GOVERNANCE AND THE EFFICIENCY
OF ECONOMIC SYSTEMS
GESY

Discussion Paper No. 294

Buy-It-Now prices in eBay Auctions - The Field in the Lab

Tim Grebe*
Radosveta Ivanova-Stenzel**
Sabine Kröger***

** Gesellschaft für Innovationsforschung und Beratung mbH, Zimmerstr. 56, 10117 Berlin,*
Email: t.grebe@gib-berlin.eu
*** Institut für Wirtschaftstheorie I, Humboldt Universität zu Berlin, Spandauer Str. 1, D-10099 Berlin, Germany*
Email: ivanova@wiwi.hu-berlin.de
**** Département d'économie, Université LavalPavillon J.A.DeSève, Québec City, Québec G1K 7P4, Canada*
Email: skroger@ecn.ulaval.ca

January 2010

Financial support from the Deutsche Forschungsgemeinschaft through SFB/TR 15 is gratefully acknowledged.

Sonderforschungsbereich/Transregio 15 · www.sfbtr15.de
Universität Mannheim · Freie Universität Berlin · Humboldt-Universität zu Berlin · Ludwig-Maximilians-Universität München
Rheinische Friedrich-Wilhelms-Universität Bonn · Zentrum für Europäische Wirtschaftsforschung Mannheim

Speaker: Prof. Dr. Urs Schweizer. · Department of Economics · University of Bonn · D-53113 Bonn,
Phone: +49(0228)739220 · Fax: +49(0228)739221

Buy-It-Now prices in eBay auctions – The Field in the Lab [1]

Tim Grebe[♯] Radosveta Ivanova-Stenzel[⋆]

Sabine Kröger[♮]

♯ *Gesellschaft für Innovationsforschung und Beratung mbH, Zimmerstr. 56, 10117 Berlin, t.grebe@gib-berlin.eu*

⋆ *Institut für Wirtschaftstheorie I, Humboldt Universität zu Berlin*
Spandauer Str. 1, D-10099 Berlin, Germany
Email: ivanova@wiwi.hu-berlin.de

♮ *Département d'économie, Université Laval*
Pavillon J.A.DeSève, Québec City, Québec G1K 7P4, Canada
Email: skroger@ecn.ulaval.ca

November 10, 2009

[1]The authors thank Charles Bellemare for his valuable suggestions and comments. We are grateful to the participants of the GEW conference in Magdeburg, the ESA European Meeting, the meeting of the European Economic Association and the Economics seminar at Carleton University for their comments. Financial support by the *Deutsche Forschungsgemeinschaft,* SFB Transregio 15, "Governance and Efficiency of Economic Systems" is gratefully acknowledged.

Abstract

Electronic commerce has grown extraordinarily over the years, with online auctions being extremely successful forms of trade. Those auctions come in a variety of different formats, such as the Buy-It-Now auction format on eBay, that allows sellers to post prices at which buyers can purchase a good prior to the auction. Even though, buyer behavior is well studied in Buy-It-Now auctions, as to this point little is known about how sellers set Buy-It-Now prices. We investigate into this question by analyzing seller behavior in Buy-It-Now auctions. More precisely, we combine the use of a real online auction market (the eBay platform and eBay traders) with the techniques of lab experiments. We find a striking link between the information about agents provided by the eBay market institution and their behavior. Information about buyers is correlated with their deviation from true value bidding. Sellers respond strategically to this information when deciding on their Buy-It-Now prices. Thus, our results highlight potential economic consequences of information publicly available in (online) market institutions.

JEL classifications: C72, C91, D44, D82.

Keywords: electronic markets, experience, online auctions, BIN price, buyout price, single item auction, private value, experiment

1 INTRODUCTION

Internet auction platforms have started increasingly to offer combined selling mechanisms. In such mechanisms, a call for bids in an auction is combined with a fixed price offer. For example, on eBay, one of the biggest online auction platforms, a seller may announce a "Buy-It-Now" (henceforth called "BIN") price and simultaneously call for bids. Buyers can accept the BIN price as long as no bids have been submitted to the auction and thus buy the item before the auction.[1] Otherwise, the price is determined by the auction. BIN options have become increasingly popular among sellers and buyers. Shortly after the introduction of the BIN option in November 2000, eBay reported that 30%, 35% and even 45% (eBay Q1, Q2 and Q4 2001) of all listings in eBay auctions included a BIN option. eBay.com reports that 28% of all transactions in 2004 have taken place at the BIN price (eBay Q1 and Q2 2004). Despite the popularity and the extensive use of the BIN option, the empirical and experimental literature has not so far shed light on how BIN prices are set. In this study we investigate into seller BIN price behavior.

Recently, a substantial amount of theoretical studies emerged to predict behavior of sellers and buyers in such combined mechanisms. For the case of independent private valuations and a single object, this literature shows that the use of the BIN option is preferred by agents who are risk averse, (Reynolds and Wooders (2009), Mathews and Katzman (2006), Ivanova-Stenzel and Kröger (2008)) have time preferences (Mathews (2004), Gallien and Gupta (2007)), when there are transaction costs (Wang, Montgomery, and Srinivasan (2008)), or when bidders have reference dependent preferences (Shunda (2009)).[2]

Despite the large number of theoretical explanations, there exists only a small number of empirical and experimental studies that analyze the BIN option.[3] Empirical studies find that experienced sellers use the BIN price more frequently (Durham, Roelofs, and Standifird (2004)), that BIN price offers of sellers with a high reputation are accepted more frequently (Anderson, Friedman, Milam, and Singh (2008), Durham et al.) and that auction revenues are increasing in the BIN price (Dodonova and Khoroshilov (2004)). These studies mainly focus on transactions of goods where multiple items are offered simultaneously and where a market price (e.g., resale value) is easily recognizable, e.g., American Silver Eagle coins, Palm computers, Texas Instruments calculators and

[1] The BIN price on eBay is temporary because it disappears when the auction starts. Yahoo, e.g., offers an option with a permanent BIN price that may be accepted throughout the auction.

[2] Under the standard assumptions of the symmetric independent private value (SIPV) environment with risk neutral bidders, BIN options would not be used in equilibrium. The optimal BIN price would be set so high that it is never accepted (Kirkegaard (2006)). This result holds independently of the way the buyout price is offered (temporarily as on eBay or permanently as on Yahoo) and how the arrival of the bidders is modeled. For example, Reynolds and Wooders (2009) study eBay and Yahoo auctions in a model where a buyout price is offered simultaneously to all buyers. Ivanova-Stenzel and Kröger (2008) study Vickrey auctions with a BIN price in a model with sequential arrival.

[3] For a recent survey on online auctions including the BIN option see Ockenfels, Reiley and Sadrieh (2006).

bracelets. Thus, they relate rather to common value auctions and parallel multiple auctions, but not to the case of private value single object auctions.

The few experimental studies on BIN options focus almost exclusively on buyer behavior. For example, parallel to the analysis of field data, Durham et al. conduct a field experiment, where they look at the relation between BIN prices and acceptance behavior of buyers. The experimenters acted as sellers, varying the BIN price and the seller reputation score. The authors suggest that the latter serves as signal of sellers' experience. They find that, controlling for the price, experienced buyers buy more often at the BIN price when sellers have no reputation. Lab experiments on private value auctions with a BIN option find that predictions of a model allowing for buyers to be risk averse are able to explain the observed behavior (Shahriar and Wooders (2006), Peeters, Strobel, Vermeulen, and Walzl (2007), Ivanova-Stenzel and Kröger (2008)). Ivanova-Stenzel et al. analyze also seller behavior. They find that risk preferences can partly account for the observed BIN prices.

The two caveats of those studies are the artificial lab institution used and the lack of variation in participants' experience with it. First, none of them explicitly adapts a real auction format. For example, Shahriar et al. use a clock auction format with BIN prices set by the experimenters; Peeters et al. use an auction format that permits proxy bidding as on eBay but uses an automatic extension rule instead of eBay's fixed deadline; and Ivanova-Stenzel et al. use a second–price sealed–bid auction. However, details of the auction format matter. For example, Ockenfels and Roth (2006) show that the combination of proxy bidding with a fixed end time, as used by eBay, leads to specific bidding strategies (e.g., "last minute bidding" and "incremental bidding") that may affect the auction price.

Second, empirical studies suggest that experience with eBay impacts subjects' behavior on eBay (see Durham et al., Wilcox (2000)). It has been shown that experience influence not only the own behavior, but also that subjects respond to the experience of their trading partners. Hence, it might be important whether group members differ in their experience with an institution and whether persons are informed about these differences. In artificial laboratory auctions, all participants possess similar (in)experience with the lab institution and gain experience together over the course of the experiment. Although comparing decisions in early to those in late periods in multi-period lab experiments allows to investigate the role of experience with the lab institution (as in Ariely, Ockenfels, and Roth (2005)), one cannot learn about the effects of the interaction between subjects who differ in their experience with the institution. Another possibility to study the role of experience with eBay, is to ask participants about their experience with eBay and to relate this to their behavior in the laboratory auctions, as in Garratt, Walker, and Wooders (2004). The disadvantage of this approach is that it does not reveal the relation of experience and behavior within the eBay institution. It also does not permit participants to react to the information about the experience of others.

The present study proposes an experimental design that solves the two problems by exploiting the advantages of lab and field experiments. In particular, we combine the use of a real auction market (the eBay platform and eBay traders) with the techniques of lab experiments to study how sellers set BIN prices on eBay. In our experiment, we invited eBay traders into the lab to participate in a sequence of transactions on the eBay platform. At the same time, we control participants' values for the items for sale and other aspects of the interaction, such as transaction costs, time preferences or reputation building. Additionally, we have information on traders' experience with eBay and we elicit individual risk preferences. This enables us to relate the BIN price decision to the individual characteristics of the sellers and to the information publicly available on the eBay platform. Thereby our study contributes to the analysis of decision making in online auction markets (Pinker, Seidmann and Vakrat (2003)), in particular to the scarce literature on seller BIN price behavior. In this context, it also allows to answer the question whether information publicly available on eBay can be exploited profitably.

Our results can be summarized as follows. We find that the specific eBay format may cause auction outcomes different to those expected in second–price auctions. We suggest a BIN auction model that accounts for these differences and fits the observed data better. Our empirical analysis reveals a link between the information about agents provided by the eBay market institution and their behavior. In particular, experience with the trade institution turns out to be one of the important determinants of the BIN price. Although, our model does not consider traders' experience explicitly, we are able to predict the way experience influences the variables of the model. We find that sellers increase their BIN price when facing a population of more experienced buyers. Our results also indicate that more experienced sellers ask for higher BIN prices.

The remainder of the article is organized as follows. Section 2 explains the functioning of eBay auctions with a BIN price. Section 3 describes the experimental design and procedure and gives a summary on the predictions for our experimental setting. We present the results in section 4 including a behavioral modification of the model that motivates the empirical data analysis. In section 5 we discuss our findings and section 6 concludes.

2 THE "BUY-IT-NOW"– OPTION IN EBAY AUCTIONS

The BIN option on eBay enables the seller to call for an auction and to offer the good for a take-it-or-leave-it price, the BIN price, at the same time. Buyers can either accept the BIN price or submit a bid. The first submitted bid starts the eBay auction. Once the auction has been started, the BIN price disappears and buyers can only bid in the auction. Otherwise, when a buyer accepts the BIN price, the sale is concluded at the BIN price.

Bids in eBay auctions, so called "proxy bids," are submitted secretly to eBay. The auction price is determined by the second highest proxy bid plus a minimum increment. This price is displayed publicly at any time during the eBay auction. Until a pre-specified end date, proxy bids can be revised upwards such that prices are at least one increment above the current standing price. Moreover, all proxy bids that have been outbid so far are also publicly displayed in a list of bids. At the end of the auction, the bidder with the highest proxy bid wins the auction and pays the auction price.

The duration of the eBay auction with BIN price (short: BIN auction) is chosen by the seller and can be between 1 and 10 days. Moreover, the seller can choose a reserve price for the auction. The minimum reserve price is €1. There are several other options, as e.g., a secret reserve price, placing the offer on top of a page, etc.[4] Sellers also have the option to offer an item at a fixed price only.

The information available to eBay traders before a sale takes place is limited to the trader's profile. This profile contains amongst other information a unique UserID and the number of completed transactions (both as seller and buyer). The number of completed transactions provides information about the experience a person has on eBay. After a sale is agreed upon, additional private information (e.g., name and address, bank account etc.) between the trading parties is exchanged in order to realize the transaction. At the time of the experiment, after a transaction has been made, buyers and sellers can rate each other by leaving feedback.[5]

3 THE EXPERIMENT

3.1 *The Field in the Lab*

Our experimental approach combines the use of a real auction market with the techniques of standard lab experiments. Studies conducted in the laboratory generally employ abstract goods and simplified versions of real trading mechanisms. They ensure control over the basic model assumptions, e.g., the distribution of signals and valuations, common knowledge of the number of participants etc. Although this approach delivers a very reliable test of the theoretical predictions, its relevance for understanding and predicting behavior in the field is limited. Lab environments cannot include all details of a real market mechanism, nor can participants' experience with them reflect the one of actual decision makers in real institutions.

In field experiments, participants interact in a real context over real goods. The advantage of field studies is that the research is conducted directly at an existing institution. Moreover, decision makers have experience with this institution. This, however, comes at the cost of giving up control over basic assumptions. For example, field experiments on eBay lack important information, e.g., the distribution of valuations and the knowledge of participants (and researchers) about the number of potential buyers.

[4] eBay charges the seller additional fees for their options. For example, using the BIN option cost a small fixed amount of between 0.09 and 0.99 in continental Europe and between \$0.05 and \$0.25 in the U.S. at the time of the experiment.

[5] Feedback consists of a rating (positive, negative, or neutral), and a short comment. These ratings are aggregated by eBay to the reputation score that is also publicly available. There are considerate claims that the feedback score is likely biased. These claims are based on the fact that transaction partners are not obliged to rate each other and that the fear of retaliation might suppress negative feedback (Dellarocas and Wood (2008)).

In our experiment, we bring the field into the lab: The experiment is conducted in the lab while using a real market environment, i.e., the eBay auction platform and real eBay traders. At the same time, we ensure that the assumptions of the SIPV environment are satisfied, i.e., an indivisible object for sale, independent and symmetrically distributed private valuations, common knowledge of this distribution and the number of bidders. Furthermore, we deliberately exclude other potential influences on transactions on eBay, as for example the disclosure of additional private information, time preferences, existence of outside options through competing offers, and other transaction costs. Another advantage of our experiment compared to field experiments is that we run several rounds and can observe behavior over time, as is usually done in standard lab experiments.[6]

3.2 *Experimental Design and Procedure*

The eBay Experiment

For the eBay experiment, we invited persons with a valid eBay account to the lab,[7] to participate in eBay auctions with a BIN option. The items for sale were real goods, more precisely, second hand books.[8] Subjects' private valuations for the goods were induced by the experimenters. We randomly drew values for each buyer and each item. All values were drawn independently from the commonly known set {1, 1.5, 2, 2.5,...,50}, with all values being equally likely. This means that a person who bought the good received the induced value instead of the good and his profit was the difference between his value and the transaction price. The profit of a seller was the transaction price. Buyers' values were private information, whereas it was commonly known that seller's valuation is zero. For all activities on eBay we used a fictitious currency, termed *eBay-€*, with 5 *eBay-€* being equivalent to 1 €.

In the experiment, buyers used their own eBay accounts, whereas sellers used eBay accounts licensed to the experimenters. This was common knowledge. To control for the influence of the seller reputation on buyer behavior, we used seller accounts with similar reputation scores (11-13 points).[9] Furthermore, participants knew beforehand, that they would not be rated after a transaction and we asked buyers not to rate the experimental seller accounts. This allowed

[6] In their article on fairness and price competition in one-shot interactions, Bolton and Ockenfels (2007) propose another way to combine the advantages of field and lab experiments. In their experiment, they bring the lab into the field.

[7] In a pre-experimental survey conducted with all persons registered in the experimental subject data base, we asked among other things whether a person had a valid eBay account, whether and how often a person had made a transaction via eBay. Of the 900 persons, who received the survey, 170 persons replied. These persons were then invited to our experiments.

[8] We chose mostly economics books or software books. These books really existed, such that we did not distort the eBay marketplace. If an external bidder would have decided to acquire one of the books we would have been able to complete the transaction correctly. However, no other bidders submitted bids on our books.

[9] Seller reputation is an important signal for quality of the good (Jin and Kato (2006), Resnick, Zeckhauser, Swanson, and Lockwood (2006)). Even though there is no uncertainty about quality in our experiment, we wanted to exclude any potential influence from seller reputation on buyers.

to exclude the influence of reputation building. Another advantage of this approach is that it allowed us to preserve anonymity between participants and to avoid the exchange of private information after a transaction.[10]

Before each session, we prepared all auctions using eBay accounts licensed to the experimenters. We described each item briefly, and included a reference number, consisting of letters and numbers, in the name of the item. The reserve price was set to eBay's minimum starting price of 1 €. The BIN price was the only parameter not specified yet.[11]

Each session consisted of 12 subjects. Upon arrival in the lab, they were provided detailed instructions and were informed whether they would act as sellers or as buyers throughout the whole experiment.[12] At the beginning of each session, we asked all participants to log into their own eBay account. We collected the number of completed transactions on eBay for each participant and then asked sellers to log out.

Altogether, subjects participated in six consecutive rounds, consisting of four trading groups each with two buyers and one seller. The composition of trading groups was randomly changed after each round.[13] At the beginning of each round, a seller decided about the BIN price from the set $\{1, 1.5, 2, ..., 50\}$ on a decision sheet, featuring a screen shot of the corresponding eBay page (see Appendix A.2). To keep roles confidential, we distributed together with the decision sheets of the sellers blank sheets to the buyers. All subjects had to return the sheets after two minutes. The experimenters completed the prepared auctions with the BIN prices chosen by the sellers and started the BIN auctions on eBay.

In order to map the sequential arrival in online auctions, the BIN price was offered to one of the two buyers, henceforth referred to as buyer 1. Each buyer acted as buyer 1 in three (of the six) rounds. We informed buyer 1 about their auction's reference number and their value for it. This buyer had to either submit a bid or to accept the BIN price within two minutes. After all subjects acting as buyer 1 had made their decisions, i.e., the BIN price had disappeared on eBay, we informed the remaining subjects about their valuations and the items' reference numbers. If the auction had not ended at the BIN price, both bidders could now bid on the item until the end of the auction. Sellers could follow the proceeding of their auctions at any time on eBay using the reference numbers of their items for sale.

The shortest auction duration on eBay is one day, which would have been too long in the context of this experiment. Thus, we artificially shortened the auction time to five minutes. We did this as follows: A clock, adjusted to the

[10] Only experimenters saw the private information of winning buyers who were assured in the experimental instructions that this would be kept confidential and neither used nor released to third parties.

[11] The advantage of preparing the auctions in advance is that it speeds up the experiment as it allowed us to set up the basic information of the auction before the experiment starts.

[12] See Appendix A.1 for a translated version of the instructions.

[13] To avoid unnecessary path dependencies, there was no more than one trading group consisting of the same subjects acting as seller and the buyer to whom the BIN price was offered. Moreover, two buyers were not matched into the same trading group more than once.

official eBay time, was projected on the wall, counting down the seconds to the end of the auction.[14] After all bidders were informed about their valuation and the item's reference number for the ongoing round, we fixed the auction end time and announced it publicly. Any bids arriving later than the fixed auction end time were not considered. The shortened duration of the auction has several advantages. It was long enough to enable participants to submit multiple bids, which is frequently observed in eBay auctions, but short enough to conduct several auctions within the same session and to exclude time preferences as a possible reason for accepting BIN prices. Additionally, this approach allowed us to shed more light on last minute bidding and the probability of last minute bids being lost.

In order to bring the field into the lab, we also had to make some compromises. For example, sellers did not use their own eBay account, the number of bidders and the distribution of their values were known, the duration of our experimental eBay auctions was different from that on eBay. Still, our design maintains the main characteristics of trading on eBay and uses the original eBay environment.

Eliciting risk preferences

At the end of each session, we elicited individual risk preferences with the help of a lottery experiment similar to Holt and Laury (2002). Participants had to choose between two lotteries, lottery A and lottery B. Each lottery had two possible payoffs, a high and a low amount: for lottery A €5.00 and €4.00, and for lottery B €8.20 and €0.20. The amounts were chosen to resemble the profit opportunities in the experiment. The high amounts in both lotteries were realized with the same probability p. Participants had to decide between both lotteries and had to make this choice for ten lottery pairs, whereby the probability p increased from 10% to 100%. Of all ten lottery pairs, one pair was selected randomly and the chosen lottery at this pair was played for real.

The lottery was conducted after the eBay experiment had taken place. Thus, when estimating risk preferences, we controlled for subjects' earnings in the eBay experiment. More precisely, for the estimation, we used an exponential utility function of the form $U(W+x) = (W+x)^{(1-\alpha)}/(1-\alpha)$ where α denotes the persons' constant relative risk aversion parameter, W the person's earnings from the eBay experiment and x the earnings in the lottery. Observing the lottery pair at which a person switches from choosing lottery A to lottery B allows us to determine the boundaries within which the individual constant relative risk aversion parameter α would lie: $[\arg\max \alpha : \ EU_A(W,\alpha) > EU_B(W,\alpha)] < \alpha < [\arg\min \alpha : \ EU_A(W,\alpha) < EU_B(W,\alpha)]$. With $EU_L(W,\alpha) = p \cdot U(W + L_1, \alpha) + (1-p) \cdot U(W + L_2, \alpha))$ for $L = \{A, B\}$ and where L_1 and L_2 denote the payoffs of lottery L. We take the midpoint of the interval as the risk preference of the person.[15]

[14]The official eBay time can be found at http://cgi1.ebay.de/aw-cgi/eBayISAPI.dll?TimeShow&ssPageName=home:f:f:DE

[15]The estimated individual risk preferences are presented in Tables 4 and 3 in Appendix B.

Estimated individual risk preferences range from -0.35 to 1.44. Most of the participants exhibit risk aversion, with a median level of 0.35.[16] Persons with preferences at the 25th percentile have a level of risk aversion of 0.02 and those at the 75th percentile of 0.67. When looking only at sellers, the distribution remains basically the same with risk preferences of 0.02, 0.55 and 0.78 at the 25th, 50th and 75th percentile.

3.3 *Model and predictions*

Our experimental setting consists of a seller who offers a single indivisible object for sale to two potential buyers.[17] Buyers have symmetric independent private valuations for the good, drawn from a uniform distribution with a support normalized to $[0, 1]$. The seller's value and reservation price are commonly known to be zero. The seller announces a BIN price prior to the auction. The buyer who observes the BIN price (buyer 1) can accept the offer, in which case the transaction is completed. Otherwise, he can submit a bid and start the eBay auction in which both buyers participate.[18]

The eBay auction shares some elements with sealed–bid (Vickrey) and open (English) second–price auctions: (1) Bids are submitted secretly as in Vickrey auctions. (2) Bids can be revised upwards and the current auction price is publicly displayed as in the English auction. (3) The price is determined by the second highest bid. However, the eBay auction differs from the English auction in that the auction ends at a fixed point in time. It also differs from the Vickrey auction in two aspects: bidders can revise their bids upwards as often as they choose and the second highest bid plus the increment is publicly displayed as current price at any time during the auction.

In second–price private value auctions, true value bidding is a weakly dominant strategy. This does not necessarily hold for eBay auctions. However, all equilibria involve bidding the own valuation at some point in time (Ockenfels and Roth (2006)).[19] Thus, in the auction, we assume that the bidder with the highest value wins and pays a price equal to the second highest value.[20]

[16] All participants except five buyers decided in a monotone way, i.e., once they switched from choosing lottery A to B they continued choosing lottery B. We do not consider those five observations in our analysis, however, the distribution of risk preferences was not affected when we tried different ways to incorporate those observations.

[17] This setting can be easily generalized to more than 2 bidders, see Ivanova-Stenzel and Kröger (2008).

[18] In reality, an early buyer could also choose to do nothing. One can show that this is a weakly dominated strategy. We do not consider this possibility in our analysis.

[19] Differences in the resulting prices may only occur because last minute bids have a positive probability of being lost. If this probability is negligible and if late bidders have already submitted several bids earlier, a second–price auction might be used for deriving reasonable predictions for seller revenue in eBay auctions.
Easley and Tenorio (2004) provide another rationale for bids being close to the true value. They argue that costs associated with submitting a bid and the uncertainty about future entry of bids explains that large bid increments ("jump bids"), hence bidding closer to the true value, might be a better strategy than submission of multiple bids with small increments.

[20] eBay's recommendation to its members is to submit their true value as bid. This advice can be found on all European and the North American eBay website (e.g., http://pages.ebay.com/help/buy/outbid-ov.html)

Buyer 1 will accept the BIN price if it provides a utility at least as high as the equilibrium expected utility from participating in the auction, i.e.,

$$u(v_1 - p) \geq \Pr\{win\} * u(v_1 - E[V_2|V_2 \leq v_1]) \quad (1)$$

$$\Leftrightarrow u(v_1 - p) \geq \int_0^{v_1} u(v_1 - x)dx, \quad (2)$$

where v_1 denotes buyer 1's valuation for the good, V_2 the valuation of the other bidder, p the BIN price, and $u(\cdot)$ the utility function. Making assumptions on the form of the utility function allow us to derive the decision rule for buyer 1's acceptance of the BIN price p. We restrict players' risk preferences to belong to the class of constant relative risk aversion (CRRA). In particular, the utility function is assumed to have the form $U(x) := (x^{1-\alpha})/(1-\alpha)$, where α is the Arrow-Pratt measure of relative risk aversion.[21] In this case, the price is accepted iff it is below the threshold $\bar{p}(v_1)$:[22]

$$p \leq \bar{p}(v_1) = v_1 - \left(\frac{v_1^{(2-\alpha_B)}}{2-\alpha_B}\right)^{\left(\frac{1}{1-\alpha_B}\right)}, \quad (3)$$

where α_B is the CRRA parameter of buyer 1.

For the case of risk neutral buyers ($\alpha_B = 0$), equation (3) simplifies to

$$p \leq \bar{p}(v_1) = (1 - (1 - v_1)^2)/2. \quad (4)$$

Taking into account buyer 1's threshold price, the utility maximization problem of the seller is

$$\max_p \left(\Pr\{p \leq \bar{p}(v_1)\}u(p) + (1 - \Pr\{p \leq \bar{p}(v_1)\})E_{v_1,v_2}[U(R_A)|\bar{p}(v_1) < p]\right), \quad (5)$$

where R_A is the expected revenue from the auction.

For the case of risk neutral agents ($\alpha_S = \alpha_B = 0$), problem (5) yields optimal BIN prices in the interval $[0.5, 1]$ that are never accepted. With heterogeneous risk preferences, we obtain the solution for the seller's problem (5) numerically. In this case, predicted BIN prices and acceptance rates depend on the assumptions about the distribution of preferences. For example, when facing a population of buyers with high levels of risk aversion ($\alpha_B > 1$), the model predicts BIN price of 0.73 and an acceptance rate of 27%. On the other hand, when sellers are assumed to have high levels of risk aversion ($\alpha_S > 1$) and buyers are risk neutral, the predicted BIN price is 0.42 resulting in 40% of accepted BIN prices.

To predict the outcome of our experiment based on reasonable assumptions about the distribution of risk preferences, we use the elicited preferences for sellers and buyers. In this case, the model predicts BIN prices in the interval $[0.42, 0.59]$ and an acceptance rate of 26%.

[21] This specification implies risk loving behavior for $\alpha < 0$, risk neutrality for $\alpha = 0$ and risk aversion for $\alpha > 0$. When $\alpha = 1$, the natural logarithm, $u(x) = ln(x)$, is used.

[22] The following theoretical results are equivalent to those obtained by Ivanova-Stenzel and Kröger (2008).

4 RESULTS

4.1 *Descriptive Statistics*

Altogether, we collected data from five sessions with a total of 60 participants (20 sellers and 40 buyers) and 120 transactions. Average earnings in the eBay experiment were €17.19, and in the lottery experiment €4.87. Total earnings ranged between €9.40 to €36.40 with a mean of €22.06. These amounts include a lump sum payment of €6 for buyers.

Experience with the eBay-institution

Participants' experience with the eBay institution is approximated by their individual number of completed transactions that ranges from 0 to 338. The average number of completed transactions was 29. Persons with low experience (at the 25th percentile) had 2 completed transactions and those with high experience (at the 75th and 95th percentile) 31 and 106, respectively, whereas the median participant had 11 numbers of completed transactions. The distributions separated by the subjects' role in the experiment are 1, 7 and 16 completed transactions for buyers' 25th, 50th and 75th percentiles with an average of 22, and 10, 28 and 60 for sellers' 25th, 50th and 75th percentiles with an average of 43 completed transactions.[23]

Experimental Outcomes

For ease of comparison to the theoretical model, we report our results for normalized valuations, i.e., all experimental outcomes are transformed into the $[0, 1]$ range. The distribution and a nonparametric density estimation of observed BIN prices is shown in Figure 1. BIN prices are offered in the interval $[0.15, 0.99]$ with a median price of 0.50 that is also the most frequently set single price (13% of all offers). The interquartile range is 0.205 (with 0.395 at the 25th percentile and 0.60 at the 75rd percentile). Buyers accepted slightly over one third (36%) of all BIN prices. Prices realized in the auction vary between 0.03 and 0.76 with a median of 0.23. Final prices are on average 0.32 and lie in the range of 0.03 and 0.76.

[23]The distribution of bidders' experience is quite comparable to the one Ockenfels et al. find in the data they collected on eBay-Antiques auctions. They use a bidder's feedback score as proxy for experience and report that approximately 17% of bidders had a score of 0, 33% had a score between 1 and 10 and 40% had a score between 11-100. Simonsohn and Ariely (2008) report an average feedback-score of 1.27 for bidder in DVDs auctions on eBay.
As leaving feedback is optional, feedback scores understate actual experience. Our choice of proxy trader's experience by the number of completed transactions should naturally result in higher numbers as it comprises all transactions, also those that did not receive feedback. Still, even this number represents only a lower bound of experience since it does not account for participation in auctions without a sale.

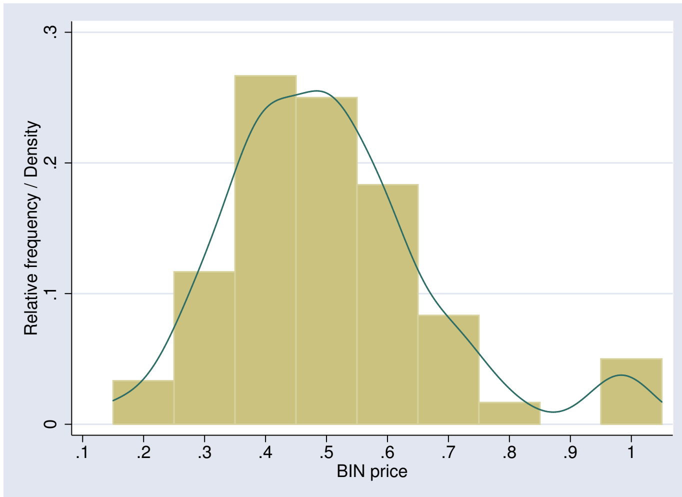

Figure 1: BIN prices

Comparison to the theoretical predictions

BIN prices and acceptance rates
The model in section 3.3 predicts BIN prices to be in the interval $[0.42, 0.59]$ with an average of 0.52. These predictions comprise only half of the observed BIN prices: 37% are below (the lower predicted bound of) 0.42; 27% are above (the upper predicted bound of) 0.59. Regarding the acceptance behavior, 82% of buyers' reactions towards the BIN price can be rationalized by the model taking buyers' individual risk preferences into account (see equation 2). However, the observed acceptance rate is significantly higher than the predicted one.[24]

Auction prices and bidding behavior
The median price determined by the auctions is 0.23, that is 19% below 0.33, the expected price of a second price auction with 2 bidders and iid standard uniform distributed valuations. There are two reasons for observing low auction prices: (i) *before* the auction: selection of low value buyers into the auction and (ii) *in* the auction: bidding strategies that deviate from true value bidding.

First, low BIN prices are accepted by high value buyers but cannot be afforded by low value buyers. Hence, low value buyers select into the auction more often. We evaluate the selection by comparing the second–highest value of buyers in groups where an auction was held to those where the BIN price was accepted. We find that the second–highest values of buyers in the auction (median value: 0.27) is 37% below those of transaction groups where the BIN price had been accepted (median value: 0.45) and 13% below those of all transaction groups (median value: 0.34).[25]

[24]Two-sided Wilcoxon Signed Rank test, $p = 0.08$, for the $n = 5$ sessions.

[25]Results remain very similar when looking at the values of loosing bidders: median values in the auction: 0.29 when the BIN price has been accepted: 0.46 of all transaction groups:

Second, 65% of the loosing bids are below the buyer's valuation. This leads to a drop of the median auction prices by 15% compared to the price that would have resulted from true value bidding.[26] This observation can be explained with the specific characteristics of the eBay auction format. First, bids can be revised upwards during the auction. Second, late bids may be lost when they arrive after the end of the auction. Thus, the combination of a fixed ending time with the possibility to adjust bids during the auction can give rise to the use of particular strategies, for example "multiple bidding" (also referred to as "(naive) incremental bidding" or "squatting") and "last minute bidding" (also referred to as "sniping"). For example, a bidder who adopts the (out-of-equilibrium) incremental bidding strategy submits first a bid below his true value. He only raises his bid after being outbid, and only as much as needed to become the highest bidder again until the own valuation is reached.[27] A bidder who adopts the sniping strategy bids his true valuation only shortly before the end of the auction, preventing rival incremental bidders to respond in time.[28]

In our experiment, we find evidence for the use of both strategies. The average number of submitted bids per auction is 4.2; the median is 3, with 2, 5 and 12 as 25th, 75th and 95th percentiles, respectively. Moreover, in 75% of the auctions we observe sniping. On the individual level, 80% of all bidders use the sniping strategy in at least one of the auctions they participated in.[29]

The incremental bidding strategy is vulnerable to sniping by a rival. An incremental bidder that has been outbid by a sniping bidder has no time to respond by increasing his bid before the end of the auction. In consequence, the auction may end with a price that is below the value of the loosing bidder. Indeed, we find that in auctions without last minute bidding, the winner pays a price close to the value of the loosing bidder whereas in auctions with sniping, the realized price is much lower.[30]

The use of the sniping strategy may also lead to low prices. Because of too much Internet traffic or other technical problems bids might be delayed and

0.35. The median value of all buyers that bid in an auction was 0.44 with an interquartile range of $[0.25; 0.71]$, whereas the median value of all buyers in the cases when the BIN price was accepted was 0.67 with an interquartile range of $[0.45, 0.86]$.

[26] Even though, bids are not displayed on eBay, loosing bids can be deduced from the auction price.

[27] There exist several explanations that justify multiple bidding in a private value environment. Two of them are learning the own value for the good (Rasmusen (2006) and Hossain (2008)) and gaining more precision of the estimate of the own value for the good over time combined with uncertainty whether to be able to place a bid in the future (Cotton (2009)). As values were known with certainty in our experiment, being naive about the second–price auction mechanism (Roth and Ockenfels (2002) and Ockenfels et al.) is the most plausible explanation for observing the phenomenon in our study.

[28] Roth et al. and Ockenfels et al. argue that sniping is a best response to the incremental bidding strategy. They also show that sniping may occur in equilibrium, despite the positive probability that last minute bids may be lost. Ariely et al. and Ely and Hossain (2009) find experimental evidence that sniping occurs primarily as best response to incremental bidding.

[29] We define bids that were submitted within the last 30 seconds as sniping bids.

[30] We compared session medians for relative deviations of the realized price from the value of the loosing bidder. Sign Test of the deviation being zero for n=5 sessions: for auctions with sniping: $p = 0.06$; for auctions without sniping: $p = 0.13$.

not arrive in time. In fact, we observe that 9.6% of the sniping bids arrive too late. Moreover, 9% of all auctions with last minute bidding are inefficient, i.e., the winning bidder has a lower valuation than the loosing bidder.[31] In contrast, all auctions without sniping are efficient.

As a consequence, given the different strategies outlined above, a bidder's final bid may well deviate from his true value. Indeed, we find that final loosing bids (with N=77) are on average 13.5% below the true value.[32] Thus, true value bidding seems not to be a good approximation for bidding behavior in eBay auctions questioning the theoretical predictions based on the assumption that (final) bids are equal to the respective valuations.

Behavioral Modification of the Model

In this section, we consider a modification of the theoretical model in that sellers and buyers account for the fact that bids are on average below the valuation. Because the focus of our article is on seller BIN price behavior, we do not model the different bidder strategies explicitly. Rather, we make the assumptions that (1) bidding below valuation is symmetric and deterministic in the sense that both bidders always bid $b(v) = (1-\gamma)v$ (with $0 < \gamma < 1$), and (2) buyer 1 knows that his rival and himself will follow this strategy in the auction. Thereby, γ denotes the relative deviation of the bid from the true value.

Under these assumptions, the threshold price of a buyer with risk aversion parameter α_B becomes

$$\widetilde{p}_{\gamma}(v_1) = v_1 - \left(\frac{v_1^{(2-\alpha_B)} - (\gamma v_1)^{(2-\alpha_B)}}{(2-\alpha_B)(1-\gamma)} \right)^{\frac{1}{(1-\alpha_B)}} \tag{6}$$

We solve the maximization problem of the seller (equation (5)) with the threshold price from equation (6) numerically.[33] The optimal BIN price in this case depends on the distribution of buyers risk preferences and the seller's own risk preference as well as by how much bids deviate from the true value. For instance, the optimal BIN price for a risk neutral seller who faces buyers with high risk aversion ($\alpha_B > 1$) and given that bids equal true values ($\gamma = 0$), is 0.73. It decreases to 0.68 when the relative deviation of bids from true values increases (e.g., $\gamma = 0.20$). On the other hand, if buyers are less risk averse ($\alpha_B = 0.5$), the same increase in the relative deviation results in a change of the BIN price from 0.55 to 0.45.

Given the observed relative deviation from true value bidding ($\gamma = 13.5\%$) and the risk preference distribution elicited from our participants, the modified

[31] Looking only at auctions where the winner submitted a successful last minute bid, we find 13% of inefficient sales.

[32] The median deviation is 5% below the own valuation (with an interquartile range of $0\%, 22\%$).

[33] Note that with true value bidding ($\gamma = 0$), the threshold price corresponds to that derived in equation (3).

model predicts BIN prices in the range of [0.38, 0.52] with an average of 0.46 and an acceptance rate of 31%.[34]

The predicted acceptance rate of the modified model (31%) is closer to the one observed in the experiment (33%) compared to the one of the original model (26%). Also, the modified model accounts by 11 percentage points better for the observed BIN prices than the original model. Thus, allowing agents to anticipate the existence of lower auction prices compared to those resulting from true value bidding improves the fit of the model substantially.

4.2 *Data Analysis*

In this section, we study in more detail how BIN prices are set. On one hand, sellers pricing strategy might be well described by the model proposed in the previous section. This model suggests that optimal BIN prices depend crucially on both, agents' risk preferences and the bidding behavior of buyers. On the other hand, sellers might also adjust their prices following an adaptive heuristic, increasing the BIN price in the following period when it was accepted and decreasing it if it was rejected.[35] We consider both possibilities.

While transacting on eBay, sellers can collect and update information about buyer characteristics as well as their behavior. If the behavior and characteristics of buyers influence the BIN price setting of sellers, we should observe adjustments in the BIN price when the information of those determinants changes. For example, sellers who expect bids closer to the bidders' valuations should increase their BIN price. On the other hand, sellers who expect bids that lead to prices below the price resulting from true value bidding should lower their BIN prices.

In our experiment, price determining bids are on average 13.5% below the loosing bidder's value. If the information about buyers' characteristics and behavior that a seller can observe is correlated with the level of deviation from true value bidding, a seller could approximate this level in the buyer population. Therefore, we will first assess whether there exists such correlation. Then, we will analyze sellers' reactions to those observable covariates when setting their BIN prices.

[34] For the case of risk neutral agents ($\alpha_S = \alpha_B = 0$) the modified model predicts BIN prices of 0.43 and an acceptance rate of 26%.

[35] For example, directional learning (Selten and Buchta (1998)) suggests that if the BIN price was accepted a seller should increase it in the following period. The rational behind is simple adaptive profit maximizing. In the opposite case, when the BIN price was rejected and the final (auction) price is lower than the offered BIN price, a seller should decrease their BIN price in the following period. This is because a lower BIN price that is above the auction price of the previous period might have been accepted and hence led to higher payoff.
Our results show that if a price change occurred at all, it can be correctly predicted by directional learning in the majority of the cases. Sellers increase their BIN price in 65% of the cases if their BIN price has been accepted. After a rejection, given that the auction price is lower than the BIN price, 55% of the BIN prices are lower than the same subject's BIN price in the previous period.

Price deviation in eBay auctions

In the auction, sellers observe the number of submitted bids by each bidder, the experience buyers have with eBay, and whether bidders submit last minute bids.

The relation between the level of deviation from true value bidding and the number of submitted bids is not as straightforward as it might appear at first glance. For example, there would be no deviation when both bidders submit their own valuations only once as a proxy bid or when both bidders bid incrementally, i.e., submit multiple bids, up to their own valuation, resulting in a price equal to the second highest valuation. On the other hand, there are several cases in which the auction might end at a price below the second highest valuation: (1) when an incremental bidder faces a last minute bidder, he might not have the time to respond by increasing his bid up to his true valuation; (2) when both bidders are last minute bidders and the probability that one (or both) bids do not arrive before the end of the auction is greater than zero. Therefore, observing multiple bids indicates incremental bidding and prices can be expected to be similar to those resulting from true value bidding in second–price auctions. Observing no multiple bidding, however, is not conclusive on bidder behavior. Furthermore, other studies on eBay suggest that the number of submitted bids varies with experience. Ariely, Ockenfels, and Roth (2005) and Ockenfels and Roth (2006) report that experienced bidders tend to submit a lower number of bids in eBay auctions. Indeed, we do find a similar relation in our data.[36]

We investigate the influence of those variables, i.e., number of bids, last minute bidding and buyers' experience, on the relative deviation of the price determining bid from true value bidding. The relative deviation is the difference between the second highest bidder's valuation and his bid normalized by the valuation, $rd_{it} = (v_{it} - b_{it})/v_{it}$.[37] We regress the relative deviation (rd_{it}) of bidder i's bid in auction t on a vector of covariates x_{it}

$$rd_{it} = \kappa_0 + x'_{it}\kappa + \varepsilon_{it}$$

The vector $x_{it} = (exB_i, exB_i^2, nb_{it}, (nb_{it} \cdot exB_i), (nb_{it} \cdot exB_i)^2, sn_i, snbe_{it}, (exB_i \cdot sn_i), so_{it})'$ contains bidder i's specific variables that are observable by a seller, such as the experience the buyer has with eBay, approximated by the number of completed transactions normalized by 10 (exB_i), a quadratic term of experience (that allows to capture nonlinear effects), a dummy variable (sn_i) that equals

[36] We ran the following median regression $nb = \theta_0 + \theta_1 exB + \theta_2 exB^2 + \varepsilon$, where the variable nb represents the number of bids and exB the number of completed transactions as a proxy for the experience a bidder has with eBay. Both variables are normalized by 10. The median bidder with no experience places 3 bids per auction ($\theta_0 = 0.325(17.45)$). This number decreases nonlinearly with experience ($\theta_1 = -0.028(-3.27), \theta_2 = 0.001(3.67)$) where t-statistics are presented in parenthesis. We chose median regression, as a few participants had some extremely high values for their experience and OLS might be vulnerable to those outliers. OLS estimates are, however, very similar and available upon request.

[37] Note that a negative relative deviation means that the bidder submits a bid above his value, and a positive number indicates that the bidder submits a bid below his value.

1 if the buyer is a last minute bidder,[38] and for each auction t, the number of submitted bids (nb_{it}) normalized by 10, a dummy variable for successful sniping ($snbe_{it}$), that equals one if the final bid of a last minute bidder has arrived before the end of the auction, and a dummy variable being one when the other person is a last minute bidder (so_{it}). As experienced bidders might use sniping strategies more often, we also allow for the interaction between experience and being a last minute bidder ($exB_i \cdot sn_i$). Given our finding of a nonlinear relation between experience and the number of bids, we allow for interaction between these variables ($nb_{it} \cdot exB_i$) as well as this interaction to enter non-linearly. Finally, the variable ε_{it} captures idiosyncratic errors and is assumed to satisfy $E(\varepsilon_{it}) = 0$.

Variable	κ	St.Dev	$P > \lvert z \rvert$
κ_0	0.0896	0.0694	0.201
exB	−0.1056	0.0473	0.029
exB^2	0.0095	0.0037	0.013
nb	−0.1575	0.1389	0.261
nb^2	0.0253	0.0525	0.631
$(nb \cdot exB)$	0.2333	0.1179	0.052
$(nb \cdot exB)^2$	−0.0606	0.0242	0.015
sn	0.1727	0.0942	0.071
$snbe$	−0.1635	0.0828	0.053
$(exB \cdot sn)$	0.0257	0.0179	0.157
so	0.0708	0.0445	0.116

Table 1: Median regression of variables influencing the relative deviation from true value bidding of price determining bids. Nobs=77.

Table 1 presents the results of a median regression.[39] Buyers' experience with eBay has a significant effect on the level of the relative deviation. This effect depends on the number of submitted bids. To better understand the influence of experience, we plotted in Figure 2 the relation between the relative deviation and experience for different number of bids using the estimates from Table 1.[40] The range displayed on the horizontal axis, $[0, 16]$, covers the 0 to 75th percentile of buyers' experience with eBay. For a low number of bids, the predicted relative deviation is lower for bidders with higher experience indicating that their bids are closer to their true value than for bidders with less experience. When the number of bids increases, the relative deviation decreases. At the same time, bidders with less experience increase their bids in bigger steps than bidders with more experience. As a consequence, for an increasing number of bids, the picture reverses and bidders with less experience bid closer to their value.

[38] A person is classified as last minute bidder if he or she submitted a bid during the last 30 seconds before the end of the auction in at least one auction.

[39] OLS estimation results are similar and available upon request.

[40] The effect of all other variables, $sn, snbe, so$, is taken at their mean values.

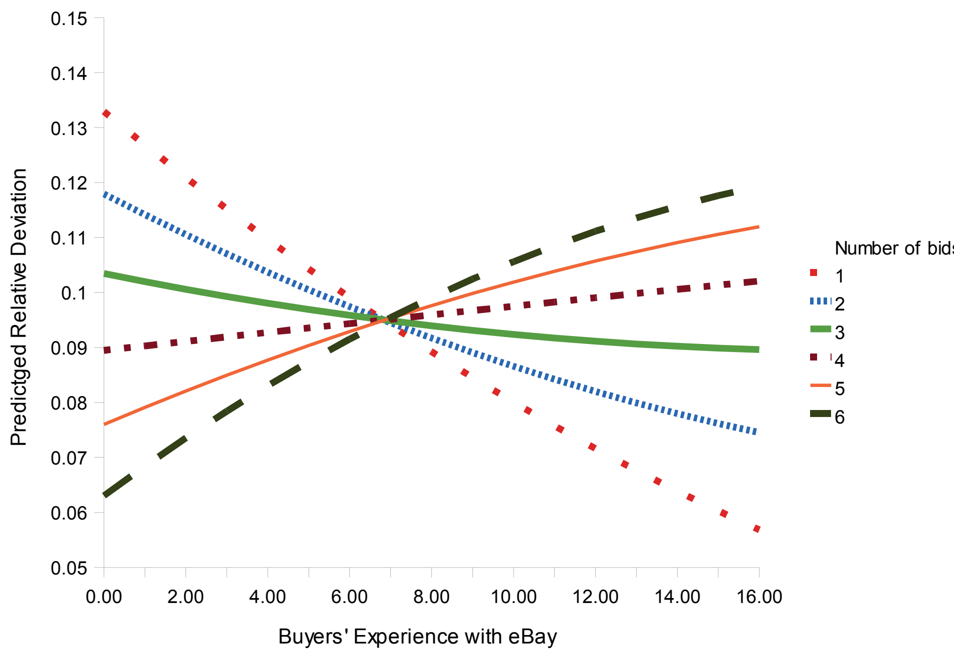

Figure 2: Relation between relative deviation and level of experience for different number of bids (1 to 6).

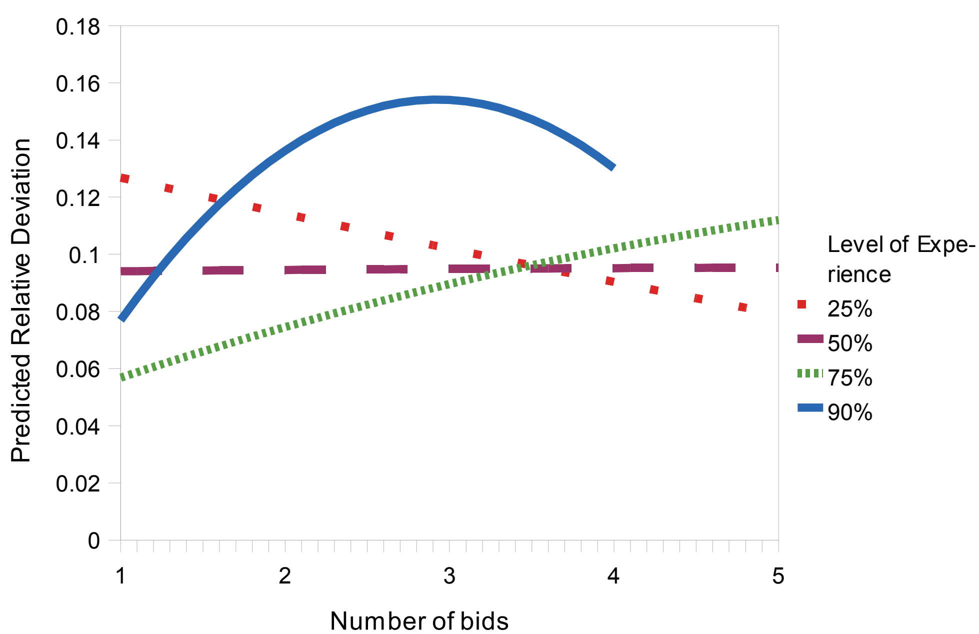

Figure 3: Relation between relative deviation and number of bids for different levels of experience (25th, 50th, 75th, 95th percentile).

Our estimation also indicates that the relative deviation decreases with the number of bids. This is not surprising because eBay accepts only an increase of the proxy bid. However, we find that this relation is mainly linear and varies with buyers' experience. Figure 3 visualizes this relation for buyers with different levels of experience using the estimates of Table 1.[41] The predicted relative deviation decreases linearly with the number of bids for bidders with little (at the 25th percentile) and also –even though less intense– for bidders with median experience. For bidders with a level of experience at the 75th percentile and higher, this relation becomes concave.[42] This suggests that a substantial number of highly experienced bidders submit only one bid that is close to their true value.[43]

If the loosing bidder uses a sniping strategy, the relative deviation increases to 17%. It is, however, reduced by 16% if the sniping is successful (i.e., the bid arrives before the end of the auction). Thus, the "net deviation" is only 1%. Finally, when the other (winning) bidder adopts a sniping strategy the price decreases by 7% on average as the loosing bidder had no chance to respond in time before the end of the auction.

BIN price setting

The data analysis so far has revealed that buyers' bidding behavior and their experience with eBay can be used to deduce the level of deviation of the observed eBay auction prices from prices based on true value bidding. Thus, we investigate to what extent sellers react to such information when setting their BIN prices.

Thereby, we apply the following model:

$$\begin{aligned} bin_{it} = \beta_0 &+ \overline{bc}'_{it-1}\beta_1 + \beta_2 D_{it-1} \\ &+ \beta_3 bin_{it-1} D_{Rit-1} + \beta_4 bin_{it-1} D_{Ait-1} \\ &+ \mu_i + \varepsilon_{it}, \qquad\qquad \text{with } t = (2, \ldots, 6). \end{aligned}$$

The BIN price bin_{it} of seller i in period t is modeled as a function of the average buyer characteristics that seller i observed in all previous 1 to $(t-1)$ periods $\overline{bc}_{it-1} = (\overline{nb}_{it-1}, \overline{ex}B_{it-1}, \overline{ex}B^2_{it-1}, \overline{sn}1_{it-1}, \overline{sn}2_{it-1})'$. When a seller chooses the BIN price he does not know with whom he will interact. Therefore, we use the empirical averages of those variables.[44] The vector of buyer characteristics contains the average number of bids per buyer submitted ($\overline{nb}_{it-1}$), the average

[41] The effect of all other variables, $sn, snbe, so$, is taken at their mean values.

[42] Whereas bidders with lower levels of experience submit up to 25 bids, bidders with a level of experience above the 90th percentile did not submit more than 4 bids.

[43] This result is inline with the finding of Ockenfels et al. that bidders who bid only once are more experienced than bidders who bid multiple times.

[44] When calculating the empirical averages, we give all information equal weights regardless at what point in time they were collected. It is reasonable to assume that sellers form expectations about the whole buyer population rendering the individual interactions equally valuable.

number of completed transactions for all buyers normalized by 10 ($\overline{ex}B_{it-1}$), and seller i's average count of observing one respectively two sniping bidders in one auction ($\overline{sn}1_{it-1}$ and $\overline{sn}2_{it-1}$). Given that buyers' eBay experience had a non-linear influence on auction prices, we also include ($\overline{ex}B^2_{it-1}$) allowing the seller to react in a non-linear way to this variable.

Some information can only be observed when an auction has been conducted, for example, the number of bids and the event of last minute bidding. Therefore, we add a dummy variable D_{it-1} that is one until the first auction has been held and zero otherwise. For example, if the BIN price was accepted in the first period, seller i has no information about buyers' auction behavior in period $t = 2$ and the dummy D_{i1} equals one.[45] It remains one until the period when for the first time the BIN price has been rejected and an auction takes place allowing the seller to collect the information about buyer behavior in the auction. This dummy variable might also be interpreted as capturing the influence of prior information on the BIN price that is not observable in the experiment.

With our experimental design we observe sellers over time, hence, we can also investigate whether sellers adjust their BIN prices in response to buyers' reaction to the previous BIN price. The adjustment of the BIN price in period t is captured with the help of dummy variables, separately for the case when the previous period's BIN price (bin_{it-1}) was accepted or rejected. Thereby, D_{Rit-1} and D_{Ait-1} equal one if the last period's BIN price was rejected and accepted, respectively. We use interaction terms of these dummies with the previous period's BIN price. Thus, the estimated parameters report the relative adjustments of the current to the previous BIN price.

The variable μ_i represents unobserved individual fixed effects. We will later use the estimated fixed effects to assess the effect of sellers' individual characteristics on BIN prices. The idiosyncratic error term ε_{it} is assumed to be uncorrelated over time ($E(\varepsilon_{it}, \varepsilon_{is}) = 0$ for $s \neq t$) as well as with the covariates and fixed effects ($E(\varepsilon_{it}|\overline{bc}_{it-1}, \mu_i) = 0$).

Table 2 presents the results of the panel MLE regression. Without accounting for any additional information, sellers set BIN prices of around 0.47. However, when taking the effect of the information into account that sellers can observe (and evaluating those variables at their mean), the offered BIN price goes up to 0.50. The estimation results show that sellers seem to react to the information on buyers' characteristics and to buyers' behavior when deciding on the BIN price. A seller increases his BIN price by 0.025 when the average number of submitted ($\overline{nb}$) bids increases by one. For example, when the average number of bids per bidder increases from 2 to 4, the seller raises his BIN price by 11% (from 0.47 to 0.52).[46]

Sellers raise the BIN price when the average experience in the buyer population ($\overline{ex}B$) increases. This relation is significant and mainly driven by the linear effect. For example, when a seller faces buyers with low experience (at the 25th percentile) and keeping all other variables at their mean value, the BIN price

[45] The value of the variables $\overline{nb}, \overline{sn}1$ and $\overline{sn}2$ are in this case set to zero.

[46] These numbers are computed using the parameter estimates of Table 2 and evaluating all other variables at their mean values.

Variables	β	St.Dev	$P > \|z\|$
β_0	0.4688	0.0713	0.000
$\overline{nb}$	0.0246	0.0091	0.009
$\overline{exB}$	0.0418	0.0016	0.012
$\overline{exB}^2$	-0.0003	0.0000	0.065
$\overline{sn}1$	-0.1431	0.0660	0.033
$\overline{sn}2$	0.0765	0.0595	0.203
D	0.0536	0.0602	0.376
$bin_{t-1}D_R$	-0.1632	0.9961	0.106
$bin_{t-1}D_A$	0.0080	0.1203	0.947
σ_μ	0.1829		
σ_ε	0.0877		

Table 2: BIN price, MLE, Nobs=100, N of sellers=20.

is set at 0.45. This price is 5% lower than the BIN price when interacting with median experienced buyers, where the BIN price is 0.48, and 12% lower when facing buyers with high experience (at the 75th percentile), where the BIN price is 0.51.

On the other hand, observing sniping ($\overline{sn}1, \overline{sn}2$) results in demanding lower BIN prices. Thereby, sellers react if they observe one sniping bidder. For example, keeping all other variables at their mean value, a decrease of the probability to interact with a sniping bidder ($\overline{sn}1$) by half, leads to an increase of the BIN price by 9% to 0.55. There is no effect of observing also a second sniping bidder ($\overline{sn}2$).

The effect of unobserved prior information on BIN prices (D) is not significantly different from zero. Furthermore, we find that sellers do not purely adjust their BIN price in the subsequent period as response to the buyer's reaction towards the BIN price ($bin_{t-1}D_R$ and $bin_{t-1}D_A$).[47]

Finally, we investigate the impact of the sellers' personal characteristics on the BIN prices. We regress the estimated individual fixed effects $\widehat{\mu}_i$ on sellers' elicited risk preferences and their eBay experience.[48] We find that individual fixed effects are not correlated with risk preferences, but with experience. Sellers with higher experience set higher BIN prices. This effect is significant and quite substantial. For instance, BIN prices of sellers with high experience (at the 75th

[47]This corroborates our finding that subjects react to all the information collected in previous periods rather than just from the last period.

[48]We looked at the linear relation between the fixed effects ($\widehat{\mu}_i$) and elicited individual risk preferences ($risk_i$) as well as the experience of our 20 sellers (exS_i, counted as number of completed transactions normalized by 10): $\widehat{\mu}_i = \gamma_0 + \gamma_1 \cdot risk_i + \gamma_2 \cdot exS_i + \varepsilon_i$. The parameter estimates obtained by median regression for the 20 sellers, are $\gamma_1 = 0.01(0.06), \gamma_2 = 0.017(0.008)$ where bootstrap standard errors (with 1000 replications) are presented in parentheses. An OLS regression results in practically the same parameters.

percentile) are 19% higher than BIN prices of sellers with low experience (at the 25th percentile) and 11% higher than those of sellers with median experience.

5 DISCUSSION

Our results indicate that sellers respond strategically to the information provided by the eBay market institution when deciding on their BIN prices. Their reaction is in line with the behavior predicted by a model that allows for deviation from true value bidding: Optimal BIN prices are higher when bidders bid their true value in the auction than when final bids are below the true value. Indeed, when the average number of submitted bids increases (which reflects bids to be closer to the true value) sellers tend to increase their BIN prices. We observe that more experienced bidders bid closer to their true value and find that bids submitted at the last minute lead to auction prices substantially lower than those resulting from true value bidding. Sellers react accordingly by increasing their BIN price when facing a population of more experienced buyers and by decreasing the BIN price when the probability of last minute bidding increases.

Our analysis suggests further that sellers' individual characteristics also have an influence on the BIN price. For example, we find that more experienced sellers set higher BIN prices. Even though lowering the BIN price might be a good response to certain behavior of buyers, too low BIN prices result in lower final prices. We find evidence for a selection of high value buyers into accepting low BIN prices and low value buyers into the auction. It seems that experienced sellers are better aware of this selection effect and thus post higher prices.[49] Sellers risk preferences, on the other hand, seem not to play a role when deciding about the BIN price. This finding corroborates the suggestion of Ivanova-Stenzel et al. that sellers risk preferences have a minor impact on BIN prices. However, we do not want to overemphasize this result as it might depend on the way risk preferences were elicited (Duncan and Isaac (2000)).

6 CONCLUSION

This article investigates how eBay sellers use the BIN option in eBay auctions. The option allows sellers to post a price at which buyers can purchase a good prior to the auction. We conducted an experiment where eBay traders interacted in the lab on the real eBay platform over several periods. At the same time we ensured that certain model assumptions were satisfied, such as an environment with private independent values for a single indivisible object, while excluding other influences, such as time preferences and transactions costs.

The observed bidding behavior suggests that the specific eBay auction format may give rise to auction outcomes different to those in standard second–price

[49] In a lab BIN auction experiment, Ivanova-Stenzel et al. find also evidence that some sellers did not account for the selection effect. However, they cannot relate this behavior to the subject's experience, as participants had the same experience with the lab institution.

auctions. We augmented a BIN auction model to account for these differences. We calibrated the parameters of the model using the observed bidding behavior and participants' elicited risk preferences. We found that the predictions of the calibrated model account better for the experimental data than those of the model based on the assumption of true value bidding.

The model predicts optimal BIN prices to decrease with an increase of the relative deviation of the price in the eBay auction from the one that would result from true value bidding. We found that information about buyers that is available on the market institution (i.e., buyers' experience with eBay) is correlated with the deviation from true value bidding. Apparently, sellers correctly respond to this information by setting higher BIN prices when buyers are more experienced. We also found that seller's own experience influences their behavior as experienced sellers post higher BIN prices.

Our results not only shed light on BIN price behavior but also lead to two further important conclusions. First, they highlight potential consequences of information publicly available in (online) market institutions. Such information can convey useful facts about trading partners and can be exploited profitably. Second, they underline the crucial role of institutional details and agents' experience with them.

A EXPERIMENT: INSTRUCTIONS AND SELLER DECISION SCREEN

A.1 *Translated Instructions*

This is a shortened and translated version of the instructions. For the original instructions in German, please contact the authors.

Please read the instructions carefully! Should you have any questions please raise your hand; we will answer your questions in private. The instructions are identical for all participants.

This experiment consists of two independent parts.

In the first part of the experiment, you are going to participate in eBay auctions. In each of these auctions, three people (one seller and two buyers) take part in the purchase of an item. At the beginning of the experiment, each participant is randomly assigned to a role (seller or buyer) and keeps this role throughout the entire experiment.

All information is provided in an experimental currency, the eBay-Euro. At the beginning of each auction, the private valuation for the product of each buyer for the item is determined. If you are a buyer, you will be informed about your valuation by the experimenters. All valuations are randomly and independently drawn from the interval 1 to 50 eBay-Euro with an incremental unit of 0,50 eBay-Euro, i.e., 1,00; 1,50; 2,00; 2,50;...; 49,00; 49,50; 50,00 with all of these values being equally likely. Each buyer is informed about his/her own valuation and will not get to know the private value of the other buyer. The seller is not informed about the private values of the buyers.

Each auction proceeds as follows:
At the beginning, the seller determines a "Buy-it-Now price" for the item. Only values that are divisible by 0.50 eBay-Euro and lie between 1 and 50 eBay-Euro are allowed, i.e., 1,00; 1,50; 2,00; 2,50;...; 49,00; 49,50; 50,00. The starting price of the auction is 1 eBay-Euro. Afterwards, one of the buyers, knowing his/her valuation, will decide if s/he wants to purchase the item at the "Buy-it-Now price" or not.

If the buyer accepts the "Buy-it-Now price", the item is sold at this price. **The auction is over**. The payoff to the buyer is the difference between his/her valuation and the price. The seller receives the price. The other buyer gets nothing and pays nothing, i.e. his/her payoff is 0.

If the buyer rejects the "Buy-it-Now price", he **must** make a bid in order to initiate a conventional eBay-auction, in which the other buyer can also participate. Both of the buyers can make bids for the product **within 5 minutes** bidding time. Again, only the bids that are divisible by 0.50 eBay-Euro and lie between 1 and 50 eBay-Euro are allowed, i.e., 1,00; 1,50; 2,00; 2,50;...; 49,00; 49,50; 50,00. The bidding will be opened and ended by experimenters with the use of a clock projected on the wall counting down seconds to the end of the auction. The auction ends once the clock on the wall reaches zero. **The end of the auction is determined by the projected clock, not by eBay! The bids that arrive on eBay after the announced auction end time will not be considered.**

At the end of the 5 minutes bidding time, the buyer who made the highest bid wins the auction and gets the item at the price at which the auction has ended (following the eBay rules). In case of a tie (when two buyers make the same bid), the bidder who has made his/her bid earlier gets the item. **The auction is over.** The payoff to the winner of the auction is the difference between his/her valuation and the price. The seller receives the price. The other buyer gets nothing and pays nothing, i.e. his/her payoff is 0.

The experiment consists of 6 auctions. In each auction, the participants in an auction (seller and two buyers) are matched randomly. Each buyer will be able to decide on the "Buy-it-Now price" in 3 out of the 6 auctions.

Experimental Procedure:

After being informed whether you are a buyer or a seller (available on the sheet "Information about your Role", please follow the steps V1-V2 and K1-K2, respectively (according to your role). Please use your own eBay ID and password to log in.

In order to assure the anonymity of the participants, only buyers will use their own eBay account. Each seller will use an eBay account licensed to the experimenters. The sellers will find the name of the eBay account on the sheet "Information about your Role" but not the passwords for the account. Thus, they cannot use them on their own.

If you are a **buyer**, please remain logged in.

If you are a **seller**, please log out from your personal account. Each auction will be prepared and executed by the experimenters on behalf of the seller (setting the category number, product-ID, product description, starting price of 1 eBay-Euro). The seller must solely determine a "Buy-it-now price" for each auction and write it down on the sheet "Decision on Buy-it-now Price", which will be distributed at the beginning of each auction. After all sellers have decided on their "Buy-it-now price" , the auctions are started.

Then, those buyers who decide on the "Buy-it-now price" in the ongoing auction, receive the information about their valuation and the relevant item's ID with the sheet "Information about your auction". Those buyers should follow steps K3 and K4 described in the sheet "Information about Your Role". Buyers who do not decide on the "Buy-it-now price", will get this information when they enter the auction, i.e., after a decision on the "Buy-it-now price" has been made. If you cannot find the product in step K4, make sure that you have typed the product-ID correctly. If you cannot find the product even when you enter the ID correctly, this means that the product has been sold to the first buyer at the "Buy-it-now price".

Summary:

The duration of each Auction is maximum 9 minutes: Decision on the "Buy-it-now price" by the seller: 2 minutes; Decision to buy or not at the "Buy-it-now price" by one of the buyers buyer: 2 minutes; In case the "Buy-it-now price" is rejected, bidding time in the auction: 5 minutes.

Please don't make any bids in the auctions **after the experiment**. **Please don't rate other participants**.

We would like to point out that except for the remuneration for your participation, no other claims can be made concerning the auctions.

We would like to point out that all eBay rules are valid for this experiment; for instance, if you are a buyer, your address might be communicated to the experimenters after the experiment (as the actual owner of the seller accounts).

We commit ourselves not to disclose this information to third parties and not to keep or use it after the experiment.

Payment Rules:

The exchange rate is: 1 eBay-Euro = €0,20.

After the experiment you will receive your payoff (in €) from all auctions. You can get your payment any time between XXXX and XXXX am starting from XXXXXX in room XXX at XXXX.

Please be aware that a buyer might incur losses! This can happen, if a buyer accepts a "Buy-it-Now price" or made a bid during the auction, which is higher than his valuation.

Buyers are granted an initial lump sum payment of €6. Should you, as a buyer, make losses, they will be deducted from your earnings (or from your initial payment).

You will get the instructions for the second part of the experiment at the end of the first part.

Instructions for the Second Part of the Experiment:

The following table includes different lotteries. The rows are numbered from 1 to 10. For each row, you must decide whether you prefer lottery A (left column) or lottery B (right column). Please mark your choice with a cross for each row.

When you come to our institute (XXXX) to get your payment for the first part of the experiment, we are going to play one of the lotteries: In your presence, we will roll a ten-sided dice twice. The first number will determine the row number of the table. The lottery that you have chosen for that row will then be played by rolling the dice for the second time. You will receive your earnings from the lottery immediately.

Example:

If the result of the first roll is "5", then the lottery that you have chosen for row number 5 will be relevant for your earnings.

If the result of the second roll is "1","2","3","4", or "5" (probability 50%), then you will earn the amount corresponding to those numbers in the chosen lottery (i.e., €5 if lottery "A" was chosen and €8,20 if lottery "B" was chosen). If the result of the second roll is "6","7","8","9" or "10" (probability 50%) then you will earn the amount corresponding to those numbers in the lottery you have chosen (i.e., €3 if lottery "A" was chosen and €0,20 if lottery "B" was chosen)

A.2 *Screen Shot of Seller BIN Price Decision*

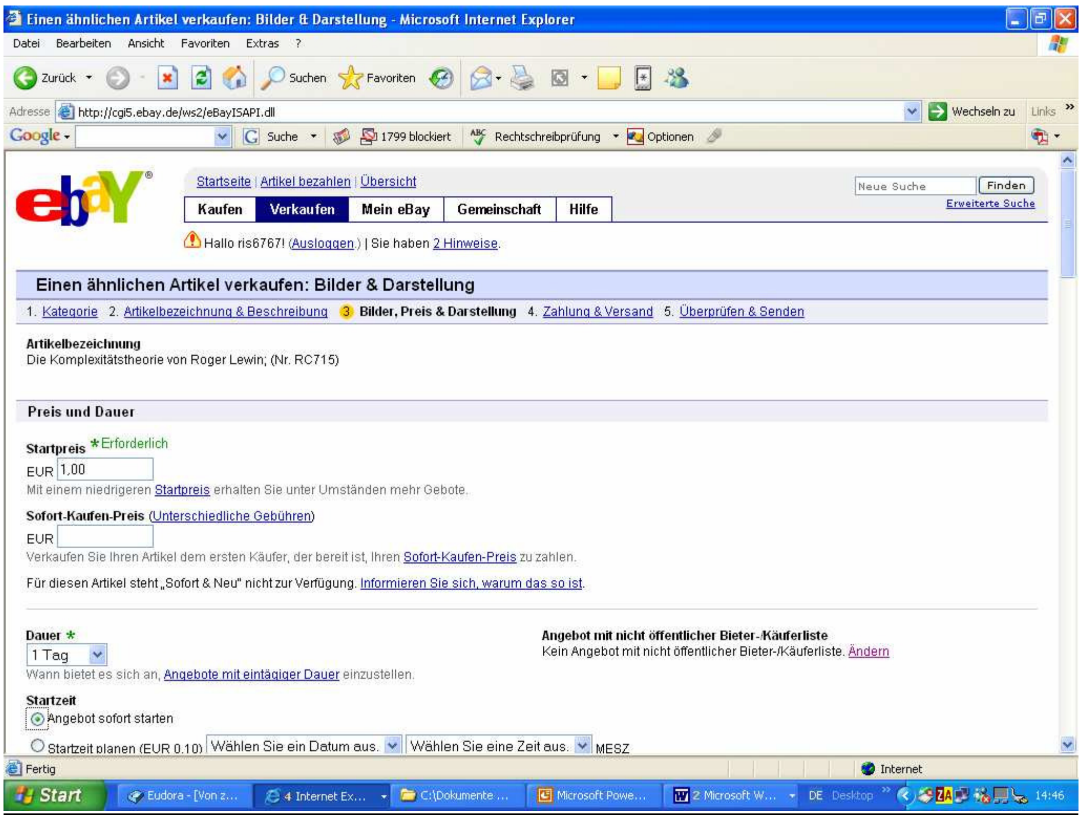

Figure 4: Screen Shot of Seller BIN Price Decision. The seller had to fill in the blanc field of the BIN price in EUR ("Sofort-Kaufen-Preis"). All items used the minimum Starting price ("Startpreis") of 1EUR.

B DATA

Sellers Participant	Earnings in eBay experiment	Switching point in lottery experiment	Estimated risk preference
1	0.38	7	0.75
2	0.36	4	-0.35
3	0.30	8	1.17
4	0.47	7	0.77
5	0.30	7	0.73
6	0.17	5	0.02
7	0.33	4	-0.34
8	0.29	7	0.73
9	0.23	9	1.44
10	0.32	6	0.37
11	0.31	4	-0.34
12	0.27	8	1.16
13	0.34	8	1.19
14	0.37	6	0.37
15	0.39	4	-0.35
16	0.39	7	0.75
17	0.55	7	0.79
18	0.23	5	0.02
19	0.42	5	0.03
20	0.23	5	0.02

Table 3: Normalized earnings in the eBay experiment, switching point in the lottery experiment and estimated risk preferences. N=20 sellers.

Buyer Participant	Earnings in eBay experiment	Switching point in lottery experiment	Estimated risk preference
1	0.23	7	0.70
2	0.11	8	1.06
3	0.15	7	0.68
4	0.07	4	-0.31
5	0.12	7	0.67
6	0.00	5	0.02
7	0.28	nm	nm
8	0.19	nm	nm
9	0.06	7	0.65
10	0.05	4	-0.31
11	0.23	5	0.02
12	0.03	9	1.37
13	0.24	5	0.02
14	0.10	4	-0.31
15	0.17	6	0.35
16	0.15	5	0.02
17	0.01	6	0.32
18	0.14	6	0.34
19	0.24	nm	nm
20	0.04	4	-0.31
21	0.10	7	0.66
22	0.26	4	-0.33
23	0.06	7	0.65
24	0.34	7	0.74
25	0.16	7	0.68
26	0.13	7	0.67
27	0.18	4	-0.32
28	0.04	6	0.33
29	0.04	nm	nm
30	0.00	7	0.63
31	0.20	nm	nm
32	0.21	6	0.35
33	0.18	5	0.02
34	0.22	5	0.02
35	0.28	5	0.03
36	0.13	5	0.03
37	0.00	7	0.63
38	0.00	7	0.63
39	0.23	7	0.70
40	0.06	5	0.02

Table 4: Normalized earnings in the eBay experiment, switching point in the lottery experiment and estimated risk preferences. N=40 buyers. N=5 persons switched several times between the two lotteries (nm=non-monotone).

References

Anderson, S. T., D. Friedman, G. H. Milam, and N. Singh (2008): "Buy it Now: A Hybrid Internet Market Institution," *Journal of Electronic Commerce Research*, 9(2), 137–153.

Ariely, D., A. Ockenfels, and A. E. Roth (2005): "An experimental analysis of ending rules in Internet auctions," *RAND Journal of Economics*, 36(4), 891908.

Bolton, G. E., and A. Ockenfels (2007): "Does Laboratory Trading Mirror Behavior in Real World Markets? Fair Bargaining and Competitive Bidding on EBay," *Working Paper Series in Economics 36, University of Cologne*.

Cotton, C. (2009): "Multiple-bidding in auctions as bidders become confident of their private valuations," *Economics Letters*, 104(3), 148–150.

Dellarocas, C., and C. A. Wood (2008): "The Sound of Silence in Online Feedback: Estimating Trading Risks in the Presence of Reporting Bias," *Management Science*, 54(3), 460476.

Dodonova, A., and Y. Khoroshilov (2004): "Anchoring and transaction utility: evidence from on-line auctions," *Applied Economics Letters*, 11(5), 307–310(4).

Duncan, J., and R. Isaac (2000): "Just who are you calling risk averse?," *Journal of Risk and Uncertainty*, 20(2), 177–187.

Durham, Y., M. R. Roelofs, and S. S. Standifird (2004): "eBay's Buy-It-Now Function: Who, When, and How," *Topics in Economic Analysis & Policy*, 4(1).

Easley, R. F., and R. Tenorio (2004): "Jump Bidding Strategies in Internet Auctions," *Management Science*, 50(10), 1407–1419.

eBay Inc. (2001, 2004): "Financial results: Fourth Quarter 2001 First and Second Quarter 2004," .

Ely, J. C., and T. Hossain (2009): "Sniping and Squatting in Auction Markets," *American Economic Journal: Microeconomics*, 1(2), 68–94.

Gallien, J., and S. Gupta (2007): "Temporary and Permanent Buyout Prices in Online Auctions," *Management Science*, 53(5), 814–833.

Garratt, R., M. Walker, and J. Wooders (2004): "Behavior in Second-Price Auctions by Highly Experienced eBay Buyers and Sellers," *University of California at Santa Barbara, Economics Working Paper Series 04-04*.

Holt, C. A., and S. K. Laury (2002): "Risk Aversion and Incentive Effects," *American Economic Review*, 92(5), 1644 – 1655.

Hossain, T. (2008): "Learning by Bidding," *RAND Journal of Economics*, 39(2), 509–529.

Ivanova-Stenzel, R., and S. Kröger (2008): "Price Formation in a Sequential Selling Mechanism," *Journal of Economic Behavior and Organization*, 67(3-4), 832–843.

Jin, G. Z., and A. Kato (2006): "Price, quality, and reputation: evidence from an online field experiment," *RAND Journal of Economics*, 37(4), 983–1005.

Kirkegaard, R. (2006): "A Short Proof of the Bulow-Klemperer Auctions vs. Negotiations Result," *Economic Theory*, 28(2), 449 – 452.

Mathews, T. (2004): "The Impact of Discounting on an Auction with a Buyout Option: a Theoretical Analysis Motivated by eBays Buy-It-Now Feature," *Journal of Economics (Zeitschrift für Nationalökonomie)*, 81, 25 – 52.

Mathews, T., and B. Katzman (2006): "The Role of Varying Risk Attitudes in an Auction with a Buyout Option," *Economic Theory*, 6(3), 597 – 613.

Ockenfels, A., D. H. Reiley, and A. Sadrieh. (2006): *Economics and Information Systems* chap. Online Auctions, pp. 571–628. Amsterdam: Elsevier.

Ockenfels, A., and A. Roth (2006): "Late and Multiple Bidding in Second Price Internet Auctions: Theory and Evidence Concerning Different Rules for Ending an Auction," *Games and Economic Behavior*, 55(2), 297–320.

Peeters, R., M. Strobel, D. Vermeulen, and M. Walzl (2007): "The impact of the irrelevant - Temporary buyout options and bidding behavior in online auctions," *Working Paper, Maastricht research school of Economics of TEchnology and ORganizations.*

Pinker, E. J., A. Seidmann, and Y. Vakrat (2003): "Managing Online Auctions: Current Business and Research Issues," *Management Science*, 49(11), 1457–1484.

Rasmusen, E. B. (2006): "Strategic Implications of Uncertainty over One's Own Private Value in Auctions," *Advances in Theoretical Economics*, 6(1).

Resnick, P., R. Zeckhauser, J. Swanson, and K. Lockwood (2006): "The value of reputation on eBay: A controlled experiment," *Experimental Economics*, 9, 79–101.

Reynolds, S., and J. Wooders (2009): "Auctions with a Buy Price," *Economic Theory*, 38(1), 9–39.

Roth, A., and A. Ockenfels (2002): "Last-Minute Bidding and the Rules for Ending Second-Price Auctions: Evidence from eBay and Amazon Auctions on the Internet," *American Economic Review*, 92(4), 1093–1103.

Selten, R., and J. Buchta (1998): *Games and Human Behaviour*chap. Experimental Sealed Bid First Price Auctions with Directly Observed Bid Functions. Mahwah (N.J.): Lawrence Erlbaum Ass.

Shahriar, Q., and J. Wooders (2006): "An Experimental Study of Auctions with a Buy Price Under Private and Common Values," *Working Paper*.

Shunda, N. (2009): "Auctions with a buy price: The case of reference-dependent preferences," *Games and Economic Behavior*, 67(2), 645–664.

Simonsohn, U., and D. Ariely (2008): "When Rational Sellers Face Nonrational Buyers: Evidence from Herding on eBay," *Management Science*, 54(9), 1624–1637.

Wang, X., A. Montgomery, and K. Srinivasan (2008): "When auction meets fixed price: a theoretical and empirical examination of buy-it-now auctions," *Quantitative Marketing and Economics*, 6(4), 339–370.

Wilcox, R. T. (2000): "Experts and Amateurs: The Role of Experience in Internet Auctions," *Marketing Letters*, 11(4), 363–374.