preferred. Otherwise bargaining is favoured if and only if the costs of both selling methods are sufficiently large. This can explain the frequent use of Best Offer on eBay.

Different results were received in Hailu & Schilizzi (2004) where the dominance of auctions format for sellers was found only for products with high values. A simulation with dynamic setting and learning bidders was performed in this study. Julien *et al.* (2001) show that the bonus in revenue for auctions rapidly decreases with the size of the market. Campbell & Levin (2006) show that if values of bidders are interdependent, then auctions are even outperformed by more straightforward and simple mechanisms such as posted price selling. This result is consistent with study of Ketcham *et al.* (1984). In their experiment posted prices had functioned as a signal for buyers and increased the final prices.

Kultti (1999) analyse choice between auctions and posted price selling by all agents, not only sellers. Three equilibrium strategies were found: usage of auction, usage of posted price selling and utilisation of both. The conclusion was that the two mechanisms are virtually equivalent in the terms of efficiency.

Empirical Evidence

Next we report results of a few empirical studies which are available. Hammond (2010) compares prices of posted price sales and auctions. Data from market of compact disks on eBay.com and Half.com were used. There was not a statistical difference between the revenue of the sample with PP and without it. Although the PP had a positive effect conditional on sale and decreased the probability of successful sale for the subsample of eBay transactions. Hammond reported several specifications of the econometric model. Results were heavily dependent on used method. He also showed that size of inventory had influenced the choice of auction format. Sellers with larger inventory are more likely to use posted prices. Anderson *et al.* (2008) did not find a significant difference between price in auctions and posted price sales. They examined a dataset of Palm Vx devices on eBay.

2.2.2 Auctions with BIN

eBay is one of the few places offering a temporary BIN price in their auctions. There have been theoretical studies and empirical tests explaining the frequent usage from both buyer and seller perspectives.

Theoretical Literature

What is the reason of usage of BIN prices and who benefits from this feature? Most frequent answers to this question focused on risk-preferences of agents. Other papers offered an explanation in impatience of both sellers and buyers. In the end of this section we summarize also other approaches to this problem than the aforementioned two.

Following papers worked with the independent private value setting and the sell of a single object. Budish & Takeyama (2001) propose a simple model with one seller and two bidders to illustrate, how the seller could benefit from permanent buy price in an English auction. She extracts a risk premium from risk-averse bidders. Hidvégi *et al.* (2006) analyse behaviour of bidders in a more complex model than Budish & Takeyama (2001) using setting of n bidders with continuous, independently distributed, and private values. Equilibrium strategies in auction with both temporary and permanent BIN were found. The equilibrium strategy in the case of temporary BIN price is very simple. Bidders find a valuation level and if their valuation is above this threshold they exercise the BIN option immediately. This valuation level is decreasing in risk-aversion and causes risk-averse bidders bid earlier. In such auction is not guaranteed that the auction is going to be won by bidder with the highest valuation. She could have already been outbid by the time of her arrival, and this causes inefficiency of such auctions. The setup in permanent BIN auction is slightly more complicated. According to this paper permanent buy prices are generally superior to temporary ones from the view of both sellers and buyers. Anyway temporary buy price can increase welfare of agents in comparison with a setting without a buy price if agents are risk-averse. On the other hand Yu *et al.* (2006) show that auction with temporary buy price dominates both an auction with permanent buy price and auction without it.

Reynolds & Wooders (2009) show that BIN auction coincide with ascending auction if bidders are risk-neutral. Introduction of BIN price can raise seller‘s revenue if bidders are risk-averse. Zhang & Sarin (2011) find equilibrium best responses for both sellers and bidders. If sellers face risk-neutral bidders they set a BIN price that will never be executed, if they face risk-averse bidders they may raise their revenue by setting an appropriate BIN price. Both risk-neutral and risk-averse bidders have the same strategy- buying for BIN price if their valuation exceeds some threshold value. This threshold is decreasing in risk-aversion and increasing in the number of other bidders who are also offered a BIN price. Also the expected revenue is decreasing in the number of early bidders. Mathews & Katzman (2006) analyse risk-aversion of sellers. Such a seller can benefit from BIN also if bidders are risk-neutral. If a seller is risk-neutral she should set such a BIN price that the BIN option is never used. Ivanova-Stenzel & Kröger (2008) come to a similar conclusion proposing a two-round model. In the first round there is a possibility to sell the item at a take-it-or-leave-it price to one buyer. If the negotiation fails an additional buyer is invited and an auction is conducted. In case of risk-neutral agents the good is always sold through the auction. Risk-heterogeneity may already cause trade in the first round. Authors conducted an experiment. The empirical results did not follow the results from the theoretical model. This could have been partly because of risk-heterogeneity of buyers.

BIN option should reduce the duration of an auction. Interested bidders can purchase goods immediately without having to wait for the end of the auction. Impatient agents can benefit from this feature. Mathews & Katzman (2006) and Mathews (2006) show that the BIN price is set so high that it is never exercised if all agents are non-discounting. Though, impatience on either side results in a BIN price with positive probability of utilization. Gallien & Gupta (2007) also come to the conclusion that if any agent is impatient the seller can raise her benefit by setting a BIN price. Temporary BIN option such as on eBay promotes early bidding.

Other factors can affect the use of BIN prices too. Wang *et al.* (2008) work with an endogenous entry frame where bidders decide whether to enter an auction based on their participation costs which are caused by the time-demanding bidding and uncertain result of an auction. In this case the seller can raise her and also bidders‘ utility using a BIN option, which would reduce the transaction costs, especially of bidders. They also performed an empirical study, which supported their findings. Kirkegaard & Overgaard (2008) offer another explanation of usage of BIN prices with specific assumptions. In their dynamic model early seller knows that there will be other seller offering the same item later and bidders demand multiple items. Then the early seller has an incentive to set a BIN price and so raise her revenue and lower the revenue of the later seller and also the sum of revenues. Shunda (2009) studies a model with reference dependent preference. BIN price influences bidders reference price. This creates an incentive for sellers to set a BIN price. Nakajima (2011) examines first-price and Dutch auctions with bidders exhibiting Allais paradox. Seller can increase her revenue by attaching a buy price when bidders have Allais preferences. Hendricks *et al.* (2005) analyse bidder behaviour under BIN prices together with the phenomenon of sniping. The study shows that behaviour depends on the time of arrival to the auction. If a bidder with high value arrives later to an auction then there is a smaller probability that she exercises the BIN option because she understands that she faces bidders with relatively small value and he is able to outbid them with a sniping bid. Ho *et al.* (2007) examine non-economic determinants such as product category and culture on the use of BIN prices.

There has been shortage of literature for the auction with common values. Shahriar (2008) studies buy prices in common value auctions. The study found that risk-averse seller has an incentive to set a buy price. Risk-preferences of bidders do not matter in this framework.

Literature also studied how to set auction features optimally if distribution of values and other key parameters are known. See Etzion *et al.* (2006) and Caldentey & Vulcano (2007) for additional information.

Empirical Evidence

Next important source of information about BIN are empirical studies. There are not many available. Usual approach of eBay surveys is to delete all auctions ending with BIN price and ignore the initial setting of BIN price. Auctions have to be monitored from the beginning to the end in order to get useful information.

Durham *et al.* (2004) have performed a basic empirical survey of auctions with BIN option. They study eBay coin market and found that BIN function is set by sellers with higher reputation. Higher reputation also increases revenue and probability of an auction ending by a buy price. Auction having a possibility of BIN are more affected by reputation and price is directly related to seller reputation and indirectly to buyer reputation. Also lower BIN price results in a higher probability of using it. They also conducted an experiment by selling coins on eBay and some of the results contradicted the ones from empirical analyses. This was probably caused by selling through an eBay account with zero reputation. It is also worth mentioning, that the results of this study were affected by a large sample bias. Out of 225 sales the first bid in 87 cases was already placed when the data were downloaded so the results of this study are questionable.

Anderson *et al.* (2008) have used data from Palm Vx sales. They study the determinants of the choice of particular auction design and its effect on the auction outcome. Initial BIN option did not have a significant impact on the price, but auctions that ended by a buy price were more expensive. Sellers with higher reputation were more likely to use BIN, this was less likely for new items. Frequent sellers were more likely to use secret reserve prices and this option increased final price.

Hendricks *et al.* (2005) used sales of calculators in empirical part of their work. They concluded that majority of winning bids in auction came in the last minutes of duration, buy prices were executed primarily within first 10 hours of duration. Auction with BIN prices ended with higher transaction price than auctions and there was not a statistically significant difference in the probability of sale between them

Lee & Malmendier (2007) collected data of board game Cashlow 101 and found that bidders bid too much in auctions even if lower buy price was available at the same time, which contradicts the rational behaviour. They concluded that this could be caused by the utility from winning an auction or not paying attention to other options.

Wan *et al.* (2003) concluded three significant results using data from Ty Beanie Baby Bears. Lower buy price, small gap between reserve price and buy price, and longer duration increase probability of using buy price by buyers.

Zhang & Sarin (2011) used data from stamps sales. Only significant results were that inexperienced sellers use BIN option more often and if an item with a BIN option was sold through an auction the price was significantly lower than by pure auctions.

Finally we also mention some interesting studies which dealt with other websites than eBay. Chen *et al.* (2006) have found differences in outcome of auctions with and without the BIN feature by studying sales of Ipod Nano on Yahoo!. This website has slightly different sales procedures than eBay; the most important difference is the permanent BIN option. Auctions with BIN resulted in significantly higher transaction prices. They also found a significant bonus in price for auction with BIN options including posted price sales when compared with pure auction. Dodonova & Khoroshilov (2004) used data from server Bidz.com where they had found that buy prices helped by formulating bidders' own valuation. Bidders are willing to pay more for an item with higher buy price.

There were also few laboratory experiments which contributed to the understanding of BIN prices. Shahriar (2008) examines BIN under both common value and private values settings in laboratory experiment. In both cases there have been an increase in revenue and decrease in its deviation when buy prices were used. On the other hand Peters (1997) fails to show that BIN options increases price and in some cases it even lowered the final price. Grebe *et al.* (2010) used laboratory experiment simulating the eBay platform. They had studied behaviour of agents and among others discovered that sellers set higher BIN price if they are more experienced.

2.2.3 Minimum Bid

There are two types of reserve prices. Public reserve price is the minimum bid that can be placed. Size of secret reservation price is not visible to buyers but its existence is known. If the winning is lower than reservation price when the auction ends, then the product will not be sold. We will summarize the literature about both. We start with the minimum bid.

Theoretical Literature

The theory does not offer an unambiguous explanation of the effect of a public reserve price (minimum bid) on the outcome of an auction. Early papers of Myerson (1981) and Riley & Samuelson (1981) show that an appropriately chosen reserve price above the seller's own value can increase revenue. They worked with independent private value environment and risk-neutrality of buyers. The benefit to the seller is caused by the fact that the reservation price works as a lower bound for the selling price if the good is sold. The effectiveness depends on the size of the reservation price and the distribution of valuation among bidders. The minimum bid will raise the price only if it is between the first and second order statistics of the distribution of bidders valuation according to Häubl & Leszczyc (2003). A simple situation with two bidders competing in an ascending auction can explain the so called price-floor or screening effect. Let the bidders have valuations v_1, v_2, $v_1 > v_2$, and r be the reserve price. If $r < v_2$, than bidder 1 wins the auction and pays v_2, this is the same situation as without a reserve. If $r > v_1$ the product will not be sold. In case $v_1 > r > v_2$ without reserve price the result would be that bidder 1 buys the good for the price of v_2, but with the reserve he has to outbid not only bidder 2 but also the reserve r, so that he has to pay the price of r. The seller's benefit from the reserve is r- v_2.

Levin & Smith (1996) study the reserve price under correlated information, including among others common values and affiliated private values. They find equilibrium for a risk-neutral seller and showed that this result does not depend on the risk-attitude of bidders. Optimal minimum bid converges to seller value as the number of bidders increases. In some cases even two bidders are sufficient. But Milgrom & Weber (1982) show that if affiliated values are present, the seller can raise her payoff through a higher reservation price because this influences the buyer's valuation.

It is important to point out that the number of bidders in these studies is taken as exogenous. The minimum price has an impact on the number of competing bidders. Higher reserve price r excludes from the bidding process the bidders with the valuation below r; this effect is even greater if the number of bidders is not taken as predetermined but as endogenous, this means that each bidder considers the entry to the auction dependent on his costs and potential benefit. The number of bidders has a positive effect on the selling price. Bulow & Klemperer (1996) show that competitive auction with $n + 1$ bidders will yield a seller more expected revenue than a format with n bidders even if the seller can use her monopoly power in such situation. The notion of stochastic entry was studied in Levin & Smith (1994), reserve prices are primary seen as a tool for entry deterrence. According to this study in a second price auction sellers cannot benefit from a reserve price above her valuation. This result holds for risk-neutral agents and both independent and affiliated values.

Engelbrecht-Wiggans (1987) looks for an optimum reservation price. This study compares the positive screening and negative entry deterrence effect and studied them in two specific examples. They find that all revenue enhancing impacts of the former are outweighed by the negatives of the latter. It is not rational to set a nontrivial reservation price. McAfee & McMillan (1987) come to a similar conclusion in a model with IPV and entry costs for bidders. The reserve price should be set at seller's own valuation. Engelbrecht-Wiggans (1993) revises both aforementioned papers by not assuming independent values. The paper shows that even though the seller can raise her revenue by setting a reservation price above her own value this increment is almost negligible and the optimum price is hardly computable, because this price has to attract the same set of bidders as the former reservation price in order to be efficient.

Other literature is also important to understand this topic, Peters (1997) and Hernando-Veciana (2005) propose models where sellers in equilibrium use a reservation price equal to their costs. See Haile (2000) and Zhoucheng Zheng (2002) for theoretical models of auctions with possibility of resale.

Low Minimum Bids on eBay

On eBay we observe reserve prices that are fairly low on average, probably lower than sellers‘ own valuation. If the sellers set the minimum bid according to their own valuation, this would mean that 34 % of sellers from our data value the iPad 2 below $10, which is unlikely. Several explanations of this phenomenon have already been proposed. One possible option can be the system how the fees are composed. The insertion fee depends on the size of the minimum bid. But as explained in the beginning of the chapter this fee is binding only for high volume sellers. Hasker & Sickles (2010) argues that market saturation can be an explanation; the minimum bid would have a negligible impact on the final price in a relatively large market. Ariely & Simonson (2003) have empirically shown that higher minimum bids increase final price but only if similar items are not listed at the same time, which again limits the effect of minimum bid to small markets. These factors could lead to the low level of reservation prices on eBay where the most markets are relatively large and lots of similar products are offered at the same time.

Confederate Bids

There is also a hidden form of reservation price which is important especially at the internet auctions. Confederate bids are bids made by the seller on her own item. She does so through different accounts or other persons. This activity is usually forbidden but it is also very hard to discover. This works in the similar way such as a minimum bids because the item will not be sold at a price lower than a specific threshold. It has also other positive effects on the revenue. Confederate bids do not limit the entry of bidders and can help to influence the valuations of buyers. Hoppe & Sadrieh (2007) used an experiment to assess the effect of both confederate and minimum bids. They have found a significant positive effect of both if set at an optimal level. The optimal mechanism is using of low minimum bids and confederate bids at higher level. Minimum bids positively influence the insertion fees and so negatively the revenue. They have also found that this option has been probably already used among sellers.

Empirical Evidence

Some of the empirical studies show a positive relationship between minimum reserve price and final price. Häubl & Leszczyc (2003) understand the minimum price as consisting of two different parts: minimum bids and fixed price components such as shipping costs. Both have a positive impact on total final price. They show that the cause of higher price for items with higher minimum bids is probably the effect of minimum bids on bidders‘ valuation. There were multiple bidders who had bid more than the reserve price. This fact contradicted the screening effect. Explanation of the positive impact of fixed price components is most likely the bidders‘ irrationality to count these factors into the final price. Hossain & Morgan (2006) used the expression effective reserve price for the sum of minimum bid and shipping and handling. They sold items online and found out that setting of a low minimum bid and high shipping costs yields more revenue than the reverse. But this did not hold in cases where the effective reserve was excessive, defined as 50 % of the resale value.

Haruvy & Leszczyc (2009) show that when there are simultaneous auctions such as on eBay a high minimum bid can suppress revenue. Bidders decide to start bidding first on an auction with lower reserve price than on one with higher minimum bid and they do not switch between auctions often, so the auction with low minimum bid receives a momentum and the increased competition raises revenue. Suter & Hardesty (2005) used an experiment on AuctionAnything.com and have found that higher minimum bids slightly increased final price.

2.2.4 Secret Reserve Price

The seller can hide the true reserve price. Details about the secrete reserve price on eBay were explained in the beginning of the chapter.

Theoretical Literature

Early papers Riley & Samuelson (1981) and Milgrom & Weber (1982) do not recommend the usage of secret reservation price. The seller would not benefit from hiding her own valuation.

There are few important channels how the secret reserve price can influence the results of the auction. Vincent (1995) shows by an example that in the common-value environment of English auction the seller can raise her revenue by setting a secret reservation price. Secret reservation does not discourage the participation in such an extent as public reservation price. If the public reservation price was set some bidders would not enter the auction and would not reveal their signals. Li & Tan (2000) have shown another reason for usage of secret reserve prices; risk-aversion. In an IPV first price-auction a seller can benefit from keeping the reservation price secret if the bidders are sufficiently risk-averse. However, they conclude that the seller has no advantage from the secret reserve if the type of auction is English or second price.

Brisset & Naegelen (2006) theoretically assess the dominance of either secret or public reservation price with respect to the revenue in the private value environment. The public price dominates the secret price in ascending auction with one exception. When bidders are risk-averse and seller can commit to the reservation price before knowing her value, she learns her value during the auction. They also argue that this should not be the case of online auctions where the sellers probably know their value. Hossain (2008) assumes that some bidders do not know their own valuation and they learn about through the bidding process. Now an optimally set secret reservation price is dominating the public reservation price in the terms of expected revenue. Rosenkranz & Schmitz (2007) examine the model with reference-based utility of bidders. They show that the optimum reserve price is increasing in the number of bidders and a secret reservation price can dominate the public one. This holds even if the reference effect is very small.

Empirical Evidence

Bajari & Hortacsu (2000) used data from eBay. They found out that minimum bid was the key determinant of entry for bidders. Combination of secret reserve price and low minimum bid can be profitable since the secret reservation price does not deter entry. This strategy is particularly efficient for goods with higher value because of the fee for the setting of the secret reserve price. Dewally & Ederington (2004) studied the market of comic books on eBay. The results of their study are that secret reserve prices reduce the number of bidders but have an insignificant effect on the final price. They explain the reduction of bidders by two possible options. The bidder seeing a secret reserve is afraid of an unreasonably high reserve price. The second explanation is that the secret reserve price can work as a signal that the seller concealed any information.

Katkar & Lucking-Reiley (2001) auctioned Pokémon cards on eBay. Some of them were set with a minimum bid and some with a secret reserve price equal to this minimum bid of the first group. The impact of the secret reserve price was unambiguously negative for the seller. It reduced the probability of sale and the final price. Hasker & Sickles (2010) have pointed that we cannot make conclusions about the relationships between reservation price and revenue based on this study because of the small size of dataset, which was used. Reiley (2006) presented a study of a sale of game cards in a first-sealed bid auction. The study found that reserve prices reduced number of bidders, decrease probability of an item being unsold, and raise revenue conditional on sale.

2.3 Summary

Literature on the studied topics offers ambiguous results. Theoretical models in the presented literature are very sensitive to exact assumptions.

In the simplest setting an auction outperforms posted price sales, it is sufficient to set a reservation price equal to posted price, and auction will yield higher revenue. If we assume additional costs linked to the sales through auctions or posted price sales, auctions still tend to offer higher revenues. Interdependent values can work as an anchor for valuations and raise price of posted price sales when compared to auctions. Large markets erase the difference between designs.

Use of BIN option is usually explained by three most important factors. It can raise revenues if either bidders or sellers are risk-averse. BIN shortens the duration of an auction and so increases welfare of impatient agents. In online auctions the BIN lowers the transaction costs, when the whole auction process is reduced to one click on the button. Last reason was not studied in the literature in such an extent as the previous two were, but we think that it is especially important in online auctions.

There are three significant effects of the reservation price. Screening can raise revenue according to the classical theory and a high minimum bid can serve as an anchor for bidders‘ valuation. On the other hand higher reservation prices deter entry of bidders. The secret reserve price can dominate the public one in the terms of revenue if bidders are sufficiently risk-averse. It also does not deter entry in such an extent .

Chapter 3

Data Description

3.1 Origin of Data

In this section we will describe the origin of our data and use descriptive statistics to explain details. We used the software Easy Web Extractor to download data about the sales of iPads 2 from eBay.com. For our analysis it was important to monitor both as the beginning so end of sale. We downloaded the data in two steps. In the first stage we monitored every five minutes the 50 newest listings of iPads 2. This stage lasted from February 24 to March 2 2013, so we received information about the beginnings of auctions in a period of one week. In the second stage we waited until March 17 2013 for the sales to be ended and downloaded the details about every listed item. We were able to collect 932 listings during the first period. By 22 listings we were not able to observe the initial setting of the auction, because the first bid had already been placed when we downloaded the information. We deleted these auctions. We were left with 910 observations for the second stage. 204 sales were cancelled by the seller before the end. The seller is allowed to do so in several situations. He can set wrong initial information, damage the item, or the item is simply not available anymore for any other reason. As we had no details about these auctions, we decided to delete them as well. The final dataset has 706 observations.

3.2 Descriptive Statistics

In this section we will present descriptive statistics of key variables of our model. This will help us develop intuition which we will utilize by the construction of econometric models.

3.2.1 Transaction Price and Frequency of Sale

The mean final price of successfully conducted sale is $331. All the observations lie between the $100 minimum price and $720 the maximum. We did not include the price of items that were sold through the Best Offer option, because we do not observe the final price. Out of 706 listings 616 resulted in a sale; this makes 87 % of listed auctions resulting in sale.

Table 3.1: Transaction Price and Frequency of Sale

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
price	331.284	64.592	100	720	563
sale	0.873	0.334	0	1	706

3.2.2 Sales Design

In this section we will summarize key characteristics for both auction-style listings and posted price sales. In the Table 3.2 you can see that auctions are more preferred format, more than two thirds of our dataset are auctions. Mean price of fixed price sales $337, which is slightly higher than mean price of auctions $330. When calculating the mean price we again excluded the fixed price sales that ended by negotiations. The price of auctions fluctuates more. 88% of auctions and 85% of posted price sales ended in sale. We can say that on average auctions yield a lower price but have a higher probability of success than posted price sales. Of course, we cannot make conclusions about final prices and probabilities of sale only from this table, so we will conduct a more complex analysis in the next chapter.

Table 3.2: Prices in Sales Designs

Format	**Mean price**	**Std. Dev.**	**Mean sale**	**N**
fixed price sales	336.719	58.413	.8468468	222
auctions	329.57	66.393	.8842975	484

3.2.3 Fixed Price Sales

Now we will look at details according to the auction format. We begin with fixed price sales. Table 3.3 shows that PP is set with a large range from 135$ to 600$. We can see that the frequency of the sale is lower if the Best Offer is present. 28% per cent of the posted price listings are offered with the Best Offer option and it is interesting that 94 % of auctions with this option also end through negotiation and not the posted price purchase. So we can conclude that setting the Best Offer options is a very strong signal that the sellers is willing to sell her item for less than posted price. To negotiate the price above the BIN is possible but buyer‘s behaviour would be highly irrational.

Table 3.3: Fixed Price Sales

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
initial price	348.23	71.445	135	600
best offer option	0.279	0.45	0	1
sale with Best Offer	0.806	0.398	0	1
sale without Best Offer	0.879	0.327	0	1
sold through negotiation	0.935	0.248	0	1

3.2.4 Auctions

The auctions differ by several key parameters. Every listing must have a determined minimum bid. From the Figure 3.1 we can see that there are two dominant tactics. Either setting a very low minimum bid or setting a minimum bid near to the expected final price, which is around \$300. 28% per cent of the auctions are set with minimum bid under \$50, median minimum bid is \$178. So we can conclude that minimum bids are set fairly low on average as proposed by Hasker & Sickles (2010)

The seller can add the BIN option or secret reserve price to the listing too. The BIN option is offered at 48% of all auctions and secret reserve price at 8% of all auctions. 35% of auctions with the BIN option ends because of the use of BIN, the rest is sold through the ordinary bidding process or remains unsold.

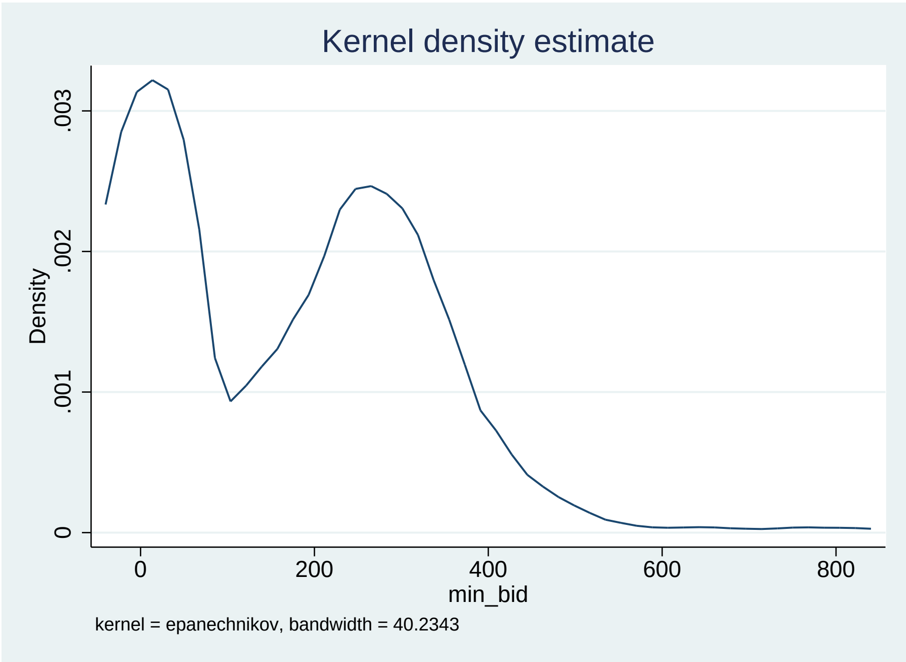
Table 3.4: Minimum Bid

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
minimum bid	166.156	153.93	0.01	800
N		484		

In the Figure 3.2 we observe a clear negative effect of minimum price on the number of bidders such as proposed by the literature.

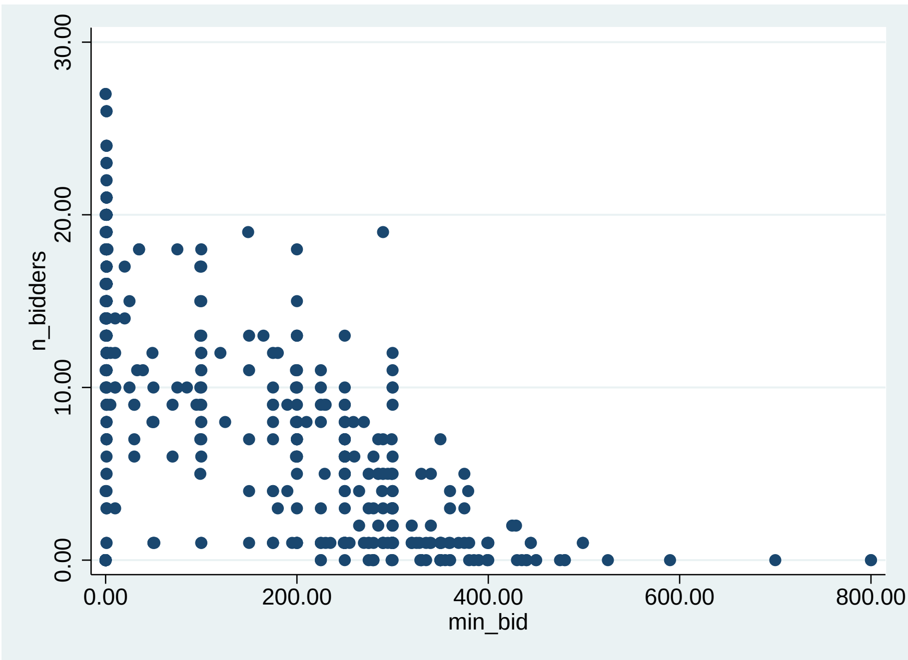
Table 3.5 summarizes the BIN options in auctions sample if it is present. We see that the BIN is higher than the average final price \$331.

Figure 3.1: Minimum Bid



Source: author's computations.

Figure 3.2: Number of Bidders and Minimum Bids



Source: author's computations.

Table 3.5: BIN

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**
BIN price	374.548	103.181	100	950
N		233		

It is interesting that secret reserve prices are usually set with BIN option together. Out of 38 listings with the secret reserve price are 29 listed also with BIN. Moreover only 7 listings ended by a bid being higher that reservations price, the BIN was 22 times executed and the rest remained unsold. In the absence of secret reserve, 242 auctions were set without BIN and 204 with it.

Table 3.6: BIN and Secret Reserve Price

	no BIN	**BIN**
secret	9	19
no secret	242	204

3.2.5 Technical Specifications

iPads 2 have several technical specifications in which they differ. There are three different types of storage capacity 16GB, 32GB, and 64GB. Two colour versions of black and white are sold. iPads are offered with ordinary wi-fi or with wi-fi plus support of 3G. eBay uses six categories of condition for electronics to distinguish between the extent of wear and tear. The options for condition are new, new other, manufacturer refurbished, seller refurbished, used, and for parts or not working. We have decided to use only one category for both new and new other option, since there is only from little to no difference

Table 3.7: Frequency of Conditions

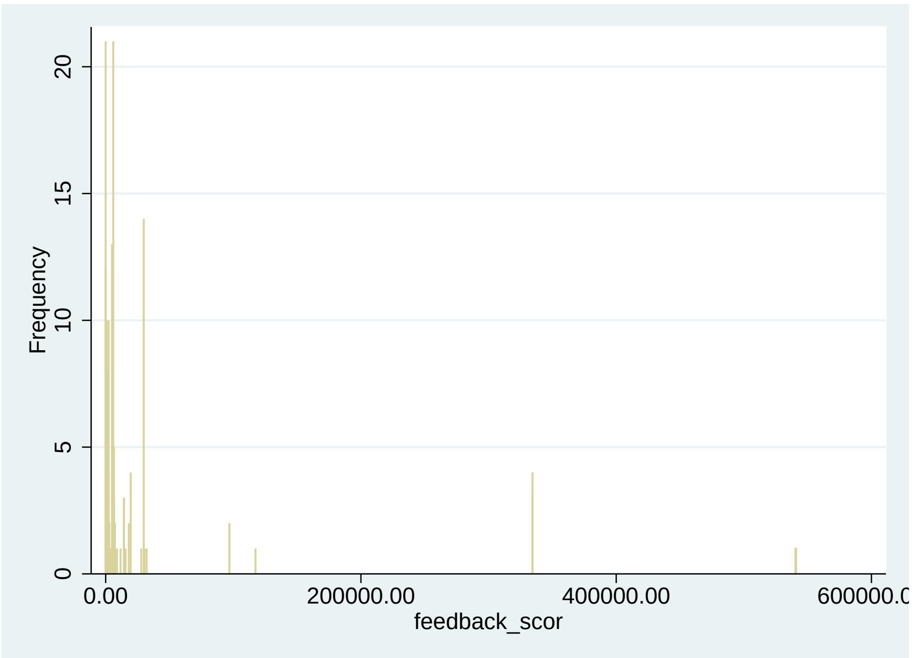
Condition	**Frequency**
new	90
seller refurbished	31
manufacturer refurbished	31
used	534
not working or for parts	77

between them. Most of the iPads in our dataset are used (%68), followed by new and for parts or not working, both slightly over 10 %. Categories seller refurbished and manufacturer refurbished are used rarely to describe the item.

3.2.6 Seller Characteristics

The trade in eBay auctions heavily depends on the honesty of both sellers and buyers. The seller possesses almost all information about the sold item and the buyer has only the knowledge which was publicly made by the seller. There is an information asymmetry. To suppress the dishonest behaviour there has been created a reputation system. After each trade the buyer can give a positive/neutral/negative rating to the seller and she can write a comment about behaviour. This can be done also vice versa by seller rating a buyer. From these ratings a reputation score is created as for each positive/neutral/negative rating is received 1/0/-1 points. These points are summed up and are visible directly next to the name of each member on eBay. Figure 3.3 allows us to better understand the distribution of feedback score among sellers. It is highly skewed with minimum -1, median 167, mean 7183, and maximum 540682. In our econometric analysis we use the logarithm of feedback score so we report overview of this variable as well, distribution of this variable is caught in Figure 3.4.

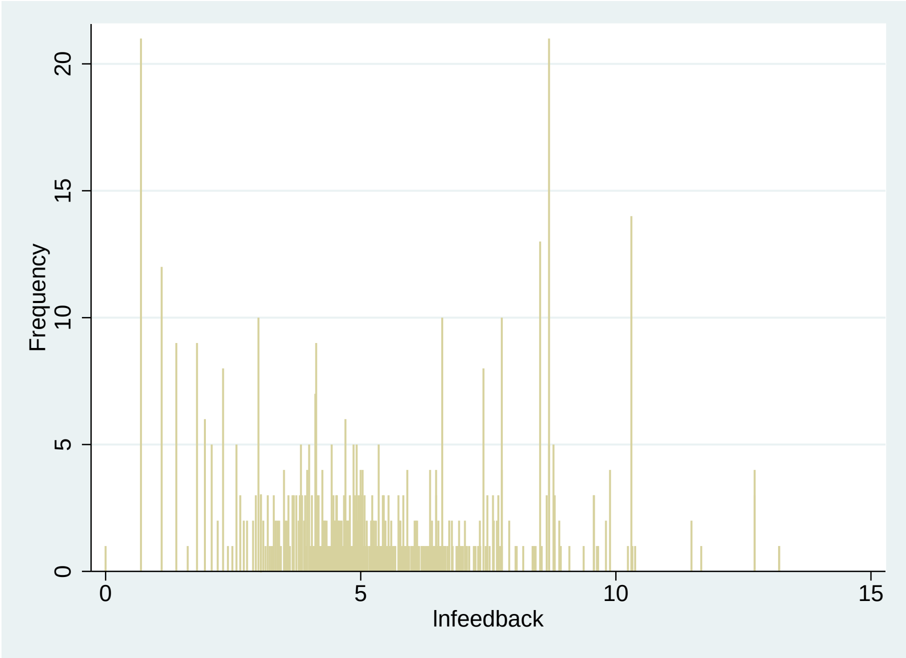
Figure 3.3: Distribution of Feedback Score



Source: author's computations.

Most of the items were listed by different sellers; our 706 listings were created by 516 different sellers. 447 sellers listed only one item and we had only five sellers who listed more than 10 iPads, our highest volume sellers listed 26

Figure 3.4: Distribution of Logarithm of Feedback Score



Source: author's computations.

items. Now we will now look at the distribution of number of listed iPads. We will count one listing as an observation and not one seller as an observation. We do so to get an idea how much of the trade is created by high volume sellers with experience on this particular market. Number of listed iPads is correlated with logarithm of reputation score with correlation coefficient 0.5.

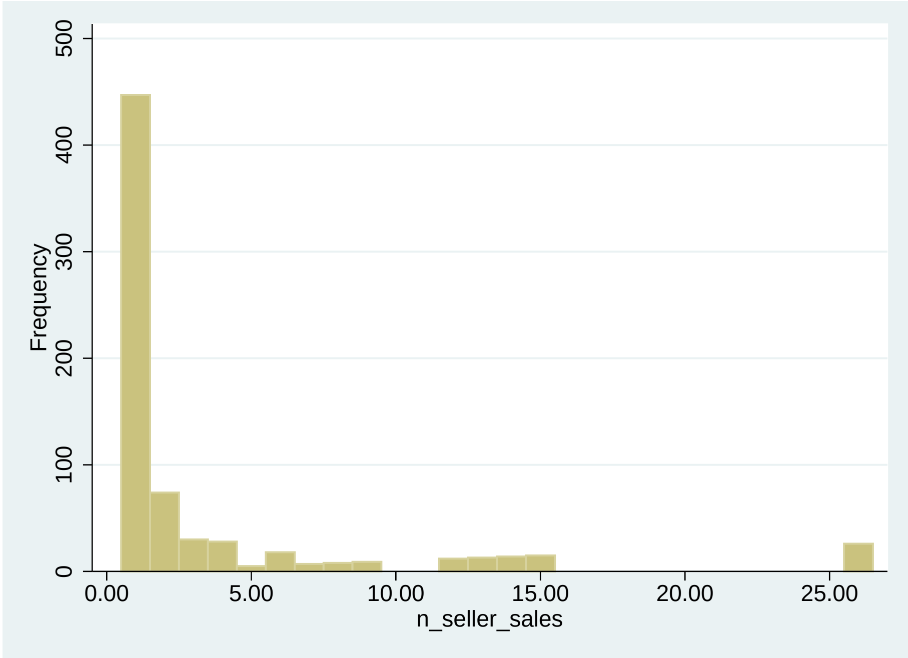
Giving negative rating points is quite rare in comparison with giving positive ones. The mean ratio of negative points to overall feedback is 0.005 and 396 listings were made by a seller without a negative points.

We will now look at relationship between the sellers‘ characteristics used design. We can see that the mean reputation score is higher by sellers using auctions design. But users of posted prices sold more iPads on average. This description offers only a poor guide to the fact who uses which design. The analysis with more explanatory variables will be conducted in the next section.

Table 3.8: Design and Sellers‘ Characteristics

Design	**Mean of lnfeedback**	**Mean of ipadsls.**	**N**
Posted	5.081211	3.788288	222
Auctions	6.254523	3.497934	484

Figure 3.5: Number of Listed iPads



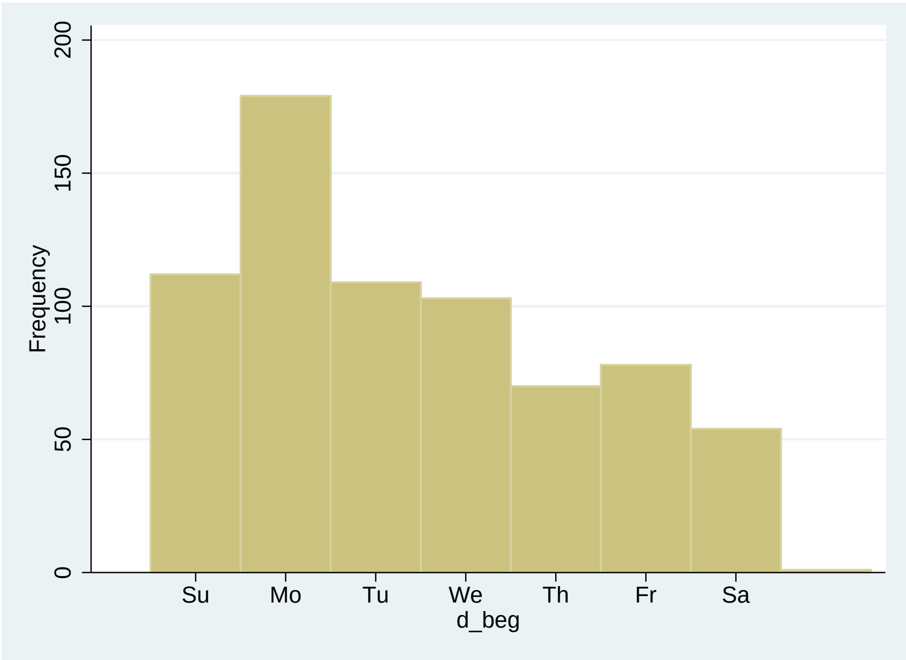
Source: author's computations.

3.2.7 Time Structure

Figure 3.6 summarizes the listing dates. The first bar represents the first day of our data collection- Sunday. The highest number of auctions is on Monday, followed by Sunday. It is interesting that the least number of auctions is listed on Saturday; the literature usually assumes a higher trade activity during weekend days. The most auctions are posted in the evening and late afternoon hours thus as expected. For illustration we report the Kernel density estimate of the time of listing (Figure 3.7).

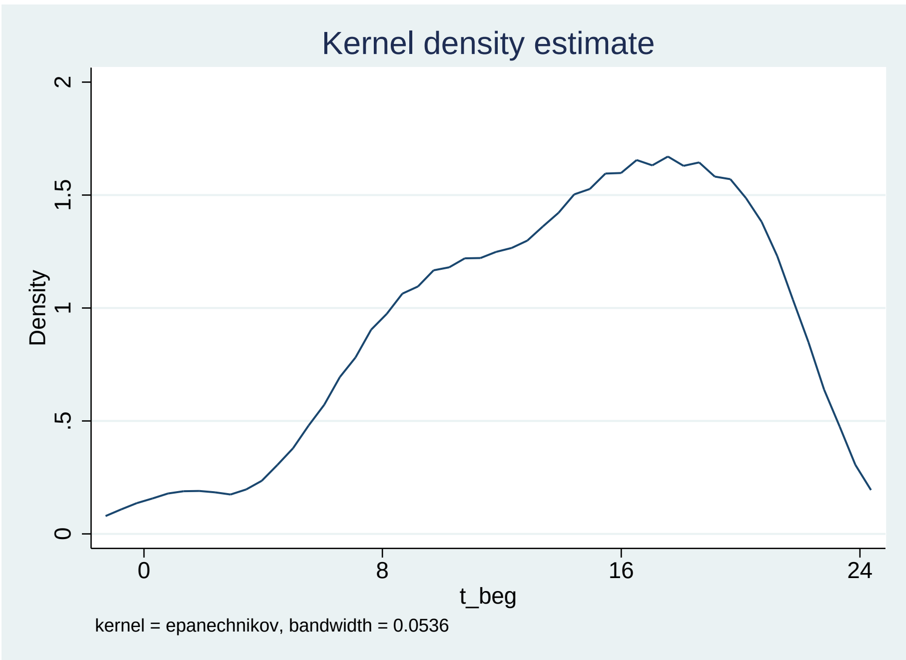
Table 3.8 summarizes the information about durations of auction-style listings. The most favourite duration length for BIN auctions and pure auctions is seven days. Auctions lasting 10 days are barely used; in our data we had only 8 observations. The mean duration of an auction is 4.5 days. Highly experienced auctioneers indicated by reputation score use 1 day auctions; on the other hand mean feedback score 3.9 by the sellers of 10 day auctions indicates the opposite. There are only small differences between reputation in the rest of duration types. Mean *ipadsls* indicates the similar when 1 day auctions are used by the most frequent sellers and 10 day by the least ones.

Figure 3.6: Days of Listings



Source: author's computations.

Figure 3.7: Time of Listing



Source: author's computations.

Table 3.9: Duration Summary

Duration	**Mean of lnfeedback**	**Mean of ipadsls.**	**N**
1 day	6.067097	8.90625	96
3 days	4.797415	2.028302	106
5 days	5.058184	2.698925	93
7 days	4.856689	2.047337	169
10 days	3.925312	1	8

Chapter 4

Econometric Analysis

Our main goal in this section is to examine how the initial setting of design is set and how it influences the result of the sale on eBay. We will study these effects for the whole sample and then separately for subsamples with specific characteristics. We choose a similar approach such as Anderson *et al.* (2008). First, we investigate the effect of exogenous item properties and sellers‘ characteristics on the decision what selling format to choose, then we will investigate how these decisions influence final price and probability of sale.

The use of design and its effect depend on agents‘ characteristics. Most important determinants are risk-aversion, time-preferences, and details about costs of using specific formats.

We will now introduce variables which are used in our model. We have divided them in five groups: seller characteristics, item characteristics, auction design, other factors, and outcome of the sale. The intuition behind this division is the following. Specific characteristics of the product and the characteristics of the seller may influence the decision on auction format. In the second phase we introduce a model that will look for connections between seller and item characteristics, auction design, and other factors on one side and outcome of the sale on the other side.

We do not include any bidders' characteristics in our model. However several theoretical and empirical studies has shown that bidders‘ experience has significant effect on price. For example Sun (2005) performed an empirical analysis of eBay sales and concluded that experienced bidders pay lower prices on eBay. Our aim is to study the effect of the design of a listing on the outcome of the sale, we do not propose a model explaining the complex construction of price. Analysis of bidders behaviour and effect of their characteristics is beyond the scope of this thesis. These reasons made us to omit number of unique bidders, number of bids and buyer's reputation from our model. In the following paragraphs the variables are explained according to the group which they belong to.

4.1 Variables

Item Characteristics Variables in this section describe the technical specification and condition of the particular Ipad 2. We use dummy variables to control for the category to which the item belongs. We named the variables in our model: *new*, *manref*, *selref*, *used*, and *notwor* for conditions new, manufacturer refurbished, seller refurbished, used, and for parts or not working respectively.

The technical variables are again dummies with following names: *s16*, *s32*, *s64*, *yes3g*, *white*. First three control for different size of storage among iPads, *yes3g* refers to the access to 3G above an ordinary wi-fi connection. The last variable shows the colour of the tablet.

Seller Characteristics Reputation score is usually used as a proxy for seller's experience. There have been many studies examining the effect of reputation. See Hasker & Sickles (2010) for a survey on this topic. Based on the current literature there is not a clear conclusion if reputation score has a significant impact on price. The skewed distribution of feedback score created a numerous influential points. We have decided to work with the reputation in the logarithmic form. This seems reasonable because the explanation of the percentage change in rating can be more useful and the statistical influence of extremely high ratings is suppressed. For purpose of our model we use *lnfeedback* which is the natural logarithm of feedback score +2. The addition of two points is made to avoid taking the logarithm of a nonpositive number. We observed how many items in our dataset were listed by a particular seller. This number *ipadsls* is used as a proxy for frequency of sales on this particular eBay market and experience with it. Standifird (2001) showed that negative ratings for sellers are much more influential than the positive ones, so we had decided to include the ratio of negative ratings to the overall reputation score *negratio* in our model. eBay shows number of negative ratings in last 1,6 and 12 months, number of negative ratings in the last 12 months is used.

Sales Design Under the term sales design we will understand all characteristics of the sales format, which are set by the seller before the auction begins. We split our analysis in the examination of two major designs, posted price sales and auction-style sales. Details about the design were explained in Chapter 2. We use dummy variable *posted* to mark the fixed price sales. If not stated otherwise auction-style sales are chosen as a base group.

Next to the choice of the auction format the seller chooses other specifications. Sellers using posted price sales have the possibility to set the size of BIN price, we label it *binpr*. *bestoffer* is a dummy variable marking the presence of Best Offer option.

There are more options for auction-style listings. *minbid* is the minimum bid; the first bid has to be at least as high as this amount. *binopt* is a dummy variable equal 1 if the BIN price is incorporated into the listing and 0 otherwise, *binpr* will mark the size of BIN price in dollars. The presence of a secret reservation price is distinguished by the dummy variable *secres*. We do not include the size of this variables, it is beyond the scope of this thesis to reveal its true value.

As the next specification the seller has to choose is the duration of the auction. eBay allows to set the length of the auction at 1, 3, 5, 7, or 10 days. The duration of posted price sales is determined endogenously with the maximum set by the seller. Gonzalez *et al.* (2009) and Lucking-Reiley *et al.* (2007) found a positive impact of the length of the auction on the revenue. We will work with duration in the categorical form rather than in the continuous form, this reflects more of the decision a buyer faces when setting her listing. Dummy variables *dur1*, *dur3*, *dur5*, *dur7*, and *dur10* label the specific length of auction duration.

The rest of options are common for both settings. We include *shipp* as a next variable. Observation of shipping costs is problematic because an exact amount is often not stated. Sometimes the bidder is instructed to contact the buyer to find out the details about shipping or automatic calculators for different areas are used. *shipp* is therefore not the exact amount of shipping costs. This variable is equal to the precise shipping included by the seller if available, 0 otherwise. The standard microeconomic theory suggests a direct negative relationship between shipping costs and final price. The buyer should be indifferent to particular components of the final price he has to pay. But Hossain & Morgan (2006) show that setting of a lower minimum bid and higher shipping costs enhances bidding on the item and creates higher revenues. This finding can suggest partially irrational behaviour of bidders.

The buyer has the possibility to describe her item by words. It is beyond the scope of our model to assess the quality of each description but we can use the length of the description as a proxy variable. Anderson *et al.* (2004) did the same and found a marginally significant effect of the length of the description on the final price. In our model *desclen* stands for the number of characters used to describe the sold item. But we have to point out that iPads are homogenous products which differ only in few specifications, also the interface created for the sale of iPads is standardized and almost all descriptions are created only by filling out the specimen formulary about technical details. So we do not expect a significant impact of the description of our items.

Other Factors The outcome can be influenced also by other impacts that are not controlled by the seller. We decide to include dummies for the day of the auction to eliminate potential shocks in both demand and supply on eBay.com anyway. Roth & Ockenfels (2002) find out that most of the bids are submitted directly before the end of the auction. The only one bid executing the BIN option also determines the end of the sale. According to these facts we have decided to use the end days and not beginning of the auction to control for a time trend. Dummy variables *d1*, ..., *d13* marking the day of end are used.

Outcome of the Sale The last group of variables contains all parameters that are determined after the auction has ended. For our analysis the most important are *finalprice* and *sale*. The *finalprice* is the price at which the item was sold, so either the winning bid or BIN price or PP. The second variable is a dummy having value 1 if the item was sold and 0 if the item remained unsold. We have one other variable in this section. *binex* is again a dummy variable equal 1 if the item was sold through the BIN option, 0 otherwise.

4.2 Seller‘s Decision and its Determinants

In this first part of the model we will look for determinants of the sellers' choice which design of sale to use. Explained variables are from the categories of auction design, explanatory ones from sellers' characteristics and item specification. We are particularly interested in the effect of *lnfeedback* and *ipadsls*. It will also be interesting to observe how item characteristics influence the decision about the sales format. The results of regressions are reported in three tables according to the used model. Regression 1-4 in the first table are results of the logistic regressions, regressions 5-9 in the second table came from an ordinary least square analysis and the last third table reports the result of multinomial logistic regression (this table can be found in Appendix).

4.2.1 Auctions or Posted Price Sales?

First, we will examine the determinants of the choice between fixed-price and auction-style listings. We use a logistic regression of *posted* on aforementioned variables. The results can be found in Regression 1. Variables *white*, *selref*, *manref*, and *lnfeedback* have positive and significant effect. Variable *ipadsls* affects *posted* negatively.

If we look only on the signs of coefficients we can see that items with better technical parameters (i.e. higher storage and access to 3G) have higher probability of being offered through posted sales. But these coefficients are not significant. Very significant and positive *white* shows how item characteristics which do not have an impact on functionality of products can influence the design of how the product is sold. Average marginal effect (AME) of *white* is 10%. Both refurbished categories have higher probability of being offered through a posted price sale. It is worth mentioning that we do not observe significant differences between the most used categories- new and used ones, which are taken as a base.

Further we can see a contradicting effect of *lnfeedback* and *ipadsls*. Sellers with higher reputation tend to use posted price sales more frequently, on the other hand frequent sellers of iPads prefer the auction design. A percentage increase in *lnfeedback* reduces the probability of using posted price sales on average by 6%. The average marginal effect of *ipadsls* is 1%. A possible explanation could be the difference in markets, strategies optimal for one market are not optimal in another. Experienced sellers can be used to other markets with different regularities, it is possible that they do not adjust their behaviour for the market of iPads. Differences in fees can matter as well. Listing fees are free for 50 first auctions, whereas they are paid by posted price sales. On the other hand the expected final value fee is higher for auctions, this difference should more than outweigh lower insertion fee. In the next regressions we will mainly use subsamples of our data.

4.2.2 Fixed Price Sales

Regression 5 shows the determinants of the size of PP. We use OLS to analyse the size of the posted price. The significant parameters of item characteristics are straightforward, signalising higher posted prices for better conditions or better technical functions. The only significant seller characteristics *ipadsls* is negative indicating that more frequent sellers with higher experience at iPad sales usually set a lower posted prices. The PP decreases $3.3 for each additionally listed iPad of the specific seller.

Regression 2 is a logistic regression explaining the use of Best Offer options in the posted price sales subsample. A not working item or an iPad with higher storage capacity is more likely being offered with the Best Offer. The effect of *notwor* is large; a not working iPad has 51% greater probability of being offered with Best Offer option. The Best Offer options is used for products with non-frequent characteristics. This shows that bargaining prevails in thin markets. Both *ipadsls* and *lnfeedback* are negative which indicates that more frequent and experienced sellers rather avoid the option Best Offer. It seems reasonable as bargaining would impose large transaction costs on frequent sellers.

4.2.3 Auctions

For the subsample of auctions first we will use logistic regression to examine the determinants of setting a BIN option (Regression 3). New iPads and the ones with storage 32GB have a higher probability of being sold with BIN option, but both of these variables are only marginally significant at 10% significance level. New iPads have 13% higher probability of having BIN options than the used ones. More experienced sellers tend to use BIN less probably. Both *lnfeedback* and *ipadsls* are negative but only the *ipadsls* is significant. Higher share of negative ratings increase probability of setting a BIN price.

Next we look for determinants of the size of BIN prices (Regression 6), we can see a significant effect of technical characteristics. More frequent sellers of iPads use lower BIN prices, this result is consistent with our findings about price in the fixed-price sales, magnitudes of effects of *ipadsls* are also similar. Overall reputation influenced neither the setting of BIN option nor its size.

Logistic regression (Regression 4) with *secres* being the explained variable shows only higher usage of secret reserve prices for manufacturer refurbished items and that this option is less likely for frequent sellers of iPads, this could be a response to the fees, because for hiding the reservation price additional costs are inquired. The AME of *ipadsls* is -2%.

The size of minimum bid is not influenced by the technical specifications but minimum bids reflect the condition of the item. The minimum bid is higher for new items and lower for refurbished and not working ones. The significant and negative coefficients by *lnfeedback* and *ipadsls* indicates that more experienced and frequent sellers tend to set lower minimum bids, as can be seen in the able the magnitudes are not negligible. Variable *white* has a positive effect on the minimum bid and so again influences the initial setting of a listing. White iPads have 24$ higher minimum bids.

For the choice of duration of the auction we preferred using of multinomial logistic regression over OLS, because of the categorical form of this variable. We chose the most frequent 7-day duration as a base group and we have received following results. Some of the item characteristics are significant. *ipadsls* is positive and significant by the 1-day auctions, and negative and significant by 10-day auctions. Frequent sellers avoid very short and very long auctions; the 10-day auctions are also available only for an additional fee. These coefficients are the only significant sellers‘ characteristics in the multinomial regression.

Common Settings There two common features for both major categories, description length and shipping costs (Regressions 8 and 9). We use ordinary least square. Refurbished products have longer description; seller has to describe how the product differs from the new one. Sellers with higher reputation score write shorter descriptions. The size of coefficients seems large but we have to take in account that the average length of description is almost 6000 characters. Shipping costs are set higher for iPads with storage of 32GB and the white ones. Condition variables also influence the size of shipping costs, manufacturer refurbished iPads are offered with higher shipping costs and not working products on the other hand with lower shipping costs. More experienced sellers set higher shipping costs to raise their revenue but frequent sellers tend to lower the shipping costs. A percentage increase in reputation raises the shipping costs by almost a dollar.

	(1) posted	(2) bestoffer	(3) binopt	(4) secres
main				
s32	0.329	0.668	0.488*	-0.433
	(0.128)	(0.148)	(0.053)	(0.340)
s64	0.174	1.018**	-0.00361	-1.039
	(0.493)	(0.041)	(0.990)	(0.162)
yes3g	0.0307	0.0252	0.0303	-0.367
	(0.883)	(0.948)	(0.896)	(0.437)
white	0.521***	-0.258	0.116	-0.267
	(0.004)	(0.511)	(0.586)	(0.459)
manref	0.993**		0.532	2.519***
	(0.014)		(0.304)	(0.002)
selref	1.067***	0.497	-0.140	
	(0.002)	(0.517)	(0.790)	
new	0.238	0.0237	0.559*	0.205
	(0.417)	(0.965)	(0.056)	(0.678)
notwor	0.189	3.124***	-0.316	0.0593
	(0.517)	(0.000)	(0.332)	(0.918)
lnfeedback	0.302***	-0.186*	-0.0132	-0.0100
	(0.000)	(0.076)	(0.811)	(0.916)
negratio	-0.00234	-24.65	2.640**	2.114
	(0.996)	(0.383)	(0.020)	(0.124)
ipadsls	-0.0623***	-0.265***	-0.0777***	-0.263***
	(0.000)	(0.002)	(0.000)	(0.004)
_cons	-2.772***	0.365	-0.0101	-1.717***
	(0.000)	(0.578)	(0.974)	(0.001)
N	677	198	465	451

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	(5) PP	(6) binpr (auctions)	(7) minbid	(8) desclen	(9) shipp
s32	26.18***	33.88***	10.05	11.79	2.504*
	(0.004)	(0.001)	(0.498)	(0.907)	(0.068)
s64	81.70***	136.0***	26.75	-66.39	-0.421
	(0.000)	(0.000)	(0.264)	(0.379)	(0.741)
yes3g	27.87***	38.17***	9.354	-35.33	1.201
	(0.000)	(0.005)	(0.574)	(0.603)	(0.334)
white	-2.796	6.838	23.61*	-37.70	2.636**
	(0.680)	(0.515)	(0.082)	(0.586)	(0.013)
manref	12.22	10.55	-56.81*	418.5***	8.459***
	(0.272)	(0.507)	(0.100)	(0.000)	(0.000)
selref	-0.219	-17.75	-103.2***	302.7***	0.415
	(0.985)	(0.418)	(0.002)	(0.004)	(0.815)
new	59.29***	65.61***	57.59**	73.67	3.609
	(0.000)	(0.000)	(0.019)	(0.251)	(0.103)
notwor	-90.44***	-124.5***	-78.63***	-174.2	-2.491**
	(0.000)	(0.000)	(0.000)	(0.105)	(0.014)
lnfeedback	2.130	-1.731	-14.76***	-67.12***	0.839***
	(0.141)	(0.579)	(0.000)	(0.000)	(0.001)
negratio	-17.20	-55.31	-37.78	86.05	0.838
	(0.907)	(0.329)	(0.485)	(0.247)	(0.496)
ipadsls	-3.288***	-4.190**	-5.729***	5.480	-0.172**
	(0.000)	(0.024)	(0.000)	(0.383)	(0.016)
_cons	319.5***	350.9***	251.9***	6295.1***	-2.499**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.045)
N	212	220	465	677	676
R^2	0.588	0.447	0.238	0.049	0.057

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.3 Price

In this and next sections we will study the outcomes of the sales and particularly the effects of the auction design. The explained variables belong to the group outcome of the sale and the explanatory are from the remaining groups. We do not include seller characteristics *ipadsls* as in the previous section. This variable is not directly visible by buyers and so it should not have an effect on the outcome of listings. We will start the analysis with the model explaining the final price of sales.

We have to take in account the sample bias in our data. We observe only the price of the sold products and do not know the price of the unsold ones. Former literature used several options to deal with this problem. Anderson *et al.* (2008) had ignored this problem and deleted all of unsold auctions from his dataset. Since unsold items were only a very little fraction of his dataset, so we might expect that this did not have a radical influence on results. Hammond (2010) considered two possible ways how to solve this problem. He was choosing between two models. In the first one the selling price of unsold items was considered as completely unobserved, in the second one the reserve price or the posted price served as a cap for the true selling price. These two possible understandings would have lead to the use of sample-selection model or censored-regression model respectively. To decide between these two Hammond used Vuong likelihood-ration test for non-nested models with the result of sample-selection model being more accurate. Chen *et al.* (2006) used a sample selection model as well.

For our model we use first the sample selection model (Heckit model), but the sample selection is not statistically significant in a single regression, for simplicity we report the results of OLS run on the constrained sample of sold items. Results of the sample selection regressions can be found in Appendix. For interested readers we include also the censored normal regressions in the same place. The interpretation is different in this model because it assumes that the selling price of unsold items is less than minimum bid or BIN or PP. Some sellers do not have additional costs in relisting an unsold item. This depends on their personal characteristics and eBay also offers the second listing of an unsold item for free. So there is a possibility that the sellers care only about results of successful sales and not about the unsuccessful ones. In such an environment the censored normal regression does not present useful results.

There is a danger that each design variable could be endogenous. Some of the literature considered the setting of the BIN options as an endogenous variable. Hammond (2010) and Chen *et al.* (2006) used this approach. We will take the setting of BIN as a exogenous variables. I will explain why our approach differs. Chen *et al.* (2006) did not have many variables available. They did not even observe the reputation of sellers and so a model assuming endogeneity was appropriate. We include in our model almost all possible product characteristics (with the exception of the assessing of the whole description, which is beyond the scope of this thesis). All characteristics of sellers that are visible by potential buyers are incorporated too. Anyway, it is possible that some of the design characterstics could serve as credible signals of sellers‘ characteristics that are not included in our model. For example if bidders knew that the posted price sales were used by more reliable sellers, than we would observe a biased effect of *posted*. But we have no information that such signals have occurred on eBay. We think we have not omitted an important variable, which could be correlated with auctions design, and influence the final price at the same time.

To support the clarity of the text we do not display the day indicators in regressions reported in this chapter.

4.3.1 Auctions versus Posted Price Sales

In this section we will study the determinants of final price for both formats. We have one additional problem next to the aforementioned sample bias. We have not observed the price of sales that ended by bargaining. We incorporate this problem into our previously suggested analysis using censored normal regression with PP price as a maximum cap for price. We reasonably assume that negotiations end at a lower price than PP, because buying at PP is an outside option to Best Offer. We will proceed exactly the same as in the part studying posted price sales.

First we will look if there is a difference between posted price sales and auctions. Regression 1 shows the result for the OLS run on the whole sample of finished sales. Variables *s32*, *s64*, *yes3g*, *new* and *shipp* increase the final price, on the other hand variable *notwor* decreases it.

posted is negative but this result is not significant. This is the most important result of this part of the analysis. Final prices of auctions and posted price sales do not significantly differ.

Some of the day indicators (not displayed) are significant, which indicates changes in prices over time. The interesting fact is that *shipp* is positive. We would expect it to be negative or zero. We have to again realize that *shipp* is not the final size of shipping costs but the amount listed on the item‘s webpage. So a possible explanation of such a result is that buyers prefer to buy goods with a predetermined and exact price of shipping rather than buying goods where the price of shipping is not immediately visible.

In this section we will also describe the signs of item specifications and product conditions. The estimated price for a used iPad with storage 16GB and without 3G access is \$267. We observe raises in price for higher storage, \$29 and \$58 for 32GB and 64GB respectively. A tablet with wi-fi+3G is \$21 more expensive than the one with an ordinary wi-fi. New iPads are estimated to be sold for \$60 more than the used ones, on the other hand not working ones even for \$119 less. We do not observe a statistically significant difference between the used and refurbished tablets. We will not describe the effects of item specification on price in the next sections, because their interpretation is straightforward and so far not interesting for economic analysis. In our further analysis of final price we will focus on particular subsamples of our data. We will examine separately the posted price and auction-style listings, which we will further study depending of the presence of BIN option or not.

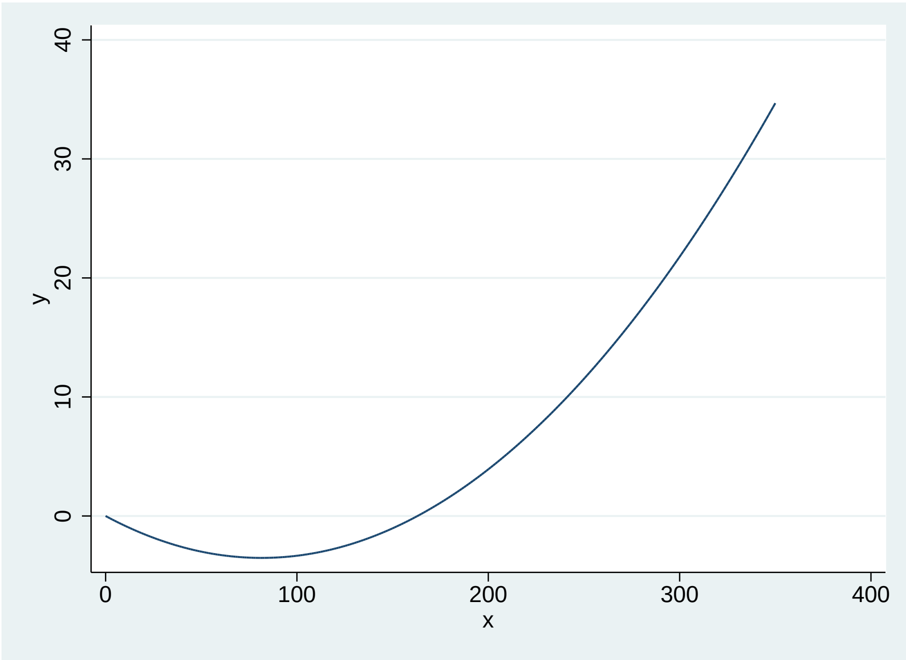
4.3.2 Auctions

Variables *sqminbid* and *dur5* significantly increase price, variables *minbid* and *shipp* decrease it. Opposite signs of minimum bid variables indicate a positive effect only for higher minimum bids. The positive effect outweighs the negative for minimum bids above \$165. We can see on the Figure 4.1 that the marginal effect of minimum bid is substantial. A minimum bid equalled \$200 has marginal effect on price \$3.92.

Interesting is the impact of the duration. We do not observe that longer auction would yield higher revenue, instead the 5-day auction dominates all other possible durations. The final price if this duration is set is \$18 higher than for the 7-day auctions that serve as a base group. Shipping affects the final price in the expected way in this subsample. An additional dollar of shipping costs decreases the final price by \$0.9.

BIN option is not significant and its magnitude is negligible anyway. *secres* increases the final price by more than 10$ but this effect is not statistically significant. Now we will focus on subsamples with and without BIN option.

Figure 4.1: Marginal Effect of Minimum Bid



Source: author's computations.

4.3.3 Pure Auctions

In this regression we use only pure auctions without BIN. Variables *dur1* and *dur5* increase the final price. We can see a significant difference between 7-day auctions and 1-day or 5-day auctions. 5-day auctions offer a $20 bonus on revenue and 1-day an even higher one.

The seller characteristics do not influence the outcome. None of the auction design variables are significant with the exception of duration. The size of minimum bids does not play a significant role for pure auctions. Minimum bid variables are jointly insignificant. We omitted *shipp* in this regression, for this sample we have only several nonzero observations available. All were set lower than 1$, this caused unrealistic results in the regression.

4.3.4 BIN Auctions

Variables *secres*, *sqminbid*, *dur5* raise the price in this subsample, variables *negratio*, *minbid*, and *shipp* supress it. The reputation score is not significant in this sample, but *negratio* has a marginally significant negative impact, the magnitude of the coefficient is large, but if we take an average seller and increase the number of negative feedbacks by one, the final price will fall only by $0.005.

A nonlinear effect of minimum bid is again significant; *minbid* is negative and *sqminbid* positive. *secres* is marginally significant in this subsample. Auctions with this option are estimated to yield $16 more. Remember that most of the secret reserve price are offered together with the BIN option and so belong in this subsample. Similarly as for pure auction *shipp* affects the outcome in the expected way. We observe the bonus for 5-day auction in this subsample as well.

4.3.5 Posted Price Sales

Posted price auctions do not have as many design options as auction-style listings do. The seller can set only the size of the PP, the Best Offer option, and shipping costs. Of course she chooses the style of description too. We use a similar approach as for the whole sample in the terms of choice of the particular model. We do not include *binpr* as a regressor. This variable is equal to the explained variable if a transaction ends in sale and has not a useful interpretation for us.

In the sample model we find only significant variable *shipp* next to the technical parameters. *shipp* is surprisingly positive. The best offer option lowers the price but the coefficient is not significant.

	(1) whole sample	(2) auctions	(3) pure auctions	(4) BIN auctions	(5) posted price
posted	-6.515				
	(0.206)				
s32	29.38***	32.58***	34.30***	29.23***	25.21***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
s64	57.71***	53.09***	52.15***	57.68***	59.83***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
yes3g	21.24***	16.83***	6.569	27.03***	23.26***
	(0.000)	(0.002)	(0.422)	(0.001)	(0.001)
white	6.190	5.212	3.370	12.12**	7.621
	(0.115)	(0.230)	(0.646)	(0.045)	(0.218)
manref	4.696	27.96***	6.478	36.12	-4.829
	(0.440)	(0.010)	(0.618)	(0.120)	(0.570)
selref	-2.464	1.527	-2.034	-2.049	1.513
	(0.718)	(0.870)	(0.935)	(0.848)	(0.897)
new	59.89***	50.10***	49.60***	46.39***	68.51***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
notwor	-118.3***	-108.9***	-109.6***	-110.8***	-116.3***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnfeedback	-0.865	-0.357	-0.650	-0.590	1.105
	(0.398)	(0.818)	(0.834)	(0.702)	(0.442)
negratio	-17.36	-14.43	-0.654	-37.28*	84.97
	(0.297)	(0.267)	(0.970)	(0.073)	(0.494)
lndesclen	5.857	13.75	8.157	24.81	-21.05
	(0.573)	(0.336)	(0.786)	(0.212)	(0.298)
shipp	0.611***	-0.879*		-1.021*	0.385***
	(0.006)	(0.086)		(0.053)	(0.010)
binopt		-0.848			
		(0.862)			
secres		10.92	3.365	16.08*	
		(0.123)	(0.689)	(0.098)	
minbid		-0.0864	0.0392	-0.122	
		(0.151)	(0.681)	(0.111)	
sqminbid		0.000530***	0.0000484	0.000658***	
		(0.001)	(0.842)	(0.001)	
dur1		0.179	23.20*	-13.73	
		(0.981)	(0.083)	(0.226)	
dur3		-1.810	-0.471	-1.466	
		(0.810)	(0.972)	(0.858)	
dur5		17.99***	19.41**	14.48*	
		(0.004)	(0.042)	(0.073)	
dur10		-11.48		-10.48	
		(0.447)		(0.561)	
bestoffer					-17.63
					(0.233)
_cons	266.7***	184.1	252.3	64.67	468.6**
	(0.003)	(0.145)	(0.347)	(0.717)	(0.010)
N	616	402	215	187	183
R^2	0.574	0.619	0.538	0.755	0.768

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4 Probability of Sale

4.4.1 Whole Sample

In this subsection we will present results of a logistic regression, which we perform to find out important determinants of probability of sale. First, we run a regression on the whole sample including both different formats. In this regression we include only explanatory variables describing the item specifications, the seller characteristics, and we add variable *posted* to distinguish between basic auction formats.

Variables *selref* and *lnfeedback* increase the probability of sale, variable *posted* reduces it. The product specifications are generally insignificant with one exception. Seller refurbished items have better chance of being sold compared with used ones, which are used as a base group.

The fixed price sales have lower probability of success and sellers with higher reputation have better chances of selling their products. The mean probability of an item being sold is 89% for auction-style listings but only 81% for posted price sale.

Mean marginal effect of a 1% increase in reputation score is a 2% raise in probability of sale. We will examine the effect of reputation in more details. The probability of success is only 70% for the least experienced sellers. This probability rises for seller with a median reputation to 87%. Sellers belonging to the upper 10% of most experienced have even 93% chances of sale. These probabilities are calculated as mean probabilities when the *lnfeedback* is fixed at the examined level and the rest of variables varies.

4.4.2 Fixed Price Sales

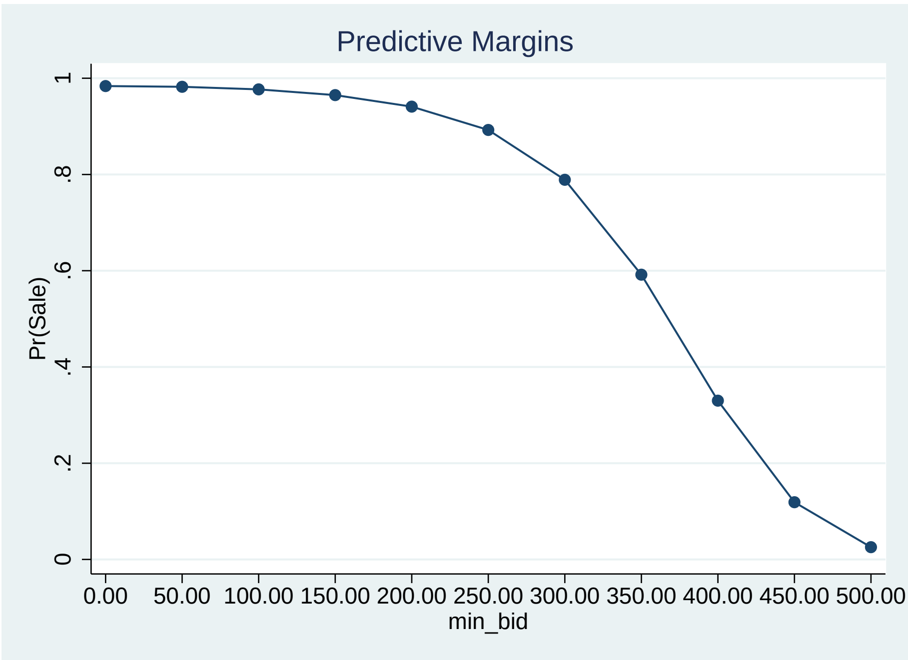
The analysis of posted price sales will be very simple. The only significant variable in our model is *white*. The colour has large effect; mean marginal effect of *white* is 17%. Higher posted price decreases the probability of sale such as we might expect. Best Offer option allowing negotiation helps to come to a result and sell the goods, but both *bestoffer* and *binpr* are not statistically significant. Even the whole model is not significant, so we can conclude that posted price sales do not have important determinant influencing their success.

4.4.3 Auctions

For the subsample with the auction format we receive a much better fitting model. Variables next to technical specification that influence the outcome are: *dur10* positively and *secres* with *sqminbid* negatively.

It is interesting that the extent of use significantly affects the outcome. The mean probability of success for used items is 87%. The number decreases for not working iPads to 79% and increases for new one to 97%. BIN option is not significant and has a positive coefficient. *secres* has a large impact and decreases the mean probability of sale by 21%. Ten days lasting auctions offer a 10% higher probability of sale. We can see that the square of minimum bid is significant and negative. Auctions with very low minimum bid below 150$ have the mean probability of sale 98%. Minimum bid 300$ which size is close to the average selling price lowers the chances to 79%. The following figure shows the predicted probabilities for different sizes of minimum bids.

Figure 4.2: Effect of Minimum Bid on Probability of Sale



Source: author's computations.

We will also examine the two subsamples of auctions- pure auction and BIN auctions. For BIN auctions we can see a positive impact of *s64*, *new*, *lnfeedback*, *minbid* and negative of *notwor*, *lndescen*, *binpr*, *secres*, *sqminbid*, *dur1*, *dur5*. The probability of success decreases with the size of BIN price. We can also see a nonlinear relationship with minimum bids. Duration affects the probability of sale in an interesting way, 1-day and 5-day auctions have significantly lower probability of sale than the base 7-day auctions. Secret reserve again decreases the probability of sale.

The last group we will examine are pure auctions. The only variable with positive effect is *lndesclen*. Variables negatively affecting *sale* are: *manref*, *notwor*, *secres*, *sqminbid*, and *dur3*. Signs of coefficients are similar as for BIN auctions but magnitudes differ.

	(1) Whole sample	(2) Posted price	(3) Auctions	(4) BIN auctions	(5) Pure auctions
sale					
posted	-0.766**				
	(0.015)				
s32	-0.0484	0.109	-0.267	0.345	1.126
	(0.879)	(0.891)	(0.579)	(0.762)	(0.483)
s64	-0.520	-0.376	1.737**	7.857***	1.079
	(0.128)	(0.602)	(0.023)	(0.004)	(0.689)
yes3g	-0.138	1.340	-0.00135	2.025	0.659
	(0.644)	(0.181)	(0.998)	(0.119)	(0.733)
white	0.224	1.425*	0.438	1.792	2.049
	(0.410)	(0.089)	(0.358)	(0.306)	(0.237)
manref	1.036		-1.860	-1.677	-15.47***
	(0.317)		(0.172)	(0.630)	(0.005)
selref	1.783*	1.748			
	(0.060)	(0.134)			
new	-0.225	0.286	3.794**	15.45***	2.260
	(0.513)	(0.772)	(0.025)	(0.000)	(0.193)
notwor	0.531	-0.215	-1.295*	-3.102**	-4.323**
	(0.259)	(0.841)	(0.066)	(0.040)	(0.012)
lnfeedback	0.239***	0.379	0.212*	0.693*	0.815
	(0.000)	(0.210)	(0.098)	(0.085)	(0.140)
negratio	0.145	-8.305	0.778	10.74	2.076
	(0.829)	(0.654)	(0.372)	(0.120)	(0.391)
lndesclen	-0.0740	-1.088	1.486	-11.88***	19.11***
	(0.932)	(0.574)	(0.702)	(0.007)	(0.009)
shipp	-0.00621	-0.000483			
	(0.461)	(0.968)			
binpr		-0.00952	-0.00277	-0.0243**	
		(0.224)	(0.580)	(0.011)	
bestoffer		0.512			
		(0.431)			
binopt			1.840		
			(0.352)		
secres			-4.402***	-6.561***	-16.05***
			(0.000)	(0.000)	(0.002)
minbid			0.00301	0.0729**	-0.0130
			(0.691)	(0.010)	(0.545)
sqminbid			-0.0000581***	-0.000269***	-0.000150**
			(0.003)	(0.003)	(0.013)
dur1			-1.274	-3.768*	-5.056
			(0.158)	(0.075)	(0.120)
dur3			-1.360	0.189	-9.365**
			(0.127)	(0.922)	(0.033)
dur5			-0.907	-2.963**	-4.130
			(0.225)	(0.046)	(0.213)
dur10			2.165*	-0.622	
			(0.055)	(0.667)	
_cons	0.113	24.59	-12.68	106.9***	-164.0
	(0.988)	(0.162)	(0.703)	(0.006)	(1.000)
N	676	145	429	160	204

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4.4.4 Usage of BIN Option

We examine the subsample of BIN auctions and look for determinants of the execution of the BIN option. We use a logistic regression with regressors from three groups: seller characteristics, item specification, and auction design.

Variables that significantly influence the probability of BIN usage are: *yes3g*, *new*, *secres*, and *minbid* positively and *notwor*, *negratio*, *dur1*, and *binpr* negatively.

We can see that iPads with 3G connection have a greater probability of being sold through a BIN. The condition of products affects this probability very significantly; the mean predicted probability of BIN execution for used iPads is 29%, for new iPads 61% and for not working only 9%. Items in better condition are much more likely to be sold at BIN. Negative ratings decrease the probability of using BIN. *lnfeedback* is not significant. Also longer description increases the probability of being sold through BIN. Secret reservation price increases the mean predicted probability by 33%. We do not see a significant effect of durations, only *dur3* is marginally significant and decreases the probability of using BIN. Higher minimum bid increases the probability of using BIN and so does lower BIN price. The effect of BIN price is higher than effect of minimum bids. Average marginal effect of BIN price is -0.3% and this is only -0.1% for minimum bid.

	(1)
	bin_ex
bin_ex	
s32	0.722
	(0.113)
s64	0.303
	(0.713)
yes3g	1.201**
	(0.014)
white	0.535
	(0.208)
manref	1.319
	(0.134)
selref	-1.331
	(0.381)
new	2.241***
	(0.000)
notwor	-2.417***
	(0.000)
lnfeedback	-0.0123
	(0.903)
negratio	-19.25**
	(0.020)
lndesclen	2.365**
	(0.018)
secres	2.273***
	(0.000)
minbid	0.00834***
	(0.000)
dur1	-1.021
	(0.125)
dur3	-0.880*
	(0.094)
dur5	-0.564
	(0.270)
dur10	-1.567
	(0.387)
binpr	-0.0225***
	(0.000)
_cons	-15.53*
	(0.077)
N	212

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Chapter 5

Discussion of Results

In this chapter we will compare the results of our econometric analysis with the relevant empirical literature, explain the differences in approaches and results. First we discuss the second part of the analysis, the effect of design on outcomes. Then we will examine results about the sellers‘ decisions regarding the sales design, we will see what most likely determinates their behaviour.

When we interpet the results from our regressions one additional problem can occur. Bidders can learn how the decisions about the sales design are made. Then some design parameters could function as signals of other characteristics (either of the product or of the seller) that are already included in the regression. This would make the interpretation of variables more difficult. We ignore this problem in our thesis.

5.1 Posted Price Sales

Our first analysis compared the fixed price sales and auction-style listings. We did not find a significant difference in price resulting from both of the mechanisms. However the posted price sales did have lower probability of a successful end. This would suggest a dominance of auctions over posted price sales. But we have to account for the fees. Total fees should be higher for auctions because of the high final value fee.

We compare our results with previous studies. Anderson *et al.* (2008) used a 2SLS regression to control for bidders‘ behaviour and did not find a significant effect on final price when selling through posted price sales. The probability of sale was not examined in this study. Hammond (2010) compared revenues (net price after fees) from posted sales and auctions. Results of the model heavily depended on the exact specification of the used method. Hammond used OLS and sample selection models, in each it was also specified if the choice of the BIN option is taken as endogenous or not. If we look only in the part of data from eBay we do not find a significant difference if the sample selection model is being used and endogeneity assumed. This was the primary model for analysis. But OLS regression conditional on sale shows a positive increase in revenue for posted price sales. Such as in our model the posted price sales have lower probability of ending in sale. All results in this study are heavily dependent on the specifications of the used model. When the author changed some assumptions (i.e. endogeneity), different results were obtained. In our thesis the differences between OLS and sample selection model reported in Appendix were not that striking. Study of Hammond and our thesis differ in one additional aspect. We used final price as an explanatory variable, Hammond used revenue, i.e. final price plus shipping minus fees. We did not use such an approach, because of the unstable environment of fees. It is very hard to make straightforward conclusion about effect of posted prices based on Hammond (2010).

Chen *et al.* (2006) studied the effect of BIN price on Yahoo! and found a significant bonus on final price if BIN is present. The same did hold when he compared BIN auctions (including fixed prise sales) and pure auctions. The difference in our findings is most likely caused by different institutional settings on eBay and Yahoo! Permanent BIN price is different than temporary one.

5.2 BIN

We did not find a significant effect of the BIN on the dependent variables in the subsample of all auctions. It does statistically influence neither the final price nor probability of sale. Previous studies Hendricks *et al.* (2005) and Durham *et al.* (2004) performed empirical examination of similar samples (omitting posted price sales). Hendricks *et al.* (2005) found an increase in price for sales with BIN option and that this feature had not a significant effect on probability of sale. They used a quite simple methodology performing only a t-test comparing price in population with and without BIN. They did not control for other important variables and so the results could be misleading. Results of Durham *et al.* (2004) are similar to ours. They did not find that the setting of BIN option would influence final price. By interpreting this paper we have to be careful because of the large sample bias, when the authors did not observe the initial setting of many auctions as mentioned in Chapter 2. Also

Anderson *et al.* (2008) find an insignificant effect of initial BIN option on final price.

5.3 BIN Execution

Several significant factors affected the usage of BIN in auctions with BIN options. Negative comments had a negative effect and seller‘s reputation did not influence it. This may be caused by the fact that negative comments indicate some bad behaviour of the seller in the past and presence of BIN option means that no other bidder was interested in this item until now, so the bidder does not receive a signal that any other bidder is willing to take the risk and buy the item for this specific price. Higher minimum bid and lower BIN price increase the probability of using BIN. These findings are consistent with Wan *et al.* (2003). In their model a smaller gap between reserve price and BIN increased the probability of exercising the BIN. Durham *et al.* (2004) also found that higher BIN price decreases the probability of using BIN, which seems as a natural result. But the seller reputation influenced the probability positively and negative comments were insignificant. Both these papers used logistic regression such as we did.

5.4 Minimum Bid

We studied the effect of minimum bid allowing nonlinear relationship. In our models we found a significant effect of both *minbid* and *sqminbid*. So we can conclude that minimum bid increases final price but only if it is high enough. This does not hold for the subsample of pure auctions, where the variables were not jointly significant. These results suggest that low minimum bids by attracting more bidders do not yield higher revenues.

We can see that higher minimum bids yield higher revenue. We have two potential sources; screening effect and valuation determination. We used very simple approach to get an idea if the effect of screening is significant. We used a t-test to compare the mean prices in samples of auctions that ended with one bid and with auctions that ended by receiving more bids. The first sample was the one where the screening effect was exercised. We tested H_0: equal means against H_1: the means are higher for sample with one bid. The result is that H_0 can be rejected at 8% significance level, this suggests that this screening effect increases revenue at marginally significant level. Unfortunately we do not have a simple tool how to measure the effect of minimum bids on valuations.

Most of the related studies of minimum bids were conducted as experiments. Häubl & Leszczyc (2003) found a positive effect of minimum bid through the effect on the valuations of bidders. Hossain & Morgan (2006) has shown that low minimum bids enhance competition and raise final price. We did observe more bidding activity for low minimum prices, but the final price for lower minimum bids was lower, too. Haruvy & Leszczyc (2009) found a negative effect of minimum bid if the market is large. It is hard to compare results of our analysis with these studies. They worked with experimental setting and usually only two types of minimum bids were set, low and high. This makes the interpretation of minimum bids as a continuous variable complicated.

We know only about two studies using similar approach such as we did. The effect of minimum bid in Anderson *et al.* (2008) is similar to our findings. They included also minimum bid in linear and quadratic form. The signs were negative and positive respectively, the same as in our study. Ariely & Simonson (2003) found a positive linear relationship of minimum bids on price.

5.5 Secret Reserve Price

Secret reserve price increases final price in our models, its magnitude is quite large, but it is marginally significant in a single subsample of BIN auctions. It also has a negative impact on probability of successful sale. Secret reserve price does not deter the entry of bidders in a drastic way. Average number of bidders is 8.3 when secret reserve price is set and 8.6 otherwise. These findings are consistent with Dewally & Ederington (2004) that also find a negative effect on probability of sale and insignificant effect on price, in this study the magnitude of secret reserve price impact was negligible. Anderson *et al.* (2008) found a very significant effect of this option increasing the final price.

5.6 Sellers‘ Decision

When we examine decision between posted price sales and auctions we find several significant variables. Sellers who offered more tablets were less likely to use posted prices. Our first finding contradicts the findings in Hammond (2010) and Anderson *et al.* (2008). In both thesis a positive effect of the size of seller‘s inventory was found. We have to mention that we do not use the size of the whole inventory, only number of iPads 2 listed in a short period. These two variables will be probably positively correlated, but anyway this is a possible source of an inconsistency with the literature. Both theses also studied different markets in a different time period than we did.

As we do not find a significant difference in prices between auctions and posted price sales we look in other possible causes of the choice of a particular format. The fees differ in both categories and for an average tablet the fee for an ended auction can be even 10$ more than for a posted price sale. So we can conclude that the selling in an auction decreases revenue. Frequent sellers may prefer higher probability of sale in auctions.

On the other hand more experienced sellers preferred the posted price selling over auctions. Positive effect of seller‘s feedback score on usage of posted price is consistent with Anderson *et al.* (2008). It is not because of the higher transaction price as we have shown but it can increase their revenue because of the fee structure. This can explain why this design is used by experienced sellers, these sellers probably precisely understand the computation of fees and respond to it. They sacrifice the higher probability of sale by auctions to increase their revenue. It can be more convenient for experienced sellers to sell at a posted price with no fluctuation as well.

New iPads are more probably sold with a BIN option. Anderson *et al.* (2008) found the same. We have found that frequent sellers are less likely to choose a BIN options in an auction format. Our result contradicts Anderson *et al.* (2008). This fact shows that final price and probability of sale or not the only features a frequent seller considers. BIN affects neither of them. The decision of frequent sellers about not using this options seems reasonable, since BIN option affects neither final price nor probability of sale in our model, but it costs an additional fee for frequent sellers. Both Durham *et al.* (2004) and Anderson *et al.* (2008) found that more experienced sellers use BIN option more often, we have not found a significant effect of this variable in our model.

It is interesting that both frequent and experienced sellers set lower minimum bids. Even though we found that higher minimum bids tended to increase the final price. There are two possible explanations. Higher minimum bids create higher listing fees and decrease probability of the items being sold. It is worth mentioning that the minimum bid increases the listing fee slightly in contrast to the high revenue from an auction with high minimum bids such as illustrated in Chapter 3. The net effect on revenue should be positive. Anderson *et al.* (2008) found more experienced and also frequent sellers to set higher minimum bids. Experienced and frequent sellers use lower minimum bids most likely to increase the probability of sale. Frequent sellers do not like the usage of secret reserve prices which are available for an additional fee.

The most important variable in the setting of the sale is *ipadsls*. When we go through its effect on the auction settings we can see that frequent sellers try to minimize the fees linked to the setting of an auction. They also maximize the probability of sale. Our findings about effect of sellers‘ experience often contradicts the Anderson *et al.* (2008), which is the most detailed study about sellers‘ decision of auction format. This study does use a dataset from 2001, since this time many institutional features have been changed so it can be to some extent cumbersome to compare our studies.

Chapter 6

Conclusion

We examined design and outcomes of sales of iPads 2 on eBay in a short time window in March 2013. The most important findings of this thesis are: selling by different formats, posted price sales and auctions, does not influence the final price. However, products have lower probability of being sold if posted price selling is used. BIN option in auctions does not significantly affect the outcome of auctions (price and probability of sale). Higher minimum bids increase price and decrease the probability of selling. We also studied determinants of sellers' choices of design. The probability of BIN being executed in an auction was studied as well.

Our thesis offers a unique literature survey of studies related to the Buy It Now feature in auctions. We offer a summary of both: the theoretical and the empirical studies.

Several drawbacks might have influenced the findings in our thesis. Because of technical difficulties most theses dealing with the similar topic did use relatively small datasets, and so did our thesis. We had only 706 useful observations available. There can be rightful doubts about the exactness of our estimates. We studied a relatively large market where the differences in effects of design can be suppressed by a high competition. A complex study working with a dataset collected across different markets on eBay would significantly contribute to the empirical literature about this topic.

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Appendix A

Other Econometric Methods

In this chapter we report the results from the sample selection model and censored normal regression. We used these two methods to examine the final price of transactions. The structure is similar to OLS reported in the main text. The last table reports the results of the multinomial logit regression used to examine the decision about durations of auctions.

Sample selection model	whole sample	auctions	pure auctions	BIN auctions	posted price
posted	4.172				
	(0.38)				
s32	29.64***	32.59***	33.98***	28.93***	25.28***
	(6.25)	(6.04)	(3.87)	(4.56)	(3.62)
s64	58.27***	52.61***	51.45***	57.46***	59.80***
	(9.40)	(8.26)	(5.50)	(6.83)	(7.64)
yes3g	23.40***	17.02***	6.722	26.95***	23.42***
	(4.90)	(3.43)	(0.87)	(4.41)	(3.82)
white	5.538	4.956	3.300	12.40**	7.925
	(1.44)	(1.10)	(0.49)	(2.21)	(1.34)
manref	0.244	28.03**	6.793	36.78**	-3.710
	(0.04)	(2.37)	(0.41)	(2.10)	(-0.31)
selref	-2.754	1.111	-1.038	-0.995	0.902
	(-0.40)	(0.09)	(-0.05)	(-0.07)	(0.07)
new	61.45***	48.90***	49.27***	47.22***	68.08***
	(8.81)	(7.04)	(4.34)	(6.10)	(7.14)
notwor	-116.4***	-108.5***	-109.4***	-111.0***	-116.0***
	(-17.65)	(-15.66)	(-10.66)	(-12.34)	(-10.81)
lnfeedback	-1.566**	-0.365	-0.608	-0.542	1.146
	(-2.04)	(-0.33)	(-0.36)	(-0.38)	(0.89)
negratio	-19.25	-14.79	-0.575	-35.83	83.33
	(-0.93)	(-0.91)	(-0.03)	(-1.47)	(0.64)
lndesclen	6.654	12.68	8.054	24.49	-21.72
	(0.66)	(0.78)	(0.28)	(1.26)	(-1.37)
shipp	0.554**	-0.916**		-1.010***	0.385***
	(2.30)	(-2.07)		(-2.59)	(2.65)
binopt		-1.015			
		(-0.21)			
secres		14.36	4.131	13.97	
		(1.36)	(0.22)	(1.39)	
minbid		-0.0953*	0.0347	-0.117*	
		(-1.65)	(0.36)	(-1.74)	
sqminbid		0.000586***	0.0000815	0.000633***	
		(3.15)	(0.26)	(3.50)	
dur1		1.212	23.23*	-14.59	
		(0.15)	(1.80)	(-1.45)	
dur3		-0.983	0.227	-1.727	
		(-0.14)	(0.02)	(-0.21)	
dur5		18.15***	19.34*	14.41**	
		(2.94)	(1.94)	(1.98)	
dur10		-12.04		-10.19	
		(-0.67)		(-0.64)	
bestoffer					-22.08
					(-0.62)
_cons	285.2***	198.6	244.6	61.41	474.5***
	(3.20)	(1.34)	(0.96)	(0.35)	(3.31)
N	676	454	242	212	211

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Censored normal regression	whole sample	auctions	pure auctions	BIN auctions	posted price
posted	-20.79***				
	(-3.81)				
s32	27.13***	30.69***	38.59***	23.66**	18.32**
	(4.71)	(4.47)	(27.06)	(2.49)	(2.46)
s64	58.93***	51.68***	51.05***	50.13***	59.77***
	(7.80)	(6.01)	(23.96)	(3.88)	(7.07)
yes3g	14.69**	9.113	8.213***	15.84	23.87***
	(2.32)	(1.25)	(4.08)	(1.47)	(3.48)
white	8.188*	6.159	4.665***	12.92*	10.95**
	(1.85)	(1.17)	(2.93)	(1.72)	(2.17)
manref	10.54	25.54	3.008*	19.72	3.357
	(0.73)	(1.09)	(1.68)	(0.40)	(0.50)
selref	3.556	4.187	-12.77***	18.91	-1.581
	(0.47)	(0.39)	(-5.48)	(1.01)	(-0.19)
new	58.79***	64.82***	51.36***	65.25***	62.17***
	(7.99)	(7.82)	(35.84)	(5.36)	(7.78)
notwor	-115.8***	-108.5***	-116.9***	-102.4***	-106.8***
	(-16.18)	(-13.79)	(-75.97)	(-7.31)	(-5.72)
lnfeedback	0.525	-0.339	-1.242***	1.120	2.248**
	(0.47)	(-0.20)	(-4.32)	(0.48)	(2.13)
negratio	-17.15	-3.996	1.127	17.99	-2.234
	(-1.59)	(-0.33)	(0.41)	(0.47)	(-0.02)
lndesclen	8.537	20.45	15.44***	6.852	-18.16
	(0.64)	(1.11)	(65.98)	(0.32)	(-1.13)
shipp	0.660***	-0.373		-0.602	0.540***
	(3.08)	(-0.58)		(-0.90)	(4.92)
binopt		0.364			
		(0.06)			
secres		-57.19***	-40.82***	-43.44*	
		(-2.72)	(-25.99)	(-1.82)	
minbid		-0.0131	0.0737***	-0.0114	
		(-0.17)	(9.56)	(-0.11)	
sqminbid		0.000146	-0.000232***	0.000300	
		(0.73)	(-9.98)	(1.23)	
dur1		-4.810	19.18***	-10.56	
		(-0.53)	(13.36)	(-0.74)	
dur3		-14.04	-11.88***	-9.718	
		(-1.37)	(-6.77)	(-0.69)	
dur5		17.52**	14.07***	22.24*	
		(2.29)	(9.00)	(1.87)	
dur10		-1.564	-146.2	11.10	
		(-0.10)	(.)	(0.54)	
bestoffer					-92.69***
					(-4.42)
_cons	40.89	-26.23	-405.0***	203.0	441.1***
	(0.22)	(-0.13)	(-199.26)	(1.03)	(3.16)
_cons	55.60***	54.14***	45.36***	55.00***	31.32***
	(11.17)	(10.90)	(644.00)	(8.72)	(14.67)
N	676	454	242	212	211

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	Mlogit duration
1	
s32	-0.888**
	(-2.10)
s64	0.0166
	(0.04)
yes3g	0.252
	(0.74)
white	-0.714**
	(-2.24)
manref	-0.366
	(-0.64)
selref	0.827
	(1.40)
new	-0.608
	(-1.23)
notwor	0.0825
	(0.16)
lnfeedback	-0.0371
	(-0.44)
negratio	7.794
	(0.77)
ipadsls	0.161***
	(5.27)
_cons	-0.742*
	(-1.73)
3	
s32	-0.371
	(-1.11)
s64	-0.102
	(-0.26)
yes3g	0.238
	(0.74)
white	-0.640**
	(-2.20)
manref	0.245
	(0.30)
selref	-1.051
	(-0.93)
new	0.149
	(0.39)
notwor	0.462
	(1.15)
lnfeedback	0.0550
	(0.67)
negratio	11.40
	(1.11)
ipadsls	-0.00896
	(-0.22)
_cons	-0.672
	(-1.48)
5	
s32	-0.396
	(-1.16)

s64	-0.0405
	(-0.10)
yes3g	0.217
	(0.67)
white	0.0407
	(0.15)
manref	0.0271
	(0.03)
selref	-18.40***
	(-41.94)
new	-0.449
	(-1.06)
notwor	0.301
	(0.69)
lnfeedback	0.0121
	(0.17)
negratio	1.129
	(1.10)
ipadsls	0.0402
	(1.23)
_cons	-0.688*
	(-1.72)
10	
s32	0.847
	(1.06)
s64	0.108
	(0.08)
yes3g	-0.102
	(-0.13)
white	-0.309
	(-0.36)
manref	-15.70***
	(-12.78)
selref	-17.64***
	(-23.73)
new	0.741
	(0.89)
notwor	-17.48***
	(-16.58)
lnfeedback	-0.0936
	(-0.43)
negratio	12.12
	(1.15)
ipadsls	-13.15***
	(-22.57)
_cons	10.54***
	(7.39)
N	454
R^2	

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$