The Role of Information in eBay Auctions

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Abstract

Using a unique eBay dataset of all auctions over a 5-month period of 5 similar tripods from one seller, we explore the determinants of final winning price. Previous literature has indicated significant correlation between winning price and the number of bidders, previous average selling price and late bidding. Using new measures, our results show that final price is also determined by the number of bids placed during the auction by the winning bidder, the number and nature of the winner's prior non-winning bids in auctions as well as the timing of the next available tripod auction.

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I. Introduction

With the advent of internet auction websites such as eBay and Amazon.com, individuals and businesses have revamped their buying and selling methods. Millions of small businesses are now able to advertise their products online at lower cost and to a wider consumer base. Companies located on the East Coast can attract buyers living in California with the help of web-based auctions, thus reducing the geographic constraint and potentially increasing their profits.[1]

Online auctions provide data for studying the strategic behavior of buyers and sellers and they can serve as controlled experiments to test economic theories. As mentioned in the survey of Hendricks and Paarsch (1995), auctions are explicit mechanisms that tell us how prices are formed; being able to understand how they work will shed light on participants' bidding strategies and firms' profit-maximizing strategies.

eBay auctions provide a large amount of easily accessible information on a wide variety of products.[2] An eBay auction resembles an English ascending-bid auction in that the person willing to pay the most wins and pays a final price one bid increment higher than the second highest willingness to pay. eBay allows bidders to automatically increase their bid by one bid increment above the current highest bid stopping upon reaching a specified maximum bid. However, eBay auctions differ in two ways from traditional English auctions. First, the seller can set a public or secret reserve price so that no transaction will take place if the final winning bid does not exceed the reserve price. Second, there is a fixed ending time for each auction and thus "sniping" (waiting until the last few moments to bid) is a common strategy among eBay bidders.

[1]Hortaçsu, Martínez-Jerez, and Douglas (2009) found increasing distance between buyers and sellers still deters trade on eBay but by less than off-line trade.

[2]Recently eBay has stopped providing information on complete bidder IDs displayed in an auction, making future research more difficult.

Some previous studies view an eBay auction as a game of incomplete information and try to find the Bayesian-Nash equilibria in the data. Other studies address the question of what determines the winning prices in eBay auctions. Previous literature has revealed significant correlation between final winning price and several important auction variables: the number of bidders, previous average selling price and late bidding. Using a unique dataset of camera tripod auctions, the current study examines what determines final winning price with measures of auction conditions, product characteristics, bidder experience, and information sets. The results confirm many of the previous findings and show a significant relationship between final price and three new measures of bidder experience and future information: the number of bids placed during the auction by the winning bidder, the number of prior non-winning bids in auctions and the timing of upcoming available auctions.

The paper is organized as follows. Section II discusses the literature on the determinants of final winning price in auctions, followed by the description of data collected on the sale of tripods by the eBay seller Amvona in section III. Section IV discusses our hypotheses and section V presents the model specifications used to test the hypotheses. Section VI gives the major findings of our study and compares them to previous empirical literature. Section VII provides concluding remarks.

II. Determinants of Final Price

Researchers have used various products from eBay auctions to try to understand the pricing mechanism. There are five categories of variables that can potentially serve as price determinants in online auctions: auction conditions, product characteristics, buyer/seller experience, past auction information and future auction information.

For auction conditions many researchers agree that the scale of an auction as well as the minimum bid impact final winning prices. Kauffman and Wood (2005) found significant positive influences on final price from the number of bidders and the starting bid but no significant weekend effect using rare coin auctions on eBay. They also found that reserve price shilling (sellers bidding on their own auctions) increases the final price in that it sends a positive signal of an item's worth to the buyers. Lucking-Reiley et al. (2007) extend the research using collectible U.S. one-cent coin auctions finding that an increase in minimum bid, reserve price and auction period will lead to higher final auction prices. The minimum bid influences the final price only in cases where one person bids. Reserve prices may act as if there were other competing bidders, which then prompts current bidders to bid even higher. Longer auction periods will potentially attract more bidders into the auction, thus raising the final prices.

Many studies have shown that the final auction price is related to product characteristics. Sailer (2006) found a positive relationship between product quality and final price using quality measures of a Personal Digital Assistant (PDA). She demonstrated significant coefficients on the age of the product, the PDA condition, and whether or not the product has defects and additional accessories. Other similar findings include that the presence of a blemish decreases a coin's value (Bajari and Hortaçsu, 2003) and new CPUs sell for higher prices than used CPUs (Hou, 2007).

Seller as well as buyer experience and reputation are also important factors in determining the final auction prices. Buyers and sellers on eBay can rate the other party's performance as positive (+1), neutral (0), or negative (-1). The rating is optional after each transaction and it serves as an indicator of a member's reputation. The total cumulative score each member receives, known as the Feedback Score, is displayed next to her ID on all pages. Houser and Wooders (2006) interpreted the Feedback Score as an indicator of bidder or seller reputation and they concluded that seller's, but not bidder's, reputation has an economically and statistically significant effect on price using eBay auctions of computer processors. Lucking-Reiley et al. (2007) found that seller reputation matters and that negative feedback of a seller has a greater effect than positive feedback, positing that buyers' prior beliefs are "people are basically good."[3] Hence, bidders consider negative feedback more informative than positive feedback. Alternatively, Bajari and Hortaçsu (2003) suggest that eBay members are fearful of retaliation leading a person's positive feedbacks to heavily outweigh negative feedbacks. The bias toward positive feedback then leads eBay users to conclude that negative ratings are more indicative of a member's reputation than the overall Feedback Score. In contrast, Bajari and Hortaçsu (2003) showed no effect from average bidder experience on auction revenues.[4]

Wilcox (2000) concluded that more experienced bidders are more likely to place their bids in the last minute of the auction. Roth and Ockenfels (2002) agreed that there is a significant amount of late bidding on eBay due to its fixed auction interval, confirming that there is clearer evidence of late bidding by experienced bidders. Furthermore, Roth and Ockenfels (2002) indicated that late bidding helps the bidder avoid a price war increasing the probability the bidder wins the auction at a lower price. Hou (2007) confirmed late bidding lowers winning prices of computer CPUs.

Given that the recent bidding history of products is public information on eBay, bidders can use past information in assessing the value of the product. Kauffman and Wood (2005) found a positive relationship between the average selling price of earlier auctions and the final price of rare coins. In Hou's (2007) analysis of computer CPUs, the coefficient on the book value of the product is positive and statistically significant for predicting the final price. Besides past information, bidders can use information on upcoming auctions to determine whether to stay in the current auction, which can affect the final price in the

[3]eBay advocates the "people are good" belief as the first of their five community values. See http://pages.ebay.com/community/people/values.html.

[4]It was not clear how Bajari and Hortaçsu measured the average bidder experience in their paper, but a reasonable assumption would be they used bidders' average Feedback Score.

current auction. Ariely and Simonson (2003) identify concurrent (observed) auctions of related items as a value indicator that bidders can rely on. Ooi et al. (2006) used the total number of auctions taking place within the 30 days before and after an observed land sale as an information variable in land auctions in Singapore, but found insignificant results.

The Feedback Score has served as a widely used measure of bidder experience, but it has limitations in assessing a bidder's experience level in auctions that deal with a particular product. So far no empirical research has used upcoming auction information to predict final price on eBay. Because of the unique data described below, we construct alternative and novel measures of bidder experience: the number of bids placed during an auction by the winning bidder and the number of previous non-winning bids in non-winning auctions of the same and related products. We also construct novel measures of the information available to the bidder about future auctions in the same and related products. We incorporate both the established and the new measures of auction variables in our study.

III. Amvona Tripod Auctions

The internet company Amvona specializes in photographic lighting, background and tripod products and has both an online store and an eBay store. Their eBay store sells products at a "Buy It Now" price. In addition, Amvona auctioned five related types of tripods on eBay most every day until early February 2008.[5] The tripod auction data was collected from the eBay bid history pages (see Figure 1) for five types of tripods starting on August 30, 2007. Amvona auctions one unit of each type of tripod at different times of the day always with a starting price of 99 cents and in an auction lasting for exactly seven days. The end

[5] The "Buy It Now" prices of the tripods are in general much higher than the final auction prices and comparable to the online (non-eBay) store prices.

time each day for the auction of a unit of a given tripod type tended to be consistent every auction except on the few occasions where multiple single unit auctions of a given type ended on the same day.[6] The shipping costs of the five tripods were not identical, although the difference was almost negligible.[7]

Table 1 lists the product characteristics of the five tripod types. All five tripods have sliding center columns to adjust height, with tripod 104 extending the highest at 71 inches, followed by tripod 105 with 70.2 inches. As can be seen, there is not a large difference among tripods 101 through 103 in terms of the maximum height. Tripod 101 weighs the least whereas tripod 105 weighs the most. The difference in tripods' self weight between 102 and 103 as well as 104 and 105 is negligible. Photographers sometimes will put heavy equipment on the camera tripod and so the maximum carry weight of the tripod is an important indicator of the tripod versatility. Tripods 102 and 103 have the same maximum carry weight of 17.6 pounds while 104 and 105 can carry 22 pounds. The product characteristics of the five types provide tradeoffs between portability and functionality.

Interestingly, the average price of tripod 102 over the entire auction period of our sample is lower than tripod 101. On the other hand, tripod 103 sells at a higher average price than 101 despite having similar features to 102. Furthermore, though tripods 104 and 105 have similar features, tripod 105 has a much higher average price than 104.

Some tripods had a more active auction history, as there were days when certain tripods were not sold at all while others were sold multiple times. As a result, the dataset is an imbalanced panel. Initially Amvona sold a single unit of each tripod type almost every single day in September.[8] Four tripods had auctions starting on both weekdays and

[6]The latter occurred primarily during the holiday season.

[7]The shipping costs of tripod types 101 through 105 were \$17.95, \$16.95, \$15.55, \$18.95, and \$18.95, respectively.

[8]All auctions were for a single unit. No multi-unit auctions were conducted during the time period of the data sample.

weekends and one started only on weekdays. Despite the weekday/weekend pattern, the September dataset was fairly complete. As time progressed, however, the auctions became more sporadic as certain tripods had days of inactivity whereas others had consistent daily auctions. The variability allows us to analyze the effect of auction interval on final prices. The last auction was on February 6, 2008, concluding the auction history of the five tripods from Amvona.

From the bid history page (see Figure 1), data collected included the start and end times of each auction, bidder ID of every bid placed, every bidder's Feedback Score and the amount and time for every bid. The bids on the bid history page consist of only actual bids, not every single automatic bid generated by the proxy system up to a bidder's maximum bid.[9] The Feedback Score is calculated by eBay as the number of members who left a positive feedback message minus the number of those who left a negative message. Since, in general, the number of people who leave positive feedback greatly outweighs the number of those leaving negative comments for each bidder, we use the Feedback Score as just one measure of the experience level of a bidder.

IV. Hypotheses

Given the unique data drawn from an auction setting where one seller auctions five related tripods over a fixed period, and that each auction starts at the same minimum price, we cannot analyze the effects of price determinants such as the reserve price, the minimum bid, the seller reputation, nor the auction period. In our model the final winning price of each tripod auction is determined by five categories of explanatory variables: auction conditions, product characteristics, bidder experience, past information and future infor-

[9]Only actual bids and the final bid (proxy or not) are shown on the bid history page. Automatic bids that are outbid by other bidders or proxies are omitted.

mation. Table 2 summarizes the variable definitions and our prior beliefs of the variables' expected influence on the final winning price of the auction. Table 3 summarizes the mean values of the independent variables by tripod type. Consistent with the prior literature, the dependent variable is the natural logarithm of the final winning price.

We present the following hypotheses based on the auction setting and previous findings in the literature.

Auction Conditions: An increase in the number of bidders increases the final auction price. The number of participants in an auction indicates the demand for the product. When the demand increases, given constant supply, we expect an increase in the price. Since the tripods in our study sell at a much higher price outside of the online eBay auctions, a large number of bidders should raise the final auction price of the tripod closer to the outside market value in a bidding war.

Auctions ending on a weekend day have higher prices than auctions ending on a week day. People have fewer constraints on their time during the weekend and thus may spend more time on eBay auctions. They are more likely to monitor the final bidding period carefully and involve themselves in a bidding war. Given the same number of bidders in an auction period, participants might place more late bids in a weekend auction versus a weekday auction, thus raising the final price.

Product Characteristics: The influences of tripod characteristics on final winning price are indeterminate. Product characteristics, such as quality and versatility, are important value cues for buyers. People are usually willing to pay more for higher-quality products or items that have more features. The five tripods have different mixes of three product characteristics: maximum height, self-carry weight, and maximum carry weight. Given that the product characteristics do not monotonically vary from Tripod 101 to Tripod 105 we have no prior expectations on which product dummy variable's coefficient will differ significantly from Tripod 101. However, increases in the maximum height attainable and maximum carry weight should increase the final winning price.

Bidder Experience: An increase in the median bidders' experience decreases the final winning price. Bidders are a heterogeneous group in terms of previous bidding experience. Experienced bidders tend to bid late and submit fewer bids in an auction (Roth and Ockenfels, 2002). Increasing the median bidder experience in an auction should decrease the final price due to fewer early bids and fewer bids overall. Besides the overall level of experience of bidders, the winning bidder's behavior and experience influences the final winning price even after controlling for the median bidder experience. A decrease in the number of bids placed in an auction by the winning bidder should decrease the final winning price, ceteris paribus. Winning bidders who have placed more prior non-winning bids for the same, or any, tripod type are expected to pay a lower final winning price. Bidders learn from their prior bidding experiences how much to bid and when to stay in or leave an auction.[10]

Winning bidders who enter the auction in the last minute are expected to pay a lower final winning price. People who enter an auction early typically find themselves outbid towards the end of the auction period. Since bidders' final purchase decisions could be influenced by their emotions, competitive behaviors and a desire to "win" (Ariely and Simonson, 2003), bidders might keep increasing their bids to a level much higher than they originally intended. Winners who enter the auction in the last minute, however, tend to avoid a bidding war, thus lowering their final winning price (Roth and Ockenfels, 2002; Hou, 2007).

Past Information: Higher previous winning prices predict higher final winning prices of future auctions. Since eBay keeps the auction data of the previous 15 days available to

[10] The prior bidding experience could be interpreted as either learning about their own valuation of the product or as "shopping" for an auction they can win given their lower valuation.

the public, bidders can determine their own value of the product based on the previous auction history. Bidders can use prior winning prices to assess the going auction price for a given tripod type and the relative going prices between tripod types.

Future Information: Increases in the time interval until the next auctions leads to increases in the final winning price. Auctions that start shortly before a succeeding auction tend to attract fewer buyers given that bidders arrive randomly over time. Furthermore, concurrent auctions of the other tripod types may influence a bidder's decision to enter or leave an auction by providing additional value assessment information (Ariely and Simonson, 2003). As a result, bidders could bid in these overlapping auctions either within the same tripod type or across different tripod types. Thus, as the length of time until the end of the next available auction increases, final winning prices will increase.

A probit specification is used to analyze what determines the likelihood of a bid becoming a winning bid. The hypothesis is that higher individual bidder experience increases the probability of submitting a winning bid. Late bidding has also been shown to increase the likelihood of winning (Hayne et al., 2003). However, it is not expected that product characteristics play a role in terms of each tripod's likelihood of a given bid winning even though certain tripods might attract more bids.

V. Model Specifications

Several alternative ordinary least squares (OLS) regression models are estimated with different combinations of determinants of price in eBay auctions.[11] The regression equations regress the natural log of final winning price on auction conditions, product characteristics, bidder experience, past information and future information. A probit model is used

[11] While only four OLS models are reported, extensive robustness checks were made by varying the included variables. The reported results are robust with respect to the model specification.

to determine the likelihood of a bid winning.

The first model estimated uses tripod dummies to control for product characteristic variation along with all the independent variables from the other four categories listed in Table 2. The second model replaces the tripod dummies with two of the three product characteristics: maximum height and maximum carry weight. The third and fourth models include only the median bidder experience along with the last minute dummy or the entire set of winning bidder's characteristics to check for the robustness of the other influences with respect to how bidder experience is measured.

Since the dependent variable, natural log of final winning price, is indexed by bidder, auction and tripod type, it is reasonable to question whether clustering may occur by the three categories. Examination of the data reveals very few cases of bidders who bid across different tripods and won multiple auctions. Furthermore, it is difficult to justify that auctions occurring at approximately the same time share common characteristics. Bidders arrive randomly and there is little seasonal sale variation with tripods. With regard to the holidays, some buyers could be shopping for gifts far before the holiday whereas others may wait until the last minute. Finally, the tripod dummies control for unobserved heterogeneity across tripods. Therefore, there is not enough evidence to support adjusting for clustering in the regression specifications using tripod dummies.[12] The second model which uses two tripod attributes instead of tripod dummies have at most five distinctive values representing each of the tripods. Thus the second model's estimates have been adjusted for clustering.

The probit model specifies the dependent variable to equal 1 if a bid is a winning bid for an auction and 0 otherwise. The data consists of all bids across all auctions. The explanatory variables are the natural log of the bidder's Feedback Score (denoted as LnBidderExperience), the last minute dummy, and the four tripod dummies. The probit

[12] Even given these qualifications, adjusting for clustering in the estimation process does not alter the qualitative results.

model assumes normality of the error term and yields estimates of the change in the probability of a bid being a winning bid due to a change in the explanatory variables.

VI. Results

Table 4 presents the results of estimating the determinants of the winning price. Several explanatory variables are consistently statistically significant across all models. The R-squared statistic for the full specification (Model I) is approximately 63%.

Auction Conditions: The number of bidders is positively correlated with the final auction price for all regression models, confirming that increasing the number of bidders increases the final price. The results do not show any weekend effect. The insignificance of the weekend dummy could be attributed to the low percentage of weekend observations in the data, as there are only 41 auctions that end on a weekend day.

Product Characteristics: Tripods 102 and 105 consistently exhibit significant coefficients whereas tripods 103 and 104 are not statistically different from the reference group, tripod 101. Interestingly, even though tripod 102 can carry more weight and extend higher compared to 101, the coefficients on tripod 102 turn out to be negative and significant at the 99% level. It could be that the increase in maximum height and carry weight in 102 relative to 101 is more than offset by its increase in self weight. On the other hand, tripod 105 sells for a higher price than 101 at a 99% significance level. The maximum height and carry weight of tripod 105 are greater than 101, probably to an extent where these two characteristics outweigh the increase in the self weight of tripod 105 relative to 101. The same should be true, given the characteristics, for tripod 104. However, tripod 104 does not sell for a significantly higher price than 101. Given these results, heterogeneity in the unmeasured and observed characteristics of the five tripod types may explain the results.

The second model replaces the tripod dummies with two important tripod characteristics: maximum attainable height and maximum carry weight. The R-squared statistic for the model is 52%. Neither of the coefficients on the tripod characteristics are significant given the correction for clustering.[13] The sign of the coefficient on MaxHeight is positive, indicating the greater the height the tripod can extend to, the higher the price. However, the sign of the coefficient on maximum carry weight of the tripods is negative which is counter-intuitive. It would be expected that the greater the weight the tripod can carry the more people are willing to pay. It could be that the correlation between final price and the two tripod characteristics is not linear and thus cannot be fully captured by the two characteristic measures. Overall, the results are weaker in model II than in model I. The two measured characteristics do not fully capture the heterogeneity of the five tripod types.

Bidder Experience: Bidder experience was measured as both the median experience level of all bidders in an auction and by four measures of the winning bidder's experience. The median experience level of all bidders was negative but insignificant in all three models, which is consistent with Bajari and Hortaçsu (2003). Three measures of the winning bidder's experience were statistically significant in all models (with one exception) and had the predicted signs. The results support that inexperienced bidders bid more frequently and pay higher final prices. The results also support that bidders who have placed more non-winning bids in prior auctions of the same type tripod and/or in any type of tripod paid lower prices.[14] The results provide direct evidence that prior bidding experience in a particular product leads to lower winning prices. The LastMinute dummy was estimated to have a negative relationship with the final price, but was significant only in the second and third models. While the estimated sign was as predicted, the robustness level provides

[13] The clustering correction was estimated based on maximum height. Correcting for clustering based on maximum weight does not change the qualitative conclusions.

[14] Alternative specifications used the number of prior non-winning auctions to replace the number of prior non-winning bids in all models and yields similar results.

only partial confirmation of Hou's (2007) findings.

Past Information: The average lagged price is a consistently significantly positive determinant of final price. The coefficients are significant at the 95% or higher level in all models while being highly collinear with the constant term.[15] The results support that people look back to the available auction history to form their expectations of a winning bid. Higher past prices predict higher future prices.

Future Information: The positive significant coefficients on both IntervalWithin and IntervalAcross in all model specifications indicate that the longer the bidder has to wait for the next available auction, the more she will pay for the product in the current auction. The coefficient on IntervalAcross is larger than IntervalWithin indicating that interval between auctions across tripods has a greater influence on the final winning price than the auction interval within a certain tripod. The differential effect from the two auction interval variables suggests that the five tripods are not perfect substitutes. Since different tripods are auctioned at different times of the day and Amvona for the most part only auctions one unit of each type of tripod per day, an increase in auction interval across tripods is usually accompanied by a much larger increase in auction interval within the same particular tripod. If people only bid within a particular tripod, they would have to wait longer than the auction interval measured across tripods, thus explaining the larger magnitude of the coefficients on IntervalAcross than IntervalWithin. The data does support that there are far more people who bid within a particular tripod than across tripods.[16]

Probit Estimation: Table 5 provides the probit estimates of whether or not a submitted bid is a winning bid using all 4912 bids. The natural logarithm of the bidder's

[15] Collinearity diagnostics of Model I show that the only condition index larger than 30 is 116.76, where the variable LnLaggedPrice and the constant term both have a portion of 99 percent while the variable Tripod105 has a portion of 47 percent. All three variables are statistically significant.

[16] Out of the 1009 total bidders in the data, there are 729 people who bid within a particular tripod compared to only 280 who bid across different tripods.

experience is positively correlated with the likelihood to win, meaning that the higher experience level a bidder has, the more likely she will win an auction. The marginal effect of bidder experience is 0.0036, indicating that a one-unit increase in the bidder experience will increase the probability of a bid winning by only 0.36%. The last minute dummy variable is positive and significant. Thus, a bid that is submitted in the last minute of an auction is more likely to be a winning bid, and its probability is estimated to increase by 29%, providing further support of Hou (2007).

Tripods 102 and 103 do not appear to be significantly different from 101 in their likelihood of a bid winning. Tripods 104 and 105, however, exhibit a lower chance of winning compared to 101 and their estimated coefficients are significant at the 90% level. The discrepancy in the probability of winning among the five tripods is due to each tripod having a different number of total bids and auctions.[17] Tripods 104 and 105 have a higher total bids/auctions ratio compared to tripods 101 through 103, thus exhibiting a lower chance of winning.

VII. Concluding Remarks

Obtaining more insight into the determinants of final winning price in online auctions helps both buyers and sellers to improve their strategy and optimize their costs or profits. Previous research has already identified certain factors that contribute to higher final prices: the number of bidders, minimum bids, reserve price, and late bidding. Our study explores other potential factors that might be of importance focusing on the buyer's strategy.

Using eBay auction data of five related types of camera tripods, the study holds constant several supply side determinants - only one seller, homogeneity of product within product

[17] The total numbers of bids for tripods 101 through 105 are 1144, 988, 960, 543, and 1293, respectively. The total numbers of auctions for tripods 101 through 105 are 103, 93, 86, 45, and 92, respectively.

type - while varying the timing and availability of those units. The study confirms four findings from the prior literature. First, an increase in the number of bidders in a given auction increases the winning price. Second, product characteristics matter although there might be threshold effects involved when dealing with very similar products. Third, late bidding helps lower the final price and increase the chance of a bid winning. Finally, past winning prices are important to bidders when they form an estimate the value of the product.

The study contributes alternative measures of bidder experience and future information that have not been discussed in the previous literature. Bidders who bid often in an auction pay higher prices; reflecting inexperience in bidding. Bidders gain valuable experience from their attempts to win an auction and may learn new strategies as the number of their non-winning bids or non-winning auctions increases. As a result, when they do win later on, they pay a lower price given their experience gained. Concurrent auctions also matter: the longer a bidder has to wait for the end of the next available auction, the higher price he is likely to pay at the current auction. Thus, bidders not only care about the auction history of the product, but they also look at upcoming auctions for value cues, supporting Ariely and Simonson's (2003) claim that bidders' auction entry/exit decisions are influenced by concurrent (observed) auctions of related items.

Future work with the unique eBay history of Amvona auctions could include using nonparametric techniques to estimate the distribution of bidder values for tripods, and exploring further the quasi-experimental design of the timing of the auctions to estimate optimal bidding strategies for bidders. eBay recently stopped reporting complete bidder IDs in an auction which has increased the difficulty of measuring individual bidder experience and will reduce the ability of researchers to explore optimal bidder strategies.

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Figure 1: The Bid History Page for an Amvona Camera Tripod 101 Auction

Buy | Sell | My eBay | Community | Help

Hi, l_yiyan! (Sign out)

Site Map

All Categories | Search | Advanced Search

Categories ▾ | Motors | Express | Stores

Back to item description

Bid History

Item number: 360006634271

PRO PHOTO CAMERA CARBON FIBER TRIPOD BASE LEGS AT-A101T

Winning bid: **US $54.33**

Bidders: 3 Bids: 8 Time Ended: Dec-24-07 09:30:00 PST

This item has ended.

Only actual bids (not automatic bids generated up to a bidder's maximum) are shown. Automatic bids may be placed days or hours before a listing ends. Learn more about bidding.

Show automatic bids

Bidder	Bid Amount	Bid Time
usalove91 (5)	**US $54.33**	**Dec-22-07 22:34:43 PST**
11top (300)	US $53.33	Dec-22-07 08:26:15 PST
usalove91 (5)	US $49.99	Dec-22-07 22:33:33 PST
usalove91 (5)	US $45.00	Dec-22-07 22:30:55 PST
usalove91 (5)	US $40.00	Dec-22-07 22:30:16 PST
usalove91 (5)	US $32.00	Dec-22-07 22:28:21 PST
usalove91 (5)	US $30.00	Dec-22-07 22:28:06 PST
2036rich (32)	US $6.00	Dec-20-07 20:54:26 PST
Starting Price	US $0.99	Dec-17-07 09:30:00 PST

If you and another bidder placed the same bid amount, the earlier bid takes priority. You can retract your bid under certain circumstances only.

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Table 1: **Tripod Characteristics**

Tripod	Maximum Height (inches)	Self Weight (pounds)	Maximum Carry Weight (pounds)	Average Winning Price ($)	Auctions (count)
101	58.3	2.6	11	68.52	103
102	63	3.4	17.6	60.32	93
103	60	3.35	17.6	70.29	86
104	71	4.4	22	83.24	45
105	70.2	4.45	22	116.38	92

Notes: The average winning price of each tripod is calculated using all available winning bids in our dataset. Not all auctions are used in the regressions due to missing values.

Table 2: **Variable Definitions**

Dependent:		
LnPrice	Natural log of the final winning price of each auction	
Independent:		**Effect**
Auction Conditions		
Bidders	Total number of bidders in each auction	positive
Weekend	Equal to 1 if the auction ends Saturday/Sunday; 0 otherwise	positive
Products		
Tripod102	Equal to 1 if the product is tripod 102; 0 otherwise	uncertain
Tripod103	Equal to 1 if the product is tripod 103; 0 otherwise	uncertain
Tripod104	Equal to 1 if the product is tripod 104; 0 otherwise	uncertain
Tripod105	Equal to 1 if the product is tripod 105; 0 otherwise	uncertain
MaxHeight	Maximum extendable height of a particular tripod in inches	positive
MaxCarryWeight	Maximum weight a particular tripod can carry in pounds	positive
Bidder Experience		
LnExperience	Natural log of the median value of bidders Feedback Scores in each auction	negative
WinBidsPlaced	Number of bids placed during auction by winning bidder	positive
NonWinsWithin	Total number of previous non-winning bids by the winner within the particular type of tripod, excluding the current auction	negative
NonWinsAcross	Total number of previous non-winning bids by the winner across all the other four types of tripods	negative
LastMinute	Equal to 1 if the winner entered the auction during the last minute before it ended; 0 otherwise	negative
Past Information		
LnLaggedPrice	Natural log of the average winning price of a particular tripod in the previous 15 days	positive
Future Information		
IntervalWithin	The interval between the end times of the current and succeeding auction within a particular tripod type, measured in days	positive
IntervalAcross	The interval between the end times of the current tripod auction and the succeeding auction across all the other four types of tripods, measured in days	positive

Note: All final winning prices, median Feedback Scores, and average previous winning prices have a value of one or above before being transformed by the natural logarithm.

Table 3: **Mean Values of Independent Variables by Tripod**

Independent Variables	Tripod 101	Tripod 102	Tripod 103	Tripod 104	Tripod 105
Auction Conditions					
Bidders	6.22	6.51	6.81	6.76	7.48
Weekend	0.10	0.06	0.10	0.00	0.17
Bidder Experience					
LnExperience	3.89	3.72	3.52	4.10	3.81
WinBidsPlaced	2.18	2.08	1.99	1.98	2.39
NonWinsWithin	1.64	1.54	1.35	2.09	2.59
NonWinsAcross	1.11	2.75	1.86	2.69	0.75
LastMinute	0.40	0.54	0.62	0.58	0.49
Past Information					
LnLaggedPrice	4.18	4.22	4.26	4.48	4.59
Future Information					
IntervalWithin	1.50	1.74	1.85	3.11	1.75
IntervalAcross	0.49	0.59	0.31	0.09	0.59

Notes: Product characteristics are omitted in this table since they are described in Table 1. The mean values of these independent variables are calculated using all available winning bids in our dataset. The mean values of the two dummy variables, Weekend and LastMinute, indicate the percentage of auctions that occur during a weekend and the percentage of winners who enter the auction in the last minute.

Table 4: **Determinants of Price**

	Model I	Model II	Model III	Model IV
Auction Conditions				
Bidders	0.0170***	0.0235*	0.0158**	0.0175***
	(0.0062)	(0.0086)	(0.0064)	(0.0062)
Weekend	-0.0161	0.0442	-0.0073	-0.0197
	(0.0381)	(0.0616)	(0.0393)	(0.0379)
Product Characteristics				
Tripod102	-0.1784***	.	-0.1900***	-0.1760***
	(0.0331)	.	(0.0339)	(0.0330)
Tripod103	-0.0092	.	-0.0208	-0.0039
	(0.0346)	.	(0.0356)	(0.0341)
Tripod104	0.0737	.	0.0623	0.0698
	(0.0493)	.	(0.0508)	(0.0491)
Tripod105	0.3447***	.	0.3450***	0.3444***
	(0.0468)	.	(0.0483)	(0.0468)
MaxHeight	.	0.0249	.	.
	.	(0.0191)	.	.
MaxCarryWeight	.	-0.0161	.	.
	.	(0.0204)	.	.
Bidder Experience				
LnExperience	-0.0132	-0.0167	-0.0227	.
	(0.0140)	(0.0286)	(0.0143)	.
WinBidsPlaced	0.0190***	0.0193*	.	0.0199***
	(0.0052)	(0.0085)	.	(0.0051)
NonWinsWithin	-0.0053**	-0.0025	.	-0.0053**
	(0.0027)	(0.0019)	.	(0.0027)
NonWinsAcross	-0.0050**	-0.0089**	.	-0.0050**
	(0.0023)	(0.0025)	.	(0.0023)
LastMinute	-0.0364	-0.0556**	-0.0433*	-0.0384
	(0.0236)	(0.0131)	(0.0243)	(0.0235)
Past Information				
LnLaggedPrice	0.4011***	0.7333**	0.4052***	0.4043***
	(0.0843)	(0.1896)	(0.0868)	(0.0842)
Future Information				
IntervalWithin	0.0124***	0.0104***	0.0127***	0.0124***
	(0.0029)	(0.0020)	(0.0030)	(0.0029)
IntervalAcross	0.0527***	0.0403***	0.0549***	0.0517***
	(0.0123)	(0.0063)	(0.0127)	(0.0122)
Constant	2.4049***	-0.3107	2.4593***	2.3364***
	(0.3554)	(1.1652)	(0.3673)	(0.3478)
Observations	402	402	402	402
R-squared	0.627	0.520	0.598	0.627

Notes: The dependent variable is the natural logarithm of final price. Estimates are ordinary least squares. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. There are 18 observations in the dataset where either variable IntervalWithin or IntervalAcross has values greater than seven. Excluding those observations from our dataset does not significantly alter the results.

Table 5: **Likelihood of Bid Winning**

	Coefficient (Standard Error)	Marginal Effect
LnBidderExperience	0.0283*	0.0036
	(0.0154)	.
LastMinute	1.2544***	0.2907
	(0.0616)	.
Tripod102	-0.0842	-0.0103
	(0.0822)	.
Tripod103	-0.1209	-0.0146
	(0.0842)	.
Tripod104	-0.1768*	-0.0203
	(0.1017)	.
Tripod105	-0.1459*	-0.0176
	(0.0796)	.
Constant	-1.6669***	.
	(0.0784)	.
Observations	4912	.
Log Likelihood	-1221.3227	.

Notes: The dependent variable is whether or not the bid is a winning bid. Probit regression standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The variable LnBidderExperience is the natural log of each bidder's Feedback Score. Bidders with a Feedback Score less than one are assigned one instead to indicate their experience level.