Does it Pay Off to Bid Aggressively? An Empirical Study

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Abstract

We empirically investigate the payoff of signaling through aggressiveness 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 aggressive bidding, used in an attempt to signal a high valuation to deter other auction participants, on the probability of winning an auction. We analyze more than 600,000 bids placed manually by approximately 2,600 distinct auction participants. We find a strong and significant positive effect of aggressive bidding on the total number of bids placed, and on the total number of participants in an auction. The strong and significantly negative effect of aggressive bidding on the individual probability of winning an auction supports the finding that aggressive bidding is ineffective as a strategy for deterring competitors in an online auction.

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. [3]

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 $68.6 billion. It is hardly surprisingly, then, that for over a decade online auctions have featured prominently as a study topic in the IS literature (e.g., [7], [17]) as well as in the economics literature (e.g., [29], [25]). One central topic in this literature concerns the analysis of different types of bidders and bidding strategies – such as aggressive bidding – in these auctions (e.g., [9], [6], [23]). The quote by Harry Kemelman may be taken as anecdotal evidence that an aggressive bidding strategy promises a positive return for the respective bidder. However, Kemelman cannot be sure that he won 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 using a more cautious bidding strategy.

The existence of aggressive bidding strategies – typically called jump bidding – in ascending price (online) auctions has been documented extensively in the literature (e.g., [3], [14], [12], [20]). Cranton [11] defines jump bidding as “the act of raising a high bid by much more than the minimum increment”. Empirical studies suggest that jump bidding occurs quite frequently. For example, Easley and Tenorio [14] report that more than 30% of bidders in their sample submitted jump bids. Naturally, a significant literature has emerged, analyzing these strategies theoretically and empirically (for an extensive literature review see, e.g., [28]). In general, signaling (e.g., [3], [12]) and impatience (e.g., [20]) 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 a high valuation on the actual likelihood of winning an auction. Thus, the question, whether Kemelman won the auction because of the effectiveness of his bidding strategy or merely because of his high valuation of the land remains until today unanswered.

This gap in the literature may be explained by two important challenges: First, the distinction between aggressive bids that are attributable to impatience and aggressive bids that are attributable to signaling is hard to make. Second, and more importantly, even when impatience is ruled out as a cause for aggressive bids, in typical ascending price auctions these bids may imply two simultaneous effects: (1) By definition, an aggressive bid always increases the auction price by
more than the minimal bid increment. Thus, naturally, an aggressive bid deters auction participants or potential auction participants with valuations lower than the aggressive bid from continuing or entering the bidding process. However, in these cases, winning the auction is not explained by the bidder’s aggressive bidding strategy, since it could equally be won with a more cautious bidding strategy — maybe even with a lower bid. We call this deterrence effect the price effect of aggressive bidding. (2) An aggressive bid may also deter auction participants with a higher valuation than the aggressive bidder from continuing or entering the bidding process [3], [12]. In this case, the aggressive bidder wins the auction because of their aggressive bidding strategy and not because of their higher valuation. This second effect will be referred to as the aggressiveness effect of aggressive bidding. Typically, it is not possible to distinguish between the price effect and the aggressiveness effect of an aggressive bid in a regular ascending price auction setup.

Online pay-per-bid auctions (e.g., beezid.com, bidcactus.com) — which constitute a variant of ascending price auctions — have seen a significant rise in popularity in recent years. The increase in this type of auctions helps to overcome the aforementioned challenges. In particular, we are able to rule out impatience as a reason for aggressive bidding, as well as the price effect of an aggressive bidding strategy, and thus are able to isolate the aggressiveness effect of an aggressive bid. 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. The participant who places the bid has to pay the fixed bidding fee of 50 cents. During the bidding process, auction participants can delegate their bidding to an automated bidding agent at any time. 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.

As with other auction formats, bidders in a pay-per-bid auction can adopt aggressive bidding strategies. But unlike other auction formats, bidders in a pay-per-bid auction cannot use typical jump bids to signal their 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.

Accordingly, pay-per-bid auctions allow novel and innovative approaches to the study of aggressive bidding strategies. Our research setup was designed to rule out impatience as a cause for aggressive bidding, as well as the price effect of an aggressive bidding strategy, thereby enabling us to isolate the aggressiveness effect of an aggressive bidding strategy. This unique advantage can be attributed to two key features:

First, the specific format of pay-per-bid auctions and the existence of the automated bidding agent allow us to eliminate impatience as potential explanation for aggressive bidding. Adopting an aggressive bidding strategy in a pay-per-bid auction has a negligible effect on the total duration of an auction. Hence, we do not expect any auction participant to adopt an aggressive bidding strategy due to impatience. In addition, since an impatient bidder always has the opportunity to delegate bidding to an automated bidding agent, it does not make sense for him or her to use aggressive bidding to speed up the auction. 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.

Second, and more importantly, the pay-per-bid auction format isolates the aggressiveness effect caused by an aggressive bidding strategy. As the bidding increment is fixed to a very small amount (e.g., 1 cent), placing a bid in a pay-per-bid auction has only a negligible effect on the current bid. Consequently, pay-per-bid auctions typically end with winning bids which are substantially lower than the retail prices for the respective products (in our sample on average around 80% lower). Accordingly, the current bid very

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1 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 [26].
2 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 the difference between the respective threshold and the actual value of the auction countdown.
rarely deters potential or existing auction participants from placing further bids in an auction. As a consequence, in this specific auction setup, the price effect of an aggressive bidding strategy is negligible.

To summarize, our research setup allows us to address both of the aforementioned challenges, and, thus to investigate the following research question: What effect does the aggressiveness of an aggressive bidding strategy have on a bidder’s chance of winning an auction? Our explicit aim is to consider the inherent usefulness of aggressive bidding as a strategy for deterring competitors in an online auction. In other words, we aim to resolve empirically the incongruity of the conclusions drawn from various theoretical and simulation studies. In particular, while prior theoretical studies (e.g., [3], [12]), and anecdotes provided by [3] suggest an inherently positive payoff from aggressive bidding, studies in support of bidders’ impatience as a cause of aggressive bidding imply that the payoff is insignificant (e.g., [21], [20]).

Our research, therefore, seeks to add to the existing literature on aggressive bidding strategies in the following way: By analyzing aggressive bidding in the pay-per-bid auction context, we are able to isolate the aggressiveness effect of an aggressive bidding strategy. This, then, allows us to be the first to provide an empirical answer to the question of whether signaling aggressiveness is a useful strategy for deterring competition in an online auction. Considering the different theoretical predictions of 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 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 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 a strong and significant negative effect of aggressive bidding on the likelihood of winning an auction.Confirming this result, we find that a higher proportion of aggressively placed bids increases the total number of bids placed in an auction as well as the total number of auction participants.

2. 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., [3], [4], [8], [10], [12], [14], [18], [21], [20], [24], [27], [28]). Theoretical studies have identified signaling and impatience as major explanations for jump bidding. Avery [3] shows that jump bids in a common value setting where bidding is not costly can be interpreted as coordinating devices among bidders. By contrast, the models constructed by Daniel and Hirshleifer [12], Easley and Tenorio [14], and Hörner and Sahuguet [18] for the analysis of jump bidding in ascending price auctions where bidding is costly, conclude that jump bidding occurs as a result of 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 [3] 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 [12] 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.

An alternative explanation for jump 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 jump bids to increase the speed of the auction. Banks et al. [4] 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. [20] 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 [14] 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 [22] as well as Isaac et al. [21] provide some empirical and experimental evidence that jump bidding is driven by the impatience of auction participants and, thus, has no detrimental, or, indeed, may even have a positive effect on the end price of an auction. These results are reinforced by Kwasnica and Katok [24] who find that higher bidder impatience results in greater jump bids. Carpenter et al. [10] 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 linked to impatience. Consistent with Isaac and Schnier [22] and Isaac et al. [21] they find that jump bidding due to impatience increases auction revenue. Banpa et al. [8] 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 of winning an auction, and, due to the slightly higher average winning bid, may even result in a negative total payoff for the auction participant. In a recent study, Grether et al. [16] examine why bidders engage in jump bidding in used car markets. However, their study on two different markets arrives 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.

In sum, 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 [20], jump bidding as a signal of aggressiveness is associated with a negative effect on this price ([13]; [12]). A lower expected end price of an auction increases the probability of winning an auction. Thus, the studies of Avery [3] and Daniel and Hirshleifer [12] both suggest a positive effect of bidding aggressively on the probability of winning an auction while the study of Isaac et al. [20] 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 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.

3. Research Setup

3.1. 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 three 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 the own valuation of the auctioned product and thus, trying to discourage potential competitors from placing further bids. This strategy is called the aggressive strategy. The second strategy is to wait until the very last seconds of an auction to place a bid. This strategy is typically called sniping (e.g., [29]) and has been documented in several theoretical and empirical studies (e.g., [5], [15]). The third strategy involves placing the bids at a random point in time but not immediately after another auction participant has placed hers and not in the very last seconds of an auction. We call this third strategy the normal strategy.

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 higher 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 number of bids required 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. 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 the following, we empirically investigate, on the auction level, the impact of an aggressive bidding strategy on the total number of participants and on the total number of bids placed in an auction. Then, we analyze the effect of bidding aggressively on an auction participant’s individual winning probability.

3.2. 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 and its suggested retail price, the bid increment, the time increment, as well as start and end times. On 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 registration, the complete history of auction participations, as well as some demographical data, such as 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 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. Agent bids are bids placed within the last 3 seconds of an auction. Agent bids are bids placed by an automated bidding agent. Analogous to the aggressive bids, we divide the number of sniping and agent bids by the total number of bids placed in this auction. We identify a bid as aggressive if it is placed within 3 seconds after the preceding bid.

We use the variables Proportion Sniping and Proportion Agent to control for the proportions of sniping and agent bids. A bid is identified as a sniping bid if it is placed within the last 3 seconds of an auction. Agent bids are bids which are placed using an automated bidding agent. Analogous to the aggressive bids, we divide the number of sniping and agent bids by the total number of bids in this auction to calculate the respective variable.

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 actual bidding behavior of auction participants.

The number of participants as well as the total number of bids placed in an auction may also be influenced by the total number of registered users on our auction website. To control for these effects, 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. Furthermore, there may be effects on the winning probability linked to an 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 ending during nighttime hours. Accordingly, we divide the day into 24 one hour intervals, starting at midnight, and include 23 end time dummy variables to control for the end time of the auction. Table 1 shows summary statistics for these variables.\(^3\)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participants</td>
<td>69.06</td>
<td>101.92</td>
<td>35</td>
</tr>
<tr>
<td>Total Bids</td>
<td>922.98</td>
<td>1998.15</td>
<td>256</td>
</tr>
<tr>
<td>Proportion Aggressive</td>
<td>0.1631</td>
<td>0.0856</td>
<td>0.1567</td>
</tr>
<tr>
<td>Proportion Sniping</td>
<td>0.1926</td>
<td>0.1042</td>
<td>0.1780</td>
</tr>
<tr>
<td>Proportion Agent</td>
<td>0.4258</td>
<td>0.2218</td>
<td>0.4375</td>
</tr>
<tr>
<td>Buy-it-now Dummy</td>
<td>0.8237</td>
<td>0.3811</td>
<td>1</td>
</tr>
<tr>
<td>Registered Users</td>
<td>192.872</td>
<td>113,648</td>
<td>230,473</td>
</tr>
</tbody>
</table>

### 4.3. 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 fixed effects regression models to investigate two relationships: the relationship between the proportion of aggressively placed bids and the total number of placed bids and the relationship between the proportion of aggressively placed bids and the total number of participants in an auction, respectively. We further add the aforementioned control variables. Thus, our econometric model for the auction level analysis is:

\[
Y_{it} = \beta_1 X_{1it} + \zeta X_{2it} + \epsilon_{it}
\]

where \(Y_{it}\) denotes the time demeaned variables Log Participants and Log Total Bids, respectively, for product \(i\) in auction ending at time \(t\); \(X_{it}\) is a vector of auction level covariates; The coefficient of interest is \(\beta_1\) and measures the potential impact of aggressively placed bids (denoted by \(X_{1it}\)) on the number of participants and the total number of placed bids in an auction, respectively. The error term \(\epsilon_{it}\) captures all omitted influences, including any deviations from linearity. Our econometric model will consistently estimate the effect of the potential impact of the proportion of aggressively placed bids if \(\text{Cov}(X_{1it}, \epsilon_{it}) = 0\).

### 4.4. Results

Table 2 reports the results of the fixed effects regressions of our econometric models for the dependent variables Log Participants (Column (1)) and Log Total Bids (Column (2)). Throughout, all standard errors are robust against arbitrary heteroskedasticity and serial correlation.

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proportion</td>
<td>3.799**</td>
<td>8.031**</td>
<td>4.154**</td>
<td>10.03**</td>
</tr>
<tr>
<td>Aggressive</td>
<td>(0.0953)</td>
<td>(0.140)</td>
<td>(0.141)</td>
<td>(0.208)</td>
</tr>
<tr>
<td>Proportion</td>
<td>1.667**</td>
<td>3.047**</td>
<td>1.977**</td>
<td>3.892**</td>
</tr>
<tr>
<td>Sniping</td>
<td>(0.0836)</td>
<td>(0.123)</td>
<td>(0.0722)</td>
<td>(0.107)</td>
</tr>
<tr>
<td>Proportion</td>
<td>1.677**</td>
<td>5.451**</td>
<td>1.427**</td>
<td>5.053**</td>
</tr>
<tr>
<td>Agent</td>
<td>(0.0468)</td>
<td>(0.0687)</td>
<td>(0.0479)</td>
<td>(0.0706)</td>
</tr>
<tr>
<td>Buy-it-now Dummy</td>
<td>-0.189**</td>
<td>-0.106**</td>
<td>-0.191**</td>
<td>-0.115**</td>
</tr>
<tr>
<td>Dummy</td>
<td>(0.0266)</td>
<td>(0.0390)</td>
<td>(0.0278)</td>
<td>(0.0409)</td>
</tr>
<tr>
<td>Log Registered Users</td>
<td>0.147**</td>
<td>0.00327</td>
<td>0.155**</td>
<td>0.0236*</td>
</tr>
<tr>
<td>End Time Dummies</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Product Fixed Effects</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>R²</td>
<td>0.345</td>
<td>0.563</td>
<td>0.286</td>
<td>0.519</td>
</tr>
<tr>
<td>Number of observations</td>
<td>6,987</td>
<td>6,987</td>
<td>6,987</td>
<td>6,987</td>
</tr>
<tr>
<td>Number of products</td>
<td>408</td>
<td>408</td>
<td>408</td>
<td>408</td>
</tr>
</tbody>
</table>

Note: (Cluster-robust) standard errors are in parentheses. *\(p < 0.05\); **\(p < 0.01\).

Column (1) shows an estimated coefficient for the potential impact of aggressively placed bids on Log Participants of 3.163 (s.e. = 0.119). This suggests that an auction with a higher proportion of aggressively placed bids typically has a significantly higher total number of auction participants. The coefficient estimate implies a potentially large effect of aggressively placed bids on the number of auction participants. 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 3%.

The second column of Table 2 mirrors this result. The estimated coefficient for Proportion Aggressive on Log Total Bids is 6.407 (s.e. = 0.178). Thus, a higher proportion of aggressively placed bids has also a significant positive effect on the total number of placed bids in a pay-per-bid auction. According to this estimate, a one percentage point increase in the proportion of aggressively placed bids increases the
These findings suggest that bidders cannot use an aggressive bidding strategy to deter potential competitors. In contrast, our findings indicate that aggressive bidding has a significant positive effect on the number of competitors as well as on the number of bids placed in an auction. From the perspective of a pay-per-bid auction platform operator, our results suggest that a higher proportion of aggressively placed bids implies a positive benefit through the larger number of placed bids in an auction.

### 4.5. Robustness Checks

One may argue that our definition of aggressive bids erroneously identifies some normally placed bids as aggressive. There may be some bidders who try to place their bids in the very last seconds of an auction. Depending on the connection between the auction website and these bidders it is possible to have 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 the bid normally. We address this issue by assigning each bid placed in the first second after a foregone bid to the normally placed bids. Columns (3) and (4) of Table 2 show that our results remain qualitatively unchanged for this robustness check.

### 5. Individual Level Analysis

#### 5.1. Main Variables

At the individual level, we measure aggressively and normally placed bids as well as sniping bids with the variables \textit{Ratio Aggressive}, \textit{Ratio Normal} and \textit{Ratio Sniping}. The variables are calculated as follows: For each manually placed bid we determine whether the respective auction participant placed the bid aggressively, normally or as a sniping bid. We identify a bid as aggressive if it is placed within 3 seconds of the previous bid. If a bid is placed more than 3 seconds after the preceding bid and less than 3 seconds before the end of an auction it is characterized as normally placed. Bids that are placed within the last 3 seconds of an auction are characterized as sniping bids. To account for potential product specific effects, we multiply the respective aggregated number of aggressively and normally placed bids as well as the sniping bids by the fixed bidding fee and divide the results by the suggested retail price of the auctioned product.

Furthermore, we include the variable \textit{Ratio Agent} to control for the number of bids placed using an automated bidding agent. Analogous to the variables \textit{Ratio Aggressive}, \textit{Ratio Normal} and \textit{Ratio Sniping} 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 \textit{Number of Participations} and \textit{Wins Before} as historical experience measures in our model. \textit{Number of Participations} is defined as the number of participations by a specific participant in different auctions since the day of registration. \textit{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 ([2], [13]).

In addition, we divide the day into 24 one hour intervals, starting at midnight, and include 23 dummy variables to control for any potential effects of the end time of an auction. Table 3 shows summary statistics for these variables.

#### 5.2. 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 [19]. 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 expect that the individual specific effects can 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 \textit{Ratio Aggressive}. As such a correlation is only allowed in fixed effects models [30], we estimate a fixed effects logistic regression model to test for the effects of aggressive and normal bidding strategies on the likelihood to win an auction. The variables of interest for this analysis are \textit{Ratio Aggressive}, \textit{Ratio Normal} and \textit{Ratio Sniping}. If the coefficient for \textit{Ratio Aggressive} turns out to be significantly larger than the coefficients for \textit{Ratio Normal} and \textit{Ratio Sniping}, this would indicate a positive impact of an aggressive bidding strategy on the likelihood of winning an auction and provide support for the theoretical predictions of Avery [3] and Daniel and Hirshleifer [12]. 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. Therefore, we consider the following model in latent variable form [30]:

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

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

$Y_{it}$ 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 auctioned product; $X_{2it}$ is the ratio of the value of the normally placed bids and the suggested retail price of the auctioned product; $X_{3it}$ is the ratio of the value of the 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 $\epsilon_{it}$ 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 on the individual level in a meaningful and robust manner [1].

### Table 3: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Winner</td>
<td>0.0958</td>
<td>0.2944</td>
<td>0</td>
</tr>
<tr>
<td>Ratio Aggressive</td>
<td>0.0137</td>
<td>0.0505</td>
<td>0</td>
</tr>
<tr>
<td>Ratio Sniping</td>
<td>0.0153</td>
<td>0.0540</td>
<td>0.0004</td>
</tr>
<tr>
<td>Ratio Normal</td>
<td>0.0095</td>
<td>0.0322</td>
<td>0.0004</td>
</tr>
<tr>
<td>Ratio Bidding Agent</td>
<td>0.0754</td>
<td>0.1901</td>
<td>0</td>
</tr>
<tr>
<td>Number of Participations</td>
<td>33.36</td>
<td>54.15</td>
<td>14</td>
</tr>
<tr>
<td>Number of Wins</td>
<td>2.83</td>
<td>5.53</td>
<td>1</td>
</tr>
</tbody>
</table>

5.3. Sample

As the conditional fixed effects model requires variation in the independent variable [30], 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 bids, 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 data consisting of 2,601 individuals and 72,752 observations. Table 3 lists summary statistics for this sample.

### Table 4: Individual Level Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ratio Aggressive</td>
<td>0.602*</td>
<td>0.868**</td>
<td>0.841</td>
</tr>
<tr>
<td></td>
<td>(0.279)</td>
<td>(0.281)</td>
<td>(0.450)</td>
</tr>
<tr>
<td>Ratio Sniping</td>
<td>3.773**</td>
<td>3.120**</td>
<td>2.801**</td>
</tr>
<tr>
<td></td>
<td>(0.234)</td>
<td>(0.239)</td>
<td>(0.199)</td>
</tr>
<tr>
<td>Ratio Normal</td>
<td>2.887**</td>
<td>1.562**</td>
<td>1.290**</td>
</tr>
<tr>
<td></td>
<td>(0.408)</td>
<td>(0.420)</td>
<td>(0.386)</td>
</tr>
<tr>
<td>Ratio Bidding Agent</td>
<td>1.381**</td>
<td>1.415**</td>
<td>1.418**</td>
</tr>
<tr>
<td></td>
<td>(0.0588)</td>
<td>(0.0615)</td>
<td>(0.0615)</td>
</tr>
<tr>
<td>Number of Participations</td>
<td>0.0101*</td>
<td>0.0101**</td>
<td>0.0108**</td>
</tr>
<tr>
<td></td>
<td>(0.0008)</td>
<td>(0.0009)</td>
<td>(0.0009)</td>
</tr>
<tr>
<td>Number of Wins</td>
<td>-0.0856**</td>
<td>-0.0850**</td>
<td>-0.0853**</td>
</tr>
<tr>
<td></td>
<td>(0.0062)</td>
<td>(0.0066)</td>
<td>(0.0065)</td>
</tr>
<tr>
<td>End Time Dummies</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Individual Fixed Effects</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>Product Fixed Effects</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>

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

5.4. Results

The first column of Table 4 presents the estimates of our basic model for the individual level. The coefficients on Ratio Aggressive, Ratio Normal Ratio Sniping and Ratio Agent are all positive and significant. In particular, we have estimated coefficients of 0.602 (s.e.=0.279) for Ratio Aggressive, 2.887 (s.e.=0.408) for Ratio Normal, 3.773 for Ratio Sniping (s.e.=0.234) and 1.381 (s.e.= 0.0588) 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.\(^4\) 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

\(^4\) The odds are defined as $\frac{P(Y_{ij}=1)}{1-P(Y_{ij}=1)}$.  

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increases the odds of winning by 0.6% for aggressively placed bids, 2.9% for normally placed bids, 3.8% for sniping bids, and by 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 bidding strategy as well as for bids placed using an automated bidding agent. This difference is highly significant. Thus, our estimates suggest that bidders are not advised to use aggressive bidding strategies to signal a high valuation and, thus, to deter potential competitors. Indeed, these first findings indicate that aggressive bidding has a significant negative effect on the likelihood of winning a pay-per-bid auction. Comparing the coefficients for the best bidding strategy (the sniping strategy) with those 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 with a normal bidding strategy.

5.5. 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 make more extensive use of 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.

To deal directly 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. Still, the coefficients of interest remain positive and significant and the coefficient on Ratio Aggressive (0.8676, s.e.=0.2814) is smaller than the coefficients on Ratio Normal (1.5620, s.e.=0.4198) and Ratio Sniping (3.1197, s.e.=0.2391). 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 insignificant. These results indicate that the coefficients in column (1) of Table 3 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 best possible bidding strategy and (insignificantly) worse than the normal strategy. Thus, we have confirmation for our claim that the aggressiveness effect of an aggressive bidding strategy does not increase the chances of winning an auction.

As for the auction level analysis, one may also argue that our definition of aggressive bids erroneously identifies some normally placed bids as aggressive. Thus, we assign each bid placed in the first second after a previous bid to the normally placed bids. Column (3) of Table 4 shows that our results remain qualitatively unchanged for this robustness check.

6. Conclusion

The existence of aggressive bidding strategies such as jump bidding has been documented theoretically and empirically in the literature. In general, signaling (e.g., [3], [12]) and impatience (e.g., [20]) have been named as potential explanations for jump bidding. It is surprising, then, that there has not been any empirical research to date on whether aggressive bidding intended to signal a high valuation actually affects one’s likelihood of winning an auction. In other words, the question whether there is any positive return associated with the aggressiveness effect of aggressive bidding still remained unanswered. Our paper attempts to fill this void in the literature. Our analysis shows that, controlling for the number of bids placed, aggressive bidding has a substantial negative effect on a participant’s winning probability. Empirically supporting the simulation results of Bapna et al. [8], 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 and auctioneers in pay-per-bid as well as in ascending price auctions. First, 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 substantial amount of aggressively placed bids, aggressive bidders could c.p. substantially increase their chances of winning an auction by utilizing a sniping 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 added – and possibly a
negative – value in adopting an aggressive bidding strategy. Second, for the auction platform operator, a higher proportion of aggressively placed bids offers a positive benefit. Thus, our findings suggest that platform operators of pay-per-bid auctions seeking to increase their returns would be better off using auction mechanisms which allow for or even encourage aggressive bidding strategies.

7. References