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How eBay Sellers set "Buy-it-now" prices – Bringing The Field Into the Lab [1]

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Abstract

In this paper we introduce a new type of experiment that combines the advantages of lab and field experiments. The experiment is conducted in the lab but using an unchanged market environment from the real world. Moreover, a subset of the standard subject pool is used, containing those subjects who have experience in conducting transactions in that market environment. This guarantees the test of the theoretical predictions in a highly controlled environment and at the same time enables not to miss the specific features of economic behavior exhibited in the field. We apply the proposed type of experiment to study seller behavior in online auctions with a Buy-It-Now feature, where early potential bidders have the opportunity to accept a posted price offer from the seller before the start of the auction. Bringing the field into the lab, we invited eBay buyers and sellers into the lab to participate in a series of auctions on the eBay platform. We investigate how traders' experience in a real market environment influences their behavior in the lab and whether abstract lab experiments bias subjects' behavior.

JEL classifications: C72, C91, D44, D82.

Keywords: Online Auctions, Experiments, Buyout Prices

1 INTRODUCTION

When auctions are conducted in the laboratory, one usually uses abstract terminology in instructions, abstract goods, and induced valuations. While this approach ensures a very reliable test of the theory in a highly controlled environment, its relevance for predicting behavior in the field is limited.

In field experiments economists use subjects from the field, field goods, and field context. The observed behavior in such experiments often reveals key features of economic transactions that cannot be seen in the lab. However, one characteristic of field experiments compared to lab experiments is that deviations from the theoretical predictions might be an artifact due to the loss of control in the field and the fact that in a field experiment one cannot guarantee that all assumptions of the theoretical models are satisfied.

In this paper we introduce a new type of experiment that combines the advantages of both, lab and field experiments. We propose to bring the field into the lab. This guarantees the test of the theoretical predictions in a highly controlled environment and at the same time enables not to miss the specific features of economic behavior exhibited in the field. The experiment is conducted in the lab, using an unchanged market environment from the real world. Moreover, a subset of the standard subject pool is used, containing subjects who have experience in conducting transactions in that market environment.

We apply the proposed type of experiment to study seller behavior in single unit auctions preceded by a negotiation stage, i.e. where early buyers have the opportunity to buy the item for sale at a pre-specified price prior to the auction. The reason for the growing interest in this and similar mechanisms is their use by many internet auction platforms. For example, eBay, Amazon, and Yahoo, the biggest online auction platforms, use such a feature, albeit with different characteristics. Whereas eBay's "Buy-It-Now" (henceforth called "BIN") price can only be accepted as long as no standard bids have been submitted, the BIN price on Yahoo Auctions may be accepted throughout the auction. In this paper, we focus on eBay's BIN option.

We invited students who have already used the eBay platform into the lab to participate in real eBay auctions. Therefore, participants bring experience with the task of the experiment and knowledge of the trading institution. Moreover, certain information concerning their previous trading activities can be used for the analysis. This implies two substantial advantages over standard lab experiments. First, one would expect that field experience could play a major role in helping individuals make their decisions. We can answer the question how traders' experience on eBay influences subjects' behavior in the lab. Second, we can check whether abstract lab experiments bias subjects' behavior and investigate in which way behavior on eBay differs compared to behavior in standard lab experiments.

However, our eBay experiment is not a standard field experiment. Using the taxonomy of Harrison and List (2004), our eBay experiment might be classified as a "framed field experiment" since there is field context in the task and the information set that subjects can use. However, Harrison and List's definition of "framed field experiment" assumes a nonstandard subject pool. Moreover, in our setting, we keep essential characteristics of a conventional lab experiment and avoid the loss of control which is inevitable for a field experiment. Another advantage of our experiment compared to field experiments is that we run several rounds and can observe changes in behavior over time, as is usually done in standard lab experiments.

To sum up, our eBay experiment combines the advantages of both lab and field experiments. It might be considered as the first step towards the development of an "ideal" experiment, in the sense that we are able to observe subjects in a controlled setting but where they do not perceive any of the controls as being unnatural.

The proposed new type of experiment aims at improving the prediction power of field experiments. In the field of online auctions, e.g., Ockenfels (2005) and Garratt et al. (2004) pursue the same objective. Ockenfels (2005), conducted only a one-shot field experiment on eBay, by selling artificial goods to subjects registered on eBay, whose valuations were induced. Garratt et al. (2004) recruited experienced eBay traders and requested them to bid in second-price sealed bid auctions with induced valuations. The auctions were conducted on the Internet, but neither on the eBay platform nor in a controlled environment.

The design of previous field experiments on online auctions did not allow to study BIN price setting behavior of sellers, because the experimental auctions were set up by the experimenters and not by the subjects. For example, Durham et al. (2004) study the impact of buyer reputation, seller reputation, and the magnitude of the BIN price on buyer behavior.

Ivanova-Stenzel and Kröger (2005) study sellers' BIN price setting behavior in a conventional lab experiment. Contradicting the theoretical predictions under risk neutrality, they observe a high number of transactions at the BIN price, caused by low price offers by the sellers or acceptance of too high prices by the buyers. Whereas buyers' deviating behavior could be explained by risk aversion, seller behavior, especially the significant amount of too low price offers, remains a puzzle.

Our experimental design allows to study seller behavior in a field environment. Our aim is to examine whether the puzzle observed in conventional lab auctions extends to online auctions. We investigate sellers' BIN price setting decisions, taking into account the effect of buyer behavior on eBay, experience with the eBay market platform, learning during the experiment, and risk aversion. To that aim, we also elicit traders' risk aversion by simple lottery choice experiments, as introduced in Holt and Laury (2002).

We find that the phenomenon of sellers setting too low BIN prices does not vanish when the transactions take place in a real world market environment. The majority of buyers' decisions on the BIN price are rational, but deviations are mostly towards acceptance of too high prices. In the auctions, buyers systematically underbid their value. Experience with trading on eBay does not reduce the non-optimal price setting. Adaptation of BIN price setting during the experiment indicates that "mislearning" from previously conducted transactions might even lead sellers away from optimal prices. Finally, a comparison of our results to those of the lab experiment by Ivanova-Stenzel and Kröger (2005) reveals similarities in the price setting behavior.

The remaining paper is organized as follows: In Section 2, we report some empirical results on the role of the BIN price in naturally-occurring auctions. Section 3 reviews the theoretical predictions on price setting behavior in our experimental auctions. Section 4 spells out the specifics of our novel experimental design. The results are presented in Section 5. In Section 6, we present the comparison of our results to those of a conventional lab experiment. Section 7 concludes.

2 EMPIRICAL OBSERVATIONS

BIN prices have become increasingly popular among buyers and sellers. eBay.com reports for 2004 that a share of 28% of all transactions have taken place at the BIN price. Chiu and Cheung (2004) observe that depending on the product category, between 13% and 60% of newly offered items on eBay can be bought at a BIN price.

There is a number of empirical papers studying the BIN option on eBay. For example, in Durham et al. (2004) and Anderson et al. (2004), it has been found that experienced sellers use the BIN price more frequently and that BIN price offers of sellers with a high reputation are accepted more frequently. Moreover, the higher the BIN price, the higher is the final sale price. Both studies have in common that they analyze transactions of goods where multiple items are offered simultaneously and where a market price (resale value) is easily recognizable (American Silver Eagle coins and Palm computers, respectively).

We, however, are interested in private value auctions. Therefore, we collected market data of items where the assumption of independent private valuations is a reasonable approximation.[1] We decided to collect data on antiques, furniture, used music instruments and individual collectibles, goods with no easily recognizable market value. We justify our choice by the uniqueness of the items in question and by their low value which, due to transaction and shipping costs, lets resale seem a rather unlikely option. We collected data from eBay auctions in March and April 2002. Altogether we observed 668 items, 199 of which were sold.

Among those items where a BIN price is offered, 33% of sales occur at that price. The reservation price is 27.4% below the BIN price on average. When the BIN price is rejected, the reservation price was 31% below the BIN-Price, compared to 21.7% when it is accepted. This indicates that BIN prices are

[1] Of course it will always remain an approximation. As Boatwright et al. (2006) highlight, there is significant disagreement among auction experts in which categories on eBay private value auctions are to be found.

more frequently accepted when an auction is not able to yield substantial savings. Interestingly, only 8% of the auctions end at a price above the BIN price. This indicates that rejection decisions by players can be assumed to be mostly rational.

Moreover, BIN prices are frequently executed towards the end of the auction. The average time span "saved" by the BIN price is only 2.9 days whereas the average auction duration is 7 days. The time the BIN option is executed is very similar to the time where the first bid is submitted (3.05 days before the auction ends). As we consider auctions for arts, antiques and collectibles, and as shipping normally takes several days in any case, this suggests that time preferences play a weak role, if any, in the acceptance decisions. We often found auctions where the BIN price was even executed on the last day of the auction.

3 THEORETICAL PREDICTIONS

We consider a setting with one seller, who sells one indivisible good to one of two buyers. The buyers have symmetric independent private valuations, drawn from a uniform distribution with support [0,1]. The seller's reservation value is zero. In order to model the sequential arrival in online auctions, we assume that the seller specifies a BIN price which is offered to one of the buyers, henceforth referred to as buyer 1. If buyer 1 accepts the price, the transaction is completed. Otherwise, an auction with both buyers takes place.[2] When confronted with the BIN price, buyer 1 thus compares his utility from accepting the BIN price to the expected payoff from participating in an auction. The seller chooses the BIN price such that his utility is maximized, anticipating the acceptance decision of buyer 1. Thereby, he has to take into account that the expected utility from an auction depends on the BIN price, as in case of a rejection, information about buyer 1's valuation is revealed.

If the auction is modelled as a second-price sealed bid auction (as in Ivanova-Stenzel and Kröger (2005)), true value bidding is a weakly dominant strategy and buyer 1 faces the following problem when confronted with a BIN price p:

$$u(v-p) = \int_0^v u(v-x)f(x)dx \tag{1}$$

Hence, for the case of risk neutrality, a critical valuation above which a price p is accepted by buyer 1, i.e., the acceptance threshold can be derived as

[2] Note that the setting can be easily generalized to n bidders and any independent distribution of private values. In an eBay auction, there is always a "bidder 1", who, by submitting a bid, can prevent all bidders arriving later from accepting the BIN price.

$$v^*(p) = \begin{cases} 1 - \sqrt{1-2p} & \text{if } p < \frac{1}{2} \\ 1 & \text{if } p \geq \frac{1}{2} \end{cases}$$

Thus, BIN prices at or above $\frac{1}{2}$ should never be accepted. Solving the sellers' maximization problem

$$\max_{p \in [0,1]} \Pi^S(p) = p \int_{v^*(p)}^{1} f(x)dx + \int_0^{v^*(p)} y g_{(1)}(y, v^*(p))dy \int_0^{v^*(p)} f(x)dx \tag{2}$$

yields optimal BIN prices at or above $\frac{1}{2}$ (that are never accepted).[3] Therefore, sales will always take place in the auction. Ex ante expected earnings are thus $1/3$ for the seller and $E[v_i^2/2] = 1/6$ for each buyer.

However, the non-existence of transactions at the BIN price derived above does not hold if buyers and/or sellers are risk averse. In the following, we assume heterogeneous risk preferences. For our analysis we restrict risk preferences to belong to the class of constant relative risk aversion[4]

$$u(x) = \frac{x^{(1-\alpha)}}{1-\alpha}$$

In this case, as shown in Ivanova-Stenzel and Kröger (2005), one cannot explicitly derive an acceptance threshold. However, we can derive numerical solutions, including the individual risk aversion parameter for each buyer and seller, assuming that sellers also know the distribution of risk preferences among the buyers. In order to derive these numerical solutions for our case, we elicit individual risk preferences and estimate CRRA parameters for all participants using a lottery choice experiment (see Section 4). The results from that experiment are used to derive both a distribution of risk preferences and predictions for individual price setting and acceptance behavior. We predict BIN prices in the interval [0.45,0.55], and an acceptance rate of 18.9%. Since seller risk aversion drives prices down whereas buyer risk aversion has the opposite effect, the lower bound of the predicted prices is still close to that predicted under risk neutrality. However, the prediction of no transactions at the BIN prices is not maintained for the case of heterogeneous risk preferences.

[3] Thereby, $g_{(1)}(y, v^*(p)) = (1 + v^*(p) - 2y)/v^*(p)$ is the density function of the minimum value (the first order statistic) for the cdf $G(x) = x/v^*(p)$ when either one or both bidders' valuations lie in the interval $[0, v^*(p)]$.

[4] 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.
By assuming CRRA, we can compare our findings to the existing results e.g. in Goeree et al. (2003) or Holt and Laury (2002).

This result is in line with findings reported in the literature. For example, Mathews (2002), Katzman and Mathews (2002), Reynolds and Wooders (2004) and Budish and Takeyama (2001) develop models in which the use of BIN prices can be part of an equilibrium when either sellers or buyers are risk averse, albeit modelling either the bidder arrival or the auction mechanism differently.

Since in our experiment we use the eBay platform, our auctions can obviously not be considered as second price sealed–bid auctions. Still, as Ockenfels and Roth (2003) show, bidding more than one's own valuation is a weakly dominated strategy. Further, there is no longer any dominant strategy. However, it is shown that all equilibria involve bidding the true valuation at some point in time. Differences in the resulting prices may only occur because last minute bids have a positive probability of being lost. On the other hand, if this probability is negligible and if late bidders have already submitted several bids earlier such that their final bid is already substantially above the minimum bid, the presented second price sealed bid auction model can be used for deriving reasonable predictions for seller revenue in eBay auctions. In comparison to Ockenfels (2005) and Ockenfels and Roth (2003), our design allows to observe bids arriving too late[5] and thus to compute the risk of a last minute bid being lost. This probability is indeed low in our experiment (in 5% of the cases where a bidder has submitted bids in the last 30 seconds of the auction, one of these bids arrived too late) and there is a significant amount of multiple bidding (on average each bidder submitted 4.2 bids per auction[6]).

Nevertheless, there are other reasons why final prices in eBay auctions may be below the second highest valuation. For example, Ockenfels and Roth (2002) introduce "naive incremental bidding" as a possible off–equilibrium strategy: A bidder who adopts this strategy always tries to be the high bidder until their valuation is reached. Thus, the bidder only raises his bid after being outbid, and only as much as needed to become the high bidder again. This strategy is obviously vulnerable to last minute bidding. If such an "incremental" bidder loses the auction his final bid (and thus the price) may be below his valuation. They also conjecture that subjects may wrongly perceive eBay auctions as first-price English auctions.[7] Both effects reduce the seller's expected auction revenue. Thus, the seller must take into account these effects when computing the optimal BIN price. Therefore, BIN prices below 0.45, the lower bound of the predicted price interval, may be optimal. More specifically, if the expected price in an auction is only γv_l, where $\gamma \in [0,1]$ and v_l the second highest valuation, and if the object is still allocated to the bidder with the highest valuation, the acceptance threshold for buyer 1[8] can be derived from

[5]As we describe in more detail in section 4, in our experiment the time to submit bids in an eBay auction was 5 minutes.

[6]Among those who submitted bids too late, the average number of bids is even 8.3.

[7]This means that they are unaware of eBay's proxy bidding system and think that in case of winning they have to pay the maximum bid they submit.

[8]Buyer 1 is still assumed to decide rationally.

$$u(v-p)=\int_0^v u(v-\gamma x)f(x)dx \tag{3}$$

Under risk neutrality, it can be shown that for BIN prices in the interval $\left[\frac{\gamma}{2},\frac{1}{4-2\gamma}\right]$, there are two threshold values, a lower and an upper one. Buyer 1 accepts the BIN price if his valuation is between these thresholds. The lower threshold $\underline{v}^*$ and the upper threshold $\overline{v}^*$ can be derived as

$$\underline{v}^*(p)=\frac{1-\sqrt{1-4p+2\gamma p}}{2-\gamma}$$
$$\overline{v}^*(p)=\min\left\{1,\frac{1+\sqrt{1-4p+2\gamma p}}{2-\gamma}\right\}$$

Note that given the observed underbidding in our experiment ($\gamma = 0.865$), the upper threshold is only relevant for BIN prices in a very narrow interval [0.43,0.44].

Solving the maximization problem of the seller leads to an optimal BIN price of 0.43. The predicted acceptance rate is 23%.

Combining the estimated risk preferences with the observed underbidding in our experiment we predict BIN prices in the range of [0.43, 0.51], and an acceptance rate of 25%.

Risk Preferences*	Underbidding	BIN Price	Acceptance Rate	Avg. Transaction Price
RN	No	[0.5, 1]	0%	0.33
	Yes	0.43	23%	0.29
RP	No	[0.45,0.55]	19%	0.34
	Yes	[0.43,0.51]	25%	0.30

*RN refers to the risk neutrality assumption and RP to the inclusion of the measured risk preferences

Table 1: Theoretical Predictions

Table 1 summarizes our theoretical predictions. The bottom line is that BIN prices below 0.43 cannot be explained by any variant of the model. Only in the baseline case (risk neutrality, no underbidding), all sales are predicted to take place in the auction. Given the estimated CRRA parameters, prices increase slightly when risk preferences are included.

Finally, we mention that there are other attempts of explaining transactions at the BIN price in equilibrium. E.g., Bose and Daripa (2006) show that posted price selling followed by an auction with a temporary buy-now option implements the optimal mechanism if buyers' valuations are discontinuous. Mathews (2004) and Montgomery et al. (2004) explain BIN transactions by assuming time preferences or bidding cost. With our experimental design, we can exclude these explanations.

4 EXPERIMENTAL DESIGN AND PROCEDURE

4.1 *Preparation of the Experiment*

The first step in the recruitment process was a survey that we conducted among all students that were registered in our experimental database. We asked all 900 students whether they had a valid eBay account and how often they had bought or sold items on eBay in the past. About 170 students replied. Among those students, who were mainly undergraduate economics and business students, we recruited our 120 subjects. We made sure that all of them possessed a valid eBay account which they had registered before we started the recruitment process.[9]

Before each experimental session, we prepared 24 auctions, using four eBay accounts, licensed to the experimenters. We made sure that all seller accounts were similar with respect to the number of reputation points. In each auction, we offered one used book.[10] 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 reserve price of one Euro. The BIN price was not specified yet.

4.2 *Experimental Procedure*

As mentioned before, we used the eBay platform to conduct the experiment. Nevertheless the controlled environment was maintained since during the whole experiment all traders were present in the laboratory. Buyers used their existing eBay accounts. Sellers did not use their own accounts. They had to enter their decision on the BIN price manually on a paper, featuring a screen shot of the eBay page (see the screen shot in Appendix B). The actual auctions were then conducted using the experimenters' accounts (see above). The aim of this procedure was to avoid the address exchange between subjects that would normally have taken place after completed transactions. Moreover, we wanted to eliminate the possible influence of sellers' reputation scores on buyer behavior. For all activities on eBay we used a fictitious currency, termed *eBay-Euro*, with 5 *eBay-Euros* being equivalent to 1 real Euro.

Altogether we ran seven sessions with 12 participants each. Due to technical problems during the first two sessions we decided to drop them from the data analysis.[11]

[9] This did not necessarily imply that they had already completed a transaction. However, we think that subjects who have registered at eBay, are somewhat familiar with the trading system.

[10] We chose mostly economics books or software books because we wanted to avoid distortions by fun bidders. 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.

[11] For example, in the first session, the Internet connection was so slow that some behavior observed in real online auctions (e.g. multiple bidding) would not have been possible.

Before each session, we randomly drew values for each buyer and each item. All buyers' values were drawn independently from the commonly known set {1, 1.5, 2,....,50}, with all values being equally likely.

Each session consisted of six auction rounds. Upon arrival in the lab, participants were provided detailed instructions (see Appendix A) and were informed whether they would act as sellers or as buyers throughout the whole experiment. The sellers were also given a sheet containing the reference number of all of their items, such that they were able to observe the proceeding of the auction at any time, without using their account.

At the beginning of each round, the sellers received the decision sheets mentioned above, on which they had to specify a BIN price in the set {1, 1.5, 2,...., 50}. In order to keep the roles anonymous, 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 auctions.

In each round, the trading group (1 seller and 2 buyers) were randomly determined. Thus, in each round there were four buyers acting as buyer 1, who could decide on the BIN price, and four buyers acting as buyer 2, who could only participate in case the BIN price was rejected. Each buyer acted as buyer 1 in three (of the six) rounds. To avoid unnecessary path dependencies, there was no more than one trading group consisting of the same subjects acting as seller and buyer 1. Moreover, two buyers were not matched into the same trading group more than once.

When all auctions were started and appeared on eBay, i.e., they could be found by entering the reference number into the eBay search engine, 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 posted BIN price within two minutes.

After all subjects acting as buyer 1 had made their decisions, we informed buyer 2 about their valuations and the items' reference numbers. If the auction had not ended at the "Buy-It-Now" price, both bidders had now five minutes to bid on the item. A clock was projected on the wall, counting down seconds to the end of the auction. We adjusted this clock to the official eBay time[12] and fixed the auction end time. Any bids who arrived later than this given time were not considered. The aim of the chosen auction duration was to enable participants to submit multiple bids, because this is frequently observed in eBay auctions. At the same time, it was short enough to exclude time preferences as a possible reason for accepting BIN prices. By using the reference number of the items both buyers and sellers were able to observe the auction at any time.

We asked all our participants not to rate the sellers after the auction and promised not to rate the participants ourselves.

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

4.3 *Follow-Up Experiment*

At the end of each session, subjects participated in a follow-up lottery experiment which was designed similarly to the one discussed in Holt and Laury (2002). In this experiment, subjects had to choose among 10 pairs of lotteries, determined by the probability to win a high or a low amount of money. Among each pair of lotteries, the probability of winning the higher amount was equal, but the amounts were different. Each pair consisted of a risky lottery, in which the low amount was €0.20 and the high amount €8.20. In the less risky lottery, the amounts were €4.00 and €5.00. From lottery pairs 1 to 10, the probabilities of winning the high amount increased from 10% to 100%. More details on the lottery choices can be found in Appendix C. We designed the stakes such that they were similar to the range of possible earnings in an eBay transaction.

We are aware that there is critique, e.g. the one by Heinemann (2003), saying that lottery experiments cannot measure risk aversion without taking subjects's wealth into account. We notice that this critique does not apply to our setting, because our aim is not to elicit utility functions of the subjects but rather to compare estimated levels of risk aversion from BIN price acceptance decisions to the level exhibited in lottery choices. We thus are not interested in subjects' overall risk aversion but only in risk averse behavior in our experiment. The reason is that the external wealth level of a subject is the same both in the auction and in the lottery experiment. Of course, earnings in auctions could influence behavior in the lottery experiment. However, Holt and Laury (2002) have not found evidence for such level effects.

Another possible criticism might be that conducting the lottery experiment after the auction experiment biases the choice behavior. Goeree et al. (2003) have conducted lottery choice experiments before and after their main experiment. Their results show that such order effects are negligible.

4.4 *Payment*

Within some days after the experiment, subjects could collect their earnings at the institute. At that occasion, one of the lotteries was determined by rolling a die. The lottery was then played by another roll of the die. Subjects received both their payoff from the auctions and from the lottery experiment. Subjects' total earnings ranged between €9.40 to €36.40 with a mean of €22.06. Thereby, the average earnings from the eBay transactions was €17.19. These amounts include a lump sum payment of 6 Euros for the buyers.

5 RESULTS

Altogether, we collected data from 120 auctions, with 60 participants (20 sellers and 40 buyers). As buyers and sellers were re-matched every round, observations within treatments are not independent. We thus have $n = 5$ independent observations.

A first overview on the results is given in Table 2. 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 average BIN price is 0.5. Profits of sellers and buyers are also quite close to the predictions of the baseline model (risk neutrality and no underbidding). However, in 36% of the transactions, the BIN price was accepted, and thus there was no auction. This rate increases to 60% if one only considers the cases where buyer 1's valuation is above the BIN price. Average BIN prices and acceptance rates do not change substantially over time.

In 87% of the transactions, the outcome is efficient. Considering auction transactions only, the share of efficient allocations is 94%.

		Price Offer		**Acc.**	**Profits**			
				Rate	**Sellers**		**Buyers**	
Period	N	Avg.	(SD)	(in %)	Avg.	(SD)	Avg.	(SD)
1	20	0.51	(0.17)	50	0.37	(0.15)	0.18	(0.23)
2	20	0.50	(0.16)	35	0.31	(0.19)	0.15	(0.25)
3	20	0.54	(0.17)	30	0.36	(0.21)	0.13	(0.2)
4	20	0.50	(0.17)	35	0.32	(0.16)	0.17	(0.21)
5	20	0.48	(0.17)	35	0.30	(0.21)	0.18	(0.24)
6	20	0.49	(0.19)	30	0.32	(0.16)	0.15	(0.21)
all	**120**	**0.50**	**(0.17)**	**36**	**0.33**	**(0.18)**	**0.16**	**(0.23)**

Table 2: Overview on Results

Figure 1 reports the distribution of the BIN prices. The most frequently set single price is 0.5 (16 offers), followed by 0.4 (12 offers). Notably, 47% of all BIN prices are below the baseline prediction of 0.5. On the individual level, 20% of the sellers always set BIN prices below 0.5 whereas 25% constantly set prices above.

Figure 2 looks at seller revenue. It shows that the higher the BIN price the higher the revenue. Indeed, the Spearman rank correlation coefficient is highly significant ($\rho = 0.33$, $p = 0.00$).[13]

RESULT 1 *Almost half of the BIN prices are below 0.5. BIN prices and seller revenues are significantly positive correlated.*

In the following, we investigate into the effects of buyer behavior on eBay, risk aversion, experience with the eBay market platform, and learning during the experiment on sellers' BIN price setting decisions.

[13] One exception are very high prices. However, this result must be handled with care, as only one subject set constantly BIN prices close to 1.

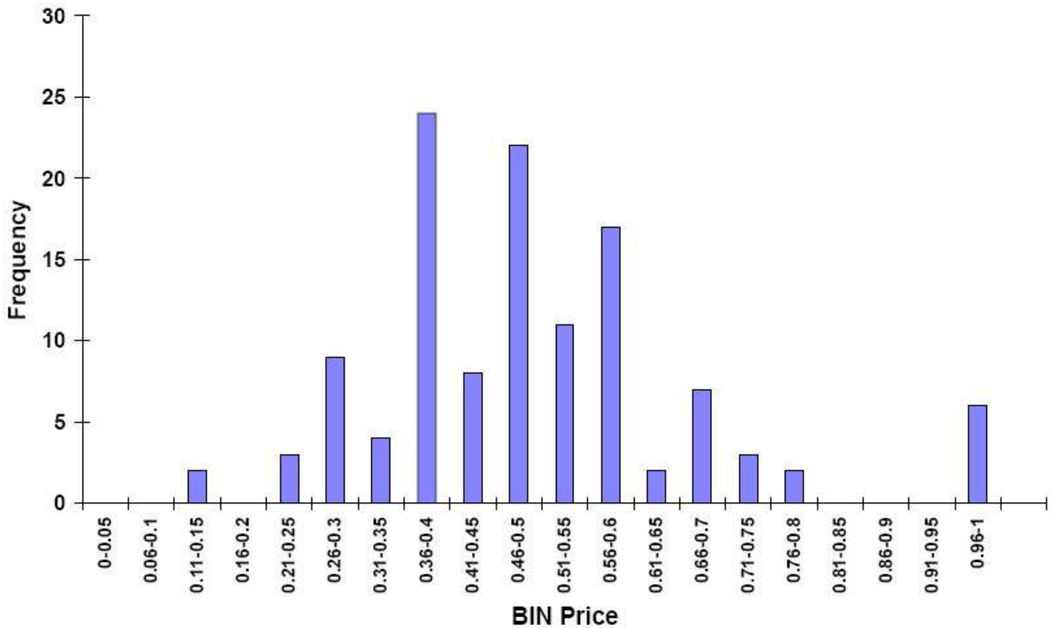

Figure 1: BIN prices

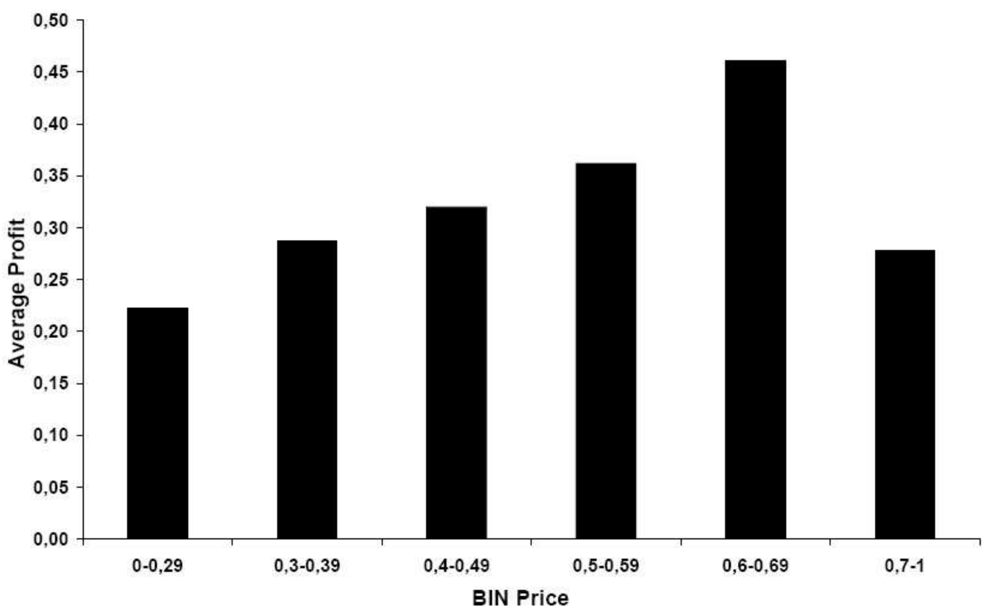

Figure 2: Seller's profits

5.1 *Buyer Behavior*

In each auction, buyer 1 has to decide whether to accept the BIN price or not. As a first approach, we compare the respective buyer's payoff from accepting the BIN price and his expected payoff from participating in the auction. If we assume that the buyer is risk neutral, believes that his opponent bids his true value in the auction, and also plans to do this, 85% of all acceptance/rejection decisions are optimal. If we only count complex decisions, i.e. those where the decider's valuation did not lie below the BIN price, we get a value of 76%. A closer look at the complex decisions shows that irrationality has an interesting pattern. Whereas rejection decisions are rational in 86% of the cases, acceptance decisions are rational in only 69% of the cases. This indicates that rejections occur almost always in cases where the expected payoff from acceptance would have been lower than the payoff from the auction. Subjects thus seem not to have a preference for participating in an auction. On the other hand, acceptance decisions can also be observed when the expected payoff from an auction is higher than the payoff from BIN acceptance. As we discuss in more detail in the next subsection, one possible explanation for this pattern is risk aversion.

Since we observed underbidding (see below), expecting a price 13.5% below the loser's valuation, would be rational. Modifying the analysis in that way, our findings on the rationality of acceptance/rejection decisions are confirmed. We get 70% of rational decisions, (86% rational rejections, but only 59% rational acceptances).

RESULT 2 *The majority of buyers' decisions are rational assuming risk neutrality. However, the deviations from the predicted decisions seem to be systematically biased towards acceptance.*

Bidding should (theoretically) not be influenced either by the existence and rejection of the BIN price nor by buyers' risk attitudes since bidding the own value is an equilibrium strategy in any case. We find that only 19% among the losing bids were equal to the bidder's valuation, increasing to 36% in the last round. Considering bids within a range of 0.05 around the valuation, we get 64% and 73%, respectively.[14] In contrast to the repeated findings of overbidding in second price sealed bid auctions in lab experiments, we find that 65% of the price determining bids are below bidders' valuation [15]. On average, the price determining bid was 13.5% below the respective valuation.

The average number of bids per bidder and auction was 4.2. There was thus a significant amount of multiple bidding. The multiple and underbidding may support the hypothesis that eBay auctions are perceived as first price auctions by some bidders (see, e.g., Ockenfels and Roth (2003)) who thus bid more carefully, as found, e.g., in Kagel et al. (1987).

[14]Note that for the selling price in an auction, only the losing bid is relevant, since it determines the price.

[15]In fact, there was only one bid that was more than 0.05 above the bidder's valuation

Similar to what can be observed in (real) eBay auctions, we observed a lot of 'sniping', i.e., bidding shortly (in the last 30 seconds) before the auction ends. Obviously people did not play our auctions as recommended by eBay (bid your willingness to pay early[16]) or as a standard second price auction. In 75% of the auctions, bids were submitted in the last 30 seconds. Interestingly, sniping seems to increase the winners' payoff on average. Whereas in auctions without last minute bidding, the winner roughly pays a price equal to the predicted one (4.6% below the theoretical prediction), in auctions with sniping, the realized price is lower (16.4% below the theoretical prediction). A reason for this may not be equilibrium behavior, but rather the fact that sniping is an optimal reaction to naive incremental bidding, as shown by Ockenfels and Roth (2003).

The observation is confirmed by a Wilcoxon Signed Rank Test: We compared session averages for relative deviations of the realized price from the theoretically predicted price. We get $p = 0.063$ in a two-tailed test.

RESULT 3 *There is a lot of multiple bidding, underbidding as well as sniping. Sniping leads to higher profits for buyers on average.*

5.2 *The Role of Risk Aversion*

As mentioned before, we elicited subjects' risk preferences using a lottery choice experiment. We exclude 5 out of the 60 subjects whose choices are inconsistent.[17] Assuming constant relative risk aversion, we estimate an average risk aversion parameter of 0.24 for the sellers and 0.18 for the buyers. Following the classification introduced in Holt and Laury (2002), we find that only 6 of 55 players are very or highly risk averse, ($\alpha > 0.68$). The largest fraction of subjects (26) can be classified as risk averse or slightly risk averse ($0.68 \geq \alpha > 0.15$) and 13 subjects as risk neutral ($0.15 \geq \alpha > -0.15$). Finally, 10 subjects are classified as risk loving ($-0.15 \geq \alpha > -0.49$). In other experiments, e.g., Goeree et al. (2003) and Cox and Oaxaca (1996) average estimated risk aversion parameters ranged from 0.28 to 0.67, depending on the task.[18]

A high fraction 73% of BIN prices is outside the range of predicted BIN prices given the observed underbidding in the auction and the risk aversion estimates for sellers and buyers (0.43 to 0.51). Thereby, most deviations are to prices that are too low. Especially, 35% are at or below 0.4, which cannot be explained either by any parameter of risk aversion observed among our

[16] This recommendation can be found on all European and the North American eBay website, e.g., on eBay.com at http://pages.ebay.com/help/buy/outbid-ov.html

[17] For these subjects, it was impossible to determine a risk aversion parameter because they switched from the safe to the risky lottery or vice versa more than once.

[18] Apparently, measured risk aversion turns out to be higher when elicited from more complex tasks. For example, Cox and Oaxaca (1996) elicited risk aversion parameters from behavior in first price auctions (estimated RA parameter of 0.67), whereas Goeree et al. (2003) used lottery choice experiments similar to ours (estimated RA parameter of 0.28).

sellers, or by the observed underbidding in the auctions. There is also no correlation between risk aversion and BIN price setting. Finally, we observe a much higher fraction of BIN transactions (36%) compared to the predicted 25%. We thus find that overall, risk aversion is not a good explanation for observed seller behavior.

Concerning the buyer side, when we incorporate the individual risk aversion parameters into the model, we still have approximately the same rate of rational acceptance/rejection decisions (83%). However, the deviations become much more "symmetric": The fraction of rational acceptance and rejection decisions become more similar (76% and 68%, only considering the "complex decisions"). This shows that incorporating risk aversion does increase the explanatory power of the theory concerning acceptance decisions, but decreases the rationality of some rejection decisions. If one assumes symmetric error making of subjects, this can thus explain some of the behavior of the buyers. However, explanatory power is reduced if underbidding is included into the analysis: The rate of rational acceptance decisions decreases to 67% whereas rational rejection decisions are at 75%. This shows that buyer behavior is still slightly biased towards overly frequent acceptance.

RESULT 4 *Risk aversion can only partly help in explaining buyer behavior. It performs badly in predicting price setting behavior.*

5.3 *The Role of Experience with trading on eBay*

Since we used a real auction platform, we were able to observe participants' prior experience on eBay by their reputation scores. Our participants were differently experienced: They had reputation scores of 0 to 194 with an average of 23 and had previously completed 29 eBay transactions on average, thereof 6 as a seller and 23 as a buyer.

Figure 3 shows a box plot of all set BIN prices for each of the 20 sellers, sorted by their experience with selling on eBay. As one can see, more experience does not have a systematic influence on price setting behavior. Both sellers with no selling experience and sellers having previously sold 20 or more items, vary their BIN prices substantially. Only half of the sellers who kept their prices rather constant have conducted more than 10 previous sales. Comparing the median BIN prices of each seller to the individual predicted BIN price (given the CRRA parameters), we find that more selling experience does not lead to an improved fit of the theoretical predictions.

We find that experience has some impact on the bidding behavior. Considering rather inexperienced subjects (less than 10 eBay transactions), the average (losing) bid is 19% below the valuation, whereas among more experienced subjects, the bid is only 7% below valuation.[19] This difference is significant (Wilcoxon Signed Rank Test, based on session averages, p=0.043,

[19]This supports the hypothesis of "naive incremental bidding", which is apparently more pronounced among unexperienced subjects.

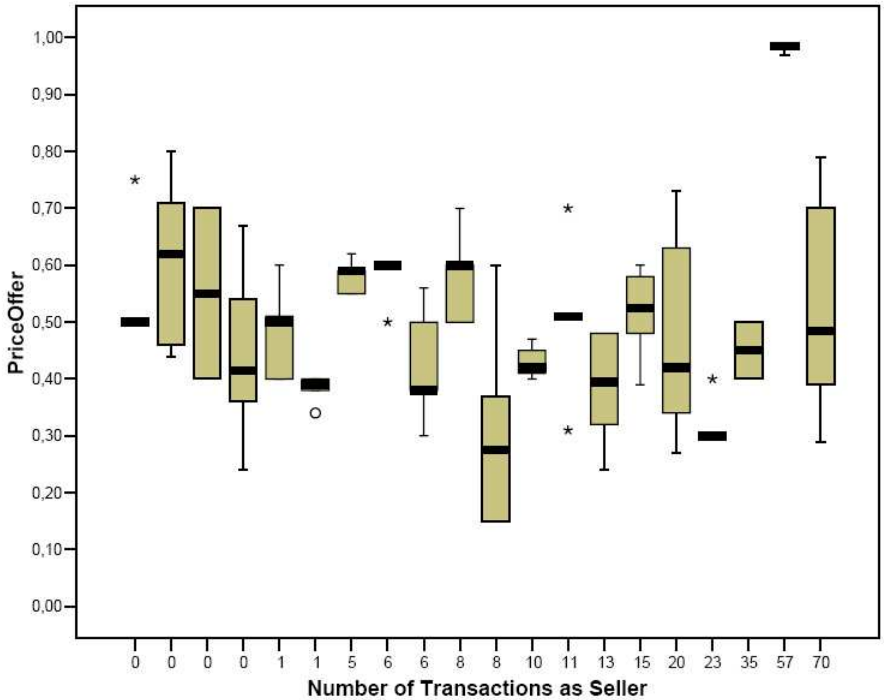

Figure 3: BIN Prices and eBay Experience

two-tailed). Moreover, the rate of 'snipe bids' not arriving in time goes down from 11% for unexperienced bidders to 4% for experienced bidders. Finally, taking individual averages, we find a weak negative relation between experience on eBay and the number of bids per auction. Both the Pearson correlation coefficient and the Spearman rank correlation coefficient are negative, but not significantly so.

RESULT 5 *We find no systematic relation between experience and BIN price setting. However, there are differences in the bidding behavior between experienced and unexperienced subjects. Experienced bidders bid in a seemingly more sophisticated way.*

5.4 *Learning During the Experiment*

One advantage of our design compared to other field auction experiments is that we can conduct more than one round and hence study changes in behavior over time. This allows us to investigate if and how subjects learn during the experiment. Besides the analysis of the absolute level of BIN prices, we are also interested in investigating the adaptation of the price levels during the experiment. Our conjecture is that learning to set BIN prices optimally is rather difficult. Sellers who start with low BIN prices might observe that they make higher gains in BIN transactions than in auctions and thus form false expectations about the prospects of an auction. A seller who offers low

BIN prices is more likely to experience lower profits in the auction: buyers with relatively high values might accept low prices, but buyers who cannot even afford those low price offers, reject and go to the auction. This leads to the selection of low value buyers into the auction and consequently to low auction prices, reinforcing seller's expectation about low prospects of the auction.[20] Sellers who reason this way forgo profit opportunities. This is clearly confirmed by the data. The average BIN transaction yields a payoff of 0.4 whereas the average auction only yields 0.26. This leads to the hypothesis that earnings in the previous round may have an influence on BIN setting behavior. Therefore, we calculated coefficients for the correlation between previous round earnings when there was an auction and BIN price setting in the subsequent round.

The Pearson coefficient for the correlation between the previous round earnings if there was an auction and the adaption of the BIN price (0 when the BIN price is kept constant by the subject) is 0.33, which is significant on the 1-%-level. Using Spearman's ρ, we get a coefficient of 0.34, also significant on the 1-%-level. Thus, the more a subject earns in an auction, the more they increase the BIN price in the next round. This is robust to replacing the change by the level of the BIN price or to including all transactions, not only auction transactions.

Considering individual behavior, we find that only 3 subjects exhibit a significantly positive correlation between previous round earnings and the BIN price adaption in the subsequent period (Spearman rank correlation coefficient, at 5%-level), 14 have an insignificant positive correlation and 3 an insignificant negative correlation.

RESULT 6 *There is evidence for "mislearning": The lower a BIN price is set, the less a seller earns when an auction takes place. Transactions at the BIN price are therefore incorrectly perceived as more desirable. Thus sellers tend to lower their BIN prices after unsuccessful auctions, resulting in foregoing profit opportunities.*

6 COMPARISON WITH THE RESULTS OF A STANDARD LAB EXPERIMENT

Although conducted in the lab, subjects in our experiment do not only bring experience with and knowledge of the experimental task, but also act in the environment in which this experience was acquired. Therefore, we can investigate in which way behavior in such an experiment differs from behavior in standard lab experiments.

In the following, we compare our results concerning seller behavior to those of the lab experiment by Ivanova-Stenzel and Kröger (2005). As mentioned

[20]Charness and Levin (2005) discussed the fact that bayesian updating fails when it clashes with reinforcement learning. In a comparable way to their decision situations, subjects in our experiment may fail to realize that a profitable BIN transaction reveals good market conditions, i.e. that an auction or an even higher BIN price would have been likely to yield higher revenue.

above, in their standard lab experiment, sellers offer a BIN price to one of two buyers. If this price is not accepted, a second price sealed bid auction takes place.

It was observed that differently to our eBay auctions, in the lab experiment bidders submitted bids close to their valuations. Although the bidding procedure (and the bidding behavior) in our eBay auctions is not as in a second price sealed bid auction, as discussed in Section 3, the predictions concerning the BIN prices without underbidding can be used. Therefore, a comparison of the seller behavior in the two frameworks is meaningful.

Table 3 summarizes the results of both experiments. We observe that in both experimental settings, roughly one third of all trades occur at the BIN price. Furthermore, average price offers, seller and buyer profits are strikingly similar.

Format	N	**Price offer** Avg. (SD)	**Acceptance Rate** in %	**Sellers' Profits** Avg. (SD)	**Buyers' Profits** Avg (SD)
Lab	960	0.51 (0,17)	33	0.33 (0.19)	0.15 (0.22)
eBay	120	0.50 (0.17)	36	0.33 (0.18)	0.16 (0.22)

Table 3: Comparison Between eBay and Lab Results

Figure 4 reports the cumulated density function of BIN prices set by the sellers in both experiments and shows that the price setting behavior of subjects in the lab resembles quite closely the behavior on eBay.

Using a Mann-Whitney-U test, we check whether average BIN prices differ in both experiments on the session level.[21] We cannot reject the hypotheses of identical means ($p = 1$). A Kolmogorov-Smirnoff test shows that BIN price distributions in both experiments are not significantly different (p=0.19).

Figure 4 indicates that in both experiments a large fraction of sellers set BIN prices substantially below 0.5, inconsistent with the risk neutral predictions. More specifically, 52% of BIN prices are below 0.5 in the lab, and 47% in the eBay experiment. Furthermore, in both experiments, we observe substantial fractions of BIN prices below the lower bound of the predicted price ranges (37.5% on eBay and 29% in the lab).

Only 25% of the sellers constantly set BIN prices at or above 0.5 in the eBay experiment whereas 20% constantly set prices below. These numbers cannot be compared easily to the lab experiment, as that experiment consisted of 32 periods. Drawing 6 random trading periods per seller, we get 20% of sellers setting BIN prices above 0.5 and 10% constantly setting prices below 0.5, respectively.

In the previous section, we have mentioned that "mislearning" might play a role in explaining seller behavior. This can also be found in the data from the

[21] In both experiments, one session defines one independent observation.

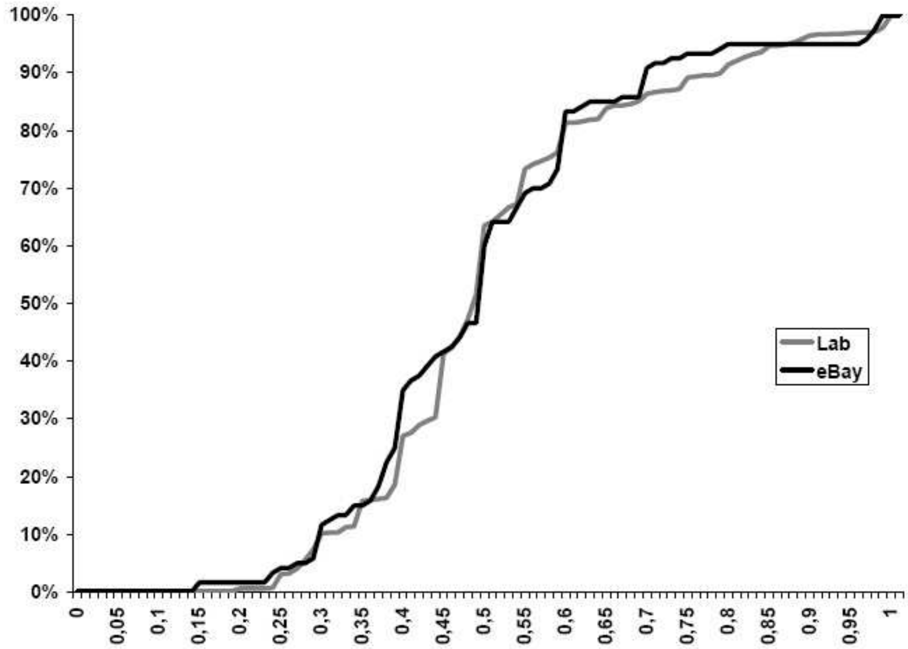

Figure 4: CDF of set BIN prices

lab experiment. We find that the Spearman rank correlation coefficient between previous round earnings and the BIN price adaption in the subsequent period is significantly positive (on the 5%-level, 1-tailed) for 12 out of the 30 sellers. Another 16 subjects exhibit an insignificant positive correlation and only 2 a (insignificant) negative correlation. An important precondition for "wrong learning" is that subjects do not realize the relation between rejected BIN prices and low earnings in an auction. To check whether subjects recognize that the expected profit from an auction is lower when a BIN price below 0.5 is rejected, beliefs concerning the expected profits were elicited in the lab experiment: In 5 of the 10 sessions, this belief was elicited before sellers learn buyer 1's decision, but after the seller had specified a BIN price; in the other 5 sessions this belief was only elicited after the BIN price was rejected. The results indicate that most of the sellers do not update their beliefs after rejection of the BIN price. The average expected profit is 0.34, regardless at which time the expectations are elicited.[22] Whereas 0.34 is close to the theoretical and to the realized profit in the whole mechanism, it represents a strong overestimation of the profits in auctions after the BIN price is rejected. Actually, theoretical and actual profits are overestimated by 0.08 on average, which is more than 27%.

RESULT 7 *Despite the differences in the auction formats and, consequently, in the bidding behavior, price setting behavior is similar in both environments.*

[22]We excluded expectations of 0 and 1 from the data, as they were obviously submitted by non-serious players. However, including them does not change the qualitative results.

Using a more realistic trading institution does not lead to an improved fit of the theory. "Mislearning" seems to occur in both environments.

7 CONCLUSION AND DISCUSSION

In this paper, we introduce a new type of experiment that brings the field into the lab. We have applied this type of experiment to study BIN price setting behavior of sellers in online auctions.

We observe that 37.5% of the BIN prices are too low to be explained by any of the presented theoretical predictions. This non-optimal seller behavior reduces revenue compared to higher prices. A possible reason is the observed "mislearning". Sellers tend to lower their BIN prices after unsuccessful auctions, resulting in foregoing profit opportunities. Experience with trading on eBay does not prevent sellers from setting prices non-optimally.

The majority of buyers' decisions are rational assuming risk neutrality. However, the deviations from the predicted decisions seem to be systematically biased towards acceptance. Risk aversion can only partly help in explaining buyer behavior. Experience with the eBay platform influences bidding behavior. Experienced bidders bid in a seemingly more sophisticated way.

A comparison of our experimental results with results from a standard lab experiment reveals no significant differences in the price setting behavior. Using a more realistic trading institution does not lead to an improved fit of the theory.

Although we excluded the possible role of time preferences, our results resemble the findings from the empirical data presented in Section 2. For example, there is a significant share of transactions (approximately one third) at the BIN price and a similar fraction of auctions ends below the (rejected) BIN price.

We are aware that the applied experimental design and procedure still contain a number of artificial elements. For example, sellers could not use their own eBay account. A bidding period of only 5 minutes is different from the bidding period in an eBay auction. The number of bidders and the distribution of their values is known. However, our design still maintains the main characteristics of trading on eBay and thus enables subjects to use their experience from the real world trading institution. The shortened duration of the auction allows to study repeated interactions and to shed more light on last minute bidding and the associated risk of bids being lost.

Our results show that lab experiments are still a reasonable tool to study auction behavior. On the other hand, bringing a field market institution into the lab helps to detect specific features of behavior in the environment to be studied that may be missed otherwise.

A TRANSLATED INSTRUCTIONS

Please read the instructions carefully! Should you have any questions please raise your hand; we will answer your questions personally. The following instructions are the same for all participants. This experiment consists of two independent parts. In the first part of the experiment, you participate in eBay auctions. Three people (one seller and two buyers) take part in the purchase of an item in each of these auctions. Your role (buyer or seller) is determined randomly at the beginning of the experiment. You keep your role throughout the experiment. All amounts will be provided in an experimental currency, the eBay-Euro. At the beginning of each auction, each buyers' valuation for the item is determined. If you are a buyer, you will be informed about your valuation by the experimenters. Valuations are randomly 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. All of these values are equally likely. The valuations of the two buyers are independent from each other, i.e. they are usually different. Each buyer knows his/her own valuation but not the one of the other buyer. The seller is not informed about any of them. Each auction will be proceed as follows: At the beginning of the auction, 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. Then, one of the buyers will decide, knowing his/her valuation, 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 and the auction is over. The (net) payoff to the buyer is the difference between his/her valuation and the price. The seller receives the price paid. 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 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 time will be started and ended by experimenters with the use of a clock projected on the wall. The end of the auction is determined according to the projected time, not according to the time in eBay! The bids that are made after the end of the auction will not be counted. At the end of 5 minutes bidding time, the buyer who made the highest bid gets the product at the price at which the auction ends (in accordance with 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 (net) payoff to the buyer is the difference between his/her valuation and the price. The seller receives the price paid. 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 seller and two buyers will be randomly matched. Each buyer will be able to decide on the "Buy-it-Now price" in 3 out of 6 auctions.

Course of the Experiment:

After being informed whether you are a buyer or a seller, which is indicated 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 the buyers will use their own eBay accounts during the experiment. Each seller will receive an eBay account from the experimenters to be used in the experiment. The sellers will find their account information on the sheet “Information about your Role”. They will not, however, know the passwords for these accounts and they cannot, hence, 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 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 will start. Now, those buyers who decide on the "Buy-It-Now price", are informed about their valuation and the relevant item’s ID from the sheet “Information about your auction”. These buyers should follow steps K3 and K4 described in “Information about Your Role”. Buyers who do not decide on the “Buy-it-now price”, will get this information only when they enter the auction. 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: Each auction lasts for a total of 9 minutes: Decision on the “Buy-it-now price” by the seller: 2 minutes; Decision to buy or not at “Buy-it-now price” by the first buyer: 2 minutes; In case the “Buy-it-now price” is rejected, both of the buyers bid in the auction during 5 minutes.

Please don’t make any bids in the auctions after the experiment. Please don’t rate other participants. Notice that except for the renumeration for your participation, no claims can be made concerning the auctions. We would like to also inform you that all eBay rules are valid for this experiment as well; for instance, if you are a buyer, your address might be communicated to the experimenters after the experiment (as the actual owner of seller accounts). We commit to ensuring that this information will not be disclosed to third parties and that it will not be kept or used after the experiment.

Rules regarding the Payments: 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 10:00 and 12:00 am starting from 23.01.2006 in room 121 at the Institute of Economic Theory I. Please be aware that a buyer might incur losses! This can happen, if a buyer accepted a “buy-it-now price” or made a bid during the auction, which was higher than his valuation. Buyers are granted an initial 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 after the first part is over.

Instructions for the Second Part of the Experiments:

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 (Institute for Economic Theory I) to get your payment for the first experiment, we are going to play one of the lotteries: 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 you roll "5" in the first roll, then the lottery that you have chosen for row number 5 will be relevant for your earnings. If you roll "1","2","3","4", or "5" (with probability 50%) in the second roll, then you will earn the amount corresponding to those numbers in the relevant lottery (i.e., €5 if lottery "A" was chosen during the experiment and €8,20 if lottery "B" was chosen during the experiment). If you roll "6","7","8","9" or "10" (with probability 50%) in the second roll, 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

B SCREEN SHOT OF SELLER BIN PRICE DECISION

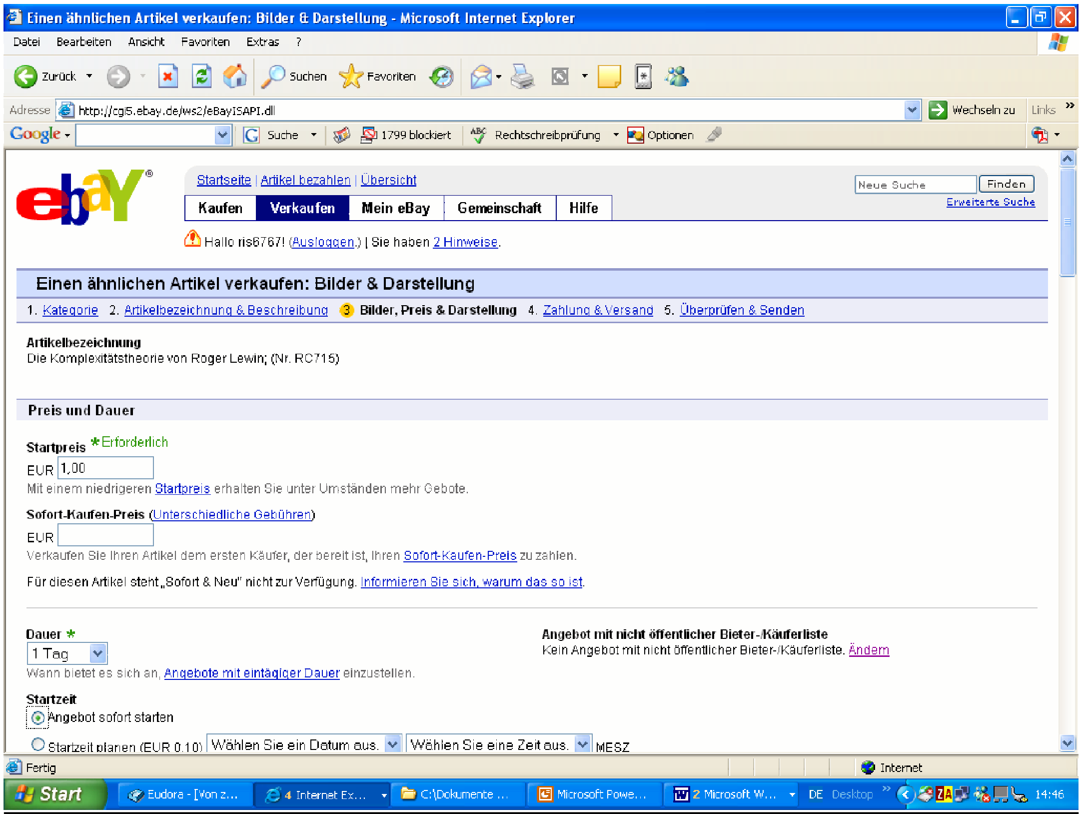

Figure 5: Screen Shot of Seller BIN Price Decision

C LOTTERY EXPERIMENT

Subjects could select between 0 and 10 safe choices. Table 4 presents the appropriate estimated measures of α in equation (3).

Safe Choices	α	Interval median
0	$< -1,523$	no median
1	$-0,874 > \alpha > -1,523$	-1,195
2	$-0,477 > \alpha > -0,874$	-0,675
3	$-0,175 > \alpha > -0,477$	-0,33
4	$0,083 > \alpha > -0,175$	-0,046
5	$0,325 > \alpha > 0,083$	0,204
6	$0,571 > \alpha > 0,325$	0,448
7	$0,848 > \alpha > 0,571$	0,71
8	$1,228 > \alpha > 0,848$	1,038
9	$\alpha > 1,228$	no median
10	makes no sense	no median

Table 4: Risk aversion estimates

References

Anderson, S., D. Friedman, G. Milam and N. Singh (2004): "Buy it Now: A Hybrid Internet Market Institution," *Working Paper*.

Arieli, D., A. Ockenfels, and A. Roth (2003): "An experimental analysis of ending rules in Internet auctions," *Working Paper*.

Boatwright, P., Borle, S. and B. Kadane (2006): "Common Value/Private Value Categories in Online Auctions: A Distinction without a Difference?" *Working Paper*.

Brint, A. (2003): "Investigating buyer and seller strategies in online auctions" *Journal of the Operational Research Society*, 54, 1177-1188.

Bose, S. and A. Daripa (2006): "The Buy-Now Option in Auctions," *Working Paper*

Budish, E. and L. Takeyama (2001): "Buy Prices in Online Auctions: Irrationality on the Internet?," *Economics Letters* 72, 325-333.

Chiu, Y. and F. Cheung (2004): "Price Formation in a Sequential Selling Mechanism," *Working Paper*.

Charness, G. and D. Levin (2005): "When Optimal Choices Feel Wrong: A Laboratory Study of Bayesian Updating, Complexity, and Affect," *American Economic Review* 95(4), 1300-1309.

Cox, J. and L. Oaxaca (1996): “Is Bidding Behavior Consistent With Bidding Theory for Private Value Auctions,” *Research in Experimental Economics* 6, 131-148.

Durham, Y., M. Roelofs and S. Standifird (2004): “eBay’s Buy-It-Now Function: Who, When and How,” *Topics in Economic Analysis & Policy* 4(1), 28.

Gallien, J. and S. Gupta (2005): “Temporary and Permanent Buyout Prices in Online Auctions,” *Working Paper*

Garratt, R, Walker, M. and J. Wooders (2004): “Behavior in Second-Price Auctions by Highly Experienced eBay Buyers and Sellers,” *Working Paper*

Goeree, J., C. Holt and T. Palfrey (2003): “Risk Averse Behavior in Generalized Matching Pennies Games,” *Games and Economic Behavior* 45, 97-113.

Gonzalez, R, Hasker, K. and R. Sickles (2004): “An Analysis of Strategic Behavior in eBay Auctions,” *Working Paper*

Harrison, G, and J. List (2004): “Field Experiments,” *Journal of Economic Literature* 42(4), 1013-1059

Heinemann, F.(2003):“Risk Aversion and Incentive Effects: Comment, *Working Paper*

Holt, C. and K. Laury(2002): “Risk Aversion and Incentive Effects,” *American Economic Review* 92, 1644-1655

Hidvégi, Z., Wang, W. and B. Whinston(2006): “Buy-price English auction,” *Journal of Economic Theory* 129, 31-56.

Ivanova-Stenzel, R. and S. Kröger (2005): “Price Formation in a Sequential Selling Mechanism,” *Working Paper, Humboldt-University at Berlin.*

Kagel, J., Harstad, R. and D. Levin (1987): “Information impact and allocation rules in auctions with affiliated private values.” *Econometrica*, 55, 1275-1304.

Katkar, R. and D. Lucking-Reiley “Public Versus Secret Reserve Prices in eBay Auctions: Results from a Pokémon Field Experiment.” *Working Paper, University of Arizona.*

Katzman, B. and T. Mathews (2002): “The Role of Varying Risk Attitudes in an Auction with a Buyout Option,” *Economic Theory*, forthcoming.

Lucking-Reiley, D. (2002) “Using Field Experiments to Test Equivalence Between Auction Formats: Magic on the Internet” *American Economic Review*, 89(5), 1063-1080

Mathews, T. (2002): “A Risk Averse Seller in a Continuous Time Auction with a Buyout Option,” *Working Paper.*

MATHEWS, T. (2004): "The Impact of Discounting on an Auction with a Buyout Option: a Theoretical Analysis Motivated by eBay's Buy-It-Now Feature ," *Journal of Economics*, 81(1), 25-52.

MATHEWS, T. (2005): "Bidder Welfare in an Auction with a Buyout Option," *Working Paper*.

MONTGOMERY, A., K. SRINIVASAN AND X. WANG (2004): "When Auction Meets Fixed Price: A Theoretical and Empirical Examination of Buy-it-Now Auctions," *Working Paper*.

OCKENFELS, A.(2005): "Bidding in Private Value eBay Auctions: A Controlled Field Experiment," *Working Paper*.

OCKENFELS, A. AND A. ROTH (2003): "Late and Multiple Bidding in Second Price Internet Auctions: Theory and Evidence Concerning Different Rules for Ending an Auction," *Working Paper*.

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.

PINKER, E., SEIDMANN, A. AND Y. VAKRAT (2003): "Managing Online Auctions: Current Business and Research Issues," *Management Science*, 49(11), 1457-1484.

REYNOLDS, S. AND J. WOODERS (2004): "Auctions with a Buy Price," *Working Paper*.