Evaluating the Impacts of Auction Bidding Restrictions on Consumer Surplus and Behaviors — An Empirical Study of Penny Auctions

Completed Research Paper

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Abstract

Penny auction is an innovative, popular online auction format in which bidders are charged a small fee for placing each bid. A penny auction typically ends up with an extremely low final auction price, such that only one winning bidder can derive positive consumer surplus whereas other bidders lose out from the bidding costs. This makes it challenging to retain bidders who rarely win. Using a field experiment, we empirically evaluate how novel auction rules can improve overall consumer retention and long-term bidding participations. Specifically, we implemented three restrictions on bidding activities of customers. Our results show these restrictions enhance the overall number of bids by 50%. The intuition is to restrict the winning probability of a small group of bidders who won most of the auctions so that more bidders can enjoy the thrill and fun of winning an auction, inducing them to bid more in the long run.

Keywords: Penny auction, bidding restrictions, consumer behavior, surplus, bidder retention
Introduction

Online penny auction sites are becoming more popular due to their ability to provide huge bargains (e.g., 95% discount off manufacturer-suggested retail prices). Indeed, online traffic analyses show that quibids.com, one of the leading penny auction websites in the U.S., has attracted more than 4 million unique visitors within a month, and four of the leading penny auction websites worldwide have already had 11% as many unique visitors as eBay in March 20111.

Penny auction applies a Pay-to-Bid mechanism (Platt et al., 2010) and is considered as a special form of all-pay auction. Specifically, bidders will be charged each time they place a bid in penny auctions. However, bidders do not need to pay for the auction item unless they win it as in a traditional online auction such as eBay. In addition to bidding fee, a penny auction also differs in how the auction price is determined. A penny auction typically starts from a zero price and increases by a constant but small amount, such as USD$0.10, each time a bid is placed. Because of the zero starting price and the pay-to-bid mechanism, in reality, the auction winner often gets the auctioned item at a very low price. For instance, in penny auctions, an iPhone 4 with a retail price USD$700 can be sold for as low as USD$150. Penny auction websites can collect revenues from both product sales and cumulative bidding fees from all participating bidders. Many websites set the increment of auction prices at $0.01 and therefore $150 implies 15,000 bids. If the cost of each bid is USD$0.10, the penny auction can earn $1,500 from the bidding fees, which is more than sufficient to cover their loss in selling an iPhone 4 at $150. This example illustrates the importance of the bidding fees to the profit of penny auction sites.

The penny auction format and its extremely low final auction price is a double-edged sword. On one hand, low auction prices attract bidders to participate in this type of auctions. On the other hand, in each penny auction, there is only one winner who potentially earns a very high surplus whereas all losing bidders suffer some loss in bidding fees incurred. In contrast, in conventional eBay auctions, no bidder suffers monetary loss from losing the auctions. For example, in our iPhone example, a penny auction winner can gain as high as $549.90 (i.e., $700 - $150 - $0.10) of surplus if he wins the item with only one bid whereas all other bidders’ expenditures of $1,500 bear no returns for them. If there are some experienced or intelligent bidders who can win most of the items, most other bidders will suffer anguish and monetary losses. If a novice bidder participates in several penny auctions but he cannot win any auctions in the short run, it is natural to conjecture that he may accumulate significant losses in bidding fees, becomes disenfranchised with the auction site, and thus exit from the penny auction site altogether. Over the long run, as the number of bidders decreases, the participants in each auction may decrease, and the focal site’s profit may deteriorate sharply. Therefore, managing the retention of customers in penny auctions is an instrumental part of achieving profits in such sites.

Motivated by this issue, we conducted a real-world field experiment with a leading penny auction provider in Asia. Before September 23rd, 2010, the auction site operators observed few bidders winning most of the auctions and they started to receive complaints from customers who incurred high bidding charges but could not win any auction items. Working with the site operators, we implemented 3 rules to equalize bidders’ participation in auctions, with the intention to curb a small group of bidders’ aggressive bidding strategies and to rebalance the winning probability of auctions among a larger pool of customers. The 3 rules implemented are as follows: (1) each bidder is allowed to win a maximum of 8 auctions within 28 days; (2) each bidder cannot win the same item more than once within 28 days; (3) each bidder is allowed to participate in only \( X \) concurrent auctions where \( X = 8 \) minus the number of auctions won in the past 28 days. Although focusing on different dimensions, these 3 rules share the same purpose of reducing the auction participation capacity of those frequent, aggressive bidders such that the opportunities of winning auctions are not concentrated among these bidders.

The objective of this paper is to empirically analyze how these three rules may impact bidders’ retention and participation in auctions. Specifically, we answer the following research questions:

Does the implementation of bidding restriction rules in penny auctions

(1) Contribute to a more equalized distribution of bidders’ surplus across an auction market?

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1 Based on analyses from Compete.com in March 2011. The four leading websites are swoopo.com, beezid.com, quibids.com and bideactus.com.
Twenty questions to bid at least once in each subsequent week?
(3) Increase the numbers of auctions joined and bids submitted by a unique bidder in each ensuing week?

The contributions of this research lie in clarifying the answers to the above three research questions which have not been studied before in the context of penny auctions. Answers to these questions will help to quantify precisely the individual bidder level and aggregate market level impacts of the bidding restriction rules implementation. These will help penny auction web sites to address and manage the crucial issue of bidder attrition and customer retention, in order to maximize customer lifetime values (Ho, et al. 2006).

Our analysis results show that a skewed or lopsided consumer surplus distribution is highly correlated to more bidder attrition on our penny auction website. The implementation of the bidding restriction rules improves the surplus distribution in a more equal manner such that the Gini coefficients for consumer surplus drop significantly by 10% after the rule changes. We also find evidence that customer retention rate of most bidders are higher after the rule changes, and that they increased the number of auction participations and the number of bids placed in auctions. These benefits exceed the loss or reduction in the auction bidding and participation activities by a small group of aggressive, frequent bidders.

Our research findings in this study imply that rather than emphasizing on the total amount of customer surplus at the aggregate level, penny auction operators should not ignore the issue of maintaining a fair distribution of consumer surplus, which may positively affect customer satisfaction and retention levels. The three restriction rules designed provide a convenient and economical way to equalize the distribution of consumer surplus in penny auctions. Therefore, with this rigorous analysis of the impacts of three bidding rules, we are able to offer the industry an effective and cost efficient solution to improve customer retention rates and lifetime values in penny auctions.

The rest of the paper is as follows. In the next section, we compare penny auction with a typical eBay auction and elaborate a literature review of relevant fields. Section 3 describes the field experiment design, and Section 4 contains the data description, data field definitions and empirical methodology which specify three econometric models of interest. Section 5 discusses the empirical results and robustness checks. Section 6 provides implications, limitations, and future directions of this research.

Background and Literature Review

Comparison of Penny Auction and eBay Auction

To provide a better understanding of online penny auction, we compare it with a typical eBay auction in terms of auction mechanisms and outcomes in Table 1. In addition to the most important difference in bidding fees, a penny auction starts at a zero price and the auction price is increased by a constant but small amount each time a bidder places a new bid. In contrast, an eBay seller can set any starting price of his choice while the bidders can submit ascending bid prices at any time. The last significant difference is that a penny auction has an extensible end time whereas most eBay auctions have a fixed ending time.

<table>
<thead>
<tr>
<th>Auction Parameters</th>
<th>Penny Auction</th>
<th>eBay Auction</th>
</tr>
</thead>
<tbody>
<tr>
<td>Starting price</td>
<td>Zero</td>
<td>Depends on sellers</td>
</tr>
<tr>
<td>Bidding fee (token fee)</td>
<td>Constant</td>
<td>Zero</td>
</tr>
<tr>
<td>Bidding increment</td>
<td>Constant but small</td>
<td>Variable across price ranges</td>
</tr>
<tr>
<td>Ending time</td>
<td>Extended by fixed seconds (soft-closing)</td>
<td>Fixed (hard-closing)</td>
</tr>
<tr>
<td>Final auction price</td>
<td>Heavily discounted in most cases</td>
<td>Depends on the second highest willingness-to-pay of bidders</td>
</tr>
</tbody>
</table>

Literature Review

Penny Auction

Penny auction has been a nascent yet increasingly studied topic in the auctions literature. However to date, there are only a few papers on penny auction to the best of our knowledge. Augenblick (2010) is a
pioneering dissertation paper in this area based on both analytical and empirical approaches. He used a simple economics model to characterize the equilibrium of the penny auctions. In the equilibrium, bidders will bid non-deterministically (a mixed strategy equilibrium). Based on his analytical model, the author carefully examined the empirical data collected from Swoopo.com. Specifically, the author estimated the survival rates on the probability a bidder will bid again in each auction. He found evidence that bidders overbid significantly due to the fallacy of sunk costs, resulting in a considerable profit for the auctioneer. There is also evidence showing that experienced bidders will learn to apply aggressive bidding strategies to increase their winning probabilities. The aggressive strategy demonstrated by such bidders is to bid immediately whenever possible, showing their determination to win in a war of attrition.

To the best of our knowledge, there are only three other recent papers that have discussed penny auctions. Platt et al. (2010) proposed and tested a model of penny auction to predict the distribution of ending prices. Their results suggest that bidders of penny auctions are risk-taking to some extent. Hinnosaar (2010) found evidence of boundedly rational behaviors in penny auctions, and he argued that these behaviors result from the similarities between gambling and penny auction. Thus, bidders in a penny auction can receive additional positive utilities (i.e., enjoyment) from participating. Byers et al. (2010) analyzed the impacts of information asymmetry in penny auctions. They concluded that the profitability of penny auctions is fragile, especially with the possible existence of collusion and shill biddings.

Similar to Augenblick (2010), we observed that experienced bidders in our sample data learned to develop aggressive bidding strategies, consequently driving away other bidders though still contributing a significant amount of profits to the auctioneer. Different from Augenblick (2010)’s argument that this kind of aggressive bidding may have contributed to Swoopo’s continued profitability, we believe that such aggressive bidding strategies should be intervened to improve the long-term business model viability and profitability of the auctioneer. Indeed, such uncurtailed aggressive bidding behaviors in Swoopo may have been one of the contributing factors which led to its closure in March 2011. This thus provides an important motivation to investigate the impact of auction bidding restrictions in online penny auctions.

Online Auction

Various properties of traditional auctions have been studied in IS literatures. We here only selectively summarize the auction papers published in top IS journals. One highly cited recent paper is Bapna et al. (2004). The authors applied data mining techniques to classify bidders based on their bidding strategies and showed how bidders’ heterogeneity may affect the profitability of auctions operators. Along this line of work, Chua et al. (2007) is among the few papers in this area that use a qualitative study to show that trading communities may be helpful in managing the auction fraud problem. Engelbrecht-Wiggans and Katok (2008) investigated two types of regrets in auctions, in terms of overpaying and missing an auction in first-price sealed-bid auctions. Hinz and Spann (2008) studied the impacts of information diffusion of the secret reserve price in name-your-own-price auctions. Bapna et al. (2008) designed an innovative approach to measure the consumer surplus of bidders in eBay auctions. Their results suggested that the median surplus is at least $4 per eBay auction. Gregg and Walczak (2008) used field experiments to show that increasing the quality of an auction business’ reputation does increase consumers’ willingness to transact with the business, and increases auction bid prices. Bapna et al. (2009) investigated bidders’ behaviors in overlapping auctions with the same products. Easley et al. (2011) showed that more experienced bidders may apply more sophisticated bidding strategies and can avoid the winners’ curse.

Distributive Justice

Distributive justice refers to the perceived fairness of economic and social-emotional outcome that a person receives (Folger and Konovsky 1989; Cropanzano et al. 2001; Deutsch 1985). Such perceptions of fairness and equity are likely to influence individual behaviors and attitudes (Ajzen 1982; Cohen and Greenberg 1982). We draw inferences below from a survey of related IS research in distributive justice in the areas of negotiation support systems (NSS), e-commerce and e-business systems to motivate the importance of investigating the distribution of consumer surpluses in penny auctions.

In the NSS literature, the factor of distributive justice affects individual attitudes and behaviors by generating forcing behaviors from the expected gains of negotiation outcomes (Wolfe and Murthy 2006).
Zeleznikow (2009) stresses the importance of incorporating NSS design attributes that account for justice perceptions by proposing several principles to encourage fairness and justice in the development of NSS.

In the area of e-commerce research, Benbasat et al. (2008) argued that distributive justice, as one of the significant factors of trust, can be used to explain how fairness of e-commerce interactions affects behavioral intentions. Several studies also found that Internet users apply a cost-benefit analysis when sharing or revealing of their private information is involved (Culnan and Bies 2003; Dinev and Hart 2006; Tam et al. 2002). Such a cost-benefit analysis constitutes the basis of justice comparisons. Specifically, consumers are only willing to correctly reveal their private information when they perceive a relatively fair benefit from what they have sacrificed in terms of privacy loss (Son and Kim 2008).

In the context of e-business systems, Chiu et al. (2007) concluded that distributive fairness positively affects Internet learners’ satisfaction with an e-learning website and their intention to reuse the system. Turel et al. (2008) also argued that distributive justice has positive effects on user’s acceptance of e-business services with the addition of perceived trust as a moderator. Therefore, distributive justice is a pivotal factor closely linked to a user’s e-business system acceptance and intention for return usage.

Customer Retention

Customer retention has important implications for the management of customers and profits in a business. Importantly, it is widely documented across various industries that it is more costly to acquire a new customer than to retain existing customers (Reinartz and Kumar 2003). In addition, increasing the share of returning customers, relative to new customers, can hugely contribute to a firm’s profit and market share (Reichheld 1996; Dick and Basu 1994; Dwyer 1989). A poor customer retention rate will have more negative effects on profit than other factors such as the reduction in consumers’ purchase quantities per order or transaction (Borle et al. 2005). In sum, all these point to the importance of retaining existing customers in a penny auction website and minimizing customer attrition due to customer complaints or dissatisfactions with bidding outcomes.

From the theoretical viewpoint, the number of bidders is particularly important for auction sites. Most theories suggest that the number of bidders is positively correlated to the final auction price (Krishna 2009). For example, in the second-price auction mechanism, the final auction price is the willingness-to-pay (WTP) of the second highest bidder. The more the bidders are in an auction, the higher the second highest WTP among all bidders. Due to the competitive nature of penny auctions, the number of bidders is even more critical for generating larger profits for the penny auctioneer.

With the important pertinent factors of aggressive bidding behaviors, distributive justice and distribution of bidders’ surpluses, and their potential impacts on retention behaviors identified from our literature review, we worked with a major penny auction operator to design a field experiment to evaluate the exogenous impacts of bidding restriction rules. We elaborate the research design and method below.

Research Design: A Field Experiment

Motivation of the Field Experiment

The dataset of this study is collected from a leading penny auction website in Asia, which we named PennyLeader². PennyLeader is a website launched in July 2010. It has 17,000 registered bidders till January 2011. PennyLeader offered around 38 penny auctions per day and has an average of 920 active bidders per day. The main items auctioned on PennyLeader are electronic products, games, PCs, clothing, and other products that may appeal to younger target customers.

The procedure for a bidder to participate in an auction on PennyLeader is similar to other penny auction sites. First, bidders need to purchase tokens (credits) from the website. Each token costs 75 cents. Next, bidders can choose any active auction(s) to join and place bids accordingly. Each bid consumes one token and increases the auction price by a fixed amount (15 cents on our site). The ending of the auction is

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² PennyLeader is not the actual name of the penny auction website. We are not able to report the real name of the web site due to confidentiality agreements.
decided by a countdown timer, which will be increased by 20 seconds each time there is a bid. The ending
time is thus extendable till there are no further bids. When the auction ends, the winner pays the final
auction price for the product, and the website collects revenue from the product sales (i.e., final auction
price) and the tokens sales (i.e., tokens spent by all bidders). Figure 1 shows a typical penny auction.

Since its inception in July 2010, PennyLeader experienced a period of high growth. In the first month, an
average of 145 new users signed up per day, and the maximum number of new registrations in one day
reached 616. Some products sales were extremely successful. For example, an iPhone auction on August
2010 attracted 290 participants and generated USD$1,400 in revenue. However, since September 2010,
PennyLeader had received several complaints from customers about the difficulty to win an auction. Some
customers even questioned the credibility of PennyLeader on PennyLeader’s Facebook fan page:

“I don’t know if this KIDDYWEAR is really a private user or commercial reseller, .... One person
needs so many of the same items? Or he/she is very rich and really got very extended family. If
bidding like that, who will want to try bidding with him?”... September 5, 2010 at 1:54am

“Well, I think we should all be a little smart here ... If we see people like KIDDYWEAR or anyone
like him, we should not go and fight against them ... As long as we fight these aggressive bidders,
the website operators will be happy to lined their pockets with our bids. Afterall, if we don’t bid,
we don’t get hurt. What can we lose?”... September 22, 2010 at 4:20pm

Simple statistics of the completed auctions confirmed the above complaints. We note that only 10.2% of
the total bidders have won at least one auction before the implementation of the bidding restriction rules.
on PennyLeader. Figure shows the distribution of unique winners in completed auctions. Among those winners, roughly 20% (Y-axis) won 60% (X-axis) of the auctions and 50% (Y-axis) won 80% (X-axis) of the auctions. In other words, roughly 5% (i.e., 10.2% × 50%) of all bidders won 80% of the auctions, suggesting an extremely skewed distribution of bidders winning items in the auctions.

The Field Experiment

To recap, the 3 bidding restriction rules implemented in the field experiment were:

- Rule 1: Each bidder is allowed to win a maximum of 8 auctions within 28 days.
- Rule 2: Each bidder cannot win the same item more than once within 28 days.
- Rule 3: Each bidder is allowed to participate in X concurrent auctions where X is equal to 8 minus the number of auctions won in the past 28 days.

Rule 1 is the most important restriction that directly limits the participation of the bidders and also distributes winning chances to a broader set of customers. Rule 2 restricts the resale opportunities of bidders since some bidders buy items at extremely low prices and later resell them somewhere else for a profit. Because PennyLeader also regularly conducts many auctions of bidding token packs, Rule 2 eliminates the opportunities for the same bidder to win a lot of tokens at low costs and later use those tokens to execute aggressive “predatory” bidding strategies. Rule 3 is similar to Rule 1 in spirit but it further restricts the number of concurrent auctions that a bidder could participate in.

The 3 bidding restrictions became effective from September 23rd in 2010, two months after PennyLeader was launched. Notifications and announcements were sent to all bidders to ensure that all users were aware of the new restrictions. PennyLeader started keeping track of the number of items won for each bidder after September 23rd. That is, a bidder could have won 9 items on September 24th. However, after 28 days of a “grace period”, all bidders must have won less than 8 auctions in the past 28 days.

We choose the sample period for data analysis as 8 weeks before and after the rules implementation. There are several rationales for the choice of this sample period. First, it is the longest available symmetric sample period around the rules implementation date. Second, this sample period fortunately does not extend to December, during which sales surged because of the Christmas holiday season. For this sample period, we track the unique bidders’ bidding behaviors on products auctions only (i.e., non-token ones).

The Impacts of the Field Experiment and Our Research Questions

Utilizing the field experiment on PennyLeader, this paper examines the following research questions.

Research Question #1 (RQ1): Does the implementation of bidding restriction rules in penny auctions contribute to a more equalized distribution of bidders’ surplus across an auction market?

Figure demonstrated the extremely unequal distribution of winners in auctions. As mentioned, 5% of the bidders won 80% of the auctions. These three rules targeted at mitigating this issue by enforcing a maximum number of auctions that a bidder can join and win. With the extent of aggressive bidding now limited, as long as there are more chances for bidders to win auctions, the surplus distribution should be more equalized. RQ1 can be considered as our experiment’s treatment validity test as well.

Research Question #2 (RQ2): Does the implementation of bidding restriction rules in penny auctions increase the probability of a unique bidder to bid at least once in each subsequent week?

Previously, the low probability of winning an auction is an important factor that deterred most of the novice bidders to participate in penny auctions. Winning an item could enhance the credibility of

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3 The X-axis of Figure denotes the cumulative percentage of auctions, and the Y-axis presents the cumulative percentage of winners. The figure reveals the percentage of completed auctions that is corresponding to a certain percentage of unique bidders in the website.

4 The bidding rules’ parameters of 8 auctions and 28 days were selected in consultation with the auction site. The managers decided these numbers by their experience and the judgment that these parameters should be strict enough to tame extremely aggressive or frequent bidders while increasing bidding participation levels by the others. Optimizing these parameters can be a fruitful future research direction.
PennyLeader to that winning bidder because he learns from first-hand experience that it is possible to win or procure an auctioned good at a low price. It can also enhance the auction provider’s credibility via online word-of-mouth from these winning bidders. Therefore, we hypothesize that as the three rules enable more bidders to win an item, more bidders may stay with PennyLeader over a longer period.

**Research Question #3 (RQ3):** Does the implementation of bidding restriction rules in penny auctions increase the number of auctions participated and the number of bids submitted by a unique bidder in each subsequent week?

Similarly, with the help of the three rules, bidders should be more inclined to participate in more auctions and place more bids in the auctions they participated. The main reason is that winning bidders in the past may have higher expectations of their winning probabilities in the future auctions. For the penny auction models discussed in the extant literature (Augenblick 2010, Byers et al. 2010), higher expectations of winning probability will induce bidders to bid more aggressively in an auction. This is a result different from the standard second-price sealed-bid auction (Krishna 2009) in which bidders’ bid price typically is a function of their own willingness-to-pay.

**Data Definitions and Empirical Methodology**

**Data Source**

Since we have access to the proprietary dataset from PennyLeader, we have all of the data fields needed to examine our research questions. We compile a weekly panel dataset at the unique bidder’s level. Specifically, we consider only active bidders by applying the following criteria: (1) a bidder should bid at least once both before and after the rule changes; (2) it should be a bidder who registered on the website before the rules were implemented. In the first criterion we also exclude bidders who only bid before the rule changes. This is because for these bidders they may have left this site forever and thus were not informed or affected by the rules change. As a result, in the 16 weeks of sample period, we collected data of 271 products, 924 auctions, and 91,472 bids from 504 unique bidders. The average age of these bidders is 31 year old, and 322 out of the 504 bidders are male (64%).

**Independent Variable**

**Dummy Variable of Rule Changes**

We create a dummy variable $d_{rule}$ indicating if the three rules have been implemented across the weeks. In the weekly panel dataset, $d_{rule}$ is 1 if the week number is larger than the 38th week of 2010 (i.e., the week when the rules were introduced), otherwise it is equal to 0.

**Dependent Variables**

**Consumer Surplus**

In the context of penny auction, we define the consumer surplus for bidder $j$ as follows. For each auction,

$$S_j = \begin{cases} 
\text{Suggested Retail Price} - \text{Final Auction Price} - \text{Tokens Cost}, & \text{if bidder } j \text{ wins} \\
- \text{Tokens Cost}, & \text{if bidder } j \text{ loses}
\end{cases}$$

Here, since we do not have the WTP of each bidder, we use the suggested retail price as a proxy. The suggested retail price is listed on the PennyLeader website and is observable to all bidders. Consequently, this measure of consumer surplus should be interpreted as the surplus for a bidder to use PennyLeader, benchmarking against buying the same product from other retailers at the suggested retail price. The suggested retail prices posted in PennyLeader’s auctions are generally higher than average actual retail prices – a common pricing tactic that takes advantage of the framing effect (Tversky and Kahneman 1981).

**Equality Measure of Consumer Surplus**

The most prevalent measure of inequality in the literature is Gini Coefficient, which is widely used to measure income disparity. The standard Gini coefficient ranges from 0 to 1, and a value of 0 represents perfect equality. A value of 1 expresses extreme inequality where one person earns all the income.
We need to adopt a modified Gini coefficient in Model 1 (i.e., the econometric model used to evaluate RQ1 on page 11) because many bidders have negative surplus. The procedure to compute a standard Gini coefficient simply treats all negative records as zero. The economics literature (Mishra et al. 2002) suggests an alternative formula to account for the negative surplus of consumers in penny auctions:

\[ G^* = \frac{(2/n) \sum_{j=1}^{n} s_j - \frac{n+1}{n} \left(1 + \frac{2}{n} \sum_{j=1}^{m} s_j \right) + \frac{1}{n} \sum_{j=1}^{m} s_j \left(\frac{\sum_{j=1}^{n} s_j}{m+1} - (1 + 2m)\right)}{[1 + (2/n) \sum_{j=1}^{m} s_j] + (1/n) \sum_{j=1}^{m} s_j \left(\frac{\sum_{j=1}^{n} s_j}{m+1} - (1 + 2m)\right)} \]

where \( s_j = s_j/n \) and \( \bar{s} = \sum_{j=1}^{n} s_j / n > 0 \). \( n \) denotes the total number of bidders, \( s_j \) is the surplus of bidder \( j \), \( s_j \) is the share of surplus of bidder \( j \), and \( m \) denotes the size of the subset of the bidders whose accumulated surplus is zero in the order of \( s_1 \leq \cdots \leq s_m \).

**Consumer Retention**

For each unique bidder in each week, we create a dummy variable (for Model 2 on page 11) that is coded as one when the bidder spent at least one token in that week and is zero otherwise.

**Auctions Participation**

We operationalize “participation” (for Model 3 on page 11) in 2 ways: (1) number of auctions participated by a unique bidder in one week; (2) number of bids submitted by a unique bidder in one week.

**Key Control Variables**

**Bidder Types**

To investigate the differential impact of the rule changes, we categorize bidders into two groups: frequent (or aggressive) bidders and occasional (or marginal) bidders. Frequent bidders are defined as bidders who violated any one of the three rules before September 23rd 2010. In other words, it is highly possible that these bidders may be constrained by the three rules after September 23rd. Occasional bidders are the rest of the bidders who never violated any of the conditions stipulated in the three rules before September 23rd 2010. Thus, these bidders’ bidding behaviors should not be directly curtailed by the three rules after September 23rd 2010. However, they may be indirectly affected by the rules change because frequent bidders will bid less after the rules change. Occasional bidders may therefore win more and also could bid more due to their higher expectations of auction winning chances.

It is straightforward to infer that the three rules may have opposite impacts on these two types of bidders. Those frequent aggressive bidders are the target group whose bidding behaviors are more constrained whereas those occasional marginal bidders are the target group to be encouraged to participate more in the auction site. Thus, we will conduct regression analyses separately on these two groups of bidders in order to evaluate the differential impacts on bidding behaviors after the rules change implementation.

**Consumer Surplus History**

Our conceptual framework proposes that the bidding restrictions may lead to more equalized consumer surplus. Suppose consumers form expectations based on their previous experience at the penny auction site. We believe consumers with larger surplus in the past may participate more in future auctions.

We create four control variables based on the history of consumer surplus of each unique bidder. First, we use the weekly consumer surplus right before a focal week. We further redefine this variable into two variables: surplus gain and surplus loss if the bidder receives positive and negative surplus respectively. Specifically, surplus gain is defined as the total surplus that a bidder obtains in a week if it is positive and it is zero otherwise. This approach is consistent with prior work in the marketing literature (Narayan and Manchanda 2011). The rationale is that bidders may have different sensitivity in bidding

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5 We also categorize bidders into 2 groups based on above or below (including equal to) the 75th and 90th percentiles of the numbers of auctions and bids placed by bidders. Results based on these alternative bidder classifications returned essentially very similar empirical findings and conclusions.
participations to their previous surplus gains and losses. For example, if the bidders are risk-averse or loss averse, they may react more to surplus loss than to surplus gain.

Second, for completeness, we also create two similar variables measuring the cumulative life-time total surplus gain and surplus loss. In particular, we also note that variables for the lagged one-week surplus gain and loss control for recency effects in auction participation outcomes, while the variables measuring cumulative total surplus gain and loss control for primacy effects in participation outcomes. Theoretically, the past surplus and cumulative surplus measures are motivated by the literatures on recency and primacy effects (Miller and Campbell 1959; Davelaar et al. 2005; Farr 1973; Anderson and Barrios 1961).

**Number of Products Auctioned in One Week**

It is intuitive to assume that the number of available auctions and the popularity of products could be correlated with various dependent variables of bidding participations. Particularly, if there are more popular products auctioned in a specific week, more participation from any type of bidders may occur.

We therefore include two variables to control for the impacts of available product offerings in auctions. One variable is the number of hot products sold in a focal week. We define hot products by finding the 10% most popular products during the 16-weeks sample period. The popularity of products is calculated by ranking the associated auctions from high to low by the number of participants. The rest of products are defined as common products. We use the number of common products as the other control variable.

**Descriptive Statistics**

Descriptive statistics of our sample data are reported in Table 2 at the bidder-week level (except for the last 2 rows at weekly level). Specifically, we have 435 occasional bidders and 69 frequent bidders in this balanced panel dataset of 8 weeks before and after the rules change. With simple eyeballing of the descriptive statistics, we observe that the 3 rules seem to have an impact on bidding behaviors. Retention rate of the occasional bidders increases from 19% to 26%. The average number of bids from occasional bidders increases from 6.60 to 7.59, and the number of auctions participated increases from 0.52 to 0.57. On the contrary, the average number of bids from frequent bidders decreases from 44.68 to 31.54, and the number of auctions participated decreases from 2.71 to 1.69. Thus, we find preliminary evidence of the impacts of the 3 rules on auction bidding behaviors. Table 3 shows the correlations between variables examined in our study.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Before rule changes</th>
<th>After rule changes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Obs</td>
<td>Mean</td>
</tr>
<tr>
<td>Occasional bidders</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Customer retention dummy</td>
<td>3480</td>
<td>0.19</td>
</tr>
<tr>
<td>Number of bids</td>
<td>3480</td>
<td>6.60</td>
</tr>
<tr>
<td>Number of auctions</td>
<td>3480</td>
<td>0.52</td>
</tr>
<tr>
<td>Surplus gain last week</td>
<td>3480</td>
<td>2.35</td>
</tr>
<tr>
<td>Surplus loss last week</td>
<td>3480</td>
<td>-2.93</td>
</tr>
<tr>
<td>Cumulative surplus gain</td>
<td>3480</td>
<td>9.68</td>
</tr>
<tr>
<td>Cumulative surplus loss</td>
<td>3480</td>
<td>-12.11</td>
</tr>
<tr>
<td>Frequent bidders</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Customer retention dummy</td>
<td>552</td>
<td>0.50</td>
</tr>
<tr>
<td>Number of bids</td>
<td>552</td>
<td>44.68</td>
</tr>
<tr>
<td>Number of auctions</td>
<td>552</td>
<td>2.71</td>
</tr>
<tr>
<td>Surplus gain last week</td>
<td>552</td>
<td>27.26</td>
</tr>
<tr>
<td>Surplus loss last week</td>
<td>552</td>
<td>-9.83</td>
</tr>
<tr>
<td>Cumulative surplus gain</td>
<td>552</td>
<td>100.46</td>
</tr>
<tr>
<td>Cumulative surplus loss</td>
<td>552</td>
<td>-31.45</td>
</tr>
<tr>
<td>Unique No. of Products</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of hot products</td>
<td>8</td>
<td>14.38</td>
</tr>
<tr>
<td>Number of common products</td>
<td>8</td>
<td>23.38</td>
</tr>
</tbody>
</table>
Table 3. Correlation Between Variables

<table>
<thead>
<tr>
<th>Variables</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) Number of bids</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(2) Number of auctions</td>
<td>0.60</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(3) Surplus gain last week</td>
<td>0.28</td>
<td>0.22</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(4) Surplus loss last week</td>
<td>-0.15</td>
<td>-0.21</td>
<td>0.03</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(5) Cumulative surplus gain</td>
<td>0.26</td>
<td>0.23</td>
<td>0.40</td>
<td>-0.16</td>
<td>1.00</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(6) Cumulative surplus loss</td>
<td>-0.14</td>
<td>-0.17</td>
<td>-0.08</td>
<td>0.37</td>
<td>-0.41</td>
<td>1.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(7) Number of hot products</td>
<td>0.00</td>
<td>-0.02</td>
<td>-0.01</td>
<td>-0.02</td>
<td>0.13</td>
<td>-0.30</td>
<td>1.00</td>
<td></td>
</tr>
<tr>
<td>(8) Number of common products</td>
<td>0.06</td>
<td>0.08</td>
<td>0.01</td>
<td>-0.04</td>
<td>-0.06</td>
<td>0.16</td>
<td>-0.39</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Regression Models

Model 1: Linear Regression on Gini Coefficient

To examine our research question 1, we use a simple OLS regression model with the adjusted Gini coefficient as the key dependent variable. We are interested in whether Gini coefficient decreases after the rules change. Therefore, we have the regression model

\[ G_t = \alpha + \beta_d \text{rule}_t + \varepsilon \]

where \( G_t \) is the value of the adjusted Gini coefficient at time \( t \), \( \text{rule}_t \) is a dummy variable indicating if the rules are implemented at time \( t \).

Model 2: Logistic Regression on Bidder Retention

To investigate our research question 2, we use the following panel logistic regression (Wooldridge 2009). This analysis is conducted at the unique bidder-week level in this panel dataset. We choose one week as the time unit of analysis due to the following reasons. First, there are extensive day-to-day fluctuations in bidding behaviors across the days in a week. Using a weekly panel data smoothes out the daily level fluctuations in our variable values. Second, weekly panel data leads to an appropriate number of sample observations as compared to a daily or monthly level aggregation.

Therefore, we model the probability of a bidder’s participation in a week as (Cameron and Trivedi, 2005):

\[
\Pr (y_{it} = 1|x_{it}) = \frac{\exp(x_{it}\beta)}{1 + \exp(x_{it}\beta)}
\]

where \( y_{it} \) is the binary outcome dependent variable in which 1 represents participation, i.e., a bidder \( i \) bids at least once in a week \( t \) and \( y = 0 \) otherwise. \( x_{it} \) is a vector of covariates for bidder \( i \) at week \( t \) which includes (1) dummy variable of rule changes, (2) past consumer surplus, and (3) auction product types.

Model 3: Negative Binomial Regression on Bidder Participation

There are two common econometric models, Poisson and Negative Binomial, for count data. To choose one over the other, we need to compare the mean and standard deviation of the count dependent variable. As can be seen from Table 2, over dispersion in the numbers of auctions and bids exists in our dataset. Specifically, the standard deviation of the numbers of bids and auctions are many times larger than their mean values. Accordingly, the Negative Binomial model should be used as the principal count regression model to specify the number of auctions and number of bids (Wooldridge 2009). The Poisson model will be used as a robustness check. The specification of the Negative Binomial model is as follows:

\[
\text{Marginal density of } y_{it}, h[y_{it}|\mu, \delta] = \frac{\Gamma(\delta + y_{it})}{\Gamma(\delta)\Gamma(\mu + \delta)} \left( \frac{\delta}{\delta + \mu} \right)^\delta \left( \frac{\mu}{\delta + \mu} \right)^{y_{it}}
\]

\[
\mu_i = E[y_{it}|\mu, \delta] = \exp(x_{it}'\beta) \quad \text{(1)}
\]

\[
V[y_{it}|\mu, \delta] = \mu(1 + \mu/\delta)
\]
where \( y_{it} \) denotes bidder \( i \)'s number of auctions participated (or number of bids placed) within a week \( t \). \( x_{it} \) is a vector of covariates including the dummy variable of rule changes and other control variables. \( \Gamma(.) \) denotes the gamma integral which reduces to a factorial for an integer argument, and \( \mu \) is the conditional mean of the dependent variable \( y_{it} \). \( \delta \) is a parameter for estimation.

## Results and Discussions

### RQ1: Equality of Consumer Surplus

Figure plots the time series of the adjusted Gini coefficients based on bidder’s weekly surplus. As shown in this figure, Gini coefficients are higher before the rules change (i.e., the 38th week of the year), and they fluctuated between 0.96 and 0.99. Since 0.99 means extremely unequal distribution, this is consistent with our earlier observation that a small proportion of the bidders earn most of the consumer surplus in the penny auctions, resulting in a high level of inequitable distribution of surplus.

The introduction of the 3 rules did not improve the surplus distribution immediately. There is no drop until the 40th week, 2 weeks after the rule changes (presumably due to the grace period). The Gini coefficients were much lower between the 40th and the 43rd week, which visually confirms our prediction that the rules can improve the surplus distribution. However, the Gini coefficients seem to deteriorate (rise) again from 44th week onward, which could imply the effect of the rules change diminished slowly.

We further conduct a linear regression to check if there is a statistically significant effect of the 3 rules on the Gini coefficients across 16 weeks. As shown in Table 4, the dummy variable of rules change is significantly negative. Hence, the 3 rules indeed mitigated the inequality among the auction bidders in that the Gini coefficients became smaller after the 38th week. In sum, we can conclude that the three bidding restrictions contribute to a more equalized distribution of consumer surplus in penny auctions.

### RQ2: Bidder Retention

Table 5 reports the regression results of Model 2 and Model 3. In Model 2, bidder retention is modeled as a bidder’s probability of bidding at least once in a specific week. Results of Model 2 are shown in column (a) and (b). As can be seen, the coefficient of the focal independent variable (i.e., the dummy of rules change) has opposite and significant effects on occasional bidders and frequent bidders. Specifically, the coefficient is significantly positive for occasional bidders, suggesting that occasional bidders’ participation probability has been increased after the rule changes. We further calculate the marginal effects of the rules change on bidding probability to be 0.11 (averaged across occasional bidders). This implies that on average, an occasional bidder’s probability of participation is increased by 11% with the rules change. Therefore, we conclude that the bidding restrictions have an economically and statistically significant impact on occasional bidder’s retention.

However, for frequent bidders, though the coefficient is not statistically significant, the rules reduce their participation probability by 4% (i.e., marginal effect on bidding probability). In our results, this drop is relatively smaller than the corresponding increase from the occasional bidders. Since there are a much larger number of occasional bidders, the overall effect should be positive and beneficial to PennyLeader.

<table>
<thead>
<tr>
<th>Table 4. Regression Results for Model 1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Independent Variable</strong></td>
</tr>
<tr>
<td>Dummy of rules change</td>
</tr>
<tr>
<td>Constant</td>
</tr>
<tr>
<td>Observations</td>
</tr>
<tr>
<td>R-squared</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05, * p<0.1
In column (b), we provide regression results of the fully specified Model 2, where we include control variables of consumer surplus history and numbers of hot and common products per week. The results corroborate the prior finding that occasional bidders significantly increase their participation probability after the rule changes (marginal effect = 12.8%), whereas frequent bidders reduced their participation probability significantly (marginal effect = -2.5%).

Moreover, most coefficients on the control variables of surplus gains and losses are consistent with our conjecture that penny auction bidding behaviors depend on historical surplus outcomes. Almost all signs of these control variables are intuitively correct. Our results also show that bidders are more sensitive to losses than to gains (since coefficients of surplus losses are larger than those of surplus gains).

**RQ3: Bidder’s Auction Participation**

We analyze bidders’ auction participation from two perspectives: the number of auctions they participated and the number of bids they placed. The results are shown from column (c) to (f) in Table 5. Generally, the rules have positive effects on occasional bidders but negative effects on frequent bidders, both in terms of the numbers of auctions and bids. All estimated model coefficients on the control variables are very significant in most cases.

The interpretations of the coefficients of the rules change dummy in Column (c) are as follows: the three rules increase the expected number of bids of occasional bidders by 1.43 (=exp(0.3593)) times whereas they decrease the expected number of bids of frequent bidders by 0.86 (=exp(-0.1538)) times. This result is qualitatively similar to that in our model 2. Because there are 86% occasional bidders in our sample, we can conclude that the 3 rules increase the expected number of bids by 1.43 × 86% + 0.86 × 14% = 1.35 times. If we use the results from the full model in Column (d), the 3 rules become even more impactful, it could increase the expected number of bids by 1.5 times or 50% more.

With respect to the results for the number of auctions in Column (e), after the rules change, occasional bidders participated in 1.37 (=exp(0.3121)) or 1.69 (=exp(0.5243)) times more auctions, whereas frequent bidders participated in 0.75 (=exp(-0.2862)) or 0.55 (=exp(-0.5984)) times fewer auctions. The overall effect is that the 3 rules could have increased the participation extent in the number of auctions by 28% or 53% (based on either the simple or full specifications respectively).

**Robustness Checks**

Due to the page limit, we only report results from two robustness checks below.

First, in Model 3, we also apply the Poisson regression (Cameron and Trivedi 2005). Assumptions of the Poisson model as applied in our econometric modeling context include (1) the dependent variable follows a Poisson distribution, and (2) the incidences of participating in an auction and submitting a bid are independent of each other. The probability density function for estimation is then given by:

\[ f(y_{it}|x_{it}, \beta) = e^{-\exp(x_{it}' \beta)} \exp(x_{it}' \beta)^{y_{it}} / y_{it}! \]

where \( y_{it} \) denotes the number of auctions participated (or number of bids placed) within a week \( t \), \( x_{it} \) is a vector of covariates including the dummy variable of rule changes and other control variables.

Table 6 reports the results of the Poisson regressions. Results are qualitatively the same as those in Table 5, almost all significant variables have the same signs of coefficients in our main results. Specifically, the rules change dummy is significantly positive for occasional bidders, and it is significantly negative for frequent bidders. Therefore, we reach the same conclusion that the 3 rules increase occasional bidders’ participations and limit frequent bidders’ behaviors in terms of the numbers of bids and auctions.

---

\(^6\) This marginal effect can be derived by equation (1). The difference of the logarithm of the expected dependent variable is equivalent to the coefficient. Therefore, exponential of the coefficient represents the ratio changes of the dependent variable.
Table 5. Regression Results for Model 2 and Model 3

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Model 2 (Logistic regression on Bidder retention)</th>
<th>Model 3-1 (Negative Binomial regression on Number of bids)</th>
<th>Model 3-2 (Negative Binomial regression on Number of auctions)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(a) Simple specification</td>
<td>(b) Full specification</td>
<td>(c) Simple specification</td>
</tr>
<tr>
<td></td>
<td>Occasional bidders</td>
<td>Frequent bidders</td>
<td>Occasional bidders</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Frequent bidders</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(1) Simple specification</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(2) Full specification</td>
</tr>
<tr>
<td>Rules change dummy</td>
<td>0.4466*** (0.0598)</td>
<td>-0.1600 (0.1334)</td>
<td>0.4957*** (0.0707)</td>
</tr>
<tr>
<td></td>
<td>(0.0873) (0.2210)</td>
<td>(0.1385) (0.1059)</td>
<td>(0.0816) (0.1328)</td>
</tr>
<tr>
<td>Surplus gain last week</td>
<td>0.0106*** (0.0019)</td>
<td>0.0058*** (0.0017)</td>
<td>0.0028*** (0.0004)</td>
</tr>
<tr>
<td></td>
<td>(0.0873) (0.2210)</td>
<td>(0.0004) (0.0073)</td>
<td>(0.0003) (0.0073)</td>
</tr>
<tr>
<td>Surplus loss last week</td>
<td>-0.0193*** (0.0022)</td>
<td>-0.0184*** (0.0036)</td>
<td>-0.0053*** (0.0007)</td>
</tr>
<tr>
<td></td>
<td>(0.0101) (0.0271)</td>
<td>(0.0003) (0.0054)</td>
<td>(0.0008) (0.0073)</td>
</tr>
<tr>
<td>Cumulative surplus</td>
<td>-0.0001</td>
<td>0.0006*** (0.0003)</td>
<td>0.0005*** (0.0002)</td>
</tr>
<tr>
<td>gain</td>
<td>(0.0006) (0.0033)</td>
<td>(0.0002) (0.0046)</td>
<td>(0.0001) (0.0033)</td>
</tr>
<tr>
<td>Cumulative surplus</td>
<td>0.0084*** (0.0010)</td>
<td>0.0014</td>
<td>0.0008** (0.0004)</td>
</tr>
<tr>
<td>loss</td>
<td>(0.0011) (0.0044)</td>
<td></td>
<td>(0.0005) (0.0026)</td>
</tr>
<tr>
<td>Number of hot products</td>
<td>0.0794*** (0.0133)</td>
<td>0.1364*** (0.0280)</td>
<td>0.0756*** (0.0093)</td>
</tr>
<tr>
<td></td>
<td>(0.0248) (0.0693)</td>
<td>(0.0165) (0.0568)</td>
<td>(0.0016) (0.0568)</td>
</tr>
<tr>
<td>Number of common</td>
<td>0.0040*** (0.0047)</td>
<td>0.0414*** (0.0112)</td>
<td>-0.0028</td>
</tr>
<tr>
<td>products</td>
<td>(0.0070) (0.0240)</td>
<td>(0.0002) (0.0046)</td>
<td>(0.0070) (0.0002)</td>
</tr>
<tr>
<td>Constant</td>
<td>-</td>
<td>-</td>
<td>-2.9964***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.0044) (0.0042)</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.1850) (0.3244)</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>-1.5510***</td>
</tr>
<tr>
<td></td>
<td>-</td>
<td>-</td>
<td>(0.0565) (0.0965)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,960</td>
<td>1,088</td>
<td>6,960</td>
</tr>
<tr>
<td></td>
<td>1,088</td>
<td>1,088</td>
<td>1,104</td>
</tr>
<tr>
<td>Number of bidders</td>
<td>435</td>
<td>68</td>
<td>435</td>
</tr>
<tr>
<td></td>
<td>68</td>
<td>68</td>
<td>69</td>
</tr>
</tbody>
</table>

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
### Table 6. Robustness Checks for Model 3

<table>
<thead>
<tr>
<th>Independent variables</th>
<th>Model 3-1</th>
<th>Model 3-2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Poisson regression on Number of bids</td>
<td>Poisson regression on Number of auctions</td>
</tr>
<tr>
<td></td>
<td>Simple specification</td>
<td>Full specification</td>
</tr>
<tr>
<td></td>
<td>(1) Occasional bidders</td>
<td>(2) Frequent bidders</td>
</tr>
<tr>
<td>Rules change dummy</td>
<td>0.1393*** (0.0090)</td>
<td>-0.3483*** (0.0099)</td>
</tr>
<tr>
<td></td>
<td>0.0035*** (0.0001)</td>
<td>0.0010*** (0.0000)</td>
</tr>
<tr>
<td></td>
<td>-0.0049*** (0.0001)</td>
<td>-0.0028*** (0.0001)</td>
</tr>
<tr>
<td>Surplus gain last week</td>
<td>0.0052*** (0.0001)</td>
<td>0.0019*** (0.0001)</td>
</tr>
<tr>
<td>Cumulative surplus gain</td>
<td>-0.0005*** (0.0000)</td>
<td>-0.0001*** (0.0000)</td>
</tr>
<tr>
<td>Cumulative surplus loss</td>
<td>0.0052*** (0.0001)</td>
<td>0.0019*** (0.0001)</td>
</tr>
<tr>
<td>Number of hot products</td>
<td>0.0908*** (0.0018)</td>
<td>0.0849*** (0.0021)</td>
</tr>
<tr>
<td>Number of common products</td>
<td>0.0239*** (0.0007)</td>
<td>0.0366*** (0.0008)</td>
</tr>
</tbody>
</table>

Observations 6,960 1,104 6,960 1,104 6,960 1,104 6,960 1,104
Number of bidders 435 69 435 69 435 69 435 69

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

### Table 7. Robustness Checks Using Subsamples Excluding Grace Period

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Model 2</th>
<th>Model 3-1</th>
<th>Model 3-2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Logistic regression on Bidder retention</td>
<td>Negative Binomial regression on Number of bids</td>
<td>Negative Binomial regression on Number of auctions</td>
</tr>
<tr>
<td></td>
<td>(1) Occasional bidders</td>
<td>(2) Frequent bidders</td>
<td>(1) Occasional bidders</td>
</tr>
<tr>
<td>Rules change dummy</td>
<td>-0.0313 (0.0792)</td>
<td>-0.8206*** (0.1752)</td>
<td>-0.0440 (0.0677)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.8896*** (0.0494)</td>
<td>-1.8022*** (0.0727)</td>
<td>-1.4811*** (0.0661)</td>
</tr>
</tbody>
</table>

Observations 4,320 780 4,320 792 4,320 792
Number of bidders 360 65 360 66 360 66

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Second, in Model 2 and Model 3, we also examine a subsample that excludes observations during the grace period. Specifically, the observations from the 39th week to the 42nd week are removed. Therefore, the new sample contains observations from the 30th week to the 37th week as well as observations from the 43rd week to 46th week. Table 7 provides the results of this new subsample. As can be seen from Table 7, frequent bidders have significantly negative coefficients for the rules change dummy whereas all coefficients for occasional bidders become insignificant. There are two explanations. First, we have only half of the subsample after the rules change, making it more difficult to obtain significant results in the model estimations. Second, this implies that the rules change may have only shorter effects (as shown in Figure ). In the longer term, either the impact of the rules change became ineffective, or other factors, such as stronger competition or rivalry within and across auctions, may have caused the participation levels of the occasional bidders to drop again.
Implications

Theoretical Implications

Penny auction is a relatively new phenomenon and auction theorists are still studying its theoretical properties. As a result, one weakness of our study is the lack of theoretical results or foundations that we can apply or adapt for empirical testing in this new area of penny auctions research. Different from the conventional eBay auction, penny auctions seem to be too complicated to be solved by game theory. The current frontier of the analytical modeling literature can only solve a model with restrictive assumptions (Platt et al. 2010; Mittal 2010; Byers et al. 2010; Hinosaar 2010). Intuitively, in conventional auction theories, each bidder either always bids his own WTP of the auction item or only needs to form a belief about the WTP of the competing bidders. In a penny auction, each bidder needs to guess the probability other bidders may outbid him in the next round, which only indirectly relates to bidders’ WTP, adding another layer of complexity to the solution concept of this kind of game.

Nevertheless, our exploratory empirical study here does shed light on this novel e-business phenomenon of penny auctions in the following aspects. Since bidders’ strategies may depend on how they form the belief of other bidders’ “willingness-to-bid”, more complicated bidding behaviors evolve in this auction environment. Most auction models in the literature do not consider cross-auctions effects on the same auction site. Our results show that some bidders may bid aggressively in earlier auctions to build up predatory reputations and gain perceptible advantages in later auctions. Second, due to the Revenue Equivalence Theorem in Auction Theory, existing literature does not consider the profit-maximization of an auction site and also does not consider how the consumer surplus history may affect future bidding equilibria and the auction site’s profitability. Our results show the history of surplus gains and losses may indeed affect a bidder’s future bidding behaviors. Lastly, our empirical findings could provide some preliminary evidence regarding how bidders may adapt and evolve in a new, complicated, and competitive gaming environment.

Practical Implications

Our empirical findings can contribute to the business practice of e-commerce sites in which consumers compete with each other. This kind of sites includes online multi-player games with competition, online gambling that depends on the players’ skills, and open innovations. These sites all share the same properties that few users may gain immensely at the expense of other users.

The famous Pareto Rule suggests that 20% of the customers may typically generate 80% of the sales or profits of any company. However, we find that this is not the case for those e-business sites on which consumers compete with each other. Our penny auction study shows that indeed a small proportion of customers contributes to a large portion of bidding fees and won most of the auctions. However, those winners may create negative consequences or losses to a penny auction provider in the long run. Across auctions, if only a small group of bidders win most auctions, it is natural to infer that the rest of bidders will gradually turn away from the penny auctions. Without retaining a large number of bidders, any type of auctions business model may fail miserably in the long run. Our study contributes to the practice in providing new evidence that restricting frequent bidders may indeed encourage the rest of bidders to bid more and therefore these three bidding restriction rules can be a novel business strategy for customer retention in the penny auction context.

Second, on sites with competition among users, the service provider faces a fundamental dilemma. They wish to intensify the competition among users so that they can gain directly from their participative contributions. Specifically, in our penny auction context, it means more competing bidders typically leads to more bidding fees and higher ending auction price. However, the intensified competition may hurt most users and the deteriorated or inequitable distribution of consumer surplus may drive away users gradually. Our study proves the importance of this tradeoff and suggests that penny auction operators should adjust the number of auctions in proportion to the number of potential bidders to maintain an appropriate probability of winning for each customer. The broader the “winners base”, the larger the “customers base” will be in the long run.
Conclusions

In this study, we conduct a field experiment on a penny auction website to analyze the effects of bidding restrictions on surplus distribution, customer retention and bidding behaviors. We provide evidence that the surplus distribution is highly skewed on the penny auction website before the implementation of the restrictions. Then we use three regression models to analyze the impacts of restrictions. Our empirical results show that these rules can significantly equalize customer surplus and mitigate the issue that frequent bidders win most of the auctions, potentially leading to defection or churn of the majority of other bidders. With a more equalized surplus distribution, occasional bidders are shown to be more probable to bid again with an increase in likelihood of 12.8%. Besides, they are likely to place more bids in the auctions they participated, such that the expected increase is about 64%. Overall, across both customer segments of frequent and occasional bidders, the 3 bidding restriction rules implemented are shown to increase the expected number of bids by 50% more.

This study is not without limitations, which also provide opportunities for future research. First, our research design is a quasi-experiment. It would be ideal if researchers can conduct a natural experiment with randomly assigned bidders. Obviously, it is difficult to find any e-commerce company to conduct this kind of experiment at the risk of offending their customers. With a randomly assignment experiment, we can better control for unobservable covariates, particularly those that relate to different time points during the sample period. Also, by an (quasi-)experiment with more treatment groups, we may be able to find out the profit-maximizing rules similar to our three bidding restriction rules. Specifically, from our observation, we feel the restriction on the number of auctions won in Rule 1 may not be strict enough. Another related future research direction is to study the impacts of the 3 rules separately, which we cannot do in this study due to the simultaneous implementation of the 3 rules on a single day.

Second, due to the limitation of page length, we focus on analyzing the impacts on the aggregated consumer behaviors. It could be a fruitful and important research direction to investigate the impacts of the 3 rules on the bidding strategies of bidders and the profitability associated with each bidder. Third, implicitly, we conceptually assume the 3 rules increase occasional bidders’ surplus and next, because of the increased consumer surplus, occasional bidders will bid more in penny auctions. However, empirically, we only show that the 3 rules correlate with better customer retention rates and more participations in terms of auctions joined and bids placed. Logically, it could be due to other (psychological) effects. For example, it could be the perception of unfairness is driving the results, not because of the value of consumer surplus. It could also be the reputation or trust of the penny auction site has been improved because of the implementation of the 3 rules. We need other more rigorous empirical research design to study these issues separately.

Fourth, “learning” is generally a popular topic in the academic literature across disciplines. We could use our dataset to study the learning of bidding strategies within and across auctions in the penny auctions context.

Last, with our dataset, we can study several interesting bounded rational behaviors in the penny auction setting. For example, we can carefully examine the sunk costs effects in auctions. Theoretically, a bidding decision should not be related to how many tokens have been spent in the same auction, not to mention tokens spent in other auctions in the same day. However, we may be able to empirically verify the impacts of sunk costs in this setting.

References


