DOES IT PAY OFF TO BID AGGRESSIVELY? AN EMPIRICAL STUDY

Research-in-Progress

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Abstract

In this research, we empirically investigate the payoff of aggressive bidding in an online auction. To address our research question, we use a unique and very rich dataset containing actual market transaction data for approximately 7,000 pay-per-bid auctions. Our research design allows us to isolate the impact of bidding aggressively in an attempt to signal a high valuation on the probability to win an auction. In particular, we analyze more than 600,000 bids placed manually by approximately 2,600 distinct auction participants. The strong and significantly negative effect of aggressive bidding on the likelihood of winning an auction revealed by our analysis suggests that an aggressive bidding strategy is not beneficial in increasing the chances of winning an online auction.

Keywords: *Internet Markets, Electronic Markets, Auctions, Aggressive Bidding, Jump Bidding.*

Introduction

"Another issue related to bidding strategy is whether to be bold or cautious in opening bidding. The man who strongly desires an item will jump in with both feet, as it were, or try to rout the enemy by starting out with a high, possibly loud, bid intended to "knock out" his opponents. Sometimes he even tops his own bid. This approach may discourage competitors at the outset and prevent them from ever getting caught up in the spirit of the bidding. In a very different strategy, a prospective buyer, even though determined to purchase an item, bids tentatively and cautiously in order to feel out the opposition. He hopes that by indicating a low regard for the offering he will lull opponents into a false sense of security." (Cassady 1967)

"… he bid seventy-five grand for the land when the other operators were offering bids in the low fifties…. Naturally he got it … and made himself a sweet little bundle. After he bought it, I told him he could have got it for twenty thousand less, and you know what he said? 'I never try to buy a property as cheap as possible. That way you're in competition with the other operators. They keep kicking each other up and before you know it, you're paying more than you intended and more than it's worth to me, and that's what I offer. That way you discourage the competition. It takes the heart right out of him." –Harry Kemelman, Wednesday the Rabbi Got Wet. (Avery 1998)

Cassady describes two contrasting ways of placing bids in an auction: Bidders can adopt either an aggressive or a cautious bidding strategy. In an aggressive strategy, bidders try to signal a high valuation of the auctioned product and, thus, aim to discourage potential competitors from the outset. By contrast, in a cautious strategy, tentative bidders intend to conceal their valuation for as long as possible. This bidding strategy is also referred to as *ratchet bidding*, *straightforward bidding*, or *pedestrian bidding*. The quote by Harry Kemelman may be taken as anecdotal evidence that aggressive bidding strategies promise a positive return for the respective bidder. However, Kemelman cannot be sure that he wins *because* of his aggressive bidding strategy. It is also possible that he is simply the bidder with the highest valuation of the auctioned product and, thus, could also have won with a lower bid and a more cautious bidding strategy.

The existence of aggressive bidding strategies – typically called *jump bidding* – in ascending price auctions has been covered extensively in the scientific literature (e.g., Avery 1998; Easley and Tenorio 2004). Cramton (1997) defines jump bidding as *"the act of raising a high bid by much more than the minimum increment"*. Empirical studies suggest that such bidding behavior occurs on a very frequent basis. For example, Easley and Tenorio (2004) report that more than 30% of the bidders in their sample submit jump bids. Not surprisingly, a significant literature has emerged, analyzing these strategies theoretically and empirically (for an extensive literature review see, e.g., Raviv 2008). In general, signaling (e.g., Avery 1998; Daniel and Hirshleifer 1998) and impatience (e.g., Isaac et al. 2007) have been named as potential explanations for jump bidding. However, none of the existing studies empirically investigated the impact of jump bids as a way of signaling one's own valuation on the actual likelihood to win an auction. Thus, the question, whether Kemelman won the auction because of his bidding strategy or merely because of his high valuation of the land, has until today remained unanswered. This gap in the literature may be explained by the fact that it is not easy to distinguish between jump bids that are attributable to impatience and jump bids that are attributable to signaling.

Online pay-per-bid auctions (e.g., beezid.com, bidcactus.com)[1], which constitute a variant of ascending price auctions, have seen a significant rise in recent years. The increase in this type of auctions helps to overcome the above-mentioned challenge. Each such auction starts at a price of zero and with a fixed end time on a countdown clock. Auction participants are restricted to bidding a fixed bid increment (e.g., 1 cent) above the current bid and must pay a non-refundable fixed fee (e.g., 50 cents) for each bid placed. Each bid extends the duration of the auction by a given time increment (e.g., 10 seconds). For example, in an auction where the current bid is $2.32 with 12 seconds on the auction countdown, an additional bid

[1] In September 2011, 5.5 million unique visitors visited pay-per-bid auction websites. This corresponds to 7.3% of the unique visitors on the biggest auction website worldwide – ebay.com (Platt et al. 2012).

increases the current bid by 1 cent to $2.33 and extends the auction countdown by 10 seconds.[2] The participant who places the bid has to pay the fixed bidding fee of 50 cents. A participant wins the auction if her bid is not followed by another bid. The winner has to pay the current bid (in addition to the bidding fees already paid) to obtain the item. If the participant in our example is the last bidder, she would win the auctioned product for $2.33.

As with other auction formats, bidders in a pay-per-bid auction can adopt aggressive bidding strategies. But, unlike with other auction formats, bidders cannot use typical jump bids to signal a high valuation since the bidding increment is fixed. However, bidders can use the *timing* of their bids as a signaling device. Instead of delaying until the last second of an auction, auction participants can re-raise the current bid immediately after another auction participant has placed their bid.

By its very design this specific auction format enables us to isolate the effect of an aggressive bidding strategy, used to signal a high valuation, on the likelihood of winning an auction. As each placed bid extends the duration of a pay-per-bid auction by the same amount of time, the respective bidding strategies have no influence on the total duration of an auction. Consequently, in this auction format, aggressive bidding cannot be caused by an auction participant's impatience but must be attributable to their attempt of signaling a high valuation for the auctioned product in order to try to increase their chances of winning.

To summarize, our research setup allows us to examine the impact of this specific form of aggressive bidding on the likelihood of winning an auction, and in particular, to answer the following research question: *What effect does aggressive bidding in a pay-per-bid auction have on the bidders' chances of winning an auction?*

Our explicit aim is to consider the inherent usefulness of aggressive bidding as a strategy for increasing the chances of winning an online auction. In other words, we aim to empirically resolve the incongruity of the conclusions drawn from various theoretical studies. In particular, prior theoretical studies (e.g., Avery 1998; Daniel and Hirshleifer 1998), as well as anecdotes provided by Avery (1998) suggest an inherently positive payoff from aggressive bidding, whereas the simulation study by Bapna et al. (2003) suggests a (slightly) negative payoff from such bidding behavior. In addition, studies in support of bidders' impatience as a cause of aggressive bidding imply that the payoff is insignificant (e.g., Isaac et al. 2005; Isaac et al. 2007). Our research, therefore, seeks to add to the existing literature on aggressive bidding strategies in the following way: By analyzing aggressive bidding in a pay-per-bid auction context, we are able to rule out impatience as a reason for aggressive bidding. This, then, allows us to be the first to provide an empirical answer to the question of whether signaling aggressiveness is a useful strategy to increase the chances of winning an online auction. Considering the different theoretical predictions on the effect of aggressive bidding and the vast number of aggressively placed bids, this answer would offer new insights relevant to information systems and behavioral economics research that will benefit both practitioners and researchers.

To answer our research question, we use a unique and very rich dataset provided by a German website offering pay-per-bid auctions. This dataset includes detailed customer level bidding and transaction data from approximately 7,000 auctions conducted between August 2009 and May 2010. The main result of our analysis is as follows: Controlling for the total investment of an auction participant, we find that the likelihood of winning an auction is significantly influenced by a participant's bidding strategy. Contrary to the prediction that aggressive bidders increase their chances of winning an auction, we find a strong and significant *negative* effect of aggressive bidding on the likelihood of winning an auction.

Literature Review

There is a substantial stream of research that has examined the concept of jump bidding theoretically, empirically, and experimentally. A broad range of studies have highlighted the existence of such bidding behavior. In particular, earlier studies have analyzed jump bidding in the context of different types of ascending price auctions (e.g., Avery 1998; Banks et al. 2003; Bapna et al. 2003; Carpenter et al. 2011;

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[2] The time increments add up linearly for each placed bid. For instance, if two bids are placed simultaneously, the countdown extends by another 10 seconds to 32 seconds.

Daniel and Hirshleifer 1998; Easley and Tenorio 2004; Hörner and Sahuguet 2007; Isaac et al. 2005; Isaac et al. 2007; Kwasnica and Katok 2007; Plott and Salmon 2005; Raviv 2008).

Theoretical studies have identified signaling and impatience as major explanations for jump bidding. Avery (1998) shows that jump bids in a common value setting where bidding is not costly can be interpreted as coordinative devices among bidders. Daniel and Hirshleifer (1998), Easley and Tenorio (2004), and Hörner and Sahuguet (2007) analyze jump bidding in ascending price auctions where bidding is costly. In their models, jump bidding follows from the cost of submitting and revising bids. The element common to both explanations is that bidders use jump bidding to signal their valuation of the auctioned product and, thus, to discourage potential competitors. For example, Avery (1998) writes that after a jump bid *"... the losing bidder may drop out in equilibrium even though his value is (certain to be) strictly larger than the current price."* In his model as well as in the model of Daniel and Hirshleifer (1998) jump bids are able to deter competitors with a higher valuation and, thereby, increase jump bidders' chances of winning while simultaneously reducing the expected revenue of the seller.

Another explanation for jump bidding in ascending auctions is the presence of bidding costs associated with the necessary time required to participate in an auction. Bidders may be impatient and, therefore, use jump bids to increase the speed of the auction. Banks et al. (2003) state that: *"Jump bidding is encouraged by impatient bidders who may sacrifice potential profit in their desire to speed-up the pace of the auction and reduce their transactions' cost."* Based on the observation of small, yet persistent, jump bids in the spectrum license auctions conducted by the US Federal Communications Commission and 3G spectrum auctions in the UK, Isaac et al. (2007) construct a model in which jump bids occur due to impatience. In their model, jump bidding as a result of impatience has no effect on the probability of winning an auction and a neutral or even positive effect on seller revenue.

There are also some empirical and experimental studies on jump bidding in ascending price auctions. On the one hand, in an empirical setup, Easley and Tenorio (2004) show that early jump bidding in an auction has a negative effect on the total number of bids placed in this auction. The authors interpret this finding as indirect evidence for the signaling value of jump bids. On the other hand, Isaac and Schnier (2005) as well as Isaac et al. (2005) provide some empirical and experimental evidence that jump bidding is driven by impatience of auction participants and, thus, has no or, indeed, may even have a positive effect on the end price of an auction. These results are reinforced by Kwasnica and Katok (2007) who find that higher bidder impatience results in greater jump bids. Carpenter et al. (2011) experimentally analyze the effect of jump bidding on auction revenue in the context of silent auctions. Within their experimental design, the authors successfully modify the incentives to use jump bids due to impatience. Consistent with Isaac and Schnier (2005) and Isaac et al. (2005) they find that jump bidding due to impatience increases auction revenue. Bapna et al. (2003) analyze jump bidding using a simulation framework for Yankee-type auctions. Consistent with the impatience hypothesis, they find that jump bidding has no effect on the likelihood to win an auction, and, due to the slightly higher average winning bid, even results in a negative total payoff for the auction participant. In a recent study, Grether et al. (2011) examine why bidders engage in jump bidding in used car markets. However, their study on two different markets arrived at contradictory results. In one market, they find support for the impatience explanation, while in the other market they find support for the signaling explanation of jump bidding.

To summarize, signaling and impatience provide two competing theoretical explanations for jump bidding in ascending price auctions. While jump bids due to impatience are typically associated with no – or even a positive – effect on the end price of an auction (Isaac and Schnier 2007), jump bidding as a signal of aggressiveness is associated with a negative effect on this price (Avery 1998; Daniel and Hirshleifer 1998). A lower expected end price of an auction increases ceteris paribus the winning probability of an auction participant. Thus, the studies of Avery (1998) and Daniel and Hirshleifer (1998) both suggest a positive effect of bidding aggressively on the probability of winning an auction while the study of Isaac and Schnier (2007) suggest no – or even a negative effect – on this probability. For the auctioneer, jump bidding due to impatience has a neutral or positive effect on the auctioneer revenue and a negative effect for jump bids due to signaling. The empirical evidence on this issue is mixed. While most of the empirical studies conclude that the main driver for jump bidding is bidder impatience, there is also anecdotal and weak empirical evidence that signaling with jump bids can deter other potential competitors from participating in an auction. Nevertheless, it is not clear whether the higher value of the jump bid increases the winning probability or whether jump bidding by itself induces this effect. In addition, it may also be the case that both signaling and impatience are factors that influence jump bidding. We are not aware of any empirical study which systematically investigates the signaling value of jump bids.

Research Setup

Study Design

When the participants on the website we analyzed are at the point of taking part in an auction they have to make several decisions (not necessarily in the following order): they need to decide how many bids they want to place, whether they want to place their bids manually or use an automated bidding agent; and if they choose to place their bids manually, they also need to decide, on a bid level, the exact point in time when they want to place it. In this paper, we concentrate only on timing decisions of manually placed bids.

In simplified terms, manual bidders can choose between two different strategies for timing their bids. The first strategy consists of instantly overbidding other auction participants in an aggressive manner as a way of signaling a high valuation of the auctioned product, and thus trying to discourage their potential competitors from placing further bids. We call this strategy the *aggressive strategy*. The second strategy involves placing the bids at some random point in time but not immediately after another auction participant has placed theirs. We call this second strategy the *normal strategy*.[3]

The aggressive strategy is conceptually very close to jump bidding in ascending price auctions. By submitting jump bids, bidders deliberately reveal more information than necessary about their (presumably high) valuation of the auctioned good. This comes at the risk of bidding more than the minimal winning bid. For example, consider a typical ascending price auction with two bidders and a bid increment of $1. The first bidder has a valuation of $20 and the second bidder a valuation of 50$. The second bidder could win the auction with a minimal bid of $21. If this bidder submits a jump bid of $25, she overbids the minimal winning bid by $4. The same argumentation holds for aggressive bidders in pay-per-bid auctions: By bidding immediately after another auction participant, bidders reveal their keen interest in the bidding process and hence, in winning the auction. Thus, aggressive bidders waive the chance of waiting for other auction participants to place their bids. As each bid is costly, this strategy comes at the risk of placing more than the required number of bids to win an auction. For example, consider a pay-per-bid auction with three remaining bidders. The first bidder is willing to place a maximum of 10 additional bids, while the second and the third bidders are willing to place 3 additional bids each (all bidders are equally likely to place a bid). If all three bidders were to wait for the last second of an auction to place their bids, the first bidder would win the auction by placing 4 additional bids. However, by adopting an aggressive strategy, the first bidder needs to place 7 bids to win the auction.

Dataset

The data for our study come from a large German website offering pay-per-bid auctions. Our dataset contains customer level bidding and transaction data for all auctions conducted between August 28, 2009 and May 9, 2010. For each auction, we know the auctioned product, a suggested retail price for this product, the bid increment, the time increment as well as start and end times. On the participant level, we have information about the actual bidding behavior, the exact point in time when a participant placed a bid, the date of registration, the complete history of auction participations, as well as some demographics like age and gender. Overall, we have data for 482,253 auction participations involving 87,007 distinct participants. These participants placed 6,448,708 bids in 6,987 auctions for 408 different products. Bid

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[3] Apparently, the normal strategy can consist of a subset of different strategies. For example, there may be some auction participants who place their bids always in the very last second of an auction (the cautious strategy from the introduction). This strategy is typically called sniping (Roth and Ockenfels 2002) and has been documented in several theoretical and empirical studies (e.g., Bapna 2003; Ely and Hossain 2009). However, due to space restrictions, we have to defer the breakdown of the normal strategy into a subset of different strategies to future research and in this paper, focus on the distinctions between normal and the aggressive strategies.

increments are 0.01€ for 74%, 0.02€ for 15%, 0.05€ for 9% and 0.10€ for 2% of the auctions. The bidding fee is constant at 0.50€ for each auction while the time increment varies between 10 and 20 seconds.

Main Variables

We measure the aggressively and normally placed bids, respectively, with the variables *Ratio Aggressive*, and *Ratio Normal*. The variables are calculated as follows: For each manually placed bid we determine whether the respective auction participant placed their bid aggressively or normally. We identify a bid as aggressive if it is placed within 3 seconds after the previous bid. All bids that are placed more than 3 seconds after the foregone bid are characterized as normally placed. To account for potential product specific effects, we multiply the respective aggregated number of aggressively and normally placed bids by the fixed bidding fee and divide the results by the suggested retail price of the auctioned product.

As control variables, we include the variable *Ratio Agent* to account for the number of bids placed using an automated bidding agent. Analogous to the variables *Ratio Aggressive* and *Ratio Normal* this variable is calculated as the product of the number of bids placed using an automated bidding agent and the fixed bidding fee, divided by the suggested retail price of the auctioned product. To account for potential time-varying heterogeneity across auction participants, we include the variables *Number of Participations* and *Number of Wins* as historical experience measures in our model. *Number of Participations* is defined as the number of participations by a specific participant in different auctions since the day of registration. *Number of Wins* is defined as the aggregated number of wins of this participant. Such experience measures are widely used to control for customer heterogeneity in both the marketing literature and industry practices (Anderson and Simester 2004; De et al. 2010). Furthermore, there may be effects on the winning probability arising from the auction's end time. Especially in pay-per-bid auctions, it is crucial for bidders to closely track the auction to the very end. There may also be less competition in auctions which are set to end during nighttime hours. Accordingly, we divide the day into four 6 hour intervals, starting at midnight, and include three dummy variables (*Midnight – 6 a.m. Dummy*, *6 a.m. – Noon Dummy*, *Noon – 6 p.m. Dummy*) to control for the end time of the auction.

Empirical Analysis

Basic Model

We use a conditional fixed effects logistic regression model to examine the impact of aggressive bidding on the likelihood of winning an auction.[4] The dependent variable for this analysis is a binary variable equaling one, if an auction participant wins an auction. In our model specification, the individual specific fixed effects allow us to control for any individual, specific, time constant unobserved heterogeneity (Hsiao 2003). We do not present the results of a random effects model as we expect the individual specific effects to be correlated with our explanatory variables. For example, a very assertive person may bid more aggressively while participating in a pay-per-bid auction. This would imply a high correlation between the individual specific effect and the variable Ratio Aggressive. For random effects models, such correlation is not allowed (Wooldridge 2010). Confirming our expectation, the result of a Hausman test (1978) shows that the individual specific effects are correlated with the explanatory variables.[5]

The variables of interest for this analysis are *Ratio Aggressive*, and *Ratio Normal*. As additionally placed bids should increase the probability of winning an auction irrespective of the bidding strategy used, we expect a positive coefficient for both of these variables. If the coefficient for *Ratio Aggressive* turns out to be significantly larger than the coefficient for *Ratio Normal*, this would indicate a positive effect of an aggressive bidding strategy on the likelihood of winning an auction. In this case, bidders could use an

[4] All of our results are robust to random effects logit, fixed effects probit, and random and fixed effects linear probability models as well.

[5] The value of the Hausman test statistic is negative for the logit models (-8,157). Following the suggestion of Schreiber (2008), we use the absolute value of this statistic to decide about the appropriateness of the random effects model. For the linear probability model the test statistic is positive (1,318) and highly significant providing further evidence for the correlation between the individual specific effects and the explanatory variables.

aggressive bidding strategy effectively to signal a high valuation and, thus, increase their chances of winning an auction. We further add the control variables introduced above. Therefore, we consider the following model in latent variable form (Wooldridge 2010):

$$\begin{aligned} Y^{*}_{ij} &= \alpha + \beta_1 X_{1ij} + \beta_2 X_{2ij} + \boldsymbol{\beta} D_i + \boldsymbol{\varsigma} Z_{ij} + \varepsilon_{ij} \\ Y_{ij} &= 1\,[Y^{*}_{ij} > 0], \end{aligned} \tag{1}$$

Y_{ij} is a dummy variable equaling one if a participant i wins an auction j; X_{1ij} denotes the variable *Ratio Aggressive*; X_{2ij} denotes the variable *Ratio Normal*; D_i is a set of dummy variables indicating individual fixed effects; Z_{ij} is a vector of control variables; and ε_{ij} is the random error term. This model will consistently estimate the effects of the different bidding strategies on the winning probability if $Cov(X_{kij}, \varepsilon_{ij}) = 0$.

Note that our model specification controls for all the time-invariant factors, including any inherent differences between participants. More importantly, the individual fixed effects, along with the time-variant participant specific variables, Number of Participations and Number of Wins, collectively address concerns regarding the self-selection of auction participants who make use of aggressive bidding strategies. Thus, this model allows us to address endogeneity concerns on the individual level in a meaningful and robust manner (Allison 2005).

Sample

As the conditional fixed effects model requires variation in the independent variable (Wooldridge 2010), we restrict our sample to individuals who participated in at least two auctions and won at least once but not in each of their participations. This leaves us with a sample of 2,601 distinct individuals who totaled 72,752 participations in different auctions, and an average of 28 participations per individual. Within these participations, auction participants placed in total 226,852 aggressive and 417,952 normal bids. The individuals in our sample won a total of 6,972 auctions. To summarize, our sample is an unbalanced panel data consisting of 2,601 individuals and 72,752 observations. Table 1 lists summary statistics for this sample.

Table 1: Summary Statistics

	Mean	Std. Dev.	25th Pctl.	50th Pctl.	75th Pctl.	Max
Winner	0.0958	0.2943	0	0	0	1
Ratio Aggressive	0.0137	0.0505	0	0	0.0075	2.34
Ratio Normal	0.0248	0.0710	0	0.0038	0.0185	3.36
Ratio Bidding Agent	0.0754	0.1901	0	0	0.0393	2.89
Number of Participations	33.36	54.15	3	14	38	462
Number of Wins	2.83	5.53	0	1	3	50
Midnight – 6 a.m. Dummy	0.1541	0.3612	0	0	0	1
6 a.m. – Noon Dummy	0.1238	0.3293	0	0	0	1
Noon – 6 p.m. Dummy	0.3161	0.4650	0	0	1	1

Preliminary Results

The first column of Table 2 presents the estimates of the conditional fixed effects model. The coefficients on *Ratio Aggressive*, *Ratio Normal*, and *Ratio Agent* are all positive and significant. In particular, we have estimated coefficients of 0.4642 (s.e.=0.2661) for *Ratio Aggressive*, 3.5150 (s.e.=0.1921) for *Ratio*

Normal, and 1.3548 (s.e.= 0.0583) for *Ratio Agent*. As we estimate a logistic regression model, the coefficients cannot be interpreted as the change in the mean of Y_{ij} for a one unit increase in the respective predictor variable, with all other predictors remaining constant. Rather, they can be interpreted as the natural logarithm of a multiplying factor by which the predicted odds of $Y_{ij} = 1$ change, given a one unit increase in the predictor variable, holding all other predictor variables constant.[6]

Table 2. Preliminary Results

Variable	Main Model	Controlling for Product Specific Effects
Ratio Aggressive	0.4642* (0.2661)	0.5882** (0.2676)
Ratio Normal	3.5150*** (0.1921)	2.6336*** (0.1989)
Ratio Bidding Agent	1.3548*** (0.0584)	1.3677*** (0.0612)
Number of Participations	0.0101*** (0.0008)	0.0107*** (0.0009)
Number of Wins	-0.0854*** (0.0063)	-0.0844*** (0.0066)
Midnight – 6 a.m. Dummy	-0.6369*** (0.0491)	-0.4828*** (0.0559)
6 a.m. – Noon Dummy	0.3823*** (0.0416)	0.3311*** (0.0495)
Noon – 6 p.m. Dummy	0.1854*** (0.0320)	0.1533*** (0.0379)
Individual Fixed Effects	✓	✓
Product Fixed Effects		✓
Log likelihood	-16,685.19	-15,859.09
Number of observations	72,752	72,752
Number of participants	2,601	2,601

Note: Standard errors are in parentheses.
* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

Given this interpretation and congruent with our expectations, all coefficients imply a positive effect of an additionally placed bid on the probability of winning an auction. In particular, a one percentage point increase in our bidding variables increases the odds of winning by 0.5% for aggressively placed bids, 3.5% for normally placed bids, and 1.4% for bids placed using an automated bidding agent. As can be seen from these estimates, the effect of aggressively placed bids on the likelihood of winning an auction is substantially lower than for bids placed following a normal bidding strategy, as well as for bids placed using an automated bidding agent. This difference is highly significant for *Ratio Normal* ($\chi^2 = 55.72$, $p < .001$) as well as for *Ratio Agent* ($\chi^2 = 10.66$, $p < .01$). Thus, compared to the normal bidding strategy, our estimates suggest that aggressive bidding is not beneficial in further increasing the chances of winning

[6] The odds are defined as $\frac{P(Y_{ij}=1)}{1-P(Y_{ij}=1)}$.

an auction. In contrast, these first findings indicate that following an aggressive bidding strategy has a significant *negative* effect on the likelihood of winning a pay-per-bid auction. Comparing the coefficient for the normal bidding strategy with the coefficient of the aggressive bidding strategy shows that a bidder could achieve the same increase in the winning probability with either seven aggressively placed bids or with just one normally placed bid. We further investigate this result in the next subsection.

Considering Product Specific Effects

One may argue that the estimated coefficients are influenced by potential product specific effects. For example, in a recent study of pay-per-bid auctions, Platt et al. (2012) find deviating bidding behavior for products from the category videogames in their dataset. We address this issue by adding 407 product specific fixed effects to our model. The second column in Table 2 shows the estimates for this robustness check. Still, the coefficients of interest remain positive and significant and the coefficient on *Ratio Aggressive* (0.5882, s.e.=0.2676) is significantly smaller ($\chi^2 = 24.72$, $p < .001$) than the coefficients on *Ratio Normal* (2.6336, s.e.=0.1989). These results indicate that the coefficients in column (1) of Table 2 at least partly reflect product specific effects for our main variables. Nevertheless, our main result remains qualitatively unchanged for this robustness check. Still, the aggressive bidding strategy performs significantly worse than the normal bidding strategy. Thus, we have confirmation for our claim that the aggressiveness bidding strategy has a negative effect on the chances of winning an auction

Conclusion and Ongoing Research

The existence of aggressive bidding strategies such as jump bidding has been proven theoretically and empirically. In general, signaling (e.g., Avery 1998; Daniel and Hirshleifer 1998) and impatience (e.g., Isaac et al. 2007) have been named as potential explanations for jump bidding. It is surprising, then, that there has not been any empirical research to date on how aggressive bidding caused by the attempt to signal a high valuation affects one's likelihood of winning an auction. This research-in-progress paper attempts to fill this void in the literature. Our analysis shows the seemingly counterintuitive finding that, controlling for the total investment of an auction participant, aggressive bidding has a *negative* effect on a participant's winning probability. Supporting the results of Bapna et al. (2003), our study suggests that bidding aggressively is not an effective tool for increasing the chances of winning an auction. Further research, particularly experimental studies that randomly manipulate participants' bidding strategies, would be able to present additional evidence for this effect in other auction formats.

The results presented in this paper have important implications for bidders in pay-per-bid as well as in ascending price auctions. Our findings suggest that bidders in pay-per-bid auctions perform substantially worse if they use aggressive bidding as a strategic tool to increase their chances of winning an auction. Given the substantial amount of aggressively spent bids, aggressive bidders could ceteris paribus substantially increase their chances of winning an auction by utilizing a normal bidding strategy. Transferring this to a typical ascending price auction, our results suggest that, apart from speeding up the auction and, thereby, incurring fewer costs associated with the bidding process, there is no additional – and possibly a negative – value in adopting an aggressive bidding strategy.

We plan to extend this research-in-progress paper in three major ways. First, we plan to investigate why the aggressively placed bids have such a large negative effect on one's likelihood of winning an auction. This calls for a more in-depth analysis of the strategic bidding behavior in pay-per-bid auctions. Second, we want to investigate the effects of aggressive bidding on the overall investments on an auction level. With this analysis, we hope to provide an answer to the question of whether aggressive bidding increases or decreases the total auction revenue. Preliminary results of this analysis show that aggressive bidding has a positive effect on the auctioneer revenue. In addition, our preliminary auction level results indicate that a higher proportion of aggressively placed bids are positively correlated with the number of participants in an auction. This finding provides a first indication that our results can be explained by the inability of an aggressive bidder to deter competitors. Third, there may be lessons for participants in pay-per-bid auctions. It would be interesting to analyze the different bidding strategies displayed on our auction website from a learning perspective.

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