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How do sellers benefit from Buy-It-Now prices in eBay auctions?

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Abstract

We investigate experimentally on eBay how sellers set prices in “Buy-It-Now” (BIN) auctions. We find that the eBay format leads to prices substantially below those expected in second-price auctions. Moreover, our results reveal that the information available on eBay about buyer experience and bidding behavior correlates with the observed price deviation. Sellers respond strategically to this information. More experienced sellers ask for higher BIN-prices, whereas seller risk aversion does not affect their price decisions. Compared to an eBay auction without a BIN-price, the BIN-auction is more efficient and generates significantly higher revenue.

Keywords:

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

JEL classifications:

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1 Introduction

“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)

Online platforms offer a variety of selling mechanisms, posted price and pure auction being the most popular ones. Recently, more complex trading mechanisms combining both, posted price and auction, have been successfully introduced. For example, eBay, one of the biggest online auction platforms, offers sellers the possibility to announce a “Buy-it-Now” price (*BIN*-price) and to call for bids simultaneously. By accepting the *BIN*-price, buyers can buy the item before the auction starts. Otherwise, the price is determined by the auction. The *BIN*-auction has become increasingly popular (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.¹ 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 complex environment. Our study aims at filling this gap.²

The theoretical literature offers several explanations why sellers post 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), Chen et al. (2013), one or both market sides are impatient (Mathews (2004), Gallien and Gupta (2007)), considering participation and transaction costs (Wang et al. (2008)) and when 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 and the theoretically optimal *BIN*-price given risk aversion of buyers. They find that the observed buyer behavior is in line with the theoretical predictions. Peeters et al. (2016) apply an auction format that permits proxy bidding as on

¹ Under the standard assumptions of the symmetric independent private value (SIPV) environment with risk-neutral bidders, the use 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)).

² 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.

eBay, but unlike eBay uses an automatic extension rule instead of a fixed end-time.³ They compare *BIN*-auctions with 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.

Moreover, 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. Comparing *BIN*-auctions to situations in which sellers can choose between pure auctions and fixed-price listings, Bauner (2015) finds that while buyers might benefit from the *BIN*-auction, seller surplus is lower. Finally, Anderson et al. (2008) observe that the existence of a *BIN*-price has a positive but not significant impact on the sale price.⁴

The experimental studies on *BIN*-auctions typically employ an artificial auction institution with which participants gain experience together over the course of the experiment. However, empirical studies demonstrate that heterogeneity in experience matters. For example, Durham et al. (2004) and Anderson et al. (2008) observe that experienced sellers use the *BIN*-option more frequently. Durham et al. (2004) find that buyers with higher reputation buy more often at the *BIN*-price when sellers have no experience. This evidence suggests that three sources of influence need to be considered when studying seller behavior in eBay *BIN*-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). The drawback of this approach is that participants cannot react to the information about the experience of others.

In this paper, we present the results of a laboratory 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. Participants were eBay traders, and the experiment was conducted on the eBay auction platform. This approach yields several advantages. First, it allows us to observe behavior in the real eBay market institution and to aid subjects with understanding of the environment by presenting the incentives in a “natural” context. Second, it provides the needed variation in experience of the traders with this institution. Third, it allows us to investigate

³ For a description of the functioning of the eBay proxy bidding procedure see supplementary material part 1.

⁴ 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), Chen et al. (2013), and Kagel and Levin (2016), p. 617-18.

whether real-world experience in auctions and the information publicly available on eBay help sellers to solve the cognitively very demanding decision task of choosing the optimal *BIN*-price.

By bringing the field into the laboratory, we intervene in the eBay environment with the purpose of creating public knowledge about what traders know regarding the auction format (e.g., number of traders, distribution of private valuations) and payoffs. The controls enable us to focus on the role of experience with the trading institution. They allow us to refer our results to a formal theoretical frame and to observe aspects of behavior that are not easily available in field data (e.g., over- and underbidding). Finally, they enable us to measure the effect of the existence of the *BIN*-option on seller revenue by controlling for other influences, such as resale opportunities, product quality, competition between sellers with different reputation and experience, endogenous participation as well as time preferences.

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.⁵ We find a correlation between how much eBay auction prices deviate from prices based on true value bidding and the information about buyer experience and bidding behavior that is available on eBay. More importantly, sellers react to this information. They increase their *BIN*-prices when observing a higher number of bids, less last-minute bids, and more experienced buyers. Our empirical analysis also 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 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 Experiment and theoretical predictions

The setting studied in our experiment consists of a seller who offers a single indivisible object for sale to two potential buyers.⁶ Buyers have symmetric independent private values for the good, drawn from a uniform distribution. A buyer is randomly selected prior to the auction. The seller offers a *BIN*-price to this buyer who

⁵ 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 websites.

⁶ 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 on eBay auctions of Ariely et al. (2005) employs two bidders.

either accepts or submits a bid.⁷ In the former case, the transaction is completed. In the latter case, the *BIN*-price disappears, and an auction takes place with both buyers.⁸

2.1 Design and Procedure

All participants in our experiment were eBay traders.⁹ At the beginning of a session, we collected their feedback score on eBay. In our analysis, we use the feedback score to approximate individual experience with the eBay institution.¹⁰ Persons with low experience (at the 25th percentile) had a feedback score of 2 and those with 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 (average: 23). The distribution of the experience in our experiment is quite comparable to the one Ockenfels and Roth (2006) report from eBay-Antiques auctions.

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 exclude any potential influence of seller reputation on buyer behavior. 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 exclude the influence of reputation building on *BIN*-price behavior (Michael Melnik und James Alm, 2003). Third, we avoid the usual exchange of private information on eBay after a transaction preserving the anonymity between participants.

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. We described each object for sale and included a unique reference number.¹¹ The reserve price was set to *eBay-€*1 (eBay's minimum starting price). The *BIN*-price was the only parameter not yet specified.

Upon arrival in the lab, we assigned subjects randomly to the computer terminals. They received detailed instructions and were informed about their role, either seller or buyer. Roles were kept fix throughout the whole experiment. It was commonly known that buyer private values for each item were drawn independently from the set {1, 1.50, 2,...,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.

⁷ 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.

⁸ 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.

⁹ Most participants were students of economics, business administration, or industrial engineering at [blinded for review process].

¹⁰ As leaving feedback is optional, feedback score of eBay traders understates their actual experience. However, it can be used either as a proxy for reputation (Melnik and Alm (2002), Lucking-Reiley et al. (2007), Cabral and Hortacsu (2010)) or as a proxy for experience (Roth and Ockenfels (2002), Ockenfels and Roth (2006), Bolton and Ockenfels (2014)).

¹¹ As objects for sale we used second-hand books.

The experiment comprises six rounds. At the beginning of each round, a seller decided on the *BIN*-price from the set $\{1, 1.50, 2, \dots, 50\}$ on a decision sheet, featuring a screen shot of the corresponding eBay page.¹² Together with the decision sheets of the sellers, we distributed blank sheets to the buyers to hide the position of sellers in the lab and thus sustain confidentiality of the roles. All subjects had to return the sheets after two minutes. The experimenters filled in the *BIN*-price chosen by the sellers in the prepared online auction-form and started the *BIN*-auctions. At first, the *BIN*-price was offered to one of the two buyers (henceforth *BIN*-buyer). We informed all subjects in the position of the *BIN*-buyer about their items' reference numbers and values. These buyers had two minutes within which either to accept the *BIN*-price or to submit a bid. After the *BIN*-price had disappeared on eBay (i.e., all subjects acting as *BIN*-buyers had made their decisions), we informed the remaining buyers about their items' reference numbers and values. All buyers could now participate in the eBay auction if the *BIN*-price had not been accepted. Sellers could follow the proceeding of their auction at any time on eBay and, therefore, collect and update their information about buyer behavior as well as buyer experience.

The shortest auction duration on eBay of one day would have been too long in the context of our experiment. Thus, we artificially shortened the auction time to five minutes as follows: After all buyers were informed about their items' reference numbers and values, we fixed the auction end-time and announced it publicly. A clock, adjusted to the official eBay time, projected on the wall, counted down the seconds to the end of the auction. Any bids arriving later than the fixed auction end-time were not considered. The five-minute auctions have several advantages. They were long enough to enable participants to submit multiple bids. At the same time, they were short enough to enable us to conduct several auctions, and thus to observe behavior of the same market participants over time. Additionally, it allowed us to observe last-minute bids arriving after the end of the auction.

A session consisted of 12 subjects. There were four trading groups, each with two buyers and one seller. The composition of the trading groups changed randomly after each round. Each buyer acted as *BIN*-buyer in three (of the six) rounds. To avoid unnecessary path dependencies, no more than one trading group consisted of the same subjects acting as seller and the *BIN*-buyer. Moreover, two buyers were assigned only once to the same trading group. We also conducted a control “*NoBIN*” treatment with the same parameter set (buyer values and configuration of trading groups) as in the treatment with the *BIN*-option but with pure eBay auctions without a *BIN*-price.

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.¹³

¹² For the screenshot see supplementary material part 2.2.

¹³ For details on the elicitation procedure and the estimation of risk preferences see supplementary material part 3.

2.2 Theoretical benchmark

The predictions for our *BIN*-auctions build on the existing theoretical literature on eBay auctions and on combined mechanisms. Ockenfels and Roth (2006) show that all equilibria in eBay auctions involve bidding the own value at some point in time. Thus, in the eBay auction, it is reasonable to assume that the bidder with the highest value wins and pays a price equal to the second-highest value. As shown in Ivanova-Stenzel and Kröger (2008) and Grebe et al. (2016), a *BIN*-buyer is indifferent between accepting the seller price offer and rejecting it, if the *BIN*-price provides the same utility as the equilibrium expected utility from participating in the auction, i.e.,

$$u(v_{BIN} - p) = \Pr\{win\} * u(v_{BIN} - E[V_2|V_2 \leq v_{BIN}]), \quad (1)$$

where v_{BIN} denotes buyer 1's valuation for the good, V_2 the valuation of the second highest bidder and p the *BIN*-price offer. Based on equation (1), the *BIN*-buyer has a threshold price $\bar{p}(v_{BIN})$, above which he will not accept any price offer. The seller should condition on this threshold. Thus, the utility maximization problem of the seller is

$$\max_p (\Pr\{p \leq \bar{p}(v_{BIN})\}u(p) + (1 - \Pr\{p \leq \bar{p}(v_{BIN})\})E[U(R_A)|\bar{p}(v_{BIN}) < p]), \quad (2)$$

where R_A is the expected revenue from the auction.

In the case of risk neutral agents all trades end in the auction. In particular, if buyer valuations are drawn from a uniform distribution with a support normalized to $[0,1]$, optimal *BIN*-prices lay in the interval $[0.50,1.00]$ with an average price of 0.75. Those prices are never accepted resulting in expected profits for the seller from the auctions of 0.33. With heterogeneous risk preferences, we can solve numerically for the optimal *BIN*-prices.¹⁴ Given the elicited risk preferences of our participants,¹⁵ the predicted *BIN*-prices lay in the interval $[0.35,0.63]$ with an average price of 0.53. Compared to the risk-neutral case, the *BIN*-price interval is narrowed and shifted downwards, because of two reasons: First, the auction outcome is more volatile, which risk-averse sellers dislike. Second, there is a strategic effect from interacting with risk-averse buyers: low *BIN*-prices from risk-averse sellers are increased and at the same time *BIN*-prices from risk-neutral or risk-loving sellers are decreased because risk-averse buyers are willing to accept higher prices. The expected profit of sellers is 0.34 and thus larger compared to the risk neutral case (0.33). The predicted acceptance rate is 31%. Thus, allowing for general risk preferences opens a price floor within which agreements are possible at the *BIN*-price. The exact magnitude depends, however, on the specific preference distribution.

¹⁴ For more details on the derivation of the theoretical predictions for any type of risk preferences, see Ivanova-Stenzel and Kröger (2008) and supplementary material part 4.

¹⁵ To save on computation time, we classified sellers and buyers in groups of risk preferences, rounding to the closest multiple of 0.10 starting at -0.05 up to 2.45 with a total of 9 groups for buyers (at $-0.05, 0.25, 0.45, 0.55, 0.75, 0.85, 1.15, 1.75, 2.45$) and 7 groups for sellers (at $-0.05, 0.25, 0.55, 0.85, 0.95, 1.25, 1.75$).

3 Results

The aim of this study is 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 outcomes in the *BIN*-auctions.

3.1 Overview of the results in the *BIN*-auctions

We collected data from 5 sessions with a total of 60 participants (20 sellers and 40 buyers) and 120 transactions. ¹⁶ Table 1 reports descriptive statistics of the experimental outcomes for all periods and Table 4 provides summary statistics on revenue and efficiency (column 1 “All *BIN*”).

Table 1 approximately here

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).¹⁷ 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. The theoretical predictions comprise 70% of the observed *BIN*-prices. The average *BIN*-price remains stable over time and is not significantly different from the predicted price of 0.53 (t-test, $p=0.35$, $n=5$ sessions).

Figure 1 approximately here

The observed average acceptance rate is 36% and not significantly higher than predicted (t-test, $p=0.180$, $n=5$ sessions). When calculating the acceptance rate only for *BIN*-prices in the predicted range [0.35,0.63], the acceptance rate of 31% is virtually the same as the predicted one. Regarding the acceptance behavior, 79% of buyers’ reactions towards the *BIN*-price can be rationalized by the model taking buyers’ individual risk preferences into account (i.e., are in line with equation (1)). Seller average earnings are with 0.32 though slightly lower not significantly different from the predicted profits (t-test, $p=0.31$, $n=5$ sessions). These results show that the experimental outcomes on the aggregate level are to a great extent well captured by the benchmark prediction with heterogeneous risk preferences.

In case of *BIN*-price rejection, sellers receive an average auction revenue of 0.27 which is significantly lower compared to the expected auction price of 0.33. 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

¹⁶ Average earnings in the *BIN*-experiment were €17.19, and in the lottery €4.87. Total earnings ranged between €9.40 to €36.40 with a mean of €22.06. These amounts include a lump sum payment of €6 for buyers.

¹⁷ For ease of comparison to the theoretical predictions and with other studies, all results are reported for normalized values, i.e., all experimental outcomes are transformed into the [0,1] range.

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) are 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.¹⁸

Such deviation from true value bidding can be explained by the use of particular bidding strategies typically 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” (also referred to as “sniping”). A bidder who adopts the incremental bidding strategy first submits a bid below his true value, raises the 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.¹⁹ 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). Moreover, in 75% of the auctions we observe last-minute bids, i.e., bids submitted within the last 30 seconds.²⁰

Observing multiple bids indicates incremental bidding and final bids that are closer to the true value. Thus, we can expect prices resulting from multiple bidding to be close to those predicted 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, we can observe one bid 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 price 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 occur because of 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.

¹⁸ Even though, bids are not displayed on eBay, losing bids can be recovered from the auction price.

¹⁹ Roth and Ockenfels (2002) refer as “last-minute bidding” or “sniping” to bids submitted in the last 5 minutes in auctions that last at least one day.

²⁰ 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. In both studies, the authors 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.

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

$$rd_t = \kappa + x_t' \lambda + \varepsilon_t. \quad (3)$$

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 time variant and invariant bidder characteristics: the number of submitted bids (nb_t), the experience the buyer has with eBay, approximated by his feedback score (exB), quadratic terms of the experience and the number of submitted bids to capture potential nonlinear effects, a dummy variable ($lastmin_t$) that equals 1 if the bidder submitted a last-minute bid that arrived on time and a possible nonlinear interaction between the number of bids and experience ($nb_t \cdot exB$). All variables enter twice, once for the losing bidder (subscript "0") and once for the winning bidder (subscript "1"). We add another interaction term $nb_{t,0} \cdot nb_{t,1}$ as the number of bids is correlated between bidders. Finally, ε_t captures auction idiosyncratic errors and is assumed to satisfy $E(\varepsilon_t) = 0$.

Table 2 approximately here

Table 2 presents the results of a median regression.²¹ There is a positive price deviation of about 20%. The more experience the losing bidder has the lower the deviation. However, experience enters additionally via the interaction term with the number of bids and we can evaluate its total effect 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 2.²² For all number of bids, the predicted relative deviation is 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 approximately here

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

²¹ We chose median regression as a few participants had some extremely high values for their experience and OLS might be vulnerable to those outliers.

²² The figure depicts the case when both bidders have the same experience $exB_0 = exB_1$ and submit the same number of bids $nb_0 = nb_1$. The effect of other variables, $lastmin_0$ and $lastmin_1$, is taken at their mean values.

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 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.²³ 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 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 sellers observe, 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 start 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 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:

$$bin_{it} = const + \beta_1 \overline{BC}_{it-1} + \beta_2 \overline{L}_{it-1} + \mu_i + \varepsilon_{it}, \text{ with } t = (2, \dots, 6). \quad (4)$$

The *BIN* price of seller *i* in period *t*, bin_{it} , is modelled as a function of the average buyer characteristics and behavior $\overline{BC}_{it-1} = (\overline{nb}_{it-1}, \overline{exp}_{B_{it-1}}, \overline{lastmin}_{1_{it-1}}, \overline{lastmin}_{2_{it-1}})$ that seller *i* observed in all previous 1 to (*t*-1) periods.²⁴ The vector of buyer characteristics contains the average number of bids per buyer

²³ The details of the counterfactual analysis are presented in supplementary material part 5.

²⁴ 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.

(\overline{nb}_{it-1}), the average feedback score for all buyers as a proxy for experience ($\overline{exp}_{B_{it-1}}$), and seller i 's average count of one ($\overline{lastmin}_1$) and two ($\overline{lastmin}_2$) last-minute bidders in an auction. 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 own past experience.

Furthermore, we check for learning with the matrix $L = (period, NoHist_{it-1}, answer_{it-1})$. 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{BC}) can only be observed when an auction has been conducted. Therefore, 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 behavior in the experiment (\overline{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, 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 seller fixed effects. We will then use the estimated fixed effects to assess the impact of seller individual characteristics on *BIN*-prices.²⁵ 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 bidder fixed effects ($E(\varepsilon_{it} | \overline{bc}_{it-1}, \mu_i)=0$).

Table 3 approximately here

Table 3 presents the results of a panel regression with bidder fixed effects adjusting errors for within-cluster correlation.²⁶ 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,²⁷ the offered *BIN* price increases to 0.50. The estimation results show that sellers appear to react to 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

²⁵ Bolton and Ockenfels (2014) provide some evidence for a link between seller eBay experience and their choice of eBay auction format.

²⁶ 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.

²⁷ The numbers are computed using the parameter estimates of Table 3 and evaluating all other variables at their mean values ($\beta_0 = 0.416$, $\overline{nb} = 4.5$, $\overline{ex B} = 13.68$, $\overline{lastmin}_1 = 0.438$, $\overline{lastmin}_2 = 0.294$, $answer = 0.33$, $NoHist = 0.04$, $period = 4$).

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, 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.

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 μ_i on seller elicited risk preferences and their eBay experience.²⁸ 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.²⁹ 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

²⁸ We looked at the linear relation between the fixed effects (μ_i) and elicited individual risk preferences (*risk_i*) as well as the experience of our 20 sellers approximated by the feedback score (*exS_i*): $\mu_i = \gamma_0 + \gamma_1 \cdot risk_i + \gamma_2 \cdot exS_i + \varepsilon_i$. The parameter estimates obtained by OLS for the 20 sellers are $\gamma_1 = 0.083(1.20)$, $\gamma_2 = 0.0016(2.05)$ using total experience, where t-values are presented in parentheses.

²⁹ 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).

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 are and thus set higher prices.³⁰

3.3 Do sellers benefit from using the *BIN*-option?

The existing experimental and empirical literature so far provides mixed evidence on the impact of the *BIN*-price on seller profits. 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 in *BIN*-auctions compared to the case when the seller can choose between a pure auction and a posted price. In contrast, Jiang et al. (2013) find 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.

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, the outcome is inefficient when the *BIN*-price was accepted by the buyer with the lower value. Third, experiencing the *BIN*-price prior to the auction might affect bidding behavior in general.

To investigate whether and to what extent the existence of the *BIN*-option impacts seller revenue and efficiency, we compare the outcomes of the *BIN*-auctions with those of the *NoBIN* treatment, where we collected data from four sessions with a total of 48 participants (16 sellers and 32 buyers) and 96 transactions. For the *NoBIN* sessions, we used the parameter sets of four (out of the five) randomly selected *BIN* sessions. Hence, we have four pairs of directly comparable *BIN* and *NoBIN* sessions.

Table 4 approximately here

The first column of Table 4 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.³¹ The second and third columns of Table 4 present a comparison between the *NoBIN* sessions and the corresponding (four) sessions in the *BIN* format.³² 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*-

³⁰ In a standard laboratory *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 subjects' experience, as participants had the same experience with the lab institution.

³¹ We consider an allocation as efficient when the buyer with the highest value gets the object.

³² 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.

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 4 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 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 his 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 behavior of real eBay traders on the real eBay market platform. Thus, participants were experienced with the (experimental) task and made their decisions in the environment in which they acquired their experience. In fact, we find experience with eBay of both, sellers and buyers, to influence their behavior. 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 and number of bidders. This allows us to observe aspects of bidding behavior and their impact on 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. 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 their *BIN*-price. In particular, they decrease 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 information available on eBay helps them to 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: it 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 influence 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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Variables	Period						
	1	2	3	4	5	6	All
Number of observations	20	20	20	20	20	20	120
<i>BIN</i> price	0.51	0.50	0.54	0.50	0.48	0.49	0.50
Acceptance rate	0.50	0.35	0.30	0.35	0.35	0.30	0.36
Number of auctions	10	13	14	13	13	14	77
Number of bids/auction	5	3	5	5	4	3	4
Relative price deviation $(V_2 - \text{price})/V_2$	0.13	0.04	0.06	0.15	0.14	0.22	0.12
Relative underbidding $(V_L - \text{bid}(=\text{price}))/V_L$ of losing bidder	0.13	0.14	0.11	0.18	0.18	0.21	0.16

Table 1 Descriptive statistics of experimental mean outcomes.

Variable	λ	Std.
time invariant		
κ	0.200**	0.080
exB_0	-0.073*	0.039
exB_0^2	0.009**	0.004
exB_1	-0.007	0.072
exB_1^2	0.000	0.008
time variant		
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
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
$nb_0 \cdot nb_{t,1}$	0.290	0.202

Table 2 Median regression of time variant and invariant variables influencing the relative deviation from true value bidding of price determining bids, Nobs=77, Std. = Standard error, ***: $p < 0.001$, **: $p < 0.05$, nB and exB normalized by 10.

Variable	Parameter estimate	Std.
$const$	0.416***	0.057
\overline{nb}	0.023**	0.009
$\overline{lastmin1}$	-0.164**	0.065
$\overline{lastmin2}$	-0.060	0.070
\overline{expB}	0.003**	0.001
$period$	-0.001	0.086
$NoHist$	0.004	0.034
$answer$	0.098***	0.023
σ_{μ}	0.168	
σ_{ε}	0.091	

Table 3 BIN price setting, Nobs=100, N=20 sellers, Std = Standard error, ***: $p < 0.001$, **: $p < 0.05$.

	<i>All BIN</i> (1)	Corresponding Parameter Sets			
		<i>BIN</i> (2)	<i>NoBIN</i> (3)	Auctions	
				<i>BIN</i> (4)	<i>NoBIN</i> (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 <i>BIN</i> -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 <i>BIN</i> price was accepted	74 [43]	76 [38]	– –	– –	– –
in auctions	90 [77]	89 [57]	72 [95]	90 [52]	75 [52]

Table 4 Descriptive statistics of outcomes in *BIN* and *NoBIN* treatments.

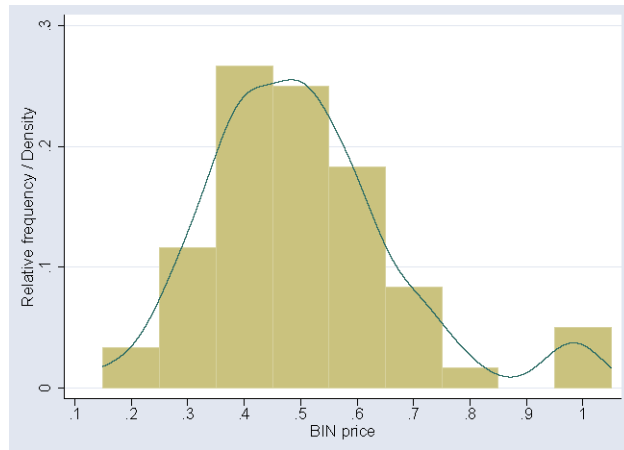


Figure 1 BIN-prices, N=120.

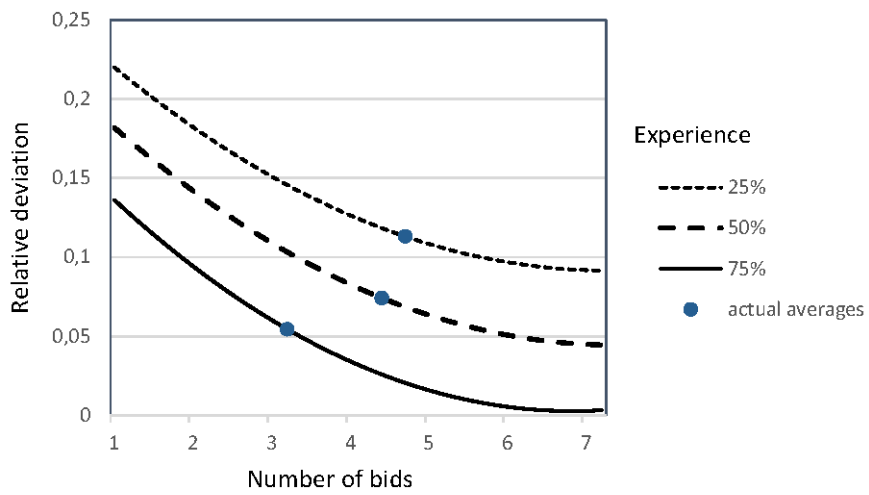


Figure 2 Predicted relative deviation by number of bids and observed average number of bids for different levels of experience (25th, 50th, and 75th percentile).