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An Empirical Analysis of Jump Bidding in Internet Auctions

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Abstract

This paper attempts to shed an empirical light on so-called jump bidding in ascending auctions. There is a jump when a participant in an auction outbids the last proposal by more than what is required by the rule of the auction. Using a data set from eBay, we find that the initial price, the selling price and the average degree of participant expertise are the main drivers of jump bidding.

Key Words: Internet Auctions, Jump Bidding, eBay, Econometric Model.

Résumé

On analyse dans cet article le phénomène de sauts dans les enchères électroniques. On dit qu'il y a un saut quand un enchérisseur dépasse la dernière mise par un montant qui dépasse celui requis par les règles de l'enchère. En utilisant des données d'eBay, on trouve que le prix initial demandé, le prix de vente et l'expertise des participants sont les principales variables explicatives du phénomène.

Mots clés : Enchères sur Internet, saut, eBay, modèle économétrique.

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1 Introduction

Until recently, most people pictured an auction as a special event in a luxurious setting, during which a rare wine or a Picasso is put up for sale by a famous auction house. The arrival, and high level of adoption, of Internet auctions has rendered this image obsolete. For instance, eBay, a recognized leading auction site, daily offers hundreds of thousands of items in 4,500 product categories (Bunnell (2000)). Since its start in 1995, this Website has hosted over 2 billion auctions, and now has more than 100 million registered users (see auction-sellers-resource.com, and company overview at www.ebay.ca). The reasons cited for the site's popularity include easy access to computers, low transaction costs, product information available worldwide, and a more competitive market than live auctions (Lin and Joyce (2004)).

There are many types of auctions (see, e.g., Klemperer (1999) or McAfee and McMillan (1987) for a survey). In an *ascending auction*, bidders intervene sequentially, and the final bid (necessarily the highest) corresponds to the selling price. It may be the case that, for a new offer to be admissible, it has to outbid the previous one by at least a certain prespecified amount called a *minimal increment* (MI). In the case of eBay auctions, this increment depends on the amount of the last bid. For instance, the MI is \$50 if the current price (or last bid) falls within the interval \$2,500 - \$5,000, whereas it is 25 cents when the last bid is between one and five dollars.¹

Why would a participant adopt a *jump-bidding* strategy when she has as many opportunities as she wishes, to intervene in the auction (until the auction's closing date), i.e., why would she raise the price by an amount higher than the minimal increment? This is our main research question. More specifically, we wish to determine the drivers of such a strategy.

A number of arguments, mainly theoretical, have been put forward in the literature to explain jump bidding in an ascending auction. A first explanation is that a jump is meant to signal high valuation with the hope of intimidating opponents and hence deterring them from continuing to bid (Avery (1998)). Note that such a strategy may just as well produce the reverse effect, i.e., an escalation. Another explanation is *bluffing*.² In the context of *Independent Private Values*, Hörner and Sahuguet (2007) show that this strategy could give an advantage to a player with a moderate valuation of the product. It is a rather expensive strategy for a player with low valuation, and an unsatisfactory one for

¹Minimum increment as function of last bid:

Last bid	0.01 – 0.99	1 – 4.99	5 – 24.99	25 – 99.99	100 – 249.99
MI	0.05	0.25	0.50	1.00	2.50
Last bid	250 – 499.99	500 – 999.99	1000 – 2499.99	2500 – 4999.99	≥ 5000
MI	5.00	10.00	25.00	50.00	100.00

²Bluffing occurs when a weak player seeks to deceive her opponent into thinking that she is strong.

a player with high valuation.³ A third explanation for jump bidding is that it seeks to avoid high costs of submitting or revising bids, as in Daniel and Hirshleifer (1998). The authors consider the case of takeovers where bidding costs may be substantial (fees for legal counsel and investment bankers, opportunity cost of executive time, etc.) In the case of eBay, the source of our data, the only cost borne by a bidder is the opportunity cost of time. In auctions involving the general public, one would expect the bidding cost to be low, and hence bidders to favor *ratchet strategy*.⁴ Further, Isaac et al. (2007) show that the use of jump bidding is due to strategic concerns and impatience. They also analyze the impact of jump bidding on revenues, and provide some guidelines for auction design. For Kirkegaard (2006), jump bidding could be a good counterstrategy to phantom bids placed (illegally) by the seller herself. The reasons for placing such bids are: (i) updating beliefs and valuations by observing how bidding progresses in the auction; (ii) misleading buyers by manipulating their beliefs; and, (iii) discriminating between buyers. Finally, some of the auction's features, e.g., a fixed end-time or secret reserve price, may have an impact on the participant's bidding strategy.

The empirical literature on jump bidding is sparse. The paper closest to ours is that of Easley and Tenorio (2004). Their main findings are: (i) bidders are more inclined to make high jump bids at the beginning of an auction; (ii) bidders place jump bids to discourage potential rivals from taking part in the auction; (iii) the magnitude of a jump bid increases with the item's valuation; and finally, (iv) a jump bid is often present when the initial bid is very low compared to the item's real value. The main differences between Easley and Tenorio (2004) and this attempt to explain jump bidding are the following. First, these authors deal with B2C multi-unit auctions (using data from uBid.com and Onsale.com), whereas here we focus on C2C single-unit auctions. Second, the items considered in Easley and Tenorio (2004) come directly from manufacturers, which eliminates, or at least greatly reduces, the uncertainty regarding delivery and warranty and the corresponding impact on prices. Moreover, the authors focused on consumer and electronic products, while, in our study, we deal with rather inexpensive sporting goods. Finally, their auctions have a soft deadline of 24 hours, with automatic extension of 5 to 10 minutes as long as someone places a bid within these additional periods. We deal here with predetermined end-times that vary from 3 to 10 days.

The rest of the article is organized as follows. Section 2 introduces the model and Section 3 presents and discusses the results. The last section concludes and proposes some research avenues.

³One distinguishes between auctions with *Independent Private Values* (IPV) and those with *Common Values* (CV). In an IPV setting, each bidder knows her value with certainty but faces uncertainty about the other bidders' values. Here, bidders gain no additional information by observing the bids of others. In a CV context, the true value of the item is the same for all bidders, ex post, because, e.g., the true value is determined through resale or exploitation of a common technology. However, this true value is not known with certainty ex ante and must be estimated by each bidder (Wilcox (2000)).

⁴*Ratchet strategy*, here means that the new bid exceeds the previous one by the minimum increment required.

2 The Model, Data and Variables

In order to achieve our goal of explaining jump bidding in single-unit C2C auctions, we specify a simple econometric model and apply it to a data set taken from the eBay Website (www.ebay.com). This set contains the history of 418 auctions for sport items. These auctions took place in January 2002.

The dependent variable is defined as the ratio of the number of jump bids to the total number of bids. We believe that such a relative measure of the phenomenon is more intuitively appealing than adopting an absolute measure, i.e., the number of jumps. Denote by B_t the current bid, and by B_{t-1} the previous one. We say that a jump occurs if

$$B_t - B_{t-1} \geq \alpha MI$$

where α is a parameter greater than one. We shall run the econometric model using different values for α , namely, $\alpha = 1.5, 2, 5, 10$. The average, for the 418 auctions, of the proportions of jumps for the different values of α are given in Table 1.⁵ As one can see, the proportion of jumps is quite high, even for high values of α .

Although the above definition of a jump is mathematically clear, we have to clarify its implementation in practice. A participant in an eBay auction has the choice between entering herself a bid, or using the "automatic bidding option". In this last case, the bidder provides the maximal amount she is willing to pay for the product. This information is, of course, not public knowledge. The system outbids, by the required minimal increment, the current observed bid or the current highest maximum willingness-to-pay bid. To clarify, consider the following example taken from eBay's Website:

The current bid for an item is \$10.00. Tom is the high bidder. (Tom has placed a maximum bid of \$12.00 on this item, but his maximum bid is kept confidential from other eBay members.) Laura views this item and decides to place a maximum bid of \$15.00. Laura becomes the high bidder because her bid is greater than Tom's bid. A bid increment of \$0.50 is added to Tom's maximum bid of \$12.00. That means that Laura's current bid is now \$12.50. Tom is sent an email that he has been outbid.

An observer of this auction would have seen two data points (bids): Tom's bid of \$10.00 and Laura's bid at \$12.50. Suppose $\alpha = 1$. Laura's last bid is then considered, according to our formula, as a jump bid, because it exceeds previous observation by more than the minimal increment of \$0.50. Now suppose that Tom did not use the automatic bidding option, but Laura does. Then, the system would place a bid of \$10.50 on behalf of Laura. This is not a jump bid. The implication is that the presence of the automatic bidding option has an impact on the auction evolution, rendering the distinction between a jump bid and a ratchet bid difficult in some instances. There is no way to account properly for this in eBay, because we cannot distinguish between a human bid and a system one.

⁵It is interesting to note that this average varies little for α in the interval $[1.00001, 2]$. Indeed, for $\alpha = 1.00001$, the average of proportions of jumps is 0.5982, with a standard deviation of 0.2188.

Table 1: Average of proportion of jumps for different values of α

α	Average of proportions of jumps	Standard deviation
1.5	0.5826	0.2188
2	0.5684	0.2161
5	0.3035	0.1982
10	0.1593	0.1583

Using eBay's data requires, therefore, to make the assumption that a person who uses the automatic bidding option, would have behaved in the same manner should she had to enter herself her bid. This apparent randomness is somehow part of the error term. Actually, the presence of this option led Wilcox (2000) to define eBay's auctions as a hybrid auction, and not exactly as a standard ascending auction.

We now introduce the potential drivers of jump bidding.

2.1 Independent variables

2.1.1 The initial price

Easley and Tenorio (2004) found that the the seller's initial asking price, compared to its real value, the higher the probability of observing jump bids. The intuition is that a low initial price is not credible. By making jumps, bidders hope to quickly clarify the selling price and degree of competition. We make the following hypothesis:

H1: The lower the initial price, the higher the proportion of jump bids.

2.1.2 The item's price

Easley and Tenorio (2004) find that the probability of observing jump bids increases with the item's value (measured ultimately by its sale price), and that the price positively affects the magnitude of these jumps. Intuitively, this may be explained by the idea that participants who are eager to acquire such high-value items implement a jump-bidding strategy to discourage others from continuing to participate in the auction (because their continued participation would lead to an increase in the price), and hence maximize their surplus, as measured by the difference between their own valuation and the sale price. Further, the higher the item's *true* value, the higher it attracts expert bidders who place a few strategic, and most likely, jump bids (Roth and Ockenfels (2002)).

H2: The higher the observed final price, the higher the proportion of jump bids.

2.1.3 The selling's mechanism

Two types of auctions are available on eBay: standard ascending auctions, and auctions with *secret reserve price* (SRP). In an SRP, the beginning of the auction, the seller specifies

the initial price and a reserve price, i.e., the lowest price for which she is willing to sell the product. This precise reserve price is not public, and is actually never revealed to bidders, even after the contract's fulfillment. If the reserve price is reached in the course of an auction, then eBay informs the bidders, without however, ending the auction, which continues until the seller-selected end time.

Katkar and Lucking-Reiley (2006) state that including an SRP in an auction incites participants to bid aggressively, e.g., to jump bid, in order to quickly exceed this price. Further, an SRP is synonymous to an additional aggressive bidder and hence to a more competitive auction.

H3: Compared to a standard auction, an auction with SRP exhibits a higher proportion of jump bids.

2.1.4 The seller's reputation

A number of studies have been interested in the relationship between the seller's reputation and the bidder's degree of risk aversion, in both traditional and online auctions (see, e.g., Engwall (1976), Graham and Hardaker (2001), Massad and Tucker (2000), and Hofacker (1999)). To the best of our knowledge, there is no empirical evidence linking the seller's reputation to specific types of strategic bidder behavior. Nevertheless, it seems intuitive to conjecture that the higher the confidence one has in the seller, the higher is the temptation to place a jump bid to increase one's chance of winning the bid. It is interesting to note that eBay provides a measure of the seller's reputation, called *feedback score*. Indeed, after a listing is completed, the buyer and the seller can give a positive rating (+1), a negative rating (-1) or a neutral rating (0), as each leaves a comment about the other. We retain the number of positive ratings as a measure of the seller's reputation and state the following:

H4: The higher the seller's reputation, the higher the proportion of jump bids.

2.1.5 The degree of bidder experience

The question here is whether or not there is a relationship between the type of bidder (experienced or not) involved in an auction, and the frequency with which a jump-bidding strategy is used. On a general level, Roth and Ockenfels (2002) state that the degree of expertise of a bidder affects her time to react, the reasons to this reaction, and the manner in which she will react. Wilcox (2000) finds that expert bidders are less inclined to place multiple bids in the same auction than are less experienced bidders, and that more experienced bidders on eBay bid later than less experienced ones. This last statement is also made by Roth and Ockenfels (2002) who find that expert bidders take part in auction during its final minutes (*sniping strategy*) to avoid a price war at the beginning, or to not divulge valuable information concerning the product. These results lead us to assume that the higher the average degree of participant expertise meaning a high number of expert bidders participating, the higher the number of jump bids, because each expert places one

strategic jump bid hoping to deter competitors from going further. We suppose that the average feedback ratings of all the bidders participating in the auction constitute a good measure of the average degree of experience. A high value indicates that the auction has attracted a high number of expert bidders, and hence, we state the following:

H5: The higher the degree of expertise among participants, the higher the proportion of jump bids.

2.1.6 The duration of the auction

There are four possible auction durations available on eBay: 3, 5, 7 and 10 days. The question here is whether or not this duration matters in terms of bidding strategies. The literature has worked out the impact of having an ending rule, and of the possibility of an automatic extension, on bidders' behavior, but not the impact of the duration itself. For instance, Roth and Ockenfields (2002) analyzed the difference between the fixed-end-time rule on eBay, and the automatic extension one on Amazon, and obtain that the ending rule plays a strategic role in last-minute bidding. Using the percent time of a bid as an exogenous variable,⁶ Easley and Tenorio (2004) find that the probability of entering a jump bid, as well as its magnitude, decrease as time passes. Translated in terms of auction duration, this result would suggest that the longer the auction, the lower the number of jump bids. Put differently, the bidders can adopt a less aggressive behavior, or a wait-and-see strategy, when they have more time to react. Thus our assumption to be tested is as follows,

H6: The longer the duration of an auction, the lower the proportion of jump bids.

2.1.7 Product category

The 418 auctions in our database are divided into four subcategories, namely, *Autographs*, *Memorabilia*, *Sporting Goods* and *Trading Cards*. Looking at sellers' (and not bidders') strategies, Bajari and Hortaçsu (2000) and Katkar and Lucking-Reiley (2006) analyze the impact of using an SRP on the seller's benefit. Bajari and Hortaçsu (2000) find that the use of SRP in the case of US coins, an expensive product, is beneficial to the seller. Katkar and Lucking-Reiley (2006) reach the opposite conclusion for Pokémon cards, a less expensive product. Putting the two results together, we are tempted to assume that the product category matters when it comes to determining the seller's best strategy. Although, there is neither theoretical rationale nor empirical evidence, stating that jump bidding (a bidder strategy) is correlated with the type of product, we still wish to explore the relevance of such a variable. Given the state of the literature on this point and the exploratory nature of this work, we refrain from assuming a particular sign for the coefficients of the different products involved in this study.

⁶The percent time of a bid is the time at which the bid is placed, expressed as a percentage of elapsed auction time (Easley and Tenorio (2004)).

H7: There is a relationship between the type of product and the number of jump bids.

Before formally stating the model, it is interesting to comment on the similarities with, and the differences from, the model closest to ours, i.e., Easley and Tenorio (2004). Both models consider the winning bid and the initial bid as exogenous variables. However, in Easley and Tenorio, both variables are expressed in terms of number of increments. Further, they account for the bid's percent time as the time at which the bid is placed, expressed as a percentage of elapsed auction time. Here, we only include the end time determined by the auctioneer herself (3, 5, 7 or 10 days). Easley and Tenorio deal with bidders who order three or more units (called *dealers*) which is not included in our single-unit auctions and finally, they consider units available as dummy variables among their independent ones. By including other variables in our model, i.e., the type of selling mechanism, the seller's reputation, the degree of expertise via feedback, and the type of product, we wish to shed an additional light on the jump-bidding phenomenon. Finally, whereas Easley and Tenorio include the total number of bidders, we do not. The main reason is that our dependent variable is the ratio of number of jump bids to total number of bids. Thus, including the total number of bids as an exogenous variable may not only constitute an endogeneity problem, as pointed out by Easley and Tenorio, but also a serious collinearity problem as well.

To summarize, our model can be written as

$$jump_{\alpha} = f(IP, SP, SR, BE, Mech, 3d, 5d, 7d, Auto, Memo, Sport) + \epsilon,$$

where the function f is linear (in parameters), with the variables defined as follows:

$$\begin{aligned}
 jump_{\alpha} &= \frac{\text{Number of jump bids for given } \alpha}{\text{Number of total bids in the auction}}, \\
 IP &= \text{initial price,} \\
 SP &= \text{selling price,} \\
 SR &= \text{seller's reputation,} \\
 BE &= \text{bidders' average experience,} \\
 Mech &= \begin{cases} 1, & \text{if the selling mechanism includes an SRP,} \\ 0, & \text{otherwise,} \end{cases} \\
 3d &= \begin{cases} 1, & \text{if duration of the auction is 3 days,} \\ 0, & \text{otherwise,} \end{cases} \\
 5d &= \begin{cases} 1, & \text{if duration of the auction is 5 days,} \\ 0, & \text{otherwise,} \end{cases} \\
 7d &= \begin{cases} 1, & \text{if duration of the auction is 7 days,} \\ 0, & \text{otherwise,} \end{cases}
 \end{aligned}$$

Table 2: Descriptive statistics

Variables	Min	Max	Mean	Standard deviation
<i>IP</i>	0.01	995.00	58.20	158.39
<i>SP</i>	1.80	5900.00	228.51	529.38
<i>SR</i>	0.00	24496.00	1255.23	2197.41
<i>BE</i>	0.00	1417.44	149.64	182.03
<i>No SRP</i>	0.00	1.00	82.78 %	
<i>With SRP</i>	0.00	1.00	17.22 %	
<i>3d</i>	0.00	1.00	7.66 %	
<i>5d</i>	0.00	1.00	13.40 %	
<i>7d</i>	0.00	1.00	62.68 %	
<i>10d</i>	0.00	1.00	16.27 %	
<i>Auto</i>	0.00	1.00	18.90 %	
<i>Memorabilia</i>	0.00	1.00	28.47 %	
<i>Sport</i>	0.00	1.00	27.51 %	
<i>Trading Card</i>	0.00	1.00	25.12 %	

$$\begin{aligned}
 \textit{Auto} &= \begin{cases} 1, & \text{if the product is an autograph,} \\ 0, & \text{otherwise,} \end{cases} \\
 \textit{Memo} &= \begin{cases} 1, & \text{if the product is a memorabilia,} \\ 0, & \text{otherwise,} \end{cases} \\
 \textit{Sport} &= \begin{cases} 1, & \text{if the product is a sporting good,} \\ 0, & \text{otherwise.} \end{cases}
 \end{aligned}$$

Table 2 provides some descriptive statistics. The mean starting price is \$58, with a minimum that can be as low as 1 cent, and the mean selling price is \$228. The highest recorded selling price in the 418 auctions studied is \$5,900. Note that most auctions do not include a secret reserve price (SRP) and have a seven-day duration.

The term ϵ is the error term, which is assumed stochastic with the mean $E(\epsilon) = 0$, the variance $Var(\epsilon) = cst$ and covariance $Cov(\epsilon_n, \epsilon_m) \neq 0$ ($n \neq m$ and n, m respectively represent one item's auction). We have used OLS regression to estimate the parameters' coefficients.

As a first step, we verify if each variable, whether dependent or independent, violates the OLS assumptions (normality, linearity and heteroscedasticity⁷). All assumptions are satisfied, except for normality, which is highly violated by the exogenous continuous variables. To remedy this, we apply a logarithmic transformation to these variables. Our

⁷The autocorrelation assumption is not relevant since our data are not chronological.

model the becomes a semi-log model and is written as follows:⁸

$$\begin{aligned} jump_{\alpha} = & f(\log IP, \log SP, \log SR, \log BE, \\ & Mech, 3d, 5d, 7d, Auto, Memo, Sport) + \epsilon. \end{aligned}$$

3 Results

Table 3 provides the results for the different values of $\alpha = 1.5, 2, 5, 10 \dots$. Generally, all models are statistically significant (see F Statistic), and more or less explain the same percentage of total variance (see the \bar{R}^2 , the adjusted R^2). Further, none of the models present a multicollinearity problem, and, through an analysis of partial regression plots for each independent variable, we did not detect any nonlinear pattern. However, the models with $\alpha = 5$ and $\alpha = 10$ present a serious heteroscedasticity problem.⁹ Therefore, care must be taken when interpreting the results in these two cases.

Turning now to the hypothesis, our results call for the following comments:

1. Hypothesis H1, i.e., the lower the initial price, the higher the proportion of jump bids, is validated for all values of α . The same applies to H2, i.e., the higher the selling price, the higher the proportion of jumps. This confirms the similar results obtained by Easley and Tenorio (2004) in the context of B2C multi-unit auctions. Thus our study complements their findings by showing that initial and final prices matter independently of the auction type (i.e., C2C versus B2C, and multi-units versus one item).
2. Although we did not find in the literature any empirical evidence of a relationship between the seller's reputation and jump bidding, we hypothesized a positive link between the two variables, based mainly on a risk-aversion argument. The results show that the seller's reputation has a significant, and negative impact only for $\alpha = 5$. Given the presence of a heteroscedasticity problem in this case as well as for $\alpha = 10$, we are tempted to place more trust in the first two models, and conclude an absence of a relationship between the seller's reputation and jump bidding.
3. Our results confirm the intuition and the findings in Wilcox (2000) and Roth and Ockenfels (2002) that experts bid more aggressively than "naive" bidders. Hypothesis H4, stating that the higher the degree of expertise among participants, the higher the proportion of jump bids, is confirmed.

⁸Although the *Kurtosis* of $\log SR$ is equal to 5.317, indicating that the normality assumption is violated, a simple visual check of the histogram shows that this variable actually satisfies the normality assumption. As stated in Hair et al. (1998), not only statistical tests but also graphical plots should be used to assess the actual degree of departure from normality. Besides, they explain that *Skewness* and *Kurtosis* values are just rule of thumb and that they depend on the desired significance level.

⁹The violation of this assumption means that all coefficients' parameters are unbiased but are inefficient. WLS estimation was used to remedy this problem, but in doing so created a multicollinearity one.

Table 3: Results for different values of α

	$\alpha=1.5$	$\alpha=2$	$\alpha=5$	$\alpha=10$
	Coeff.	Coeff.	Coeff.	Coeff.
<i>cst</i>	0.159	0.155**	0.077	-0.025
$\log IP$	-0.038***	-0.037***	-0.032***	-0.027***
$\log SP$	0.098***	0.096***	0.063***	0.054***
$\log SR$	0.000	-0.001	-0.008**	0.001
$\log BE$	0.014**	0.013*	0.021***	0.013**
<i>Mech</i>	0.032	0.030	0.077***	0.090***
<i>3days</i>	0.026	0.020	0.062	0.043
<i>5days</i>	-0.003	-0.002	0.001	0.016
<i>7days</i>	0.041	0.042	0.014	0.009
<i>Auto</i>	0.012	0.017	0.070***	0.049**
<i>Memo</i>	0.025	0.029	0.033	0.034*
<i>Sport</i>	0.042	0.045	-0.002	-0.010
\bar{R}^2	0.333	0.328	0.271	0.315
SEE	0.17834	0.17675	0.16917	0.13121
F	19.955***	19.527***	15.069***	18.441***

(***) Significant at the 0.01 level.

(**) Significant at the 0.05 level.

(*) Significant at the 0.10 level.

(SEE) Standard Error of the Estimate.

4. Including a secret reserve price (SRP) is assumed to have a positive impact on the proportion of jump bids. Our results show that it is indeed the case for high values of alpha ($\alpha = 5, \alpha = 10$). If one places more trust in the other two models, then one concludes that including an SRP in an ascending auction does not influence the proportion of jump bids. Note that we may have a selection problem here, i.e., more aggressive bidders are more likely to participate in auctions with SRP. It is clearly worth it to investigate further this issue.
5. Contrary to what we stated in hypothesis H6, the duration of an auction does not explain the use of jump bidding. Recall that the literature has not considered this possible relationship, but analyzed the effect of end time and end rule on strategic behavior. Further, the type of product seems to play little role in explaining jump bidding.

To summarize, the initial price, selling price and degree of competition are the main explanatory variables of jump bidding. This holds true whatever the definition of jump is adopted, and thus we can claim the robustness of the results.

4 Concluding Remarks

Using a simple econometric model, this paper sheds an empirical light on jump bidding, a phenomenon that is frequently seen in online auctions. Our analysis complements the one in Easley and Tenorio (2004), where the focus is on B2C, multi-unit auctions. The results support most of our hypotheses, and, importantly, they are rather robust with respect to the definition of a jump (the parameter α).

This study can be extended in several directions. First, it would be interesting to check for the generalizability of the results in terms of product categories. Would the results remain (qualitatively) the same if one considered, e.g., one-of-a-kind items? Second, it would be interesting to deal with auctions having other features than those on eBay. For instance, auctions with end rules that differ from eBay's (i.e., automatic extensions) to assess the impact of such features on jump-bidding strategy. Third, our approach does not take into account the moment at which a participant makes a jump bid. The inclusion of the jump timing could improve the validity of the model in terms of the percentage of explained variables.

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