To Bid or Not to Bid Aggressively?

An Empirical Study

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Abstract

We analyze aggressive bidding, used as a strategy to intimidate auction competitors, with regards to its impact on the likelihood of winning an online auction. To answer our research question, we use a dataset containing actual market transaction records for approximately 7,000 online pay-per-bid auctions. Our research design allows us to isolate aggressive bids that are used in an attempt to deter other auction participants by signaling a high valuation. Thus, we can analyze the effects of this strategy on the probability of winning an auction. We find a significant negative effect of aggressive bidding on one's likelihood of winning an auction. Our results suggest that aggressive bidding is not successful in deterring auction competitors. When comparing the effectiveness of different strategies, we find sniping to be up to seven times more effective than aggressive bidding.

Keywords: Economics of IS, Internet Markets, Auctions, Bidding Strategies, Aggressive Bidding, Sniping, Information Revelation.

1. Introduction

"… 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. [5]

Online auctions have become a mainstream economic phenomenon. For example, in 2011, the total value of goods sold on eBay – one of the biggest online auction websites worldwide – was approximately $70 billion.[1] It is hardly surprising, then, that for over a decade online auctions have featured prominently as a research topic in the IS literature [e.g., 8, 11] as well as in the economics literature [e.g., 26]. One central theme in this literature concerns the analysis of different types of bidding strategies in these auctions [e.g., 10, 7, 24].

Important components of these bidding strategies are bidders' decisions about when to reveal information about their own valuation of the auctioned good. In general, bidders may decide not to reveal any information for as long as possible whereas others, like the bidder in Kemelman's example, intentionally reveal information about the own valuation early on in the bidding process. Bidders who follow the first strategy, customarily referred to as sniping [e.g., 29], wait for the last moment of an auction to submit a bid. In contrast, bidders who follow the second

[1] Data from http://www.ebayinc.com/who. Last visited on February 25, 2013.

strategy, which we call aggressive bidding, intentionally submit a (high) bid early on in the bidding process.

While there is theoretical [27], experimental [4], and field experimental [17] evidence that sniping is an optimal response to naïve bidding[2], the theoretical literature on aggressive bidding suggests at least two competing theoretical explanations for this bidding strategy: signaling and impatience. More importantly, the differing theoretical explanations also offer different predictions about the effects of aggressive bidding. According to the signaling explanation, by deliberately revealing information about their valuation early on, bidders can signal a presumable high valuation. Thereby, they can intimidate their competitors and, thus, increase their chance of winning an auction [e.g., 5]. In contrast, the impatience explanation suggests that the early revelation of information is attributable to the attempt to speed up an auction [21] and has no effect on a bidder's winning probability. The empirical evidence on this issue is inconclusive. While some empirical studies conclude that the main driver for aggressive bidding is bidder impatience [e.g., 22], there is anecdotal as well as some evidence from a field experiment that bidders who submit these bids can deter at least some of their competitors [e.g., 17].

To this date, we do not know of any empirical study which rigorously evaluates the effect of an aggressive bidding strategy in an attempt to intimidate one's opponents in an (online) auction. For example, the understanding of how the aggressive bidding strategy compares with other bidding strategies is still lacking. Nevertheless, the quote by Harry Kemelman may be taken as anecdotal evidence that such an aggressive bidding strategy promises a positive return for the respective bidder. However, Kemelman cannot be sure that the bidder won *because* of his aggressive bidding strategy. It is also possible that he is simply the bidder with the highest

[2] Roth and Ockenfels [29] refer to this strategy as incremental bidding.

valuation of the auctioned product and, thus, could also have won with a lower bid using a sniping strategy.

The gap in the literature may be explained by the difficulty involved in isolating those bidding situations where bidders submit aggressive bids to signal a high valuation in an attempt to intimidate their opponents. Online pay-per-bid auctions (e.g., beezid.com, bidcactus.com)[3] – which constitute a variant of ascending price auctions – allow us to address this important challenge. In this specific auction format we can rule out impatience as a reason for aggressive bidding and, thus, are able to answer our research question: *What effect does an aggressive bidding strategy in an attempt to intimidate one's opponents have on a bidder's chance of winning an auction?*

Our explicit aim is to consider the inherent usefulness of an aggressive bidding strategy to intimidate one's opponents in an online auction. By analyzing aggressive bidding in a pay-per-bid auction context, we are the first to empirically evaluate the signaling value of aggressive bidding. More generally, we provide a first empirical answer to the question of whether revealing information early on in an online auction context does pay off for the bidder. Recognizing the competing theoretical explanations for the existence of aggressive bidding and the different predictions of these explanations as well as the lack of empirical evidence on the signaling value of aggressively placed bids, answering our research question offers new insights relevant to information systems and behavioral economics research that can 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

[3] In September 2011, 5.5 million unique visitors visited pay-per-bid auction websites. This corresponds to 7.3% of unique visitors on the biggest auction website worldwide, ebay.com [28].

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 deter their competitors and, thus, increase their chances of winning an auction, we find that aggressive bidding performs no better than a more cautious bidding strategy, and significantly worse than a sniping strategy.

2. Related Literature

There is a substantial stream of research on bidding strategies where bidders strategically reveal information about their own valuation. In general, bidders may follow a sniping strategy and decide not to reveal any information for as long as possible, whereas others follow an aggressive strategy and intentionally reveal information about the own valuation early on in the bidding process.

In their seminal work on sniping, Roth and Ockenfels [29] suggest that bidders do not reveal any information early on in the bidding process as an optimal response to naïve bidding. This suggestion was supported in an experimental study conducted by Ariely et al. [4] as well as in a field experiment conducted by Ely and Hossain [17] on eBay.com. Thus, in the presence of bidders who follow a naïve bidding strategy, sniping can actually decrease the final price of an auction and, ceteris paribus, increase the snipers chance of winning the auction.

For the early revelation of information in auctions, theoretical studies have identified signaling and impatience as major explanations. In the models of Avery [5] and Daniel and Hirshleifer [14], aggressive bidders use their bids to signal their value to other bidder in an attempt to discourage potential competitors. In both models aggressive bidders are able to deter competitors – even those with a higher valuation than the aggressive bidder – and thereby increase their chance of winning an auction. For example, Avery [5] writes that after an aggressive bid *"... the losing bidder may drop out in equilibrium even though his value is (certain to be) strictly larger than the current price."*

An alternative explanation for aggressive bidding in ascending price 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 aggressive bids to increase the speed of the auction [6]. Isaac et al. [21] construct a theoretical model in which aggressive bids are placed due to impatience. In their model, aggressive bids have no effect on a bidder's probability of winning an auction, and no or even a positive effect on seller's revenue.

The empirical and experimental evidence on the competing explanations for aggressive bidding is mixed. In an empirical study of Yankee auctions, Easley and Tenorio [16] show that aggressive bidding (in the form of jump bidding) has a negative effect on the total number of bids placed in an auction. The authors interpret this finding as indirect evidence for the signaling value of aggressive bids. In addition, in a field experiment conducted on eBay.com, Ely and Hossain [17] find that an early bid in an auction reduces the total number of auction participants. In a recent study, Grether et al. [18] examine why bidders engage in aggressive bidding in used car markets. Their study on two different markets arrives at contradictory results. In one market, they find support for the Signaling explanation, while in the other market they find support for the impatience explanation of aggressive bidding. Isaac and Schnier [23] as well as Isaac et al. [22] provide empirical and experimental evidence suggesting that aggressive bidding is driven by the impatience of auction participants and, thus, has no effect on the end price of an auction, or, indeed, may even increase it. These results are reinforced by Kwasnica and Katok [25] who find that greater bidder impatience results in more aggressive bids. Carpenter et al. [12] experimentally analyze the effect of aggressive bids on auction revenue in the context of silent auctions. Within their experimental design, the authors successfully modify the incentives to use aggressive bids linked to impatience. Consistent with Isaac and Schnier [23] and Isaac et al. [22], they find that aggressive bids due to impatience increases auction revenue. Bapna et al. [9] analyze aggressive bidding using a simulation framework for Yankee-type auctions. Consistent with the impatience hypothesis, they find that aggressive bidding has no effect on the likelihood of winning an auction. Aggressive bidding may even result in a negative total payoff for the auction participant due to a slightly higher average winning bid.

Please note that none of the previous empirical studies could rule out one of the competing explanations for aggressive bidding and, thereby, isolate the effect of the respective other explanation. More importantly, despite ample evidence of using aggressive bidding for signaling and hoping to benefit from such signals, there still exists no clear evidence on the effectiveness of such signaling. Thus, clearly, the opportunity is potent for empirical studies where the signaling effect for aggressive bidding is thoroughly evaluated while the impatience explanation is ruled out.

Having been given access to very rich dataset from a pay-per-bid auction website, we are in the fortunate position of being the first to be able to isolate the effects of aggressive bidding in an attempt to signal a high valuation. Thus, we contribute to the literature on the strategic revelation of information in auctions by providing a first rigorous evaluation of aggressive bidding, used as a strategy to signal a high valuation and thereby to intimidate auction competitors, with regards to its impact on the likelihood of winning an online auction.

3. Research Setup

3.1. Description of the Auction Mechanism

Each pay-per-bid auction starts at a price of zero and with a fixed end time displayed on a countdown clock. Auction participants are restricted to bidding in fixed bid increments (e.g., 1 cent) above the current bid and must pay a non-refundable fixed fee (e.g., 50 cents) for each bid placed. At the beginning of an auction, each bid extends the auction duration by a given time increment (e.g., 10 seconds). For example, in an auction where the current bid is $2.32 with 32 seconds on the auction countdown, an additional bid increases the current bid by 1 cent to $2.33 and extends the auction countdown by 10 seconds.[4] The participant who places the bid has to pay the fixed bidding fee of 50 cents. During the bidding process, auction participants can at any time delegate their bidding to an automated bidding agent. This agent automatically places a predetermined number of bids on behalf of the agent owner. 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 incurred) to obtain the item. If the participant in our example is the last bidder, she would win the auctioned product for $2.33.

3.2. Study Design

When the participants on our focal website are at the point of taking part in an auction they have to make several decisions (not necessarily in this order): They need to decide how many

[4] At the beginning of an auction, the time increments add up linearly for each placed bid. Applied to our example, if two bids are placed simultaneously the countdown extends by another 10 seconds to 52 seconds. When the auction countdown falls below a specific threshold for the first time, this threshold is set as a maximum for the remaining duration of an auction. If the threshold is 15 seconds, the auction countdown cannot exceed 15 seconds after it falls below this value for the first time. Thus, the time increment for each bid is adjusted to the minimum of the original time increment and to the difference between the respective threshold and the actual value of the auction countdown.

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 which bidding strategy to adopt. As with other auction formats, bidders in a pay-per-bid auction can choose between different strategies for the timing of publicly revealing information about their own valuation. In particular, manual bidders can use this timing to implement three different bidding strategies: An aggressive strategy, a sniping strategy, and a normal strategy.

The aggressive strategy consists of instantly overbidding other auction participants as a way of signaling the own valuation in an attempt to intimidate opponents. By bidding immediately after another auction participant, bidders publicly reveal the information that they are still participating in the bidding process. By making this information publicly available, 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 number of bids required to win, if the respective bidder does not reveal this information early. For example, consider a pay-per-bid auction with three remaining bidders. The first is willing to place a maximum of 10 additional bids, while the second and the third are willing to place 3 additional bids each. 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.

In line with existing literature, we define the sniping strategy as a strategy where bidders wait until the very last seconds of an auction to place a bid. By following this strategy, bidders do not reveal more information than strictly necessary in the early stages of the bidding process.

Finally, we define a third strategy which covers all bids that are placed neither immediately after other auction participants nor in the very last seconds of an auction. We call this strategy the *normal strategy*.

One big advantage of analyzing pay-per-bid auctions is that it allows us to rule out impatience as a cause for aggressive bidding. This allows us to isolate the effect of an aggressive bidding strategy adopted with the intention of intimidating opponents, and thereby to measure the strategy's effect on the likelihood of winning an auction. This unique advantage can be attributed to two key features: First, adopting an aggressive bidding strategy in a pay-per-bid auction has virtually no effect on the total duration of an auction. Hence, auction participants cannot adopt an aggressive bidding strategy to speed up an auction. In addition, impatient bidders always have the opportunity to delegate their bidding to an automated bidding agent. Consequently, in our setting, aggressive bidding cannot be caused by the impatience of auction participants, but rather, must be attributable to the attempt to signal a high valuation for the auctioned product and, thus, to deter potential competitors.

3.2. Dataset

The dataset for our study is provided by a large German website[5] offering pay-per-bid auctions. Between August 28, 2009 and May 9, 2010, 6,995 pay-per-bid auctions had been conducted on this website. 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 and its suggested retail price, and have data on the bid increment, the time increment, as well as start and end times. At the participant level, we have information about their actual bidding behavior, the exact point in time when a participant placed a bid, the date of

[5] The website has requested to remain anonymous.

registration, the history of auction participations, as well as some demographical data, such as age and gender. Overall, we have data for 482,253 auction participations by 87,007 distinct participants. These participants placed 6,448,708 bids in 6,987 auctions for 408 different products. Bid 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.

3.3. Operationalization of Bidding Strategies

Each bidder has a specific timespan during which to submit a bid. Depending on the state of the auction, this timespan varies between 10 seconds, at the minimum, and several hours. We characterize a bid as aggressively placed if it is submitted within 3 seconds after a previous bid. Bids that are placed within the last 3 seconds of an auction are characterized as sniping bids. Bids that are not submitted within 3 seconds after a preceding bid and less than 3 seconds before the end of an auction are characterized as normally placed. Figure 1 illustrates our operationalization approach. Please note that all of our results are robust to other specifications of the cutoff value where we characterize a bid as aggressively placed or as a sniping bid.

INSERT FIGURE 1 ABOUT HERE

3.4. Bidder Strategies

To gain more insight into the bidding strategies in our dataset, we first investigate whether manual bidders deliberately select a specific bidding strategy, and follow it consistently, or if they place their bids at random points in time during an auction.[6] For this analysis, we restrict our sample to manual bidders who placed 10 or more bids in a specific auction. These 49,141

[6] Bapna et al. [10] and Adomavicius et al. [1] find stable bidding strategies for bidders in Yankee-type auctions as well as in combinatorial auctions.

bidders placed a total of 1,222,909 bids. Of these, 39.41% (481,915 bids) were placed following an aggressive bidding strategy, 33.69% (411,865 bids) following a sniping strategy, and 26.91% (329,129 bids) following a normal bidding strategy. This distribution of bids provides a first indication that manual bidders do not place their bids at random points in time during an auction. Given the relatively short timespan available for placing aggressive or sniping bids, we would expect a substantially larger fraction of normal and smaller fractions for aggressive and sniping bids if participants had placed their bids at random points in time. In contrast, bidders seem to prefer placing their bids either directly after another bidder or within the last seconds of an auction.

We further investigate the bidding behavior of auction participants by computing the number of bidders who submitted a specific fraction of their bids with one of the bidding strategies. Table 1 shows the number of bidders who placed up to 25%, 25%-50%, 50%-75%, or more than 75% of their bids following an aggressive bidding strategy (column (1)), a sniping strategy (column (2)), or a normal strategy (column (3)). Each bidder who submitted 10 or more bids shows up three times in Table 1. For example, a bidder who submitted a total of 4 bids with the aggressive strategy and 6 bids with the sniping strategy would show up in column (1) in the 25% - 50% row, in column (2) in the 50% - 75% row, and in column (3) in the 0% - 25% row. Thus, the first entry in the first row of this table shows that 11,857 manual bidders placed between 0% and 25% of their bids following an aggressive bidding strategy.

INSERT TABLE 1 ABOUT HERE

If we assume that bidders randomly pick for each submitted bid one of the three bidding strategies with probability 39.41% for the aggressive bidding strategy, 33.69% for the sniping strategy, and 26.91% for the normal bidding strategy,[7] we can also compute the expected number of bidders who submit a specific fraction of their bids with a specific bidding strategy. To get this number, we first compute the probability p_k that a bidder who places exactly *n* bids submits *k* bids with one of the three bidding strategies. This probability p_k can be written as:

$$p_k = \binom{n}{k} p^k (1-p)^{n-k},$$

where *p* is the respective probability for each bidding strategy (39.41% for the aggressive bidding strategy, 33.69% for the sniping strategy, and 26.91% for the normal bidding strategy). For each bidding strategy and for each *n*, we add up the probabilities p_k to compute the probabilities $p_{y,n}$ where $y \in \{0.25, 0.50, 0.75, 1.00\}$ and $p_{y,n}$ is the probability that a bidder who submits exactly *n* bids places less than 25%, 25%-50%, 50%-75%, or more than 75% with a specific bidding strategy. In particular, $p_{y,n}$ can be written as:

$$p_{y,n} = \sum_{i=0}^{k} p_k \text{ where } k/n \leq y.$$

Then, we multiply $p_{y,n}$ by the fraction of observations who submit exactly *n* bids to weight them according to their occurrence in our sample. Adding up these weighted probabilities for all *n* results in the probabilities p_y that bidders in our sample place less than 25% for $p_{0.25}$, 25%-50% for $p_{0.50}$, 50%-75% for $p_{0.75}$, or more than 75% for $p_{1.00}$ with one of the three bidding strategies. Finally, to compute the expected number of bidders who submit a specific fraction of their bids with one of the three bidding strategies, we multiply probability p_y by the total number of bidders who submitted 10 or more bids. The results of these calculations are presented in Columns (4), (5), and (6) of Table 1. This table shows the expected number of bidders who place up to 25%, 25%-50%, 50%-75%, or more than 75% of their bids with a specific bidding strategy.

[7] These probabilities are equal to the fractions of bids which are submitted with a respective bidding strategy. Please note that our results remain qualitatively unchanged if we assume that bidders choose each of the bidding strategies with probability 1/3.

By multiplying this expected number by $(1 - p_y)$, we can also calculate the variance of the expected number of bidders.

Comparing the expected numbers of bidders with the actually observed numbers provides strong evidence that a substantial fraction of bidders does not randomly choose their bidding strategy. For example, we have more than 2,000 bidders who place more than 75% of their bids following an aggressive strategy. If bidders had randomly chosen their bidding strategy for each bid, we would expect only 153 (s.e.=12.35) of these bidders. The difference between these two values is highly significant. The same holds for both the normal and the sniping strategy. Based on these calculations, we can falsify the assumption that bidders randomly choose a bidding strategy for each bid. On the contrary, we conclude that a substantial fraction of bidders deliberately chooses to follow an aggressive or a sniping strategy. In what follows, we investigate the potential effects of these decisions on a bidder's individual probability of winning an auction.

4. Individual Level Analysis

4.1. Main Variables

At the individual level, we measure aggressively and normally placed bids as well as sniping bids with the variables *Ratio Aggressive, Ratio Normal* and *Ratio Sniping*. These variables are calculated as follows: For each individual in each auction, we compute the total number of aggressively placed, sniping and normal bids. We multiply the respective numbers by the fixed bidding fee and divide the results by the suggested retail price of the auctioned product. This variable definition controls for potential effects of the price of the auctioned product on a bidder's winning probability. For example, it may take substantially more bids to win an iPhone compared to a game for a Nintendo Wii.

Furthermore, we include the variable *Ratio Agent* to control for the number of bids placed using an automated bidding agent. Analogous to the variables *Ratio Aggressive, Ratio Normal* and *Ratio Sniping* this variable is calculated as the product of the number of bids placed by an individual in an auction using an automated bidding agent and the fixed bidding fee, divided by the suggested retail price of the auctioned product.

A substantial number of auctions in our dataset contain a so-called buy-it-now option. This option allows participants to directly buy the auctioned product for the suggested retail price net of their already spent bidding fees. We add the dummy variable *Buy-it-now Dummy* to control for any potential effect of this option on the likelihood of winning an auction.

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 from 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 consumer heterogeneity in both the marketing literature and industry practices [3, 15]. In addition, we divide the day into four six hour intervals, starting at midnight, and include three dummy variables to control for any potential effects of the end time of an auction.

4.2. Basic Model

The dependent variable for our empirical analysis is a binary variable equaling one, if an auction participant wins an auction. The panel structure of our dataset allows us to address any concerns regarding the individual time constant heterogeneity across auction participants [20]. Accordingly, we use a logistic panel regression model to examine the impact of aggressive bidding on the likelihood of winning an auction. For our dataset, we can expect the individual specific time constant unobserved heterogeneity to be correlated with the explanatory variables. For example, a very assertive person may bid more aggressively while participating in a pay-per-bid auction, which would imply a high correlation between the individual specific effect and the variable *Ratio Aggressive*. Confirming this expectation, the result of a Hausman test [19] shows the individual specific effects to be correlated with the explanatory variables.[8] Since such a correlation is only allowed in fixed effects models [31], we estimate a fixed effects logistic regression model to test for the effects of an aggressive bidding strategy on the likelihood to win an auction.

The variables of interest for this analysis are *Ratio Aggressive*, *Ratio Normal* and *Ratio Sniping*. If the coefficient for *Ratio Aggressive* were to turn out significantly higher than the coefficients for *Ratio Normal* and *Ratio Sniping*, this would indicate a positive impact of an aggressive bidding strategy on the likelihood of winning an auction and, thus, provide support for the theoretical predictions of Avery [5] and Daniel and Hirshleifer [14]. In this case, bidders could use an aggressive bidding strategy effectively to signal a (presumably) high valuation and, thus, discourage their potential competitors.

We further add the control variables introduced above. To answer our research question, we consider the following model in latent variable form [31]:

$$Y^*_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \boldsymbol{\beta} D_i + \boldsymbol{\varsigma} Z_{it} + \varepsilon_{it}$$

$$Y_{it} = 1\ [Y^*_{it} > 0],$$

Y_{it} is a dummy variable equaling one if a participant *i* wins an auction ending at time *t*; X_{1it} is the ratio of the value of the aggressively placed bids and the suggested retail price of the

[8] The value of the Hausman test statistic is negative for the logit models (-8,157). Following the suggestion of Schreiber [30], we use the absolute value of this statistic to decide on 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.

auctioned product; X_{2it} denotes the ratio of the value of normally placed bids and the suggested retail price of the auctioned product; X_{3it} is the ratio of the value of sniping bids and the suggested retail price of the auctioned product; D_i is a set of dummy variables indicating individual fixed effects; Z_{it} is a vector of control variables; and ε_{it} is the random error term.

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 at the individual level in a meaningful and robust manner [2].

4.3. Sample

As the conditional fixed effects model requires variation in the independent variable [31], 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. Thus, we have an average of 28 participations per individual. Within these participations, auction participants placed a total of 226,852 aggressive, 260,175 sniping, and 157,777 normal bids. The individuals in our sample won a total of 6,972 auctions. To summarize, our sample is an unbalanced panel consisting of 2,601 individuals and 72,752 observations. Column (1) and (2) of Table 2 show summary statistics for all of our variables for the individual level analysis separated for auction winners and for participants who failed to win their auction.[9]

INSERT TABLE 2 ABOUT HERE

[9] To save space, we excluded the summary statistics for the end time dummy variables.

4.4. Results

The first column in Table 3 presents the estimates of our basic model. The coefficients on *Ratio Aggressive*, *Ratio Normal*, *Ratio Sniping*, and *Ratio Agent* are all positive and significant. In particular, we have estimated coefficients of 0.619 (s.e.=0.278) for *Ratio Aggressive*, 3.757 (s.e.=0.233) for *Ratio Sniping*, 2.935 for *Ratio Normal* (s.e.=0.408), and 1.358 (s.e.= 0.058) 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.[10] Given this interpretation and according to our expectations, all coefficients imply a positive effect of additionally placed bids on the probability of winning an auction. In particular, a one percentage point increase in our bidding variables increases the odds of winning by 0.6% for aggressively placed bids, 3.0% for normally placed bids, 3.8% for sniping 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 or a sniping strategy as well as for bids placed using an automated bidding agent. This difference is highly significant.

INSERT TABLE 3 ABOUT HERE

Thus, our estimates suggest that bidders are not advised to use aggressive bidding strategies to signal a high valuation as a means to deterring potential competitors. Indeed, these findings indicate that, given the same number of placed bids, following an aggressive bidding strategy has

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

a significantly *negative* effect on the likelihood of winning a pay-per-bid auction. Comparing the coefficient for the best bidding strategy (the sniping strategy) with that of the aggressive bidding strategy shows that a bidder could achieve the same increase in the winning probability with either six aggressively placed bids or just one sniping bid. If we compare the aggressive bidding strategy with the normal strategy, we find that an aggressive bidder needs to place five additional bids to achieve the same increase in the winning probability than a bidder using a normal bidding strategy. We further investigate this result in the robustness checks section.

4.5. Robustness Checks

One potential concern is that the estimated coefficients partly reflect omitted product specific effects. There may be a higher degree of competition in auctions for particularly popular products like iPhones. Participants in more competitive auctions may extensively use aggressive bidding strategies to deter their competitors. However, in this case, the smaller coefficient for *Ratio Aggressive* cannot be attributed to the aggressive bidding strategy, but is caused by the higher degree of competition for specific products. For example, in a recent study of pay-per-bid auctions, Platt et al. [28] find deviating bidding behavior in auctions for products from particularly popular product categories.

To directly deal with this issue we add 407 product specific fixed effects to our model. Column (2) in Table 3 shows the estimates for this robustness check. The coefficients of interest are still positive and significant and the coefficient on *Ratio Aggressive* (0.862, s.e.=0.281) smaller than the coefficients on *Ratio Sniping* (3.040, s.e.=0.239) and *Ratio Normal* (1.461, s.e.=0.420). However, the absolute magnitude of the coefficients for *Ratio Normal* and *Ratio Sniping* substantially decreased, while the coefficients on *Ratio Aggressive* and *Ratio Agent* increased for this robustness check. In addition, the difference between the coefficients on *Ratio*

Normal and *Ratio Aggressive* is no longer significant. These results indicate that the coefficients for our main variables presented in column (1) of Table 3 partly reflect product specific effects. Nevertheless, our main result remains qualitatively unchanged for this robustness check. Still, the aggressive bidding strategy performs significantly worse than the best possible bidding strategy and (insignificantly) worse than the normal strategy. Thus, we can reaffirm our finding that aggressive bidding in an attempt to signal a high valuation does not *increase* a bidder's chances of winning an auction.

Another concern one might have is that the degree of competition does not only vary with different auctioned products, but also between individual auctions for the same product and even within one auction. In this case, following an aggressive bidding strategy may only reflect a higher degree of competition at some point in time during an auction. In this case, the comparably smaller coefficient on *Ratio Aggressive* cannot be attributed to the aggressive bidding strategy by itself, but must be attributed to the higher degree of competition in situations where auction participants follow such a strategy. To address this issue, we control for the degree of competition in an auction just before an auction participant enters an auction. We use two variables to measure this degree: *Bids Last 5 Minutes* and *Participants Last 5 Minutes. Bids Last 5 Minutes* is defined as the total number of placed bids in the last 5 minutes before an auction participant enters an auction whereas *Participants Last 5 Minutes* is defined as the total number of distinct bidders within this timespan.[11] Column (3) of Table 3 shows regression results if we include these additional variables. Confirming our expectations, the coefficients on both additional competition measures are negative. Thus, a higher degree of competition when entering an auction decreases participants' chances of winning this auction. However, only the

[11] Our results do not change if we extend this timespan to 10 minutes. The results of this further robustness check are available upon request by the authors.

coefficient on *Participants Last 5 Minutes* is significant. More importantly, both of these competition measures have only little effect on our coefficients of interest. In particular, reconfirming our main result, the coefficient on *Ratio Aggressive* is 0.917 (s.e.=0.280), whereas the coefficients on *Ratio Sniping* and *Ratio Normal* are 3.026 (s.e.=0.239) and 1.321 (s.e.=0.421), respectively.

Since our dataset spans a period of over 8 months, one may further argue that our results are influenced by some time trends on our focal website. To directly deal with this issue, we include 36 week dummies in our model. Column (4) of Table 3 shows the estimates for this extended model. Again, we see only marginal changes in the estimated coefficients and all of our results remain qualitatively unchanged.

Another potential concern is that our definition of aggressive bids erroneously identifies some sniping bids as aggressively placed. There may be some bidders who try to place their bids in the very last seconds of an auction. Depending on the latency caused by the Internet connection between the auction website and these bidders it could cause a delay between the submission and the arrival of a bid. Such a bid may arrive one second after a previous bid and, thus, is identified as aggressive even if the respective bidder intended to place a sniping bid. We address this issue by identifying each bid placed in the first second after a foregone as sniping bid. Column (5) of Table 3 shows that our results remain qualitatively unchanged for this robustness check.

A final intuitive explanation for our results is that aggressive bidding can only be a successful strategy in auctions where other bidders actively perceive the signal sent by the aggressive bidder. This may not be the case in auctions where the majority of auction participants place their bids using an automated bidding agent.[12] We examine this explanation for our result by restricting our sample to auctions where 100% of bidders submit their bids manually. This restriction as well as the necessary restriction for the fixed effects model leaves us with 530 observations for 133 distinct participants. The results in Column (6) of Table 3 qualitatively echo the results from the previous analyses. Still, we do not find any positive effect of bidding aggressively on the likelihood to win an auction. In contrast, the coefficient for *Ratio Aggressive* is negative and insignificant. Thus, even when all bidders have the opportunity to perceive the signal sent by the aggressive bidder, aggressive bidding does not increase a bidder's chances of winning an auction.

5. Auction Level Analysis

Another explanation for our results is that aggressive bidders can only deter some but not all of their competitors. In this case, aggressive bidding would be detrimental for the aggressive bidder but may help competing bidders by lowering the total degree of competition in an auction. We investigate this potential explanation of our results by analyzing the effects of aggressive bidding at the auction level. In particular, we study the effects of a higher proportion of aggressively placed bids on the total number of participants in a specific auction. In the presence of a deterrence effect of an aggressive bidding strategy, we would expect that, controlling for product specific effects, auctions with a higher proportion of aggressively placed bids would have a lower number of participants. This result would provide support for a positive signaling value of aggressively placed bids. However, based on the individual level results, this potential

[12] Nevertheless, we still observe a substantial fraction of bidders who deliberately follow an aggressive bidding strategy in these auctions.

positive signaling value is outweighed by the significantly higher costs of implementing an aggressive bidding strategy.

5.1. Sample

At the auction level, we have a total of 6,987 auctions for 408 different products. Thus, on average, we have 17 auctions for each product. Within these auctions, 482,253 auction participants placed a total of 6,448,861 bids. Around 16% of these bids were placed with an aggressive bidding strategy. Each auction averaged 69 participants.

5.2. Main Variables

The dependent variable for our auction level analysis is *Log Participants. Log Participants* is defined as the natural logarithm of the total number of participants in an auction. We measure the proportion of aggressively placed bids with the variable *Proportion Aggressive*. This variable is calculated as follows: For each auction, we divide the number of aggressively placed bids by the total number of bids placed in this auction. As for the individual level analysis, we identify a bid as aggressively placed if it is placed within 3 seconds after the preceding bid.

As for the individual level analysis we add the dummy variable *Buy-it-now Dummy* as well as three end time dummy variables to control for any potential effect of a buy-it-now option and the end time of an auction on the number of auction participants. We also include 36 week dummies to capture any changes in the popularity of our focal website. As a further control for this effect, we include the variable *Log Registered Users* into our analysis. This variable is defined as the natural logarithm of the total number of registered users prior to the commencement of a specific auction. Table 4 shows summary statistics for these variables.[13]

INSERT TABLE 4 ABOUT HERE

5.3. Basic Model

The panel structure of our dataset allows us to control for any time-constant, product specific heterogeneity. As we expect these product specific effects to be correlated with the explanatory variables, we use a fixed effects[14] regression model to investigate the relationship between the proportion of aggressively placed bids and the total number of participants in an auction. We further add the aforementioned control variables. Thus, our econometric model for the auction level analysis is:

$$Y_{it} = \beta_1 X_{1it} + \boldsymbol{\varsigma} X_{it} + \varepsilon_{it}$$

where Y_{it} denotes the time demeaned variables *Log Participants* for product *i* in an auction ending at time *t;* X_{it} is a vector of auction level covariates; The coefficient of interest is β_1 and measures the potential impact of aggressively placed bids (denoted by X_{1it}) on the number of participants in an auction. The error term ε_{it} captures all omitted influences, including any deviations from linearity.

[13] To save space, we excluded the summary statistics for the end time dummy variables as well as for the week dummies.

[14] Again, the results of two Hausman tests [19] confirm that the product specific effects are correlated with the explanatory variables. In particular, the test statistics are -2,646.84 for the models with *Log Participants* as dependent variable and 2,011.69 for the models with the dependent variable *Log Total Bids.*

5.4. Results

Table 5 reports the results of the fixed effects regressions of our econometric model for the dependent variable *Log Participants* (Column (1)). Throughout, all standard errors are robust against arbitrary heteroskedasticity and serial correlation.

INSERT TABLE 5 ABOUT HERE

Column (1) shows an estimated coefficient for the potential impact of aggressively placed bids on *Log Participants* of 1.745 (s.e.=0.109). This suggests that auctions with a higher proportion of aggressively placed bids have a significantly higher total number of auction participants. This coefficient estimate implies a potentially large correlation between aggressively placed bids and the number of participants in an auction. In particular, an increase of one percentage point in the proportion of aggressively placed bids is associated with an increase in the total number of auction participants by more than 1.5%.

This finding confirms our result from the individual level analysis that bidders cannot use an aggressive bidding strategy to deter potential competitors. In contrast, we find a significant positive correlation between aggressive bidding and the number participants in an auction.

6. Conclusion

The existence of bidding strategies where bidders intentionally reveal information about their private valuation has been widely documented from both, a theoretical and empirical perspective. In general, signaling [e.g., 5, 14] and impatience [e.g., 21] have been named as potential theoretical explanations for these strategies. It is surprising, then, that there has not been any empirical research to date on whether such bidding intended to intimidate one's opponents actually improves one's likelihood of winning an auction. In other words, the question whether there is any positive return associated with aggressive bidding is still unanswered. Our paper attempts to fill this void in the literature. Our analysis shows that, compared to the best possible bidding strategy, aggressive bidding has a substantial *negative* effect on a participant's winning probability. Thus, our study suggests that bidding aggressively is not an effective tool for discouraging competitors. Further research, particularly experimental studies that randomly manipulate participants' bidding strategies would be able to present further evidence for this effect in other auction formats.

The results presented in this paper have important implications for bidders in particular in pay-per-bid, and in general for bidders 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 discourage their competitors. Given the huge amount of aggressively placed bids, aggressive bidders could, ceteris paribus, substantially increase their chances of winning an auction by adopting another 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, adopting an aggressive bidding strategy brings no added – and possibly even a negative – benefit.

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Figure 1: Operationalization of Bidding Strategies

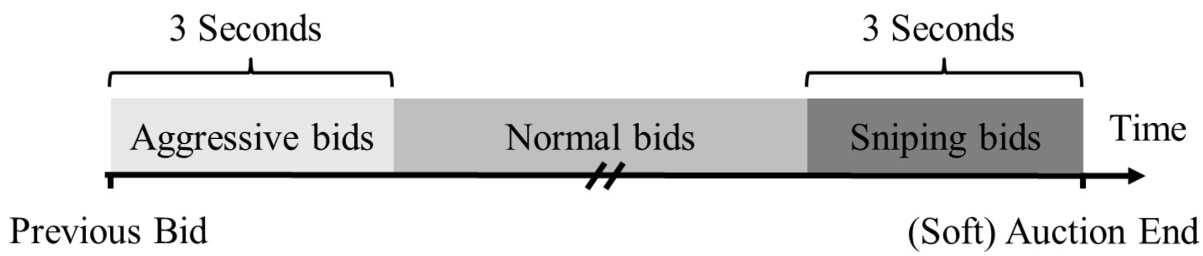

Table 1: Individual Bidders Bidding Strategies

	Aggressive Strategy	Sniping	Normal Strategy	Expected Aggressive	Expected Sniping	Expected Normal
0%-25%	11,857	21,556	23,599	5,731 (71.15)	11,313 (93.32)	22,514 (110.45)
25%-50%	22,748	14,282	16,013	36,505 (96.89)	34,859 (100.65)	25,776 (110.71)
50%-75%	12,390	10,357	7,737	6,752 (76.32)	2,925 (52.45)	844 (28.81)
75%-100%	2,146	2,946	1,792	153 (12.35)	44 (6.64)	7 (2.73)
∑	49,141	49,141	49,141			

Note: Standard errors for expected bidders are in parentheses.

Table 2: Summary Statistics

	(1) N = 65,780		(2) N = 6,972	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Ratio Aggressive	0.01260	0.04756	0.0238	0.0718
Ratio Sniping	0.01377	0.05022	0.0296	0.0799
Ratio Normal	0.00871	0.02997	0.0173	0.0476
Ratio Bidding Agent	0.06466	0.18213	0.1766	0.2296
Number of Participations	33.63	54.42	30.82	51.42
Number of Wins	2.73	5.38	3.88	6.70
Buy-it-Now Dummy	0.82905	0.37647	0.8239	0.3810
Bids Last 5 Minutes	36.01	46.21	27.08	38.04
Participants Last 5 Minutes	9.12	7.26	7.07	6.52

Table 3: Individual Level Results

Variable	(1)	(2)	(3)	(4)	(5)	(6)
Ratio Aggressive	0.619^{*}	0.862^{**}	0.917^{**}	0.951^{**}	0.948^{*}	-1.235
	(0.278)	(0.281)	(0.280)	(0.281)	(0.448)	(2.069)
Ratio Sniping	3.757^{**}	3.040^{**}	3.026^{**}	3.029^{**}	2.727^{**}	3.710
	(0.233)	(0.239)	(0.239)	(0.239)	(0.198)	(3.060)
Ratio Normal	2.935^{**}	1.461^{**}	1.321^{**}	1.255^{**}	1.090^{**}	6.416^{*}
	(0.408)	(0.420)	(0.421)	(0.423)	(0.387)	(2.974)
Ratio Bidding Agent	1.358^{**}	1.408^{**}	1.399^{**}	1.398^{**}	1.401^{**}	
	(0.058)	(0.062)	(0.062)	(0.062)	(0.062)	
Number of Participations	0.010^{**}	0.011^{**}	0.011^{**}	0.010^{**}	0.011^{**}	0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
Number of Wins	-0.085^{**}	-0.087^{**}	-0.088^{**}	-0.089^{**}	-0.088^{**}	-0.057
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.042)
Buy-it-now Dummy	0.069	-0.309^{**}	-0.326^{**}	-0.436^{**}	-0.329^{**}	0.360
	(0.041)	(0.064)	(0.064)	(0.076)	(0.064)	(0.442)
Bids Last 5 Minutes			-0.0003	-0.0004	-0.0003	
			(0.0005)	(0.0005)	(0.0005)	
Participants Last 5 Minutes			-0.012^{**}	-0.010^{**}	-0.012^{**}	
			(0.003)	(0.003)	(0.003)	
End Time Dummies	✓	✓	✓	✓	✓	
Individual Fixed Effects	✓	✓	✓	✓	✓	✓
Product Fixed Effects		✓	✓	✓	✓	
Week Fixed Effects				✓		
Log likelihood	-16,637	-15,812	-15,797	-15,764	-15,798	-209
Number of observations	72,752	72,752	72,752	72,752	72,752	530
Number of participants	2,601	2,601	2,601	2,601	2,601	133

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

Table 4: Auction Level Summary Statistics

	N	Mean	Std. Dev.
Participants	6,987	69.06	101.92
Proportion Aggressive	6,987	0.1631	0.0856
Buy-it-now Dummy	6,987	0.8237	0.3811
Registered Users	6,987	192,872	113,648

Table 5: Auction Level Results

Variable	(1)
Proportion Aggressive	1.745**
	(0.109)
Buy-it-now Dummy	0.029
	(0.052)
Log Registered Users	2.935**
	(0.408)
End Time Dummies	✓
Product Fixed Effects	✓
Week Fixed Effects	✓
R^2	0.1836
Number of observations	6.987
Number of products	408

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