EVALUATING THE IMPACTS OF AUCTION BIDDING RESTRICTIONS ON CONSUMER SURPLUS AND BEHAVIORS — AN EMPIRICAL STUDY OF ONLINE PENNY AUCTIONS

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Summary

Penny auction is an innovative and blooming online auction 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. Therefore, in each auction, only one bidder can enjoy positive surplus whereas other bidders suffer from bidding costs incurred.

In this thesis we firstly provide detail introduction to penny auction as well as its specific features. We then target at solving the bidder retention issue in penny auction which is caused by a skewed distribution of bidder surplus. Specifically, we manage to identify a small group of aggressive bidders who are dominating occasional bidders and win most of the items in penny auction. We design three restrictions on bidding activities on all customers with the intention to limit aggressive bidders' behaviors and adjust the skewed surplus distribution. Then we empirically investigate the dynamics of consumer surplus and bidding behaviors by conducting a field experiment. At a macro level analysis we apply Gini coefficient and the Foster-Greer-Thorbecke (FGT) metrics to measure the equality of surplus distribution. At a micro level analysis, bidder's participation and bidding behaviors (like number of auctions participated and number of bids placed) are analyzed using multiple econometric models.

At first sight, these restrictions may hurt the auction provider's profitability. However, our results show these restrictions could enhance overall customer retention rate. 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 at the target website in the long run.

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1. Introduction

Though traditional online auction formats like eBay auctions have been widely applied for a long period of time, there are more and more innovative online auction formats emerging that attract both practitioners and scholars' attentions. Among these innovations penny auction is a typical one that is still understudied by IS scholars.

Online penny auction sites are becoming more and more popular due to their ability to provide huge bargains (e.g., it is not uncommon to get discounts of up to 95% off the manufacturer-suggested retail price of auctioned goods). Traffic analysis[1] shows that quibids.com, one of the leading penny auction websites in the US, has attracted more than 4 million unique visitors within a month, and the four leading penny auction websites[2] worldwide combined have already had 11% as many unique visitors as eBay in March 2011.

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, while they do not need to pay for bidding in a traditional online auction such as eBay. In addition to such bidding fee, a penny auction 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$0.1, each time a bid is placed. In reality, the auction winner often gets the auctioned item at a very low price. For instance,

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[1] Analysis from Compete.com in March 2011.

[2] These four websites are swoopo.com, beezid.com, quibids.com and bidcactus.com, respectively.

in penny auctions, an iPhone 4 with retail price USD$700 can be sold for as low as USD$150. With deeply discounted final prices, penny auctions have successfully attracted the many eyeballs of online bidders, as is reported in previous studies like Augenblick (2009). Penny auction websites can collect revenues from both the product sales and the bidding fees from all participating bidders. For example, 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$0.1, the penny auction can earn $1,500 from the bidding fees, which is sufficient to cover their loss in selling an iPhone 4 at $150. This example illustrates the reality that penny auction sites may make profits from the bidding fees alone.

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 can be only one winner who potentially earns very high surplus whereas all losing bidders suffer some loss in having incurred the bidding fees. In contrast, in conventional eBay auctions, no bidder ever suffers monetary loss even if they fail to win the auction. For example, in our iPhone example, a penny auction winner can gain as high as $700-$150-$0.1 of surplus if he wins the item with only one bid whereas all other bidders' expenditure of $1500 bears no returns for them. If there are some experienced or intelligent bidders exist who can win most of the items, most of the other bidders will suffer. 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, become disenfranchised with this auction site, and thus exit from the penny auction site altogether.

Over the long run, as the number of bidder decreases, the participants in each auction may decrease, and the penny auction website'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 operator, we implemented 3 rules to equalize bidders' surplus 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 is 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.

In this thesis, we firstly give detailed introduction to online penny auction, focusing on the specific its features such as bidding fee, bidding increment, auto-bidding agents and extendable countdown timer. Varying these settings provide diverse implementations of penny auction. For example, normal auctions have a bidding increment of 15 cents, while five cent auctions increase item price by only 5 cents each time. Free auctions, compared with normal auctions, don't have bidding fees incurred. Then we conduct detailed comparisons of these features with eBay auctions.

The main objective of this thesis 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?

(2) Increase the probability of a unique bidder to bid at least once in each subsequent week?

(3) Increase the average number of auctions and the number of bids by a unique bidder in each subsequent 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 the penny auction industry to address and manage the crucial issue of bidder attrition and customer retention in the long run, 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. In addition, we find evidence that the customer retention rate of marginal, occasional 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 for the marginal occasional bidders, however, are offset by the loss or reduction in the auction bidding and participation activities by the aggressive, frequent bidders.

To further verify our results, we conducted another analysis of bidder's surplus using Foster-Greer-Thorbecke (FGT) metrics, which provides the capability of accounting for heterogeneous individuals with respect to their surplus level. Using Probit models, we successfully identify the poverty line of 13.5 SGD. That is, bidders with weekly surplus larger than 13.5 SGD are counted as the "rich" among all bidders; and bidders who have weekly surplus smaller than 13.5 SGD are at a state of "poverty" in our context. Utilizing this poverty cutoff, we manage to observe that, with the 3 rules, the majority of bidders who are not "rich" have increasing participation probabilities, and the minority "rich" bidders are less likely to join in penny auctions. This provides consistent results as the previous models. Besides, we explored the potential cause of the skewed surplus distribution in penny auction. It is verified that there exist addiction behaviors among penny auction bidders, where we define addiction in penny auction as a positive correlation between a bidder's previous amount of bids and his current amount of bids. It is argued that such behaviors may induce the aggressive bidding behaviors in the context of penny auctions.

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 distribution of consumer surplus, which may ultimately impact on customer satisfaction levels. The three bidding restriction rules designed provide a convenient and economical way to potentially equalize the distribution of consumer surplus in penny auctions. Therefore, with this systematic analysis of the three bidding rules, we are able to offer the industry an effective and efficient solution to maximize customer retention rates and lifetime values in penny auctions.

The rest of the thesis is as follows. In the second chapter, we provide an introduction to penny auction and related literature reviews. Chapter 3 describes the dataset used in this study. Chapter 4 contains research method that covers research design, data definition and research models. Analysis and findings are provided in Chapter 5. In Chapter 6 we provide discussions and implications, and finally conclusions are drawn in Chapter 7.

2. Background and Literature Review

2.1. Penny Auction and Its Features

The process of a typical penny auction is as follows. The penny auction website launches a new auction by specifying the item to sell and the auction starting time. Bidders can bid anytime as long as the auction does not end. Each time they place a bid, one token will be consumed from their accounts and the item price will be increased by the amount of pre-determined bidding increment. If there are several bidders bidding simultaneously, the price increment will be multiplied by the number of simultaneous bids. Instead of bidding individually, bidders can also use auto-bidding agents to bid for them, by specifying a price interval and the number of bids that the bidder wants to place in this price interval. When item price reaches the price interval the auto-bidding agents will be activated and automatically place a bid or bids for the bidders. The countdown timer will be reset to (or increased by, depended on specific setting) 20 seconds each time there’s a new bid. Only when no other bidders are willing to place bids can the auction ends. Finally, when a penny auction ends the last bidder becomes the winner and needs to pay for the item at the final item price. This process is shown graphically in Figure 2-1.

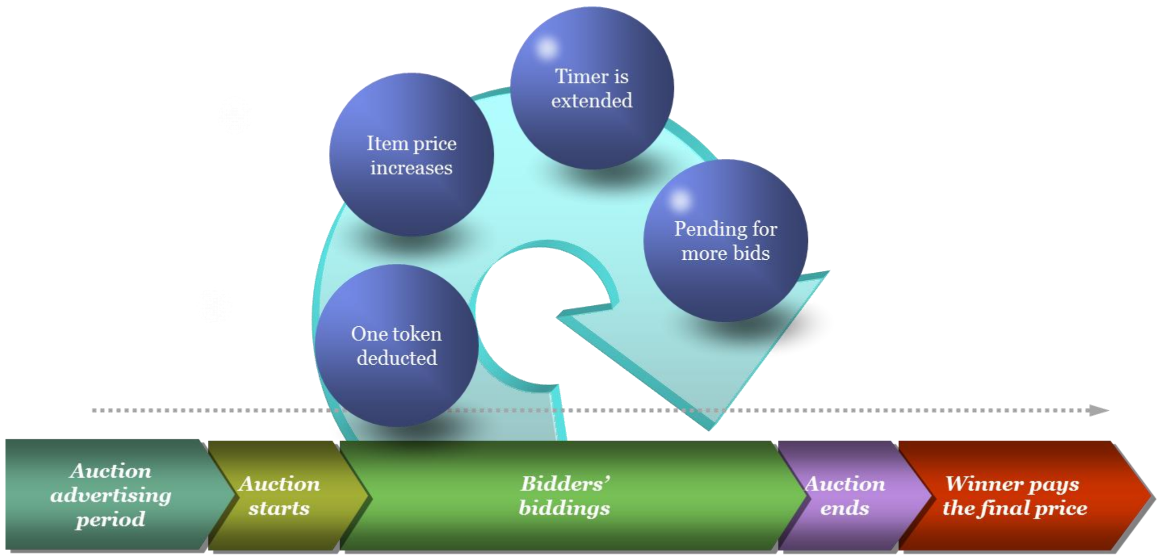

Figure 2-1 : Process of a Typical Penny Auction

2.1.1. Bidding Fee

The most significant feature of penny auction comes from its non-zero bidding fee. Compared to normal online auctions like eBay, in penny auction each time a bidder places a bid he will be charged one token that usually costs 75 cents. As such bidding fee is just a small amount of money, it is affordable for most bidders to place multiple or even many bids in an auction. Because the penny auction winner can always get the item with a deep-discounted price, the small amount of bidding fee is then offset by the large surplus derived from the auction. This is why though bidders need to pay for each of the bids they still keep pouring into penny auctions.

However, such a bidding fee does not guarantee the bidder can win the auction and get the item; in fact, even if a bidder spends a lot amount on bidding fees, he may still lose the auction. This occurs when other bidders have sufficient tokens and willingness to play, or when the bidder does not place a bid in time before the countdown timer ends. Thus the bidding fee is merely a “ticket” for him to participate in penny auction.

From penny auctioneer’s perspective, bidding fee constitutes the majority of the profits. Though it is just a small amount of money, it may still become considerably large when there are a lot of bids. In penny auction, the final item price is usually very low. For example, a USD$700 iPhone 4 may be sold at only a few hundred dollars. The gap between such low item price and the product cost is filled by bidding fees. In reality the bidding fee is designed subtly multiple times larger than bidding increment, this consists of the source of profit for penny auctioneers. If a bid costs 75 cents (i.e. the bidding fee) and increases the item price by 15 cents (i.e. the bidding increment), each bid contributes 60 cents revenue (i.e 75 – 15 = 50 cents) to the auctioneer. In this way N bids bring 60*N cents’ revenues. As long as the cumulative number of bids is large enough so that 60*N is sufficient to cover the item cost, then the auctioneer can make profit. Take the previous iPhone 4 as an example, if there are 1167 bids (i.e. 700/0.6) then the auctioneer has already break even in this auction. 1167 bids make the item price only to 175.05 dollars, and it can foresee that bidders will still be attracted by such a low item price and continue bidding. In this way the bidding fee contributes to the auctioneer’s profit.

Bidding fee is linked with tokens because token is the way that bidding fee is charged. Before a bidder participates in penny auction he will have to purchase a number of tokens. Token cost is equal to the bidding fee, and each time a bidder places a bid one token will be deducted from his account.

Penny auctioneers may vary the amount of bidding fee. BidCactus.com imposes a bidding fee of 75 cents and Quibids.com charges 60 cents for a bid, while beezid.com offers several bid packages where the bidding fee ranges from 55 cents to 90 cents. There are also auctions that have no bidding fee, which are called free auctions. Free auctions inherit other features of penny auction such as bidding increment and extendable countdown timer. Hence free auctions cannot be counted as traditional auctions.

Though bidding fee may vary under different settings, it should be well designed so as to achieve a balance between obtaining more profit for auctioneer (by increasing the bidding fee) and stimulating bidder's bidding (by reducing the bidding fee). A bidder will be charged more if the bidding fee is increased under the same number of bids. They may behave more "conservatively" and place fewer bids. In contrast, bidders may be happier if the bidding fee is lower, but this may cause a loss of profit from auctioneers' views of point. Therefore, it would be an interesting question pending for future research.

The existence of bidding fee may keep bidders bidding, provided that they have already placed at least a bid. This is because bidders will incur a certain amount of loss if they leave earlier without winning the auction. The only way to compensate the loss is to keep bidding till the bidder wins the auction. Therefore, the existence of bidding fee may play a positive role in retain bidders within an auction.

2.1.2. Bidding Increment

Bidding increment is the amount of item price that will be increased when a bidder places a bid. The bidding increment, when multiplied by number of bids in the auction, gets the final item price. This final item price is the actual price that the auction winner needs to pay for the item. For example, if in an iPhone 4 auction the bidding increment is 15 cents and there are totally 2000 bids, the winner of this auction can get the iPhone using only

300 dollars (i.e 15 cents per bid multiplied by 2000 bids). Such a deep-discounted final price is the main reason bidders are pouring into penny auction.

Similar to bidding fee auctioneers can vary bidding increment from case to case. Beezid.com, Quibids.com and bidcactus.com implement a bidding increment of 1 cent, while other penny auction websites like swoopo.com maintain a bidding increment of 15 cents.

Bidding increment needs to be carefully designed to obtain more profit from the penny auctioneer's perspective. Auctioneer's profit is the sum of final item price and total bidding fee less the item cost. At a first glance a larger bidding increment may help the auctioneer collects more profits given the same number of bids; but it also causes a fast increasing item price that may scare bidders from bidding. In contrast, if the bidding increment is low bidders may be benefited while the auctioneer will suffer from the losses from item selling. Therefore, a good bidding increment should be able to achieve a balance between bidder's interests and auctioneer's interests, conditional on other auction settings like bidding fee and time increment.

2.1.3. Extendable Countdown Timer

In penny auction, there is an extendable countdown timer which will be increased to 20 seconds each time a new bid is placed. The intuitive purpose of the timer is to ensure the auction lasts as long as possible. Only when there are no other bidders bidding can the auction ends. Compared with hard-closing auctions like eBay auctions where there are pre-determined auction ending times, such extendable ending mode in penny auction is called soft-closing.

A smaller time increment may reduce bidders' cost of time, as they don't have to wait too long for another bid. The time cost may be quite significant in an auction that has a large number of bidders. For example, each bid extend the timer to 20s and thus 2000 bids may make the auction last for 11 hours. Most of the bidders will bear a large time cost tracing this 11 hours auction. However, the small time increment could also cause an auction to end earlier and some bidders may miss the auction, resulting in a loss of money from the auctioneer's point of view. Therefore, it is necessary to come out with a smart design of the countdown timer in penny auction, so as to cater for both bidders and auctioneers' interests.

2.1.4. Starting Price

To attract the eyeballs of as many bidders as possible, penny auctions implement a zero starting price mechanism. That is, all the items sold on penny auction websites have initial prices of zero. In marketing this is called the loss-leader, meaning sacrificing one product price (i.e. to set deep-discounted selling price) to increase the user traffic. Penny auctions are extreme cases of loss-leader as all the items are of zero initial prices while loss-leader only suggests one or several such free products. In traditional loss-leader settings, the revenues of the sellers come from sales of other non-free products due to the increased traffic. In penny auction, however, the revenues come mainly from bidding fees and item final price.

2.1.5. Auto-bidding Agents

Auto-bidding agents have been widely applied on online auctions. The purposes of employing such auto-bidding agents are two-folded: (1) they provide more timely biddings, as the speed of placing a bid is obviously faster for an auto-agent than a human being using mouse. Where bidding time is important such auto-bidding agents become more important. (2) Auto-bidding agents are time saving tools and thus they reduce costs of time for bidders. In the context of penny auction, the auction ending time is undetermined as the existence of the extendable countdown timer and uncertain number of participants. Auto-bidding agents help those bidders to bid according their pre-configured strategies. When setting an auto-bidding agent, a bidder needs only to determine the interval of the expected item price (i.e. the upper-bound of the item price and the lower-bound of the item price) and the number of tokens the bidder is willing to place. Then the auto-bidding agent will automatically place bids when the actual item price locates in the interval.

For simplicity purpose, we treat auto bids the same as single bids (i.e. the bids place by a bidder individually) in the following analysis in this thesis. Such simplification is reasonable as auto-bidding agents, most of the cases, truly describe how a human bidder will react on specific current item price. When treating the bidding process as a black box, it won’t differ too much to unitize single bids and auto bids.

2.1.6. Comparisons with eBay Auctions

Table 2-1 shows the comparisons between penny auctions and eBay auctions. Penny auctions show significant differences from eBay auctions in term of both auction mechanisms and auction results. The constant bidding fee does not exist in eBay auctions because bidders are free to place bids in eBay auctions. Besides, each bid of penny auction will increase the item price by a small but constant amount, while in eBay auctions such increment can be quite flexible depending on the actual bid price that a bidder bid. For example, if the current item price is 10 dollars for an iPhone 4, next moment the item price will always be (10 plus bidding increment) in penny auction. However, the price may jump to 51 dollars in eBay auctions as long as there is a bidder that is willing to pay for the iPhone 4 at 51 dollars.

Auction ending time is also different between penny auctions and eBay auctions. As mentioned, penny auctions implement a soft-closing ending mode where the ending time will be extended if there is a new bid. Thus the ending time is uncertain in penny auction. If there are interesting bidders who keep bidding, the penny auction may last for a very long time; otherwise if no one is willing to bid then the penny auction will end early. In contrast, on the eBay website the ending time of an auction is pre-determined and is known before a bidder participates.

Starting price is constantly zero in penny auctions. This is mainly for the purpose of attracting bidders' eyeballs so as to encourage them to participate in penny auction. In eBay auctions, however, the actual auction starting price is depended on the sellers. Sellers of eBay auctions may be too risky to launch a zero-starting price auction, because they cannot compensate the loss of item sell from bidding fees (like penny auctions).

As for the auction outcomes, penny auctions can always end up with a deep-discounted price, and losers of a penny auction will have to pay for the bidding fees that constitute profits for auctioneers. However, in eBay auctions the outcomes are quite different. Firstly the final item price of an eBay auction may not be too low as it is the only source of profit for eBay auctioneers. Besides, a bidder who does not win the eBay auction needs not to pay any fee.

Each of these novel features of penny auction are of interest for further research. It will be interesting to come out with an optimal combination of penny auction settings that can maximize either seller profit or consumer surplus.

Table 2-1 : Comparison of Penny Auction and eBay Auction

	Penny Auction	eBay Auction
Auction Mechanisms		
Bidding fee	Constant	No
Bidding increment	Constant but small	Flexible
Ending time	Extendable	Fixed
Starting price	Zero	Depends on sellers
Auction Results		
Final item price	Deeply discounted	Flexible
Auction losers	Pay the token fees	No monetary cost to bid
Auctioneer profit	Mainly from token fees incurred by all bidders	Mainly from auction commissions of winners

2.2. Research Motivation

Though bidders will have to pay for bidding fees in penny auctions, the winner can still obtain considerable positive surplus from winning the auction. Therefore it is of bidders' interests to win more auctions and grab larger surpluses. Previous penny auction studies suggest the existence of aggressive bidders who can utilize their experience and adopt more competitive bidding strategies to increase their winning probabilities. Compared with novice bidders who have less experience, it is reasonable to foresee that the aggressive bidders may dominate the novice bidders and win more auctions. These aggressive bidders may even build a reputation to scare novice bidders off from participating in penny auctions, which will result in a reducing number of total bidders.

However, from penny auctioneers' perspectives it is important to maintain a large pool of bidders. This is because the source of penny auction mainly comes from cumulative bidding fees and item sales, which is substantially a linear function of number of cumulative bids. And only when there are sufficient number of bidders can they generate sufficient number of cumulative bids to create enough revenue. Therefore, the dominance of aggressive bidders may cause a loss of profit for auctioneers because they reduce the number of total bidders.

The dominance of aggressive bidders may become even more deteriorated in reality. In fact, we are reported from managers of PennyLeader[3], one of the leading penny auctions in Asia that, there is a severe bidder retention issue on their website due to the existence of a small group of aggressive bidders. These aggressive bidders win the majority of the auctions, and there is an upheaval of complaints from the rest of the bidders about their difficulties in winning an auction. This phenomenon initiates our interests to help the penny auction industry solve the issue of bidder retention issue.

2.2.1. The Case of PennyLeader

PennyLeader is a leading penny auction website in Asia. PennyLeader launched in July 2010. It has 17,000 registered bidders till January 2011. PennyLeader offered around 38 penny auctions per day and has 920 active bidders on average per day. Main items auctioned on PennyLeader are electronic products, games, PCs, clothing, and other products that may appeal to younger target customers.

[3] PennyLeader is a disguised name for the real penny auction website. We are not able to report the real name of the web site due to the confidentiality agreements.

Since its inception in July 2010, PennyLeader experienced a period of high growth. In the first month, 145 new users signed up per day on average; and the peak of daily new registrations is 616. Some products sales were extremely successful. For example, the iPhone auction on August 2010 attracted 290 participants and generated $1400 USD in sales. 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 all over the Internet forums, including on PennyLeader's Facebook page. For example, some customer feedbacks were as follows:

> *"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? No fun already."... 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. After all, if we don't bid, we don't get hurt. What can we lose?"... September 22, 2010 at 4:20pm*

Simple statistics of the winning auctions confirmed the above complaints. Figure 2-2 shows the distributions of winning auctions among winners[4]. We note that only 10.2% of the total bidders have won at least one auction before the implementation of the 3 bidding

[4] The X-axis of Figure 2-2 denotes the cumulative percentage of auction, and the Y-axis presents the cumulative percentage of winner. The figure reveals the percentage of winning auctions that is corresponding to a certain percentage of unique bidders in the website.

restriction rules on PennyLeader. As shown in Figure 2-2, 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. 0.102*0.5) of all consumers won 80% of the auctions, an extremely skewed distribution of winning items. Because the only way to obtain positive surplus in penny auctions is via winning an auction, the results also suggest an extremely lopsided surplus distribution among bidders.

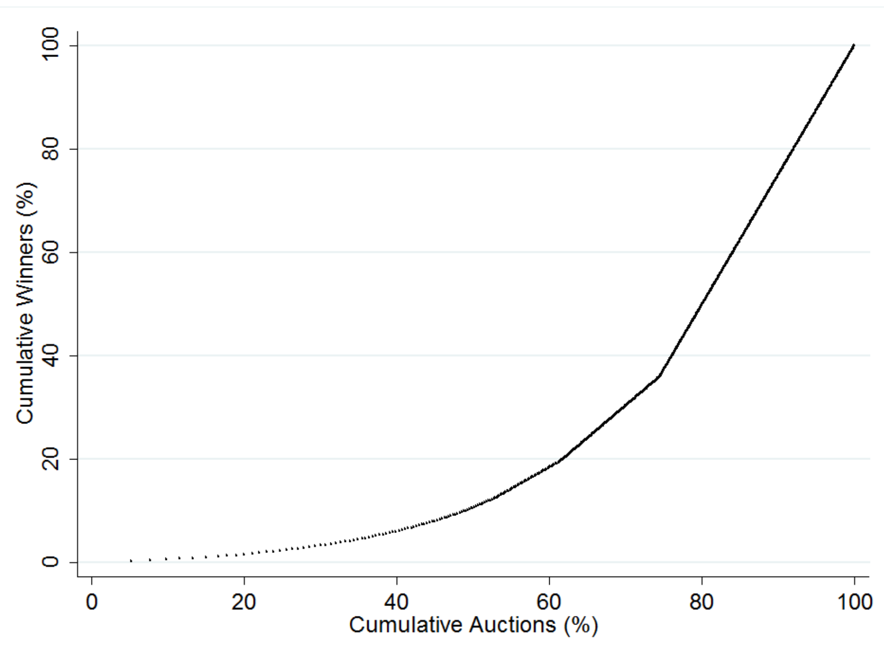

Figure 2-2 : Winner Distribution of Ended Auction

2.3. Research Questions

To target the above issue of skewed surplus distribution, we implement the following three rules on PennyLeader's website:

- 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".

The rationale behind these 3 rules is to adjust surplus distribution among bidders by limiting the behaviors of aggressive bidders. Therefore, we examine 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 2-2 demonstrates the extremely unequal distribution of winning auctions. As mentioned, 5% of the bidders won 80% of the auctions. These three rules targeted at mitigating this issue by enforcing the maximum number of auctions that a bidder can join and win. Since only the winner gains huge, as long as there are more bidders who can win, the surplus distribution should be more equalized. RQ1 examines the impacts of the three rules by comparing the equality of distribution of bidders' surplus. It could be considered as our experiment 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 marginal bidders to participate in penny auctions. Winning an item could enhance the credibility of PennyLeader to that winning bidder because he learns from first-hand experience that it is possible to win or procure an auctioned good at such a low price. It could also enhance the auction provider's credibility via online word-of-mouth from these winning bidders. Once a bidder can win an item, he may also raise his expectation about future winning probabilities. Therefore, we hypothesize that three rules enable more bidders to win an item, and 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 average number of auctions and the number of bids by a unique bidder in each subsequent week?

Similarly, with the help of the three rules, bidders are 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 2009, Byers et al. 2010), higher expectations of winning probability will induce them to bid more aggressively in an auction, a result different from the standard second-price sealed-bid auction (Krishna 2009). Therefore, we propose two empirical models to test RQ3, which is discussed in more details in following chapters.

2.4. Literature Review

2.4.1. Penny Auction

Penny auction has been a nascent yet popular topic in the auctions literature, and there are only a few papers on penny auction to the best of our knowledge. Augenblick (2009) is a pioneering paper in this area. He analyzed consumer behaviors in penny auctions by investigating the survival and hazard rates as well as the bidder's bidding strategies. He found evidence that bidders overbid significantly, resulting in a considerable profit for the auctioneer. There is also evidence showing that experienced bidders will learn to apply certain bidding strategies to increase their winning probabilities. Among these strategies, the aggressive bidding strategy which implies bidding immediately whenever possible can lead to higher consumer surplus. This implies that bounded rational behavior by bidders may exist in penny auctions.

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 auction are risk-taking to some extent. Hinnossar (2010) found evidence of bounded rational behaviors in penny auctions, and he argued that these behaviors result from the similarities between gambling and penny auction. In other words, bidders in a penny auction can receive additional positive utilities (i.e., enjoyment) from participating. Using the simulation method, Byers et al. (2010) systematically analyzed the impacts of information asymmetry in penny auction settings. The authors concluded that the profitability of penny auctions is fragile, especially with the possible existence of collusion and shill biddings.

Congruent to the findings from the literature, in our sample data set of penny auction biddings, we observe the existence of aggressive bidding strategies by a small group of bidders. Working with the penny auction operator, we thus designed a field experiment to restrict those aggressive bidders from winning and participating in more than 8 auctions. Unlike other prior studies of penny auctions, we thus can evaluate the exogenous impacts of the 3 bidding restriction rules implemented in order to provide a unique piece of research evidence and contribution to the penny auctions literature.

2.4.2. Online Auction

Various properties of traditional auctions have been studied in IS literatures. One of the highly cited pioneering paper in IS 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 studies, Chua et al. (2007) examined the importance of limiting online auction fraud. Engelbrecht-Wiggans and Katok (2008) investigated two types of regret 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 on eBay bidders. Their results suggest the median surplus is at least $4 per eBay auction. Gregg and Walczak (2008) examined two online auction businesses utilizing different company names and auction listing styles to sell items in parallel over the course of one year.

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.

Some studies have also paid attention to adding restrictions to online auctions. For example, Adomavicius et al. (2009) pointed out that, in the case where bidders are restricted to a certain number of bids, this restriction has very little effect on a bidder's ability to place strategic bids. However, it is also suggested that the number of such allowable bids is more important from the seller's perspective, especially if the seller wants to restrict strategic bidding (Adomavicius et al. 2009). Bapna et al. (2002) indicated that most of the time the auctioneers cannot make optimal decisions in respect of auction design factors such as bid increment. This causes substantial losses especially in a market with already tight margins.

2.4.3. Loss Leader

In marketing, the loss leader strategy distinguishes from other retailer price promotion strategies by its deep discount price which usually is set at or below retailer cost. Losses can be made up on subsequent sales because such promotions with intense low price can incur incremental traffic to the stores, and as there are economies of scale in shopping, the sale of complementary items may grow (Neslin et al. 1995; Armstrong et al. 1993).

In the field of IS, the strategy of loss leader can be applied into contexts such as free and open source software (FOSS). Hecker (2000) and Raymond (1999) propose several FOSS business strategies and argue that loss-leader is beneficial for market creating. Fitzgerald, B. (2006) give an example that, the free open source Sendmail product can enlarge the subsequent market for Sendmail Pro, a product with extra functionality that is distributed for a fee.

Penny auction is an extreme case of loss leader application. In penny auctions all the item are sold at zero starting prices. It is reasonable to argue that with this strategy can contribute a significant increase of website traffic to penny auctioneers.

2.4.4. Switching Cost

Switching costs refers to the cost of switching from one service to another (Weiss and Anderson, 1992), or the incurred investment that constrains changes (Nielson, 1996). This may include perceived monetary and psychological costs, perceived disutility, and costs of switching providers (Jones et al., 2002; Chen and Hitt, 2002; Burnham et al., 2003).

Hannan and Freeman (1984) explain the linkage of structural inertia and organization change using switching costs. Their results suggest that even under unpleasant situation customers may still be reluctant to give up what they are doing with the existence of switching costs. Similarly, switching cost of an information system can affect the retention of customers and explain the continuous usage of an installed system (Hong et al., 2008; Chen and Hitt 2000). Whitten and Wakefield (2006) provide detailed discussion on switching cost and propose a model to measure switching cost in IT outsourcing services.

The unique feature of bidding fee constitutes the source of switching cost in penny auctions. Once a bidder places a bid he may be reluctant to leave the penny auction until the auction ends. Therefore, switching cost from bidding fee helps penny auctions to keep bidder to continue bidding.

2.4.5. Soft Closing Auction

Soft closing auctions are auctions that implement an extendable ending time mechanism. In this type of auctions if there is a new bid, the auction will be extended by a certain amount of time. Contrast to soft closing auctions is the hard closing auctions which have a fixed ending time for each auction.

Houser and Wooders (2005) conduct a field experiment on auction closing rules and find that soft closing auctions result in significantly higher revenue for sellers than hard closing auctions. The study by Glover and Raviv (2007) suggests that there is a 40% increase of final item price in soft closing auctions than in hard closing auctions. Besides, Sherstyuk (2009) concludes that simultaneous ascending auctions with the soft closing rule yield the most efficient auctions.

In penny auction, the soft closing mechanism is supported by the extendable countdown timer. Given that penny auctions are simultaneous auctions with ascending prices and soft closing, it is reasonable to argue that penny auctions is a type of efficient auctions, as suggested by Sherstyuk (2009).

2.4.6. 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 costs more to acquire a new customer than to retain existing customers (Rosenberg and

Czepiel 1993). In addition, increasing the share of returning customers, relative to new customers, can hugely contribute to the seller's profits and market shares (Reichheld 1996; Dick and Basu 1994; Dwyer 1997). A poor customer retention rate will have more negative effects than other factors such as the reduction in a consumer's 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 dissatisfactions.

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 one 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 ending at a higher final price and generating larger profits for operators.

3. Data Description

3.1. PennyLeader Dataset

Starting from July 2010 and ending at mid-January 2011, our total dataset has five major tables: auction table, user table, bid table, ended auction table and user won auction table.

The auction table contains basic information of 7488 auctions, covering the associated product names, auction names, auction types, auction starting and ending time, number of participants and so on. There are ten types of penny auctions, each having special auctions settings. Among the ten auction types, normal auction and free auction take up the majority, which have 1771 auctions and 5162 auctions, respectively.

The user table is about bidder registration information such as login name, nickname, gender, birthday, address and postcode, registration date and account closing date. There are totally 17113 records in this table, containing bidders (all) from Singapore at the average age of 30. Around two-third of the bidders are male.

Bid-level information is stored in the bid table. The bid table contains only a few variables but it is large. Each observation of this table contains information such as auction ID, timestamp, bid type (i.e. auto bid or single bid) and the current bidding price and bidder name. There are around 1.5 million records in the table.

There are two other tables. The ended auction table stores information of auctions that have ended. It tells about the winner ID, auction ending time, final item price, sales and profits and so on. This table has 7338 observations and that means there is 7338 auctions' information.

The final table, the user won auction table, is organized in the way that describes which auction is won by which specific bidders. In other words, this table is from the winner's perspective and is helpful for analyzing winner's information. This contains auction and user IDs, number of tokens spent by the winner, closing bid time, and closing bid price. There are 7326 observations in this table.

3.2. Selected Sample Dataset

In this study we select a sample dataset consisting of 16 weeks' data that is centered on 23rd Sep 2010 (i.e. the 38th week of 2010) when the 3 rules are imposed. 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 we cannot tell if it is the rules or their previous experiences that caused them not to bid even before the implementation of three rules. Besides, we also considered bidders' closing their accounts. In this case, observations later than their closing time are removed. As a result, in the 16 weeks of sample period, we collected data of 271 products, 924 auctions, and 263,435 bids from 586 unique bidders. The average age of these bidders is 31 year old, and 381 out of the 586 bidders are male (65%).

3.3. Descriptive Analysis of the Effects of the Rules

We conduct a descriptive analysis to show the effects of the rule changes on all bidders. Table 3-1 shows daily statistics data comparing before the rule change with after the rule change. In the column of rule change, 0 represents before the rule change and 1 is after the rule change. Here we compare only free auctions where there are no bidding fee and normal auctions that have a bidding fee of 75 cents.

As can be seen from Table 3-2, it seems that all variables (e.g. profit per auction, sales per auction, number of bidder per auction) are reducing. However a further analysis shows that this is caused by the fact that number of auction launched per day is increasing dramatically after the rule change compared to before the rule change. Hence, by dividing by a larger base of auction number, the variables may reduce.

Table 3-3 shows statistics data of each bidder on an average level. As can be seen, each individual bidder increases their involvements on penny auction, in the sense that there are significantly increased profits contributed by each bidder, sales per bidders and number of auctions participated per bidder. In fact, the results suggest that bidders are more likely to participate in penny auction with the introduction of the 3 rules.

Similarly, we plot Figure 3-1 to show the change of winning auction distribution after the rule introduction. As can be seen, the blue line suggests that auctions are won by larger percentages of bidders. For example, previously around 60 percent of the auctions (Y-axis) are won by 20 percent of the bidders. After the rule change, 20 percent of the bidders are only able to win around 50 percent of the auctions, leaving more opportunities for other bidders to win. Hence, it suggests a fairer surplus distribution among bidders after the rule change.

Table 3-1 : Descriptive Statistics (Overall)

Auction Type	Rule Change	Stat	Profit	Sales	Fee Sales	Product Sales	# Participants	#Auctions	#Unique Bidders
Free Auction	0	Mean (Std. Dev)	-37.94 (45.07)	583.63 (198.91)	0.00 (0.00)	583.63 (198.91)	298.98 (127.37)	20.16 (7.94)	113.87 (24.97)
	1	Mean (Std. Dev)	-214.74 (62.26)	616.30 (83.81)	0.00 (0.00)	616.30 (83.81)	358.92 (69.85)	28.74 (2.07)	155.74 (28.73)
Normal Auction	0	Mean (Std. Dev)	426.89 (606.56)	1704.96 (990.68)	1394.96 (810.56)	310.00 (180.12)	190.75 (97.19)	6.03 (2.22)	139.89 (74.13)
	1	Mean (Std. Dev)	418.85 (544.36)	1701.79 (901.50)	1392.37 (737.59)	309.42 (163.91)	155.41 (49.08)	8.43 (1.91)	107.21 (28.08)
Total	-	Mean (Std. Dev)	149.01 (495.03)	1151.55 (872.53)	696.84 (885.79)	454.71 (218.06)	250.92 (121.90)	15.79 (10.15)	129.14 (48.07)

Table 3-2 : Descriptive Statistics (By Auction)

Auction Type	Rule Change	Stat	Profit Per Auction	Sales Per Auction	Fee Sales Per Auction	Product Sales Per Auction	#Bidder Per Auction
Free Auction	0	Mean (Std. Dev)	-1.79 (2.04)	30.41 (7.82)	0.00 (0.00)	30.41 (7.82)	15.12 (3.31)
	1	Mean (Std. Dev)	-7.48 (2.15)	21.41 (2.16)	0.00 (0.00)	21.41 (2.16)	12.49 (2.25)
Normal Auction	0	Mean (Std. Dev)	73.65 (108.64)	288.57 (161.63)	236.10 (132.24)	52.47 (29.39)	33.91 (18.26)
	1	Mean (Std. Dev)	47.21 (66.60)	199.93 (92.80)	163.57 (75.93)	36.35 (16.87)	18.46 (4.01)
Total	-	Mean (Std. Dev)	28.03 (72.13)	135.47 (147.31)	100.21 (128.58)	35.26 (20.77)	20.07 (12.71)

Table 3-3 : Descriptive Statistics (By Bidder)

Auction Type	Rule Change	Stat	Profit Per Bidder	Sales Per Bidder	Fee Sales Per Bidder	Product Sales Per Bidder	#Auctions Per Bidder
Free Auction	0	Mean (Std. Dev)	-0.33 (0.37)	5.04 (1.35)	0.00 (0.00)	5.04 (1.35)	0.17 (0.06)
	1	Mean (Std. Dev)	-1.45 (0.55)	4.02 (0.56)	0.00 (0.00)	4.02 (0.56)	0.19 (0.03)
Normal Auction	0	Mean (Std. Dev)	2.60 (3.95)	12.63 (5.64)	10.33 (4.61)	2.30 (1.02)	0.05 (0.02)
	1	Mean (Std. Dev)	3.30 (4.53)	15.17 (4.82)	12.42 (3.95)	2.76 (0.88)	0.08 (0.01)
Total	-	Mean (Std. Dev)	1.03 (3.59)	9.21 (6.08)	5.68 (6.48)	3.53 (1.47)	0.12 (0.07)

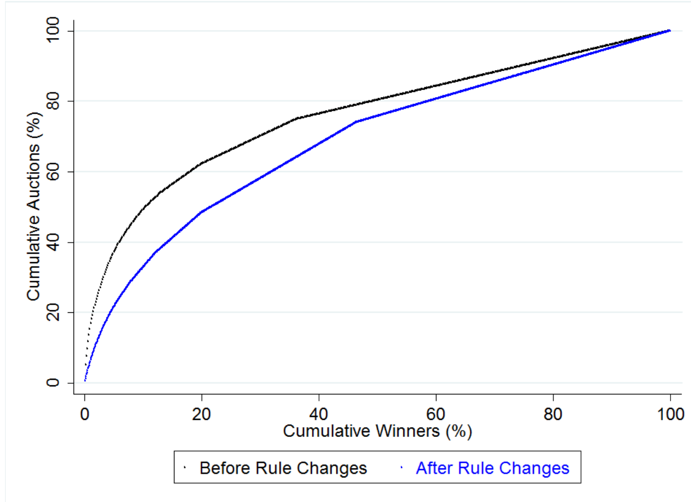

Figure 3-1 : Winner Distribution of Ended Auction (Post)

3.4. Descriptive Analysis of Each of The 3 Rules

We provide descriptive statistics of each rule. For example, Table 3-4 shows the comparison between rule 1 violators and non-violators. Focusing only on normal auctions, individual surplus increases after the rule change for non-violators and number of bids increases as well. For rule 1 violators, they have a reducing number of bids and reducing surplus. Combined together, the results suggests that after the rule change, non-violators of rule 1 are on average better off and increase their involvements, while violators reduce their aggressive bidding behaviors after the rule change, as a result of the reducing surplus. Similarly, comparison of rule 2 in Table 3-5 draws similar conclusions.

Table 3-6 shows the statistic results of rule 3. Though the results are not fully consistent with our perdition, it is still reasonable in our context. This is because rule 3 is quite a loose rule that, essentially, not well designed. There are in fact not many bidders bidding concurrently on several auctions, and even if they bid concurrently they may not be accounted as the frequent (or aggressive) bidders. Hence rule 3 violators may contain both aggressive bidders and non-aggressive bidders. The results shown here mainly for statistical purpose and may not be suggestive enough.

There is a limitation of the results shown here. In this study, we impose the 3 rules concurrently and do not separate them. In this case it may not be appropriate for us to do the analysis separately for each of the rule, because the effect of one rule may have been affected by other rules. To overcome this limitation, in the future we may conduct a new field experience by imposing each of the rules one by one.

Table 3-4 : Comparison between Rule 1 Violators and Non-violators

Auction Type	Violator of Rule 1	Rule Change	Stat	No. of Auctions Participated	No. of Bids	Individual Surplus	No. of Auctions Won
Free Auction	0	0	Mean (Std. Dev)	2.26 (0.63)	28.07 (6.64)	3.85 (1.18)	0.12 (0.04)
		1	Mean (Std. Dev)	2.04 (0.39)	23.68 (6.32)	4.49 (2.05)	0.15 (0.07)
	1	0	Mean (Std. Dev)	4.28 (1.62)	68.62 (28.81)	12.74 (7.81)	0.44 (0.25)
		1	Mean (Std. Dev)	2.44 (1.22)	33.09 (28.59)	6.18 (7.63)	0.21 (0.24)
Normal Auction	0	0	Mean (Std. Dev)	1.34 (0.15)	13.23 (5.60)	-3.42 (4.16)	0.03 (0.02)
		1	Mean (Std. Dev)	1.31 (0.13)	18.03 (8.63)	-1.06 (9.24)	0.08 (0.06)
	1	0	Mean (Std. Dev)	1.91 (0.56)	39.02 (22.79)	20.39 (41.87)	0.23 (0.16)
		1	Mean (Std. Dev)	1.60 (0.48)	36.18 (32.02)	9.34 (39.39)	0.20 (0.19)
Total	-	-	Mean (Std. Dev)	2.14 (1.20)	32.42 (25.85)	6.57 (22.10)	0.18 (0.19)

Table 3-5 : Comparison between Rule 2 Violators and Non-violators

Auction Type	Violator of Rule 2	Rule Change	Stat	No. of Auctions Participated	No. of Bids	Individual Surplus	No. of Auctions Won Per Bidders
Free Auction	0	0	Mean (Std. Dev)	2.44 (0.75)	30.85 (7.98)	4.51 (1.35)	0.15 (0.05)
		1	Mean (Std. Dev)	2.07 (0.40)	24.24 (6.16)	4.68 (1.96)	0.16 (0.07)
	1	0	Mean (Std. Dev)	5.08 (2.63)	106.70 (69.90)	20.49 (20.06)	0.71 (0.65)
		1	Mean (Std. Dev)	2.51 (1.77)	34.87 (30.94)	5.10 (11.29)	0.17 (0.34)
Normal Auction	0	0	Mean (Std. Dev)	1.38 (0.17)	15.04 (6.80)	-2.05 (3.96)	0.05 (0.02)
		1	Mean (Std. Dev)	1.35 (0.13)	19.86 (9.19)	-0.03 (9.62)	0.10 (0.06)
	1	0	Mean (Std. Dev)	1.82 (0.87)	37.09 (56.57)	19.87 (55.33)	0.24 (0.30)
		1	Mean (Std. Dev)	1.43 (0.52)	60.29 (74.28)	-2.70 (91.93)	0.24 (0.33)
Total	-	-	Mean (Std. Dev)	2.27 (1.66)	39.61 (48.99)	6.43 (35.17)	0.22 (0.35)

Table 3-6 : Comparison between Rule 3 Violators and Non-violators

Auction Type	Violator of Rule 3	Rule Change	Stat	No. of Auctions Participated	No. of Bids	Individual Surplus	No. of Auctions Won
Free Auction	0	0	Mean (Std. Dev)	1.84 (0.35)	20.77 (4.94)	3.24 (1.17)	0.10 (0.04)
		1	Mean (Std. Dev)	1.88 (0.38)	20.22 (5.68)	4.07 (2.16)	0.14 (0.07)
	1	0	Mean (Std. Dev)	3.78 (1.42)	57.25 (18.29)	8.47 (3.32)	0.28 (0.12)
		1	Mean (Std. Dev)	2.42 (0.70)	32.38 (13.33)	5.81 (3.33)	0.20 (0.11)
Normal Auction	0	0	Mean (Std. Dev)	1.28 (0.14)	11.44 (4.93)	-4.73 (4.22)	0.02 (0.02)
		1	Mean (Std. Dev)	1.18 (0.11)	11.56 (6.85)	-4.84 (6.57)	0.04 (0.06)
	1	0	Mean (Std. Dev)	1.70 (0.29)	27.28 (12.44)	8.92 (15.90)	0.14 (0.06)
		1	Mean (Std. Dev)	1.52 (0.23)	29.62 (14.85)	5.39 (16.56)	0.17 (0.10)
Total	-	-	Mean (Std. Dev)	1.95 (0.99)	26.36 (17.79)	3.30 (10.05)	0.14 (0.11)

4. Research Method and Models

4.1. Research Design: A 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 price and later resell it somewhere else for a profit. Also, Rule 2 redistributes "bargain tokens" to a more dispersed group of bidders. PennyLeader also regularly conducts many auctions of 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. But, after 28 days of "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, that is, from the 30th week to the 46th week, centered on the 38th week when the 3 rules were implemented. There are several benefits of this sample period. First, it is longest symmetric sample period around the rules implementation date. Second, fortunately, this sample period does not extend to December, during which sales surged because of the Christmas holiday, avoiding possible seasoning effects.

In the following steps of experiment, we will track the unique bidders' behaviors on products auctions (non-token auctions) during the sample period. We also controlled for product assortment before and after the rule implementation. Among the products auctioned off that were included in our empirical analysis, these constitute 90% of all products auctioned off in the same period.

4.2. Definitions of Variables

4.2.1. Independent Variable

(1) A Dummy Variable That Indicates Before and After the Rules Change.

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.

4.2.2. Dependent Variables

(1) Consumer Surplus (for Model 1)

We define the consumer surplus for bidder j as follows.

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

Here, since we do not have the willingness-to-pay of each bidder, we are forced to use the suggested retail price as a proxy. The suggested retailed price is listed on the PennyLeader website and is observable to all bidders. As a consequence, to be more precise, 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 price posted on PennyLeader is higher than the average actual retail price, which is a common marketing tactic that takes advantage of the framing effect (Tversky and Kahneman 1981).

(2) Gini Cofficients (for Model 1)

The most prevalent measure of inequality in the literature is Gini Coefficient, which is widely used to measure the income disparity. The standard Gini coefficient ranges from 0 to 1, and a value of 0 represents perfect equality (Christian and Weiner, 2000). Similarly, a value of 1 expresses a status of extreme inequality, in which one person earns all income while the others earn nothing.

We need to adopt a modified Gini coefficient in this study 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 our penny auctions context:

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

where $s_j = S_j/n\bar{S}$ 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 $S_1 \leq \cdots \leq S_m$.

(3) FGT Metrics (for Model 1)

As a supplement of the Gini coefficient, we include the FGT metrics that can also be used to analyze equality of surplus distribution. There are three well-known FGT metrics: (1) headcount (HC) that measures the incidence of poverty; (2) poverty gap index (PGI) that reveals the intensity of poverty; and (3) squared poverty gap index (SPGI) that depicts the income inequality among the poor. The higher values these metrics are, the higher level of poverty there is. The general specification of FGT metrics is

$$FGT_{\alpha}=\frac{1}{N}\sum_{i=1}^{H}\left(\frac{z-y_i}{z}\right)^{\alpha}$$

where z is the poverty line, N is the number of individuals in the system, H is the number of poor, y_i is the income of individual i, and α is a parameter determining the specification of the formula. When α is set as 0, the above formula results in the headcount equation:

$$HC = \frac{1}{N}\sum_{i=1}^{H} 1 = \frac{H}{N}$$

Similar, when α equals to 1 or 2, we have formulas of the Poverty Gap Index (PGI) and Squared Poverty Gap Index (SPGI), respectively, which are specified as

$$PGI = \frac{1}{N}\sum_{i=1}^{H} \frac{z - y_i}{z}$$

$$SPGI = \frac{1}{N}\sum_{i=1}^{H} \left(\frac{z - y_i}{z}\right)^2$$

As α increases, individual with lower income is given more weight in the measure.

(4) Consumer Retention (for Model 2)

For each unique bidder in each week, we create a dummy variable: it is one when the bidder spent at least one token in that week and is zero otherwise.

(5) Auctions Participation (for Model 3)

We operationalize "participation" in two ways: (1) the number of auctions participated by a unique bidder in one week; (2) the number of tokens spent by a unique bidder in one week.

4.2.3. Key Control Variables

(1) Bidder Types (for Models 2 and 3)

We split bidders into two groups: frequent (aggressive) bidders and occasional (marginal) bidders. Frequent bidders are defined as bidders who violated any one of the three rules before September 23^{rd} 2010. In other words, it is highly possible that these bidders may be constrained by the three rules. Occasional bidders are the rest of the bidders who never violated three rules before September 23rd 2010. In other words, those bidders supposedly may not be affected 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 win more and also could bid more due to their higher expectation of winning chances.

It is straightforward to infer that three rules may have opposite impacts on these two types of bidders: those frequent aggressive bidders are the target to be confined whereas those occasional marginal bidders are the target to be encouraged to participate more. Therefore, we will conduct regression analyses on two groups of bidders separately.

(2) Consumer Surplus History (for Models 2 and 3)

Our conceptual framework proposes that three rules 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 the 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 the target week. We further redefine this variable into two variables: win surplus and loss surplus if the bidder receive positive and negative surplus, respectively. Specifically, win surplus is defined as the total surplus that a bidder obtain in a week if it is positive and it is zero otherwise. This approach is consistent with the marketing literature (Narayanan and Manchanda 2006). The rationale is that bidders may have different sensitivity to their previous gains and loss. For example, if the bidders are risk-averse or loss aversion, they may react more to the loss surplus than the win surplus. For completeness, we also create two similar variables using the cumulative life-time total win surplus and loss surplus, rather than the lagged one week's surplus. In particular, we also note that variables for the lagged one-week win and loss surplus controls for recency effects in auction participation outcomes, while the variables measuring cumulative total win surplus and loss surplus control for primacy effects in auction participation outcomes. Theoretically, the past surplus and cumulative surplus are motivated by previous literatures of recency and primacy effects (Miller and Campbell 1959; Davelaar et al. 2005; Farr 1973; Anderson and Barrios 1961).

(3) The Number of Products Auctioned in One Week (for Models 2 and 3)

In order to explain bidder participation behaviors in Models 2 and 3, it is intuitive to assume that the number and the type of products are highly correlated with the bidding participation of all bidders. Particularly, if there are more popular products auctioned in a specific week, on average more participation from any type of bidders may occur.

We include two variables to control for the impacts of product offerings. One variable is the number of hot products sold in the target 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.

(4) Profile of Overall Bidder Surplus (for Model 2 and 3)

There is a gap between the first research question and the other two. Specifically, research question 1 analyzes the effect of bidding restriction at a macro level, that is, the overall bidder surplus distribution. Research question 2 and 3, however, target at a micro level by analyzing individual number of auctions participated and number of bids place within a period of time. Hence, it is necessary to bridge this gap by linking the macro level analysis and the micro level analysis.

To do this, we include several control variables that measure the profile of overall bidder surplus in Model 2 and 3. For example, Gini coefficients calculated above are included. The 90th percentile, 75th percentile as well as 50th percentile and 25th percentile of bidder surplus in the group[5] are also used to reveal the effects of bidder surplus changes on bidder participation behaviors. More specifically, the 90th percentile of bidder surplus is the value of top 10 percent surplus achieved by bidders in the group last week. The 75th percentile and 50th percentile of surplus apply the same idea as well. Note that these percentile surpluses are lagged for one week.

Table 4-1 provides descriptive statistics of the above mentioned variables, and Table 4-2 depicts correlation between continuous variables. Except in the last six rows, the number of observations is at the bidder-auction level. In other words, 3480 observations mean 435 unique bidders in 8 week. Therefore, we have 435 occasional bidders and 69 frequent bidders in this balanced panel dataset. Without any sophisticated statistical analysis, we can observe that 3 rules seem to be quite influential 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 where as the number of auctions participated increases from 0.52 to 0.57. On the contrary, the average number of bids

[5] The term of "group" indicates either a bidder belongs to frequent bidder or occasional bidder.

from frequent bidders decreases from 44.68 to 31.54 where as the number of auctions participated increases from 2.71 to 1.69. We will rigorously examine the impacts of 3 rules after controlling for various covariates.

Table 4-1 : Descriptive Statistics										
Variable	Before rule changes					After rule changes				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
Occasional bidders										
Dummy of customer retention	3480	0.19	0.39	0.00	1.00	3480	0.26	0.44	0.00	1.00
No. of bids	3480	6.60	36.36	0.00	900.00	3480	7.59	35.32	0.00	859.00
No. of auctions	3480	0.52	1.45	0.00	14.00	3480	0.57	1.40	0.00	16.00
Amount of win last week	3480	2.35	28.19	0.00	927.25	3480	2.42	23.79	0.00	752.50
Amount of loss last week	3480	-2.93	16.62	-396.00	0.00	3480	-4.48	18.91	-576.25	0.00
Cumulative amount of win	3480	9.68	65.02	0.00	927.25	3480	36.15	128.30	0.00	1263.00
Cumulative amount of loss	3480	-12.11	42.49	-567.75	0.00	3480	-52.22	86.04	-812.25	0.00
Frequent bidders										
Dummy of customer retention	552	0.50	0.50	0.00	1.00	552	0.47	0.50	0.00	1.00
No. of bids	552	44.68	126.88	0.00	1721.00	552	31.54	77.66	0.00	716.00
No. of auctions	552	2.71	4.12	0.00	25.00	552	1.69	2.93	0.00	19.00
Amount of win last week	552	27.26	120.68	0.00	1512.25	552	23.68	101.11	0.00	1090.75
Amount of loss last week	552	-9.83	31.83	-467.25	0.00	552	-13.68	32.74	-287.00	0.00
Cumulative amount of win	552	100.46	278.33	0.00	1813.25	552	391.31	658.70	0.00	3357.50
Cumulative amount of loss	552	-31.45	61.05	-561.75	0.00	552	-175.17	144.36	-736.50	0.00
Unique Number of Products (Weekly)										
No. of hot products	8	14.38	1.19	12.00	16.00	8	12.88	3.98	8.00	18.00
No. of common product	8	23.38	7.63	11.00	34.00	8	36.25	7.05	21.00	43.00
Gini Coefficient	8	0.98	0.01	0.97	1.00	8	0.96	0.03	0.91	0.99
90th Percentile Surplus	8	11.44	23.57	-0.75	60.75	8	19.41	29.63	-0.75	82.00
75th Percentile Surplus	8	-1.59	0.63	-3.00	-0.75	8	-1.31	0.53	-2.25	-0.75
50th Percentile Surplus	8	-5.25	1.06	-6.75	-3.75	8	-5.06	2.43	-9.75	-1.50

Table 4-2 : Correlation Between Continuous Variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) No. of Bids	1.00											
(2) No. of Auctions	0.60	1.00										
(3) Amount of Win Last Week	0.28	0.22	1.00									
(4) Amount of Loss Last Week	-0.15	-0.21	0.03	1.00								
(5) Cumulative Amount of Win	0.26	0.23	0.40	-0.16	1.00							
(6) Cumulative Amount of Loss	-0.14	-0.17	-0.08	0.37	-0.41	1.00						
(7) No. of Hot Products	0.06	0.08	0.01	-0.04	-0.06	0.16	1.00					
(8) No. of Common Products	0.00	-0.02	-0.01	-0.02	0.13	-0.30	-0.39	1.00				
(9) Gini Coefficient	-0.03	-0.01	0.00	0.04	-0.07	0.14	-0.48	-0.39	1.00			
(10) 90th Percentile Surplus	0.15	0.23	0.17	-0.11	0.18	-0.15	-0.15	-0.03	0.16	1.00		
(11) 75th Percentile Surplus	0.05	0.08	0.06	-0.01	0.01	0.03	0.05	-0.14	0.01	0.49	1.00	
(12) 50th Percentile Surplus	-0.11	-0.14	-0.06	0.09	-0.15	0.13	0.03	-0.07	-0.04	-0.20	0.15	1.00

4.3. Regression Models

4.3.1. Model 1: Linear Regression

To examine our research question 1, we use a simple OLS regression model with the adjusted Gini coefficient as the key dependent variable (Wooldridge 2009). We are interested in whether Gini coefficient decreases after the rules change. Therefore, we have the regression model

$$G_t = \alpha + \beta d\_rule_t + \varepsilon$$

where G_t is the value of the adjusted Gini coefficient at time t, d_rule_t is a dummy variable indicating if the rules are implemented at time t.

As a supplement of Gini coefficient, we calculate the Foster-Greer-Thorbecke (FGT) metrics to measure the equality of bidder surplus. There are three metrics provided by FGT: headcount, poverty gap index (PGI) and squared poverty gap index (SPGI). Similar to Gini coefficient, we run a linear regression on these three metrics to test the significance of the rule dummy. The regression model of FGT metrics is as follows:

$$headcount_t = \alpha + \beta d\_rule_t + \varepsilon$$

$$PGI_t = \alpha + \beta d\_rule_t + \varepsilon$$

$$SPGI_t = \alpha + \beta d\_rule_t + \varepsilon$$

where $headcount_t$ is the value of headcount at week t, PGI_t is the value of poverty gap index at the week of t, and $SPGI_t$ is the associated squared poverty gap index.

4.3.2. Model 2: Logit Regression

To investigate our research question 2, we use the following panel logit regression (Wooldridge 2009). This analysis is conducted at the unique bidder level with "one week" as one period in this panel dataset. We choose one week due to the following reasons. First, there is a bidding pattern differences on different weekdays. Using weekly panel data eliminates the weekday effects. Second, weekly panel data leads to an appropriate number of sample records.

Therefore, we model the probability of bidder's participation as (Cameron and Trivedi, 2005)

$$\Pr\,(y = 1|\boldsymbol{x_{it}}) = \frac{\exp\,(\boldsymbol{x_{it}}\beta)}{1 + \exp\,(\boldsymbol{x_{it}}\beta)}$$

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

4.3.3. Model 3: Negative Binomial Regression

As can be seen from Table 4-1 about descriptive statistics, there exists an issue of over dispersion in our dataset. Specifically, the variances of the variables are larger than the means of the associated variables, which may be caused by unobserved heterogeneity. To take into account this observation, we apply Negative Binomial model as the principal count model to estimate number of auctions and number of bids. The specification of the Negative Binomial model is as follows:

$$h[y|\mu,\delta] = \frac{\Gamma(\alpha^{-1}+y)}{\Gamma(\alpha^{-1})\Gamma(y+1)}\left(\frac{\alpha^{-1}}{\alpha^{-1}+\mu}\right)^{\alpha^{-1}}\left(\frac{\mu}{\alpha^{-1}+\mu}\right)^{y}$$

$$\mu_i = \exp\,(\boldsymbol{x}_i'\beta)$$

$$V[y|\mu,\alpha] = \ \mu(1+\alpha\mu)$$

where y denotes number of auctions participated (or number of bids placed) within a week, x is a vector of covariates including the dummy variable of rule changes and control variables, $\Gamma(.)$ denotes the gamma integral which specializes to a factorial for an integer argument, and $\alpha = 1/\delta$.

5. Results and Findings

5.1. RQ1: Equality of Consumer Surplus

Figure 5-1 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. This is consistent with our earlier claim that a small proportion of the bidders earn most of the consumer surplus, resulting in a high level of unfairness.

The introduction of three rules did not improve the surplus distribution immediately. There is no drop until the 40th week, 2 weeks after the rule changes. This could result from the grace period. The Gini coefficients were much lower between the 40th and the 43rd week, which visually confirms our prediction that the rules may improve the surplus distribution. However, the Gini coefficients seem to deteriorate (rise) again after Week 44th, which could imply the effects of rules change diminished in the end.

We further conduct a regression to check if there is a statistically significant effect of the rules on the Gini coefficients. As shown in Table 5-1, the dummy variable of rules change is significantly negative. Hence, three rules indeed improve the inequality among bidders: Gini coefficients became smaller. In sum, we can conclude that the three bidding restrictions contribute to a more equalized distribution of consumer surplus.

Table 5-1 : Regression on Gini Coefficients

Independent Variable	Dependent Variable: Gini Coefficients	
	8 Weeks' Window	4 Weeks' Window
Dummy of Rule Change	**-0.0260**** **(0.0110)**	**-0.0428*** **(0.0181)**
Constant	0.9814*** (0.0078)	0.9830*** (0.0128)
Observations	16	8
R-squared	0.2860	0.4822
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1		

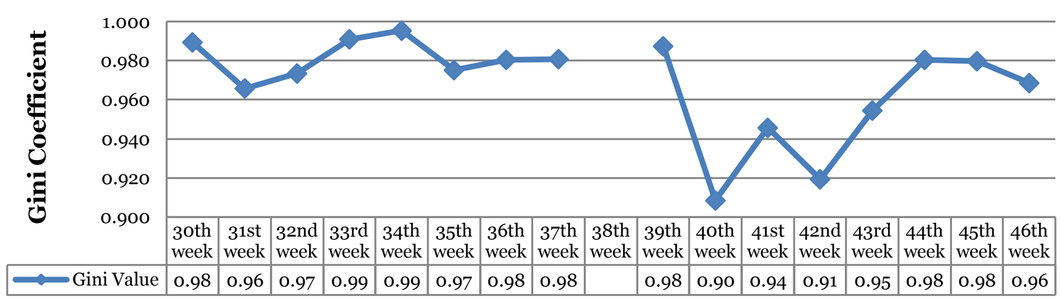

Figure 5-1 : Comparison of Gini Coefficients

5.2. RQ2: Bidder Retention

Table 5-2 reports the results of Model 2 that applies Logit model to estimate bidder's retention rate. Bidder retention is defined as a bidder's probability of participation in Model 2, results of which are shown in column (a). As can be seen, the coefficient of the independent variable (the dummy variable of rule change) has different effects on occasional bidders and frequent bidders. Specifically, the coefficient is significantly positive for occasional bidders, suggesting that the rules increase occasional bidder's participation probability. We further calculate the marginal effects of the dummy variable, from which we get 0.11. This implies that occasional bidder's probability of participation is increased by 11% with the introduction of the rules. *Therefore, we conclude that the bidding restrictions have an economically and statistically significant impact on occasional bidder's retention.*

For frequent bidders, the rules do not reduce their participation rate, as the coefficient of the rule dummy is not significant. This suggests the ideal outcome that we expect: frequent bidders all maintain the same level of participation whereas occasional bidders increase their chances to bid.

To further acquaint more understandings of the effects of the rules, covariates such as bidder's surplus history and website specific variables are added to the model. The estimated results of these additional models are shown in Column (b) and Column (f) of Table 5-2. As shown, controlling either bidder-specific or website-specific variables does not change the previous results. The coefficients of the rule dummy are consistently positive for occasional bidders, while they are negative for frequent bidders.

5.3. RQ3: Auctions Participation by Bidders

Using Negative Binomial models, we analyze bidder's auction participation from two perspectives: the number of auctions they participate and the number of bids they place. The results of the regressions are shown in Table 5-3 and Table 5-4. Generally, the rules have positive effects on occasional bidders but negative effects on frequent bidders, either it is with respect to number of bids or number of auctions. All control variables are significant in most of the cases.

The interpretations of the coefficients of the dummy variables in Column (a) of Table 5-3 are as follows: the three rules increase the expected number of bids of occasional bidders by 1.43 (=exp(0.3593)) times whereas three rules 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 three 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), three rules become even more impactful, it could increase the expected number of bids by 1.79 times.

With respect to the number of auctions in Column (e), our results suggest that occasional bidders participated in 1.37 (=exp(0.3121)) or 2.10 (=exp(0.7422)) times more auctions whereas frequent bidders participated in 0.75 (=exp(-0.2862)) or 0.35 (=exp(-1.0617)) times fewer auctions. The overall effect is that three rules could have increased the participation in the number of auctions by 28% or 86%.

Table 5-2 : Results of Model 2 (Binary Logit Model of Participation Probability)

VARIABLES	(a) (1) Occasional Bidders	(a) (2) Frequent Bidders	(b) (1) Occasional Bidders	(b) (2) Frequent Bidders	(c) (1) Occasional Bidders	(c) (2) Frequent Bidders	(d) (1) Occasional Bidders	(d) (2) Frequent Bidders
Dummy of Rule Changes	0.4466***	-0.1600	0.8477***	-0.1741	0.8494***	-0.5203**	1.1128***	-1.0442***
	(0.0598)	(0.1334)	(0.0736)	(0.1963)	(0.0873)	(0.2219)	(0.1004)	(0.3436)
Amount of Win Last Week			0.0105***	0.0060***	0.0105***	0.0058***	0.0105***	0.0049***
			(0.0019)	(0.0017)	(0.0019)	(0.0017)	(0.0020)	(0.0017)
Amount of Loss Last Week			-0.0209***	-0.0197***	-0.0193***	-0.0184***	-0.0190***	-0.0151***
			(0.0022)	(0.0036)	(0.0022)	(0.0036)	(0.0022)	(0.0036)
Cumulative Previous Amount of Win			-0.0002	0.0005**	-0.0001	0.0006**	-0.0001	0.0005*
			(0.0006)	(0.0003)	(0.0006)	(0.0003)	(0.0006)	(0.0003)
Cumulative Previous Amount of Loss			0.0094***	0.0014	0.0084***	0.0014	0.0085***	0.0011
			(0.0010)	(0.0010)	(0.0010)	(0.0011)	(0.0010)	(0.0012)
No. of Hot Product in the Week					0.0794***	0.1364***	0.1567***	0.1160*
					(0.0113)	(0.0280)	(0.0207)	(0.0594)
No. of Common Product in the Week					0.0040	0.0414***	0.0140***	0.0726***
					(0.0047)	(0.0112)	(0.0054)	(0.0144)
Gini Coefficient of the Week							13.1460***	-4.8867
							(2.4034)	(8.1720)
90th Percentile Surplus Among Bidders in the Group							-0.0024	0.0062***
							(0.0016)	(0.0013)
75th Percentile Surplus Among Bidders in the Group							0.3668***	-0.0082***
							(0.0837)	(0.0031)
50th Percentile Surplus Among Bidders in the Group							-0.0766***	-0.0279
							(0.0262)	(0.0181)
Observations	6,960	1,088	6,960	1,088	6,960	1,088	6,960	1,088
Number of bidder_id2	435	68	435	68	435	68	435	68

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

Table 5-3 : Results of Model 3 (Negative Binomial Regression of No. of Bids)

VARIABLES	(a) (1) Occasional Bidders	(a) (2) Frequent Bidders	(b) (1) Occasional Bidders	(b) (2) Frequent Bidders	(c) (1) Occasional Bidders	(c) (2) Frequent Bidders	(d) (1) Occasional Bidders	(d) (2) Frequent Bidders
Dummy of Rule Changes	0.3593***	-0.1538*	0.4003***	-0.3018***	0.4957***	-0.4891***	0.7065***	-0.9042***
	(0.0509)	(0.0854)	(0.0546)	(0.1120)	(0.0707)	(0.1328)	(0.0782)	(0.1940)
Amount of Win Last Week			0.0031***	0.0014***	0.0028***	0.0014***	0.0030***	0.0013***
			(0.0004)	(0.0002)	(0.0004)	(0.0003)	(0.0004)	(0.0003)
Amount of Loss Last Week			-0.0061***	-0.0052***	-0.0053***	-0.0045***	-0.0051***	-0.0037***
			(0.0007)	(0.0008)	(0.0007)	(0.0008)	(0.0007)	(0.0009)
Cumulative Previous Amount of Win			0.0004*	0.0005***	0.0005**	0.0005***	0.0004*	0.0005***
			(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Cumulative Previous Amount of Loss			0.0013***	0.0003	0.0008**	0.0000	0.0008*	-0.0001
			(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0004)	(0.0005)
No. of Hot Product in the Week					0.0756***	0.0900***	0.1421***	0.0577
					(0.0093)	(0.0165)	(0.0172)	(0.0354)
No. of Common Product in the Week					-0.0028	0.0198***	0.0068	0.0375***
					(0.0039)	(0.0070)	(0.0044)	(0.0086)
Gini Coefficient of the Week							11.1602***	-6.6893
							(1.9646)	(4.9171)
90th Percentile Surplus Among Bidders in the Group							-0.0022	0.0041***
							(0.0014)	(0.0008)
75th Percentile Surplus Among Bidders in the Group							0.2775***	-0.0050**
							(0.0690)	(0.0020)
50th Percentile Surplus Among Bidders in the Group							-0.0564**	-0.0264**
							(0.0222)	(0.0108)
Constant	-2.9964***	-1.8345***	-3.0197***	-1.9592***	-4.0478***	-3.7047***	-16.0112***	2.1900
	(0.0442)	(0.0679)	(0.0451)	(0.0714)	(0.1850)	(0.3244)	(2.1763)	(5.2460)
Observations	6,960	1,104	6,960	1,104	6,960	1,104	6,960	1,104
Number of bidder_id2	435	69	435	69	435	69	435	69

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

Table 5-4 : Results of Model 3 (Negative Binomial Regression of No. of Auctions)

VARIABLES	(a)		(b)		(c)		(d)	
	(1) Occasional Bidders	(2) Frequent Bidders	(1) Occasional Bidders	(2) Frequent Bidders	(1) Occasional Bidders	(2) Frequent Bidders	(1) Occasional Bidders	(2) Frequent Bidders
Dummy of Rule Changes	0.3121***	-0.2862***	0.4525***	-0.3510***	0.5243***	-0.5984***	0.7422***	-1.0617***
	(0.0503)	(0.0816)	(0.0559)	(0.1119)	(0.0709)	(0.1258)	(0.0772)	(0.1803)
Amount of Win Last Week			0.0035***	0.0009***	0.0033***	0.0010***	0.0035***	0.0008***
			(0.0004)	(0.0002)	(0.0004)	(0.0002)	(0.0004)	(0.0002)
Amount of Loss Last Week			-0.0068***	-0.0048***	-0.0060***	-0.0044***	-0.0059***	-0.0034***
			(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Cumulative Previous Amount of Win			0.0001	0.0004***	0.0001	0.0003***	0.0001	0.0003***
			(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)
Cumulative Previous Amount of Loss			0.0029***	0.0006	0.0023***	0.0006	0.0024***	0.0005
			(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
No. of Hot Product in the Week					0.0709***	0.0786***	0.1411***	0.0329
					(0.0091)	(0.0158)	(0.0170)	(0.0329)
No. of Common Product in the Week					-0.0020	0.0272***	0.0076*	0.0445***
					(0.0038)	(0.0067)	(0.0043)	(0.0081)
Gini Coefficient of the Week							11.6413***	-8.6883*
							(1.9259)	(4.5762)
90th Percentile Surplus Among Bidders in the Group							-0.0021	0.0044***
							(0.0014)	(0.0007)
75th Percentile Surplus Among Bidders in the Group							0.3172***	-0.0061***
							(0.0685)	(0.0019)
50th Percentile Surplus Among Bidders in the Group							-0.0620***	-0.0185*
							(0.0221)	(0.0101)
Constant	-1.5510***	-0.5252***	-1.5014***	-0.6305***	-2.4758***	-2.3492***	-14.9171***	5.7871
	(0.0565)	(0.0880)	(0.0596)	(0.0922)	(0.1861)	(0.3157)	(2.1334)	(4.8800)
Observations	6,960	1,104	6,960	1,104	6,960	1,104	6,960	1,104
Number of bidder_id2	435	69	435	69	435	69	435	69

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

5.4. Robustness Check

To conduct robustness of the Negative Binomial model, we use the panel Poisson regression which is widely applied to model nonnegative integer dependent variable (Cameron and Trivedi, 2005). In order to apply the Poisson model, following assumptions are made: (1) the dependent variable has a Poisson distribution; and (2) the occurrences of a bid and participating in an auction (i.e. auction participation) are independent. Therefore, we have the Poisson regression model specification:

$$f(y|\boldsymbol{x_{it}}, \beta) = e^{-\exp(x_{it}'\beta)} \exp(\boldsymbol{x_{it}}'\beta)^{\mathrm{y}} /\mathrm{y}!$$

where y denotes number of auctions participated (or number of bids placed) within a week, x is a vector of covariates including the dummy variable of rule changes and control variables.

As shown in Table 5-5 and Table 5-6, there provide consistent results as Table 5-3 and Table 5-4: the variable of interests (i.e. the dummy of rule changes) is of the same coefficient sign as the original models. Besides, we also consider the effect of the grace period in this robustness check. The grace period covers the first 28 days after 23rd Sep 2010. We exclude observations during this period and rerun Model 2 and 3. The results of which are shown in Table 5-7. The results verify our previous results as well. In a nutshell, we are satisfied with the robustness of results from our original models.

Table 5-5 : Results of Model 3 (Poisson Regression of No. of Bids)

VARIABLES	(a) (1) Occasional Bidders	(a) (2) Frequent Bidders	(b) (1) Occasional Bidders	(b) (2) Frequent Bidders	(c) (1) Occasional Bidders	(c) (2) Frequent Bidders	(d) (1) Occasional Bidders	(d) (2) Frequent Bidders
Dummy of Rule Changes	0.1393***	-0.3483***	0.8246***	-0.0255	0.5855***	-0.2760***	0.6621***	-0.7067***
	(0.0090)	(0.0099)	(0.0120)	(0.0157)	(0.0136)	(0.0164)	(0.0162)	(0.0230)
Amount of Win Last Week			0.0038***	0.0009***	0.0035***	0.0010***	0.0036***	0.0009***
			(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Amount of Loss Last Week			-0.0052***	-0.0031***	-0.0049***	-0.0028***	-0.0051***	-0.0024***
			(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Cumulative Previous Amount of Win			-0.0005***	-0.0000	-0.0005***	-0.0001***	-0.0006***	-0.0001***
			(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Cumulative Previous Amount of Loss			0.0052***	0.0017***	0.0052***	0.0019***	0.0052***	0.0017***
			(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
No. of Hot Product in the Week					0.0908***	0.0849***	0.0997***	0.0325***
					(0.0018)	(0.0021)	(0.0032)	(0.0043)
No. of Common Product in the Week					0.0239***	0.0366***	0.0200***	0.0440***
					(0.0007)	(0.0008)	(0.0008)	(0.0010)
Gini Coefficient of the Week							1.9846***	-9.5377***
							(0.3585)	(0.5634)
90th Percentile Surplus Among Bidders in the Group							-0.0018***	0.0034***
							(0.0003)	(0.0001)
75th Percentile Surplus Among Bidders in the Group							0.3147***	-0.0065***
							(0.0123)	(0.0003)
50th Percentile Surplus Among Bidders in the Group							-0.1239***	-0.0276***
							(0.0042)	(0.0013)
Observations	6,960	1,104	6,960	1,104	6,960	1,104	6,960	1,104
Number of bidder_id2	435	69	435	69	435	69	435	69

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

Table 5-6 : Results of Model 3 (Poisson Regression of No. of Auctions)

VARIABLES	(a) (1) Occasional Bidders	(a) (2) Frequent Bidders	(b) (1) Occasional Bidders	(b) (2) Frequent Bidders	(c) (1) Occasional Bidders	(c) (2) Frequent Bidders	(d) (1) Occasional Bidders	(d) (2) Frequent Bidders
Dummy of Rule Changes	0.0970***	-0.4746***	0.5004***	-0.4352***	0.4899***	-0.6275***	0.7319***	-1.0247***
	(0.0326)	(0.0417)	(0.0397)	(0.0650)	(0.0465)	(0.0677)	(0.0517)	(0.0957)
Amount of Win Last Week			0.0042***	0.0007***	0.0041***	0.0008***	0.0042***	0.0007***
			(0.0003)	(0.0001)	(0.0003)	(0.0001)	(0.0003)	(0.0001)
Amount of Loss Last Week			-0.0059***	-0.0047***	-0.0054***	-0.0045***	-0.0056***	-0.0036***
			(0.0005)	(0.0004)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Cumulative Previous Amount of Win			-0.0012***	0.0001*	-0.0012***	0.0000	-0.0013***	-0.0000
			(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Cumulative Previous Amount of Loss			0.0043***	0.0006**	0.0040***	0.0009***	0.0041***	0.0008**
			(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
No. of Hot Product in the Week					0.0667***	0.0568***	0.1397***	0.0086
					(0.0063)	(0.0088)	(0.0115)	(0.0178)
No. of Common Product in the Week					0.0032	0.0296***	0.0114***	0.0432***
					(0.0025)	(0.0034)	(0.0028)	(0.0042)
Gini Coefficient of the Week							11.9876***	-8.4364***
							(1.2886)	(2.4491)
90th Percentile Surplus Among Bidders in the Group							-0.0019**	0.0043***
							(0.0009)	(0.0004)
75th Percentile Surplus Among Bidders in the Group							0.4083***	-0.0075***
							(0.0443)	(0.0010)
50th Percentile Surplus Among Bidders in the Group							-0.0883***	-0.0069
							(0.0151)	(0.0053)
Observations	6,960	1,104	6,960	1,104	6,960	1,104	6,960	1,104
Number of bidder_id2	435	69	435	69	435	69	435	69

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

Table 5-7 : Results of Regressions (Excluding the Grace Period within 28 Days After 23rd Sep 2010)

Independent Variable	Dummy of Bidder Participation				No. of Bids				No. of Auctions			
	Logit Model (Simple Specification)		Logit Model (Full Specification)		Negative Binomial (Simple Specification)		Negative Binomial (Full Specification)		Negative Binomial (Simple Specification)		Negative Binomial (Full Specification)	
	Occasional Bidders	Frequent Bidders	Occasional Bidders	Frequent Bidders	Occasional Bidders	Frequent Bidders	Occasional Bidders	Frequent Bidders	Occasional Bidders	Frequent Bidders	Occasional Bidders	Frequent Bidders
Dummy of Rule Changes	-0.0313	-0.8200***	0.3467	-1.7187**	-0.0440	-0.5766***	0.1423	-1.3525***	-0.0969	-0.6663***	0.1684	-1.3395***
	(0.0792)	(0.1752)	(0.2704)	(0.7754)	(0.0677)	(0.1177)	(0.2260)	(0.4787)	(0.0672)	(0.1153)	(0.2237)	(0.4553)
Amount of Win Last Week			0.0107***	0.0139***			0.0029***	0.0013***			0.0032***	0.0008***
			(0.0023)	(0.0047)			(0.0005)	(0.0003)			(0.0005)	(0.0003)
Amount of Loss Last Week			-0.0158***	-0.0177***			-0.0071***	-0.0034***			-0.0073***	-0.0032***
			(0.0027)	(0.0047)			(0.0011)	(0.0011)			(0.0012)	(0.0011)
Cumulative Previous Amount			0.0004	0.0007**			0.0009***	0.0006***			0.0007**	0.0004***
of Win			(0.0007)	(0.0003)			(0.0003)	(0.0001)			(0.0003)	(0.0001)
Cumulative Previous Amount			0.0092***	0.0014			0.0020***	0.0004			0.0033***	0.0008
of Loss			(0.0013)	(0.0014)			(0.0006)	(0.0007)			(0.0006)	(0.0007)
No. of Hot Product in the			0.1192***	0.1320			0.1036***	0.0650			0.1083***	0.0452
Week			(0.0394)	(0.0932)			(0.0330)	(0.0572)			(0.0326)	(0.0545)
No. of Common Product in the			0.0390***	0.1128***			0.0259***	0.0652***			0.0277***	0.0668***
Week			(0.0069)	(0.0222)			(0.0057)	(0.0131)			(0.0056)	(0.0127)
Gini Coefficient of the Week			5.2063	17.0903			5.7050	6.2339			6.2509	6.4881
			(6.1188)	(13.2905)			(5.0889)	(8.3559)			(5.0298)	(8.0132)
90th Percentile Surplus			-0.0004	0.0021			-0.0009	0.0007			-0.0008	0.0020
Among Bidders in the Group			(0.0019)	(0.0041)			(0.0016)	(0.0024)			(0.0016)	(0.0023)
75th Percentile Surplus			0.4225***	-0.0030			0.3388***	-0.0009			0.3656***	-0.0023
Among Bidders in the Group			(0.0984)	(0.0046)			(0.0808)	(0.0029)			(0.0797)	(0.0027)
50th Percentile Surplus			-0.0854***	0.0298			-0.0679***	0.0165			-0.0714***	0.0163
Among Bidders in the Group			(0.0308)	(0.0326)			(0.0256)	(0.0200)			(0.0253)	(0.0193)
Constant					-2.8896***	-1.8022***	-10.4394**	-10.4660	-1.4811***	-0.6148***	-9.5738*	-9.3609
					(0.0494)	(0.0727)	(5.2604)	(8.8336)	(0.0661)	(0.0965)	(5.1973)	(8.4615)
Observations	4,320	780	4,320	780	4,320	792	4,320	792	4,320	792	4,320	792
Number of bidder_id2	360	65	360	65	360	66	360	66	360	66	360	66

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

5.5. Further Testing of RQ1: A FGT Metrics Method

5.5.1. Measuring Bidder Surplus Using FGT Metrics

Though our Gini coefficients have well demonstrated the trend of surplus distribution changes, there is still a gap for us to analyze the surplus changes at individual level. In particular, RQ 1 is at a macro level, while RQ 2 and RQ 3 are at a micro level to measure the effect of the rules. To fill this gap, we apply the Foster-Greer-Thorbecke (FGT) metrics to reveal the surplus distribution from 3 perspectives: the extent of low surplus, the intensity of low surplus and the surplus inequality among the low-type bidders (Foster et al., 1984). With a predefined threshold (or cutoff), low surplus refers to bidder's weekly surplus that is lower than the threshold. Low-type bidders are bidders with low surplus. Similarly, there are high-type bidders with surplus that is higher than the threshold, i.e., the high surplus.

FGT metrics are used to measure poverty level in an economy (Foster, J., et al. 1984). There are three well-known FGT metrics: (1) headcount (HC) that measures the incidence of poverty; (2) poverty gap index (PGI) that reveals the intensity of poverty; and (3) squared poverty gap index (SPGI) that depicts the income inequality among the poor. The higher values these metrics are, the higher level of poverty there is.

There are several reasons for applying FGT to measure surplus distribution in penny auction. First, it is simple, and it has the ability to tolerate negative incomes (or surplus). Unlike the complicated adjusted Gini formula in previous chapter, FGT has simple specifications and thus is easier for interpretations. Second, FGT provides diverse metrics in analyze poverty level, which provides better insights of the phenomenon. For example, in SPGI, individuals with lower surplus are given more weight in the measure. In this case, we would be able to consider the heterogeneity of bidders in respect of their surplus levels. Finally, FGT can fit very well into the context of penny auction. For example, in penny auction bidder's surplus distribution is biased and different bidders are likely to have different surplus. Low bidder surplus is analogous to low income in macroeconomics (i.e. income below the poverty line), and high bidder surplus can be analogous to high income. With these similarities the penny auction context can be modeled using FGT metrics.

5.5.2. Determining the Surplus Threshold

To subjectively decide the surplus threshold z, we apply Probit model using probability of participation as dependent variable and bidder's surplus of last week as independent variable. Intuitively, this surplus threshold would be better if it could satisfy two criteria. First, it should be positive; otherwise it contradicts the common understanding of "poverty line". Second, it would better if it is of a reasonable order of magnitude. A too large threshold in the penny auction context is not a sound one. This is because an extreme small group of the bidders (5%) are winning the majority of the auctions, resulting in a poor surplus for the majority of bidders. Such poor surplus wouldn't be too large. Therefore, if the threshold is too large it cannot be applied to all the bidders.

We separately estimate the model both before and after the rule changes at the 38th week of the year. Occasional bidders and frequent bidders are considered as a whole but not separate. This provides us with insights of how bidders' surplus affects their participation behaviors. The result is depicted in Figure 5-2. This figure shows the relationship between bidder's weekly surplus and the corresponding estimated participating probability. In general, higher surplus is related to higher probability of participation. The two curves intersect at the point (13.5, 0.696), which provides us a cutoff of 13.5 SGD per week. This cutoff is reasonable because it is located within a reasonable range, positive but not too large.

As shown in Figure 5-2, bidders with surplus smaller than 13.5 SGD per week are stimulated by the 3 rules, as they are more likely to participate in penny auction after the rule changes. In contrast, if a bidder has a surplus level above 13.5 SGD per week, he is inclined to participate less with the 3 rules. This is probably due of the bidding restrictions that hamper him to obtain larger surplus, thus discouraging them to participate.

As a result, we can use this threshold (i.e. 13.5 SGD per week) to define high-type bidders and low-type bidders, using similar method that is been widely applied in macroeconomics to define the rich and the poor. Bidders above this threshold seem to be constrained by the rules, as their participation probability is reducing after the rule change. These bidders, therefore, can be treated as the high-type bidders. On the other hand, bidders below this threshold are struggling for a better surplus, and they form the low-type bidders.

Besides, the result in Figure 5-2 is helpful for us to roughly estimate new bidders' bidding intentions [6]. As can be seen, bidders with zero-surplus have increased probabilities of participation. Specifically, when surplus equals to zero, the associated probability increases by 1 percent and reaches 0.69. Though it is not a significant (and large) increase, it is consistent with our prediction. Our intention to introduce the three rules is to retain the majority of bidders. This intention is, substantially, to obtain a higher likelihood of bidder's participating. The implication of this result is important. Without the help of additional research methodology such as survey, we managed to measure potential entrants' likelihood to participate in penny auction.

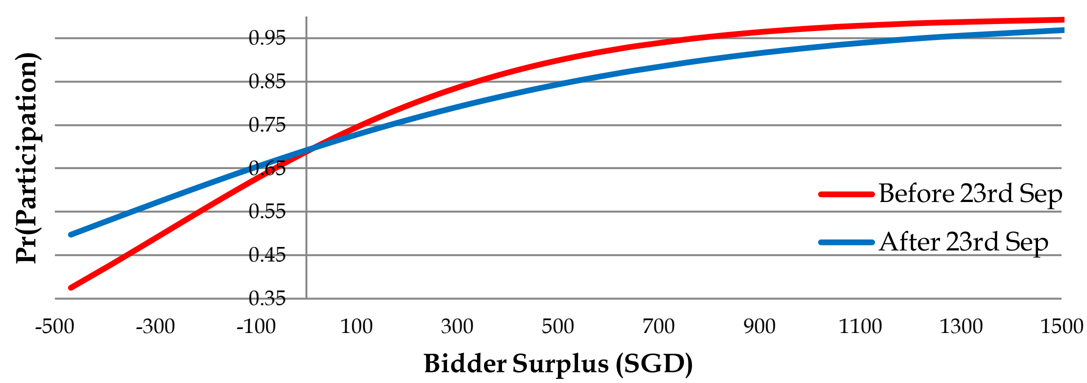

Figure 5-2 : Probability of Participation Using Probit Model

[6] New bidders, in this case, are those bidders who have zero surpluses. This is reasonable in the context of penny auction due to the effect of bidding fee. As long as a bidder places a bid, one token will be deducted from his account and thus causes a negative surplus for him.

5.5.3. Results of FGT Estimations

To apply FGT, the only obstacle is how to define the level of low surplus (i.e. the poverty line). Instead of determining it intuitively, we use Probit model to come out with the exact value of this threshold. As a consequence, we determine the threshold as 13.5 SGD. That is, a bidder with weekly surplus larger than 13.5 SGD is treated as high-type bidder (or, the rich), and low-type bidders are those who obtain weekly surplus lower than 13.5 SGD (including negative surplus).

The results of the 3 FGT metrics are shown in Figure 5-3 to Figure 5-5. There are consistent conclusions which suggest that the majority of bidders have better surplus after the 3 rules were introduced. Take Figure 5-3, the average headcount ratio is lower after the rule implementation (at the 38^{th} week). Besides, after a significant drop between the 40^{th} week and the 42^{nd} week, the headcount ratio is approaching towards a stable and low level.

As depicted in Figure 5-4 and Figure 5-5, there are significant drops of either PGI or SPGI at the 39^{th} week, suggesting that the 3 rules are indeed mitigating the level of low surplus among the low-type bidders. In both figures, the values of indices are temporally higher between the 35^{th} week and the 38^{th} week. That suggests there is larger proportion of low-type bidders during this period. This is consistent with the fact that a small group of bidders are winning most of the auctions.

Furthermore, we conduct regressions on the three FGT metrics using the rule dummy as the independent variable. As can be seen in Table 5-8, the coefficient of the rule dummy, though not significant, suggests negative effects of the three rules. That means after the rule changes the FGT metrics are reduced, though the reductions are not significant. We can confirm such reduction from Figure 5-3 to Figure 5-5.

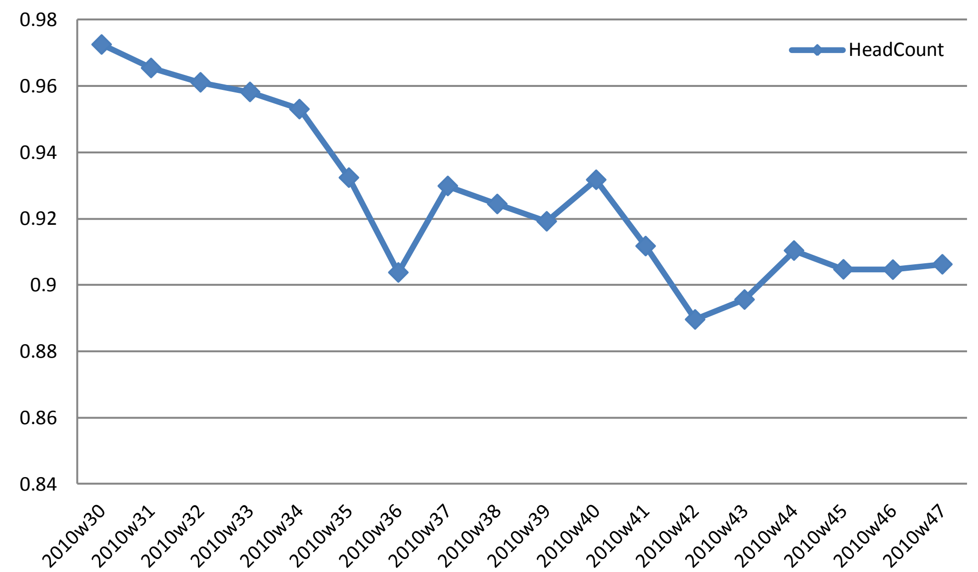

Figure 5-3 : Headcount of PennyLeader

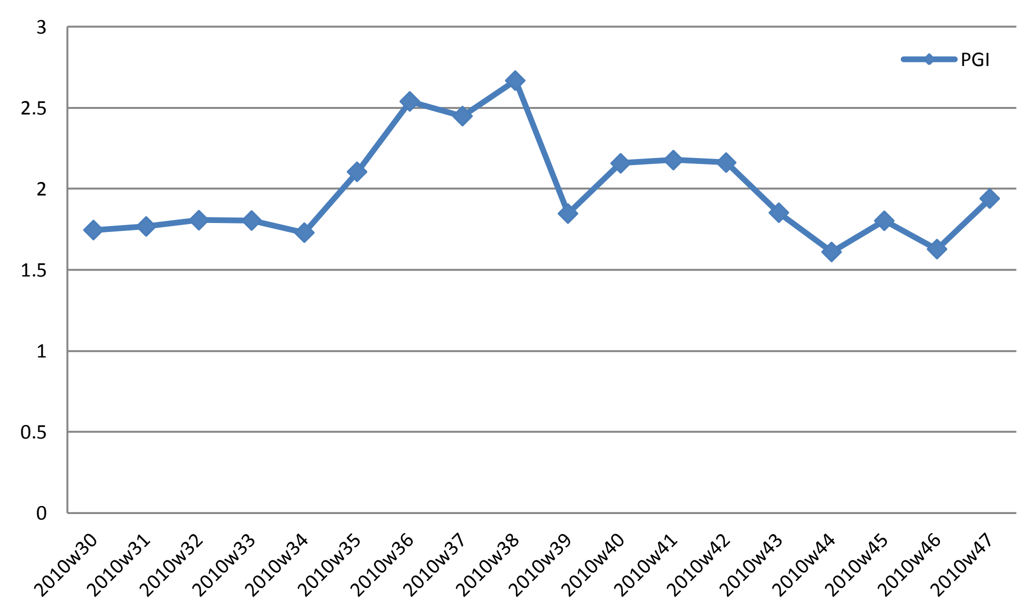

Figure 5-4 : Poverty Gap Index (PGI) of PennyLeader

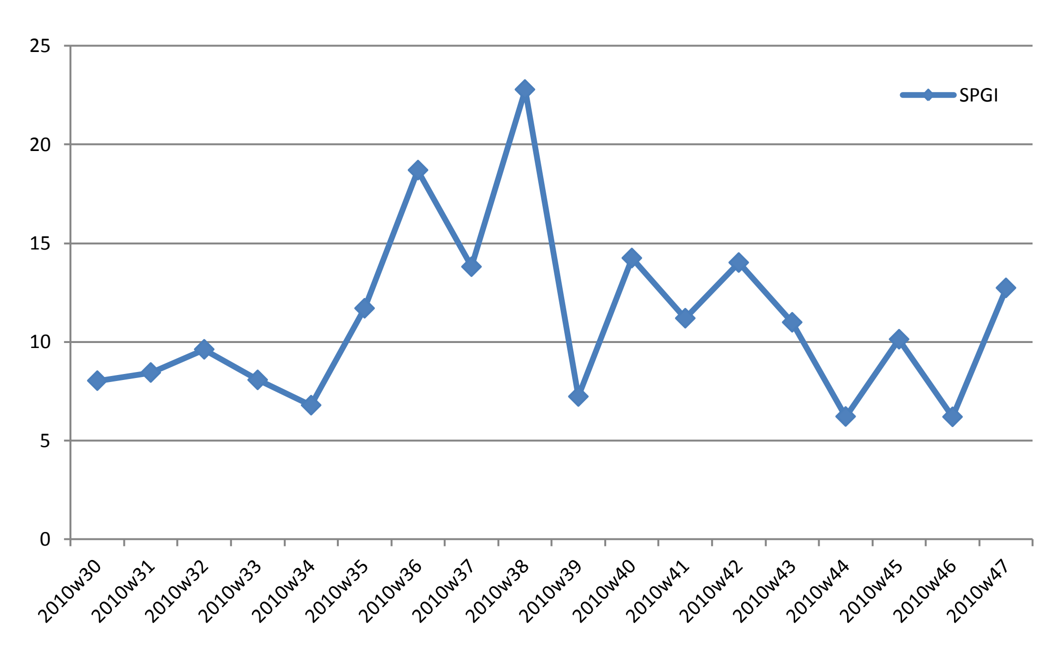

Figure 5-5 : Squared Poverty Gap Index (SPGI) of PennyLeader

Table 5-8 : Regression on FGT Metrics

Independent Variable	8 Weeks' Windows			4 Weeks' Window		
	(1) Headcount	(2) PGI	(3) SPGI	(1) Headcount	(2) PGI	(6) SPGI
Dummy of Rule Change	**-0.0423*** (0.0093)**	**-0.0928 (0.1561)**	**-0.6180 (1.8095)**	**-0.0205 (0.0131)**	**-0.1282 (0.2184)**	**-1.0779 (2.9624)**
Constant	0.9466*** (0.0066)	2.0811*** (0.1104)	10.6432*** (1.2795)	0.9291*** (0.0093)	2.3126*** (0.1544)	12.7476*** (2.0947)
Observations	16	16	16	8	8	8
R-squared	0.5953	0.0246	0.0083	0.2895	0.0543	0.0216

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

To obtain a more insightful view of how the values of the poverty line change across time, we depict Figure 5-6 that shows the weekly value of the poverty cutoff from week 39 to week 46. Note that we need two curves, both before rule change and after rule change, to generate the intersect point that determines the poverty line. Hence, we vary the window size from 1 week to 8 weeks and generate 8 different values of poverty line.

As can be seen, from the first week after the rule change, the values of the cutoff point rise as time increases. For instance, at week 39 the cutoff point is -42.5. This indicates that as long as a bidder have weekly surplus larger than -42.5 SGD, he can be counted as above the surplus standard. Hence, it is suggested that the majority of bidders are experiencing extremely negative surplus at that week. As time increases, the value of the poverty cutoff increases as well. Somewhere between the 43rd week and the 44th week, it reaches a positive value. After 8 weeks, at the 46th week, it reaches 13.5. As the value of the cutoff represents the "living standard" of bidders, it is obvious that bidders are improving in respect of their weekly surplus. Therefore, it supports our purpose of designing the 3 rules that they can mitigate the skewed surplus distribution.

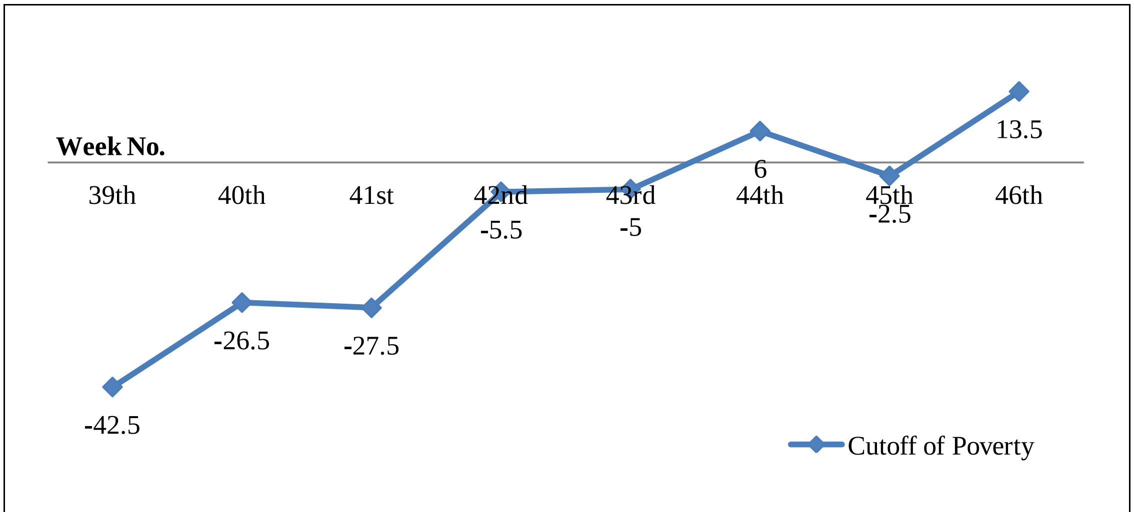

Figure 5-6 : Cutoff of "Poverty" Across Weeks

5.6. Analysis of Rule Effects across Time

In previous chapters, it is tested that the rule dummy significantly affects the changes of bidder's bidding behaviors and participating behaviors. At this step, the rule dummy is replaced by the time trend variables to gain a more insightful view of the rule effects. That is, we include time dummies indicating each of the weeks, in order to check how bidders' participations are changing across time. Note that we don't include website specific control variables such as number of hot/common products and the several percentile surpluses. This is because these control variables are on a weekly basis and they will be omitted when including the week dummies. The results of the checks are shown in Table 5-9, where the dummy of the 47th week is omitted by the regression models.

The coefficient of a time dummy reveals the changes of dependent variables in the specific week. The larger the coefficient is, the more influential the three rules are at that specific time. As can be seen in Column (a.1), coefficients of time dummies rise from the first week (i.e. the 30th week) and experience the peak in the 38th week, which is the week of rule changes. Besides, by comparing the coefficient before and after the rule change in the 38th week, on average the coefficients after the rule changes are larger than those of before. This implies that, occasional bidders increase their number of bids more after the rule changes than before the rule changes. After controlling factors such as their surplus history, the results of Column (a.1) suggest that the three rules have positive effects on stimulating bidder's number of bids.

As for results of frequent bidders in Column (a.2), the coefficient of time dummies are significantly higher before the rule changes and they are declining dramatically within several weeks after the 38th week. Such a trend implies a significant negative effect of the rules on frequent bidders' bid numbers. Therefore, using a Negative Binomial model, we show consistent results with the Poisson regression of bid number in Model 3.

Regarding the number of auctions joined, the results are shown in Column (b). Similarly, by comparing the values of the time dummy coefficients, occasional bidders are most positively influenced after the 38th week, while frequent bidders reduce their number of participations after the rule changes. Hence, the robustness check confirms the previous results of participation number in Model 3 as well.

Furthermore, the time dummy coefficients in Table 5-9 also suggest a diminishing effect of the rules in the long term. Though the coefficients are larger for occasional bidders afterward, these values are reducing and become insignificant once again. This observation, however, is consistent with our previous results of the Gini coefficient in Figure 5-1. Such diminishing effect may be explained by the reality that occasional bidders are also constrained by the three bidding restrictions. For example, they may be prohibited to bid for the same item more than once, even if they really need the same item again. Hence, an unpleasant feeling may be aroused and drive the bidders to participate less in penny auctions.

Table 5-9 : Robustness Check of Model 3 Using Week Dummies				
Independent Variables	Dependent Variables			
	(a) No. of Bids Placed (Negative Binomial)		(b) No. of Auctions Joined (Negative Binomial)	
	(1) Occasional Bidders	(2) Frequent Bidders	(1) Occasional Bidders	(2) Frequent Bidders
Week == 30	0.1579 (0.1592)	0.3505 (0.3240)	0.1268 (0.1592)	0.1827 (0.3180)
Week == 31	0.0650 (0.1604)	0.7383** (0.3023)	0.0512 (0.1597)	0.5079* (0.2953)
Week == 32	0.1557 (0.1584)	0.8003*** (0.2980)	0.0932 (0.1587)	0.6103** (0.2905)
Week == 33	0.2007 (0.1563)	1.1306*** (0.2835)	0.1400 (0.1563)	0.9278*** (0.2749)
Week == 34	0.1812 (0.1566)	0.8673*** (0.2881)	0.1271 (0.1564)	0.7526*** (0.2788)
Week == 35	0.3266** (0.1525)	1.4133*** (0.2708)	0.2883* (0.1521)	1.3681*** (0.2571)
Week == 36	0.5222*** (0.1478)	1.4515*** (0.2670)	0.5000*** (0.1470)	1.3855*** (0.2526)
Week == 37	0.6219*** (0.1449)	1.3697*** (0.2641)	0.6304*** (0.1436)	1.2976*** (0.2508)
Week == 38 (Rule Change)	1.0102*** (0.1372)	1.4826*** (0.2592)	0.9902*** (0.1361)	1.3181*** (0.2447)
Week == 39	0.9372*** (0.1382)	1.0980*** (0.2630)	0.9407*** (0.1366)	0.8686*** (0.2524)
Week == 40	0.8169*** (0.1403)	1.0748*** (0.2616)	0.7816*** (0.1391)	0.8594*** (0.2495)
Week == 41	0.5807*** (0.1449)	0.6678** (0.2682)	0.5467*** (0.1441)	0.5379** (0.2564)
Week == 42	0.5016*** (0.1473)	0.4906* (0.2757)	0.5034*** (0.1463)	0.3962 (0.2648)
Week == 43	0.3385** (0.1511)	0.1005 (0.2926)	0.3277** (0.1504)	-0.0431 (0.2846)
Week == 44	0.0149 (0.1611)	0.2645 (0.2828)	0.0243 (0.1604)	0.2125 (0.2721)
Week == 45	0.0758 (0.1601)	0.0928 (0.2870)	0.0974 (0.1593)	0.1151 (0.2773)
Week == 46	-0.2634 (0.1739)	-0.2482 (0.3144)	-0.2670 (0.1734)	-0.3207 (0.3052)
Amount of Win Last Week	0.0027*** (0.0004)	0.0013*** (0.0002)	0.0026*** (0.0003)	0.0008*** (0.0002)
Amount of Loss Last Week	-0.0056*** (0.0006)	-0.0034*** (0.0008)	-0.0062*** (0.0007)	-0.0033*** (0.0008)
Cumulative Amount of Win	0.0002 (0.0002)	0.0006*** (0.0001)	0.0001 (0.0002)	0.0004*** (0.0001)
Cumulative Amount of Loss	0.0006* (0.0004)	-0.0004 (0.0004)	0.0020*** (0.0004)	0.0002 (0.0005)
Constant	-3.2556*** (0.1203)	-3.0571*** (0.2427)	-1.6962*** (0.1269)	-1.4960*** (0.2487)
Fixed effect	Yes	Yes	Yes	Yes
Observations	9,126	1,422	9,126	1,422
Number of bidders	507	79	507	79
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1				

6. Discussion and Implications

6.1. Cause of Aggressive Bidding in Penny Auction: Addiction

Penny auction combines features of both auctions and gambling. On the one hand, the amount of bids (i.e. tokens) is not monotonically related to the probability of winning the auction, which is similar to lotteries. For instance, a bidder who has placed a lot of bids may still be outbid by others, as long as other bidders have sufficient tokens and willingness to bid. It is also possible that a bidder places only a few tokens but still wins the auction, provided that none of the others are willing to bid. Therefore, number of tokens does not guarantee winning in penny auction. From this perspective a penny auction is like a gamble or a lottery. On the other hand, unlike lottery winning probability in penny auction is not exogenously determined because it is influenced by factors such as number of participants. Hence, a penny auction is not a pure random game as gambling. Raviv (2009) proposed the concept of “gambling auction”, which is an early format of penny auction.

According to Narayanan and Manchanda (2006) who study gambling and gaming industry in the United States, there are evidences showing that gambling addiction exists in casino gambling. Given the similar mechanism as gambling, it is reasonable to argue that there exist gambling addiction behaviors in penny auction. In this context, gambling addiction is defined as a positive correlation between bidder’s previous number of bids and bidder’s current number of bids, as suggested by Narayanan and Manchanda (2006). Therefore, an addicted bidder will keep bidding more and more over time.

However, the new rules, especially rule 1 that stipulates a maximum of 8 auctions won within 28 days, will reduce bidder's addiction for two reasons. If a bidder has already won the maximum number of auctions, he will not be able to join any auction in following days, mitigating his mania of the auctions. On the other hand, if the maximum allowance has yet been reached, a bidder may become more hesitative about whether to join the next auction or not, because that will reduce his ability of participating in future auctions. In both cases, bidder's level of addiction to the game will reduce.

6.1.1. A Difference-in-Differences Method

We use difference-in-differences method to model the effects of the 3 rules on bidder addiction. We compare number of bids placed by a bidder in normal penny auction with those in free auctions. Free auction is a special type of penny auction in which there is no bidding fee. It is similar, but not exactly same as traditional eBay auction in the sense that it retains other features of penny auction, such as soft-closing ending and zero starting prices. Free auctions are of interests because the format of free auction is consistent with other widely applied auctions, such as those auctions on eBay or Amazon, in which there is no bidding cost. As mentioned above, bidder's addiction reflects on a positive relationship between previous number of bids and current number of bids, and the rule changes may reduce such relationship as suggested by our hypothesis. This study applies the difference-in-differences approach as a statistical methodology to address this research question.

Identifying effects of the rules requires more than simply comparing the coefficient of a variable before the rule changed with its counterpart estimated after the rule changed.

This is because there are many other factors that may have been changed across time. For example, there will be new bidders to register on the penny auction website, and thus the user pool is changing. Besides, the penny auction website's reputation may be growing over time, which may generate different effects on bidders. These latent changes may cause an estimation bias and need to be taken into account. Difference-in-differences approach has been applied to address this issue in many other contexts (Gruber and Poterba, 1994; Triest, 1998). For instance, Eissa (1995) addressed the effect of tax code change on the labor supply of married woman by comparing two different groups of woman samples. Furthermore, culture-specific advertising strategy on women's magazine was studied by Dallmann (2001), basing on the comparison of general-interest magazine.

The goal of this difference-in-differences model is to verify the existence of addiction behaviors and to identify the net effects of rule changes in normal auctions. Therefore, it is necessary to control any effects from other factors beyond the rule changes. Such control is done by making a comparison with free auctions. As discussed previously, free auctions include no bidding cost. In free auctions, bidder's behaviors are less affected by the introduction of the 3 rules, mainly due to the absence of bidding fee. Hence, free auctions are more stable under the rule change and can be used as the baseline. Therefore, a comparison of normal penny auction and free auction can rule out other affects[7].

In this study, the difference-in-differences approach is used within a panel regression model. Narayanan and Manchanda (2008) developed an auction model using

[7] Technically, both normal auctions and free auctions are affected by other factors beyond the rules. By comparing the changes of free auctions with the changes of normal auctions, we can eliminate the effects of other factors beyond the rules.

disaggregated level data to measure gamblers' level of addiction. In their study, Narayanan and Manchanda (2008) defined addiction as a positive relationship between previous amount of bet and current bet decision. This study develops a similar reduced-form model and focuses on bidder's number of bids. Combining with the difference-in-differences approach, specification of model 1 is given as

$$\ln(nob_{it}) = \mathrm{nob}_{\mathrm{i,t-1}}\alpha_i + D_{rule}\beta_1 + D_{normal}\beta_2 + D_{rule} \times D_{normal}\beta_3 + \epsilon_{it}$$

Where t denotes the time and i denotes bidder, $\mathrm{nob}_{\mathrm{i,t-1}}$ is the number of bids placed by bidder I at time t-1, nob_{it} is the number of bids placed by bidder i at time t, $nob_{i,t-1}$ is the number of bids placed previously, D_{rule} is a dummy variable indicating whether it is after the rule changed or not, D_{normal}, similarly, is a dummy variable of free auction, ϵ_{it} is an unobservable factor that affects the bid amount.

There are two focuses in this model. First, the coefficient of $\mathrm{nob}_{\mathrm{i,t-1}}$ that indicates the level of bidder addiction, which is suggested by previous literatures. The other focus is the interaction effect of D_{rule} and D_{normal}, which reveals the effect of rule changes. The results of the model are shown in Table 6-1.

Recall that if we are going to analyze the effect of rules on addiction to penny auction, we need firstly to confirm the existence of addiction. As can be seen from Table 6-1, number of previous number of bids is significantly related with the dependent variable, number of current number of bids. This suggests that a bidder will escalate his commitments in penny auction gradually. This suggests a symptom of addiction based on definition of addiction. Technically, the result suggests an additional bid placed previously will increase 1.15 bids (i.e. exp(0.138)) at current auction. Therefore, we confirm the existence of addiction behaviors in penny auction.

Table 6-1 : Result of Difference-in-Differences Model

Independent Variables	All Obs	Free Auction		Normal Auction	
		Before Rule Change	After Rule Change	Before Rule Change	After Rule Change
No. of Bids Last Week	0.138*** (0.00427)	0.0915*** (0.00603)	0.120*** (0.00530)	0.119*** (0.0135)	0.173*** (0.0135)
Dummy of Normal Auction	-0.895*** (0.295)				
Dummy of Rule change	-1.300*** (0.237)				
Normal * Rule	2.456*** (0.415)				
Constant	11.45*** (0.182)	11.02*** (0.200)	10.36*** (0.124)	10.76*** (0.350)	11.28*** (0.389)
Observations	56,076	17,702	20,067	9,317	8,990
Number of bidder_id2	4,455	1,642	2,044	2,202	1,602
Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1					

The two dummy variables of rule changes and normal auction and their interaction term $D_{rule} \times D_{normal}$ are significant as shown in Table 6-1. In difference-in-differences approach, the coefficient of the interaction term is of interests because it reveals how the rule changes affect free auctions, eliminating other unobserved effects from other factors. As we can see, the coefficient of the interaction term is significantly positive. It is interpreted in this way: comparing with before the rule changes, in normal auctions bidder's number of bids is increased by 11.66 (i.e. exp(2.456)) after the rule changes. In other words, bidder's level of participation increases after introducing the rules.

6.2. Implications

6.2.1. Theoretical Implications

Penny auction is a relatively new phenomenon and auction theorists are still studying its theoretical properties. Different from the conventional eBay auction, penny auctions seem to be more complicated to be solved by game theory. The current frontier of the modeling literature can only solve a model with restrictive assumptions (Platt et al. 2010; Mittal 2010; Byers et al. 2010; Hinnosaar 2010). The equilibria derived in those theoretical papers are mixed-strategy equilibrium, which means a bidder will bid at each price following a probability distribution so that the other bidders will feel indifferent between bidding or not at any price. Since they feel indifferent between bidding or not, they will adopt the same probability distribution for bidding at each price. This kind of equilibrium could be thought-provoking to applied game theorists but is unrealistic and is difficult to convince executives its practical value. As a result, one weakness of our study is the tie to theoretical foundation because not many theoretical results that we can borrow for empirical testing in this new area.

At the same time, our exploratory empirical study does shed light on this novel e-business phenomenon. Auction models in the literature do not provide a complete analysis about the interaction and competition among bidders across auctions on the same auction site. Our results show the importance of protecting the interests of most bidders to maintain a reasonable distribution of surplus, even at the cost of restricting the bidding of those “very loyal bidders” (frequent bidders). At first sight, restricting frequent bidders’ participation may look like “slaughtering cash cows”. However, in the penny auctions context, frequent bidders cause negative externality to other bidders. Bidding restrictions could benefit more customers so that they will bid more, leading to higher profitability to the auction provider in the long run.

6.2.2. Practical Implications

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 the penny auction business because of its innovative tweak in the auction rules. We find that indeed few customers won most of the auctions. However, those winners may create *loss* to a penny auction provider whereas all other bidders contribute to the revenue and profits to the penny auction provider. 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 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 rules could be a novel business strategy for customer retention in the penny auction context.

Second, penny auctioneers should adjust their product assortment strategies by considering from bidders' perspectives. Though more bidders would benefit the website in the short run, if the number of products remains the same, bidders may be threatened by the growing number of competitors in each auction, ending losing more tokens. Over the long run, the effect of customer acquisition may be traded-off. Therefore, auctioneers should design suitable product offerings as the retention strategy to cater to this issue.

Besides, it is necessary to maintain an optimal frequency or probability of winning for each customer, to maintain a reasonable level of customer retention rate. With higher opportunities of winning, bidders are motivated to participate more. It implies a similar incentive mechanism as promotion in traditional marketing. That is, if given any additional benefit, customers are more willing to involve in the websites.

7. Conclusions

In this study, we analyze one of the emerging online auction formats -- penny auction. We firstly provide detailed discussions on penny auction and each of its unique features like bidding fee, bidding increment and extendable countdown timer. Given that the winner of a penny auction can derive large amount of positive surplus, it is of the penny auctioneers' interests to maintain a more equalized surplus distribution. This is because if the surplus distribution is skewed for aggressive bidders and against occasional bidders, the occasional bidders may leave the website and thus there generates a bidder retention issue for auctioneers.

Focusing on this issue, we design 3 auction bidding rules with the intention to restrict aggressive bidders' behaviors and adjust the surplus distribution. We conduct a field experiment on a penny auction website to empirically analyze the effects of bidding restrictions on customer retention and surplus distribution. We provide evidence that there is skewed surplus distribution on the penny auction website before the implementation of the restrictions. Then we use three empirical models to analyze the impacts of restrictions. Empirical results show that the rules can significantly equalize customer surplus and mitigate the issue that frequent bidders win most of the auctions. With a more equalized surplus distribution, occasional bidders are shown to be more probable to bid again. Besides, they are more likely to place more bids in the auctions they participated. Additional tests like FGT metrics are used to verify our findings. Finally, we discuss the possible cause of the aggressive bidding behaviors in penny auction. It is argued that there exist addiction behaviors in penny auction, and such addiction behaviors will probably lead to aggressiveness.

This study is not without limitations, which also provide opportunities for future research. First, our research design is a quasi-experiment. It would be perfect 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 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 rules. For example, we can find the optimal restriction on the numbers of auction in our Rule 1. A related research direction is to study the impacts of 3 rules separately. In addition, with a better experimental design in the future, we would be able to compare a control group where bidders are not constrainted by any rules, and a treatment group where bidders are restrcited by our rules. In this way we can provide more convincing results if we can observe an higher participation and bidder retention rate in the treatment group.

Second, 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 3 rules on the bidding strategies of bidders and the profitability associated with each bidder.

Third, implicitly, we conceptually assume three rules increase occasional bidders' surplus and next, because of the increased consumer surplus, occasional bidders will bid more in penny auctions. But, empirically, we only show that three rules correlate with better customer retention and more participation. Logically, it could be due to other (psychological) effects. For example, it could be the aversion of unfairness is driven the results, not just the value of consumer surplus. It could also be the reputation of the penny auction site has been improved because of the three rules. We need other 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 in the penny auctions context.

Firth, 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. But, we may be able to empirically verify the impacts of sunk costs in this setting.

Finally, the gambling analogy where we argued there are addiction behaviors in penny auctions is relatively weak and is pending for more research. The definition of addiction in our context is adopted from Narayanan and Manchanda (2008) who studied casino gambling. Visiting a casino is more costly in reality than on Internet, and thus gambling addition seems to more reasonably reflect on number of visits under casino gambling than under penny auction. However, in fact the cost of visiting PennyLeader is not trivial. According to analysis the world’s leading Web information company Alexa.com, more users visit PennyLeader from their workplaces than from their homes. With the existence of monitoring in workplaces, visiting an entertainment website like PennyLeader is not cost-free. Therefore, if a working person increases his participation in penny auction, he is showing a certain symptom of addition to penny auction. This provides interesting spaces for future research.

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Appendix A: Process of PennyLeader

This appendix graphically shows the interface of PennyLeader and the key changes during the auction process. Figure A-1 shows the basic interface of the auction. As can be seen, the left part contains product images and basic product information. The right part has the bid history window that contains bid price, bidder's name and bid type. Each time a bidder places a bid the right window will be updated. The middle part contains bid price (i.e. current item price), current winner (e.g. AlexJame in the figure), countdown timer, the bid button, and basic statistics of price information (e.g. retail price, discount price).

Figure A-2 shows the changes of penny auction when there is a new bid. The bid history window in the right hand side has one more record that indicates the latest bidder's information. The bid price is increased by 15 cents (i.e. bidding increment). The timer is reset to 20 seconds. Subtly one token that cost 75 cents is consumed from the latest bidder's account. Figure A-3 shows the ended auction. As can be seen, the item is sold at a deep-discounted price. The winner gets the item at only 8.7 SGD.

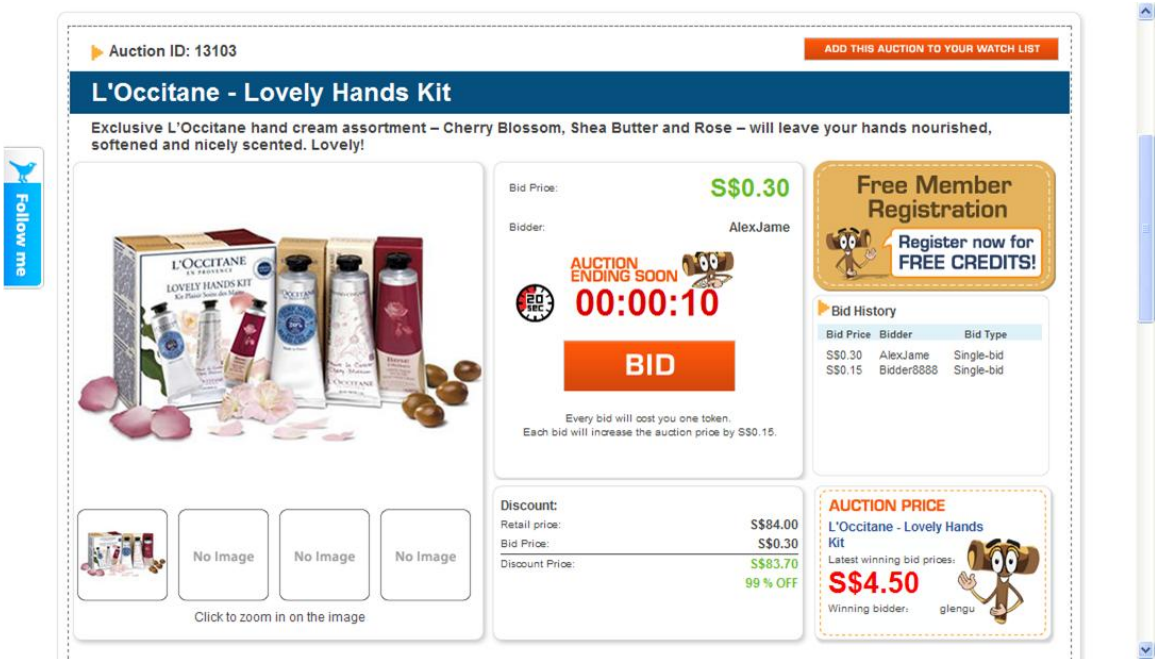

Figure A-1 : PennyLeader Interface (Initial)

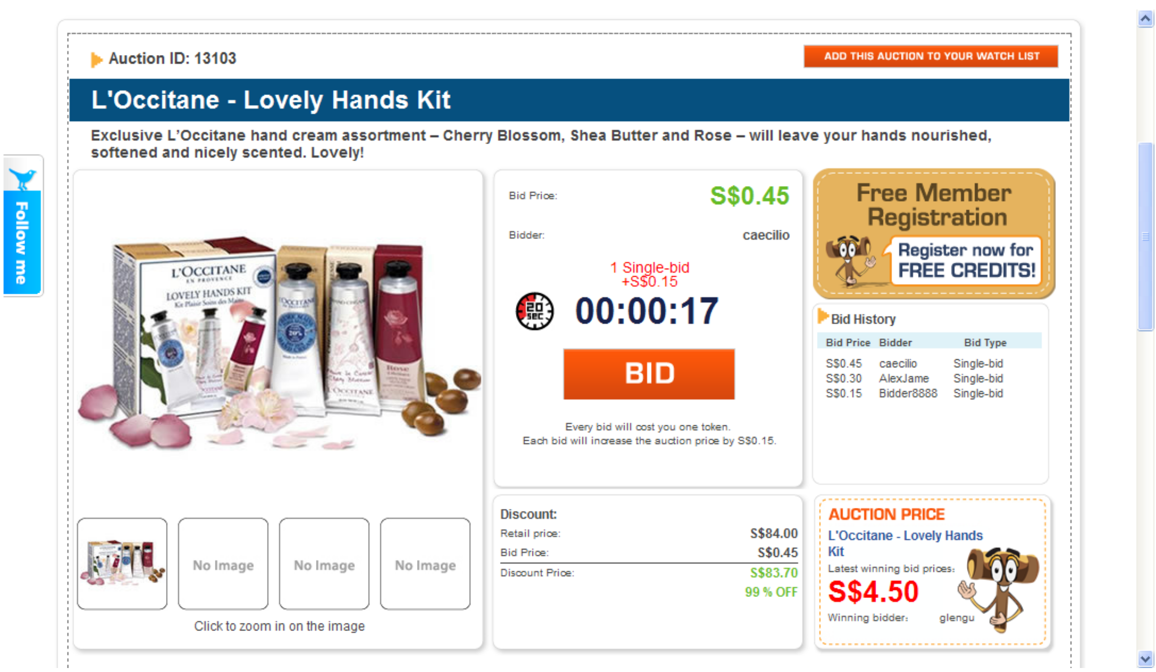

Figure A-2 : PennyLeader Interface (After a new bid is placed)

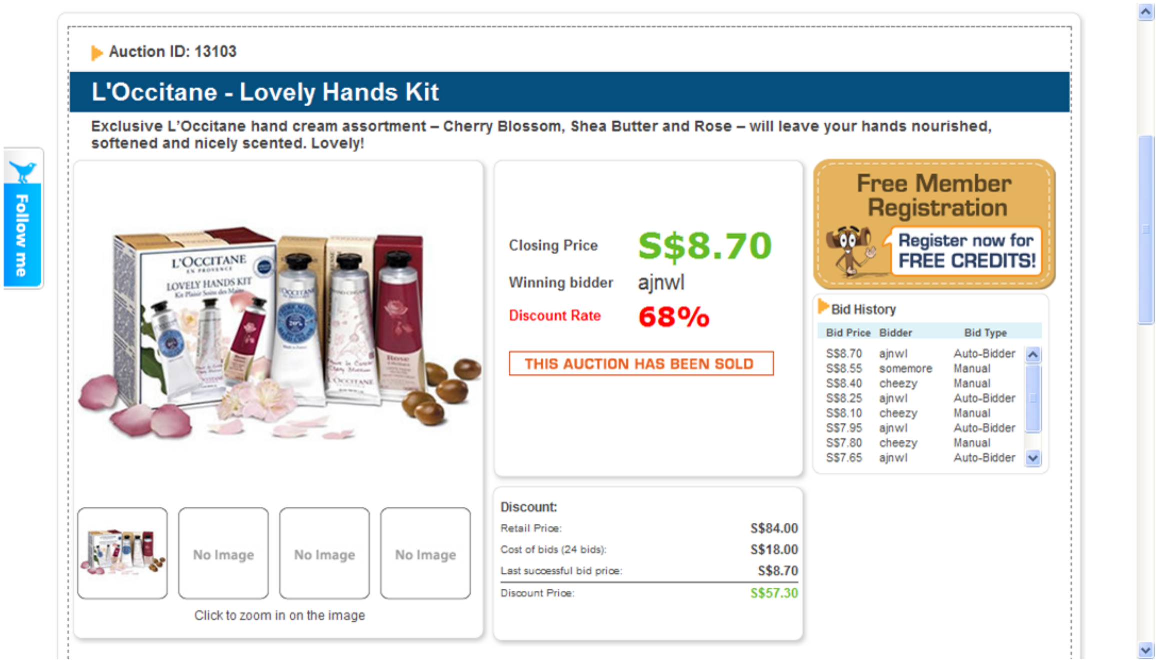

Figure A-3 : PennyLeader Interface (When the auction ended)