Factors Affecting Bidding Behavior and Winning Bids

An Empirical Analysis of eBay Auctions

Yingjie Zhang[1,*]

[1] Management School, University of Sheffield, Sheffield, United Kingdom, S10 2TN

*Corresponding author. Email: yzhang631@sheffield.ac.uk

Abstract. With the development of technology, eBay auctions have become one of the main formats of online auctions nowadays. Many researchers begin to pay attention to the factors that influence bidding behavior and winning bids in this auction format. However, due to the rapid changes on eBay, the data in most studies is outdated and the variables they chose are not comprehensive enough. Therefore, this article aims to examine what and how are the factors influencing bidding behavior and winning bids. In order to achieve this, this article selected the most recent data and the most comprehensive variables based on the existing literature. In addition, because of the endogeneity in the variables, the 2SLS method has been chosen to estimate the model in this paper. The study found that the number of bidders, the quantity of bids and the starting bid all positively related to the winning bids.

Keywords: Winning bid, EBay, The number of bidders, Endogeneity.

1 Introduction

Historically, auctions have always been a very popular mechanism for selling, situations where prices are higher than the seller's expectation arise as there can be fierce competition between bidders. With the rapid development of internet technology, online trading has become a popular transaction method and people start to prefer online auctions to offline auctions.

Currently, it can be argued that the dominant player in this area is eBay, its net revenue reaches \$10.42 billion in 2021. In addition, the number of its users who remain highly active in 2021 reaches 187 million. As a result, how bidding behavior and winning bids change on eBay has attracted the attention of many academics.

Roth & Ockenfels first studied the second-price auctions on eBay and found the existence of "bid sniping" [1]. Bid sniping means the bidders on eBay tend to bid at the last minute, even though there is a risk of bid submission failure. And it is also indicated that the number of bidders is likely to increase when sellers have high overall ratings, the minimum bid is low or the book value of the object is high [1]. Peters & Severinov further explained the reason for the existence of "bid sniping", which is because bidders tend to observe the opportunity to deal with all sellers before they bid [2]. Doing so can

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avoid finding sellers who post lower reserve prices after they bid. Furthermore, Zeithammer showed that bidders usually bid lower when they predict they can buy a similar item in a future auction [3]. According to the infinite-horizon model described by Hendricks et al., bidders are usually focused more on the number of their opponents than on the value of the object [4]. Onur & Velamuri further optimized the research on how the number of bidders affects the winning bids by using the closing interval as an entirely new instrumental variable [5]. This addressed the number of bidders' endogeneity in the model. According to Onur & Tas, it was suggested that the optimum number of bidders is 6 and 8 respectively, under which the auction is most efficient [6].

Different from traditional auctions, besides stipulating that the highest bidder in a given period gets the item, a Buy-It-Now (BIN) price is also offered on eBay, which means that the buyer can pay the BIN price directly to get the item when the bid is below the BIN price. Therefore, in the research of Onur, he realized the effects of BIN price on bidding behavior and argues that the effects are positive, which means that when the average BIN price is high, bidders would prefer to stay in the auction [7]. Meanwhile, Hasker & Sickles noticed that not only the BIN price function but also the bargaining function can influence bidding behavior, but they were not sure of the exact impact [8]. However, even though BIN price and bargaining function influence bidding behavior, bidders do not seem to care about delivery costs. Tyan, Hossain & Morgan and Brown et al. all found that buyers tend to underestimate delivery costs compared to regular prices [9-10]. All of the above literature provided a variety of analyses of the factors influencing bidding behavior and winning bids. However, in their analysis, they all neglected the influence of some other factors, which may lead to inaccurate results. In addition, it can be seen that research in related areas is relatively outdated. EBay is a rapidly evolving online auction format in which the bidding behavior of bidders may have changed over time. Therefore, there is a need for a study on the factors influencing bidding behavior on eBay.

The research based on the latest data will have a significant implication for potential sellers on eBay, as they will be able to better set reserve prices, BIN prices and auction end times to generate higher revenues. It will also help bidders to bid rationally to maximize their utility and enrich future auction research. Therefore, this study collects the latest data from eBay auctions. And two-stage least squares (2SLS) regression is used to conduct a comprehensive analysis of the factors influencing bidding behavior and winning bids.

The rest of this article is divided into the following main sections: section 2 specifies the data collected and the estimation model used in this article, section 3 describes the results obtained from the analysis and discusses the results, and section 4 states the conclusions of this study.

2 Method

2.1 Data collection and description

The dataset used in this study was collected from auctions of TI-83 Calculators displayed on eBay. The range of data collection is from the auctions where goods were successfully sold between 1 March and 30 May 2022. The reason for using this TI-83 Graphing Calculator as a sampling object is because it has a relatively high number of relevant auctions on eBay and a relatively homogeneous nature. Compared to other items up for auction on eBay, the TI-83 is less disparate in its characteristics of the item.

In each TI-83 auction, the following information is collected: winning bid, starting bid, quantity of bids, number of bidders, auction end time slots, weekend, closing interval and seller rating. Table 1 provides the set of variables.

Table 1. Set of variables

	Variable	**Explanation**
Explained Variables	Winning Bid ($)	Highest recorded bid per auction
Explanatory Variables	Number of Bidders	The total number of participants who
	Quantity of bids	The total quantity of bids at the end of
Control Variables	Starting Bid	Starting price of the auction set by the
	Morning	1 for the period 6 am - 12 pm end, 0 for
	Afternoon	1 for the period 12 pm - 6 pm end, 0
	Evening	1 for the period 6 pm - 0 am end, 0 for
	Night	1 for the period 0 am - 6 am end, 0 for
Instrumental Variables	Seller Rating	If the comment is positive, then +1, neutral is 0, negative is -1. The seller's
	Closing Interval (h)	Represents the time in hours between the last bid and the end of the auction
	Weekend	1 if the auction ends on the weekend, 0 on other weekdays

As mentioned in the previous research by Roth & Ockenfels, most of the serious bids happen in the last few minutes of the auction [1]. Therefore, four dummy variables (morning, afternoon, evening and night) were created as control variables to monitor the impact of the endpoint of the auction on bidding behavior. Furthermore, according to Onur & Velamuri, seller rating, closing interval and weekend can be used as instruments for the endogenous regressor [5]. However, the BIN prices of TI-83 could not be collected into the dataset in this study as the auction of a successfully sold item on eBay would clear the BIN option. In addition, according to Tyan, Hossain & Morgan and Brown et al., the delivery costs do not seem to affect bidding behavior [9-10]. Therefore, the delivery costs are also not included in the dataset. The description of the sample data is presented in Table 2.

Table 2. Statistics description

Variable	**Minimum**	**Maximum**	**Mean**	**Std. de-**
Winning Bid ($)	3.75	64	20.708	12.271
Quantity of bids	1	18	5.46	4.769
Number of Bidders	1	8	2.66	1.710
Starting Bid	0.01	60	11.082	11.208
Morning	0	1	0.14	0.351
Afternoon	0	1	0.32	0.471

Evening	0	1	0.52	0.505
Night	0	1	0.02	0.141
Weekend	0	1	0.38	0.490
Closing Interval (h)	0	170	12.677	32.918
Seller Rating	2	4558	431.54	807.786

2.2 Empirical strategy

The relationship between the above variables and the winning bid in an auction will be examined by estimating the following linear model:

$$WB_i = NBer'_i\beta_1 + X'_i\beta_2 + \mu_i \tag{1}$$

where WB_i is the log of winning bids in the ith auction, $NBer$ is the number of bidders, X is auction characteristics' vector, and β_1 and β_2 are the coefficients of the influence of the number of bidders and the auction characteristics on the winning bids, respectively.

It seems that ordinary least squares (OLS) can be the appropriate method for estimating the above relationship. However, due to the reason mentioned in section 1, some auction characteristics may affect potential bidders' willingness to engage in the auction. Meanwhile, these same characteristics may also affect the winning bid. This endogeneity of bidder engagement in decision making will lead to inconsistent OLS estimates of Eq. Hence, in order to deal with this endogeneity, the two-stage least squares (2SLS) regression method is selected to estimate the above relationship in this study.

As mentioned in the introduction to the relevant literature, this study proposes the following hypotheses regarding the impact of the number of bidders and the quantity of bids on winning bids [5-6]:

H1: The number of bidders positively affects the winning bids.

H2: The quantity of bids positively affects the winning bids.

H3: The starting bid positively affects the winning bids.

3 Results and discussion

This study analyses the factors that influence bidding behavior and winning bids. Due to the number of bidders' endogeneity in the model, the 2SLS method is selected to analyze the model in this study. To investigate the impact of this endogeneity, the OLS method is also used in the study to analyze the model as a comparison. Table 3 presents the coefficient estimates obtained from the analysis of the model by OLS and 2SLS methods respectively.

In Table 3, estimates in column (2) are from the OLS regression, estimates in column (3) are from the 2SLS regression, and the numbers in parentheses are the p-value of each variable. According to the p-values it can be seen that the coefficient estimates of the starting bids, the quantity of bids, the number of bidders and the seller rating are significant at the 5% level. However, none of the other control variables are significant at conventional levels. In addition, to examine whether the instrumental variables in the model are valid, this study also conducted the weak instrumental variable diagnostics, the results of the diagnostics have been presented in Table 4. It can be observed that Cragg-Donald F-statistic is 34.21, which is larger than 10. Therefore, the null hypothesis of weak identification is rejected. All the three instrumental variables significantly affect the bidder's participation (number of bidders).

Table 3. OLS and 2SLS estimates

	OLS	**2SLS**
# Number of Bidders	0.895	2.675
	(0.034)	(0.023)
Quantity of bids	0.690	0.889
	(0.028)	(0.029)
Starting Bid	1.034	1.035
	(0.000)	(0.000)
Morning	-2.893	-3.427
	(0.491)	(0.389)
Afternoon	-3.121	-3.388
	(0.365)	(0.267)
Evening	-1.645	-2.093
	(0.675)	(0.553)
Night	-4.183	-4.228
	(0.623)	(0.593)
Weekend	-0.054	IV
	(0.098)	
Closing Interval	-0.019	IV
	(0.058)	
Seller Rating	-0.0004	IV
	(0.008)	

Table 4. Weak instrument diagnostics

Cragg-Donald F-statistic:			34.21
Stock-Yogo TSLS critical values			
Relative bias		Size	
5%	16.85	10%	24.58
10%	10.27	15%	13.96
20%	6.71	20%	10.26
30%	5.34	25%	8.31

According to the results of the empirical analysis above, the following relationships are discussed in this section: the relationship between the endogeneity of the number of bidders and the results of the analysis, and the effects of the number of bidders and other factors on the winning bids.

3.1 The effect of the number of bidders on the winning bids

In the 2SLS estimates, it can be observed that the winning bid has increased about 267.53% by the coefficient for the number of bidders, indicating an average increase of $55.41 relative to the average winning bid of $20.71. This means the relationship between the number of bidders and the winning bids is positive, hypothesis 1 holds. This result is similar to the research conducted by Hendricks et al. and Onur & Velamuri [5-6]. However, in the result of this study, the number of bidders seems to have a greater impact on the winning bids than in their previous study. This may be because the demand for TI-83 calculators has decreased significantly over time, as can be observed from the sample data in Table 2, the mean number of bidders is only 2.66, much lower than the mean number of bidders in the study of Onur & Velamuri, which was 6.72 [5]. In addition, as Figure 1 illustrated, in the random sample of fifty TI-83 auctions, the majority of the auctions had less than three bidders. The largest number of these were the auctions with the number of bidders at 2, which had 20 auctions. Therefore, when a new bidder participates in an auction with a low number of bidders, the winning bid can be significantly increased, but this conjecture has not been confirmed.

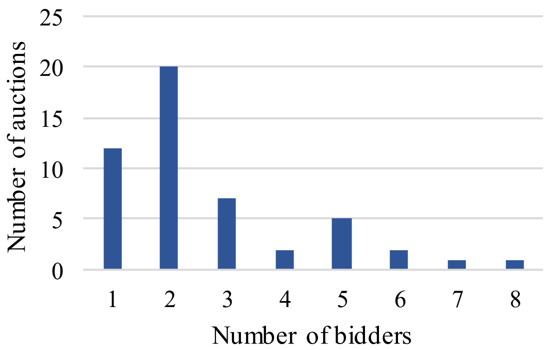

Fig. 1. Number of auctions corresponding to different numbers of bidders.

3.2 The effect of the endogeneity of the number of bidders on the results of the analysis

The impact of the endogeneity of the number of bidders on the analysis results can be reflected by comparing the number of bidders' coefficient estimates in the OLS and 2SLS analysis. As Table 3 presented, the coefficient estimates for the number of bidders in the OLS and 2SLS analysis are 0.895 and 2.675 respectively, this shows that the OLS estimate underestimates the impact of the number of bidders on the winning bids by about 200%, which is a considerable bias. Hence, the result supports that the number of bidders is indeed endogenous, and ignoring this endogeneity would underestimate the relationship between the number of bidders and the winning bids.

3.3 The relationship between other factors and the winning bids

In the 2SLS analysis, the coefficient of the quantity of bids is estimated as 0.89 implying that the quantity of bids also positively affects the winning bids, but this effect is not as significant as the effect of the number of bidders. In addition, according to Table 3, it can be noticed that, besides the number of bidders and the quantity of bids, the starting bid positively affects the winning bids as well. This effect is more significant than the effect of the quantity of bids, and less significant than the effect of the number of bidders. This is because the coefficient estimate of starting bid is 1.035, which is between 0.889 and 2.675. Therefore, hypothesis 2 and hypothesis 3 hold. Nevertheless, it is also worth mentioning that in the OLS estimates, the seller rating has a minor negative influence on winning bids. This indicates that when the seller rating is high, the winning bid will be slightly lower. This seems to be contrary to common sense. Furthermore, the four time period dummy variables set in this study were not significant in the regression, which seems to suggest that the period in which a bidder participates in an auction does not affect the winning bid.

In summary, these results are basically consistent with the predictions made at the beginning of this article and provide evidence of the following: (i) the quantity of bids, the starting bid and the number of bidders all have a positive impact on the winning bid, in which the number of bidders has the greatest impact and the quantity of bids has the least impact; (ii) the number of bidders is endogenous and ignoring this endogeneity underestimates its impact on the winning bids; (iii) seller rating has a slight negative impact on the winning bids; (iv) the timing of the end of the auction does not affect the winning bid. These findings have significant consequences for seller profitability and bidder behavior on eBay, as well as, more broadly, for the optimal design of eBay auctions.

4 Conclusion

This research uses a sample of TI-83 calculator auctions on eBay to examine the factors that influence bidding behavior and winning bids. And the study found that the quantity of bids, the starting bid and the number of bidders each had a positive impact on the winning bids, whereas, the seller rating has a negative impact on the winning bids. These can be possibly explained by the following facts. First, the rules of eBay auctions are that bidders can keep bidding until the auction ends. During the auction, each bid cannot be lower than the current highest bid. At the end of the auction, the object goes to the bidder with the highest bid. Therefore, when the quantity of bids or the number of bidders is high in an auction, the winning bid will be higher. Moreover, another rule of eBay auction is that the starting bid is set by the seller first and bidders cannot bid below the starting bid. In other words, the starting bid determines the lower limit of the winning bid, and when the starting bid is high, the winning bid can also be high. In addition, in common sense, when a seller has a higher rating, it is easier to gain the trust of the buyer and thus stimulating the willingness to bid. However, when a seller's rating is too high, it may raise doubts about its authenticity and thus reduce the willingness to bid of potential bidders and decrease the winning bid.

The result of this study has significant consequences for the design of both traditional and online auctions and all potential bidders. Closing intervals and seller ratings, for example, can be valuable proxies for seller competition in online auctions. It may also provide sellers with information on how they should set their starting bids to achieve maximum revenue. Furthermore, because this study has selected the most recent data and the most comprehensive variables as possible, the results of this study can offer valuable information to supplement future studies. However, due to the limitations of the eBay app, this study could not collect the BIN prices, which is also likely to have a potential impact on the *winning bid* (see Table 1 for explanation). In addition, as discussed above, the effect of seller ratings on the winning bids is probably non-linear. Further refinements on the above relevant variables could be made in the future to facilitate further research on this topic.

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