How Do Sellers Benefit From Buy-It-Now Prices in Ebay Auctions? – an Experimental Investigation

Tim Grebe ()
Radosveta Ivanova-Stenzel (TU Berlin)
Sabine Kröger (Laval University)

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Ludwig-Maximilians-Universität München | Humboldt-Universität zu Berlin
Spokesperson: Prof. Dr. Klaus M. Schmidt, University of Munich, 80539 Munich, Germany
+49 (89) 2180 3405 | info@rationality-and-competition.de

How do sellers benefit from Buy-It-Now prices in eBay auctions?
– An experimental investigation –

Tim Grebe[a,1], Radosveta Ivanova-Stenzel[b,2], Sabine Kröger[c,3,*]

[a] *Forster Str. 43, 10999 Berlin, Germany*
[b] *Technische Universität Berlin, Department of Economics and Management, Strasse des 17. Juni 135, D-10623 Berlin, Germany*
[c] *Université Laval, Département d'économique, Pavillon J.A.DeSève, Québec City, Québec G1K 7P4, Canada*

Abstract

In Buy-It-Now (*BIN*, hereafter) auctions, sellers can make a "take-it-or-leave-it" price offer (*BIN* price) prior to an auction. We analyse experimentally how eBay sellers set *BIN* prices and whether they benefit from offering them. Using the real eBay environment in the laboratory, we find that the eBay auction format supports deviations from truthful bidding leading to auction prices substantially below those expected in second-price auctions. Our results reveal that the observed price deviations are not an artefact due to the existence of the *BIN* price, rather a consequence of the specific features of the eBay-auction format – a mixture between sealed-bid and open second-price auction with a fixed end-time. Moreover, we find that information available on eBay can be used as indicator for the price deviation and that sellers respond strategically to this information. Seller risk aversion does not affect *BIN* prices and more experienced sellers ask for higher *BIN* prices. The introduction of *BIN* prices to eBay auctions has an enhancing effect: the eBay *BIN* auction is more efficient and generates significantly higher revenue compared to a standard eBay auction without a *BIN* price.

Keywords:
experience, online markets, eBay, *BIN* price, private value, experiment

JEL classifications:
C72, C91, D44, D82, L1

[*] Corresponding author
[1] tim.grebe@web.de
[2] ivanova-stenzel@tu-berlin.de
[3] skroger@ecn.ulaval.ca

"*If you decide to do the BIN [option] think long and hard on the price you are asking.*"
(eBay-user: dollydj (2740), 100% positive feedback, Buying Guides)

1. Introduction

Online platforms offer a variety of selling mechanisms, posted price and pure auction being the most popular ones. In the recent past, more complex trading mechanisms, combining both, posted price and auction, have been successfully introduced. For example, on eBay, one of the biggest online auction platforms, a seller may offer a so called Buy-It-Now auction (*BIN* auction). In this format, a seller announces a "take-it-or-leave-it" price (*BIN* price) and simultaneously calls 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. The *BIN* auction has become increasingly popular among sellers and buyers (see, e.g., eBay user's opinion posted on eBay Buying Guides, 2011). At first glance, this popularity appears surprising. Sellers use auctions because the relevant information on buyer willingness to pay is incomplete, making it difficult to post the "right" price. Therefore, using a *BIN* price means at least partly giving up the advantage of the competitive environment created by the auction.[4] Furthermore, contrary to the pure auction and the posted price format, in the *BIN* auction, sellers face a cognitively very demanding decision task (for an illustrative example, see Seideman (2016)). The challenge in this sequential mechanism is to consider the adverse selection effect the *BIN* price has on the auction price. While for the case of single-object auctions with independent private values, theory has provided different rationales why it may be beneficial for sellers to use a *BIN* price, the experimental and empirical literature lacks insight on seller behavior in this environment. Our study aims at filling this gap.[5]

The theoretical literature offers several explanations why 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 et al. (2008)), and if bidders have reference dependent preferences (Shunda (2009)).

The few experimental studies on private value *BIN* auctions use predetermined *BIN* prices and thus are mainly concerned with buyer behavior. For example, Shahriar and Wooders (2011) employ a clock auction format with only one *BIN* price, the theoretically optimal *BIN* price given risk aversion of buyers. They find that the predictions of a model allowing for buyers to be risk averse capture observed buyer behavior. Peeters et al. (2016) apply an auction format that permits proxy bidding as on eBay but unlike eBay uses an automatic extension rule instead of a fixed end-time.[6] They compare *BIN* auctions with

[4]Under the standard assumptions of the symmetric independent private value (SIPV) environment with risk-neutral bidders, the existence of a "take-it-or-leave-it" price offer prior to the auction can indeed not be explained. The optimal price is set that high that it is never accepted (e.g., Kirkegaard (2006)). This result holds independently of the way the price is offered and how the arrival of the bidders is modeled (Reynolds and Wooders (2009), Ivanova-Stenzel and Kröger (2008), Grebe et al. (2016)).

[5]In the recent literature, some papers look at different selling formats adopted by online trading platforms, Sun et al. (2010), Jiang et al. (2013), Einav et al. (2018), and Bauner (2015) to name a few. They examine issues quite different than we are concerned with here. In general, they are looking at which selling mechanism generates most revenue to sellers considering different factors that affect the choice of the selling format.

[6]For a description of the functioning of the eBay proxy bidding procedure see supplementary material part 1.

two levels of *BIN* prices (low and high) and a standard auction without a *BIN* price. The comparison reveals that bidders use the *BIN* price as a reference point for the values of other bidders, i.e., the number of bids above the *BIN* price is lower when a *BIN* price is available compared to auctions without a *BIN* price. Durham et al. (2013)) consider three levels of *BIN* prices (low, medium, high) in the context of two institutions with a fixed end-time: an ascending-bid auction with and without proxy bidding. They observe that a *BIN* price affects the bid timing: in the case of proxy bidding, the existence of a *BIN* price leads to an increase of the number of early bids.

The experimental studies so far do not provide a clear-cut answer to the question whether sellers benefit from the use of the *BIN* option. While Shahriar and Wooders (2011) and Durham et al. (2013) identify a revenue-enhancing effect of the exogenously chosen *BIN* prices, Peeters et al. (2016) demonstrate that the introduction of a *BIN* price may reduce seller revenue. Empirical studies report similar contradictory results. For example, Dodonova and Khoroshilov (2004), and Durham et al. (2004) report that auction revenues are increasing in the *BIN* price. Bauner (2015) finds that while buyers might benefit from the *BIN* auction, seller surplus is reduced when *BIN* auctions are available compared to a situation in which sellers can choose only between auctions and fixed-price listings. Anderson et al. (2008) observe that the existence of a *BIN* price has a positive but not significant impact on the sale price.[7]

The experimental studies on *BIN* auctions employ usually an artificial auction institution, and participants gain experience with it to the same extent over the course of the experiment. Empirical studies and field experiments conducted on eBay find, however, that heterogeneity in experience matters. For example, Durham et al. (2004) and Anderson et al. (2008) observe that experienced sellers, i.e., sellers with higher feedback score, use the *BIN* option more frequently. Durham et al. (2004) find that *BIN* price offers from sellers with a high reputation are accepted more frequently but also that buyers with higher reputation buy more often at the *BIN* price when sellers have no experience (i.e., have a zero feedback score). Such evidence suggests that three sources of influence need to be considered when studying seller behavior in eBay auctions: first, the level of experience market participants have with the institution, second, the degree of heterogeneity in experience, and, third, the presence of information about experience of other market participants. One possibility is to relate the experience of participants with the eBay market institution to their behavior in laboratory second-price sealed-bid auctions, as in Garratt et al. (2015). However, this approach does not permit participants to react to the information about the experience of others.

In this paper, we present the results of an experiment designed to investigate how sellers set *BIN* prices in eBay auctions and whether they benefit from the use of the *BIN* auction compared to a pure eBay auction. The experiment is conducted in the lab while using eBay traders and the eBay auction platform. This approach yields several advantages. First, it allows us to observe behavior in the real eBay market institution and, in addition, provides the needed variation in experience of the traders with this institution. Second, it allows us to relate seller *BIN* price decisions to their individual characteristics and to the information publicly available on eBay. Third, it allows us to measure the effect of the existence of the *BIN* option on seller revenue by controlling for other influences, such as resale opportunities,

[7] For a survey on the empirical and experimental literature that studies online auctions including different types of auctions with a buy price, see Ockenfels et al. (2006), Durham et al. (2013), and Kagel and Levin (2016) p. 617-18.

competition between sellers with different reputation and experience, as well as endogenous participation. Further, it ensures that the assumptions of the private value environment are satisfied. This allows us to observe aspects of bidding behavior that are not easily available in field data.

The results of our experiment reveal that the combination of proxy bidding with a fixed end-time in eBay auctions supports deviations from truthful bidding leading to auction prices substantially below those expected in second-price auctions.[8] We find a correlation between how much eBay auction prices deviate from prices based on true value bidding and the information that is available on eBay. Sellers adjust their *BIN* prices according to this information. Our empirical analysis reveals that more experienced sellers ask for higher *BIN* prices and that seller risk preferences do not affect *BIN* price offers. Finally, a comparison of the outcomes between auctions with and without a *BIN* price shows that the former is more efficient and generates significantly higher revenue.

The remainder of the paper is organized as follows. Section 2 describes the experimental design and procedure. We present the results and the analysis of the data in section 3. Section 4 concludes.

2. Experimental Design and Procedure

The setting we study in our experiment consists of a seller who offers a single indivisible object for sale to two potential buyers.[9] Buyers have symmetric independent private values for the good, drawn from a uniform distribution. The seller announces a *BIN* price to one of the buyers who is randomly selected prior to the auction.[10] The buyer who observes the *BIN* price either accepts the offer or submits a bid. In the former case the transaction is completed. In the latter case, the *BIN* price disappears and an auction is held with both buyers.[11]

For the experiment, we recruited eBay traders and invited only persons with a valid eBay account.[12] At the beginning of each session, we collected the individual feedback score on eBay of each participant that we use to approximate their experience with the eBay institution.[13] The average feedback score was 23. Persons with low experience (at the 25th percentile) had a feedback score of 2 and those with

[8]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 (plus an increment). 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.

[9]Empirical studies on eBay auctions report a rather small average number of bidders. For example, Bajari and Hortasu (2003) report three bidders on average. The laboratory experiment of Ariely et al. (2005) employs two bidders.

[10]In 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. Buyers arriving later are not informed about the rejected price offer. They can only participate in the auction.

[11]For a detailed description of the functioning of eBay *BIN* auctions at the time the experiment was conducted and for a translated version of the instructions see supplementary material part 1 and 2, respectively.

[12]Before the experiment, we conducted a survey with all subjects registered in our experimental subject data base. Among other things, we asked in the survey 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. Those persons were then invited to participate in our experiment. We made sure that all participants possessed a valid eBay account which they had registered before we started the recruitment process. Most participants were students of economics, business administration, or industrial engineering at Humboldt University or Technical University Berlin.

[13]As leaving feedback is optional, feedback scores of eBay traders understate their actual experience. It is however commonly used as a proxy for experience, see e.g., Roth and Ockenfels (2002), Ockenfels and Roth (2006), Bolton and Ockenfels (2014).

high experience (at the 75th and 95th percentile) a feedback score of 29 and 87, respectively, whereas the median participant had a feedback score of 11. The distribution of the experience in our experiment is quite comparable to the one Ockenfels and Roth (2006) reported from eBay-Antiques auctions. They also use a bidder 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 (see their figure 2, p. 313).

In our experiment, buyers used their own eBay accounts, whereas sellers used eBay accounts licensed to the experimenters with similar reputation scores (11-13 points), both of which were common knowledge. This approach provides several advantages. First, it allows us to control for the influence of seller reputation on buyer behavior. Seller reputation is an important signal for the quality of the good (see Jin and Kato (2006), Resnick et al. (2006)). Even though there is no uncertainty about 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. Thus, we ensured that eBay's Terms of Service were fulfilled.

For all activities on eBay in the experiment, we used a fictitious currency, termed *eBay-€*, with 5 *eBay-€* being equivalent to €1. Before each session, we prepared all auctions using the experimental eBay accounts. We described each object for sale briefly, and included a reference number, consisting of letters and numbers, in the name of the item.[14] The reserve price was set to *eBay-€*1 (eBay's minimum starting price). 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.

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. It was commonly known that buyer private values for each item were drawn independently from the set {1, 1.5, 2, 2.5,...,50}, with all values being equally likely, and that seller values for the goods were zero. A buyer who bought the item received as profit the difference between the private value and the final price. The seller payoff was the final price.

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.[15] Together with the decision sheets of the sellers, we distributed blank sheets to the buyers. This was necessary to keep roles confidential. 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. The *BIN* price was first offered to one of the two buyers (henceforth buyer 1). We informed all subjects in the position of

[14]As objects for sale 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. However, no bidder outside the experiment submitted bids in our experimental auctions.

[15]For the screenshot see supplementary material part 2.2.

buyer 1 about their items' reference numbers and their values for it. These buyers had two minutes within which either to 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 buyers about their values and their 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 buyer behavior as well as buyer characteristics (i.e., buyer feedback score).

In total, subjects participated in six consecutive rounds. 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: After all bidders were informed about their value and the items' reference numbers for the ongoing round, we fixed the auction end-time and announced it publicly. A clock, adjusted to the official eBay time, was projected on the wall, counting down the seconds to the end of the auction. 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. At the same time, it was short enough to observe behavior of market participants over several rounds. Additionally, it allows us to shed more light on last-minute bidding and the probability of last-minute bids being lost.

In each round, there were four trading groups each with two buyers and one seller. Each buyer acted as buyer 1 in three (of the six) rounds. 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. Thus, each session consisted of a total of 12 subjects.

At the end of each session, we elicited individual risk preferences with the help of a lottery experiment similar to Holt and Laury (2002). Estimated individual risk preferences range from -0.055 to 2.5. Most of our subjects exhibit risk-aversion, with a median level of 0.53. There are no significant differences in the distributions of the estimated risk preferences for sellers and buyers.[16]

We collected data from 5 sessions with a total of 60 participants (20 sellers and 40 buyers) and 120 transactions. Average earnings in the eBay experiment were €17.19, and in the lottery experiment €4.87. Total earnings ranged between €9.40 to €36.40 with a mean of €22.06.[17]

3. Results

With this study, we seek to answer two questions: first, how do sellers set their *BIN* prices and, second, do they benefit from the option to offer a *BIN* price. Each of these will be answered in order after presenting an overview of the results.

[16]For details on the elicitation procedure and the estimation of risk preferences see supplementary material part 3.
[17]These amounts include a lump sum payment of €6 for buyers.

3.1. Overview of the results

In the *BIN* auction, seller revenue depends on one of two outcomes: either sellers sell at the *BIN* price, if it is accepted, or they get the auction price, if the buyer to whom the *BIN* price is offered rejects it. In our experiment, *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).[18] The interquartile range is 0.2, with 0.4 at the 25th percentile, 0.6 at the 75th percentile, and 0.7 at the 90th percentile. The distribution and a nonparametric density estimation of observed *BIN* prices is shown in Figure 1. Summary statistics are presented in Table 3 (column 1 "All *BIN*"). Buyers accept slightly over one-third of all *BIN* prices (43 out of 120). This leads to an average seller revenue of 0.42 when the *BIN* price is accepted. In case of rejection, sellers receive an average auction outcome of 0.27. Thus, the revenue generated by the auction relative to the expected auction price (i.e., the second-highest value) is 82%.[19]

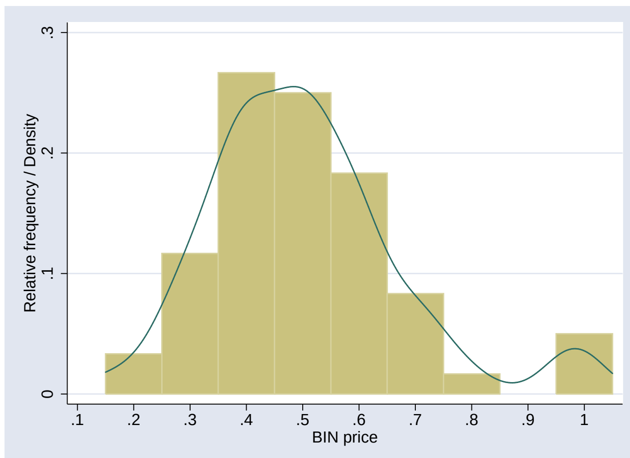

Figure 1: *BIN* prices, N=120.

There are two reasons for observing low auction prices: (i) *before* the auction: the selection of low-value buyers into the auction and (ii) *in* the auction: the 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, only 34% of all observed losing bids are based on true value bidding. The other 66% are on average 7% below the buyer value.[20]

[18]For ease of comparison with other studies, all results are reported for normalized values, i.e., all experimental outcomes are transformed into the $[0, 1]$ range.

[19]True value bidding can be considered as a reasonable assumption for buyer behavior in eBay auctions. Ockenfels and Roth (2006) show that all equilibria involve bidding the own value at some point in time. Indeed, eBay's recommendation to its members is to submit their true value as a bid. This advice can be found on all European and the North American eBay website.

[20]Even though, bids are not displayed on eBay, losing bids can be recovered from the auction price.

Such deviation from true value bidding can be explained by the use of particular bidding strategies observed on eBay. The combination of a fixed end-time with the possibility to adjust bids during the auction can give rise to "multiple bidding" (also referred to as "[naive] incremental bidding") and "last-minute bidding" (in the literature 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. A bidder who adopts the last-minute bidding strategy bids his true value only once, shortly before the end of the auction.[21] In our experiment, we find evidence for the use of both strategies. Bidders submit multiple bids with an average of 4 bids per auction (the median is 3, with 2, 5 and 12 as 25th, 75th and 95th percentiles, respectively).[22] Moreover, in 75% of the *BIN* auctions we observe last-minute bidding.[23]

Observing multiple bids indicates incremental bidding and final bids that are closer to the true value. Thus, prices resulting from multiple bidding can be expected to be similar to those in second-price auctions with true value bidding. Observing no multiple bids is, however, not conclusive on bidder behavior and hence on the price deviation. For example, only one bid would be observed per bidder if (1) both bidders submit their true values only once as a proxy bid, (2) an incremental bidder faces a last-minute bidder, or (3) both bidders are last-minute bidders. Case (1) represents the 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 value, if the incremental bidder does not have the time to respond by increasing his bid up to his true value or if the probability that one (or both) last-minute bids do 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 5% of the last-minute bids arrive after the end of the auction.

To investigate whether and which of the strategies described above can account for the observed price deviation, we regress the relative deviation (rd_t) of the observed price from the theoretical price of a second-price auction on a vector of bidder covariates x_t

$$rd_t = \kappa + x_t'\lambda + \varepsilon_t. \tag{1}$$

The relative deviation observed in auction t is the difference between the second-highest value (V_{2t}) and the observed price (p_t) normalized by V_{2t}, $rd_t = (V_{2t} - p_t)/V_{2t}$. The vector x_t comprises the following bidder characteristics: the number of submitted bids (nb_t), the experience the buyer has with eBay, approximated by his feedback score (exB),[24] quadratic terms of the experience and the number of submitted bids to

[21]Roth and Ockenfels (2002) and Ockenfels and Roth (2006) argue that last-minute bidding is a best response to the incremental bidding strategy. They also show that last-minute bidding may occur in equilibrium, despite the positive probability that last-minute bids may be lost. Ariely et al. (2005) provide experimental evidence that last-minute bidding occurs primarily as a best response to incremental bidding.

[22]Several explanations exist that justify multiple bidding in a private value environment (e.g., Rasmusen (2006) and Cotton (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 and Roth (2006)) is the most plausible explanation for the observed multiple bidding in our study.

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

[24]We included the variable "experience with eBay" (exB) in the regression as the existing literature reports a relation between experience with eBay and the use of the multiple and last-minute bidding strategies (e.g., Ockenfels and Roth (2006),

capture potential nonlinear effects, a dummy variable ($lastmin_t$) that equals 1 if the bidder submitted a last-minute bid that arrived on time. Given our finding of a nonlinear relation between experience and the number of bids (see footnote 24), we allow for interaction between these variables ($nb_t \cdot exB$) as well as this interaction to enter non-linearly.[25] All variables enter twice, once for the losing bidder (subscript "0") and once for the winning bidder (subscript "1"). Because of the auction rules, the number of submitted bids is correlated between bidders. Therefore, we add another interaction term $nb_0 \cdot nb_1$. Finally, ε_t captures auction idiosyncratic errors and is assumed to satisfy $E(\varepsilon_t) = 0$.

Variable	λ	St.Dev
κ	0.200**	0.080
exB_0	−0.073*	0.039
exB_0^2	0.009**	0.004
nb_0	−0.417***	0.129
nb_0^2	0.098**	0.046
$(nb_0 \cdot exB_0)$	0.171*	0.105
$(nb_0 \cdot exB_0)^2$	−0.043	0.027
$lastmin_0$	0.059*	0.031
exB_1	−0.007	0.072
exB_1^2	0.000	0.008
nb_1	−0.055	0.357
nb_1^2	−0.061	0.271
$(nb_1 \cdot exB_1)$	−0.212	0.275
$(nb_1 \cdot exB_1)^2$	−0.069	0.123
$lastmin_1$	0.077***	0.030
$nb_0 \cdot nb_1$	0.290	0.202

Table 1: Median regression of variables influencing the relative deviation from true value bidding of price determining bids, Nobs=77, ***: $p < 0.001$, **: $p < 0.05$, nB and exB normalized by 10.

Table 1 presents the results of a median regression.[26] There is a positive price deviation to start with of about 20%. The more experience the losing bidder has the lower the 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 2 depicts the relation between the relative price deviation and the number of bids (lines) as well as the average number of bids (points) for different levels of experience computed using the estimates from Table 1.[27] For all number of bids, the predicted relative deviation is

Wilcox (2000)). Indeed, we find a relation between the number of submitted bids (nb) and experience (exB) in our data. We run the following OLS regression $nb = \theta_0 + \theta_1 exB + \theta_2 exB^2 + \varepsilon$ with robust standard errors and both variables normalized by 10. The average bidder with no experience places 3 bids per auction ($\theta_0 = 0.319(14.90)$). This number decreases nonlinearly with experience ($\theta_1 = -0.011(-3.96), \theta_2 = 0.0001(2.86)$) where t-statistics are presented in parenthesis.

[25] Note that in order to avoid too large numbers for the nonlinear and interaction terms, exB and nb contain values of the corresponding variables normalized by 10.

[26] 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 feedback scores of 65 and 112, respectively, which is quite extreme compared to the 13 transactions at the 75th percentile. Comparing the mean (15) and the median (8) feedback score also suggests that the outlier impact the mean value.

[27] The figure depicts the case when both bidders have the same experience $exB_0 = exB_1$ and submit the same number of

larger for losing bidders with less experience indicating that the last bid they submitted is further below their true value than the last bid submitted by more experienced bidders.

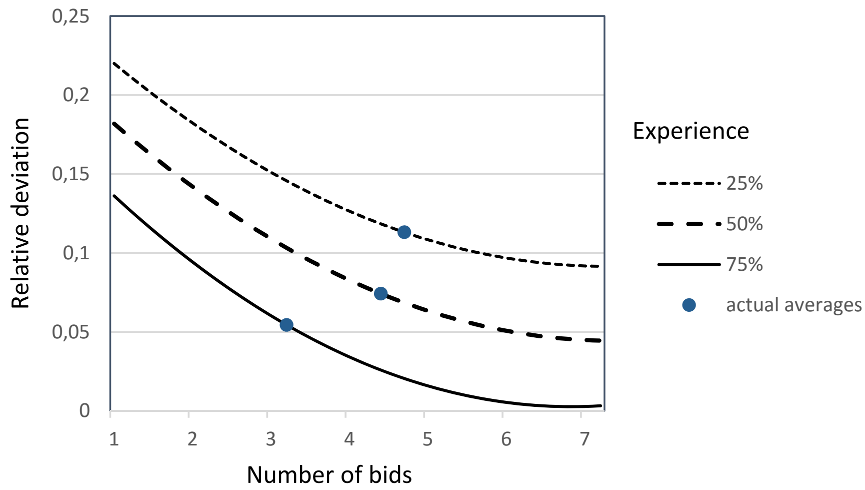

Figure 2: Predicted relative deviation by number of bids and observed average number of bids for different levels of experience (25th, 50th, and 75th percentile).

When the number of bids increases, the relative deviation decreases for all levels of experience. However, we find that this relation varies with bidder experience. Bidders with lower experience decrease their bids less when they bid multiple times compared to more experienced bidders. The variation in relative deviation of bids between different groups of experience can account for the fact that even though bidders with more experience submit less bids on average compared to bidders with median and low experience, they still bid closer to their true value. If the winning bidder submits a successful last-minute bid, the relative deviation increases, obviously, the losing bidder has no chance to react to this bid.

To sum up, we find that the less experience the losing bidder has and the less bids the losing bidder submits, the more the observed price lays below the theoretical price. Last-minute bidding, especially from the winning bidder, increases the relative deviation significantly.

3.2. How do sellers set their BIN price?

Our results so far suggest two important insights for sellers. First, they should expect deviations from true value bidding. If they ignore this circumstance and choose their *BIN* price based on the conviction that the auction price were equal to the second highest value, they might end up with lower revenue. In fact, counterfactual analysis based on the actually observed buyer acceptance and bidding behavior reveals that a *BIN* price that could be optimal under the (wrong) assumption of true value bidding generates less revenue compared to the case when that *BIN* price is lowered.[28]

Second, information available on eBay is correlated with the level of price deviation. Sellers can use this information in order to get an idea of the level of price deviation and adjust their *BIN* price

bids $nb_0 = nb_1$. The effect of other variables, $lastmin_0$ and $lastmin_1$, is taken at their mean values.

[28]The details of the counterfactual analysis are presented in supplementary material part 4.

accordingly. For example, our analysis suggests that multiple bids lead to price determining bids closer to those based on true value bidding, and consequently to higher final prices. Thus, the higher the number of bids the seller observes, the more beneficial it is for them to realize the trade in the auction, i.e., to ask for a higher *BIN* price and to provoke the execution of the auction. The same strategic reaction should be expected towards observing less last-minute bids, but also facing buyers with higher eBay feedback score. More experienced buyers bid closer to their true value rendering the auction more lucrative for the seller.

Given these observations, we conjecture that sellers react strategically to the information available on eBay: when observing higher number of bids, more experienced buyers, and less last-minute bids, sellers should increase their *BIN* price offer.

In the following, we investigate whether seller *BIN* price setting behavior can be rationalized along these lines. We propose an empirical model that allows sellers to set their *BIN* price by using the information with respect to buyer characteristics and behavior they can collect and update while transacting on eBay:

$$bin_{it} \quad = \quad const + \beta_1 \overline{\mathbf{BC}}'_{it-1} + \beta_2 \mathbf{L}_{it-1} + \mu_i + \varepsilon_{it}, \text{ with } t = (2, \ldots, 6). \tag{2}$$

The *BIN* price of seller i in period t, bin_{it}, is modeled as a function of the average buyer characteristics and behavior $\overline{\mathbf{BC}}_{it-1} = (\overline{nb}_{it-1},\ \overline{expB}it-1,\ \overline{lastmin}1_{it-1}, \overline{lastmin}2_{it-1})'$ that seller i observed in all previous 1 to $(t-1)$ periods.[29] The vector of buyer characteristics contains the average number of bids per buyer ($\overline{nb}_{it-1}$), the average feedback score for all buyers as a proxy for experience ($\overline{expB}_{it-1}$), and seller i's average count of observing one, respectively two, last-minute bidders in an auction ($\overline{lastmin}1_{it-1}$ and $\overline{lastmin}2_{it-1}$). When sellers set their *BIN* price they do not know with whom they will interact. Thus, they need to form expectations about the "average buyer" based on their past experience.

Furthermore, we check for learning with the matrix $\mathbf{L} = (period, NoHist_{it-1}, answer_{it-1})$. First, the variable *period* controls for the possibility of some general learning in form of a linear time trend. Second, the information on buyers' background characteristics and behavior (captured in $\overline{\mathbf{BC}}$) can only be observed when an auction has been conducted. Therefore, $\mathbf{L}$ also includes a dummy variable $NoHist_{it-1}$ that is one until the first auction has been held, i.e., the first (for the researcher observable) opportunity to learn about buyer characteristics and behaviour in the experiment ($\overline{\mathbf{BC}}$), and zero otherwise. Finally, to investigate whether sellers adjust their *BIN* prices in response to buyer reaction to the *BIN* price offered in the previous period, $\mathbf{L}$ contains a dummy variable, $answer_{it-1}$, that is equal to one, had the last period's *BIN* price been accepted and zero otherwise.

The variable μ_i represents unobserved individual fixed effects. We will then use the estimated fixed effects to assess the impact of seller individual characteristics on *BIN* prices.[30] The idiosyncratic error term ε_{it} is assumed to be uncorrelated over time ($E(\varepsilon_{it}, \varepsilon_{is}) = 0$ for $s \neq t$) as well as with the covariates and fixed effects ($E(\varepsilon_{it} | \overline{bc}_{it-1}, \mu_i) = 0$).

[29]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.

[30]Bolton and Ockenfels (2014) provide some evidence for a link between seller eBay experience and their choice of eBay auction format.

Variable	Parameter estimate	St.Dev
$const$	0.416^{***}	0.057
$\overline{nb}$	0.023^{**}	0.009
$\overline{lastmin}1$	-0.164^{**}	0.065
$\overline{lastmin}2$	-0.060	0.070
$\overline{expB}$	0.003^{**}	0.001
$period$	-0.001	(0.086)
$NoHist_{it-1}$	0.004	0.034
$answer$	0.098^{***}	0.023
σ_μ	0.168	
σ_ε	0.091	

Table 2: *BIN* price setting, Nobs=100, N=20 sellers, ***: $p < 0.001$, **: $p < 0.05$.

Table 2 presents the results of a panel regression with fixed effects adjusting errors for within-cluster correlation.[31] Sellers set *BIN* prices of around 0.42. However, when taking into account the effect of the information that sellers can observe (and evaluating those variables at their mean),[32] the offered *BIN* price increases to 0.50. The estimation results show that sellers appear to react on the information about buyers when deciding on their *BIN* price. A closer look at the seller reaction towards buyer bidding behavior reveals that sellers increase their *BIN* price to 0.523, i.e., by 5 percentage points, when the average number of submitted bids increases by one. Observing last-minute bidders, on the other hand, results in demanding lower *BIN* prices. Thereby, sellers react very strongly with decreasing their *BIN* price offer by 16.4 percentage points when observing one last-minute bidder. Sellers also react to the observed buyer experience with the eBay institution. They raise their *BIN* price when the average experience in the buyer population increases.

In this paragraph, we illustrate how sellers adjust the *BIN* price using some examples. When the average number of bids per bidder increases from 2 to 4, the seller raises his *BIN* price by 10 percentage points from 0.44 to 0.48. Further, a decrease of the probability to interact with at least one last-minute bidder ($\overline{lastmin}1$) by half, results in an increase of the *BIN* price by 7 percentage points from 0.50 to 0.53. There is no significant effect of observing two last-minute bidders ($\overline{lastmin}2$). Finally, when a seller faces buyers with low experience (at the 25th percentile), the *BIN* price is set at 0.46. This price increases to 0.50, i.e., by 7 percentage points, when facing buyers with high experience (at the 75th percentile). When interacting only with highly experienced buyers (at the 95th percentile), sellers offer *BIN* prices with an average of 0.63, that is 36 percentage points above the price offered to low experienced buyers.

Altogether, the results of the regression analysis provide support for our hypothesis. As conjectured,

[31]Results are robust to inclusion or exclusion of the three learning variables, *answer, NoHist,* and *period.* Additionally, we estimated the empirical model allowing for non-linear effects of the number of bids and experience including quadratic terms of both variables. Results remain very close with nonlinear effects not being significant.

[32]The numbers are computed using the parameter estimates of Table 2 and evaluating all other variables at their mean values ($\beta_0 = 0.416, \overline{nb} = 4.5, \overline{exB} = 13.68, \overline{lastmin}1 = 0.438, \overline{lastmin}2 = 0.294, answer = 0.33, NoHist = 0.04, period = 4$).

sellers increase their *BIN* price when (1) the number of submitted bids increases; (2) the probability of last-minute bidding decreases and (3) the experience in the buyer population increases.

In addition, we look at whether there is some learning over time other than about the characteristics of the buyer population. The effect of unobserved prior information on *BIN* prices ($NoHist$) is not significantly different from zero. Furthermore, changes in *BIN* price behavior does not seem to follow a simple time trend. Only the dummy-variable *answer* has a highly significant effect: sellers increase the *BIN* price on average by 9.8 percentage points when the last period's *BIN* price had been accepted. One possible explanation for the observed behavior provides directional learning theory (Selten and Buchta (1998)). Applied in the context at hand, it suggests that a *BIN* price would be adjusted upwards had it been accepted before and downwards otherwise.

Finally, given the quite substantial heterogeneity among sellers (σ_μ), we investigate the impact of the seller personal characteristics on *BIN* prices. We regress the estimated individual fixed effects $\widehat{\mu}_i$ on seller elicited risk preferences and their eBay experience.[33] First, risk preferences do not correlate with *BIN* price setting. Thus, seller risk preferences seem not to play a role when deciding on the *BIN* price. Second, experience with eBay has a substantial and significant impact on the way sellers set their *BIN* prices. The more experienced sellers are, the higher the *BIN* price they ask for. For example, *BIN* prices of sellers with high experience (at the 75th percentile) are 17% higher than *BIN* prices of sellers with low experience (at the 25th percentile) and 9% higher than those of sellers with median experience.[34] 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 less experienced sellers and thus post higher prices.[35]

3.3. Do sellers benefit from using the BIN option?

The existing experimental and empirical literature provides mixed evidence on the impact of the *BIN* price on the final outcomes. Several studies (e.g., Shahriar and Wooders (2011), Durham et al. (2004), Dodonova and Khoroshilov (2004), Durham et al. (2013)) report a revenue increase due to the existence of a *BIN* price prior to the auction. On the contrary, Peeters et al. (2016) find that the introduction of a *BIN* option may have the opposite effect, i.e., it unambiguously reduces revenue and, in the case of consistently low *BIN* price offers, also efficiency. Similarly, Bauner (2015) observes that sellers achieve lower revenue when *BIN* auctions are offered, compared to the case when the seller has a choice between a pure auction and a posted price only. In contrast, Jiang et al. (2013) demonstrate that none of the three dominates the other two when they compare the revenue generated by the three selling formats, posted price, pure auction and buy-price auction.

[33] We looked at the linear relation between the fixed effects ($\widehat{\mu}_i$) and elicited individual risk preferences ($risk_i$) as well as the experience of our 20 sellers approximated by the feedback score (exS_i): $\widehat{\mu}_i = \gamma_0 + \gamma_1 \cdot risk_i + \gamma_2 \cdot exS_i + \varepsilon_i$. The parameter estimates obtained by OLS for the 20 sellers are (i) $\gamma_1 = 0.083(1.20)), \gamma_2 = 0.0016(2.05)$ using total experience, where t-values are presented in parentheses.

[34] For those comparisons, we keep all other variables at their mean and vary only the fixed effect conditional on experience, which results in the following *BIN* prices of sellers: 0.44 (low experience), 0.48 (median experience) and 0.52 (high experience).

[35] In a lab *BIN* auction experiment, Ivanova-Stenzel and Kröger (2008) 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.

		Corresponding			
		Parameter Sets		Auctions	
	All BIN	***BIN***	***NoBIN***	***BIN***	***NoBIN***
	(1)	(2)	(3)	(4)	(5)
	Mean (Std) [Nobs]	Mean (Std) [Nobs]	Mean (Std) [Nobs]	Mean (Std) [Nobs]	Mean (Std) [Nobs]
Profits					
Sellers	0.32 (0.18) [120]	0.31 (0.18) [95]	0.25 (0.21) [95]	0.26 (0.19) [52]	0.21 (0.18) [52]
All buyers	0.16 (0.23) [240]	0.17 (0.25) [190]	0.18 (0.25) [189]	0.16 (0.22) [104]	0.16 (0.23) [103]
Buyers who bought	0.34 (0.22) [120]	0.34 (0.25) [95]	0.36 (0.250 [95]	0.32 (0.23) [52]	0.33 (0.22) [52]
Accepted *BIN* price	0.42 (0.13) [43]	0.40 (0.13) [38]	– – –	– – –	– – –
Auction Price	0.27 (0.19) [77]	0.25 (0.18) [57]	0.25 (0.21) [95]	0.26 (0.19) [52]	0.21 (0.18) [52]
	% [Nobs]	% [Nobs]	% [Nobs]	% [Nobs]	% [Nobs]
Efficiency	84 [120]	84 [95]	72 [95]	90 [52]	75 [52]
when *BIN* price was accepted	74 [43]	76 [38]	- -	- -	- -
in auctions	90 [77]	89 [57]	72 [95]	90 [52]	75 [52]

Table 3: Descriptive statistics of outcomes in *BIN* and *NoBIN* treatments.

There are several reasons why introducing a *BIN* price prior to the auction could reduce both, seller revenue and efficiency. First, too low *BIN* prices lead to the selection of high value buyers into accepting the *BIN* price and low value buyers into the auction – resulting in overall low outcomes: accepted low price offers and low auction revenue. Second, efficiency decreases in cases when a bidder who has not the highest value accepts the *BIN* price. Third, it is also possible that experiencing the *BIN* price prior to the auction affects bidding behavior in general.

To investigate whether and to what extent the existence of the *BIN* option impacts seller revenue and efficiency, we conducted an additional treatment with pure eBay auctions without a *BIN* price, the "*NoBIN*" treatment. We conducted four *NoBIN* sessions. For the additional sessions, we used the parameter sets (i.e., buyer values and configuration of trading groups) of four (out of the five) randomly selected *BIN* sessions. Hence, we have four pairs of directly comparable *BIN* and *NoBIN* sessions.

The first column of Table 3 presents the results on revenue and total efficiency of all conducted *BIN* auctions as well as the efficiency separately by whether the *BIN* price was accepted or whether there was an auction.[36] The second and third columns of Table 3 present a comparison between the *NoBIN* sessions and the corresponding (four) sessions in the *BIN* format.[37] Overall efficiency in the *BIN* treatment is with 84% quite comparable to the efficiency observed in other experimental studies on *BIN* auctions (Durham et al. (2013): 80%, Shahriar and Wooders (2011): 89%, Ivanova-Stenzel and Kröger (2008): 85%). There are two possible reasons why a *BIN* auction can be inefficient: either the bidder with the lower value accepts the *BIN* price or he wins the auction, most likely due to last-minute bidding. Our results lend support to the first explanation: The efficiency of transactions in which the *BIN* price was accepted is with 74% substantially lower compared to the 90% of efficient transactions in the auction.

An efficiency comparison between the two treatments reveals that the *BIN* treatment is significantly more efficient compared to the *NoBIN* treatment (84% vs. 72%, t-test, $p = 0.036$). This result is in contrast to Shahriar and Wooders (2011) who find efficiency to be slightly lower but not significantly different between auctions with a *BIN* price and ascending-clock auctions. Our finding is in line with Durham et al. (2013) where the introduction of the *BIN* price leads to an increase of efficiency from 66% to 80%. In our experiment, only sellers benefit from this gain in efficiency, while there is no difference in earnings for winning buyers. Sellers realize on average significantly higher revenue in the *BIN* treatment compared to the *NoBIN* treatment (0.31 vs. 0.25, t-test, $p = 0.032$).

The last two columns of Table 3 summarize outcomes based on corresponding parameter sets in both treatments, where the final price was determined only by the auction (i.e., the *BIN* price has been rejected in the *BIN* treatment). Comparing the outcomes from those "corresponding auctions" between the two treatments allows to control for selection in the auction in the *BIN* treatment. There is no significant difference ($p = 0.221$) in seller revenue generated by the auction after controlling for such selection effects.

Bidding behavior is quite comparable between the two treatments. Also in the *NoBIN* sessions, we find evidence for the use of the multiple and last-minute bidding strategies. In the auctions without a *BIN* price, bidders submit on average 2 bids, in 92% of the auctions at least one bidder submits a last-minute bid, and the probability of last-minute bids being lost is 4.5%. These findings, in particular the

[36] We consider an allocation as efficient when the buyer with the highest value receives the object.

[37] We had to exclude one auction in both treatments. In the *NoBIN* treatment, no bidder submitted a bid on time in that auction, hence there was no sale.

significantly higher number of auctions with last-minute bidding in the *NoBIN* treatment, can explain the lower efficiency observed in that treatment compared to the treatment where the *BIN* price is offered (Durham et al. (2013) report similar results): for example, if the bidder with the higher value is an incremental bidder, the more often he faces a last-minute bidder (with a lower value), the more likely it is that he does not have the time to respond by increasing the bid up to the true value. Similar to the *BIN* treatment, only 29% of all losing bids equal bidders' values. The remaining 71% of the losing bids are on average 18% below buyer value. Thus, bidding below own value is not an artefact due to the existence of a "take-it-or-leave-it" price offer prior to the auction. It seems rather to be a phenomenon of the specific features of the eBay-auction.

Altogether, our results suggest that the use of the *BIN* option on eBay enables sellers to achieve higher revenue, i.e., closer to the expected revenue in second-price auctions, and also leads to higher efficiency by mitigating to some extent the effect of last-minute bidding.

4. Conclusions

We investigate how sellers set *BIN* prices on eBay and whether they benefit from the use of the *BIN* option. Thereby, we contribute to the scarce literature studying seller behavior in online auctions. In our experiment, we combine field and lab techniques. As in field experiments, we observe real eBay traders on the real 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.[38] In fact, we find experience with eBay of both, sellers and buyers, to impact their behavior in a predictable way. Sellers who have more experience offer higher *BIN* prices. This suggests, that they are better aware of the selection effect caused by their own *BIN* price. Prices in auctions with more experienced bidders are closer to those expected in second-price auctions.

As in conventional laboratory experiments, we control for certain characteristics of the environment, such as private independent values of buyers for a single indivisible object for sale. This allows us to observe aspects of bidding behavior and how they affect revenue and efficiency that are not easily available in field data. In all our eBay auctions (with and without a *BIN* price), we find that price determining bids are on average below the true value. As a consequence, resulting auction prices are substantially below those expected and usually observed in previous laboratory experiments both, in pure second-price auctions (e.g., Ariely et al. (2005), Garratt et al. (2015)) and in auctions with a *BIN* price (Shahriar and Wooders (2011), Peeters et al. (2016), Ivanova-Stenzel and Kröger (2008)). The relatively low auction prices can be explained by the specific features of the auction format that give rise to two types of bidding strategies (incremental and last-minute bidding) and by the heterogeneity in participant experience with eBay. We find evidence for the use of both strategies. Furthermore, information about buyer experience and bidding behavior available on eBay is correlated with the deviation of the actual auction prices from those expected in second-price auctions. The most striking result is however the fact that sellers react to this information when deciding on the *BIN* price. In particular, they decrease

[38]Normann and Ruffle (2011) discuss some of the emerged criticisms w.r.t to the value of experiments in IO. Among others they point out as problems the importance of the context of the decision environment and the lack of experience of the standard student subjects with the specific market institution. Our design offers an answer to both problems.

their *BIN* price when facing a population of less experienced buyers, when observing a lower number of submitted bids or more last-minute bidding from at least one bidder. The strategic reaction of sellers to the available information helps them achieve gains that would have been forgone otherwise. For example, the offer of the optimal *BIN* price based on the (false) expectation that the auction price in the eBay auction would be equal to the second highest value, would not yield the highest revenue. Sellers can do better: the information available on eBay about buyer experience and bidding behavior enables sellers to update their expectations about the auction price and consequently to offer a more profitable *BIN* price. Thus, our results point out to another important reason for why sellers might be interested in posting a *BIN* price: the *BIN* price offer could be a useful device that permits sellers to react strategically to available information on buyer behavior.

Finally, the comparison between our experimental eBay auctions with and without a *BIN* price reveals that the presence of the *BIN* price does not impact bidding behavior but has an enhancing effect on revenue and efficiency. Altogether, our results suggest that for sellers but also for market platforms, whose profit usually comprise a share of seller revenue, the use of eBay-style auctions with a *BIN* option is highly advisable.

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Supplementary Material

[b]

The supplementary material includes detailed description of the functioning of eBay BIN auctions at the time the experiment was conducted; a translated version of the instructions, incl. screenshots and additional sheets used in the lab experiment; a description of how we elicited and estimated risk preferences, as well as revenue simulations and counterfactual computations.

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

Sellers who want to sell at eBay can use an auction with *BIN* option, allowing 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 €1. There are several other options, such as e.g., a secret reserve price, placing the offer at the top of a page, etc.[4] Sellers also have the option to offer an item at a fixed price only.

The information available to eBay traders before a sale takes place is limited to the trader's profile. This profile contains, amongst other information, a unique UserID and a feedback score. At the time of the experiment, after a transaction has been made, buyers and sellers can rate each other by leaving feedback.[5] The feedback score 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.

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

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

2. Experiment: Instructions, screenshots and other sheets used in the lab experiment

2.1. 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 or buyer) and s/he 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 time[6] 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

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

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. 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 = €0,20.
After the experiment you will receive your payoff (in €) from all auctions. You can get your payment any time between XXXX and XXXX 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 €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., €5 if lottery "A" was chosen and €8.20 if lottery "B" was chosen). If the result of the second roll is "6","7","8","9" or "10" (probability 50%) then you will earn the amount corresponding to those numbers in the lottery you have chosen (i.e., €3 if lottery "A" was chosen and €0.20 if lottery "B" was chosen)

2.2. Screen Shot of Seller BIN Price Decision and other sheets distributed in the experiment

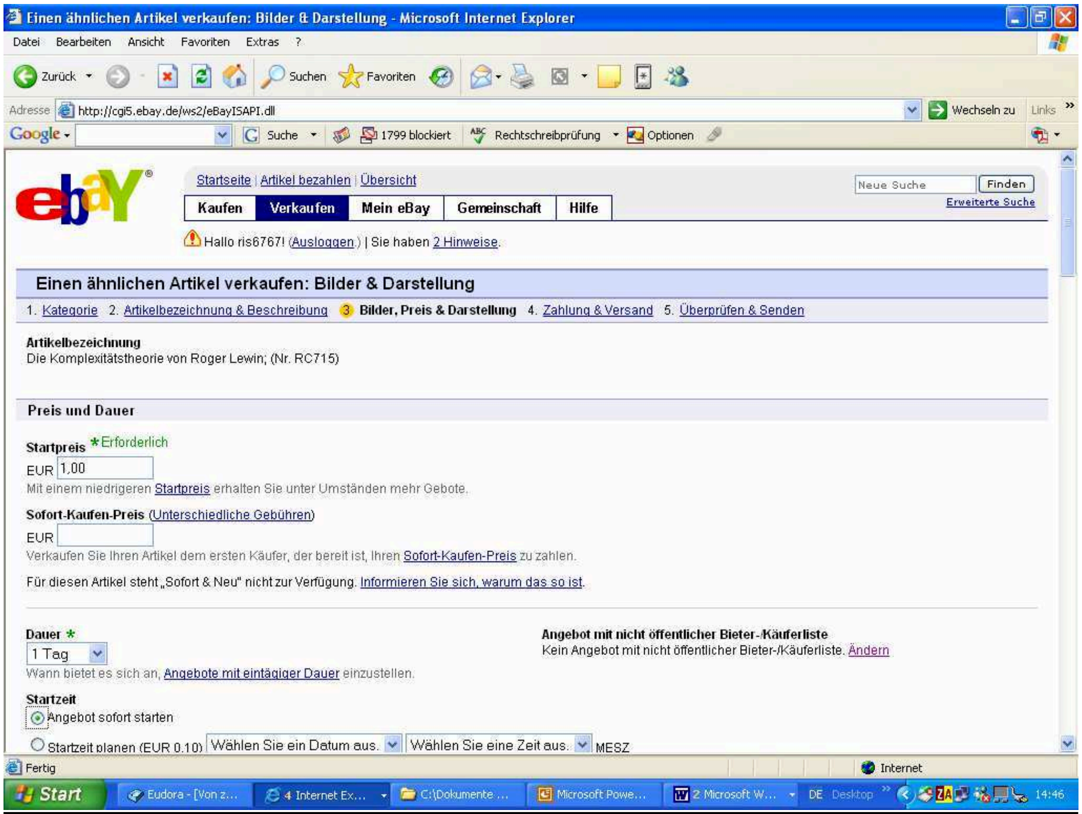


Figure 1: Screen Shot of Seller *BIN* Price Decision. The seller had to fill in the blanc field of the *BIN* price in EUR ("Sofort-Kaufen-Preis"). All items used the minimum Starting price ("Startpreis") of 1EUR.

Information about your role

<u>SELLER</u>

Name of the eBay account you will use during the experiment:

XXXXX

Item's name and reference number:

Auction 1: „Tod auf Anfrage“ by Carolyn G. Hart (Ref.-Nr. SI113)

Auction 2: “The Ballad of Frankie Silver” (Ref.-Nr. SI127)

Auction 3: “Feuer und Schwefel” by T. Adcock (Ref.-Nr. SI136)

Auction 4: “Bird” by Jane Adams (Ref.-Nr. SI141)

Auction 5: „Tell Me Your Dreams“ by S. Sheldon (Ref.-Nr. SI152)

Auction 6: „Undank ist der Väter Lohn“ by E. George (Ref.-Nr. SI168)

Information about your role

<u>BUYER</u>

Please use your own eBay ID and password to log in!

You will be informed about the name of the items and their reference numbers as well as your reselling values with the sheet “Information about your auction.”

Information about your auction

BUYER

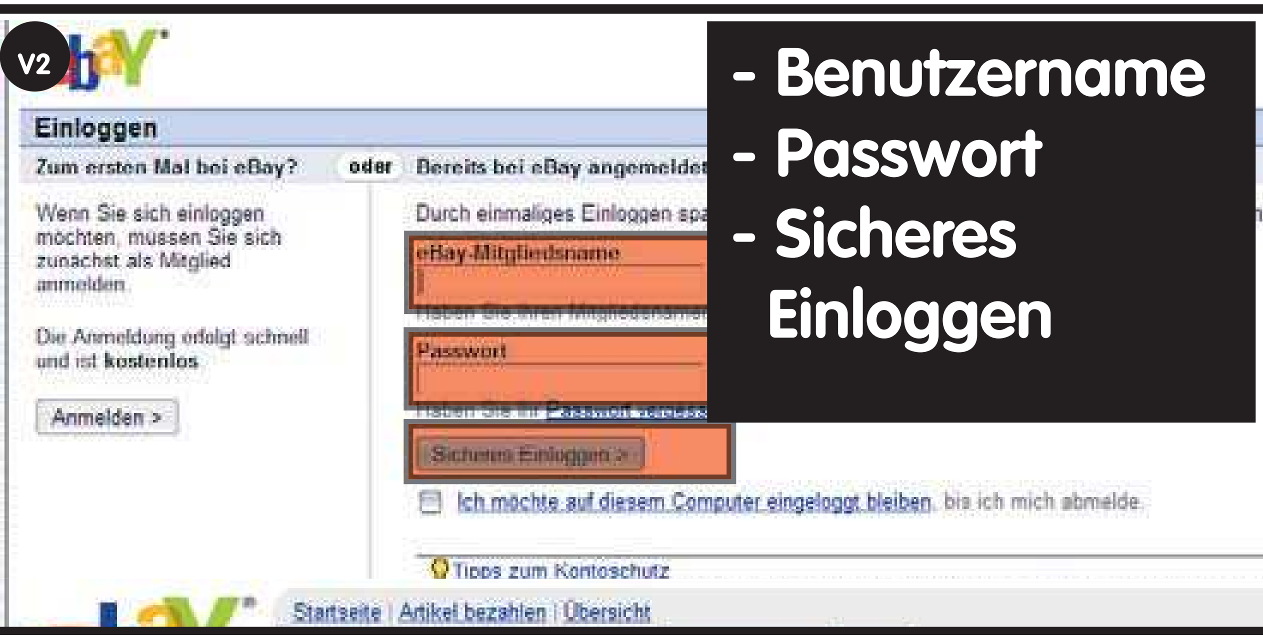
Auction:	1
Item’s name and ReferenceNr:	Tangled Vines von Janet Dailey (Ref.-Nr. SI213)
Reselling value:	48,00

VERKÄUFER: Anleitung zum Verkauf

V1

Einloggen

V2



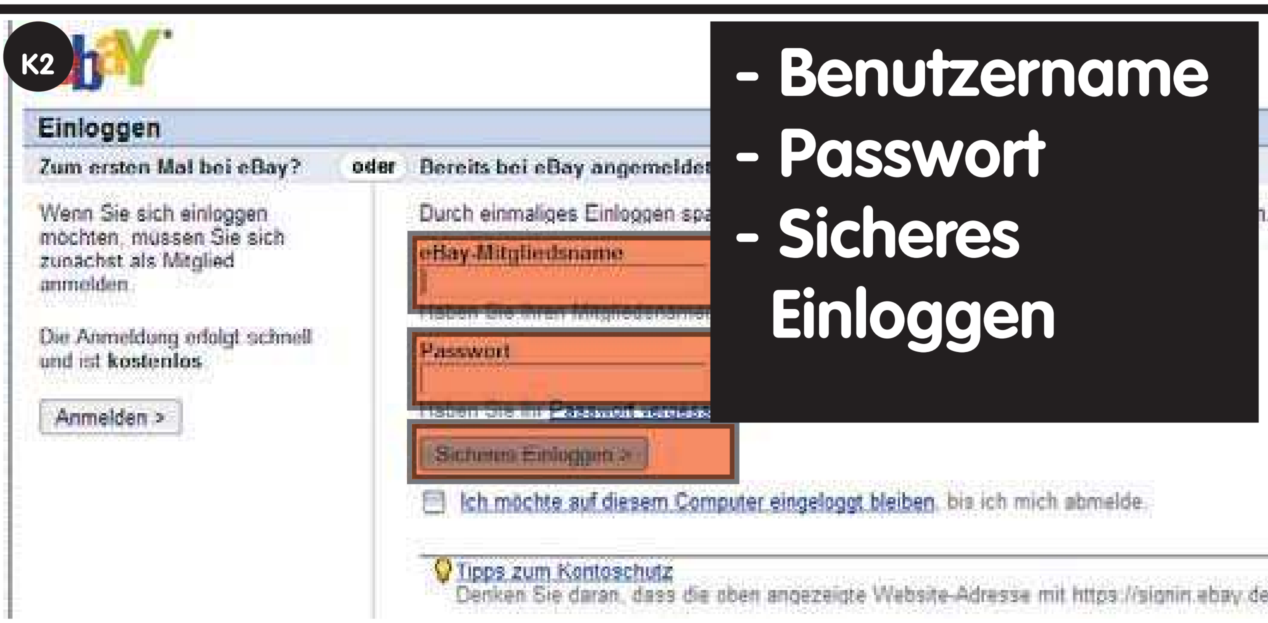
- **Benutzername**
- **Passwort**
- **Sicheres Einloggen**

KÄUFER: Anleitung zum Kauf

K1

Einloggen

K2



- Benutzername
- Passwort
- Sicheres Einloggen

K3

Kaufen

- bei Suche die Bestell-Nr. vom Blatt eintragen
- Finden
- Sofort Kaufen bzw. Gebot abgeben

3. Elicitation procedure and estimation of risk preferences

Participants had to choose between two lotteries, lottery A and lottery B. Each lottery had two possible payoffs, a high and a low amount: for lottery A €5 and €3, and for lottery B €8.20 and €0.20. The amounts were chosen to resemble the profit opportunities in the experiment. The high amounts in both lotteries were realized with the same probability p. Participants had to decide between both lotteries and had to make this choice for ten lottery pairs, whereby the probability p increased from 10% to 100%. Of all ten lottery pairs, one pair was selected randomly and the chosen lottery 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 persons' earnings from the eBay experiment and x the earnings in the lottery. This specification implies risk seeking for $\alpha < 0$, risk neutrality for $\alpha = 0$ and risk aversion for $\alpha > 0$. When $\alpha = 1$, the natural logarithm, $U(W+x) = ln(W+x)$, is used. Observing the lottery pair at which a person switches from choosing lottery A to lottery B allows us to determine the boundaries within which the individual constant relative risk-aversion parameter α would lie: $[\arg\max \alpha : \; EU_A(W,\alpha) > EU_B(W,\alpha)] < \alpha < [\arg\min \alpha : \; EU_A(W,\alpha) < EU_B(W,\alpha)]$. With $EU_L(W,\alpha) = p \cdot U(W+L_1,\alpha) + (1-p) \cdot U(W+L_2,\alpha))$ for $L = \{A, B\}$ and where L_1 and L_2 denote the payoffs of lottery L. We take the midpoint of the interval as the risk preference of the person.[7]

[7] All participants except five buyers decided in a monotone way, i.e., once they switched from choosing lottery A to B they continued choosing lottery B. Following Holt and Laury (2002), the estimation of risk preference for those subjects is based on the number of safe choices (Lottery A).

4. Consequences of ignoring deviations from true value bidding: Revenue simulations and counterfactual computations

How should sellers react if they anticipate deviations from true value bidding, i.e., potential bid shading? First of all, they should expect lower auction prices compared to the expected prices under true value bidding, which certainly affects the choice of the optimal *BIN* price.

To shed more light on how the *BIN* price will be affected in the case of bid shading, we perform revenue simulations and counterfactual computations based on the 120 pairs of randomly drawn values that we used in the *BIN* treatment. We simulate seller revenue conditional on *BIN* prices for two scenarios: (1) true value bidding and (2) bid shading. We conduct the simulations employing *BIN* prices in the range $[0.4, 0.7]$, which correspond to the 25th to 90th percentile of the *BIN* prices that we observed in the experiment.

Scenario (1):

We use the theoretical model of Ivanova-Stenzel and Kröger (2008) to determine whether buyers accept or not the *BIN* price. The model allows for heterogeneity in risk preferences and is based on the assumption of true value bidding. Thereby, we employ the elicited risk preferences of buyer participants. In the auction, we assume that bidders bid their true value.

Scenario (2):

Buyers' acceptance behavior will change, when no true value bidding is expected in the auction. Therefore, we use a probit model based on the observed acceptance behavior as an empirical approximation of buyer reaction towards the *BIN* price. In the auction, we assume that bidders shade their bid by 7 %, the relative deviation from true value bidding observed in the experiment.

We run simulations for both scenarios also without the *BIN* price (*NoBIN* treatment) to compare the effect of the *BIN* price to the effect of bid shading. Figure 2 plots the results from all computations. A comparison between the two solid lines (scenario (1): black, scenario (2): gray) illustrates that a *BIN* price optimal under true value bidding (0.65) generates less revenue when bidders shade their bids. In this case, it is more profitable for the seller to offer a lower *BIN* price. The gray and black dotted lines in figure 2 illustrate revenue in *NoBIN* auctions with and without bid shading, respectively. A comparison with the *BIN* scenarios indicates first, that *BIN* prices are revenue enhancing, probably because of buyer risk aversion. Second, comparing *BIN* scenario (2) and *NoBIN* scenario (1) (gray solid vs black dotted line) for our data, the optimal *BIN* price seems to counterbalance the bid shading effect, leaving sellers with the same expected revenue as under true value bidding.

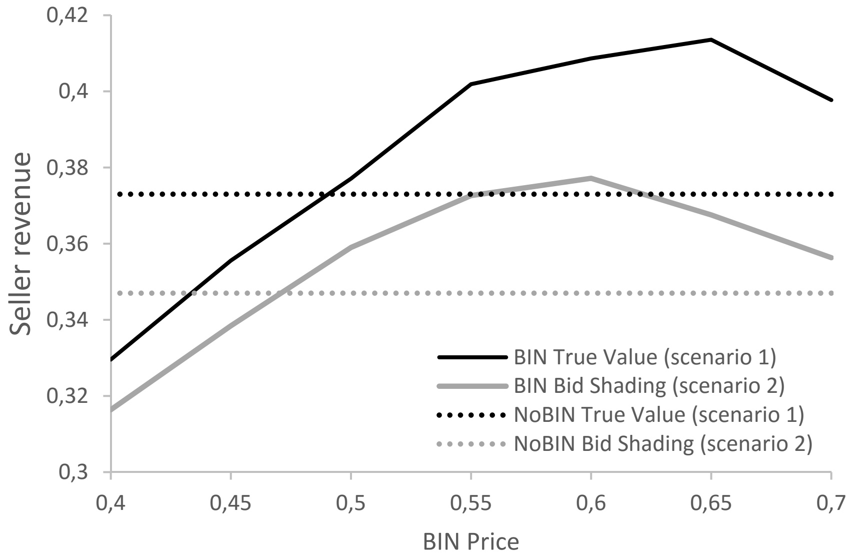


Figure 2: Mean revenue from simulations for *BIN* and *NoBIN* treatments given the value drawn in the experiment and different *BIN* prices. (N=120)

References

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Holt, C. A., Laury, S. K., December 2002. Risk aversion and incentive effects. American Economic Review 92 (5), 1644 – 1655.

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