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Buy-it-Now Prices in eBay Auctions – The Field in the Lab

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Abstract

In eBay's Buy-it-Now auctions sellers can post prices at which buyers can purchase a good prior to an auction. We study how sellers set Buy-it-Now prices when buyers have independent private values for a single object for sale. We test the predictions of a model by combining the real auction environment (eBay auction platform and eBay traders) with the techniques of lab experiments. We observe that the eBay auction format supports deviations from truthful bidding leading to auction prices below those expected in second–price auctions. Our proposed extension of the model results not only in a better fit of the data but provides new predictions to test. We find the information that is available on eBay is correlated with the level that eBay auction prices deviate from prices based on true value bidding. Sellers adjust their Buy-it-Now prices according to this information in the direction predicted by the model. They increase their BIN price when facing a population of more experienced buyers, when observing a higher number of submitted bids or more last-minute bidding from at least one bidder. More experienced sellers also ask for higher BIN prices.

JEL classifications: C72, C91, D44, D82.

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

1 Introduction

Internet auction platforms offer a variety of combinations of selling mechanisms. 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. Otherwise, the price is determined by the auction. BIN options have become increasingly popular among sellers and buyers. At first glance, this popularity appears surprising. Sellers use auctions because the relevant information on buyers' willingness to pay is incomplete, making it difficult to set the "right" price. Therefore, using a BIN price means at least partly giving up the advantage of the competitive environment created by the auction.¹ While for the case of single-object auctions with independent private values, theory has provided different rationales why sellers may nevertheless be interested in using a BIN price, the experimental and empirical literature lacks insights on seller behavior in this environment. This study aims at filling this gap by presenting experimental results on how sellers set BIN prices.

The theoretical literature suggests that, for the case of private values, sellers might be interested in posting a BIN price before an auction, when they face risk-averse buyers or are risk-averse themselves (Mathews and Katzman (2006), Ivanova-Stenzel and Kröger (2008), Reynolds and Wooders (2009)), one or both market sides are impatient (Mathews (2004), Gallien and Gupta (2007)), considering participation and transaction costs (Wang, Montgomery, and Srinivasan (2008)) or if bidders have reference dependent preferences (Shunda (2009)). Despite the numerous (partly competing) theoretical explanations for the use of the BIN option, there exist only a few empirical and experimental studies that analyze BIN auctions.² The empirical studies suggest that experienced sellers use the BIN price more frequently (Durham, Roelofs, and Standifird (2004)), that BIN price offers from 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)). However, they mainly focus on transactions of goods where multiple items are offered simultaneously and where a market price (resale value) is easily recognizable, e.g., American Silver Eagle coins, Palm computers, Texas Instruments calculators and bracelets. Thus, the environment is rather one with common values and a double auction market with multiple auctions offering comparable items simultaneously.

The number of experimental studies is even more limited. The experimental studies on private value auctions with a BIN option are mainly concerned with the buyer behavior. In general, they find that the predictions of a model allowing for buyers to be risk-averse are able to explain observed buyer behavior (Shahriar and Wooders (2010), Peeters, Strobel, Vermeulen, and Walzl (2007), Ivanova-Stenzel and Kröger (2008)). However, they do not provide insights on how BIN prices are set.³ Another drawback in the

¹Under the standard assumptions of the symmetric independent private value (SIPV) environment with risk-neutral bidders, the existence of the BIN option can indeed not be explained: The optimal BIN price is set so high that it is never accepted (see 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.

 $^{^{2}}$ For a survey on empirical and experimental literature that studies online auctions including the BIN option see Ockenfels, Reiley and Sadrieh (2006).

 $^{^{3}}$ Ivanova-Stenzel et al. also analyze seller behavior. They find that risk preferences can partly account for the observed BIN prices.

previous experimental work is the use of an artificial auction institution and the lack of variation in subjects' experience with this institution. 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. 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. In addition, empirical studies and field experiments find that experience with eBay impacts subjects' behavior on eBay. Some of them also suggest that experience influences not only the own behavior, but that persons' response to the experience of their trading partners (see Durham et al., Wilcox (2000)).⁴ Hence, it might be important whether subjects differ in their experience with an institution and whether they are informed about these differences. One possibility is to ask participants about their experience with eBay and to relate this to their behavior in 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.

In this article, we combine the use of a real auction market with the techniques of standard lab experiments. The experiment is conducted in the lab while using the eBay auction platform and eBay traders. At the same time, we ensure that the assumptions of the environment we want to study are satisfied (i.e., an indivisible object for sale, independent and symmetrically distributed private valuations, common knowledge of the value distribution and the number of bidders). This approach yields several advantages. First, it allows us to observe behavior in a real market institution –the eBay platform– and in addition provides the needed variation in experience of the traders. Second, it allows us to relate seller BIN price decisions to their individual characteristics and to the information publicly available on the eBay platform. Third, it allows us to test whether seller behavior exhibits qualitative properties similar to the theoretical predictions.

Our results can be summarized as follows. We began by testing a BIN auction model based on the assumption of truthful bidding as in standard second-price (Vickrey or English) auctions. Our experimental test revealed that the specific eBay format supports deviations from truthful bidding leading to auction prices below those expected in standard second-price auctions. We propose a modification of the BIN auction model that accounts for such deviations and calibrate it using the elicited risk preferences of buyers and sellers and the observed deviation from truthful bidding to predict the outcomes in our experiment. The new model fits the observed data better and provides new qualitative predictions that we can verify with our empirical analysis.

The empirical analysis reveals that sellers set their BIN prices consistent with the intuition of the modified model. We find the information that is available on eBay is correlated with the level that eBay auction prices deviate from prices based on true value bidding. Sellers adjust their Buy-it-Now prices according to this information in the direction proposed by the model. Sellers increase their BIN price when facing a population of more experienced buyers, when observing a higher number of submitted

 $^{{}^{4}}$ In a field experiment, Durham et al. find that controlling for the price, experienced buyers buy more often at the BIN price when sellers have no experience.

bids or more last-minute bidding from at least one bidder. Our empirical analysis also reveals that more experienced sellers ask for higher BIN prices.

The remainder of the article is organized as follows. Section 2 gives a summary of the predictions for our experimental setting. Section 3 describes the experimental design and procedure. We present the results in section 4 including a behavioral modification of the model discussed in 2 that motivates the empirical data analysis. In section 5 we discuss our findings and offer some concluding remarks.

2 Model and predictions

The setting we are going to study in our experiment consists of a seller who offers a single indivisible object for sale to two potential buyers.⁵ 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 to one of the buyers who is randomly selected prior to the auction. The buyer who observes the BIN price (henceforth referred to as buyer 1) can accept the offer, in which case the transaction is completed. Otherwise, he can submit a bid and start the auction in which both buyers participate.⁶

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 the 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)). Thus, in the auction, we assume that the bidder with the highest value wins and pays a price equal to the second-highest value.

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.,

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

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

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

⁵This setting can be easily generalized to more than two buyers, see Ivanova-Stenzel and Kröger (2008).

⁶In eBay auctions, buyers arrive at different points in time, and there is always a "decisive buyer" who will either accept the BIN price or start the auction by submitting a bid. In the latter case, the BIN price disappears; hence buyers arriving later are not informed about the rejected price offer. They can only participate in the auction.

have the form $U(x) := (x^{1-\alpha})/(1-\alpha)$, where α is the Arrow-Pratt measure of relative risk-aversion.⁷ In this case, the price is accepted if it is below the threshold $\bar{p}(v_1)$:⁸

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

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

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

$$\max_{p} \left(\Pr\{p \le \bar{p}(v_1)\} u(p) + (1 - \Pr\{p \le \bar{p}(v_1)\}) E_{v_1, v_2}[U(R_A)|\bar{p}(v_1) < p] \right),$$
(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, one can obtain the explicit 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 a 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.

In order to predict the outcome making reasonable assumptions about the distribution of risk preferences, we elicited subjects' risk preferences (for more details, see section 3). Using the elicited risk preferences of seller and buyer participants in the experiment the model predicts BIN prices in the interval [0.42, 0.59] and an acceptance rate of 26%.

3 Experimental Design and Procedure

We invited persons with a valid eBay account to the lab to participate in eBay auctions with a BIN option (see Appendix A for a detailed description of the functioning of eBay BIN price auctions).⁹ In the experiment, buyers used their own eBay accounts, whereas sellers used eBay accounts licensed to the experimenters with similar reputation scores (11-13 points). This was common knowledge.¹⁰ This approach provides several advantages. It allows us to control for the influence of the seller reputation on buyer behavior. Seller reputation is an important signal for the quality of the good (see Jin and Kato (2006), Resnick, Zeckhauser, Swanson, and Lockwood (2006)). Even though there is no uncertainty about

⁷This 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.

⁸The following theoretical results are equivalent to those obtained by Ivanova-Stenzel and Kröger (2008).

⁹Before the experiment, we conducted a survey with all subjects registered in the experimental subject data base at Humboldt University. There, among other things, we asked whether a person had a valid eBay account, how often a person had made transactions via eBay and whether they had acted as a seller or buyer. Of the 900 persons who received the survey, 170 persons replied. These were then invited to our experiments.

¹⁰See Appendix B.1 for a translated version of the instructions.

quality in our experiment, we wanted to exclude any potential influence from seller reputation on buyers. Second, participants knew beforehand that they would not be rated after a transaction and we asked buyers not to rate the experimental seller accounts. Thus, we control for (and exclude) the influence of reputation building on BIN price behavior. Third, we avoid the standard exchange of private information after a transaction on eBay and preserve the anonymity between participants. Only the experimenters saw the private information of winning buyers who were assured in the instructions that this would be kept confidential and neither used nor released to third parties. Finally, all fees charged by eBay would be paid by the experimenter. In order to fit our experimental auctions into the eBay environment and not distort the eBay market place, we used real goods, more precisely, second-hand books. If an external bidder decided to acquire one of the books we would have been able to complete the transaction correctly. ¹¹ Thus, with the use of eBay accounts licensed to the experimenters for the seller as well as physical goods for sale we made sure that none of the eBay's Terms of Service were violated.

Subjects' private valuations for the goods were induced by the experimenters. We drew values for each buyer and each item randomly. All values were drawn independently from the commonly known set $\{1, 1.5, 2, 2.5, ..., 50\}$, with all values being equally likely. Buyers' values were private information, whereas it was commonly known that sellers' valuation is zero. 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 private value and the transaction price. The profit of a seller was the transaction price. For all activities on eBay we used a fictitious currency, termed $eBay \in$, with $5eBay \in$ being equivalent to $\in 1$.

Before each session, we prepared all auctions using the experimental eBay accounts. 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 $\in 1$. The BIN price was the only parameter not yet specified. The advantage of preparing the auctions in advance is that it sped up the experiment as it allowed us to set up the basic information of the auction before the experiment started.

Each session consisted of 12 subjects. Upon arrival in the lab, subjects were randomly assigned to the computer terminals. Then subjects were given detailed instructions and were informed whether they would act as sellers or as buyers throughout the whole experiment. Thereby, we made sure that subjects with experience as a seller on eBay were assigned the role of a seller in our experiment. 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 the sellers to log out.

In total, subjects participated in six consecutive rounds. In each round, there were four trading groups each with two buyers and one seller. The composition of the trading groups was randomly changed after each round. To avoid unnecessary path dependencies, no more than one trading group consisted of the same subjects acting as seller and the buyer to whom the BIN price was offered. Moreover, two buyers were only matched once into the same trading group.

At the beginning of each round, a seller decided on 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 B.2). To keep roles confidential, together with the decision sheets of the sellers, we distributed 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.

¹¹No bidders outside the experiment submitted bids in our experimental auctions.

An auction round proceeded as follows: the BIN price was first offered to one of the two buyers (buyer 1). Each buyer acted as buyer 1 in three (of the six) rounds. We informed buyer 1 about their item's reference number and their value for it. This buyer had two minutes within which to either submit a bid or to accept the BIN price. 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. This means that during the experiment they could see, collect and update their information about buyers' behavior as well as buyers' characteristics (e.g., number of completed transactions).

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 official eBay time, was projected on the wall, counting down the seconds to the end of the auction. 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.

Our experimental design combined features of both, lab and field experiments. Like in lab experiments, for example, bidders had induced values, their distribution as well as the number of bidders in an auction was common knowledge. This ensured the comparability of our results with the theoretical predictions as well as with results from previous lab experiments on BIN auctions. Like in field experiments, our participants interacted in a real institution they had experience with. Thus, we could study whether and to what extent the real institution and subjects' experience with it may explain observed deviations from the theoretical predictions.

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 \in 5 and \in 3, and for lottery B \in 8.20 and \in 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 of 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 riskaversion 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.¹²

Estimated individual risk preferences range from -0.06 to 1.47. Most of the participants exhibit risk-aversion, with a median level of 0.50.¹³ Persons with preferences at the 25th percentile have a level of risk-aversion of 0.22 and those at the 75th percentile of 0.81. When looking only at sellers, the distribution remains basically the same with risk preferences of 0.23, 0.68 and 0.95 at the 25th, 50th and 75th percentile.

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 $\in 17.19$, and in the lottery experiment $\in 4.87$. Total earnings ranged between $\in 9.40$ to $\in 36.40$ with a mean of $\in 22.06$. These amounts include a lump sum payment of $\in 6$ for buyers.

Experience with the eBay-institution

Participants' experience with the eBay institution was approximated by their individual number of completed transactions on eBay that ranged 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. eBay also offers information about the number of completed transactions separated by the subject's trading activity (seller/buyer). The participants in the role of a seller in our experiment had on average 14 completed transactions as sellers on eBay (1, 8 and 17 for 25th, 50th and 75th percentiles, respectively).

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.

As leaving feedback is optional, feedback scores understate actual experience. Our choice of proxy for the

¹²The estimated individual risk preferences are presented in Tables 5 and 4 in Appendix C.

¹³All 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.

trader's experience by the number of completed transactions should naturally result in higher numbers as it comprises all transactions, including those that did not receive feedback. But even this number represents only a lower bound of experience as it does not account for participation in general, but only when there was a sale and, in this case, only for the two contracting parties.

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. Tables 1 and 2 provide summary statistics of the experimental outcomes for all N = 120 observations.¹⁴ 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 and average price of 0.50 that is also the most frequently set BIN price (13% of all offers). The interquartile range is 0.21 (with 0.39 at the 25th percentile and 0.60 at the 75rd percentile). Buyers accepted slightly over one-third (36%) of all BIN prices. Final prices (i.e., sellers' profits) vary between 0.03 and 0.76 and are on average 0.33. Winning buyers earn on average 0.33, as there is only one of the two buyers who bought, buyers earned on average 0.16.



Figure 1: BIN prices

Comparison to the theoretical predictions

BIN prices and acceptance rates

The model in section 2 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, 83% of buyers' reactions towards the BIN price can be rationalized by the model taking buyers' individual risk

 $^{^{14}}$ Tables 6 and 7 in Appendix D provide this information on session level.

All data analysis was performed using the software STATA. Data and "STATA-.do - file" are available upon request to the authors.

	Profits			BIN	Auction	Number of
	Sellers	All	Buyers	Price	Prices	submitted
		buyers	who bought	Offer		bids
Mean	0.33	0.16	0.33	0.50	0.28	4.2
Std.	(0.18)	(0.23)	(0.23)	(0.17)	(0.19)	(2.9)
Median	0.31	0.00	0.31	0.50	0.23	3.5
IQR	(0.24)	(0.31)	(0.29)	(0.21)	(0.22)	(4.0)

Table 1: Overview of Results, N=120

36
87
74(43)
100(19)
91(58)

Table 2: Overview of Results (continued), N=120

preferences into account (see equation 2). However, the observed average acceptance rate is significantly higher than the predicted one (two-sided Wilcoxon signed-rank test, p = 0.08, n = 5 sessions).

Auction prices and bidding behavior

The average price determined by the auctions is 0.28, that is 15% below 0.33, the expected price of a second-price auction with two bidders and uniform iid 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: use of bidding strategies that deviate from true value bidding.

First, when sellers ask for "low" BIN prices that are accepted by high value buyers but cannot be afforded by low-value buyers, low-value buyers select into the auction more often. We evaluate the selection by comparing the second-highest value of buyers (corresponding to the theoretical price in a second-price auction) 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 (mean value: 0.32) is 30% below those of trading groups where the BIN price had been accepted (mean value: 0.46) and 14% below those of all trading groups (mean value: 0.37).

Second, 65% of the losing bids are below the buyer's valuation.¹⁵ Such a strong deviation from true value bidding can be explained by the specific eBay auction format. First, bids can be revised upwards during the auction. Second, late bids will be lost if they arrive after an auction has ended. Thus, the combination of a fixed ending time with the possibility to adjust bids during the auction can give rise to strategies such as "multiple bidding" (also referred to as "[naive] incremental bidding") and "last-minute bidding" (also referred to as "sniping"). A bidder who adopts the incremental bidding strategy first submits a bid below his true value. He only raises his bid after being outbid, and only as much as is needed to become the highest bidder again until the own valuation is reached.¹⁶ A bidder who adopts the

¹⁵Even though, bids are not displayed on eBay, loosing bids can be deduced from the auction price.

¹⁶Several explanations exist that justify multiple bidding in a private value environment (e.g., Rasmusen (2006) and Cotton

sniping strategy bids his true valuation only once, shortly before the end of the auction, preventing rival incremental bidders from responding in time.¹⁷ In our experiment, we find evidence for the use of both strategies. Bidders submit multiple bids with an average of 4 bids per auction. Moreover, in 75% of the auctions we observe sniping.¹⁸

However, the relation between the level of price deviation and the number of submitted bids is not straightforward. 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 bids is not conclusive on bidder behavior and hence on the price deviation. For example, there would not be multiple bids if (1) both bidders submitted their true values only once as a proxy bid, (2) an incremental bidding strategy from standard second–price auctions and results in no deviation. In cases (2) and (3), the auction might end at a price below the second-highest valuation, if the incremental bidder did not have the time to respond by increasing his bid up to his true valuation or if the probability that one (or both) last-minute bids did not arrive before the end of the auction is greater than zero. The latter might be caused by too much Internet traffic or other technical problems. In fact, we observe that 9.6% of the last-minute bids arrive after the end of the auction.

Given the different strategies outlined above, a bidder's final bid may well deviate from his true value. Indeed, we find that final losing bids (with N=77) are on average 13.5% below the true value. Thus, true value bidding does not seem 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 bidders' respective valuations.

Efficiency

Table 2 presents the efficiency of BIN auctions separately by whether the BIN price was accepted or whether there was an auction. In the latter case, we again separate those auctions with and without last-minute bidding. The efficiency of transactions in which the BIN price was accepted is with 74% lower than that observed when the BIN price was rejected. Of all auctions with last-minute bidding, 9% are inefficient, i.e., the winning bidder has a lower valuation than the losing bidder. In contrast, all auctions without last-minute bidding are efficient.

4.2 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 final bids (and thus auction prices) might be below the valuation of the loosing bidder. Because

^{(2009)).} As values were known with certainty in our experiment, being naive about the second–price auction mechanism as adopted by eBay (Roth and Ockenfels (2002) and Ockenfels et al.) is the most plausible explanation for the observed multiple bidding in our study.

¹⁷Roth 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. find experimental evidence that sniping occurs primarily as a best response to incremental bidding.

 $^{^{18}}$ For an auction duration of 5 minutes, we define bids that were submitted within the last 30 seconds as sniping bids. The period used to define sniping depends on the circumstances and the ratio of the auction time to the possibility of last-minute bidding. Ockenfels and Roth (2002), for example, refer to bids submitted in the last 5 minutes in auctions that last at least one day as sniping bids.

we are interested in 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

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

We solve the maximization problem of the seller (equation (5)) with the threshold price from equation (6) numerically. 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.¹⁹ For instance, the optimal BIN price for a risk-neutral seller who faces buyers with a 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 relative deviation from true value bidding observed in the experiment, ($\gamma = 13.5\%$), and the distribution of the risk preferences elicited from our participants, the modified model predicts BIN prices in the range of [0.39, 0.55] with an average of 0.46 and an acceptance rate of 37%.²⁰

The predicted acceptance rate of the modified model (37%) is closer to the one observed in the experiment (36%) compared to the one of the original model (26%). Also, the modified model is 11 percentage points more accurate than the original model when accounting for the observed BIN prices. Thus, allowing agents to anticipate the existence of lower auction prices compared to those resulting from true value bidding substantially improves the fit of the model.

4.3 Data Analysis

In this section, we study in more detail how BIN prices are set. On the one hand, sellers' pricing strategy might be well described by the model proposed in the previous section. This model suggests that optimal BIN prices crucially depend on both, the agents' risk preferences and the relative deviation of buyers' bids from their true value. On the other hand, sellers might also adjust their prices following an adaptive heuristic, i.e., increasing the BIN price in the following period when it was accepted and decreasing it if it was rejected.²¹ We consider both possibilities.

While transacting on eBay, sellers can collect and update information about buyer characteristics as

¹⁹If $\gamma = 0$ (i.e., true value bidding) the threshold price corresponds to that derived in equation (3).

²⁰Note that the computation of the relative deviation from true value bidding is based on the final bids of the losing bidders. Due to the proxy bidding procedure used by eBay the final bids of the winning bidders are not revealed.

²¹For 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 that 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 would have hence led to a 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 cases. Sellers increase their BIN price in 65% of cases if their BIN price is 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.

well as about their behavior. If this information is correlated with the level the observed auction prices deviate from the expected prices based on true value bidding, a seller could approximate this level and adjust the BIN price when the level of those determinants changes. For example, sellers who expect bids closer to buyers' valuations should increase their BIN price.

In the auction, sellers observe the number of submitted bids by each bidder, the experience buyers have with eBay (i.e., the number of completed transactions on eBay), and whether bidders submit last-minute bids. First, we investigated the influence of those variables on the relative deviation of the observed price from the expected price in standard second-price auctions. The details of the analysis are presented in Appendix E. We find a significant correlation between the level of price deviation and the number of bids, buyers' experience and last-minute bidding. More precisely, we find that the more experience the (winning) bidder has and the more bids the (losing) bidder submits, the more the observed price approaches the theoretical one. There is also some interaction between experience and the number of submitted bids. For example, for the average number of bids (i.e., 4 bids), experienced buyers bid slightly closer to their true value **than inexperienced buyers**. Finally, last-minute bidding especially from the losing bidder increases the relative deviation significantly.

BIN price setting

The data analysis so far has revealed that the information that is available on eBay, i.e., buyers' bidding behavior and their experience with eBay, allows sellers to conclude on 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:

$$bin_{it} = \beta_0 + \overline{bc}'_{it-1}\beta_1 + \beta_2 D_{it-1} + \beta_3 bin_{it-1} D_{Rit-1} + \beta_4 bin_{it-1} D_{Ait-1} + \mu_i + \varepsilon_{it},$$

with $t = (2, \dots, 6).$

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 $\overline{bc}_{it-1} = (\overline{nb}_{it-1}, \overline{ex}B_{it-1}, \overline{ex}B_{it-1}^2, \overline{sn}1_{it-1}, \overline{sn}2_{it-1})'$. 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.²² The vector of buyer characteristics contains the average number of bids per buyer (\overline{nb}_{it-1}) , the average number of completed transactions for all buyers normalized by 10 as a proxy for experience $(\overline{ex}B_{it-1})$, and seller *i*'s average count of observing one, respectively two, sniping bidders in an auction $(\overline{sn}1_{it-1} \text{ and } \overline{sn}2_{it-1})$. We have found that buyers' eBay experience has a non-linear influence on the relative deviation of the auction price (see Appendix E). Thus we also include the square of the experience proxy $(\overline{ex}B_{it-1}^2)$ allowing the seller to react to this variable in a non-linear way.

Some information can only be observed when an auction has been conducted, such as the number of bids and the event of last-minute bidding. Therefore, we add a dummy variable D_{it-1} that is one until

 $^{^{22}}$ When calculating the empirical averages, we give all information equal weights regardless of 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.

the first auction has been held and zero otherwise. For example, if the BIN price was accepted in t = 1, in period t = 2 seller *i* has no information about buyers' auction behavior. Thus, the dummy D_{i1} equals one.²³ It remains one until the period when the BIN price is rejected for the first time 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.

As in our experiment sellers make several decisions over time, we can also investigate whether they 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} are equal to 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 $(E(\varepsilon_{it}, \varepsilon_{is}) = 0 \text{ for } s \neq t)$ as well as with the covariates and fixed effects $(E(\varepsilon_{it} | \overline{bc}_{it-1}, \mu_i) = 0)$.

Variables	β	St.Dev	P > z
β_0	0.469	0.071	0.000
\overline{nb}	0.025	0.009	0.009
$\overline{ex}B$	0.042	0.016	0.012
$\overline{ex}B^2$	-0.003	0.002	0.065
$\overline{sn}1$	-0.143	0.066	0.033
$\overline{sn}2$	0.077	0.060	0.203
D	0.054	0.060	0.376
$bin_{t-1}D_R$	-0.163	0.996	0.106
$bin_{t-1}D_A$	0.008	0.120	0.947
σ_{μ}	0.183		
$\sigma_{arepsilon}$	0.088		

Table 3: BIN price, MLE, Nobs=100, N of sellers=20.

Table 3 presents the results of a panel regression with MLE. Without accounting for any additional information, sellers set BIN prices of around 0.47. However, when taking into account the effect of the information that sellers can observe (and evaluating those variables at their mean), the offered BIN price increases 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 (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

 $^{^{23}\}text{The value of the variables }\overline{nb},\overline{sn}1$ and $\overline{sn}2$ are in this case set to zero.

0.52).²⁴

Sellers raise their BIN price when the average experience in the buyer population (\overline{exB}) 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 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 last-minute bidders results in demanding lower BIN prices. Thereby, sellers react when observing 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 also observing 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 adjust their BIN price in the subsequent period solely as a response to the buyer's reaction towards the BIN price $(bin_{t-1}D_R \text{ and } bin_{t-1}D_A)$.

Finally, we find quite substantial heterogeneity among the sellers (σ_{μ}). Therefore, we investigate the impact of the sellers' personal characteristics on BIN prices. We regress the estimated individual fixed effects $\hat{\mu}_i$ on sellers' elicited risk preferences and their eBay experience. Thereby, we use two specifications that differ in the way eBay experience is measured. In the first one, we consider the total experience with eBay obtained either as a seller or buyer, while in the second one, we consider experience obtained only as a seller on eBay.²⁵ Both specifications convey a similar picture. First, risk preferences do not correlate with BIN price setting. Second, experience with eBay – obtained either as an eBay seller or also as an eBay buyer – has a substantial and significant impact on seller BIN price setting behavior. The more experienced a seller is, the higher the BIN price he asks for. For example, BIN prices of sellers with high experience (at the 75th percentile) are 8% higher than BIN prices of sellers with low experience (at the 25th percentile) and 5% higher than those of sellers with median experience.

5 Discussion and Concluding Remarks

This study investigates how eBay sellers set BIN prices in eBay auctions. The findings presented here result from a controlled laboratory experiment in which real eBay traders interacted on the eBay market platform. Thus participants not only brought experience with and knowledge of the (experimental) task, but made their decisions in the environment in which this experience was acquired. As in conventional laboratory experiments, we ensured that certain model assumptions were satisfied, such as an environment with private independent values for a single indivisible object, while excluding and controlling for other influences. We observe substantial behavioral differences in our study compared to the theoretical

²⁴These numbers are computed using the parameter estimates of Table 3 and evaluating all other variables at their mean values ($\beta_0 = 0.469, \overline{nb} = 3.82, \overline{exB} = 1.78, \overline{exB}^2 = 7.19, \overline{sn1} = 0.62, \overline{sn2} = 0.29, D = 0.14, bin_{t-1}D_R = 0.34, bin_{t-1}D_A = 0.16$).

²⁵We looked at the linear relation between the fixed effects $(\hat{\mu}_i)$ and elicited individual risk preferences $(risk_i)$ as well as the experience of our 20 sellers $(exS_i \text{ counted} as the number of completed transactions, normalized by 10): <math>\hat{\mu}_i = \gamma_0 + \gamma_1 \cdot risk_i + \gamma_2 \cdot exS_i + \varepsilon_i$. The parameter estimates obtained by OLS for the 20 sellers are (i) $\gamma_1 = 0.095(1.25), \gamma_2 = 0.016(2.14)$ using total experience and (ii) $\gamma_1 = 0.125(1.68), \gamma_2 = 0.039(2.03)$ using experience as eBay seller only, where t-values are presented in parentheses.

predictions and the results of other conventional lab experiments on BIN price auctions (Ivanova-Stenzel and Kröger (2008) and Shahriar and Wooders (2010)) that can be explained by participants' heterogeneity in experience with the eBay platform and the specific auction format of eBay. In our experiment, price determining bids are on average below those based on true value bidding. This leads to auction outcomes that differ substantially from those expected and observed in conventional lab experimental second–price auctions, in which participants submit bids close to their valuation. This should and –as our data analysis reveals– did indeed influence seller BIN price setting behavior.

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 last-minute bids 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 further suggests that sellers' individual characteristics also have an influence on the BIN price. 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 more experienced sellers are better aware of this selection effect than their less experienced colleagues and thus post higher prices.²⁶ Sellers risk preferences, on the other hand, seem not to play a role when deciding on the BIN price. This finding corroborates the suggestion of Ivanova-Stenzel et al. that sellers' risk preferences have a minor impact on BIN prices.

In summary, we find that sellers' behavior is in line with the qualitative predictions of the theory if the conventional model of BIN price auctions (based on the assumption of true value bidding) is modified to respond to the specific characteristics of the considered market institution. Our results also highlight potential consequences of information publicly available in (online) market institutions and underline the crucial role of institutional details and of agents' experience with the market institution.

 $^{^{26}}$ In a lab BIN auction experiment, Ivanova-Stenzel et al. also find 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.

A The "Buy-It-Now"– Option in eBay Auctions (at the time the experiment was conducted)

The BIN option on eBay enables the seller to call for an auction and to offer a 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 that 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 a 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 $\in 1$. There are several other options, such as e.g., a secret reserve price, placing the offer at the top of a page, etc.²⁷ 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.²⁸

B Experiment: Instructions and seller decision screen

B.1 Instructions

This is a 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, you will take part in several eBay auctions. In each auction, there are three agents, one seller and two buyers. At the beginning of the experiment, each participant is assigned a role (seller

 $^{^{27}}$ 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 US at the time of the experiment.

 $^{^{28}}$ 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)).

or buyer) and keeps his/her role during the entire experiment.

All information is provided in an experimental currency, termed eBay-Euro. At the beginning of each auction, the private reselling value for the product of each buyer is determined. A buyer will receive this value from the experimenters if he/she purchases the product. All reselling values 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 reselling value but not about the reselling value of the other buyer. The seller is not informed about the reselling values of the buyers.

Each auction proceeds as follows:

At the beginning, the seller determines a "Buy-it-Now price" for the product. 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 set by 1 eBay-Euro. Then, one of the buyers, knowing his/her reselling value for the product, decides wether s/he wants to purchase the product at the "Buy-it-Now price" or not.

If the buyer accepts the "Buy-it-Now price", s/he purchases the product at this price. The auction is then over. The payoff to the buyer is the difference between his/her value 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", s/he **must** submit a bid in order to initiate a conventional eBay-auction, in which the other buyer also participates. Both buyers can now submit bids **within a 5-minute** bidding time slot. 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 the experimenters using a clock projected on the wall that counts down the seconds to the end of the auction. The clock is adjusted to the official eBay time²⁹ The auction ends once the clock on the wall reaches zero. **The end of the auction is determined by the clock in the room, not by the auction end time displayed on eBay! Any bids arriving later than the fixed auction end time by the experimenters will not be considered. After the 5-minute bidding time, the buyer who has submitted the highest bid wins the auction and gets the product at the price at which the auction has ended (under the terms of the eBay rules). In the 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 then over. The payoff to the winner of the auction is the difference between his/her value 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 trading groups (one seller and two buyers) are formed randomly. Each buyer decides whether to accept or to reject 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 (see 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.

²⁹The official eBay time can be found at

http://cgi1.ebay.de/aw-cgi/eBayISAPI.dll?TimeShow&ssPageName=home:f:f:DE

Sellers will use eBay accounts licensed to the experimenters. Each seller will find the name of the eBay account s/he is going to use on the sheet "Information about your Role" but not the password for this account. Thus, the account cannot be used outside of the experiment.

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

If you are a **seller**, please log out from your personal account. Each auction is prepared and will be executed by the experimenters on behalf of the seller (i.e., setting the category number, product reference number, product description, starting price). The seller must however determine a "Buy-it-Now price" and indicate it 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 by the experimenters. Sellers can follow the proceeding of their auctions at any time on eBay using the reference numbers of their products for sale.

Then, the buyers who decide whether to accept or to reject the "Buy-it-now price" in the ongoing auction, are informed about their reselling value and the product reference number with the sheet "Information about your auction." Those buyers must now follow steps K3 and K4 described in the sheet "Information about Your Role".

Buyers who do not make a decision on the "Buy-it-Now price", will get the information about their reselling value and the product reference number when they enter the auction, i.e., after a decision on the "Buy-it-Now price" has been made. They must now follow steps K3 and K4 described in the sheet "Information about Your Role." If you cannot find the product in step K4, make sure that you have typed the product reference number correctly. If you cannot find the product even when you enter the reference number correctly, this means that the product has been sold at the "Buy-it-Now price."

Summary:

Each Auction lasts 9 minutes: Seller decision on the "Buy-it-Now price." 2 minutes; Buyer decision to accept or not the "Buy-it-Now price." 2 minutes; In case the "Buy-it-Now price" is rejected, bidding time in the auction: 5 minutes.

Please don't submit 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 to not disclosing this information to third parties and to not keeping or using it after the experiment.

Payment Rules:

The exchange rate is: 1 eBay-Euro = $\in 0, 20$.

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

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

Buyers are granted an initial lump sum payment of $\in 6$. Should you, as a buyer, incur losses, they will

be deducted from your earnings (or from your initial payment).

The instructions for the second part will be distributed after the first part is completed.

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., $\in 5$ if lottery "A" was chosen and $\in 8.20$ 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., $\in 3$ if lottery "A" was chosen and $\in 0.20$ if lottery "B" was chosen)

B.2 Screen Shot of Seller BIN Price Decision



Figure 2: 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.

C Data

Sellers	Earnings in	Switching point	Estimated risk
Participant	eBay experiment	in lottery experiment	preference
1	0.38	7	0.86
2	0.36	4	-0.06
3	0.30	8	1.24
4	0.47	7	0.89
5	0.30	7	0.83
6	0.17	5	0.23
7	0.33	4	-0.06
8	0.29	7	0.83
9	0.23	9	1.47
10	0.32	6	0.53
11	0.31	4	-0.05
12	0.27	8	1.22
13	0.34	8	1.26
14	0.37	6	0.54
15	0.39	4	-0.06
16	0.39	7	0.86
17	0.55	7	0.92
18	0.23	5	0.23
19	0.42	5	0.25
20	0.23	5	0.23

Table 4: Normalized earnings in the eBay experiment, switching point in the lottery experiment and estimated risk preferences. N=20 sellers.

Buyer	Earnings in	Switching point	Estimated risk
Participant	eBay experiment	in lottery experiment	preference
1	0.23	7	0.81
2	0.11	8	1.12
3	0.15	7	0.78
4	0.07	4	-0.05
5	0.12	7	0.77
6	0.00	5	0.21
7	0.28	nm	nm
8	0.19	nm	nm
9	0.06	7	0.74
10	0.05	4	-0.05
11	0.23	5	0.23
12	0.03	9	1.38
13	0.24	5	0.23
14	0.10	4	-0.05
15	0.17	6	0.49
16	0.15	5	0.22
17	0.01	6	0.45
18	0.14	6	0.48
19	0.24	nm	nm
20	0.04	4	-0.05
21	0.10	7	0.76
22	0.26	4	-0.05
23	0.06	7	0.74
24	0.34	7	0.84
25	0.16	7	0.78
26	0.13	7	0.77
27	0.18	4	-0.05
28	0.04	6	0.46
29	0.04	nm	nm
30	0.00	7	0.71
31	0.20	nm	nm
32	0.21	6	0.50
33	0.18	5	0.23
34	0.22	5	0.23
35	0.28	5	0.24
36	0.13	5	0.22
37	0.00	7	0.71
38	0.00	7	0.71
39	0.23	7	0.81
40	0.06	5	0.21

Table 5: 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).

Session		Profits		BIN	Auction	Number of	
(N)		Sellers	All	Buyers	Price	Prices	$\mathbf{submitted}$
			buyers	who bought	Offer		bids
1	Mean	0.38	0.15	0.31	0.55	0.34	4.8
(24)	Std.	(0.19)	(0.23)	(0.24)	(0.08)	(0.19)	(2.6)
	Median	0.47	0.00	0.29	0.53	0.34	5.0
	IQR	(0.27)	(0.28)	(0.21)	(0.10)	(0.34)	(4.0)
2	Mean	0.33	0.16	0.32	0.44	0.34	5.6
(24)	Std.	(0.18)	(0.21)	(0.20)	(0.16)	(0.21)	(4.0)
	Median	0.32	0.00	0.27	0.45	0.34	4.0
	IQR	(0.23)	(0.27)	(0.29)	(0.29)	(0.30)	(6.5)
3	Mean	0.33	0.18	0.36	0.52	0.26	4.4
(24)	Std.	(0.21)	(0.25)	(0.24)	(0.14)	(0.22)	(3.0)
	Median	0.31	0.01	0.32	0.51	0.22	4.0
	IQR	(0.27)	(0.32)	(0.36)	(0.21)	(0.23)	(5.5)
4	Mean	0.32	0.16	0.33	0.45	0.20	3.6
(24)	Std.	(0.17)	(0.23)	(0.23)	(0.12)	(0.09)	(1.9)
	Median	0.32	0.00	0.27	0.40	0.21	3.3
	IQR	(0.19)	(0.27)	(0.43)	(0.14)	(0.11)	(2.8)
5	Mean	0.29	0.17	0.33	0.56	0.23	2.5
(24)	Std.	(0.16)	(0.22)	(0.20)	(0.26)	(0.16)	(1.1)
	Median	0.27	0.02	0.34	0.46	0.21	2.5
	IQR	(0.22)	(0.34)	(0.20)	(0.39)	(0.12)	(1.5)

D Overview of results by session

Table 6: Overview of Results

Session	1	2	3	4	5
Acceptance rate (in %)	21	33	38	50	38
Efficiency (in %)	88	88	88	88	83
when BIN price was accepted (N)	60(5)	75(8)	89(9)	75(12)	67(9)
in auction without sniping (N)	100(5)	100(6)	100(4)	100(1)	100(3)
in sniping auction (N)	93(14)	90(10)	82 (11)	100 (11)	92(12)

Table 7:	Overview	of Results	continued
10010	0.101.1011	01 100000000	contractor.

E Price deviation in eBay auctions

The relative deviation observed in auction t is the difference between the second-highest valuation (V_{2t}) and the observed price (p_t) normalized by V_{2t} , $rd_t = (V_{2t} - p_t)/V_{2t}$.³⁰ We regress the relative deviation (rd_t) in auction t on a vector of bidder covariates x_t :

$$rd_t = \kappa + x'_t \lambda + \varepsilon_t$$

The vector x_t consists of the following bidder characteristics, the experience the buyer has with eBay, approximated by the number of completed transactions normalized by 10 (exB) and a quadratic term of experience (that allows to capture nonlinear effects). For each auction t, the vector contains the number of submitted bids (nb_t) normalized by 10, a dummy variable ($sniping be_t$) that equals 1 if the bidder submitted a last-minute bid that arrived on time.³¹ Given our finding of a nonlinear relation between experience and the number of bids, we allow for interaction between these variables ($nb_t \cdot exB$) as well as this interaction to enter non-linearly. Those variables enter twice, once for the losing bidder (subscript "0") and once for the winning bidder (subscript "1"). By construction, the number of submitted bids is correlated between bidders. Therefore, we add an interaction term $nb_0 \cdot nb_1$. Finally, the ε_t captures auction idiosyncratic errors and is assumed to satisfy $E(\varepsilon_t) = 0$.

Variable	λ	St.Dev	P > z
κ	0.064	0.037	0.088
exB_0	0.017	0.014	0.246
exB_0^2	0.000	0.001	0.919
nb_0	-0.109	0.062	0.085
nb_0^2	0.045	0.024	0.066
$(n\dot{b}_0 \cdot exB_0)$	-0.043	0.039	0.272
$(nb_0 \cdot exB_0)^2$	0.001	0.007	0.872
$sniping_0$ be	0.102	0.016	0.000
exB_1	-0.049	0.022	0.032
exB_1^2	0.005	0.002	0.023
nb_1	0.056	0.151	0.711
nb_{1}^{2}	0.017	0.107	0.874
$(nb_1 \cdot exB_1)$	0.162	0.101	0.115
$(nb_1 \cdot exB_1)^2$	-0.117	0.049	0.020
$sniping_1$ be	-0.016	0.017	0.327
$nb_0 \cdot nb_1$	-0.094	0.096	0.331

Table 8: Median regression of variables influencing the relative deviation from true value bidding of price determining bids. Nobs=77.

³⁰Note that a negative relative deviation means that the observed price is higher than the one theoretically predicted, and a positive number indicates that the seller received a lower price in the experiment than theoretically predicted in standard second–price auctions.

We should also note that in 72 out of 77 auctions the outcome was efficient, i.e., the losing bidder was the bidder with the second-highest valuation.

³¹Bids that were submitted in the last 30 seconds before the end of the auction were classified as last-minute bids.

Figure 4: Relation between relative deviation and number of bids for different levels of experience (25th, 50th, and 75th percentile).

Table 8 presents the results of a median regression.³² There is a positive deviation to start with of about 6%. The more experience the (winning) bidder has the lower the price deviation. However, experience enters also via the interaction term with the number of bids and its total effect needs to be seen conditional on the number of submitted bids. Figure 3 depicts the relation between the relative deviation and experience for different number of bids using the estimates from Table 8.³³ 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 in bigger steps than bidders with more experience. As a consequence, for more than five bids, the picture reverses and bidders with less experience bid closer to their value.

Our estimation also indicates that the relative deviation decreases with the number of bids submitted by the losing bidder. This is not surprising because eBay accepts only an increase of the proxy bid. However, we find that this relation varies with buyers' experience. Figure 4 visualizes this relation for buyers with different levels of experience using the estimates of Table 8.³⁴ The relative deviation is highest and around 18% when both bidders have little (at the 25th percentile) experience and the auction ends with both bidders having submitted one bid each. For the same scenario, the relative deviation is around 14% when bidders have median experience and only 9% for experienced bidders (at the 75th percentile). If only the losing bidder or both bidders submitted successful last-minute bids, the relative deviation is around 12%.³⁵

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 $^{^{32}}$ We chose median regression as a few participants had some extremely high values for their experience and OLS might be vulnerable to those outliers. For the 95th percentile and the maximum of buyers experience, we observe values of experience 81 and 338 transactions, respectively, which is quite extreme compared to the 16 transactions at the 75th percentile. Comparing the mean (22) and median (7) also suggests that the outlier impact the mean value.

³³The figure depicts the case when both bidders have the same experience $exB_0 = exB_1$ and submit the same number of bids $nb_0 = nb_1$. The effect of other variables, $sniping_0$ be and $sniping_1$ be, is taken at their mean values.

³⁴The figure depicts the case when both bidders have the same experience $exB_0 = exB_1$ and submit the same number of bids $nb_0 = nb_1$. The effect of other variables, $sniping_0$ be and $sniping_1$ be, is taken at their mean values.

³⁵This number results from simulations with either $sniping_0 be = 1$ and $sniping_1 be = 0$, or $sniping_0 be = sniping_1 be = 1$ with all other variables entering at their median values ($\kappa = 0.064, exB_0 = 0.7, nb_0 = 0.3, exB_1 = 0.9, nb_1 = 0.3$). Using averages yields similar results.

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.
- 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).
- 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).
- 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.
- 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 (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.

(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.
- 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 (2010): "An Experimental Study of Auctions with a Buy Price Under Private and Common Values," University of Arizona Working Paper 07-19.
- SHUNDA, N. (2009): "Auctions with a buy price: The case of reference-dependent preferences," *Games* and *Economic Behavior*, 67(2), 645–664.
- 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.