Charles University in Prague

Faculty of Social Sciences
Institute of Economic Studies

BACHELOR THESIS

Price Determinants and Bidding Strategies in Internet Auctions

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Declaration of Authorship

The author hereby declares that he compiled this thesis independently, using only the listed sources and literature. The author also declares that he has not used this thesis to acquire another academic degree.

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Prague, May 16, 2012

Signature

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Abstract

This paper presents an empirical analysis of price determinants and bidders' behaviour in on-line auctions eBay.de and Aukro.cz. We focus on the effect of sellers' feedback rating score and the phenomenon of sniping. Our dataset used for the analysis consists of 7054 auctions with 209449 bids from eBay, and 2223 auctions with 8779 bids from Aukro. Buyers in on-line auctions cannot personally inspect the quality of the product, so they have to rely on the seller's honesty. In this setting, the seller's rating may significantly contribute to the final price formation. Sniping is a bidding strategy, whereby a bidder waits until the last moment of the bidding period to place her bid. According to a theory, sniping should cause a reduction in the final price, and there should be a positive relationship between the probability of bidding and bidder's experience. The empirical results for both auction web sites show that the seller's feedback rating score has a significant impact on the final price. The tests regarding sniping provide distinctive results only for eBay. The effect of sniping on the final price is not clear since we have obtained different results for different specifications, but we found out that experience of a bidder increases the probability of placing a sniping bid.

JEL Classification	D44
Keywords	auction theory, internet auctions, eBay, Aukro, price determinants, sniping

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Abstrakt

Tato práce se zabývá empirickou analýzou cenových determinantů a chování dražitelů v online aukcích eBay.de a Aukro.cz. Soustředí se především na efekt reputace prodávajícího a na sniping. Data použitá k analýze se skládají z 7054 aukcí s 209449 příhozy z eBay a 2223 aukcí s 8779 příhozy z Aukro. Nakupující v online aukcích nemají možnost osobně prověřit kvalitu zboží, a musí se tedy spoléhat na poctivost prodávajícího. V takovém prostředí může mít reputace prodávajícího tvořena hodnocením ostatních uživatelů významný vliv na výslednou cenu. Sniping je strategie přihazujících, během níž přihazující přihodí až v posledních vteřinách aukce. Teorie říká, že by sniping měl vést k nižší výsledné ceně a že by více zkušení přihazující měli tuto strategii používat častěji než méně zkušení přihazující. Empirické výsledky ukazují, že hodnocení prodávajících má významný vliv na výslednou cenu na obou aukčních portálech. Testy týkající se snipingu vykazující rozdílné výsledky, které jsou signifikantní pouze pro eBay. Efekt snipingu na konečnou cenu je nejasný, ale byl zjištěn pozitivní vztah mezi zkušeností přihazujících a pravděpodobností snipingu.

JEL klasifikace	D44
Klíčová slova	teorie aukcí, internetové aukce, eBay, Aukro, cenové determinanty, sniping

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Acronyms

CV Common value

PV Private value

Bachelor Thesis Proposal

Author	Barbora Máková
Supervisor	PhDr. Martin Gregor Ph.D.
Proposed topic	Price Determinants and Bidding Strategies in Internet Auctions

The Bachelor's thesis will be concerned with Auction Theory, with particular focus on online auctions on server Aukro.cz.

At the beginning, a description of the auction system on Aukro.cz will be given. The aim of the second part will be to analyse the bidding strategies in such online auctions - to classify these strategies, to try to find a common pattern of behaviour on Aukro.cz and to detect potential bidders' frauds during auctions. In the third part, the effect of the specific elements of the auctions (such as reputation of a seller) on final price will be examined.

The dataset will be obtained directly from Aukro.cz as the history of bids is available for 60 days after the end of the auction. A special script will be used for the data download.

Core bibliography

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Teze bakalářské práce

Autor	Barbora Máková
Vedoucí práce	PhDr. Martin Gregor Ph.D.
Navrhované téma	Analýza cenových determinantů a strategií dražitelů v online aukcích

Bakalářská práce se bude týkat teorie aukcí, konkrétně se zaměří na online aukce na serveru Aukro.cz.

V úvodu bude popsán systém fungování aukcí na serveru Aukro.cz. Cílem druhé části bude analýza strategie dražitelů během online aukcí. Bude zjištěno, jaké strategie jsou u dražitelů na Aukro.cz běžné a zda lze vypozorovat nějaké podvodné chování. Ve třetí části se bude zkoumat vliv určitých faktorů (například reputace prodávajícího) na výslednou cenu.

Data vychází ze serveru Aukro.cz, kde jsou historie příhozů k jednotlivým aukcím veřejně přístupné po dobu 60 dnů po ukončení aukce. Data budou stažena pomocí speciálního programu.

Chapter 1

Introduction

Auctions are an important part of economic life. They have been used as a market allocation mechanism for thousands of years. The first records about auctions were written down in the ancient world - in Babylonia, Greece, the Roman Empire, China, and Japan (Cassady 1980). Herodotus recorded an auction of women in wedding years to be held 500 B.C. in Babylon (Cary et al. 1904). In the Roman Empire, auctions were also quite frequent, and the Romans used them in a financial distress to sell their property and to repay their debts. It is said that even Marcus Aurelius used an auction system to sell the royal furniture, in order to cover a state deficit (Frank 1940). In 193 A.D., the whole Roman Empire was placed in an auction after the murder of the emperor by Praetorian Guard, and the winner of the auction, Didius Julianus, became the new sovereign of the empire (Durant 1944).

The range of items sold at auctions widened in the 20th century. Auctions are used for selling different types of goods, such as commodities with many close substitutes (livestock), rare and uncommon things (antiques, pieces of art, diamonds), and financial assets (government bonds). The only common factor for all these items is the need to appoint individual prices (Milgrom 1987). Despite the widespread use of auctions in the past, sold items belonged to specific areas, and most of these items were quite expensive. Therefore, the number of bidders was limited, and bidders were usually professionals. Such limitations decreased the effectiveness of empirical studies in the auction theory field.

The boom of auctions occurred after the birth of internet auctions in 1995, when also eBay was established. On-line auctions nowadays attract many people thanks to very low costs of bidding at an auction and running an auction, the variety of listed items (nearly everything can be bought at internet auctions in contrast to local markets, where the supply of goods is often very limited), and the liquidity of market for specialized categories. Further, some people consider on-line auctions as a source of enjoyment; they are interested in improving their strategies and sharing their experience with other users.

The number of transactions made through on-line auction portals (especially eBay), and the public availability of details of auctions have created a large source for empirical studies of auctions, and enabled empirical verification and extension of the theories made in the 20th century. The proxy bidding system (also called automatic bidding system) used by eBay and Aukro makes these on-line auctions resemble the second-price sealed-bid auction[1] (Lucking-Reiley 2000).

One of the most famous and largest on-line marketplaces in the world is eBay, operating in more than 20 countries. The most recent data show that the revenues of eBay for the year 2011 were $11.7 billion, which means a 27% increase compared to 2010. The growth of marketplace business in 2011 was caused mainly by an increase in buying and selling activities on eBay's web sites, and acquisitions. The marketplace business created revenue of $6.6 billion. The number of active users has been rising, reaching 100.4 million at the end of 2011. The total value of goods sold on eBay was $68.6 billion.[2]

The most popular internet auction portal in the Czech Republic is Aukro, established in 2003. The number of users at the beginning of 2012 climbed to 2.5 million, and the amount of traded goods on Aukro has been increasing as well. In the first half of 2011, there were 6.3 millions of items sold.[3]

The dataset of this experiment contains details about 7054 auctions with 209449 bids from eBay and 2223 auctions with 8779 bids from Aukro. We use the data to perform an econometrical analysis. The most interesting topics about internet auctions deal with asymmetric information using the reputation system and late bidding. These themes are well documented in the economic literature. We will provide a support of some claims through several regressions in this study. Specifically, we focus on three aspects: price creation, sniping and effect of the bidders' experience. Further, as far as we know, this is the

[1]In the proxy bidding system, bidders fill in their maximum willingness to pay and the system bids for them automatically. More detailed information about the system will be provided in the later sections.

[2]eBay's 2011 Financial Release (http://investor.ebayinc.com/)

[3]Aukro's Press Releases (http://media.aukro.cz/cs/pr/190055/na-aukru-se-za-prvni-pololeti-prodalo-6-3-mil-produktu, http://media.aukro.cz/cs/pr/201937/pocet-uzivatelu-na-aukru-roste-v-patek-13-se-registroval-2-5milionty-uzivatel)

first paper analyzing data obtained from two auctions portals, which provides us an opportunity to describe and discuss the observed differences between the two auction portals.

We find out that the seller's rating has a significant impact on the final price in auctions of used items on both eBay and Aukro; the final price of used items decreases with the auction length on eBay; the bidders' experience has a positive effect on the probability of snipping on eBay; more experienced bidders win auctions with a lower final price on both eBay and Aukro.

This paper is organized as follows: Chapter 2 presents an overview of fundamental literature regarding the main topics of our analysis, and Chapter 3 describes the principles of buying and selling on eBay and Aukro and the dataset. Chapter 4 shows descriptive statistics. Chapters 5-7 are devoted to the econometric analysis, and finally, Chapter 8 concludes the work.

Chapter 2

Literature Overview

This section summarizes some important phenomena that have been shown to occure in on-line auctions. Although some of these papers were published before the on-line auctions heyday, their results are still applicable. We will use these studies to determine the base variables in our econometric analysis.

Despite the on-line auction boom at the end of 20th century, auction literature streches back to 1960s. The second-price sealed-bid auction was first described by Vickrey (1961), a pioneer in analysing auctions as games of incomplete information; hence, the second-price sealed-bid auction is sometimes called also the Vickrey auction. Vickrey (1961) introduces an auction model with independent private values, where bidders submit their bids without the knowledge of bids placed by the other bidders. A bidder's dominant strategy in the Vickrey auction is to always bid her true value.[4] The explanation of the truth telling as a dominant strategy is very intuitive. Let us have a bidder 1 with a value v_1. She has three options for bidding: $b_1 < v_1, b_1 = v_1$ and $b_1 > v_1$. Denote b the highest bid among the bids of players $2, ..., n$. If the bidder 1 bids $b_1 < v_1$ and $b_1 > b$, she wins the auction, as she would have won with a bid equal to v_1. But if the bidder 1 bids $b_1 < v_1$ and $b_1 < b < v_1$, she loses the auction, and she would have won if she placed a bid equal to v_1, gaining expected profit $v_1 - b$. So the bidder 1 does not profit from bidding less than her true value, and she can possibly lose. If the bidder 1 bids $b_1 > v_1$ and $b > b_1$, she loses the auction as she would have lost with a bid equal to her valuation. But if she bids $b_1 > v_1$ and $v_1 < b < b_1$, she wins the auction and pays more than her true value; she loses $b - v_1$. Hence, the bidder 1 does not profit by bidding more than her true value, and she can possibly lose. The

[4]The dominant strategy for bidder i is a strategy b_i maximizing bidder i's expected profit for any strategies of the other players.

expected profit of bidder 1 decreases with a bid $b_1 < v_1$ and also with a bid $b_1 > v_1$. Garratt et al. (2004) define the bidding system used by eBay as the dynamic version of the second-price sealed-bid auction. The dynamic is created by the opportunity of bidders to observe who the highest bidder is and what the highest bid generated by the proxy bidding system is, and they can increase their proxy bids.

2.1 Sellers' Reputation

Internet auctions have significantly lowered the costs of running an auction; auctions are automated and host web sites run them practically without any costs. On-line auctions have many advantages for both sellers and bidders: fee for running an auction is low, an offered item can be viewed by many potential buyers and is sold to the one with the highest value of the given item, auctions of a required item may be identified easily, details of the auction can be effortlessly studied by all potential bidders, and a bid can be placed with a little exertion. But there are also some drawbacks, e.g. the transaction is often made between two individuals who do not know each other and have not had any previous interaction. eBay and Aukro are only mediators of transactions, they guarantee neither the quality of goods nor the delivery. That brings a risk to both sides.

Bidders on internet auction portals cannot personally investigate the quality of the products before they make a bid. According to Akerlof (1970), markets without the possibility to reliably demonstrate the quality of goods may experience a market failure. A solution to the information asymmetries is a seller's reputation, which reduces them, and thus allows the market to function. The seller's reputation can be considered a proxy for the quality (Melnik and Alm 2002).

Reputation in traditional markets is gained by many factors, e.g. buyers can inspect the goods in the local retails, they have usually regular interactions with sellers; hence, they can build sellers' reputations by their own experience ("first-hand experience"). Local friends of the buyer usually have some experience with the sellers as well and can share it easily. Further, retail sellers' reputation is built over many years. None of these reputation builders may be used in internet auctions since the buyer usually knows only a little about the seller, and she cannot inspect the product. Repeated transactions between two parts are rare, and customers do not meet each other.

In the context of on-line auction markets, reputation is defined by referrals or ratings from members in a community (Jøsang et al. 2007).

The reputation system of internet auctions web sites should provide information that help buyers to distinguish between a trustworthy and a non-trustworthy seller; it should push sellers to act honestly and discourage bidders from trade with the dishonest sellers.

Both eBay and Aukro use centralized reputation system: a reputation centre collects all rating points and derives a feedback score for every user (Jøsang et al. 2007). An advantage of the simple reputation systems used by eBay and Aukro is that anyone can understand the principle.[5] On the other hand, they are primitive and give a poor picture about the users' reputation. A problem of these reputation systems is that, theoretically, none of the buyers would leave a comment or rate the transaction to help building the seller's reputation because to do so includes a cost and does not bring any direct benefit. Additionally, it is complicated to punish free-riders. Nevertheless, the evidence from the eBay reputation system is in dispute with the theory. Resnick and Zeckhauser (2002) have found out that feedback is provided more than half the time, which indicates no pure rational game-theoretic processes in auctions on the internet. Another problem can be a bias towards positive ranking resulting from reciprocity: someone may avoid giving negative rating because of being afraid of the reaction from the other side, or give positive rating and hope to get positive rating in return.

Theoretical models create a positive relationship between the price and the reputation of the seller (Klein and Leffler, 1981; Shapiro, 1983; Allen, 1984). Shapiro (1983) claims that a bad reputation or a fall in reputation should draw a loss that is greater than the profit from the opportunistic behaviour. Hence, in equilibrium, a good reputation brings a price premium. The experimental analyses gave diverse results.

Table 2.1, inspired by the one in Resnick and Zeckhauser (2002), summarizes the literature.

One possible reason of the diverse results may be the differences in the examined items. Reputation is probably more important for some goods, since transaction with used, more expensive and less standardized items is riskier (Resnick and Zeckhauser 2002).

[5] The reputation systems will be described in detail in the Chapter 3.

Table 2.1: Sellers' Reputation Literature Overview

Citation	Items sold	Mean price	Results	Used type of regression
Ba and Pavlou (2006)	Music, software, electronics	$232	Online laboratory experiment: positive feedback increases price, negative feedback does not have any effect.	Moderated regression analysis
Bajari and Hortacsu (2003)	Coins	$47	Positive feedback increases price, negative feedback does not have any effect.	Tobit regression
Cabral and Hortacsu (2004)	Coins, IBM Thinkpad, Beanie Babies	$78, $580, $11	Overall reputation increases price, percentage of negative feedback does not have any effect.	Cross-sectional regression
Dewan and Hsu (2001)	Collectible stamps	$36	Overall reputation increases price	OLS regression, Tobit regression.
Eaton et al. (2002)	Electric guitars	$1621	Negative feedback does not have any effect.	OLS regression
Houser and Wooders (2006)	Pentium chips	$244	Positive feedback increases price, negative feedback reduces price.	GLS regression
Jin and Kato (2003)	Sports trading cards	$166	Neither positive nor negative rating has any effect.	
Kalyanam and McIntyre (2001) (2001)	Palm Pilot PDAs	$238	Positive feedback increases price, negative feedback decreases price.	
Kauffman and Wood (2000)	Coins	Not given	No significant effects.	
Lee et al. (2000)	Computer monitors, printers	Not given	Negative feedback reduces price for used items.	Hedonic regression
Livingston (2005)	Golf clubs	Not given	Positive feedback increases price.	OLS regression, Tobit regression
Bryan et al. (1999)	Coins	$173	Positive feedback does not have a effect, negative feedback reduces price.	Maximum-likelihood censored-normal regression, OLS regression
Melnik and Alm (2002)	Gold coins	$33	Positive feedback increases price, negative feedback decreases price.	Tobit maximum likelihood regression
McDonald and Slawson Jr (2002)	Dolls	$208	Overall feedback increases price.	Cross-sectional analysis
Resnick and Zeckhauser (2002)	MP3 players, Beanie Babies	Not given	Neither positive, nor negative rating has any effect.	Logistic regression
Zhang (2006)	Apple iPod	$289	Positive feedback increases price, negative feedback decreases price.	Hedonic regression

2.2 Sniping

A sniping bidder waits until the last moments of an auction, and then bids a few seconds before the end. Despite of eBay's recommendations to use the proxy bidding system and place one bid equal to the bidder's maximal willingness to pay, sniping often occurs. There are even special late bidding computer programs, such as Bidnapper for Aukro,[6] which place a bid in the last seconds of an auction for the bidder. Bidders believe that sniping raises the chance of winning and lowers the final price (Roth and Ockenfels 2002).

Considering Vickrey's theory, sniping in the second-price auctions with the private value setting is surprising. According to Vickrey (1961), sniping bidders are then either irrational or they perform in different conditions.

Sniping is discussed in many of the recent papers regarding on-line auctions, and the researches present a lot of different reasons for it. These theories are usually based on relaxing some of the Vickrey's assumptions.

Ely and Hossain (2009) relax the assumptions of bidder's rationality and profit-maximizing and introduce an escalation and competition effect. The escalation effect indicates that bidders bid more aggressively in a competitive environment, it supports late bidding to lower the aggressiveness of the opponents. The competition effect says that opponents' aggressiveness decreases with an early bid, it supports early bids to show to the potential bidders that a competition is present. The escalation effect is observable in auctions with more than one bidder. The empirical analysis by Ely and Hossain (2009) proves that the price is lower in the case of sniping.

Ku et al. (2005) relaxe the assumptions of bidder's rationality and profit-maximizing as well and discuss "auction fever". They argue that in the heat of the bidding war, bidders outbid their reserve prices. Ku et al. (2005) assume that placing a new higher bid after outbidding is a sign of an auction fever. This theory is supported by the survey made by Roth and Ockenfels (2002), who have asked sniping bidders about their reasons for sniping. Many bidders have responded that they place last minute bids because they want to avoid "getting carried away". Ku et al. (2005) have carried out an empirical analysis and proved these hypotheses: a bidder would overstep her true value more often towards the end of an auction, if she has invested more time in the auction, and if there are fewer opponents left.

Roth and Ockenfels (2002) relaxe the assumptions of bidder's rationality

[6] https://cs.bidnapper.com/

and perfect information. According to their theory, some naive new users may be confused about the bidding system and may misunderstand the dynamic second-price auction with the English ascending first-price auction. They would then place bids that are slightly higher than the actual price (if their true value exceeds the price). Then they would wait until they would be outbid and repeat these two steps up to the end of the auction. The best response to the possibility of an incremental bidder is the late bidding. Another hypothesis of Roth and Ockenfels (2002) is that late bidding is a form of a tacit collusion among the bidders. In this case, the bidders create a tacit collusion to capture the seller's surplus for the winner.

Ockenfels and Roth (2006) say that the problem is in the bidding increment since it is not contained in the classical second-price auctions, and they relaxe the assumption of perfect second-price rules. Sniping as a response to an incremental bidder was proven to be a rational strategy.

Wilcox (2000) adopts the concept of Milgrom and Weber (1982) and relaxes the assumption of independent private price. Milgrom and Weber (1982) discuss a theory of the effect of the common value. The authors show that bidders yield higher revenues by obtaining information from the bids of the opponents concerning authenticity, potential resale value, and prestige factor of the sold item. Wilcox (2000) then empirically verifies hypotheses that the more experienced bidders more likely bid at the end of auction, and that late bids are more likely placed in common value auctions.

Rasmusen (2006) claims that also in the private value setting, bidders do not necessary fully understand their true value, and they have to pay for learning it. By this condition, the assumption about perfect information is relaxed. He introduces two types of bidders: the informed one, who has a value v, but knows only the expected value of v, $E(v)$, and can pay some price to learn v, and the uninformed one, who has a value s, and knows s, but not v. There are two limit points of the cost of learning v for an uniformed bidder; c_l and c_b, $c_l < c_b$. If the price is lower than c_l, the uninformed bidder chooses to discover her true value. If the price is above c_b, the uninformed bidder chooses to approximate the true value. If the price is between c_l and c_b, the uninformed bidder places a first bid and chooses to discover her true value if and only if another bidder joins the auction and bids more. In such environment, the best response for an informed bidder is to wait and submit the bid in the final second of the auction because in that case, the victim cannot respond.

Wang et al. (2004) point out a problem of shill bidding. Shill bidding occurs when a seller logs on eBay under a different account and submits a bid slightly higher than the actual price. Using this pattern, a seller can elevate the price and not win the auction at the same time. Sniping is the best choice in this case. This type of bidding relaxes the assumption of a defined seller/bidder.

Barbaro and Bracht (2004) raise the issue of a loophole in eBay's rules which allows squeezing. The problem is that a seller can cancel any bid for her item whenever she wants to. This fact may be used by a seller, who places a large bid from a different account and finds the highest bid of the other bidders, then she cancels the bid, logs on eBay under a different account again, and submits a bid equal to the identified highest bid. If there are two bidders with the same highest bid, the winner is the one who has placed his bid first. Hence the seller can squeeze the whole excess of the winner. Again, the best response for a bidder is to bid late.

An overview of the results of some of the empirical analyses based on eBay's data is recorded in Table 2.2:

Table 2.2: Sniping Literature Overview

Citation	Items sold	Average price	Results	Model
Ely and Hossain (2009)	DVD movies	\$13	Field experiment: Sniping raises surplus and likelihood of winning	Probit analysis (for likelihood of winning)
Gray and Reiley (2004)	Video games, DVDs, coins, die cast cars	\$18, \$13, \$18, \$9	Field experiment: Sniping does not significantly raise surplus	Not reported
Haller (2007)	DVD movies, antique chairs and rugs, original paintings, silver items	\$11, \$265, \$582, \$699, \$1079	Greater experience in CV setting and higher number of substitutes raise likelihood of sniping	Standard linear probability model
Ockenfels and Roth (2006)	Computers, antiques	Not reported	Snipping is more likely in CV than in PV setting, experience raises likelihood of sniping	Probit analysis

2.3 Experience

The feedback rating can be treated also as an experience indicator since users with a higher rating have won more auctions or sold more items using the specific internet auction portal. Although feedback rating is not a precise indicator of experience, it can be used as a proxy for experience of a user. There are several theories claiming that bidders learn and improve their performance by abrepeated participation in auctions (see e.g. Kagel, 1995, Rutström, 1998).

Sun (2005) examines the influence of experience on switching costs. He divides bidders into two categories: the inexperienced and the experienced bidders, according to their rating. He assumes that each bidder has switching costs when she bids in a different auction than the auction she has first bid in, and that these costs are lower for the experienced bidders than for the inexperienced ones. As buyers tend to stick to the auctions in which they have placed their first bid, more mobile (experienced) buyers profit. He verifies this theory by an empirical experiment.

Vickrey (1961) argues that a bidder's dominant strategy in the second price auctions with the private value setting is bidding the true value. In the private value setting, bidders do not profit from observing bids of the others; thus, they are indifferent in timing. However, Milgrom and Weber (1982) point out that bidders often may be uncertain about their private values. This uncertainty arises from a common value component, whose value has to be estimated by the bidder (Wilcox 2000).[7] In this case, a bidder learns valuable information from observing bids of the others; therefore, it is optimal to bid in the last moment of an auction. Bidding in the last moment of an auction is then weakly dominant strategy.[8] Hence, a bidder's dominant strategy is placing a bid equal to her true value in the last possible moment (Wilcox 2000).

Wilcox (2000) supposes that learning leads to an improvement of a bidders' behavior, which is then more consistent with the theory described above. Therefore, more experience bidders bid more likely in the last moments of an auction.

Table 2.3 exhibits an overview of the results of the empirical analyses:

[7] In a private value system, each bidder knows her private value, and the value may differ for every bidder. Bidders do not gain any additional information by observing the bids of the others. In a common value system, there is one true value, same for all bidders, determined by e.g. a resale, and each bidder tries to estimate the true value. Bidders get valuable information by observing others' bids.

[8] It weakly dominates all other strategies if there is an uncertain factor, and is equivalent to the others if the uncertainty is not present.

Table 2.3: Bidders' Experience Literature Overview

Citation	Items sold	Mean price	Results	Model
Borle et al. (2006)	Collectible pottery, golf balls, wristwatches, writing pens, golf club bags, neckties, desktop accessories, calculators, luggage bags, telescopes and microscopes,...	Not reported	Experience bidders more likely bid at the beginning or at the end of auction, not between, they place multiple bids less often	MCMC sampling algorithm
Sun (2005)	Googles's invite-only Gmail email service	Average price $56	Experience bidders have lower entry costs, pay less, more likely bid at the beginning or at the end of auction, not between	OLS regression, McFadden's choice model
Wilcox (2000)	Pottery, neckties, drills, staplers	$416, $23, $124, $19	Experience bidders more likely bid at the end of auction	Logit regression

Chapter 3

Data Sources and Description

We have collected a unique dataset containing details about auctions on eBay.de and Aukro.cz. Aukro.cz is the most popular on-line marketplace in the Czech Republic, but, compared to eBay.de, the amount of sold items is small. For this reason, people from the Czech Republic often use also the service of eBay.de.[9] Since these on-line marketplaces are of very different sizes, we find it interesting to compare the bidders' behaviour and the price creation on these two internet auction portals.

In this section, we will provide a description of systems and principles employed by both eBay and Aukro as well as description of our dataset.

3.1 Buying and Selling on eBay and Aukro

eBay is a marketplace allowing buyers and sellers to trade nearly everything. A free registration is necessary, in order to be able to participate in the trade. Items are organized into 38 main categories and hundreds of subcategories. Sellers can choose from many different parameters of the auction before listing it. There are 3 types of selling formats: classic auction, fixed price selling called "Buy it now", and combination of these two. The duration of a listing is selectable - the options are 1, 3, 5, 7, or 10 days. A seller fills in title, item's description, details about the costs of shipping and payment, condition of goods, she also add pictures and chooses the starting price. eBay offers selling with a secrete reserve price, which guarantees that the item would not be sold for a lower than the specified price, but this option is not for free.

Further, ebay charges a fee for listing an auction, and a final-value fee. The

[9] Hereinafter referred to as eBay and Aukro.

insertion fees vary according to the starting and reserve price from EUR 0.25 to EUR 4.80; the final-value fee is fixed at 9% of the final price but cannot be higher than EUR 45.00.

eBay uses the automatic bidding system (also called proxy bidding system). Buyers are encouraged to place in the maximum amount they are willing to pay and the system bids for them using the automatic bid increment amount based on the current high bid. In other words, the system bids only as much as it is necessary to stay the high bidder, until it reaches the limit or until the auction is won.[10] The bid increments vary with the actual price from EUR 0.50 to EUR 50.00.

For searching for an item, browsing by categories or search using a keyword can be used. After searching using a keyword, all categories containing the required word are displayed, a buyer chooses a concrete category and clicks on "See all listings", where she can view a list of all auctions with the basic information (title, condition, actual price, number of bids, remaining time). After clicking on a specific auction, the buyer can also see shipping, delivery and payment details, seller information including feedback score, and item description. Number of bidders and bids, duration, time left, bidders' names, feedback score, bid amount, bid time and starting bid are displayed in the bid history.

Aukro is based on very similar principles, but since it is smaller than eBay, there are only 22 main categories. As on eBay, on Aukro, a registration is necessary, in order to be able to participate in the trade. The duration of an auction can be set to 3, 5, 7 or 10 days. The types of auctions and the other parameters of an auction are the same as on eBay. Aukro offers some improvements of auction visibility, a user can choose a charged bold title or prior listing. Secret reserve price is not available on Aukro.

The fee for listing varies from CZK 0.50 to CZK 10.00, depending on the starting price; in special categories such as cars, motorcycles, and real estate, the fee is higher climbing to CZK 150.00. The final value fee is different for each category and usually contains both a fixed amount and percentage of the final price.[11]

Aukro also uses the automatic bidding system; the principle is the same as

[10] For more detailed information see http://pages.ebay.com/help/buy/automatic-bidding.html

[11] For more detailed information see http://aukro.cz/help.php?tid=90&tids=31_250_90&zoom=N

on eBay.[12] The bid increments vary with the actual price from CZK 1.00 to CZK 100.00.

Browsing by categories or a search using a keyword can be used for searching for an item. After searching using keyword, the list of all auctions containing the keyword in a title with basic information (title, actual price, shipping costs, number of bidders and remaining time) are displayed immediately. Other information such as delivery and payment details, seller information including feedback score, and item description can be viewed in the details of the auction. Unlike eBay, Aukro does not display the duration and the starting price in the bid history.

The user's rating score on eBay is made by feedback points coming from the other members involved in the trade with the user. A user can get 1/0/-1 point(s) for positive/neutral/negative rating. All ratings are summed up and give the member's final feedback score. Next to this feedback score, eBay provides also the percentage of positive feedback, based on the total number of positive and negative feedback ratings gained during the last 12 months (multiple feedbacks from a single user for purchases ended within one week are excluded).

the feedback system on Aukro works on the same principle. After a transaction, users can rate the trade. They can choose from three options: positive, neutral, and negative rating. A user gets 1 point for each positive rating given by a member who trades with her for the first time, 1 point is subtracted for all negative ratings, and neutral rating does not change the score. Aukro also provides the percentage of positive feedback, calculated using a number of business partners who gave a positive, neutral, or negative rating. In addition, there is a table recording the ratings by the way they were gained (by buying or selling).

In the bidding details on eBay, only the bids filled in by bidders (not the automatic proxy bids) are reported, with the exception of the winning bids, whose reported value is given by the sum of the second highest bid and the bid increment. Aukro reports only the last bid filled in by a bidder and not the automatic proxy bids. The reported bid of the highest bidder is also equal to the sum of the second highest bid and the bid increment.

[12]http://aukro.cz/help_item.php?item=45

3.2 Data Description

We have decided to use the data from the auctions of electric devices, specifically Apple iPhone, Samsung Galaxy, HTC Sensation and Amazon Kindle Keyboard. We have chose these products for they are widely traded and demanded. We also assume that everyone needs only one piece of these items. Further, the prices of all of these products were stable during the time of our study.

Buying each of these items is quite a big expenditure; therefore, it is appropriate to assume that all bidders have a good overview of the market of the specific goods and of the retail prices. As the prices of electronic devices generally fall in time, a resale is not the reason for buying these goods. Given these facts, we may suppose that smartphone and electronic reader auctions have the private value setting.

We have obtained details about 7054 auctions with 209449 bids from eBay and 2223 auctions with 8779 bids from Aukro. The eBay data come from the auctions held between 18.11.2011 and 3.4.2012, whereas Aukro date from the auctions held between 10.9.2011 and 4.4.2012. We have only been interested in the real auctions, which do not end with the "Buy now" option. We have deleted the "Buy now" types of auctions, the mixed type of auctions those ended with "Buy now" option, and the auctions those were cancelled by a seller before the end from the dataset. Additionally, there were a few auctions with an unmet reserve price (21 auctions in my whole eBay data sample), we have decided to delete them as well, as we have not been able to observe met reserve prices in the dataset.

The designs of eBay and Aukro web sites are slightly different, and the design of Aukro changed many times during the data collection, which complicated the retrieval of some variables. Hence, also the obtainable details slightly vary. The obtained eBay's variables include: name of sold item, day and time of end, final price, starting price, shipping costs (sellers on eBay set only one fixed price for shipping), condition of sold item (seller chooses from five categories of level of use on eBay: new, refurbished by manufacturer, refurbished by owner, used and defect), length of auction, rating of seller, seller's percentage of positive rating points received during last 12 months, number of bidders, number of bids. eBay's bids details include date and time of bid, bid price and rating of bidder. Aukro's details contain these variables: name of sold item, day and time of end of auction, final price, costs of different types of shipping (Aukro allows to report more types of shipping with different prices), condition of sold item (Aukro offers only two categories - new and used), rating of seller, positive/neutral/negative rating points of seller gained by selling and buying, number of bidders, number of pictures. The obtained bidding details from Aukro are the same as from eBay.

We have edited the dataset in Excel and Google Refine to make it ready for testing purposes. Further, some new variables have been derived (e.g. seconds remaining to the end of an acution at the time of a bid, the day of a week, the number of opponents).

The data are available upon request.

The dataset offers many interesting results that are woth noting before the regression analysis, so summary statistics of the data were generated.

Chapter 4

Descriptive Statistics

Before submitting the data to the econometric analysis, we will provide a few descriptive statistics to better understand some phenomena on eBay and Aukro.

4.1 Volume of the Market

Table 4.1 exhibits the number of auctions listed on eBay and on Aukro during the observed time and in the monitored sections, the number of successful auctions, and sellers' statistics.[13]

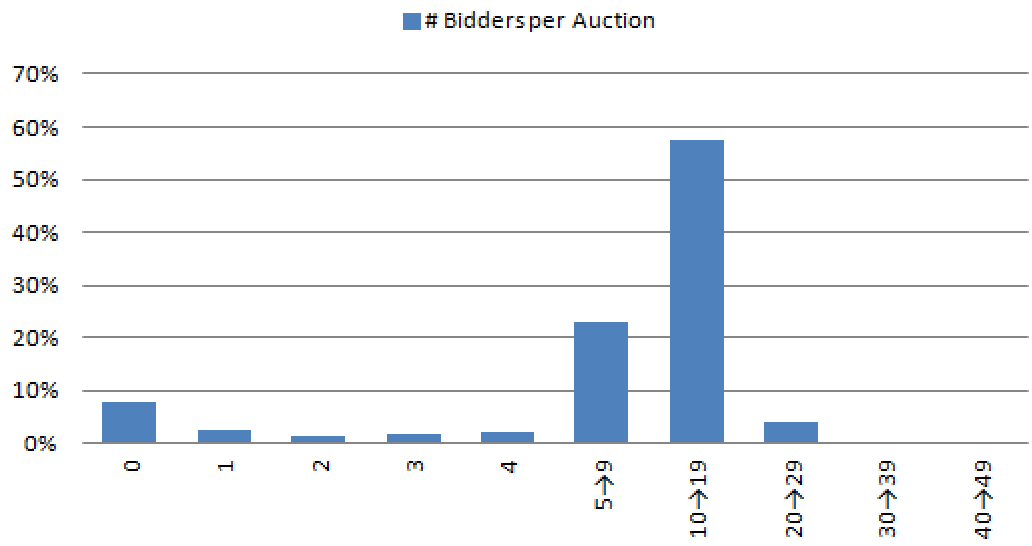
We have made an overview of how many auctions were held by a single seller on eBay and Aukro. We have filtered out only the auctions with at least one bidder (the successful auctions) to avoid counting one item twice if it was listed more than once due to an unsuccessful first auction. On eBay, 92% of the sellers sold only one item, and there were 16 people (0.3%) selling more than 5 items. The top seller sold 276 items, but the second most active seller sold only 39 items. We have found out that 85% of the sellers on Aukro sold one item, and only 10 people (1.1%) sold more than 5 items. The most active seller sold 38 items. We can conclude that despite of the diversity in the market size, individual sellers sell similar number of items on both auction portals. The biggest difference is in the size of the markets, the relative demand on eBay is higher than on Aukro, which is illustrated by the number of the successful auctions on eBay (more than 90%) and on Aukro (57%), e.g. the most active sellers on Aukro (those with more than 10 items sold) had 2.3 listings for one sold item on average, whereas on eBay the most active sellers (with more than 10 items sold) had 1.025 listings for one sold item on average.

[13]We define a successful auction as an auction ended by a sale.

Table 4.1: Market Volume - eBay vs. Aukro

	eBay		Aukro	
# auctions	7054		2223	
# succesfull auctions	6500	92.0%	1275	57.0%
# people selling 1 item	0	92.0%	772	85.0%
# people selling more that 10 items	11	0.2%	7	0.8%
Top seller	276		38	

Figure 4.1: eBay: Number of Bidders per Auction



4.1.1 Ebay

Table 4.2: eBay: Number of Bidders per Auction

Max	31
Min	0
Median	11
Average	10.49674

Figure 4.1 and Table 4.2: Most of the auctions attracted at least one bidder (91%). More than half of the auctions ended with the number of bidders between 10 and 19. The median number of participating bidders in a single auction is 11.

Figure 4.1 and Table 4.3: As expected, the number of bids per auction was higher than the number of bidders. The median of received bids is 20,

Figure 4.2: eBay: Number of Bids per Auction

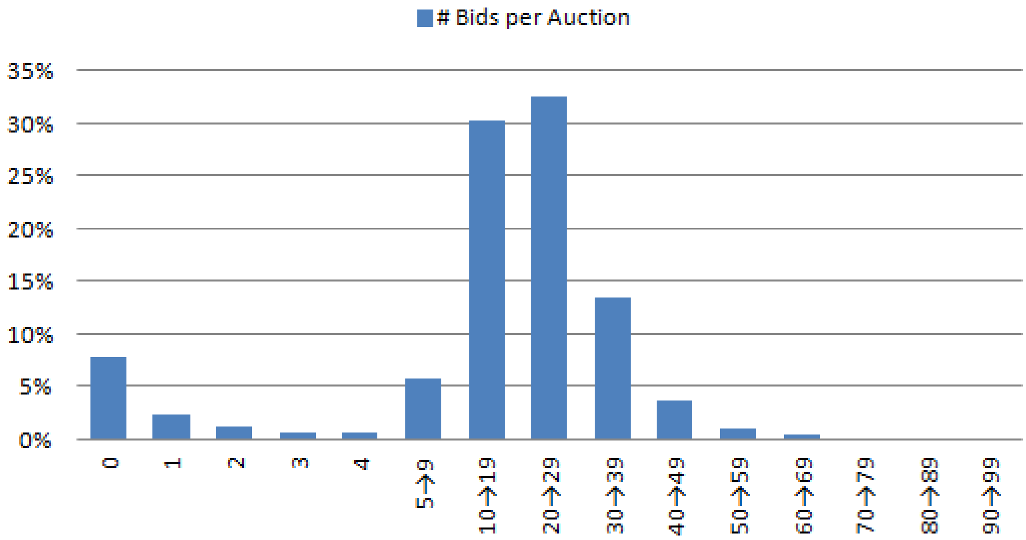
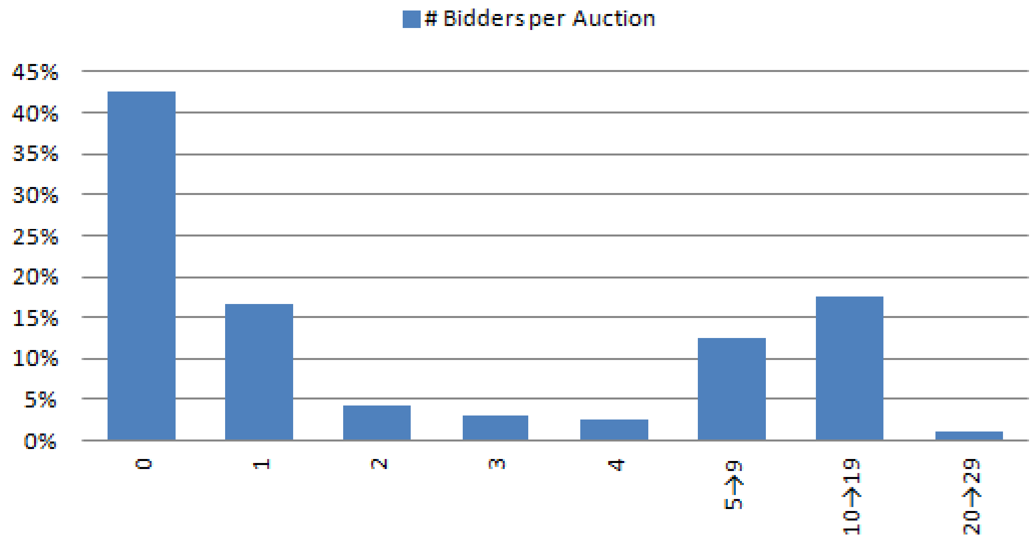


Table 4.3: eBay: Number of Bids per Auction

Max	103
Min	0
Median	20
Average	20.03587

Figure 4.3: Aukro: Number of Bidders per Auction



whereas the median value of bidders per auction is 11. That indicates that some bidders placed multiple bids. The reasons for multiple bidding are e.g. misunderstading of the auction format and bidding like in the English ascending first-price auction or change in the bidder's true value during the auction.

4.1.2 Aukro

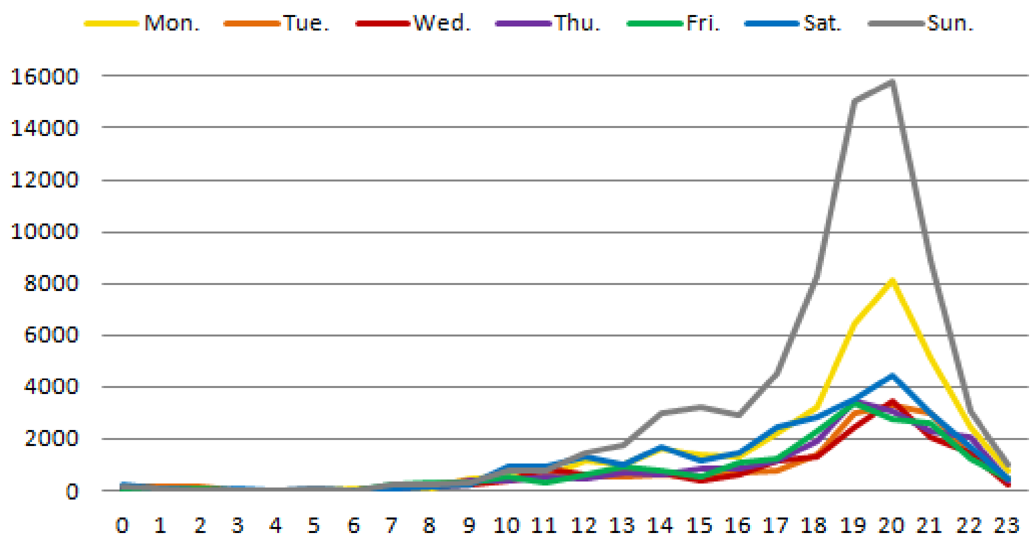
Figure 4.3 and Table 4.4: The demand on Aukro was smaller and more than 40% of the auctions ended without any bid, other 20% of the auctions attracted only one bidder. Hence, the median value of the participating bidders in an auction is equal to 1. We can observe that there are big differences between the auctions. When an auction is attractive, it draws a rather high number of people (see the amount of auctions ended with 10 and more bidders), but most of the auctions were apparently unattractive.

Aukro reports only the last bid of each bidder. Therefore, we are not able to compare the numbers of bids and bidders.

Table 4.4: Aukro: Number of Bidders per Auction

Max	29
Min	0
Median	1
Average	3.799915

Figure 4.4: eBay: Distribution of Bids



4.2 Time Structure

4.2.1 eBay

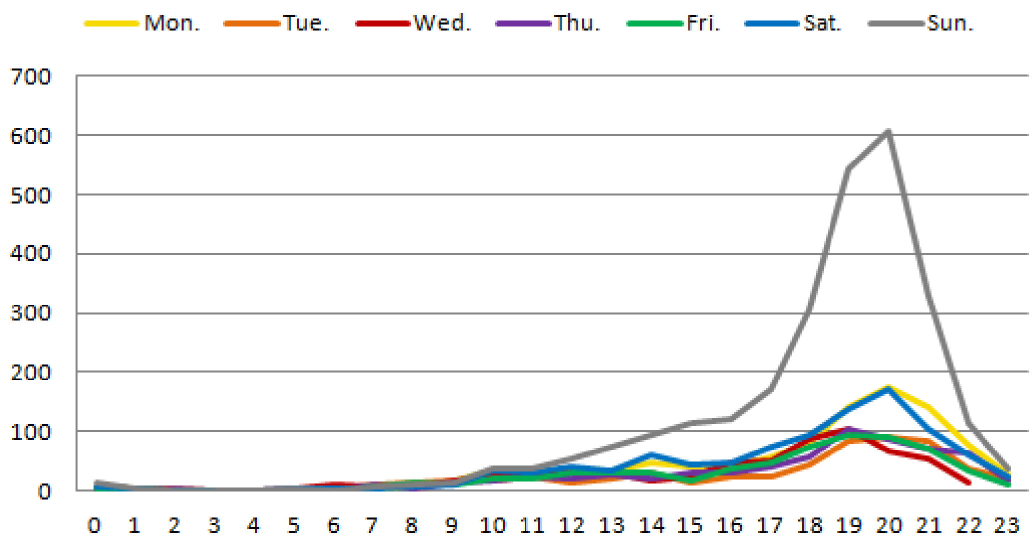
Bids

Figure 4.4: A great part of the bids (34%) were placed on Sunday, and peak-hours were between 6 p.m. and 10 p.m., when more than 60% of bids were placed. The minimal volume of bids was submitted during the night (between 2 a.m. and 7 a.m., only 0.3%). Then the volume of submitted bids slightly increased, and at 5 - 6 p.m. the amount of bids started to rise more sharply. During the weekend, the rise begined earlier, at 4 p.m., and there was a very sharp increase on Sunday and on Monday. The graph indicates that bidders place bids during their free time. There were only 10% of bids placed during the working hours (9 a.m. - 4 p.m. on Mon. - Fri.).

Auction Ends

Figure 4.5: The graph of the distribution of the auction ends follows closely the Figure 4.4. Most of the auctions (37%) ended on Sunday, 57% ended between 6 p.m. and 10 p.m., only 0.5% ended during the night, and 12% ended during the working hours. Sellers anticipate bidders' activity and adjust auction ends to it because auctions are most visible just before the end, when they are

Figure 4.5: eBay: Distribution of Auction Ends



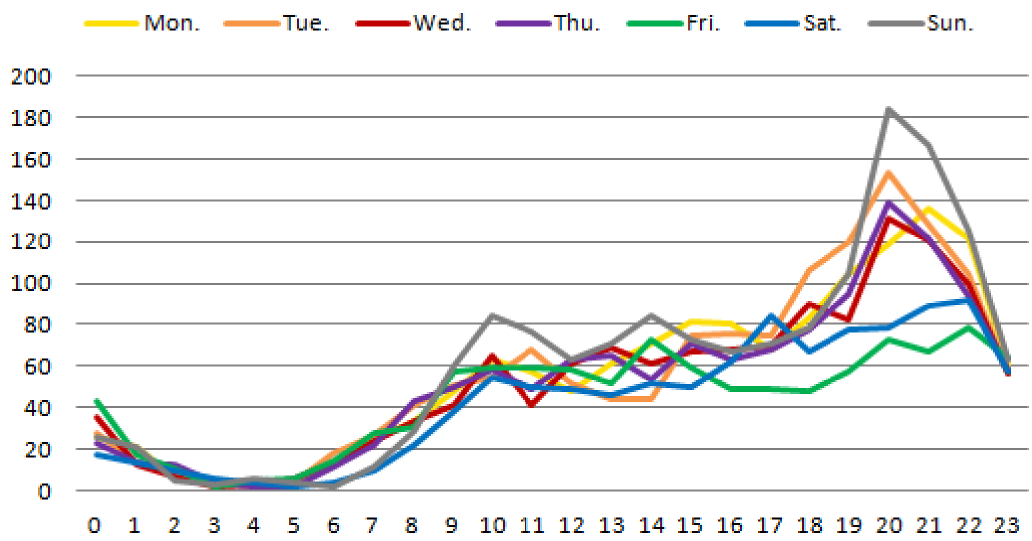
listed on the top of the list of auctions, and then they attract many bidders. The number of attracted bidders raises the probability that the consumer with the highest value notices the auction. Since the item is sold to the bidder with the highest value, the number of potential bidders also increases the probability of making the highest profit.

Table 4.5: eBay: Duration in Days

10	981	13.91%
7	2869	40.67%
5	1329	18.84%
3	1457	20.65%
1	418	5.93%

Table 4.5: Most of the auctions (over 40%) lasted seven days, and only less than 6% of all auctions were set for one day. 7-days auctions are most popular because they always cover a weekend, and their duration is long enough to attract a wide range of potential bidders, but not too long to discourage the impatient ones, who do not want to wait untill the end of the auction, at the same time. There is an evidence that sellers ought to choose longer auction duration, in order to gain a higher final price (Bryan et al. 1999).

Figure 4.6: Aukro: Distribution of Bids



4.2.2 Aukro

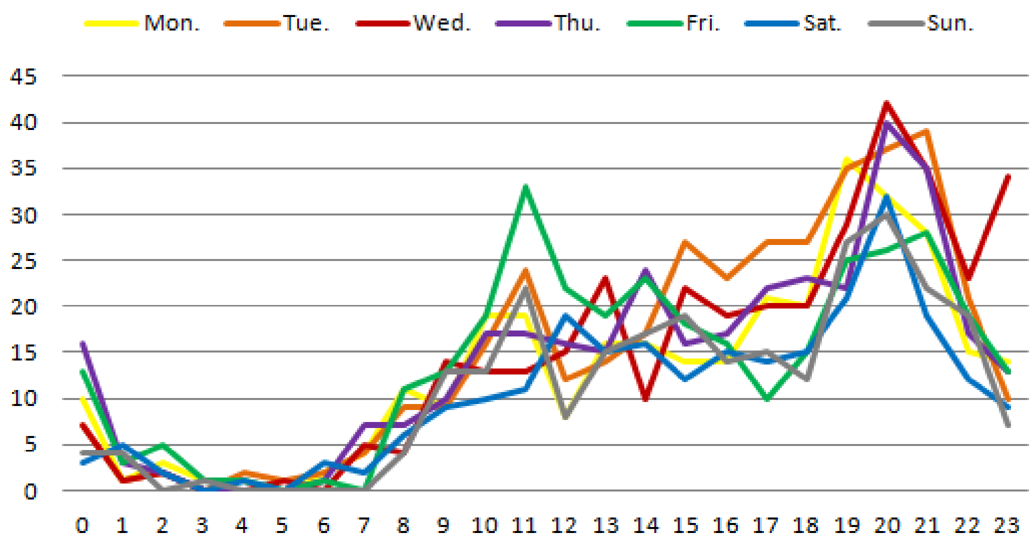
Bids

Figure 4.6: The times bid placements were different for Aukro and for eBay. The numbers of bids placed each day were more balanced on Aukro. There was a very low activity during the night hours (2.4% of the bids were placed between 2 a.m. and 7 a.m.). In contrast to eBay, there were a considerable bidding activity during the working hours, the bids placed during this time form 23% of all bids. It may be caused by e.g. a lower workload of employees or less supervision of employers in the Czech Republic than in Germany. The biggest volume of placed bids was between 6 p.m. and 11 p.m., when 41% of bids were submitted. Friday and Sunday violated this pattern, as there was not such a peak in the graph between 6 p.m. and 11 p.m.. These evenings are in the Czech Republic widely considered to be free, therefore bidders placed less bids. Most of the bids were placed on Sunday (17%), but the difference among the bids placed on different days within a week was small.

Auction Ends

Figure 4.7: There was not any pattern in the ends of the auctions on Aukro. However, some indication of a peak between 7 p.m. and 10 p.m. was noticable. In spite of the amount of bids placed on Sunday, there were less auction ends

Figure 4.7: Aukro: Distribution of Auctoin Ends



during the weekend days than during any other week day. This result indicates that sellers on Aukro anticipate the bidders activity either less, or less successfully than sellers on eBay.

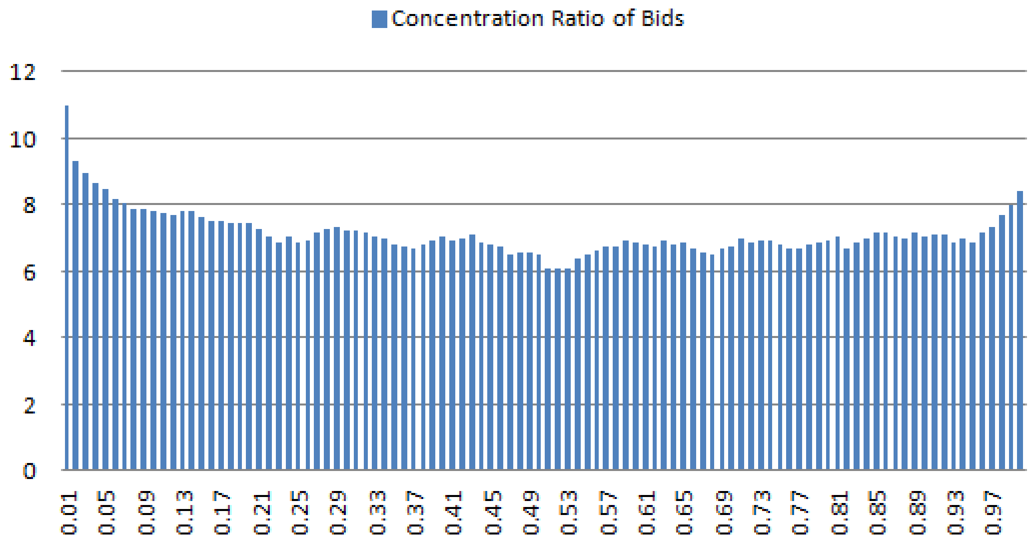
As Aukro does not report the duration of auctions, we have estimated it using the first bid in an auction and the end time of the auction. We have computed the difference between these two times and then round it to the nearest value of 3, 5, 7 and 10 days (the auction lengths allowed by Aukro). In a few cases, we have found a difference higher than 10 days (probably because of some Aukro's exception) and set the duration equal to 11 days.

Table 4.6: Aukro: Duration in Days

11	18	1.58%
10	125	10.96%
7	282	24.74%
5	171	15.00%
3	544	47.72%

Table 4.6: Some of the estimated lengths are probably shorter than the real ones, but we are not able to dispose of this bias. The estimated length of most of the auctions is 3 and 7 days, which corresponds with the popularity of 7 days auctions on eBay.

Figure 4.8: eBay: Concentration Ratio of Bids



4.3 Last Hour of the Auction

4.3.1 eBay

Figure 4.8: Most of the bids were placed during the final hours of auctions. The number of bids is taken in the natural logarithm scale since the graph does not make much sense in real numbers. 28.5% of bids were placed during the last hundredth of the auction duration, then the percentage of bids for each group sharply decreased to values smaller than zero. At the end of auction, there was a slight increase, 2.14% of bids were placed during the first hundredth of the auction duration.[14]

Figure 4.9: This graph shows that most of the bids were placed during the last hour as well - more than 28% of bids were placed at this time.

4.3.2 Aukro

Some of the estimated lengths are probably shorter than the real ones, but we want to show that most of the bids were placed during the last minutes. Since the length is in the denominator of concentration ratio, the shorter duration would move the particular bid to the right on the graph, not to the left; therefore, there would not be an artificially increased number of the late bids.

[14]Concentration ratio is a proportion of the number of seconds until the end of an auction and duration of the auction in seconds

Figure 4.9: eBay: Timing of Bids in 7-days Auctions

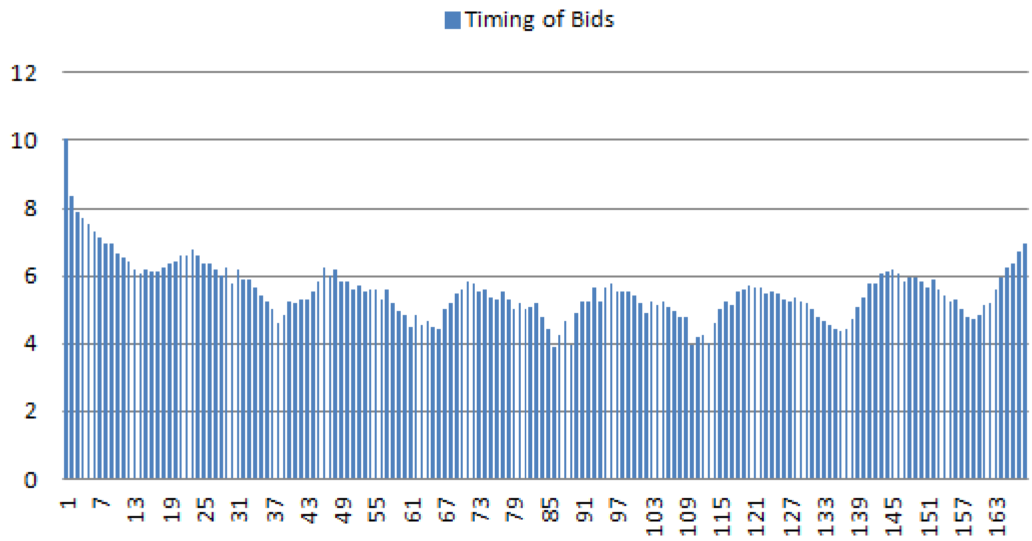


Figure 4.10: Aukro: Concentration Ratio of Bids

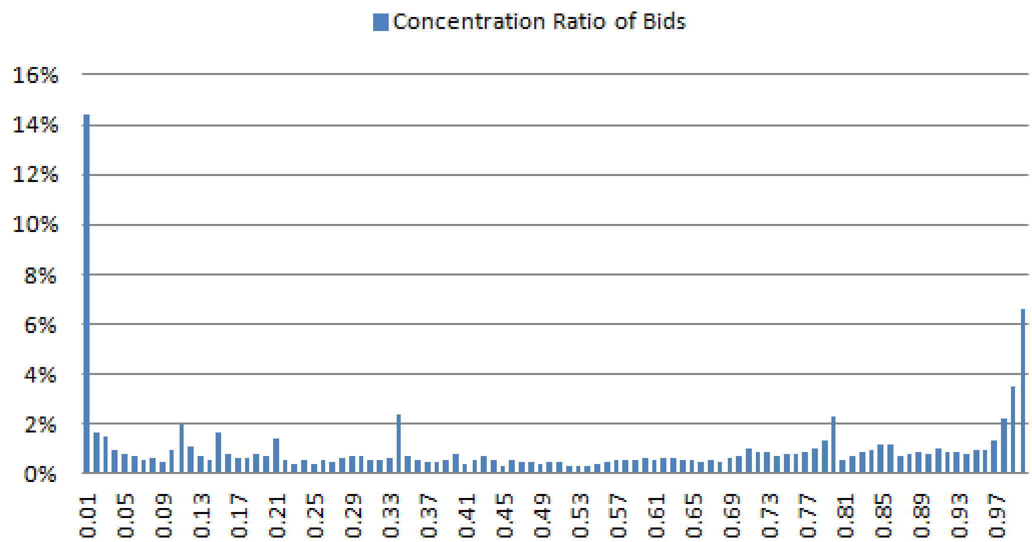


Figure 4.10: The graph shows that more than 14% of the last bids were placed during the final hours of an auction. The higher number of bids at the end of the scale of the concentration ratio can by artificially created by the estimation of length.

The figures show that late bidding is common. There are several explanations for late bidding: close to the end auctions are listed on the top, late bidders do not understand the proxy bidding, or it may be part of their strategic behaviour.[15]

4.4 Winning Bids

4.4.1 eBay

Table 4.7: eBay: Timing of Winning Bids

Max	856528
Min	0
Median	23
Average	11467.01

Table 4.7: The placement times of the winning bids are rather interesting; the median time of placing winning bid is 23 seconds before the and of an auction, which means that at least one half of the auctions were won using late biding.

Figures 4.11 and 4.12: The results are similar to the previous figures; only 31% of the last bids were placed during the last hundredth of the auction duration, while it was more than 80% among the winning bids.

4.4.2 Aukro

Table 4.8: Aukro: Timing of Winning Bids

Max	849873
Min	0
Median	5169
Average	55422

[15] See Chapter 2, Section 2 for other explanations of sniping.

Figure 4.11: eBay: Concentration Ratio of Last Bids

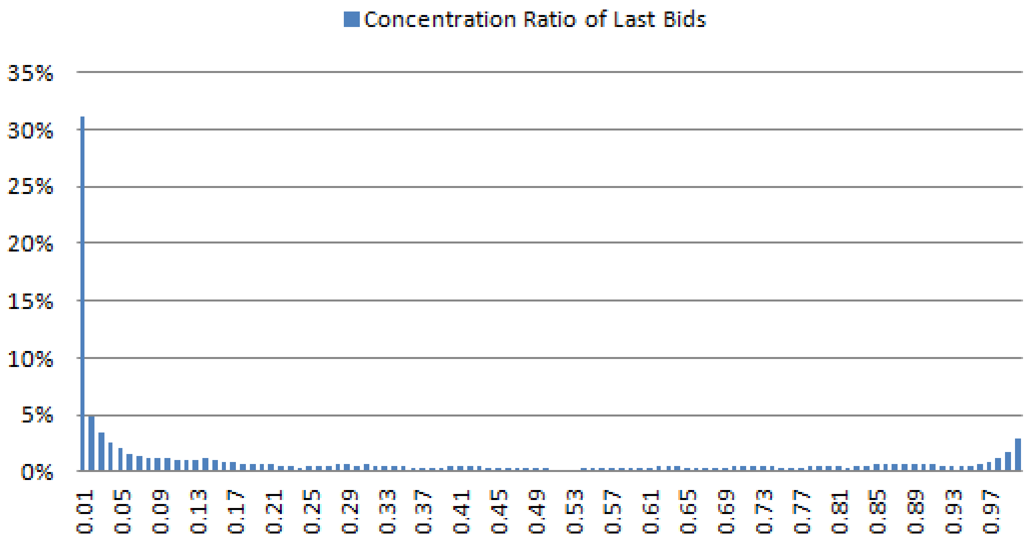


Figure 4.12: eBay: Concentration Ratio of Winning Bids

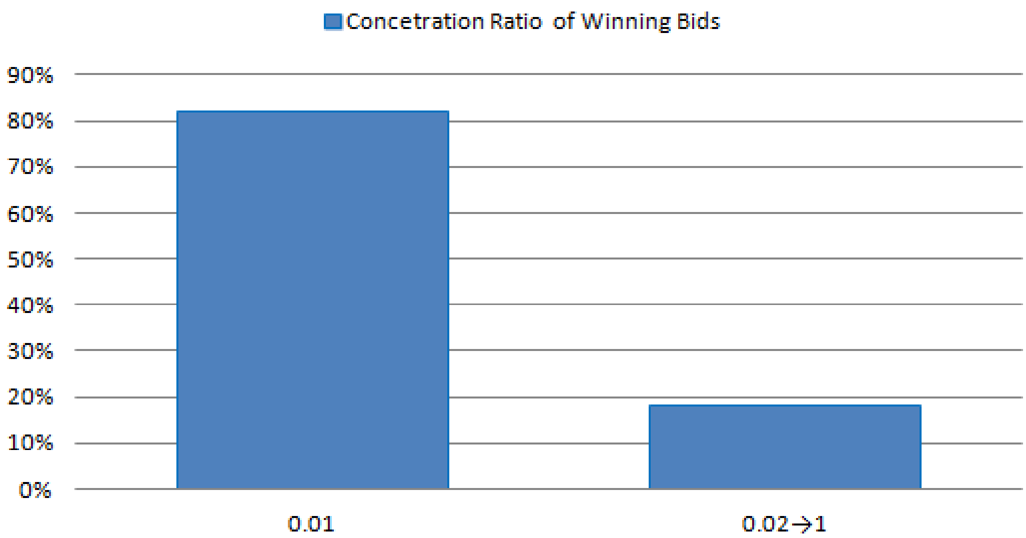


Figure 4.13: Aukro: Concentration Ratio of Winning Bids

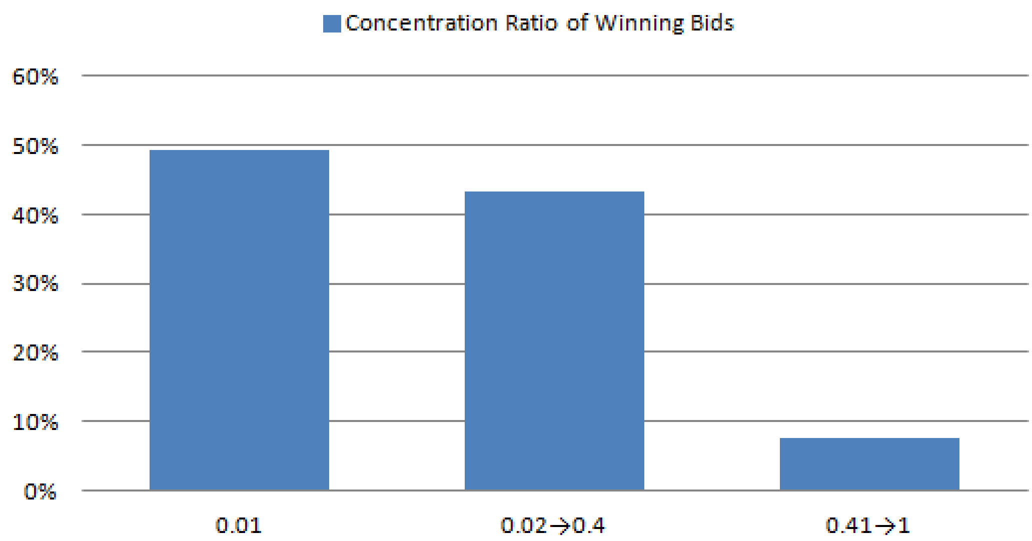


Table 4.8: It seems that late bidding on Aukro is not as usual as on eBay.

Figure 4.13: This graph shows the same effect as Table 4.8, but we can observe that, compared to the histogram of the last placed bids by concentration ratio (in section Last hour of auction), the percentage of bids placed during the last hundredth of the auction length was higher among the winner bids (nearly 50%) than among the bidders last bids (14%).

4.4.3 eBay

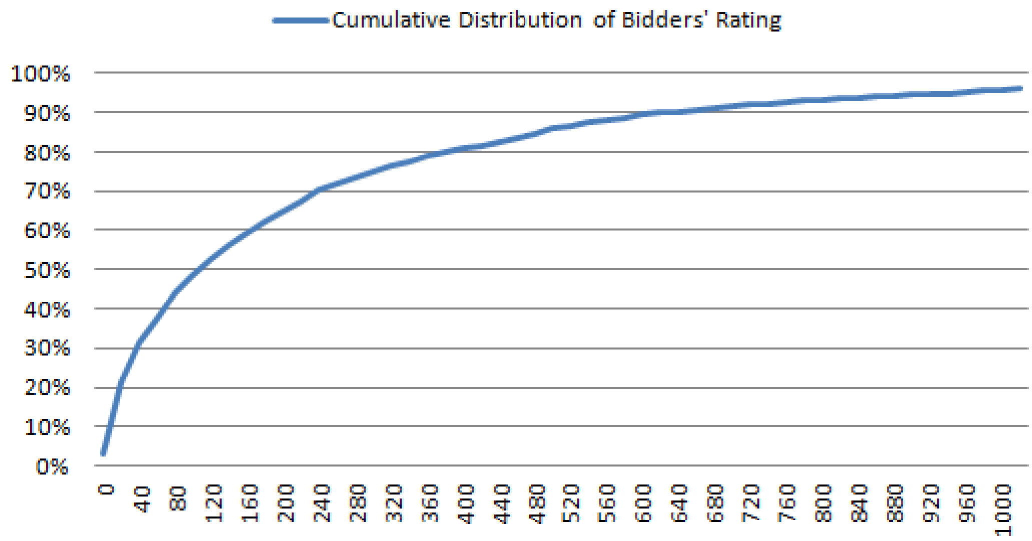
Table 4.9: eBay: Bidders' Feedback Rating Score

Max	37191
Min	-3
Median	106
Average	253.4917

Table 4.10: eBay: Winners' Feedback Rating Score

Max	37191
Min	-3
Median	80
Average	227.9261

Figure 4.14: eBay: Cumulative Distribution Function of Bidders' Rating Points



Tables 4.9 and 4.10: The second table shows that the median rating of auction winners is 80. Inasmuch as the median rating of all bidders is 106, we cannot conclude that experience represented by the feedback rating score brings bidders any advantage; the more experienced bidders did not win more often than the less experienced bidders.

Figures 4.14 and 4.15: The feedback range and distribution of winners were very similar to those of all bidders. That confirms our claim that experience (in the sense of higher feedback) has no influence on the probability of winning.

4.4.4 Aukro

Table 4.11: Aukro: Bidders' Feedback Rating Score

Max	4325
Min	-7
Median	11
Average	51.20869

Tables 4.11 and 4.12: Although the median of the winners' rating is higher than the median of rating among all bidders, the average is smaller. So

Figure 4.15: eBay: Cumulative Distribution Function of Winners' Rating Points

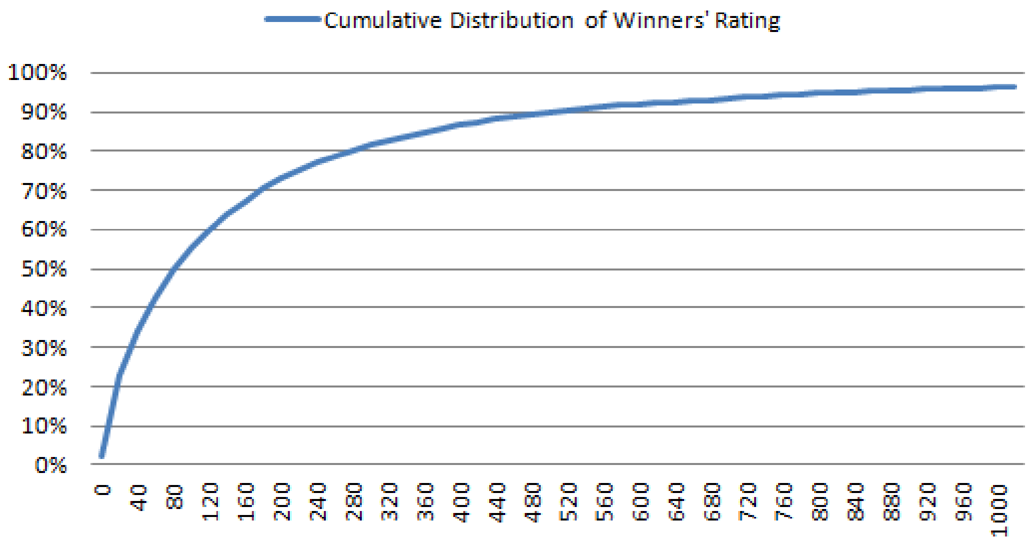


Figure 4.16: Aukro: Cumulative Distribution Function of Bidders' Rating Points

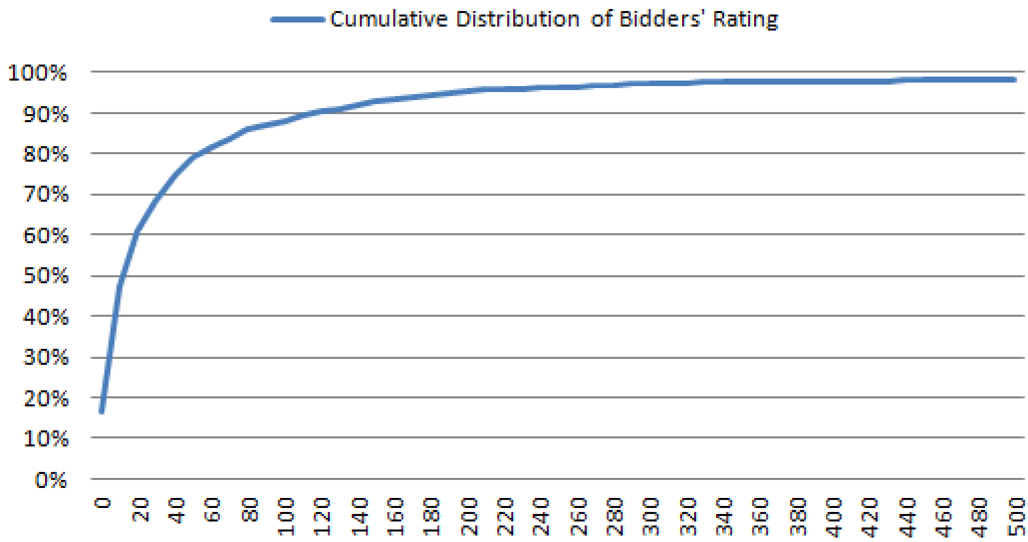
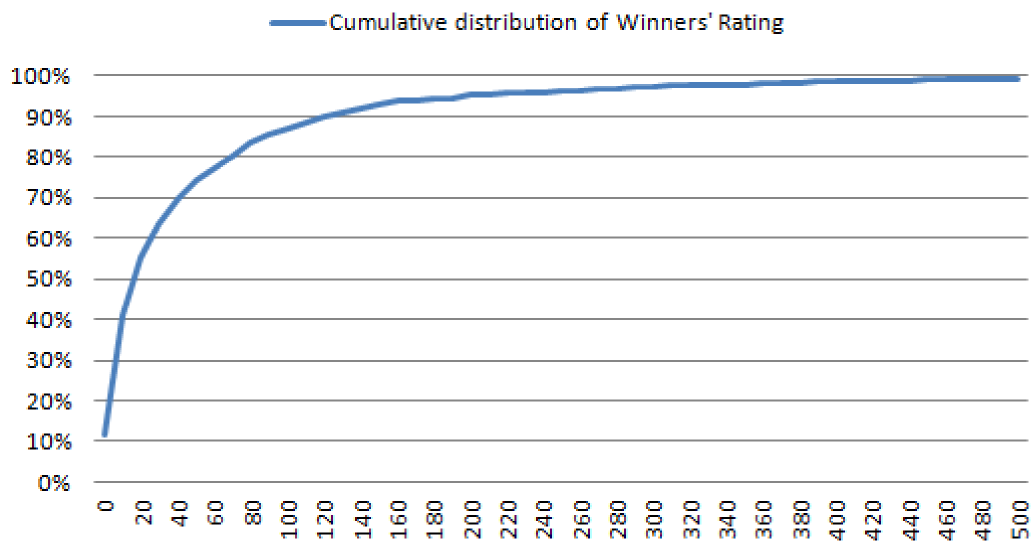


Table 4.12: Aukro: Winners' Feedback Rating Score

Max	2548
Min	-7
Median	14
Average	49.53805

Figure 4.17: Aukro: Cumulative Distribution Function of Winners' Rating Points



we are not able to conclude that the more experienced bidders win auctions more often.

Figures 4.16 and 4.17: The graphs of cumulative distribution of winners' and all bidders' rating are nearly the same, which indicates that the experience level has no effect on the probability of winning.

4.4.5 eBay

Table 4.13: eBay: Number of Bids per Bidder

Max	116
Min	1
Median	1
Average	2.152623

Table 4.14: eBay: Number of Bids per Winner

Max	58
Min	1
Median	1
Average	2.154593

Figure 4.18: eBay: Number of Bids Placed by Bidder

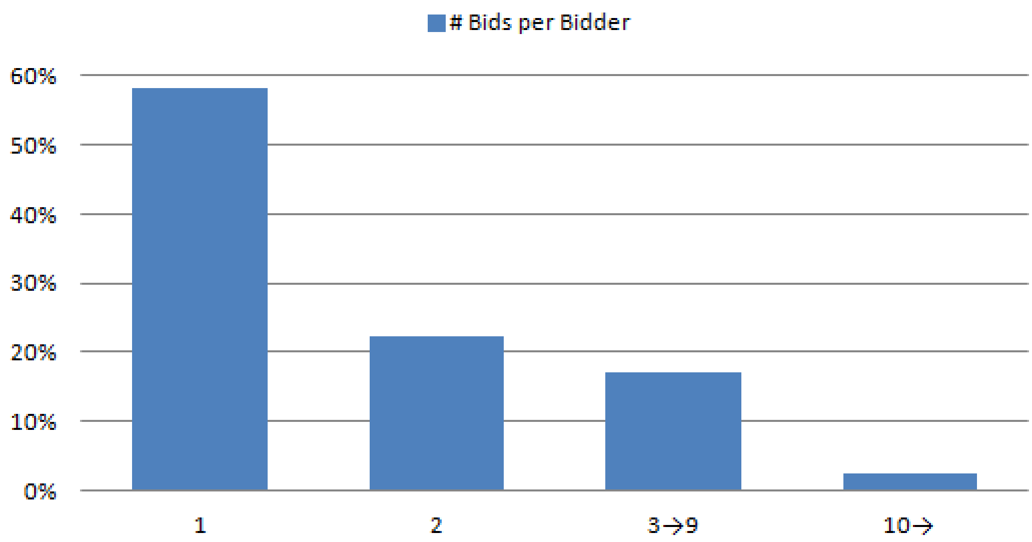
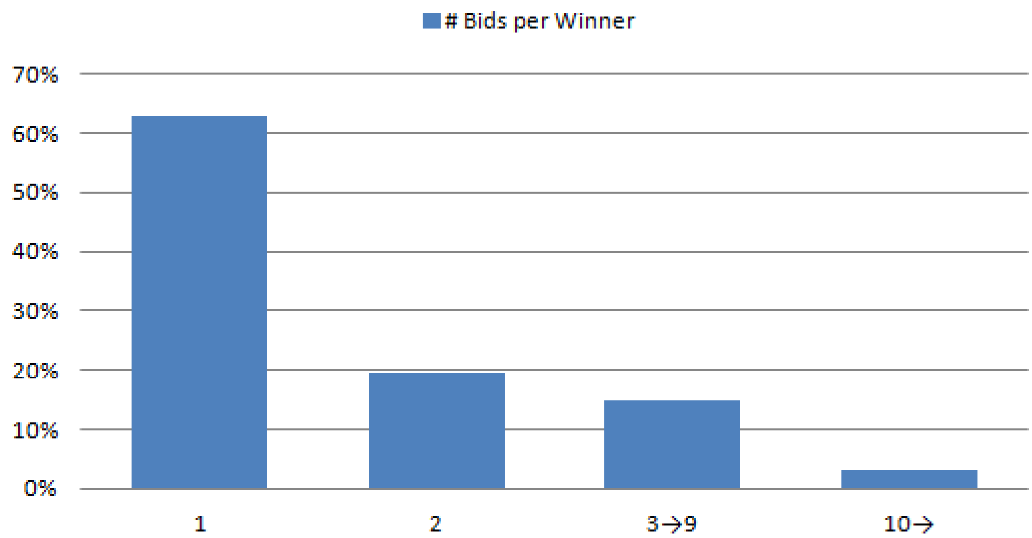


Figure 4.19: eBay: Number of Bids Placed by Winner



Figures 4.18 and 4.19: More than 40% of all bidders place multiple bids, and nearly 20% of all bidders place more than 2 bids. The proportion of bidders submitting only one bid increases from 58% for all bidders to 63% for winners. The graphs indicate that the bidders placing only one bid win more often, but the difference is small.

4.5 Reputation of Sellers

Standardization of the feedback rating scores on Aukro and eBay is a very complex task because, as pointed out above, in spite of the different market sizes, the number of sold items per individual is very similar on both web sites. On the other hand, the diversity and supply of goods on eBay is much greater than on Aukro, which gives more space for gaining points, and eBay exists for longer time than Aukro, meaning that users have had more time for collecting their points. A person who wants to gain a high rating score is more limited on Aukro than on eBay, which is verified by the highest ranking of the sellers in our sample (6750 on Aukro vs. 137222 on eBay). However, the difference in the median values is not so big (47.5 on Aukro vs. 133 on eBay). To get a basic conception of the differences in the ratings, we have found out 2nd, 4th, 6th,..., 98th, 100th percentile values of rating for both auctions web pages, then we have computed the proportion of the percentile values of each percentile group on eBay and Aukro and made an average of all these proportions except for the last four, which exhibit a sharp increase due to a few sellers with a very high rating. We have discovered that the feedback on eBay is on average 3.025 higher than the feedback on Aukro.

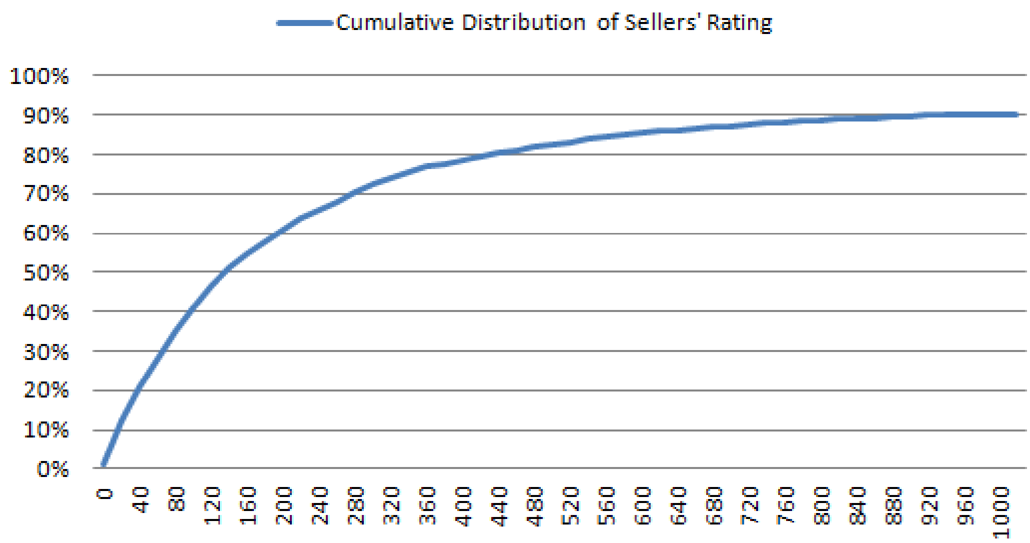
4.5.1 eBay

Table 4.15: eBay: Sellers' Feedback Rating Score

Max	137222
Min	-1
Median	133
Average	1396.023

Table 4.15 and Figure 4.20: In spite of the wide range of the feedback, 90% of the sellers have the feedback rating lower than 1000 as it is shown in the graph of the cumulative distribution functions of the sellers' feedback. The

Figure 4.20: eBay: Cumulative Distribution Function of Sellers' Rating Points



seller with a minimal rating has -1 points, which means that the number of her negative feedback points exceeds the positive feedback points. The highest rating in our sample is 137222, but most of the sellers do not trade in such big volumes, the median value of the feedback score reaches 133. The slope of the graph is degreasing meaning that number of people in each rating group is decreasing.

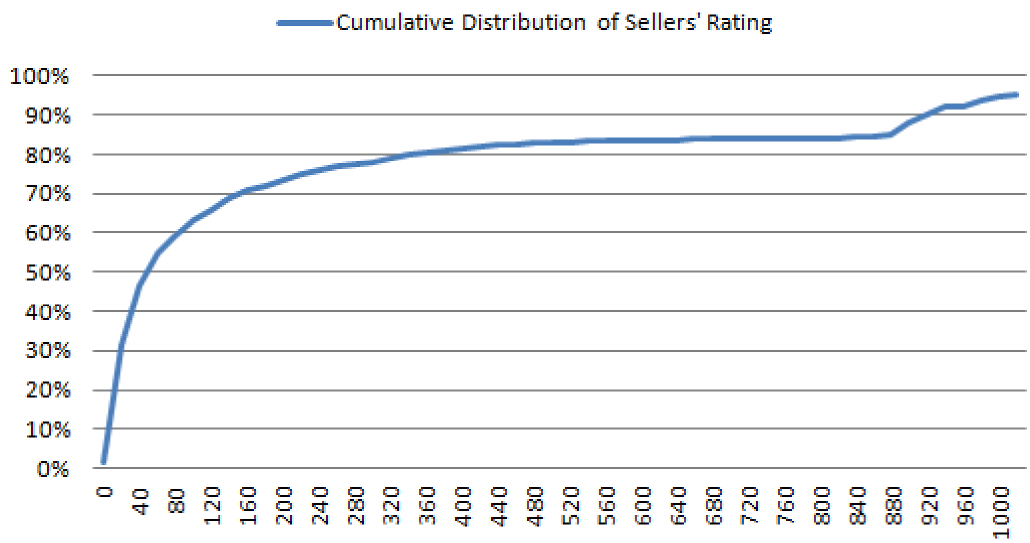
4.5.2 Aukro

Table 4.16: Aukro: Sellers' Feedback Rating Score

Max	6750
Min	-1
Median	47.5
Average	278.6746

Table 4.16 and Figure 4.21: The results are rather different. The beginnings of the graphs are very similar for both auctions; 40% of the sellers have lower rating than 94 on eBay and 30 on Aukro (according of our percentile standardization, 30 Aukro points match 90 eBay points). Then the graph of the sellers' reputation on Aukro starts to differentiate from eBay, its slope is smaller, 60% of the sellers have lower rating than 190 on eBay and than 85

Figure 4.21: Aukro: Cumulative Distribution Function of Sellers' Rating Points



on Aukro (according of our percentile standardization, 85 Aukro points match 257 eBay points). The increase pauses at 83%-84% covering the upper limit of the feedback rating in the range from 460 to 860, meaning that only 2% of the sellers have the rating in this interval. Another steeper rise occurs on the interval from 880 to 1040, at the 1040 point the cumulative distribution function reaches 96%. However, this jump is created by a single seller, who listed 246 auctions and thus she made this bias (her rating is slightly increasing in the time, hence there is not a strict jump but the slope of the distribution function is higher). In the end, it slowly increases up to 100% for 6750. Without the bias, the slope of the graph would be decreasing meaning that the number of people in each rating group decreases, and the graphs of cumulative distributions for Aukro and eBay sellers' feedback would be very similar. The seller with a minimal rating has -1, i.e. the number of her negative feedback exceeds the positive feedback points. The median value is 47.5.

4.6 Sniping

Sniping means placing a bid during the last seconds of the auction's duration. We call a bidder who place a single bid in an auction during the last seconds a "simple" sniper, and a bidder placing multiple bids in an auction with the last submitted bid during the last seconds of the auction's duration a "sophisticated" sniper. The group created by both "sophisticated" and "simple" snipers is called just snipers. eBay reports all bids made by a bidder, so we are able to find out the proportion of the "simple" snipers, while Aukro reports only the last bid of each bidder; therefore, we are not able to distinguish between the "simple" snipers and the "sophisticated" snipers.

4.6.1 eBay

Table 4.17: eBay: Snipers - Proportion among Winning Bids, among Last Bids

	Winning Bids	Last Bids
10 seconds	39.89%	9%
1 minute	58.59%	15%
10 minutes	70.36%	21%

Table 4.18: eBay: "Simple" Snipers - Proportion among Winning Bids, among Last Bids

	Winning Bids	Last Bids
10 seconds	30.02%	6%
1 minute	41.43%	9%
10 minutes	46.73%	12%

Tables 4.17 and 4.18: We can observe a strong evidence of sniping among the winning bids on eBay; 40% of winning bids were placed during the last 10 seconds, nearly 60% during the last minute and 70% during the last 10 minutes. The percentage of the "simple" snipers is lower, counting 30% of the winning bids during the last 10 seconds, 40% during the last 1 minute and 47% during the last 10 minutes.

4.6.2 Aukro

Table 4.19: There are less snipe winning bids on Aukro, but the percentage is still substantial. The difference can be caused by the propagation of sniping. We have found tens of eBay's sniping programs making late bidding more

Table 4.19: Aukro: Snipers - Proportion among Winning Bids, among Last Bids

	Winning Bids	Last Bids
10 seconds	20.85%	4%
1 minute	34.20%	8%
10 minutes	42.81%	11%

convenient (e.g. baytomat.com, mysniper.com, snip.pl/de, sniperagent.de, bidbag.de, gixen.com)[16] and German forums discussing which sniping program is the best, while we have discovered only two web sites about sniping programs in Czech (cs.bidnapper.com and prihazovac.cz)[17]. The supply of these programs may be an explanation for why sniping is more known and therefore used in Germany than in the Czech Republic.

The proportion of the snipe bids among the last bids of bidders is much lower than among the winning bids, meaning that bids submitted during the last seconds or minutes of the auction win the auction more often than bids placed before that time.

4.7 Bidders' Eperience

4.7.1 eBay

Figure 4.22: The graph shows that more experienced bidders less likely place multiple bids. There is a negative correlation between these two parameters.

Figure 4.23: Although the increase in the number of bids at the end and beginning of the auctions is obvious from this graph, a greater difference between less and more experienced bidders is not noticeable.

4.7.2 Aukro

Figure 4.24: This graph shows that more bids are placed in the beginning and at the end of auctions than in the middle of the auction. Further, one can notice that more experienced bidders place bids less often in the middle of auction than less experienced bidders.

[16] http://baytomat.com/, http://mysniper.com/, http://snip.pl/de/, https://sniperagent.de/, https://www.bidbag.de/, http://www.gixen.com/index.php

[17] https://cs.bidnapper.com/, prihazovac.cz

Figure 4.22: eBay: Scatter Plot of Bidders' Rating and Number of Bids

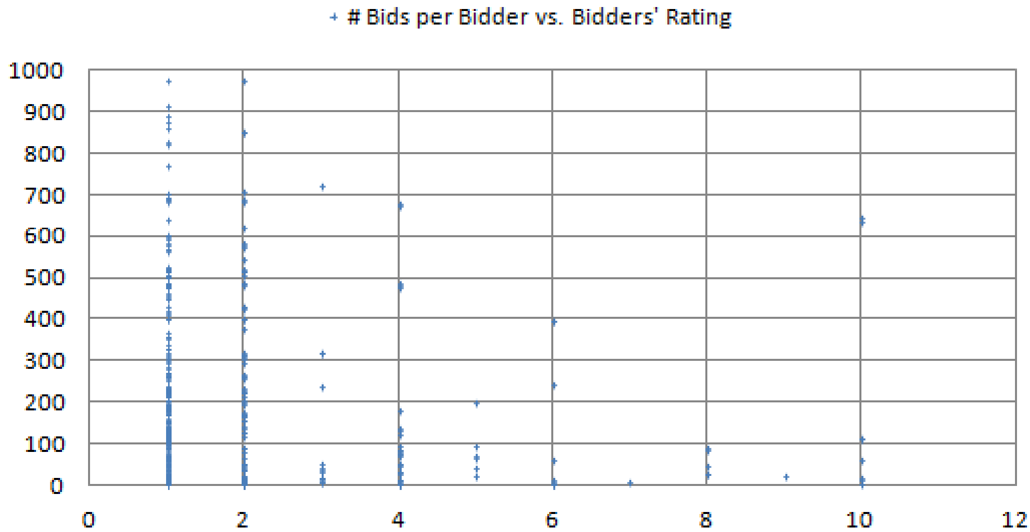


Figure 4.23: eBay: Scatter Plot of Bidders' Rating and Concentration Ratio

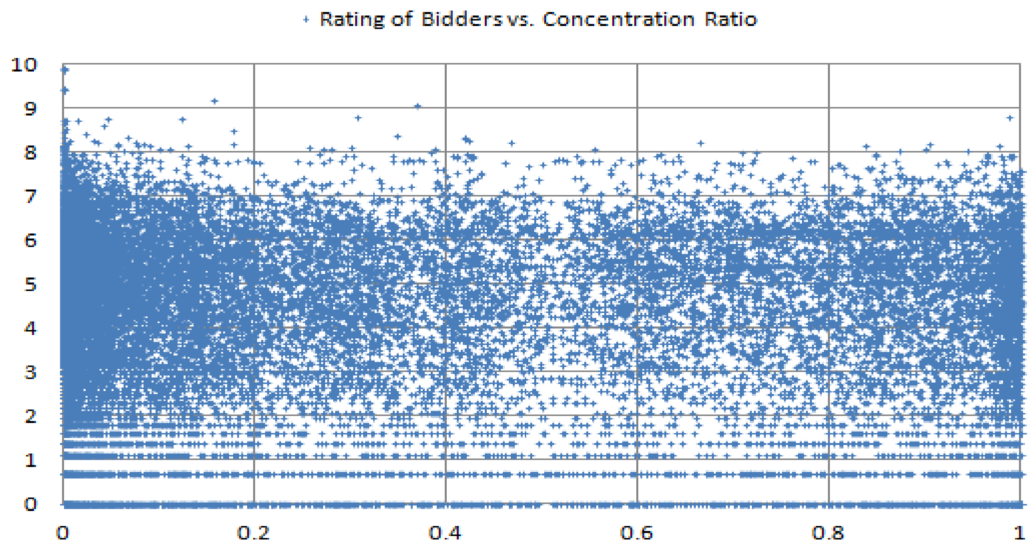
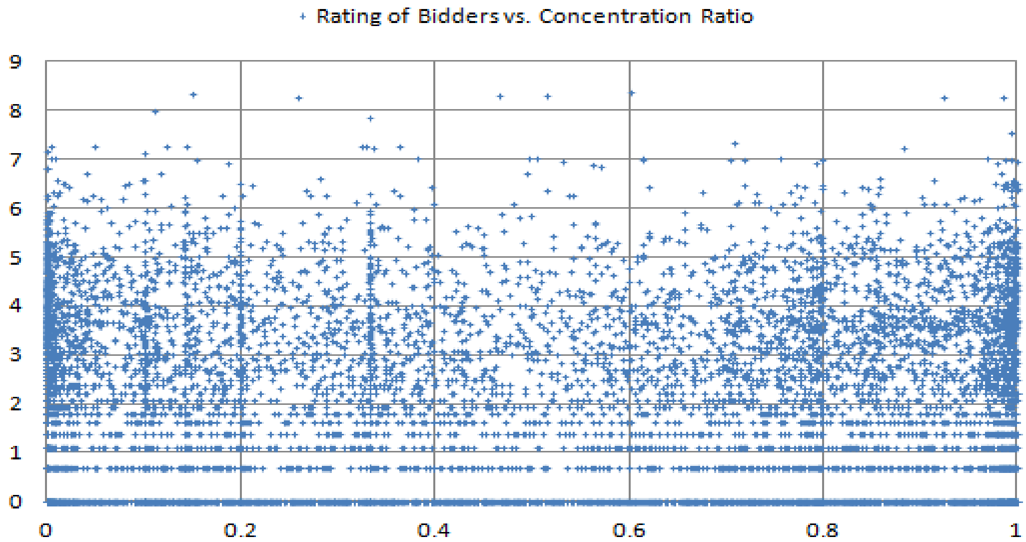


Figure 4.24: Aukro: Scatter Plot of Bidders' Rating and Concentration Ratio



Chapter 5

Impact of Auction Parameters on Final Price

Before we start the empirical analysis, we have to mention the sample selection problem of the Aukro dataset. More than 40% of the auctions on Aukro ended without any bid and we were not able to observe the starting price due to changing design of Aukro web site during the data collection. So we have information about neither the starting price nor the final price for these auctions. Therefore, we had have to omit these observations in the regressions with the final price as the dependent variable. Besides, the omitted observations are not random, there is most likely some observed or unobserved factor that discourages bidders from placing a bid. This may cause a bias brought about e.g. a spurious regression. We have to be aware of this fact while interpreting the results.

The final price of an item is affected by many parameters of the auction and the product. These parameters include e.g. market value, condition, shipping costs, day and hour of auction end, rating of seller, length of auction. In this section, we examine their impact on the final price.

As eBay and Aukro do not guarantee the quality and do not handle the delivery of the products, buyers have to rely on the seller's description of the item, attached pictures and the seller's honesty. The feedback rating can say a lot about the seller's honesty; hence, it affects whether and how much a bidder bids in the auction.

One way of describing the effect of reputation on the final price has been developed by Houser and Wooders (2006). They consider two types of bidders - the honest one, who always delivers the item after receiving the payment, and the dishonest one, who never delivers the item. Seller's reputation is the probability that the seller is honest, $r^S in(0, 1]$. The probability is publicly known. Each bidder has her own private value v_i. The winning bidder i pays b and gains pay-off $(r^S v_i - b)$. Bidder j does not win and her pay-off is 0. Houser and Wooders (2006) show that in equilibrium the bidder with the highest value wins and pays the price of the second highest bid, which is equal to the expected value of winning the auction of the buyer with the second highest value (suppose that $v_1 > v_2 > ...v_n$, in equilibrium, player 1 is the winner and pays $max_{k \neq i} b^*_k = b^*_2 = r^S v_2$). The expected pay-off of all bidders is an increasing function of seller's reputation; thus, the higher is the seller's reputation, the higher is the final price.[18]

The results of this analysis are summed up in the Section 5.4.

5.1 Variables

In this section we describe the variables used in both eBay and Aukro models, and provide reasoning of including them and expactations of signs.

5.1.1 eBay

LN(FINAL_PRICE)
The dependent variable in our estimation is the natural logarithm of the final price. We use the logarithm because it is more intuitive to express the change in the final price by its percentage.

LN(MARKET_VALUE)
The market value is the retail price of smartphones and e-book readers, obtained from guenstiger.de and idealo.de,[19] where the minimal market prices are tabled. Since there was only a chart with a line but not the accurate values for a specific time, we have taken a slightly higher value than the minimal one (as it ought to correspond more to the market), and exterminated a immense volatility (caused by fluctuating in the minimal values, an average value is more stable). A bidder's value depends on the item's market value, therefore we include it in the regression. We use the natural logarithm of the market value, since the elasticity of the final price with respect to the market value has a

[18] For more detailed information see Houser and Wooder (2006).
[19] http://www.guenstiger.de/, http://www.idealo.de/

better explanatory power. We suppose that the final price is very sensitive to changes in the market price and that the values move in the same direction. Therefore, we expect the coefficient of the variable to have a positive sign and be close to one.

SHIPPING

eBay allows to report only one fixed shipping cost value. We suppose that the higher are the shipping costs, the lower is the final price, since bidders have to add these costs to the total cost of an item. In the case of shipping cost, we find it more useful to discover what effect has one additional euro on the final price. Hence, we use the shipping cost variable in the linear form. As explained above, we suppose that values of the shipping cost and the final price move in the opposite directions, so the expected sign of the coefficient is negative. We expect that the final price is not very sensitive to changes in the shipping costs; thus, we believe the size of the coefficient should be small. Hossain and Morgan (2005) note that bidders are not sensitive to shipping costs within some reasonable range. So the coefficients of the variable may not be significant.

STARTING_PRICE

The starting price is another parameter set by a seller. The staring value determines the number of bidders in the auction. A high starting price discourage bidders, whose true value is lower than the starting price, to place their bids. Therefore, the competition in the auction is reduced. The starting price and the number of bidders are highly negatively correlated in our dataset. High competition leads towards aggressive bidding and possible bidding war causing auction fever, and thus according to Ku et al. (2005), to higher price. Lower competition reduces both the aggressiveness of bidding and the probability of bidding war; therefore, it leads to lower price. We expect the starting price to have a negative impact on the final price. The increase in the starting price from median value (EUR 1)to 90th percentile value (EUR 240) is equal to thousands of percents, which could be misleading ,so we rather keep the variable in the linear form.

Some studies include the number of bidders as an independent variable (Zhang 2006). However, Bryan et al. (1999) and Resnick et al. (2006) claim that the number of bidders is endogenously determined by bidder's choice, so we do not include the number of bidders in the regression.

CONDITION

The condition of an item affects its value. On eBay, there are five options of ranking the item: new, refurbished by manufacturer, refurbished by seller, used, and defect, but only new and used are widely used. The proportion of the items refurbished by manufacturer, by seller, or defect items is only 5.5%, so we have decided to unify the categories to new and used and create a dummy variable of condition taking value of 1 if the item is used, and 0 otherwise. A used item has a lower value than a new item, hence we suppose that the variable will have a negative coefficient.

LN(RATING+2)

The rating is the total number of received feedback points for a unique seller. It is unlikely that one additional point would have the same effect for someone with 500 prior feedback points as for someone with no prior feedback, so we use feedback rating in the logarithmic form. Because our data also contain several -1 ratings, we have had to add 2 to all observations to be able to construct the logarithm of all values. We assume that the sellers with a higher rating are more trustworthy, and therefore we expect a positive impact of the variable on the final price.

%_NEGATIVE

eBay does not report all negative points collected by a seller since the account creation, but only the negative points received during the last 12 months. Moreover, it provides a percentage of received positive points during the last 12 months and shows the information on the site with the details of the auction. We think that it is more intuitive for a bidder to look at this percentage. Since it is not very common to give negative points (in my dataset, the median percentage of received positive points is 100% and the average is 98%), a higher percentage of the negative points can indicate a dishonest seller. Trading with such seller includes a risk of not receiving the item after paying, and risk aversion may lead to a lower final price. We have used the percentage value of positive points to obtain the required percentage of received negative points. Since a higher percentage of negative points lowers the probability of the delivery of goods, it reduces also the expected pay-off. Therefore, we assume a negative impact of the variable on the final price.

LENGTH

The number of potential bidders is unobservable in our dataset because some of them do not bid in the auction once the actual price is higher than their value. However, a longer auction is supposed to be visited by more potential bidders. The more potential bidders visit the auction, the greater is the probability that a bidder with the highest true value bids in the auction. On the other hand, long auctions can discourage impatient bidders to bid in, or may lower the value of the bid. We define an impatient bidder as the one who highly values the speed of delivery. In auctions with long duration, she would have to wait until the end of the auction, so she rather bids in a shorter auction, or places a bid lowered by her value of the speed delivery. The results of the empirical study by Bryan et al. (1999) support the first effect of a longer auction. They found out that longer auctions tend to end with a higher final price. The sign of the coefficient will show which of these effects is greater. We use the length variable in the linear form, since we want to find out the impact of one day change on the final price.

LENGTH1, LENGTH3, LENGHT5, LENGTH10
Alternatively, we express the length of an auction by using dummies standing for lengths equal to 1, 3, 5, and 10 days. The two above described effects of the length of an auction may have a different impact for each length (for 7-days variable, the effect of more potential bidders increasing the final price may be greater than the effect of impatient bidders lowering the final price, and for 10-days auction the opposite may be true). The dummy variables help us to examine this issue. Length3 takes value of 1 for a 3-days auction, and 0 otherwise. Other length dummy variables are defined similarly. The signs of the coefficients of these variables are not clear. One variable must have not been used in the regression to prevent multicollinearity. It is the one representing 7-days auctions, which is the most used form.

END_ON_SUNDAY and END_AT_19_20
Auctions shown at the top of the auction list are close to the end, thus also the ending day and hour may influence the number of potential bidders. More bids are placed on Sunday and in the evening hours (between 7 p.m. and 8 p.m.); hence, more potential bidders may visit the auction during Sunday and in the evening. The two variables are dummy variables, the first one takes value of 1 if the auction ends on Sunday, and 0 otherwise; the second one takes value of 1, if the auction ends between 7 p.m. and 8 p.m., and 0 otherwise. We suppose

a positive impact of these two variables on the final price. The variables of ending during the weekend and ending time were included in the regressions by Melnik and Alm (2002), who found them significant.

Interaction terms: CONDITION and LENGTH, CONDITION and LENGTH dummies
The length of an auction may have a different effect for new and for used items. The price of a new item is quite accurately defined by the market price, and bidders' private values for such item are very similar. In this case, the price reduction caused by an impatient bidder may be higher than the price premium gained by attracting the bidder with the true highest value (since the values of all bidders are very similar). On the other hand in the auctions with used items, bidders' private values of the item vary more; therefore, we suppose that the price premium will be greater than the reduction effect of an impatient bidder. The expected sign of the coefficient is positive.

5.1.2 Aukro

LN(FINAL_PRICE)
Once again, the dependent variable is the natural logarithm of the final price.

LN(MARKET_VALUE)
The retail value of the items sold on Aukro was gained from Heureka.cz,[20] where the exact average market prices for specific days are reported. The explanation and expectation of the sign and the size of the market value variable coefficient remain the same as in the case of eBay.

SHIPPING
Sellers on Aukro can report different costs for various types of shipping. We make an average of reported prices and include it in the regression. The explanation and expectation of the sign and the size of the shipping cost variable coefficient remain the same.

CONDITION
Aukro uses only two categories of condition - new and used. Therefore, condition is a dummy variable taking value of 1 if the item is used, and 0 otherwise.

[20]http://www.heureka.cz/

The expectation about the coefficient sign is reported in the eBay variable part.

 # PICTURES

The number of pictures may positively affect the final price as the bidder can better check the condition of the item and does not have to rely on the seller's description. The expected sign of the coefficient is positive.

LN(POS_SELL+1), LN(NEG_SELL+1), LN(POS_BUY+1), LN(NEG_BUY+1)

Aukro provides more details about seller's reputation. There is a record of positive points gained by selling, positive points gained by buying, negative points gained by selling, and negative points gained by buying. Zhang (2006) shows that seller's positive points gained by selling increase the final price, and seller's negative points in her selling reputation reduce the final price, but the seller's points in buying reputation have no effect on the final price. She verified this in an empirical experiment. It is interesting to investigate the different effects of points gained from selling and buying activity. The coefficients of these variables will show if bidders distinguish between them. We have decided to include separate variables for all these indicators of rating to empirically reexamine Zhang's theory. Further, the additional positive point would probably have a higher effect for a bidder without any prior positive points than for a bidder with 500 prior positive points; hence, we use the logarithm forms and we add 1 to each observation in each category of feedback points, in order to be able to construct the logarithmic function. We expect the coefficients of the feedback points from selling activity to have a significant impact on the final price, the positive points will increase it and the negative points will reduce it. Furthermore, the feedback point gained by buying will not have a significant effect on the final price.

LN(RATING+2), LN(NEG_RATING+1)

We also examine the impact of rating on the final in a more general way and run a regression with the overall rating and the number of all negative points. We expect that the coefficient of rating will be positive and the coefficient of negative rating will be negative. The reasoning is the same as in the previous cases.

LENGTH

Aukro does not report the length of an auction. Nevertheless, because we estimated it, we try to add it to the regression. The reasoning and discussion of the impact remains the same as for the eBay sample.

LENGTH5, LENGHT7, LENGTH10
We omitted the auctions with 11-days duration, since these auctions are only exceptions and there are only 18 of them in our dataset. The length dummy variables for Aukro are defined equally as those for eBay. The missing dummy is the one for 3-days auctions, which are the most used ones.

END_AT_20_21
End_at_20_21 is similar as in the eBay data. We do not include the dummy variable for end on Sunday, since bids on Aukro are more equally distributed during the week than on eBay.

Interaction terms: CONDITION and LENGTH, CONDITION and LENGTH dummies
These are the same as in the eBay part.

5.2 Results

5.2.1 eBay

Some auctions do not receive any bids. In that case, the true value is lower than the starting price and the precise value is unknown. The starting bids vary from auction to auction; therefore, we use censored normal regression. Further, we discard the auctions without any bids, and re-estimate the same models with OLS regressions. The censored normal regressions use data about 7047 observations (regressions 1-6). OLS regressions are done with 6493 observations (regressions 7-12). Robust standard errors are reported due to the heteroscedasticity in our regressions.

Regression 1 is the basic one. Left censored observations are the actions without any bids, where the final price is equal to the starting bid. Variables *ln(market_v)*, *condition*, *ln(start_p)*, and *ln(rating+2)* are significant at the 0.1% level, *%negative* and *length* are significant at the 1% level, and the other variables are not statistically significant.

The size and the sign of the coefficient of *ln(market_v)* are the same as we expected, meaning that a 1% increase in the market value leads to a 1.06%

Table 5.1: eBay: Determinants of Final Price 1

ln(final_p)	1		2		3		4	
constant	-0.58968	***	-0.645707	***	-0.16832	**	-0.22759	**
	(0.0574)		(0.05546)		(0.06058)		(0.05892)	
ln(market_v)	1.06343	***	1.06482	***	0.997742	***	0.998268	***
	(0.00896)		(0.00896)		(0.00945)		(0.00945)	
shipping	-0.00047		-0.000562		0.001616		0.001571	
	(0.00136)		(0.00136)		(0.00145)		(0.00145)	
condition	-0.2239	***	-0.223002	***				
	(0.02106)		(0.01294)					
start_p	-0.00019	***	-0.000185	***	-0.0002	***	-0.0002	***
	(4.1E-05)		(4.1E-05)		(4.1E-05)		(4.2E-05)	
ln(rating+2)	0.009346	***	0.0103291	***	0.000665		0.001278	
	(0.00228)		(0.00233)		(0.00291)		(0.00292)	
%negative	-0.00396	**	-0.003805	**	-0.00254	+	-0.00249	+
	(0.00143)		(0.00143)		(0.00143)		(0.00143)	
length	-0.00729	**			-0.00839	***		
	(0.00237)				(0.00193)			
length1			0.0491759	*			0.058701	**
			(0.02367)				(0.01924)	
length3			0.003249				0.011381	
			(0.01636)				(0.01331)	
length5			0.0217522				0.022889	+
			(0.0165)				(0.01326)	
length10			-0.039504	*			-0.03926	*
			(0.01898)				(0.01525)	
end_sun	0.013298		0.0086937		0.008084		0.006192	
	(0.00855)		(0.00875)		(0.01013)		(0.01029)	
end_19_20	-0.00061		-0.000479		0.016262		0.016815	
	(0.00852)		(0.00852)		(0.01007)		(0.01007)	
cond*length	-0.00081							
	(0.00329)							
cond*length1			-0.057462					
			(0.03801)					
cond*length3			0.0070782					
			(0.02217)					
cond*length5			-0.005892					
			-(0.00589)					
cond*length10			-0.025125					
			(0.02512)					
sigma	0.334814		0.3345542		0.267809		0.267603	
	(0.00148)		(0.00158)		(0.00343)		(0.00343)	
(Pseudo) R2	0.6375		0.6385		0.8454		0.8463	
N	7047		7047		3310		3310	
leftcensored	554		554		270		270	
uncensored	6493		6493		3040		3040	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

Table 5.2: eBay: Determinants of Final Price 2

ln(final_p)	5		6		7		8	
constant	-1.33802	***	-1.381541	***	-0.528	***	-0.56634	***
	(0.09669)		(0.09213)		(0.05551)		(0.05363)	
ln(market_v)	1.148527	***	1.152094	***	1.053809	***	1.054835	***
	(0.01563)		(0.01566)		(0.00863)		(0.00865)	
shipping	-0.00229		-0.002449		-0.00126		-0.00133	
	(0.00235)		(0.00235)		(0.00133)		(0.00133)	
condition					-0.21419	***	-0.22139	***
					(0.02061)		(0.0125)	
start_p	-8.9E-05		-7.67E-05		0.00027	***	0.000268	***
	(7.9E-05)		(7.9E-05)		(4.6E-05)		(4.6E-05)	
ln(rating+2)	0.015338	***	0.0171584	***	0.007386	**	0.008058	**
	(0.00334)		(0.00344)		(0.00221)		(0.00226)	
%negative	-0.0065	*	-0.006102	*	-0.00276	*	-0.00268	+
	(0.0027)		(0.00271)		(0.00139)		(0.00139)	
length	-0.00513	+			-0.00523	*		
	(0.00272)				(0.00231)			
length1			-0.036736				0.036633	
			(0.03471)				(0.02319)	
length3			-0.013998				-0.0029	
			(0.01847)				(0.01584)	
length5			0.0060266				0.014791	
			(0.01794)				(0.01596)	
length10			-0.070881	***			-0.03334	+
			(0.01916)				(0.01846)	
end_sun	0.016123		0.0071726		0.002391		-0.00066	
	(0.01324)		(0.01359)		(0.00832)		(0.00848)	
end_19_20	-0.01186		-0.012113		-0.00053		-0.00032	
	(0.01322)		(0.01321)		(0.00829)		(0.00829)	
cond*length					-0.0012			
					(0.00324)			
cond*length1							-0.0303	
							(0.0376)	
cond*length3							0.015549	
							(0.02144)	
cond*length5							-0.00316	
							(0.02187)	
cond*length10							-0.00924	
							(0.02493)	
sigma	0.380269		0.3797686					
	(0.00223)		(0.00234)					
(Pseudo) R2	0.4978		0.4995		0.7376		0.7379	
N	3737		3737		6493		6493	
leftcensored	284		284					
uncensored	3453		3453					

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

Table 5.3: eBay: Determinants of Final Price 3

ln(final_p)	9		10		11		12	
constant	-0.14016	*	-0.188133	**	-1.22403	***	-1.25529	***
	(0.06029)		(0.0586)		(0.09228)		(0.08788)	
ln(market_v)	0.991305	***	0.9917713	***	1.135384	***	1.138106	***
	(0.00937)		(0.00937)		(0.01485)		(0.0149)	
shipping	0.001869		0.001835		-0.00503	*	-0.00518	*
	(0.00145)		(0.00145)		(0.00227)		(0.00228)	
start_p	0.000128	**	0.0001232	**	0.00051	***	0.000514	***
	(4.7E-05)		(4.7E-05)		(8.6E-05)		(8.6E-05)	
ln(rating+2)	0.00057		0.0011915		.0116249 .	***	0.012861	***
	(0.00289)		(0.0029)		(0.0032)		(0.00331)	
%negative	-0.00054		-0.000519		-0.00637	*	-0.00611	*
	(0.00143)		(0.00143)		(0.00261)		(0.00261)	
length	-0.00678	***			-0.00357			
	(0.00193)				(0.00268)			
length1			0.0509341	**			-0.02046	
			(0.01937)				(0.03416)	
length3			0.0057352				-0.00911	
			(0.01324)				(0.01767)	
length5			0.0181631				0.000984	
			(0.01317)				(0.01707)	
length10			-0.033255	**			-0.04806	*
			(0.01521)				(0.01899)	
end_sun	0.003491		0.0152114		-0.00159		-0.00757	
	(0.01007)		(0.01023)		(0.01272)		(0.013)	
end_19_20	0.018055		0.0186657		-0.01116		-0.0114	
	(0.01)		(0.01001)		(0.01271)		(0.01272)	
(Pseudo) R2	0.7949		0.7952		0.6473		0.6478	
N	3040		3040		3453		3453	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

increase inthe final price. The coefficient of *shipping* is not significant, as discussed by Hossain and Morgan (2005), but it has the expected negative sign. The variable *condition* has the expected sign, the final price of used items is 22% lower than the price of new items. The coefficient of *starting_price* suggests that an increase in the starting price has a significant negative impact on the final price, raising the starting price from EUR 1 (the median value) to EUR 240 (the 90th percentile value) causes a 4.5% decrease in the final price.

The coefficient of *ln(rating+2)* is significant at the 1% level. An increase from the 20th percentile value (37 rating points) to the median value in rating (314 rating points) leads to a 6.64% increase in the final price. The impact of *%_negative* is negative and significant at the 5% significance level. If the proportion of the negative points among the positive points increases by 1%, the final price decreases by 0.4%.

The coefficient of *length* is negative and statistically significant, suggesting that the impatient bidder effect is stronger than the price premium for attracting more bidders. One day increase in the auction length leads to a 0.7% decrease in the final price. In other words, a 7-days auction ends with a 4.2% lower final price than a 1-day auction. The coefficient of the interaction term is not significant, so we are not able to compare the effect of the auction length on auctions with new and used items. The coefficients of end specifying variables are also insignificant at the 10% significance level.

We can compare these results with the results of Regression 7, presenting the same specification but estimated by the OLS method. In the OLS regression, the significance of the coefficients is slightly lower than in the censored-normal regression (*%negative* and *length* are significant at the 5% level) and effects of all significant coefficients, except for the *starting_price* one, are slightly weaker. The variable with totally different effects in the censored-normal and the OLS regressions is *starting_price*, but this problem may raise due to the bias caused by omitting zero bids auctions. Hence, we do not discuss the starting price variable in the OLS regressions any more.

Regression 2 contains length dummy variables. Coefficients of *ln(market_v)*, *condition*, *starting_price*, and *ln(rating+2)* are all significant at the 0.1% level, and their size is very similar to the one estimated in the first regression. The coefficients of *shipping*, *end_sun* and *end_19_20* are again insignificant at the 10% level. The coefficient of *%negative* is significant at the 5% level, and its magnitude is also very close to that estimated in the first regression. Only dummy variables for 1-day auctions and 10-days auctions are significant at the

5% level. The coefficient of *length1* means that 1-days auctions end with a 5% higher price than 7-days auction. The coefficient of *length10* exhibits a 3.9% decrease in the final price for 10-days auctions in comparison to 7-days auctions. This also confirms the previous result that the impatient bidder effect is higher than the price premium for longer auction. The interaction terms are not significant. A comparison of Regressions 2 and 8 gives the same results as comparison of Regressions 1 and 7.

Since the coefficients of the interaction terms do not shed light upon the matter, we decided to run separate regressions on two subsamples - new items and used items.

We used the subsample of only new items for the Regressions 3 and 4 (9 and 10), and the rest was used for the Regressions 5 and 6 (11 and 12). The elasticity of the final price with respect to the market value is greater for used items, it is equal to 1.15, while the elasticity for new items is equal to 1.00, meaning that the final price of auctions with used items reacts to a change in the market value more sensitively than in the case of new items. The coefficients of the *shipping* in Regressions 11 and 12 are significant at the 5% level. The signs of these coefficients are negative and their magnitude is -0.005, meaning that 1 additional euro in the shipping costs causes a 0.5% decrease in the final price. Bidders buying used items are more sensitive to shipping costs than bidders buying new items. It may be caused by a high importance of the final price for people buying used items (otherwise they would buy a new item), so they react to changes in the shipping cost more sensitively. But as we get the significant results only for the OLS regression and not for the censored-normal one, which should be more accurate, the result can be caused by the bias of the OLS regression. *Starting_price* has a different effect in auctions of new and used items, the coefficient is significant only for new items. It may be so that the price for new items is crucial, and many bidders can be attracted by a low starting price. Also the other factors matter in the auction of used items - e.g. the credibility of seller and her item description, a low starting price can raise doubts about the true condition of items, so it does not only attract some bidders, but also discourages a part of them.

Another difference can be observed in the case of *ln(rating+2)* and *%_negative*. For new items the both rating variables do not have a statistically significant impact (at the 5% level) on the final price, whereas for used items, the coefficient of *%_negative* is significant at the 5% level in all regressions, and the coefficient of *ln(rating+2)* is significant at the 0.1%level in all regressions. The coefficient of *ln(rating+2)* indicates that an improvement of the rating from 37 rating points (20th percentile value) to 314 rating points (the median) causes a 11% increase in the final price, the *%_negative* coefficient means that a 1% increase in the proportion of negative rating points among all received feedback points leads to a 0.6% decrease in the final price. The effect of rating is greater for auctions with used items since there are no doubts about the quality of a new item, but a used item may be in a worse condition than it is described in the auction details. Therefore, sellers' trustworthiness indicated by the rating is more important for buyers of used items.

The coefficient of *length* variable in Regressions 3 and 9 (new items) is statistically significant at the 0.1% level, but in Regressions 5 and 11 (used items) the coefficient is not significant at the 5% level. The magnitude of the coefficient means that each additional day lowers the final price by 0.84% (0.68% in Regression 9). A similar effect may be observed in the regressions with the length dummy variables. In auctions with new items the 1-day auctions end with a 5-6% higher price than 7-days auctions, and the new items sold in auctions with 10-days duration end with a 3.3-3.9% lower price than auctions with 7-days duration. The effect of the 10-days length dummy is significant and negative also in the regression of used items, so the 10-days auction are probably too long, and the impatient bidder factor plays a role also for used items. The other results indicate that length of an auction significantly affects the final price of auctions with new items, but not with used items.

5.2.2 Aukro

Due to changing appearance of Aukro, we were not able to download the starting price for a large amount of auctions, thus we cannot use the censored-normal regression and we have to settle for OLS regression on the limited data of the auctions with at least one bid. The auctions with zero bids and a late submitted bid were deleted from the sample. We decided to run the regression only on a part of the data, since not all variables were downloaded for all observations. There were 907 observations used in the OLS regressions. Since our models suffer from heteroskedasticity, we estimate them with the robust standard errors.

The market value creates the base of the final price, its coefficient is positive and significant at the 0.1% level. The elasticity of the final price with respect to the market value is 1.52, meaning that a 1% decrease in the market value

Table 5.4: Aukro: Determinants of Final Price 1

ln(final_p)	1		2		3		4	
constant	-5.53364	***	-5.41802	***	-5.53367	***	-5.42887	***
	(1.06352)		(1.06235)		(1.08706)		(1.08329)	
ln(market_v)	1.524742	***	1.52055	***	1.520604	***	1.51838	***
	(0.10688)		(0.10756)		(0.10906)		(0.10933)	
shipping	-3E-05		-3.1E-05		0.000202		0.000199	
	(0.00025)		(0.00025)		(0.00028)		(0.00028)	
condition	-0.41495	***	-0.46805	***	-0.39662	***	-0.46076	***
	(0.10806)		(0.0699)		(0.10524)		(0.06943)	
pictures	0.002841		0.002783		0.002917		0.00286	
	(0.00355)		(0.00356)		(0.0035)		(0.0035)	
ln(pos_sell+1)	0.038932	***	0.039454	***				
	(0.01119)		(0.01127)					
ln(neg_sell+1)	-0.05415	*	-0.05599	*				
	(0.02707)		(0.02679)					
ln(pos_buy+1)	-0.05664	**	-0.05626	**				
	(0.0183)		(0.01834)					
ln(neg_buy+1)	-0.15361	**	-0.15401	*				
	(0.06312)		(0.06392)					
ln(rating+2)					-0.02005		-0.01949	
					(0.01818)		(0.01818)	
ln(negative)					-0.05990		-0.06209	
					(0.03137)		(0.03461)	
length	0.006958				0.005231			
	(0.00861)				(0.00839)			
length5			-0.00651				-0.0253	
			(0.06716)				(0.06524)	
length7			0.022452				0.019299	
			(0.0504)				(0.05014)	
length10			0.05059				0.03502	
			(0.06188)				(0.06051)	
end_20_21	0.006535		0.007339		-0.00311		-0.0021	
	(0.03738)		(0.03739)		(0.0375)		(0.0375)	
cond*length	0.018833				0.021681			
	(0.01903)				(0.01863)			
cond*length5			0.083189				0.077721	
			(0.09691)				(0.0988)	
cond*length7			0.019397				0.037876	
			(0.17731)				(0.17858)	
cond*length10			0.167984				0.190272	
			(0.11013)				(0.10249)	
R2	0.3385		0.3389		0.3162		0.3166	
N	907		907		907		907	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

Table 5.5: Aukro: Determinants of Final Price 2

ln(final_p)	5		6		7		8	
constant	3.893962	*	4.442796	**	3.025994	+	3.480417	*
	(1.65764)		(1.66645)		(1.64299)		(1.6681)	
ln(market_v)	0.558661	**	0.500401	**	0.64929	***	0.5992	**
	(0.17821)		(0.17801)		(0.17471)		(0.17634)	
shipping	-0.00033		-0.00028		-0.00038		-0.00033	
	(0.00046)		(0.00044)		(0.00044)		(0.00043)	
pictures	0.004423		0.003438		0.006163		0.005041	
	(0.00449)		(0.00409)		(0.00488)		(0.00452)	
ln(pos_sell+1)	0.005995		0.01045					
	(0.01729)		(0.01711)					
ln(neg_sell+1)	-0.03148		-0.03578					
	(0.0671)		(0.06702)					
ln(pos_buy+1)	-0.06184	*	-0.0552	+				
	(0.03091)		(0.02826)					
ln(neg_buy+1)	-0.13247	+	-0.1469	*				
	(0.06971)		(0.06718)					
ln(rating+2)					-0.0363		-0.02529	
					(0.03259)		(0.0294)	
ln(negative)					-0.07519		-0.08344	
					(0.05063)		(0.05085)	
length	0.002541				-0.00114			
	(0.01381)				(0.01445)			
length5			0.021306				-0.00142	
			(0.05888)				(0.05671)	
length7			-0.13693				-0.15243	
			(0.16065)				(0.16789)	
length10			0.097798				0.078515	
			(0.07412)				(0.06984)	
end_20_21	0.060822		0.059327		0.043776		0.042113	
	(0.07936)		(0.07959)		(0.07588)		(0.07603)	
R2	0.1345		0.15		0.1134		0.1289	
N	161		161		161		161	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

Table 5.6: Aukro: Determinants of Final Price 3

ln(final_p)	9		10		11		12	
constant	-8.06125	***	-8.04627	***	-7.93002	***	-7.93336	***
	(1.17304)		(1.18291)		(1.22574)		(1.23214)	
ln(market_v)	1.745467	***	1.747011	***	1.730184	***	1.733227	***
	(0.12284)		(0.12307)		(0.1278)		(0.12773)	
shipping	-3.2E-05		-3.6E-05		0.000222		0.000213	
	(0.0003)		(0.00031)		(0.00033)		(0.00033)	
pictures	0.003804		0.003838		0.003806		0.00387	
	(0.00511)		(0.00517)		(0.00506)		(0.00511)	
ln(pos_sell+1)	0.042226	**	0.042078	**				
	(0.01316)		(0.01318)					
ln(neg_sell+1)	-0.04312		-0.04292					
	(0.03423)		(0.03387)					
ln(pos_buy+1)	-0.05257	*	-0.05243	*				
	(0.02081)		(0.02094)					
ln(neg_buy+1)	-0.19777	**	-0.1972	*				
	(0.07534)		(0.07616)					
ln(rating+2)					-0.01833		-0.01833	
					(0.0203)		(0.02039)	
ln(negative)					-0.05613		-0.05620	
					(0.03776)		(0.03788)	
length	0.009278				0.007211			
	(0.00846)				(0.00827)			
length5			0.001428				-0.01941	
			(0.06681)				(0.06453)	
length7			0.040952				0.036032	
			(0.04914)				(0.04917)	
length10			0.061002				0.043009	
			(0.06123)				(0.05983)	
end_20_21	-0.00961		-0.00923		-0.01784		-0.01707	
	(0.04042)		(0.04045)		(0.04168)		(0.04168)	
R2	0.2784		0.2784		0.2516		0.2519	
N	746		746		746		746	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

causes a 1.52% decrease in the final price. The coefficient of *shipping* is not statistically significant. The coefficient of *condition* has the expected negative sign and is statistically significant at the 0.1% level. The effect of condition of the sold item is very high, used items are sold for a 40-47% lower price than new items.

The effects of all ratings variables in first two regressions are statistically significant at the 5% level, and the coefficients of the positive rating variables are significant also at the 1% level. A 1% increase in positive rating for selling causes a 0.04% increase in the final price, meaning that the increase in positive selling points from the 20th percentile value (rating 3) to the median value (rating 16) means a 12.7% increase in the price. A 1% rise in selling negative rating points leads to approximately a 0.055% decrease in the final price. The sellers have only a few negative points from selling (the median value is 0), but an increase from 0 to 1 negative selling points causes a 5.5% decrease in the final price.

The negative sign of *ln(pos_buy+1)* is very surprising. The possible explanation is that bidders trust sellers specialized only in selling more than to those engaging in both selling and buying. Bidders may suspect a seller with positive points for buying of trying to gain easy positive points, and that she is not as credible seller as it may seem from the overall feedback rating. This coefficient says that a 1% increase in positive points for buying leads to a 0.056% decrease in the final price; therefore, the positive points increasing the number of positive buying points from the 20th percentile (rating 4) to the median value (rating 14) causes a 11.2% decrease in the final price. Another surprising fact is the magnitude of the coefficient of *ln(neg_buy+1)*, which is bigger than the one of *ln(neg_sell+1)*. It can be caused by belief of bidders, that a user, who does not behave honestly as a bidder, cannot be credible as a seller at all. A 1% rise in negative feedback from buying causes a 0.154% fall in the final price, again the number of negative points is very low, but a rise from 0 to 1 points leads to a 15.4% decrease in the final price. The impact of *ln(rating+2)* and *ln(negative)* in the Regressions 3 and 4 is not significant.

The coefficients of all length variables are statistically insignificant at the 5% level in all regression, which may be caused by the inaccurate estimation of the length. The coefficients of *end_at_20_21* and the interaction terms are statistically insignificant in all specifications.

These results indicate that either the insignificant parameters are not important for value creation on Aukro (their values do not influence the bidders' values of bids), or we do not have a sufficiently large dataset to discover some patterns in the final price creation. Furthermore, a bias can be caused by omitting the zero bids auctions.

Since the effects of some variables in eBay's regressions were different for new and used items, we have decided to redo the regressions with these two subsamples. We found out that the final price of used items is more influenced by the changes in the market value than the final price of new items, and this difference is greater than on eBay. A decrease by 1% in the market value causes a 0.50-0.65% decrease in the final price of new items and a 1.7% decrease in the final price of used items. The effect of reputation seems to be more significant for buyers of used items, sellers reputation increases seller's credibility that she describes the condition of an item honestly. The previously insignificant variables stay insignificant.

5.2.3 eBay+Aukro

To be able more precisely compare the effect of the rating on the final price on Aukro and eBay, we have to unify used variables and normalize the feedback rating.

As the starting bid of many auctions ending with zero bids is not available, we have to use OLS regression only on the auctions with more than one bidder. OLS regression is done with 6493 eBay auctions and 907 Aukro auctions.

Following the eBay example, feedback ratings from different categories on Aukro are summed up to formulate the overall rating, and the percentage of negative rating is computed. For Aukro, we are able to compute only the percentage of the negative rating in the overall rating, while eBay reports percentage of the negative rating in feedback from last 12 months. Unfortunately, we are not able to unify this.

The trade volumes on eBay are much higher than on Aukro, hence sellers on Aukro have no opportunity to reach such a big rating as on eBay, but distributions of rating are very similar. Therefore, we have decided to standardized the data and we have used the way described in Chapter 4.

The variables obtained for both Aukro and eBay datasets are *ln(final_p)*, *ln(market_v)*, *ln(rating+2)*, *%_negative*, *shipping*, *condition*, and *length*. Reasoning and expected signs are the same as explained above.

Table 5.7: eBay + Aukro: Determinants of Final Price

ln(final_p)	1		2	
constant	-0.53205	***	-5.48351	***
	(0.0534)		(1.04311)	
ln(market_v)	1.05953	***	1.527355	***
	(0.00854)		(0.108)	
shipping	-0.00163		0.000181	
	(0.00166)		(0.00025)	
condition	-0.22357	***	-0.50293	***
	(0.00778)		(0.05029)	
ln(rating+2)	0.00637	**	-0.02062	
	(0.002)		(0.01572)	
%negative	-0.00275	*	-0.00424	
	(0.00107)		(0.00304)	
length	-0.00601	***	0.008713	
	(0.00171)		(0.0074)	
R2	0.7362		0.3163	
N	6493		907	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

eBay regression

The results are very similar to those obtained in the previous regressions. Market value has a big and significant effect on the final price, the elasticity of the final price with respect to the market value is 1.06. *Shipping* is statistically insignificant at the 10% level. The coefficient of *condition* is significant and has a positive sign, meaning that used items are sold for a 22.4% lower price than new items. The coefficient of *ln(rating+2)* is significant at the 1% level and its magnitude is smaller than in the previous regressions. The coefficient of *%_negative* is significant at the 5% level. A 1% rise in the negative feedback causes a 0.28% fall in the final price. The coefficient of *length* is significant and negative, the reasoning is provided above.

Aukro regression

The only statistically significant variables on the 5% significance level are *ln(market_v)* and *condition*, similarly to the previous specifications with *ln(rating+2)* and *ln(negative)*. The elasticity of the finsl price with respect to the market value is higher than on eBay, meaning that a 1% decrease in the market price causes a 1.5% decrease in the final price. It may be so that Czech people to prefer new items bought in regular shops. If the market value decrease, the item is available for more people and some of them rather pay a little bit higher value to obtain a new item than bid in an auction. Because fewer people remain in the auction, the final price is then lower. Another interesting point is the influence of condition on the final price. On eBay, used items gain a 22% lower value than new items, while on Aukro the auctions with used items ends with a 50% lower final price. It is difficult to explain this effect, but one of the possible explanations can be found in bidders preferences (Czech people may prefer the new items).

5.3 Probability of successful auction

We find it interesting to examine what affects the probability of a successful auction. We define the successful auction as an auction that ended by a sale of the auctioned item (meaning that at least one bidder placed a bid in the auction). We think that bidders are frequently discouraged by a high starting price. To verify this we run a probit regression with these independent variables: *starting_price*, *condition*, *shipping*, *rating*, *%_negative* and *length*. Since we do not have observations of the starting price for the Aukro sample, we estimate the regression without the starting price variable..

The eBay's results shows that *starting_price*, *condition*, and *length* have a significantly negative impact on the probability of a sale, and *end_sun*, *shipping*, and *rating* have a significantly positive effect on the final price.

To shed light on the size of the effect, have an auction with a new item, held by a seller with 0 feedback rating, beginning with a starting price equal to 0, lasting for 1-day, not ending on Sunday, at 7 p.m., or 8 p.m., and with free shipping, its Z-score is 2.42. The probability of successful auction associated with this Z-score is 99.22%. Looking at two auctions with the same parameters, except for the starting price. The first auction has the starting price equal to EUR 1 (that is the median value of the starting price), and second auction has the starting price set to EUR 240 (that is the 90th percentile value of the starting price), both are auctions of new item, end on Monday at 3 p.m., have free shipping costs, the sellers have not yielded any feedback points yet, and the length of both auction is 1 day. The difference in the probabilities of a successful end of these two auctions is 21%. This proves our hypothesis about a great impact of the starting price on the probability of a successful auction.

On Aukro, the variables *condition*, *end_20_21*, and *pos_sell* have a significant positive effect on the final price and the variables *shipping* and *neg_sell*

Table 5.8: eBay+Aukro: Probability of Sale

Probit	1		2	
constant	2.448876	***	0.166187	*
	(0.11041)		(0.0693)	
starting price	-0.00682	***		
	(0.0002)			
shipping	0.027324	*	-0.0009	*
	(0.01066)		(0.00045)	
condition	-0.43186	***	0.331465	***
	(0.06635)		(0.06464)	
rating	7.53E-06	*		
	(3E-06)			
%negative	-0.00249			
	(0.0093)			
pos_sell			0.000275	**
			(1E-04)	
pos_buy			-0.00013	
			(0.00038)	
neg_sell			-0.05754	***
			(0.01011)	
neg_buy			-0.03093	
			(0.03885)	
length	-0.02875	*		
	(0.01227)			
end_sun	0.19365	**		
	(0.06402)			
end_19_20	0.072515			
	(0.06629)			
end_20_21			0.526334	***
			(0.07346)	
Pseudo R2	0.4406		0.1135	
N	7047		2223	

+ significant at 10% level
* sifnificant at 5% level
** sifnificant at 1% level
*** sifnificant at 0.1% level

have a negative effect on the final price. The sign of the condition variable is surprising because it means that used items have a higher probability of sale, but have to be aware of possible strong correlation between the condition and the unobserved starting price (used items may have a lower starting price than new items), which can cause the positive sign.

Auction of a new item, ending at 3 p.m., held by a seller without any feedback points, and with CZK 0 shipping costs has a 56.7% probability to end succesfully. If the same auction ended at 8 p.m., the probability of sale would rise to 75.4%. Other variables has not such a great effect.

5.4 Conclusions

5.4.1 eBay

The elasticity of the final price with respect to the market value is close to 1 as expected. The shipping costs have generally not significant impact on the final price, which confirms the theory by Hossain and Morgan (2005). The coefficient of the condition is always significant and negative, and it shows that used items are sold for a 22% lower price than new items. The results for coefficients of variables *ln(market_v)* and *condition* are robust for given sample (or subsample).

The starting price is problematic since it takes negative values in the censored-normal regressions (as expected), but positive values in the OLS regressions. We think that this may be caused by the bias of OLS regression. The censored-normal regression detected a different impact of the starting price on the final price of new and used items, it has a significant effect only in the case of new items.

The effect of rating is different for used and new items. The rating variables have no significant effect in auctions of new items, while in auctions of used items both rating variables have a significant impact on the final price. To see the magnitude of the effect, notice that improving the rating from the 20th percentile value to the median value increases price by 8-12%, and a 1% growth in the proportion of negative points among all feedback points leads to a 0.6% decrease in final price.

The impact of the length of an auction also depends on the condition of the sold item. The length of an auction has no significant effect on the final price of used items auctions, and it decreases the final price of new items auctions. That may be caused by impatience of buyers of new items.

The coefficients of other variables are not statistically significant at the 5% level.

5.4.2 Aukro

We have to be aware of the large sample selection problem described in the beginning of this chapter, while interpreting the results.

The elasticity of the final value with respect to the market value is 1.5. Further, it is lower for new items than for used items, but the magnitude of the coefficient of market value for new items can be biased due to the sample selection problem. The used items are sold for a 40-47% lower value than new items.

The rating variables seem to be more important for buyers of used goods since they are more significant in regression with auctions of used items. It is interesting that all points gained by buying have a negative effect on the final price. The possible reason is described above. The greatest impact on the final value have the negative points gained by buying. To see the magnitude of the impact of the rating variables, notice that an increase from the 20th percentile to median value in positive selling points causes a 12.7% increase in the final price, this change in positive buying points leads to a 11.2% decrease in the final price, an increase from 0 to 1 negative points from selling is accompanied by a 5.5% decrease in the final price, and the same shift in the negative buying points causes a 15.4% decrease in the final price.

Other variables are not significant.

5.4.3 eBay + Aukro

We empirically verify the theory of the price premium for higher reputation on the eBay data, where the effects of overall rating and the percentage of negative feedback points are significant. The results from the Aukro data sample are not so clear. In the regressions with the seller's rating divided into points gained by selling and buying, we find a significant effect of the rating variables on the final price. However, in the last model, the coefficients of both rating variables are insignificant. The results from the Aukro regressions may be biased due to the sample selection problem, but the process of omitting these data is inevitable as we do not observe the starting price for most of zero-bids auctions.

The differences in the estimated coefficient for both auctions can be caused by many factors, e.g. different thickness of the markets, diverse maturity of the markets, or by biased Aukro results.

We do not have enough information about bidders to construct the bidders' behavior model, so we are not able to investigate how the parameters affect bidders' behavior. Hence, the reasoning of some estimated coefficient we provide includes only some of the possible explanations.

5.4.4 Probability of successful auction

On eBay, the starting price has a great impact on the probability of sale. Let us have two auctions of new items ending on Monady at 3 p.m. with 1 day duration, free shipping and held by a seller without any feedback points. The first auction has the starting price equal to EUR 1 (the median value), and the second auction has the starting price set to EUR 240 (the 90th perentile value). Then the first auction has 21% higher probability to end successfully. Further, the*condition* and *length* have a negative impact on the probability of a sale, and textitend_sun, *shipping*, and *rating* have a positive effect on the final price.

The observations of the starting price are not available for Aukro, hence we estimated the model without that variable. The variables *condition*, *end_20_21*, and *pos_sell* have a significant positive effect on the final price and the variables *shipping* and *neg_sell* have a negative effect on the final price.

Chapter 6

Late Bidding

Both Aukro and eBay work on similar principles and use proxy bidding systems that were described in Chapter 1. These systems process the placed bid immediately. If a new submitted bid (which has to be higher than the current price) is higher than the highest bid,[21] the bidder becomes the highest bidder and the current price is changed to a value equal to the second highest bid plus a bid increment. If the submitted bid is lower than the highest bid, the bidder does not become the highest bidder, but the current price is changed to the value of the new submitted bid plus a bid increment. The proxy bids are private information till the bidder is outbid, then the accurate value of the bid is recorded in the bid history. Snipers wait until the last seconds of the auction, and if the current price is then attractive for them (i.e. it is lower than their value), they place a bid exactly equal to their value. Suppose that the other bidders have no time to react to this bid. If the sniper's bid is the highest, the sniper wins the auction and pays the value of the second highest bid plus a bid increment. Otherwise, the sniper does not win the auction, but the price paid by the winner increases to the value of sniper's bid plus a bid increment.

The impact of sniping on the final price and the determinants of sniping are interesting topics to be investigated and we examine them in the following chapter. A summation of the results is provided in Section 6.4.

[21] The highest bid is equal to the bid with the highest value among all the submited bids. The current price is the sum of the second highest bid and the bid increment.

6.1 Model

Sniping means placing a bid during the last seconds of auction's duration. Although there are a lot of different reasons for sniping (the overview can be found in Chapter 2), the principle of sniping remains the same, and all these reasons have a common purpose - to prevent the other bidders to react to the sniper's bid. Ockenfels and Roth (2006) claim that sniping is caused by the incremental bidding system used by eBay (and also by Aukro), which causes eBay to diverge from the standard second-price model, not only by a specific intention of bidders, and that sniping in eBay auction can be a rational behaviour. They introduce a model with N bidders, a minimal initial bid m, and a constant increment s, by which the next bid has to be raised. The current price in an auction with more than one bidder is created as the sum of the second highest submitted bid and the increment, unless this sum exceed the highest submitted bid. In that case the current price is equal to the highest bid.

Bidders are not allowed to lower their bids and a submitted bid has to exceed the current price. Bids can be placed at any time $tin[0, 1) \cup \{1\}$. Slightly different conditions described below apply in the time $t = 1$. If a bidder places a bid at $t' < 1$, the other bidders have a time to react to the bid. The reaction must be strictly after t'. The earliest possible time of the reacting bid placement is t'', such that $t' < t'' < 1$. If there are two highest bids, the bidder who submitted the earlier one is the highest bidder. If two highest bids are placed simultaneously, they are randomly ordered. At $t = 1$, the bid history is known to everyone and there is time for making exactly one more bid, no one knows anything about the other bids placed at the time $t = 1$.

Bids placed at $t < 1$ are certainly successfully transmitted; however, bids placed at $t = 1$ are successfully transmitted with a probability $p < 1$. The probability p is assumed to be exogenous. They also assume that bidder j's true value is v_j, and at $t = 0$ each bidder knows her own v_j. A bidder winning the auction at a price h earns a profit equal to $v_j - h$, and a not-winning bidder earns 0. At every $tin(0, 1) \cup \{1\}$, each bidder knows the bid histories for $t'' < t$.

Ockenfels and Roth (2006) prove that in the second price eBay-model auction with private values, a bidder does not have any dominant strategies. The proof is based on an example with two bidders, i and j; the true value of bidder j, v_j, is higher than $m + s$. Bidder i is an incremental bidder, whose strategy is to place a bid equal to the minimum bid m at $t = 0$, and does not bid any more until she is outbid. If she is outbid, she places a bid equal to B with $B > v_j + s$. The best response of bidder j against such strategy is to bid her true value at the time $t = 1$. If player j bids at time $t' < 1$, bidder i observes this bid and reacts to it with a bid higher than bidder j's true value at time $t'', t' < t'' < 1$, meaning the bidder j would either not win and gain 0 pay off, or invrease her bid and her pay off would be negative, $(v_j - B - s < 0)$.

At the time $t = 1$ bidders observe only the bid history prior to t, and have time to place one more bid; hence, bidder i cannot discover that she was outbid before the end of the auction, so she is not able to react. This strategy leads to the pay off $p(v_j - m - s) > 0$, which is greater than the pay off resulting from any other strategy (bidding another bid at time $t = 1$ does not yield greater pay off of bidder j either). The same strategy played against the bidder k who does not bid at all, on the other hand, would lead to a smaller expected pay off than bidding at any $t < 1$: $p(v_j - m) < v_j - m$. Since the best response against the strategy of bidder i is not among the best responses against the strategy of bidder k, bidder j does not have the dominant strategy.

Further, Ockenfels and Roth (2006) show that bidding at $t = 1$ can be the best response to incremental bidding. Reasons for incremental bidding are e.g. psychological reasons of a bidder, who tends to increase her maximum bid during the auction, because her maximum willingness to pay rises in time or she misunderstands the bidding system. Some bidders may mix it with the English first-price auction.[22] On eBay, more than 40% of bidders placed more than 1 bid, so we can call them incremental bidders. The model by Ockenfels and Roth (2006) shows that, unlike in the standard second-price auction model, in the second-price eBay model, sniping is a rational behaviour.

6.2 Effect of Sniping on Final Price

According to some of the sniping theories, sniping may lead to a lower final price. Roth and Ockenfels (2002) introduce a concept of naive bidders who do not use the proxy bidding system but always place the minimum acceptable bid. Suppose that we have an auction with two bidders, i and j, bidder i is a naive bidder and bids first in the auction a bid equal to the starting price. If bidder j places her bid during the auction, she gives an incentive to the naive bidder to raise her bid, and the current price increases. If bidder j places

[22] Data of Ockenfels and Roth indicate that incremental bidders are relatively inexperienced; our data show that multiple bids are more often placed by less experienced bidders.

her bid at the end of auction duration (she snipes), the naive bidder does not increase her bid during the auction, and she has no time to react after the sniping bid of bidder j, so the final price is equal to the value of the minimum bid plus a bid increment. Barbaro and Bracht (2004) argue that sniping allows to avoid squeezing, and thus artificial increase of the final price by a seller. Ely and Hossain (2009) have found out in their field experiment that sniping decrease the final price.

We distinguish two different types of sniping in our dataset - “simple” sniping and “sophisticated” sniping. We call a bidder who places a single bid in an auction during the last seconds a “simple” sniper, and a bidder who places multiple bids in an auction, with the last submitted bid during last seconds of the auction duration, a “sophisticated” sniper.

The theories mentioned above are concerned with the “simple” sniper; hence, we suppose that the effect of “simple” snipping on the final price will be negative.

The effect of “sophisticated” sniping on the final price is not so clear. There are more reasons to snipe at the end of an auction after already submitting a bid before. One possible reason is to show the other potential bidders that there is a competition present. A bid of lower than the true value is placed at first, and the true value is sniped. Since the first submitted value is lower, and the bidder does not change it until the last seconds, it does not increase the aggressiveness of opponents very much, but, on the other hand, it can discourage some potential bidders from bidding, because they notice the competition. Hence, according to Elly and Hossain “sophisticated” sniping may lead to a lower price. Another possible reason for sniping is a bidding war at the end of an auction. It causes an auction fever and thus, according to Ku et al. (2005), a higher final price. The desribed reasons for “sophisticated” snipping lead to a different impact on the final price. Since our group of “sophisticated” bidders consists of snipers sniping for both reasons, and we are not able to distinguish between them, we will not discuss the estimated effect of the variable. But we add it to the regression to obtain a comparison of “simple” snipers and non-snipers. Aukro reports only the last bids of each bidder, so we are not able to distinguish between “simple” and “sophisticated” snipers, and we have to use the group of all snipers for our estimation.

We try to investigate the effect of sniping in two different ways; firstly, we utilize variable measuring time to end of an auction, and then we define three categories of sniping, according to when the bid was placed (during the last 10 seconds, last 1 minute, and last 10 minutes) and create dummies taking value of 1 if the winning bid was placed during the given time, and 0 otherwise. We create a model based on the reputation model with *length* variable. The variables are the same; nevertheless, we restrict the independent variables to the statistically significant ones (*ln(market_v), condition, starting_price, ln(rating+2), %_negative* and *length* for eBay, and *ln(market_v), condition, ln(pos_sell+1), ln(neg_sell+1), ln(pos_buy+1), ln(neg_buy+1)* for Aukro) and further add either the sniping dummy variables or *ln(sec_end)*. We use the logarithmic form of *sec_end* because we suppose that the effect on the final price is greater for bids submitted closer to the auction end.

At the same time, we have to be aware of the possible bias caused by endogeneity of the sniping decision. A low final price may be caused by snipers picking up auctions with expected low price manifested either by low starting price (not available in full sample) or some characteristics of the item that are for our analysis unobservable and not by bidders waiting until the end of an auction to bid in order to avoid bidding war and auction fever and not to give incentives to incremental bidders. Again, it would be useful to build a bidders' behaviour model to find out more about bidders decision making, but we do not have enough details about bidders to construct it.

6.2.1 Results

We have deleted the auctions without any bids, and then use OLS regression on the rest of the data. There are missing bidding details about 12 eBay auctions, so the regression is made of 6481 observations for eBay and 907 observations for Aukro. All our regressions suffer from heteroskedasticity, so we run the regressions with robust standard errors.

We have aslo tried to run a regression with the variable *sec_end* in the linear and quadratic form to detect a possible effect of *sec_end* on the final price that is positive in the beginning but changes into a negative one after some time. Nevertheless, these variables have been insignificant. Additionally, we have estimated specifications with general snipping for eBay, but the snipping dummy variables have been insignificant in all regressions as well.

eBay

The coefficients of variables taken from the reputation model are very stable and almost equal to those estimated by OLS in Chapter 5.

Table 6.1: eBay: Impact of Sniping on Final Price

ln(final_p)	1		2		3		4	
constant	-0.53156	***	-0.54163	***	-0.55603	***	-0.51029	***
	(0.05375)		(0.05363)		(0.05352)		(0.05515)	
ln(market_v)	1.05447	***	1.054772	***	1.054919	***	1.053263	***
	(0.00866)		(0.00864)		(0.00863)		(0.00865)	
condition	-0.22117	***	-0.22285	***	-0.22301	***	-0.22255	***
	(0.00775)		(0.00774)		(0.00771)		(0.00778)	
start_p	0.000274	***	0.000275	***	0.000278	***	0.00027	***
	(2.7E-05)		(2.7E-05)		(2.7E-05)		(2.7E-05)	
ln(rating+2)	0.007599	***	0.007412	***	0.007377	***	0.007251	***
	(0.00189)		(0.00189)		(0.00189)		(0.0019)	
%negative	0.002877	**	0.002899	**	0.002858	**	0.002764	**
	(0.00106)		(0.00105)		(0.00105)		(0.00105)	
length	-0.00574	**	-0.00584	**	-0.00581	**	-0.00575	**
	(0.00171)		(0.00171)		(0.00171)		(0.00171)	
ln(sec_end)							-0.00361	*
							(0.0016)	
sim_snipe10s	-0.02437	**						
	(0.0084)							
sim_snipe1min			-0.00504					
			(0.00907)					
snim_snipe10min					0.011553			
					(0.01078)			
soph_snipe10s	0.028307	**						
	(0.01077)							
soph_snipe1min			0.047985	***				
			(0.0103)					
soph_snipe10min					0.060403	***		
					(0.0115)			
R2	0.7372		0.7376		0.738		0.737	
N	6481		6481		6481		6481	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

Although it seems that "sophisticated" sniping leads to a higher final price and the effect is significant in all regressions (suggesting that the reason for "sophisticated" sniping is a bidding war); as we discuss above, we are not able to distinguish between two motivations of bidders included in "sophisticated" snipers group, thus we will not provide a broader discussion of this coefficients.

Only the coefficient of *sim_snipe10s* is significant at the 5% level. Its negative sign indicates that bidding once during the final seconds of an auction leads to a lower final price. The winning bid placed during last 10 seconds decreases the final price by 2.4% compared to a earlier submitted winning bid. The other coefficients of "simple" sniping dummies are not significant at the 5% level.

The coefficient of *ln(sec_end)* is significant at the 5% level but not at the 1% level. Its sign is negative, meaning that auctions won by an early bid end with a lower price than auctions won by a sniping bid. Auction won by a bid placed 567 seconds before end (the 70th percentile value) ends with a 8.87% lower price than an auction won by a bid submitted 23 seconds before the end (the median value). This does not support the theory of sniping leading to a lower final price.

Aukro

The coefficients of the variables from the reputation model (except for the one of *ln(neg_sell)* in Regressions 1 and 4) are statistically significant at the 5% level and their values are very close to those from the reputation model.

All coefficients of sniping dummy variables are negative and insignificant at the 5% level. The negative signs mean that, in general, sniping is a profitable strategy on Aukro, but the reduction in the final price is not significant. However, the sign of *ln(sec_end)* is positive, which does not support the theory of the final price reduction as a results of sniping. The variable is insignificant though.

6.3 What Affects the Likelihood of Sniping?

In this part we focus on the individual level of auctions. In other words, we examine the bidders' strategies.

To investigate this topic, we utilize a model inspired by Ockenfels and Roth (2006) and Haller (2007). Our regression analysis will show the relation between

Table 6.2: Aukro: Impact of Sniping on Final Price

ln(final_p)	1		2		3		4	
constant	-5.16144	***	-5.25454	***	-5.18705	***	-5.2815	***
	(1.16115)		(1.11842)		(1.10856)		(1.07778)	
ln(market_v)	1.498685	***	1.508728	***	1.502883	***	1.502741	***
	(0.11823)		(0.11347)		(0.11241)		(0.11404)	
condition	-0.47924	***	-0.48421	***	-0.47702	***	-0.47517	***
	(0.04357)		(0.04488)		(0.04618)		(0.04495)	
ln(pos_sell+1)	0.038717	**	0.038142	**	0.036811	**	0.036901	**
	(0.01121)		(0.01108)		(0.01103)		(0.01096)	
ln(neg_sell+1)	-0.04665	+	-0.05426	*	-0.05087	*	-0.04733	+
	(0.0243)		(0.02436)		(0.0248)		(0.02447)	
ln(pos_buy+1)	-0.05465	*	-0.05404	**	-0.05337	**	-0.0536	**
	(0.01857)		(0.01822)		(0.01809)		(0.01807)	
ln(neg_buy+1)	-0.14698	*	-0.14477	*	-0.1454	*	-0.1487	*
	(0.06305)		(0.06229)		(0.061)		(0.06285)	
ln(sec_end)							0.00852	
							(0.0063)	
snipe10s	-0.09279							
	(0.08384)							
snipe1min			-0.041					
			(0.05443)					
snipe10min					-0.07658			
					(0.04682)			
R2	0.3372		0.3355		0.3375		0.3374	
N	907		907		907		907	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

the number of bidders in an auction, the number of substitutes of the auctioned item, feedback of the bidders, and the likelihood of sniping.

6.3.1 Variables

SNIPING

The binary variable *sniping* measures the likelihood of sniping, taking value of 1 if the bidder's last bid is placed during last 10 minutes/1 minute/10 seconds, and 0 otherwise. It is then explained by the independent variables.

LN(RATING)

Rating is the total number of feedback points a bidder has received. The more feedback points a bidder has received, the more auctions she has won, and the more experienced she ought to be. The overall rating on eBay is given by the number of positive feedback points minus the number of negative feedback points. According to Resnick and Zeckhauser (2002), the proportion of negative feedback is very small; therefore, the negative points bias of experience, measured by the feedback rating, is negligible. Aukro uses a bit different system described in Chapter 3, but the principle is the same, and the volume of negative feedback is also very small, compared to the number of positive feedback (we can observe this in our dataset of seller's rating). Therefore, we can say that the feedback rating measures the experience of a bidder. We use it in the natural logarithm, since we suppose that the marginal experience is decreasing (learning curve has a decreasing slope). In the case that sniping is a profitable strategy; the more experienced bidders would be more aware of this fact and snipe more often than less experienced bidders.[23] We suppose that rating will have a positive impact on the probability of sniping.

OPPONENTS

The number of bidders in an auction determines the level of competition. According to Ely and Hossain (2009), a higher competition may lead to a more aggressive bidding. According to Rasmusen (2006), bidders in the private value setting may be uncertain about their true values, and, as pointed out by Haller (2007), in more aggressive state, the predicting of the value may cost more

[23] In the previous section, we showed that sniping can be a profitable strategy in some cases.

effort, which leads to more common sniping. The coefficient of this variable will detect the escalation effect and we suppose it to be positive.

Yet, there are some problems connected with this variable. Haller (2007) and Ockenfels and Roth (2006) use the number of bidders in an auction as the indicator of competition for each bid. But in the reality, the first bidder in an auction faces no visible competition, the second bidder is aware only of the first bidder, and so on. As sniping occurs during the last seconds of an auction, we suppose that auctions with more bidders receive also more bids in the regular (not sniping) time, so the definition of opponents by Haller (2007) and Ockenfels and Roth (2006) may lead to a bias towards a negative coefficient. Haller (2007) suggests that a better measurement of the competition is the real number of bidders participating in the auction before the bidder's bid. Nevertheless, this approach leads to a bias as well, since the number of opponents increases in time, and the probability of sniping increases in time as well. Artificial positive relationship between the probability of sniping and the number of opponents would thus be created.

To illustrate this problem, we used both ways of defining the opponents variables and estimated the model with both of them. Regression 1-3 include the number of opponents defined according to the proposal by Haller (2007), Regressions 4-6 include the number of opponents equal to all the bidders in an auction. The regressions give the opposite results, which show the problem of this variable described above. To avoid the bias we tried to estimate a model without the variable.

For eBay, we were able to find out the accurate number of bidders participating in the auction at a specific time of the bid, as it reports the details of all bids. Aukro reports details only about the last bid of each bidder, so we were not able to find the accurate number. We made an approximation: we assumed that each bidder bids only once and the number of opponents was defined by the order of the last bids.

SUSBTITUTES

This variable measures the number of substitutes in an auction. Haller (2007) mentions two economic reasons for including this parameter in the regression analysis. The first one says that the rising number of substitutes increases the probability of sniping. Arguably, strategic bidders bid in the auction with an interesting value for them that ends earliest. In that way, if they do not win the auction they do not lose the opportunity to bid in all auctions ending later.

Non-strategic bidder bids in an auction on the top of the listing (search results are ordered by the time remaining, the soonest closing auctions first), the number of auction of substitutes reduce the time to end of auctions listed on the first page; therefore also a non-strategic bidders bids later in the auction. The likelihood of sniping is then higher because these bids may be close enough to the end of the auction to be considered sniping.

The second reason claims the opposite. It is based on the theory of Ely and Hossain (2009). The number of substitutes decreases the competition in an auction, as there are more items to competed for. Due to a lower competition, bidders would bid less aggressively, and there would be a lower probability of sniping. The coefficient should shed light on the weights of these two hypotheses.

6.3.2 Results

Some bidders keep their reputation as a private information and we are not able to observe it then. We have had to delete these observations from the sample. Another 13 bidders have reputation lower than 0. We have deleted also these observations, in order to avoid artificial raising of the reputation in the logarithm form. We use the probit regression for estimation of the probability of sniping. We investigate only the probability of "simple" sniping, for the group of "sophisticated" bidders may be inconsistent as argued in the previous section.

We discuss only the regressions without opponents variables in regressions regarding both eBay and Aukro, as the other ones may be biased as discussed above.

eBay

The coefficient of *ln(rating)* is positive and significant in all regressions, meaning that the experience of bidders increases the probability of sniping. That corresponds with our theory. The coefficient of *substitute* is significant only for the 10-minute sniping group. It is positive, so the number of substitutes increase the probability of sniping during the last 10 minutes. It supports the first theory about the effect of substitutes mentioned above.

Table 6.3: eBay: Probit Model - Probability of Sniping 1

Probit	1		2		3		4		5	
sim_snipe	10sec		1min		10min		10sec		1min	
constant	-2.88779	***	-2.6378	***	-2.4488	***	-1.75083	***	-1.45618	***
	(0.02618)		(0.02193)		(0.01989)		(0.02545)		(0.02161)	
ln(rating)	0.108762	***	0.088953	***	0.076423	***	0.093324	***	0.074205	***
	(0.00398)		(0.0035)		(0.00321)		(0.00372)		(0.00313)	
# oppon.1	0.109176	***	0.122376	***	0.126474	***				
	(0.00141)		(0.00126)		(0.00118)					
# oppon.2							-0.01773	***	-0.01412	***
							(0.0014)		(0.00121)	
#substit.	-0.00212	***	-0.00169	***	-0.00145	***	0.000154		0.000503	*
	(0.00029)		(0.00024)		(0.00022)		(0.00025)		(0.00021)	
Pseudo R2	0.1489		0.1649		0.1662		0.0167		0.0104	
N	105989		105989		105989		105989		105989	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

Table 6.4: eBay: Probit Model - Probability of Sniping 2

	6		7		8		9	
sim_snipe	10min		10sec		1min		10min	
constant	-1.2673	***	-1.95508	***	-1.6211	***	-1.42589	***
	(0.01995)		(0.01984)		(0.01647)		(0.01504)	
ln(rating)	0.062998	***	0.09315	***	0.074196	***	0.063039	***
	(0.00288)		(0.00371)		(0.00312)		(0.00287)	
# oppon.1								
# oppon.2	-0.01353	***						
	(0.00113)							
#substit.	0.000704	***	-0.00025		0.000196		0.000411	*
	(0.0002)		(0.00025)		(0.00021)		(0.0002)	
Pseudo R2	0.0079		0.0135		0.0084			
N	105989		105989		105989			

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

Table 6.5: Aukro: Probit Model - Probability of Sniping 1

Probit	1		2		3		4		5	
snipe	10sec		1min		10min		10sec		1min	
constant	-1.47776	***	-1.43631	***	-1.29472	***	-0.50287	***	-0.43847	***
	(0.05484)		(0.04807)		(0.04473)		(0.06707)		(0.05724)	
ln(rating)	-0.00776		0.016817		0.006346		-0.01233		0.010001	
	(0.01385)		(0.01179)		(0.01103)		(0.01535)		(0.01238)	
# oppon.1	-0.01708	***	0.022263	***	0.036186	***				
	(0.00469)		(0.00377)		(0.00349)					
# oppon.2							-0.11084	***	-0.08076	***
							(0.00482)		(0.00371)	
#substit.	0.001455		-0.00532		-0.01109	**	-0.00094		-0.01005	*
	(0.00489)		(0.00422)		(0.00394)		(0.00545)		(0.00446)	
Pseudo R2	0.0036		0.0069		0.0173		0.1686		0.0944	
N	8767		8767		8767		8767		8767	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

Table 6.6: Aukro: Probit Model - Probability of Sniping 2

	6		7		8		9	
snipe	10min		10sec		1min		10min	
constant	-0.25863	***	-1.56959	***	-1.30229	***	-1.07169	***
	(0.05343)		(0.049)		(0.0419)		(0.03852)	
ln(rating)	-0.00546		-0.00707		0.015423		0.003289	
	(0.01139)		(0.01384)		(0.01174)		(0.01093)	
# oppon.1								
# oppon.2	-0.07275	***						
	(0.00334)							
#substit.	-0.01615	***	0.002071		-0.00622		-0.01236	**
	(0.00409)		(0.00487)		(0.0042)		(0.00391)	
Pseudo R2	0.0769		0.0001		0.0008		0.0016	
N	8767		8767		8767		8767	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

Aukro

We do not find any significant impact of bidders' rating (their experience) on the probability of sniping. The coefficient of *substitutes* is significant at the 5% level only in the specification of 10-minute sniping, and it has a negative sign, meaning that number of substitutes lowers the probability of sniping. Therefore, these results support the other theory of effect of substitutes on sniping.

The differences between our results may be caused by a different behaviour of bidders in the observed auctions, or by an inaccuracy of the estimate.

6.4 Conclusions

The data from eBay are more detailed and allow an analysis of the effect of sniping on the final price deeper. The coefficients of "sophisticated" sniping variables are positive and significant, indicating that this type of sniping is caused by a bidding war. "Simple" sniping during last 10 seconds of an auction has a negative impact on the final price, it lower the final price by 2.4% compared to earlier submitted bids. At the same time, the negative coefficient of *ln(sec_end)* indicates that auctions won by early placed bids end with a lower final price than auctions won by a sniping bid. These two results are then rather inconsistent. The effect of the other "simple" sniping dummies is not significant at the 10% level.

The Aukro's data allow only an analysis of the general effect of sniping. In this regard, neither the general effect nor the *ln(sec_end)* are significant.

We have detected a positive relationship between the probability of sniping and bidders' experience (given by the rating score) in eBay auctions. The results for Aukro were again not significant.

Chapter 7

Bidder's Experience

According to the theories by Kagel (1995) and Rutström (1998), bidders learn and improve their perfomance by participating in auctions. Learning should direct bidders to more profitable strategies. In this section, we examine the impact of the bidders' rating on the final price. The results are summed up in Section 7.4.

7.1 Model

Sun (2005) in his paper investigates a question about lower entry costs for experienced bidders. To answer it, he builds a model of entry costs, in which he defines two types of bidders - inexperienced, n_L, and experienced, n_H. He assumes that the number of experienced and inexperienced bidders are the same and that each experienced bidder has the rating higher than or equal to all inexperienced bidders. Each bidder wants to win only one item from a supply of x identical items. Then, he defines switching costs f_L for inexperienced bidders and f_H for experienced bidder, where $f_L > f_H$. The costs occur only in the case of switching the auctions a bidder bids in. He distinguishes between two types of the starting price - high and low. He assumes that the setting of bidding is incremental with an increment c and that there are many auctions of both types and potential bidders with identical values. Bidders bid incrementally in the auction with the lowest price. Each bidder demands only one item, so no one would be the highest bidder in more than one auction. Therefore, if the sum of the current price and the increment is lower than the bidders' true value in more than one auction, bidders bid in the cheapest one. Under these assumptions, Sun claims that an auction with a high starting price would end at a price f_H below a price of an auction with a low starting price.

He shows this on an example with two auctions having starting values 0 (auction A) and 50 (auction B), one experienced bidder with switching costs 5 and one inexperienced bidder with switching cost 10, and increment equal to 1. Both bidders start bidding in the auction A and continue bidding there until the price reaches 50. Then are the current prices equal to 50 in both auctions, but both bidders continue to bidding in the auction A, because to bid in the auction B they would have to pay a switching cost, and the overall cost would be greater. When the price hits 55, the experienced player is indifferent between bidding in A and B, whereas the inexperienced bidder would continue bidding in A. In equilibrium, inexperienced bidder wins auction the auction A for 55, and the experienced bidder wins auction B for 50. The difference is $f_H = 5$, and the auction with the lower starting price ends with a higher final price. In the case of more bidders and auctions, the result generalizes upward, and the experienced bidders should generally win auctions at a lower price than the inexperienced bidders.

7.2 Effect of Winner's Experience on Final Price

The rating of bidders can be used as a measurement of bidders' experience, for the higher rating a bidder has, the more auctions she has won.

To find out the effect of experience of bidders on the final price, we add bidders' rating variable into the model of reputation and again omit the insignificant variables. We use the logarithm form of bidders' feedback because we assume a decreasing slope of the learning curve. According to the theory described above, the coefficient should be negative.

Sun (2005) has added a dummy variable of experienced/inexperienced winner into his regression of the final price and found out that the level of winner's experience significantly influences the final price. Auctions won by more experienced bidders end with a lower final price than those won by less experienced bidders.

7.2.1 Results

We have deleted the auctions with no bids and the auction with missing information about the reputation of winner, then there are data about 6326 auctions on eBay and 902 auctions on Aukro left. We use OLS regression, and all our regressions have heterogeneity, so we run the regressions with robust standard errors.

eBay

Table 7.1: eBay: Effect of Winner's Experience on Final Price

ln(final_p)		
constant	-0.50953	***
	(0.05599)	
ln(market_v)	1.053798	***
	(0.00873)	
condition	-0.21765	***
	(0.00779)	
start_p	0.000259	***
	(2.7E-05)	
ln(rating+2)	0.00795	***
	(0.0019)	
%negative	0.002911	**
	(0.0011)	
length	-0.00618	***
	(0.0017)	
ln(rating_bidder)	-0.00526	*
	(0.00267)	
R2	0.7387	
N	6326	
+ significant at 10% level		
* significant at 5% level		
** significant at 1% level		
*** significant at 0.1% level		

The coefficient of variables taken from the reputation model are significant at the 0.1% level (except for *%_negative*), and the coefficient of *%_negative* is significant at the 1% level. Their magnitudes are very close to those estimated in the reputation model, only the effects of *%_negative* and *length* are slightly higher.

The coefficient of *ln(rating_bidder)* is significant at the 5% level and has a negative sign, which confirms the theory of Sun (2005) regarding a lower final price in auctions won by more experienced bidders (bidders with a higher reputation). Since the negative points are not so often given, we can interpret the variable as what would be the price reduction for the number of won auctions. The median rating of winners is 80 and the 20th percentile value of the rating is 15. A winner rising his rating from 15 to 80 would reduce the final price by 2.3%.

Aukro

Table 7.2: Aukro: Effect of Winner's Experience on Final Price

ln(final_p)		
constant	-5.28797	***
	1.094107	
ln(market_v)	1.516823	***
	0.11251	
condition	-0.49677	***
	0.047573	
ln(pos_sell+1)	0.039445	***
	0.011134	
ln(neg_sell+1)	-0.07112	**
	0.026049	
ln(pos_buy+1)	-0.0524	**
	0.018817	
ln(neg_buy+1)	-0.16449	**
	0.061972	
ln(rating_bidder)	-0.01973	*
	0.010061	
R2	0.3391	
N	902	

+ significant at 10% level
* significant at 5% level
** significant at 1% level
*** significant at 0.1% level

All variables from the reputation model are significant at the 1% level and their sizes are again similar, but the impacts of variables *condition* and *ln(neg_sell)* are a little larger.

The coefficient of *ln(rating_bidder)* is again negative and significant at the 5% level, supporting the theory of Sun (2005). The effect is larger than for the eBay subset of data. Moreover, negative points are hardly ever given on Aukro; therefore, we can interpret the coefficient as: if a little experienced bidder winning only 2 auctions (the 20th percentile value) wins 12 more auctions (the median value), he would cause a 11.8% reduction in the final price.

7.3 Level of Experince of Bid Leader

To further investigate the question, Sun (2005) runs a chi-squares test to find the interaction between experience and bidding. He created a two-column table, first column being a dummy variable taking value of 1 if the bidder is the first bidder in an auction, and 0 otherwise. The second value is an experience dummy variable, taking value of 1 if the bidder's rating is higher than the median of all bidder's ratings, and 0 otherwise. The dataset has to be carefully created since each bidder may place multiple bids in each auction, so we use only the first bid of each bidder.

Table 7.3: eBay: Chi-square Tabulation

	Experienced		
BidLeader	0	1	
0	49838	49856	99694
1	3302	3006	6308
	53140	52862	106002
Pearson chi2(1) = 13.1639 Pr = 0.000			

The chi-square analysis of eBay data shows the opposite to Sun's results; inexperienced bidders are bid leaders more often than experienced bidders, and the difference is statistically significant.

Table 7.4: Aukro: Chi-square Tabulation

	Experienced		
BidLeader	0	1	
0	3406	3351	6757
1	480	630	1110
	3886	3981	7867
Pearson chi2(1) = 19.5736 Pr = 0.000			

However, the result of the chi-square analysis on the data from Aukro indicates that there is a statistically significant evidence of auctions having more often an experienced bidder as a bid leader, which supports the model by Sun (2005). While interpreting the results, we have to be aware of the fact that we have only the details about the last bids of the bidders, which may cause a bias.

7.4 Conclusions

To sum up, we find a price reduction in the final price of the auction won by more experienced bidders in the dataset from both auctions web sites. Both results are statistically significant at the 5% level. The dataset including data from Aukro shows also a statistically significant evidence of more experienced bidders being more often bid leaders. However, we have showed the opposite is true for eBay data. Further, it is crucial to mention that we are not able to obtain the exact order of placed bids for Aukro, since only the last bids are reported there, so we have to determine the bid follower only in the sense of last bids, and hence the results may be biased.

Chapter 8

Conclusion

Auctions are an important market institution used for thousands of years. Yet, they were used mainly for selling expensive items from specific areas up to the end of 20th century, and the bidders were usually professionals. The turn came in 1995 with the birth of internet auctions. Since then, auctions have become a common part of everyday life. The amount of items sold at the internet auctions and the involvement of a large number of bidders create a good source for empirical studies of auctions.

The goal of this paper is to examine price creation, sniping, and a role of bidders' experience in on-line auctions using a single dataset, and thus to provide an analysis of both auctions and bidders. We have obtained details from two auction portals eBay.de, and a smaller but still local leader, Aukro.cz. Therefore, we can study the differences in the effects of the auction parameters and the bidders' behaviour on these two web sites.

We describe in details the functioning of auctions on eBay and Aukro and the dataset used for the empirical analysis. Our dataset consists of 7054 auctions with 209449 bids from eBay and 2223 auctions with 8779 bids from Aukro. The data show some interesting effects: On eBay, the time distributions of auctions ends and the placements of bids are very similar to each other, suggesting that sellers anticipate the bidders' activity and adjust the ends of auctions, in order to attract more bidders and gain a higher final value. The results for Aukro are different though, since the time distribution of auction ends does not follow bids placement, meaning that sellers on Aukro either less anticipate bidders' activity, or are less successful in their anticipations. Moreover, the dataset shows evidence of late bidding.

The rest of the study covers the econometric analysis of three topics. First, we build a model of the price creation, based on Houser and Wooders (2006). According to the theory, the seller's reputation should have a positive impact on the final price because it indicates the seller's honesty. Buyers in on-line auctions cannot personally inspect the products; hence, they have to rely on the seller's trustworthiness. We thoroughly study the effects of the auction format, product characteristics, and sellers' reputation on the final price with new and used items separately and detect interesting several interesting dissimilarities. Our findings also differ across eBay and Aukro. The effect of the rating variables is significant only in auctions with used items. The reason is intuitive - there are hardly any doubts about the quality of new items, but the quality of used items can be described dishonestly. The overall rating on eBay and positive points gained by selling on Aukro affect the final price positively, exactly as expected. The length variables are significant only in eBay's regressions and the effect depends on the item's condition: the auction length decreases the final price of new items, but does not significantly influence the final price of used items. That may be caused by impatience of buyers of new items.

Second, the theories discussed by Roth and Ockenfels (2002), Ku et al. (2005), and Barbaro and Bracht (2004) suggest that snipping should lower the final price. However, the impact of sniping on the final price is not so clear in our results; we have obtained opposing results for two different eBay's specifications and non-significant results for Aukro. While interpreting the results of the effect of sniping on the final price, we have to be aware of a possible bias caused by endogeneity of the sniping decision. The sniping probability model is derived from models by Ockenfels and Roth (2006) and Haller (2007). If sniping is a profitable strategy and bidders can learn by participating in auctions as proposed by Kagel (1995) and Rutström (1998), experience should lead to more frequent sniping. We detect a positive relationship between the bidder's experience and probability of sniping, and support this hypothesis.

In the last part of our study, we verify the theory presented by Sun (2005) that more experienced bidders are more often bid leaders and win auctions with a lower final price. We confirm this theory only for the data from Aukro. The evidence from eBay shows the opposite: less experienced bidders are more often bid leaders.

The differences between the result for eBay and Aukro may be caused by different thickness, or diverse maturity of the markets.

As a next step, it would be useful to build a model of the bidders' behaviour and then investigate how the behaviour affects the final price. However, we do not have sufficient details of bidders for building such a model. This topic may be examined in future research.

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