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Two Essays On Bidding In Multi-unit Common Value Auctions

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TWO ESSAYS ON BIDDING IN MULTI-UNIT COMMON VALUE AUCTIONS

by

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ABSTRACT

This dissertation consists of two essays on the topic of bidding in multi-unit common value auction. Essay one examines the role of capacity constraint on the auction results and bidding behavior. We consider a general case where bidders are unconstrained, and a second setting where bidders are capacity constrained. We document downward sloping demand curves for individual bidders. Bidders shade their bids by submitting quantity-price pairs and spreading their bids. The winner's curse is strong in the unconstrained treatment, but we find no evidence of the winner's curse when bidding constraints are imposed. Unconstrained bidders shade bids significantly more and their quantity-weighted prices are much lower than those in the constrained treatment. Interacting with the information structure, the capacity constraint has a significant impact on the auction results including the market clearing price, market efficiency, and the degree of market concentration. We provide evidence that efficient price discovery in multi-unit auctions with diverse information is possible, but careful attention to auction design will make this outcome more likely. Essay two examines how the introduction of a noncompetitive bidding option affects outcomes in a multi-unit uniform-price auction. The experimental design incorporates many of the characteristics of the markets that pertain to the issuance of new equity securities. Important features of the bidding environment include endogenous bidder entry, costly information acquisition, bidders that differ by capacity constraint, and substantial uncertainty with respect to the intrinsic value. We use a standard uniform-price auction as our baseline setting where only competitive bids are accepted. Our results show that introducing the noncompetitive bidding option improves auction performance by increasing revenue and reducing price error. Underpricing is found in both treatments, but is less severe in the presence of the noncompetitive bidding option. The incorporation of this option significantly increases both the small bidder participation rate and allocation, and reduces the incentive for small bidders to free ride by submitting extremely high bids. Under both treatments, information acquisition increases large bidders' profits but proves unprofitable for small bidders, and pricing accuracy is increasing in the rate of information acquisition.

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INTRODUCTION

This dissertation consists of two essays on the topic of bidding in multi-unit common value auction. Essay one examines the winner's curse problem in a multi-unit common value setting. In our experimental markets we consider two settings under the uniform-price format. In the first, each bidder is allowed to bid for the entire market supply. In the second, we add the realistic feature that bidders face bidding constraints that limit their potential demand to a fraction of market supply. Consistent with previous empirical study on the multi-unit auctions, we document the downward sloping demand curve for individual bidders. Bidders shade their bids in a multi-unit auction by submitting quantity-price pairs and spreading their bids. The winner's curse is strong in the unconstrained treatment, but we find no evidence of the winner's curse when bidding constraints are imposed. Interacting with the information structure, the capacity constraint has a significant impact on the auction results including the market clearing price, market efficiency, and the degree of market concentration. Essay two examines how to improve the performance of a traditional IPO auction through design modification. In the current IPO market, the traditional auction method is vulnerable to two major problems: the winner's curse and the free riding problem, which deter the participation of the investors. To overcome these two problems, we introduce a noncompetitive bidding option. We use laboratory experiments to examine the impact of incorporating a noncompetitive bidding option on auction results and bidding behaviors. Our results show that introducing the noncompetitive bidding option improves auction performance by increasing revenue and reducing price error. Adding a noncompetitive bidding option reduces the magnitude of the winner's curse. The incorporation of this option significantly increases both the small bidder participation rate and allocation, and reduces the incentive for small bidders to free ride by submitting extremely high bids.

ESSAY 1: BIDDING CONSTRAINTS, THE WINNER'S CURSE, AND EFFICIENT PRICE DISCOVERY IN MULTI-UNIT COMMON VALUE AUCTIONS: AN EXPERIMENTAL EXAMINATION

1.1 Introduction

Auctions have a long history as an efficient mechanism for the pricing and allocation of Treasury securities. They are widely employed in the issuance of Treasury securities throughout the world and they are the dominant mechanism in countries with well-developed financial markets. A characteristic feature of these auctions is relatively little uncertainty with respect to intrinsic value, which is due to the frequent trading of the very similar securities in the active secondary markets at the time of Treasury issuance, thus diminishing the price discovery role of the auction.

In the financial asset auctions where there is significant uncertainty with respect to the intrinsic value, auctions have been much less widely used. For example, although auctions have also been used in equity IPOs in many countries, the dominant practice is the investment bank driven bookbuilding procedure. At present, a variant of an auction is only used in four countries, and in none of these do auctions supplant the bookbuilding as the most commonly employed new issue procedure.[1]

Consistent and economically significant underpricing as an outcome of IPOs completed via bookbuilding has lead some researchers to conclude that the dominance of a suboptimal mechanism is maintained because of conflicts of interest between investment banks and issuers.

[1] See Sherman (2005) for a review of global trends in IPO methods.

For example, Ausubel and Cramton (1998) write: “Indeed, the incumbent corporate underwriters possess a strong profit motive in discouraging the advent of auctions, as they are the beneficiaries of today's substantial underpricing.” They argue for the widespread use of carefully designed auctions.

Other research has focused on the superiority of the book-building process because of its facility in price discovery in a setting where potential investors would have little incentive to engage in costly information acquisition and truthfully reveal their preferences in an auction setting.[2] In this literature auctions are criticized as producing inaccurate prices.

In this paper we investigate the accuracy of prices established in multi-unit common value auctions using an experimental economics methodology. A large experimental literature finds that the winner’s curse (pricing above intrinsic value) is the expected outcome in single-unit common value auctions. These results are not necessarily applicable to multi-unit auctions however; recent work in the theory of multi-unit auctions shows that there exist non-cooperative equilibria under the uniform-price format (the most common type of auction in financial auctions) that support collusive-seeming outcomes.[3] Moreover, in a multi-unit auction there is much more potential for bidders to learn from auction results since not only the highest bid on a single unit determines the market clearing price. Also, since bidders can be aggressive with only a portion of their demand curves, the potential for a bidder to mix speculative bids with conservative bids may have important implications for information aggregation and pricing accuracy.

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[2] The seminal paper in the large theoretical literature that examines the role of bookbuilding in solving the informational problem in new issues is Benveniste and Spindt (1989).

[3] See, for example, Wilson (1979), Back and Zender (1993), Ausubel and Cramton (1996) or Wang and Zender (2002) for theoretical results on strategic bidding in multi-unit auctions.

In our experimental markets we consider two settings under the uniform-price format. In the first, each bidder is allowed to bid for the entire market supply. In the second, we add the realistic feature that bidders face bidding constraints that limit their potential demand to a fraction of market supply.[4] In these capacity constrained markets, we also increase the number of bidders in order to partially equalize potential demand across the settings. We hypothesize that bidding constraints will improve the accuracy of price discovery since the bidder with the highest signal will have less influence on the market clearing price. Questions we consider include the following. Does the winner's curse arise in a multi-unit common value framework? Do capacity constraints play a role in affecting the possibility or magnitude of the winner's curse? Do bidders behave differently when they are facing capacity constraints? How does the interaction of the information distribution and the capacity constraints affect the auction results?

Our main results are as follows. Consistent with previous empirical study on the multi-unit auctions, we document the downward sloping demand curve for individual bidders. Bidders shade their bids in a multi-unit auction by submitting quantity-price pairs and spreading their bids. We find that the auction results differ in both treatments. The winner's curse is strong in the unconstrained (UC) treatment, but we find no evidence of the winner's curse when bidding constraints (C) are imposed. Bidders in the UC treatment shade bids significantly more than those in the C treatment; their quantity-weighted bid prices are much lower than those in the C treatment. Although on average bidders in the UC treatment bid more conservatively, they incur higher losses than those in the C treatment and the mean market clearing price is significantly

[4] In field markets, this could be due to liquidity constraints or explicit rules imposed by the auctioneer.

higher in the UC treatment. The demand curves for the first 7 units of both treatments are very similar. Interacting with the information structure, the capacity constraint has a significant impact on the auction results including the market clearing price, market efficiency, and the degree of market concentration. We therefore provide evidence that efficient price discovery in multi-unit auctions with diverse information is possible, but careful attention to auction design will make this outcome more likely.

The plan of the paper is as follows. In section II we discuss other relevant studies. In section III we explain the experimental design, in section IV we report our results, in session V we further discussion about our results, and in section VI we conclude.

1.2 Literature Review

The winner's curse arises in a single-unit common value auction with incomplete information. In 1971, Capen, Clapp and Campbell coined the phrase "winner's curse", referring to the result of low rate of return for the companies who bid for the offshore oil drilling rights in the Gulf of Mexico. In the auction literature, the winner's curse refers to either situation: 1) the winning bid exceeds the intrinsic value of the auctioned item such that the winner incurs a loss; or 2) the intrinsic value of the auctioned item is less than what the bidder anticipated, so the bidder may still have a net gain but will be worse off than anticipated. In a summarized work of the winner's curse, Kagel and Levin (2002) state that economists, particularly theorists, refer to the winner's curse as "the difference between the expected value of the item conditional on the event of winning and the naïve expectation (not conditional on the event of winning)". The existing literature measure the winner’s curse in several ways. In the first study of the winner’s curse, Bazerman and Samuelson (1983) use the average magnitude of overpayment, the difference between the actual value of the commodity and the average bid, to measure the degree and severity of the winner’s curse. In the later experimental studies by Kagel and Levin (1986), Dyer, Kagel, and Levin (1989), Lind and Plott (1991), the winner’s curse is measured by the deviation of the actual bid and risk-neutral Nash equilibrium bid function. These studies show that the phenomenon of the winner's curse in a single-unit auction is robust, even for experienced bidders.

With recent increasing research interest in the multi-unit auctions, Ausubel (2004) extends the definition of the winner’s curse in a single-unit auction setting to a multi-unit auction setting. He calls it “the champion’s plague”, or “winning more is bad news”. In his words, the winner’s curse is that “a bidder's expected value conditional on winning a larger quantity is less than her expected value conditional on winning a smaller quantity.” For auctions with uniform pricing rule, winning more is bad news only when the market clearing price is above the intrinsic value of the asset. If the market clearing price exceeds the intrinsic value, all the winning bidders will incur losses and the magnitude of each winner’s loss depends on the size of his allocation. Therefore, the degree of the winner’s curse under the uniform-pricing auctions can be simply measured by the overpayment, the difference of the market clearing price and the intrinsic value of the asset. We adopt this measurement in this paper.

Theoretical work on the divisible goods auction begins with Wilson (1979) who concludes that a share auction can yield significantly lower prices than a single-unit auction.

Back and Zender (1993) extend Wilson's (1979) work by modeling the Treasury auction. Their study shows that collusive strategies are self-enforcing in uniform price, divisible goods auctions. Ausubel and Cramton (1996) show that demand reduction is part of equilibrium in uniform price auctions. Kyle (1989) studies the imperfect competition with insider information and shows that bidders have an incentive to reduce demand. Wang and Zender (2002) derive equilibrium bid schedules that contain both strategic considerations and explicit allowances for the winner's curse. Engelbrecht-Wiggans and Kahn (1998) study bidding behaviors under a uniform-pricing multi-unit auction where each bidder can bid 2 units. The model shows underbidding for the second unit is a Nash equilibrium.

Despite theoretical results of underpricing equilibrium, empirical studies of the Treasury auctions and IPO auctions show that the price discovery is efficient in uniform-pricing multi-unit auctions. Gordy(1999), Bjønnes (2001), and Nyborg, Rydqvist, and Sundaresan (2002), Keloharju, Nyborg, and Rydqvist (2005) examine the Portuguese, Norwegian, Swedish, and Finnish Treasury auctions, respectively, and their results show little evidence of the winner's curse, which may be due to the inherent features of the treasury auction – the less uncertainty about the intrinsic value due to the existence of the secondary market. The empirical studies of French IPO auctions (Derrien and Womack (2003)), and the U.S IPO auctions (Degeorge, Derrien, and Womack (2008)) suggest that auctioned IPOs could be an effective alternative to traditional bookbuilding due to less underpricing and lower price volatility.

The majority of the existing experimental study of the multi-unit auctions have focused on the independent private value (IPV) paradigm (see Alsemgeest, Noussair, and Olson (1998), Kagel and Levin (2001, 2005), Ausubel (2004), List and Lucking-Reiley (2000), and Engelbrecht-Wiggans, List, and Reiley (2006)). Sade, Schnitzlein, and Zender (2006a, 2006b) are the first two papers which investigate the bidding behaviors and auction results under a multi-unit common value setting.

This paper examines the role of one characteristic of the financial market - the capacity constraint on the bidding behaviors and auction results. In most of the auction literature, a common assumption is that bidders are able to bid for the entire market supply. However, in the financial markets, bidders usually face liquidity constraints, and since concentrated holdings of financial assets are typically viewed as undesirable, bidding limits are typically built into auction procedures. For example, in the U.S. Treasury auctions, a single bidder is prohibited from acquiring more than 35% of a new issue. Another example is the Taiwan stock IPO auctions, where an investor is not allowed to buy more than 3% of the total shares available in an IPO auction.

The most related study of the implication of the capacity constraint in a multi-unit common value auction is Sade, Schnitzlein, and Zender (2006b), who find capacity constraints play an important role in inhibiting collusion and promoting competitive outcomes in auctions with uniform pricing rule. Fang and Parreiras (2002) and Frutos and Pechlivanos (2006) also study how the capacity constraint affects the bidding behaviors in the common value setting but differs in many aspects. Fang and Parreiras (2002) focus on the second-price common value auctions with two financially constrained bidders who have affiliated signals and their results show that the likelihood that one's opponent may be financially constrained increases the possibility that a bidder wins the object, which attenuates the winners' curse and makes a bidder more aggressive. Frutos and Pechlivanos (2006) show that the equilibrium bid functions are affected by the severity of financial constraints. Other studies of the role of the capacity constraints include McMillan (1994), Palfrey (1980), Pitchik and Schotter (1988), and Che and Gale (1996 and 1998). McMillan (1994) examines the role of the budget constraints in the FCC auctions. Palfrey (1980) studies the effects of budget constraints in a multi-unit discriminatory setting with complete information and demonstrates that a symmetric, pure-strategy Nash equilibrium only exists in the two objects and two bidders case. Pitchik and Schotter (1988) find that bidders can exploit the budget constraint of others by bidding up the price of the good offered early in sequential auctions. Che and Gale (1996 and 1998) study single-unit independent private value (IPV) auctions with budget constraints and show that even with symmetric bidders, revenue equivalence no longer holds once financial constraints are imposed.

1.3 Experiment Design and procedure

1.3.1 Experimental Design Overview

Each experiment session consists of a series of auction periods in which multiple bidders engage in bidding for 20 homogenous goods we call widgets in a uniform-pricing common value auction. In most of existing multi-unit auction models, price and quantity are assumed to be continuous. As in field markets and experimental studies, we let price, quantity, and bids to be discrete. Auction rules, information structure, and distributions of random variables are held constant so that we can compare the impact of the treatment on price discovery.

Auctions are conducted under two treatments. Table 1 Panel A displays the treatment conditions. In the unconstrained (UC) treatment, 4 bidders compete together and each bidder can bid for up to the total supply of the goods. This setting corresponds to the common assumption that bidders are not financially constrained or no explicit bidding limits are imposed, and therefore provides a benchmark case for study. In the constrained (C) setting, each bidder can bid for up to 7 widgets. The bidding constraint differentiates the UC vs. C treatments. Since competition increases with market demand and the number of bidders, the competition in a constrained setting may decrease unless the number of bidders in the constrained setting is greater than the number of bidders in the unconstrained setting. Therefore, in the constrained treatment we increase the number of bidders to 6 in order to compensate for the possible decreased competition from less market demand and partially equalize the potential competition across the settings. In both treatments, bidding capacity is common knowledge. To control for possible behavioral differences, each bidder in the same treatment faces the same bidding capacity.

We follow Kagel and Levin's (1986) experiment design to set the parameters. The true value V is randomly selected from a uniform distribution on the interval [V_L, V_H]. V is unknown to the bidders before each auction, and is revealed to the bidders when the auction is completed. Before each auction starts, bidder *i* receives a private signal S_i about the true value of the widget. Each signal is randomly drawn from a uniform distribution with support $[V + \varepsilon, V - \varepsilon]$. The information structure across bidders is symmetric. Given V_L, V_H, S_i , and ε, the range of V can be inferred, which is [max{ $V - \varepsilon, V_L$ }, min{ $V + \varepsilon$, V_H }]. Kagel and Levin

(1986) manipulate the value of ε to test how the uncertainty about the intrinsic value affects the degree of the winner's curse. In our experiment, we control the uncertainty level by holding ε constant.

Each bidder competes by submitting discrete bid schedules. Once all schedules have been submitted, the computer will assign widgets to bidders submitting the highest bids until up to 20 widgets are allocated. According to the uniform-pricing rule, all the winning bidders pay the same market clearing price for each widget he is allocated. The profit or loss for each auction is calculated as follows: Profit/loss = Number of Widgets Allocated × (True Value – Market Clearing Price). The profit (loss) is carried over from auction to auction.

1.3.2 Parameter Values and Variable Distributions

In our experiment, the monetary unit employed is the laboratory dollar (L$). To convert laboratory dollars to US$s, the exchange rate is 0.05. Each bidder starts with the same initial cash balance of L$400. The reason for imposing an initial cash balance is to avoid control issues associated with bankruptcy.

Table 1 Panel B shows information structure. The true value (V) is randomly drawn from the uniform distribution with mean of L$50 and support on the whole laboratory dollars between L$14 and L$86, inclusively. The true value varies auction by auction. ε is equal to 4. The private information signal is selected randomly from an integer interval range of [V-4, V+4]. Since we employ different numbers of bidders in the two settings and to minimize the information differences between the two settings, we let the first 4 bidders in C treatment receive the same information as those 4 bidders in the UC treatment. All information pertaining to endowment, payments, true value, signal distribution, and the rules governing auction is common knowledge.

1.3.3 Communication and Computer Displays

The auctions are conducted on networked personal computers with custom designed software. In addition to allowing the entry of bids, the software graphed individual demand curves in real time as each subject initiated the bid submission process. The aggregate demand schedule, market clearing price, and allocations for each auction are calculated by the software at the completion of each auction. After each auction, each bidder is provided with information about the market clearing price, allocation, the true value, and his profit or loss. In addition, the interface provided historical information pertaining to each subject's previously submitted demand functions matched with their allocations, profit, and percentage of available supply received for each completed auction. Over the course of experiment, subjects are not allowed to communicate with each other.

1.3.4 Subjects and Procedures

We conducted a total of 15 sessions, with 7 sessions for the C treatment and 8 sessions for the UC treatment. Each session consisted of 14 auctions in both treatments. Each experimental session consisted of 4 subjects in the UC treatment or 6 subjects in the C treatment. These 4 subjects or 6 subjects bid together. We recruited graduate and undergraduate students from the University of Central Florida in May, June, and November of 2008 and June 2009. The majority of them were undergraduates in the College of Business Administration. They were allowed to participate in only one session. None of them had previous experience in auction experiments. This randomization enables us to control for learning and experience effect.

At the beginning of each session, subjects were given written instructions. The instructions explained the auction rules, the basis on which cash payments would be made, and included graphical displays that introduce the subjects to the software used to conduct the experiment. The experimenter read the instructions to the subjects, and subjects were then given the opportunity to ask questions.

Then, each subject was assigned to one computer terminal. They competed through submitting bid schedules. The schedule indicates the number of widgets the bidder is willing to buy at a given price. Once all schedules have been submitted, the computer will assign widgets to bidders submitting the highest bids until up to the available supply of 20 widgets is exhausted. All the winning bidders will pay the same price (market clearing price) for each widget he is allocated. There were 14 auctions in each session. After an auction is completed, the computer moves on to a new auction. This auction is totally independent from the previous auction.

1.4 Experimental Results

We examine the experimental results in the following aspects: basic bidding results, the profits, bidding strategies, market clearing price, and allocations.

1.4.1 Basic Statistics

Table 2 presents basic statistics about auction results for both treatments. The difference of the market clearing price and the true value measures the degree of overpricing, which not only proxy for the degree of the winner's curse but also proxy for pricing inaccuracy. We find that market clearing prices generated in both treatments differ significantly. On average, the market clearing price in the UC treatment is L$0.83 above the true value, which is significantly different from zero. However, in the C treatment, the market clearing price is L$0.24 below the true value, though the difference is not statistically significant different from zero. This result indicates that the constrained setting promotes more accurate pricing than the unconstrained setting does. The winner's curse is alive in the UC treatment since each winner will overpay L$0.83 for each unit of his allocation. For the winners in the C treatment, the unit price paid by them is even lower than the true value and therefore they actually made profits.

The magnitude of differential in both revenue and bidder profit differential across treatments is significant. On average, the UC treatment generates L$21.51 more revenue than the C treatment, which is due to the higher market clearing price in the UC treatment. The last two columns of Table 2 show bidder's average profit. The average constrained bidder received a positive profit of L$11.43 per session while the average unconstrained bidder incurs a loss of L$59.38 per session, which is a loss of L$4.24 per auction. And the loss is statistically significantly different from zero.

1.4.2 Profits

Table 3 reports winners' profits and auction distribution data. On average, bidders in the C treatment are more likely to be winners than in the UC treatment. The proportion of the winners in the C treatment is 79% while 67% in the UC treatment. We define a winner as a bidder whose allocation is nonzero. For session *n* (*n=1, 2 …, 7* for C treatment and *n=1, 2 …, 8* for UC treatment), the average winner's profit $\overline{p}_n$ for session n is calculated by the following formula: $\overline{p}_n = \dfrac{\sum_{j=1}^{14} \sum_{l=1}^{m_{n,j}} \dfrac{p_{n,j,l}}{m_{n,j}}}{14}$ ($p_{n,j,l}$ is winner l's profit in auction j of session n; $m_{n,j}$ is the number of winners in auction j $(j=1,\ 2\ \ldots,\ 14,)$ of session n, and $l=1,2,\ldots,m_j$.) Column 6 in Table 3 reports the mean winner's auction profit by session. Each winner in the UC treatment incurs an average loss of L$9.52 per auction, which is significantly greater than zero. However, the average winner in the C treatment earns a positive profit of L$0.83 per auction, though the size of the profit is not significantly different from zero. These results indicate that the winner's curse is very strong in the unconstrained setting but we do not find the evidence of the winner's curse in the constrained setting. Table 3 also reports the auction distribution based on the winner's loss or gain. The proportion of auctions with positive winner's profit is 32% in the UC treatment and 42% in the C treatment. The difference is not significant. However, the winners incur a loss in only 22% of the auctions in the C treatment and the number greatly falls below in the UC treatment, which is 53%. These data further support the claim that the winner's curse is alive and significant in the unconstrained setting.

1.4.3 Bidding Strategies

In a multi-unit auction, bidders face a much larger bidding strategy space than in a signal-unit auction. Submitting quantity-price pairs and spreading their bids are possible strategies they can implement. We first examine whether bidders submit price-quantity pairs. Later we will examine whether and how bidders spread their bids. Figure 1 shows the percentage of auctions under each treatment in which a given number of bidders submitted more than one price-quantity pairs. In the UC treatment, auctions with all four bidders submitting multiple price-quantity pairs occur in 73% of the auctions. In the C treatment, all six bidders submitted multiple price-quantity pairs as bids in 67% of the auctions. In the UC treatment, three bidders submitted price-quantity pairs in 23% of all auctions and only two bidders submitted price-quantity pairs in 4% of the auctions. In the C treatment, five bidders submitted price-quantity pairs in 26% of the auctions and only four bidders submitted price-quantity pairs in 7% of the auctions. In all auctions, bidders use price-quantity pairs. The result is consistent with the experimental result of Sade, Schnitzlein, and Zender (2006b). Their study shows bidders use price-quantity pairs as a bidding strategy in a divisible good auction. We also find that unconstrained bidders bid at a greater number of prices than those in the constrained setting. On average, each bidder in the UC treatment submitted 4.54 bids per auction, which is higher than the 3.68 bids in the C treatment.

Now, we study whether and how bidders spread their bids. We adopt the moment analysis by Keloharju, Nyborg, and Rydqvist (2005). The quantity-weighted bid price (the first moment), standard deviation (the second moment), skewness (the third moment), and kurtosis (the fourth moment) are shown in Table 4. We keep the notation used by Keloharju, Nyborg, and Rydqvist (2005). $\{(p_{ijk}, q_{ijk})\}_{k=1}^{m}$ represents the demand schedule submitted by bidder i in auction j, where m is the number of bids bidder i submitted. p_{ij} is the quantity-weighted average bid price for bidder i in auction j, which is calculated by $p_{ij} = \sum_{k=1}^{m} w_{ijk} p_{ijk}$, where $w_{ijk} = \frac{q_{ijk}}{\sum_{k=1}^{m} q_{ijk}}$. To evaluate the bid shading relative to the market clearing price, we calculate the discount d. In auction *j* for bidder *i*, the discount *d* is measured by the difference of the market clearing price, P_j, and bidder *i*'s quantity-weighted bid price, p_{ij}. The formula for discount is $d_{ij} = P_j - p_{ij}$. The standard deviation, skewness, and kurtosis for demand schedule of bid *i* in auction *j* are calculated, respectively, as

$$\sigma_{ij} = \sqrt{\sum_{k=1}^{m} w_{ijk}(p_{ijk} - p_{ij})^2}$$

$$skew_{ij} = \frac{1}{\sigma_{ij}^3}\left[\sum_{k=1}^{m} w_{ijk}(p_{ijk} - p_{ij})^3\right]$$

$$kurt_{ij} = \frac{1}{\sigma_{ij}^4}\left[\sum_{k=1}^{m} w_{ijk}(p_{ijk} - p_{ij})^4\right]$$

To simplify the study, we normalize the bidding data by two methods: (1) setting the true value in each auction to zero; (2) setting each bidder's signal to zero. The first method enables us to measure how bidders behave relative to the true value. The second method helps us to examine how bidders behave relative to their private signals. Due to the normalization process, bid prices can be positive, negative, or zero. Table 4 Panel A shows the moments of individual demand curves when the true value is normalized to zero. Bidders in both treatments shade their bids. On average, the discount for constrained bidder is L$0.37, which is economically small and not statistically different from zero. In the UC treatment, each bidder's bid price is L$1.46 below the true value, which is significantly different from zero at the 5 percent level. We can conclude that unconstrained bidders shade their bids significantly more than constrained bidders. Bidders also submit their bids below their signals. Table 4 Panel B reports the moment statistics when each bidder's signal is normalized to zero. The discount here is measured by the difference of the quantity-weighted bid price and the private signal. Since each bidder's signal is normalized to zero, the discount directly measures the degree of bid shading relative to the private signal. Bidders in the UC treatment bid significantly below their signals than those in the C treatment. On average, a constrained bidder's quantity-weighted bid price is L$0.35 below his signal while an unconstrained bidder's bid price is L$1.43 below his signal. This bidding behavior is consistent with empirical findings in the study of Gordy(1999), Bjønnes (2001), and Nyborg, Rydqvist, and Sundaresan (2002).

The skewness and Kurtosis show some features of bid distribution. More positive skewness is observed in the UC treatment than in the C treatment, indicating that for a bidder in the UC treatment, a large portion of his bids are lower than but close to the mean quantity-weighted bid price and a small portion of high bids are located away from the mean. A bidder in the UC treatment submits some bids at very high prices but most bids are at lower prices than the mean quantity-weighted price. The Kurtosis of the bid distribution in the UC treatment is higher, also indicating unconstrained bidders submit more extreme bids than constrained bidders.

One important aspect of bidding behavior is bidding aggressiveness. We next examine whether bidding aggressiveness differs in the UC and C treatments. We use the quantity-weighted price to proxy for bidding aggressiveness. Simply comparing the mean, we find that on average constrained bidders bid more aggressively than unconstrained bidders, since the average quantity-weighted price for constrained bidder (-L$0.37) is significantly higher than that for unconstrained bidders (-L$1.46). We also run a regression to test the impact of the treatment on the bid price. The dependent variable is bidder *i*'s mean quantity-weighted bid price. The number of observations for the UC treatment is 32 and 42 for the C treatment. *Constrained* is a dummy variable with 1 for C treatment and 0 for UC treatment. We also include *Average Signal* which is the mean of the signals that one bidder received in one session. The regression equation is

$$\textit{Quantity-weighted Bid Price} = \alpha_0 + \alpha_1 \textit{Constrained} + \alpha_2 \textit{Average Signal} + \varepsilon$$

The regression result is displayed in Table 5. The estimated coefficient for the variable *Constrained* is 1.06 and significantly differently from zero, indicating that bidders in the C treatment bid more aggressively than those in the UC treatment. The coefficient for the variable *Average Signal* is not significantly different from zero and we cannot reject the null hypothesis that the mean signal has no effect on the quantity-weighted bid price. Additional evidence of more aggressiveness in the C treatment is that constrained bidders bid very close to their information signals while unconstrained bidders bid much below their signals. We conclude that constrained bidders bid more aggressively than unconstrained bidders.

In the UC treatment, the first 7 units are more likely to be allocated than the "tail" of the demand schedule. The "tail" of the demand schedule, which has little chance to be allocated, impacts on the moment statistics of the individual bidder's demand schedule. Following Sade, Schnitzlein, and Zender (2006b), we compare the individual demand schedules which are only composed of the first 7 units. In Table 4, UC (7) represents the demand schedule for the first 7 units under the UC mechanism. The data reflects no significant difference between the moments of demand schedules of UC (7) and C (7). The bidding behavior for submitting the first 7 units in both settings are similar. Figure 2 graphs the individual demand curves for UC (20 units), UC (7 units), and C (7 units). The demand schedules of UC (7) and C (7) almost coincide and the slope for UC (7 units) is -3.30 and the slope for C (7 units) is -3.48. However, the slope of the demand curve containing all 20 units in the UC treatment (-1.24) is much flatter, indicating that the demand in the UC treatment is less sensitive to the price change. Since there is no behavioral difference in submitting the first 7 units for constrained and unconstrained bidders, the large discount and the flat demand curve for the UC treatment appears to be due to the impact of the "tail". The "tail" pulls down the quantity-weighted price and therefore pushes up the discount. Figure 3 displays the distribution of bids at the bidder level. We also observe that UC (20 units) has more bids below true value zero than UC (7 units) and C (7 units), which is further evidence of the impact of the "tail."

1.4.4 Market Clearing Prices and Profit

In this section, we compare market clearing prices and bidder's profit between the two treatments. Mean market clearing prices and profit by both session and auction are reported in Table 2. Figure 4 shows the distribution of auctions by the market clearing price. Figure 5 shows the distribution of auctions by the relationship between the market clearing price and the true value. Figure 6 displays the distribution of bidders by session profit or loss. Figure 7 examines how profit evolves with experience over the 14 auctions.

Table 2 reports the mean market clearing price. The market clearing price in the UC treatment is significantly lower than in the C treatment. Figure 4 shows the distribution of auctions by the market clearing price. We can find that more auctions in the C treatment with market clearing prices below true value than in the UC treatment. Figure 5 displays the distribution of auctions by the relationship between the market clearing price and the true value.

In all 112 auctions of the UC treatment, 53% of the auctions saw market clearing prices higher than the true value. In the C treatment, only 26% of the auctions have the market clearing price higher than the true value. There are more auctions in the C treatment than in the UC treatment where the market clearing price is exactly the same as the true value, indicating the C mechanism results in more efficient price discovery than the UC mechanism. Under a uniform-pricing auction, the level of the market clearing price directly determines a bidder's profit. Figure 6 shows the distribution of bidders by session profit or loss. The figure shows bidders are more likely to incur losses in the UC treatment than in the C treatment. 66% of the bidders incur losses in the UC treatment while only 29% of the bidders incur losses in the C treatment.

The market clearing price is noticeably different in the treatments. In order to assess the impact of the capacity constraint on the market clearing price, we pool the data from all 210 auctions and estimate the following regression equation:

$$\textit{Market Clearing Price} = \beta_0 + \beta_1 \textit{Constrained} + \beta_2 \textit{Average Signal} + \beta_3 \textit{Experienced} + \varepsilon$$

In this equation, *Constrained* is a dummy variable that takes on a value of 1 for the C treatment and 0 for the UC treatment. The estimated coefficient for *Constrained* represents the difference of the effect of the capacity constraint on the market clearing price. *Average Signal* is a variable that indicates the signal level in a particular auction and is calculated by averaging the 4 signals in auctions under the UC treatment and 6 signals in auctions under the C treatment. *Experienced* is a dummy variable that takes the value of 0 for auction 1 to 7, and 1 for auction 8 to 14. It estimates the effect of a bidder's experience on the market clearing price. The null hypotheses are $\beta_1 = \beta_2 = \beta_3 = 0$.

The regression result is reported in Table 5. The estimated coefficient for β_1 indicates that the market clearing price in the C treatment is L$1.15 lower than in the UC treatment. The estimated β_1 is statistically significant at the 5% level, implying that the capacity constraint reduces the market clearing price significantly. The market clearing price is positively related to the average signal level. The estimated β_3 is insignificant and close to zero in magnitude. Therefore we cannot reject the null hypothesis that bidder's bidding experience has no effect on the market clearing price. Since the bidder's profit is directly related to the level of market clearing price, we can infer that bidder's experience has no effect on his profit. We test this by examining how profit evolves with experience over 14 auctions. The result confirms that no relationship exists between the bidding experience and the profit. Figure 7 shows the evolution of bidder's profit. The first point represents the mean profit for all 14 auctions. The second point is the mean profit for auction 2 through 14, and so on. There is no monotonically increasing or decreasing trend for both curves, indicating experience does not affect profit.

1.4.5 Allocation

Figure 8 reports the auction distribution by the number of winners for both treatments. 94% of auctions in the constrained setting allocate widgets to more than half of the bidders (3 bidders). However, in the UC treatment, only 60% of auctions allocate widgets to more than half of the bidders (2 bidders). The allocation pattern differs. Bidders in the C treatment are more likely to become winners.

We further examine the allocation pattern by evaluating the allocation asymmetry. We use the Herfindahl-Hirschman Index (HH index) to measure the award concentration. The HH index is calculated by summing the squares of the percentage allocations across the bidders in a given auction. The HH index ranges from 1/N to 1, where N is the number of bidders. The HH index equals one when all the units are allocated to one bidder. High HH index indicates high award concentration, implying high market power. The formula for Herfindahl-Hirschman Index is $H = \sum_{i=1}^{N} (\frac{q_i}{Q})^2$, where q_i is the quantity of the units awarded to bidder i, Q is the total number of the goods available for sale, and N is the number of bidders in one auction. In our experiment, a HH index of 0.25 for the UC treatment means perfectly symmetric allocation of 5 units per bidder. For the C treatment, a perfectly symmetric allocation of 3.3 ($\frac{20}{6} = 3.3$) units reflects a HH index of 0.17. Table 6 Panel A shows that the average HH index in the UC treatment (0.57) is significantly higher than 0.25, suggesting an asymmetric allocation pattern. The mean HH index in the C treatment is 0.27, which is also significantly higher than 0.17. Therefore, an asymmetric inter-bidder allocation exists in both settings. We go further to investigate which mechanism produces more asymmetric allocation by looking at the normalized HH index. The normalized HH index H^* is calculated as $H^* = \frac{H - \frac{1}{N}}{1 - \frac{1}{N}}$ and ranges from 0 to 1. Table 6 Panel B shows that the mean H^* for the UC treatment (0.42) is significantly higher than that in the C treatment (0.12). The reason lies in that bidders have higher market power in the C treatment than in the UC setting. One unconstrained bidder can take the whole market while at least three constrained bidders are needed to take the whole market. Capacity constraint directly impacts the allocation pattern and influencing the degree of market power.

1.5 Discussion

Although bidders in both treatments shade bids, constrained bidders bid more aggressively than unconstrained bidders. The average quantity-weighted bid price for a constrained bidder is -L$0.37 while -L$1.46 for an unconstrained bidder. Despite this, the mean market clearing price in the C treatment (-L$0.24) is statistically lower than that in the UC treatment (L$0.83). This is due to the effect of capacity constraint.

We compare the mean market clearing price and the bidder's quantity-weighted bid price for both treatments. We find that the constrained bidder's bid price (-L$0.37) is not significantly different from the mean market clearing price (-L$0.19) but the unconstrained bidder's bid price (-L$1.46) is significantly lower than the mean market clearing price (L$0.83). Therefore, an interesting question arises: How do we reconcile the more aggressive bidding in the C treatment with the lower market clearing price? In the previous analysis, we show that the constrained bidder's quantity-weighted bid price is lower than the unconstrained bidder's quantity-weighted bid price due to the impact of the "tail" of the demand curve. By studying the first 7 units of individual demand curves, we find no difference in the slopes of both demand curves and the average quantity-weighted bid prices. This indicates that bidders in both mechanisms have similar strategies over the first 7 units. The left 13 units located at the tail of the demand schedule actually play a role of pulling down the quantity-weighted bid price. This explains why the average quantity-weighed bid price for UC (20) is lower than C (7). The market clearing price in the C treatment is lower than that in the UC treatment due to the interaction of information structure and capacity constraint. Table 7 shows the relationship between the market clearing price and the quantity-weighted bid price. For each auction, we rank bidders' quantity-weighted bid prices from the highest to the lowest. We then compare the averaged quantity-weighted bid price in a specified rank with the market clearing price. For example, on average, the highest quantity-weighted bid price in the UC treatment is L$1.48, which is significantly different from the market clearing price L$0.83. Interestingly, the quantity-weighted bid price in each rank is very different from the market clearing price. We then examine the location of the market clearing price relative to bidders' quantity-weighted prices. The position of the market clearing price for the UC treatment is between the highest and 2nd highest bid price. The market clearing price for the C treatment is located between 3rd and 4th highest bid price. This indicates that the interaction of information structure and capacity constraint plays a critical role in influencing the market clearing price. In the UC treatment, a bidder has more market power and can take the whole market while it requires at least three bidders to take the whole market in the C treatment. A uniform-pricing rule indicates that the highest bid price in the UC treatment and the 3rd highest bid price in the C treatment are more likely to become market clearing prices. Due to the bid shading behavior, the market clearing price is lower than the highest bid price in the UC treatment and the 3rd highest bid price in the C treatment.

1.6 Conclusions

This paper examines bidding behavior and price discovery in a multi-unit auction. Consistent with theoretical predictions and previous empirical studies on multi-unit auctions, our experiment documents downward-sloping demand curves for individual bidders. Bidders employ mixed strategies and shade their bids by submitting quantity-price pairs and spreading their bids. However, we find that the auction outcomes differ in both settings. The winner's curse is strong in the unconstrained setting but we find no evidence of the winner's curse in the capacity constrained setting. At the auction level, in the unconstrained setting, the average bidder incurs a loss of L$4.24, but winners lose an average of L$9.52. In the constrained setting, the average bidder makes a profit of L$0.82, but winners make an average profit of L$0.83. Winning is bad news for winners in the unconstrained setting. Unconstrained bidders shade bids significantly more and their quantity-weighted prices are much lower than those in the constrained treatment. By studying the individual demand schedules, we find that the demand curves for the first 7 units of both constrained and unconstrained treatments are very similar. The tail of the demand curve in the unconstrained treatment significantly reduces the quantity-weighted bid price. Although unconstrained bidders submit bids more conservatively, they incur higher losses than constrained bidders, and the mean market clearing price is significantly higher than in the constrained treatment. Using the difference of the mean market clearing price and the true value to proxy for pricing accuracy, we find that the constrained treatment produces more efficient price discovery. A significant difference in the auction results in the constrained versus unconstrained setting indicates that the capacity constraint plays a critical role in determining bidding behavior and improving the accuracy of price discovery. Reducing the influence of a single bidder on the market clearing price significantly improves information aggregation, and the overall performance of the auction mechanism.

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Table 1: Experimental design

Panel A. Treatment conditions

Treatment	Mechanism	# of bidders	# of auctions	Experience	Endowment	Conversion US$/L$	Supply	Bidding capacity
C (Constrained)	Uniform price	6	14	No	L$ 400	0.05	20	7
UC (Unconstrained)	Uniform price	4	14	No	L$ 400	0.05	20	20

Panel B. Information structure

Auction #		A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	A15
True value		82	39	51	49	51	62	70	19	49	81	60	71	57	82	34
Treatment	Bidder ID	Signals														
UC	B1	80	40	53	49	50	61	67	16	50	77	61	75	57	81	30
UC	B2	84	43	51	48	53	65	71	23	45	79	64	67	57	79	34
UC	B3	78	43	55	45	49	62	69	21	45	84	61	75	58	85	32
UC	B4	81	37	48	50	47	58	68	20	46	82	57	75	61	81	32
	Mean	80.75	40.75	51.75	48.00	49.75	61.50	68.75	20.00	46.50	80.50	60.75	73.00	58.25	81.50	32.00
	std	2.50	2.87	2.99	2.16	2.50	2.89	1.71	2.94	2.38	3.11	2.87	4.00	1.89	2.52	1.63
C	B1	80	40	53	49	50	61	67	16	50	77	61	75	57	81	30
C	B2	84	43	51	48	53	65	71	23	45	79	64	67	57	79	34
C	B3	78	43	55	45	49	62	69	21	45	84	61	75	58	85	32
C	B4	81	37	48	50	47	58	68	20	46	82	57	75	61	81	32
C	B5	83	38	48	53	48	64	74	22	51	81	61	67	58	78	30
C	B6	86	37	47	50	53	62	71	23	48	82	59	71	55	79	36
	Mean	82.00	39.67	50.33	49.17	50.00	62.00	70.00	20.83	47.50	80.83	60.50	71.67	57.67	80.50	32.33
	std	2.90	2.80	3.20	2.64	2.53	2.45	2.53	2.64	2.59	2.48	2.35	3.93	1.97	2.51	2.34

Table 2: Experimental sessions and summary statistics

The nonparametric test is two-sample Fisher-Pitman permutation test for equality of means. The *p*-value is two-tailed *p*-value.

Session Date	Session#	Treatment	# of bidders	# of auctions	Mean clearing price - True value	Revenue		bidder's average Profit	
						Auction	Session	Auction	Session
05/29/08	1	C	6	14	-0.43	1167.14	16340	1.43	20.0
05/30/08	2	C	6	14	-0.29	1170.00	16380	0.95	13.3
06/02/08	3	C	6	14	0.21	1180.00	16520	-0.71	-10.0
06/03/08	4	C	6	14	-0.07	1174.29	16440	0.24	3.3
06/04/08	5	C	6	14	0.21	1180.00	16520	-0.71	-10.0
11/19/08	6	C	6	14	-0.79	1160.00	16240	2.62	36.7
06/10/09	7	C	6	14	-0.57	1164.29	16300	1.90	26.7
Mean					**-0.24**	**1170.82**	**16391.43**	**0.82**	**11.43**
t-stat					*-1.7040*	*402.9929*	*402.9929*	*1.6905*	*1.6905*
05/29/08	1	UC	4	14	0.71	1190.00	16660	-3.57	-50.0
05/30/08	2	UC	4	14	-0.21	1171.43	16400	1.07	15.0
06/03/08	3	UC	4	14	0.00	1175.71	16460	0.00	0.0
06/05/08	4	UC	4	14	0.57	1187.14	16620	-2.86	-40.0
06/06/08	5	UC	4	14	2.00	1215.71	17020	-10.71	-150.0
11/17/08	6	UC	4	14	0.57	1187.14	16620	-2.86	-40.0
06/12/09	7	UC	4	14	1.71	1210.00	16940	-8.57	-120.0
06/12/09	8	UC	4	14	1.29	1201.43	16820	-6.43	-90.0
Mean					**0.83**	**1192.32**	**16692.50**	**-4.24**	**-59.38**
t-stat					*3.0040*	*215.5172*	*215.5172*	*-2.9489*	*-2.9476*
Difference					**-1.08**	**-21.51**	**-301.07**	**5.06**	**70.80**
t-stat					*3.4414*	*3.4414*	*3.4414*	*-3.3314*	*3.3300*
Nonparametric test (p-value)					*0.0054*	*0.0058*	*0.0058*	*0.0056*	*0.0056*

Table 3: Profits and bidding for bidders and winners

The winner is defined as the bidder who is allocated with nonzero units of widgets. For each session, the winner's profit by auction is calculated by first averaging all the winners' profits in each auction to obtain the average winner's auction profit, and then averaging the mean winner's auction profit for the 14 auctions. The nonparametric test is two-sample Fisher-Pitman permutation test for equality of means. The *p*-value is two-tailed *p*-value.

Session	# of auctions	# of winners in auction	% of winners (# of winners/# of bidders)	bidder's profit (by auction)	winner's profit (by auction)	% of auctions with winner's loss (# of auctions with winner's loss/total # of auctions)		% of auctions with winner's positive proift (# of auctions with winner's positive profit/total # of auctions)		% of auctions with winner's zero profit (# of auctions with winner's zero profit/total # of auctions)	
UC1	14	2.4	0.61	-3.57	-11.07	7	50%	6	43%	1	7%
UC2	14	2.3	0.57	1.07	1.90	4	29%	7	50%	3	21%
UC3	14	3.1	0.79	0.00	-1.07	5	36%	6	43%	3	21%
UC4	14	2.4	0.59	-2.86	-10.83	7	50%	6	43%	1	7%
UC5	14	2.6	0.64	-10.71	-24.64	9	64%	2	14%	3	21%
UC6	14	3.2	0.80	-2.86	-3.93	8	57%	5	36%	1	7%
UC7	14	2.8	0.70	-8.57	-14.52	10	71%	1	7%	3	21%
UC8	14	2.5	0.63	-6.43	-12.02	9	64%	3	21%	2	14%
Mean		**2.66**	**0.67**	**-4.24**	**-9.52**	**7.4**	**53%**	**4.5**	**32%**	**2.1**	**15%**
C1	14	4.9	0.81	1.4	1.64	2	14%	5	36%	7	50%
C2	14	4.6	0.76	1.0	0.62	4	29%	7	50%	3	21%
C3	14	4.5	0.75	-0.7	-1.55	4	29%	3	21%	7	50%
C4	14	4.8	0.80	0.2	0.52	3	21%	6	43%	5	36%
C5	14	4.6	0.76	-0.7	-0.71	7	50%	4	29%	3	21%
C6	14	5.3	0.88	2.6	2.95	1	7%	8	57%	5	36%
C7	14	4.6	0.77	1.9	2.36	4	7%	9	57%	1	7%
Mean		**4.74**	**0.79**	**0.82**	**0.83**	**3.6**	**22%**	**6.0**	**42%**	**4.4**	**32%**
Difference			**-0.13**	**-5.06**	**-10.36**		**0.30**		**-0.10**		**-0.16**
t-stat			*-3.5313*	*-3.3314*	*-3.4048*		*3.9077*		*-1.2648*		*-2.5281*
Nonparametric test (p-value)			*0.0075*	*0.0056*	*0.0067*		*0.0044*		*0.2017*		*0.0202*

Table 4: Moments analysis

Panel A contains results on moment analysis when the true asset value is normalized to zero. Panel B contains results on moments analysis when the signal is normalized to zero. UC(20) represents the UC treatment where each bidder can bid up to 20 units. C(7) stands for the C treatment where each bidder can bid up to 7 units. UC(7) stands for the UC treatment where only the first 7 units submitted by bidder are studied. The analysis is at bidder level. The moments data (quantity demanded, number of bids, bid price, discount, standard deviation, skewness, and kurtosis) in the sheet is obtained by first calculating the moments data for each bidder in each auction, then getting auction mean for each bidder, finally averaging all the bidders' moments data. Each bidder is an observation. N=32 for UC treatment and N=42 for C treatment). The parenthesis is the t-statistic.

Panel A. The true value is normalized to zero.

	Q demanded	# of bids	bid price	discount	STD	Skewness	Kurtosis	signal	bid price - signal
UC(20)	18.45	4.54	-1.46	1.46	1.58	0.47	2.43	-0.09	-1.38
		14.7283	*-6.1162*	*6.1162*	*12.9701*	*5.6337*	*15.5670*	*-0.8700*	*-5.4329*
UC(7)	6.91	2.67	0.16	-0.16	0.96	-0.09	1.97	-0.09	0.23
		14.7197	*0.5039*	*-0.5039*	*9.2115*	*-1.0313*	*35.5698*	*-0.8653*	*0.6936*
C(7)	6.94	3.68	-0.37	0.37	1.59	0.09	1.99	-0.02	-0.35
		24.8022	*-1.7039*	*1.7039*	*10.3779*	*1.7413*	*33.1711*	*-0.3162*	*-1.7096*
UC(7)-C(7)		-1.01	0.53	-0.53	-0.63	-0.18	-0.02	-0.07	0.59
		-4.3064	*1.3933*	*-1.3933*	*-3.3955*	*-1.7623*	*-0.2999*	*-0.5126*	*1.4827*
UC(20)-C(7)		*0.86*	*-1.09*	*1.09*	*-0.01*	*0.38*	*0.44*	*-0.07*	*-1.03*
		2.5074	*-3.3677*	*3.3677*	*-0.0544*	*3.8717*	*2.6262*	*-0.5173*	*-3.1462*

Panel B. The signal is normalized to zero.

	Q demanded	# of bids	bid price	discount	STD	Skewness	Kurtosis
UC(20)	18.45	4.54	-1.43	1.43	1.58	0.47	2.43
		14.7283	*-5.7955*	*5.7955*	*12.9701*	*5.6337*	*15.5670*
UC(7)	6.91	2.67	0.19	-0.19	0.96	-0.10	1.96
		14.7197	*0.5712*	*-0.5712*	*9.1798*	*-1.1049*	*37.9894*
C(7)	6.94	3.68	-0.35	0.35	1.59	0.09	1.99
		24.7919	*-1.7063*	*1.7063*	*10.3842*	*1.7397*	*33.2091*
UC(7)-C(7)		-1.01	0.54	-0.54	-0.63	-0.19	-0.04
		-4.3047	*1.3879*	*-1.3879*	*-3.3957*	*-1.8253*	*-0.4431*
UC(20)-C(7)		*0.86*	*-1.08*	*1.08*	*-0.01*	*0.38*	*0.44*
		2.5079	*-3.3580*	*3.3580*	*-0.0562*	*3.8759*	*2.6295*

Table 5: Regression results

Equation1: Bid Price= a_0 + a_1Constrained + a_2 Average signal + error

Each bidder is an observation and N= 74 (32 bidders in UC treatment and 42 bidders in C treatments).

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-1.41	0.24	-5.81	0.00
Constrained	1.06	0.32	3.28	0.00
Average signal	0.50	0.30	1.66	0.10
R^2	*0.17*			
No. Obs	74			

Equation2: Market Clearing Price= b_0 + b_1Constrained + b_2 Average Signal + b_3 Experience + error

One auction is one observation and N=210 (112 UC auctions and 98 C auctions).

Regression with clustered robust

	Coefficients	*Robust Standard Error*	*t Stat*	*P-value*
Intercept	0.86	0.31	2.78	0.02
Constrained	-1.15	0.31	-3.76	0.00
Average signal	1.14	0.07	15.64	0.00
Experience	0.15	0.15	0.98	0.35
R^2	*0.55*			
No. Obs	210			

Table 6: Herfindahl-Hirschman Index

Panel A. HH index

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	Mean	STD
UC1	0.51	0.39	1.00	0.48	0.53	0.54	0.32	0.70	0.70	1.00	0.38	0.80	0.55	1.00	0.63	0.24
UC2	0.53	0.41	0.40	1.00	1.00	0.75	0.50	0.59	0.43	0.57	0.87	0.82	0.91	0.50	0.66	0.22
UC3	0.34	0.38	0.69	0.35	0.43	0.40	0.42	0.46	0.43	0.52	0.39	0.35	0.54	0.91	0.47	0.16
UC4	0.56	0.76	0.30	0.78	0.82	1.00	0.41	0.58	0.65	0.53	0.91	0.55	1.00	0.56	0.67	0.21
UC5	0.56	0.58	0.51	0.44	0.82	0.57	0.52	0.83	0.73	0.64	1.00	0.52	0.40	0.57	0.62	0.17
UC6	0.62	0.44	0.49	0.49	0.50	0.42	0.31	0.42	0.49	0.56	0.38	0.40	0.56	0.56	0.47	0.08
UC7	0.35	0.40	0.50	0.64	0.38	0.53	0.50	0.29	0.50	0.47	0.47	0.42	1.00	0.61	0.50	0.17
UC8	0.39	0.50	0.63	0.50	0.29	0.37	0.50	0.46	0.56	0.72	0.50	0.50	0.63	0.50	0.50	0.11
Mean	0.48	0.48	0.56	0.58	0.60	0.57	0.43	0.54	0.56	0.63	0.61	0.54	0.70	0.65	0.57	0.17
STD	0.11	0.13	0.21	0.21	0.25	0.21	0.08	0.17	0.12	0.17	0.27	0.18	0.23	0.19	0.18	

C1	0.21	0.24	0.27	0.29	0.28	0.27	0.28	0.24	0.23	0.27	0.22	0.27	0.23	0.24	0.25	0.02
C2	0.29	0.29	0.28	0.28	0.24	0.23	0.26	0.28	0.27	0.26	0.29	0.34	0.25	0.29	0.27	0.03
C3	0.28	0.28	0.20	0.33	0.30	0.34	0.25	0.23	0.27	0.27	0.29	0.33	0.25	0.26	0.28	0.04
C4	0.29	0.26	0.28	0.25	0.27	0.27	0.25	0.22	0.23	0.28	0.26	0.28	0.26	0.28	0.26	0.02
C5	0.30	0.27	0.28	0.30	0.28	0.31	0.29	0.24	0.34	0.30	0.25	0.34	0.21	0.29	0.28	0.03
C6	0.28	0.26	0.27	0.27	0.22	0.27	0.28	0.26	0.30	0.29	0.22	0.29	0.20	0.22	0.26	0.03
C7	0.26	0.29	0.24	0.27	0.26	0.27	0.26	0.25	0.23	0.29	0.25	0.27	0.29	0.28	0.27	0.02
Mean	0.27	0.27	0.26	0.29	0.26	0.28	0.27	0.25	0.27	0.28	0.25	0.30	0.24	0.26	0.27	0.03
STD	0.03	0.02	0.03	0.03	0.02	0.03	0.01	0.02	0.04	0.01	0.03	0.03	0.03	0.03	0.03	

Panel B. Normalized HH index

	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12	A13	A14	Mean	STD
UC1	0.35	0.19	1.00	0.30	0.37	0.38	0.10	0.59	0.59	1.00	0.17	0.73	0.40	1.00	0.51	0.32
UC2	0.38	0.21	0.19	1.00	1.00	0.66	0.34	0.46	0.24	0.43	0.83	0.76	0.87	0.33	0.55	0.29
UC3	0.12	0.17	0.59	0.13	0.24	0.21	0.23	0.28	0.25	0.36	0.19	0.14	0.39	0.87	0.30	0.21
UC4	0.42	0.68	0.06	0.71	0.76	1.00	0.21	0.44	0.53	0.38	0.87	0.39	1.00	0.41	0.56	0.28
UC5	0.41	0.44	0.34	0.25	0.75	0.43	0.36	0.77	0.65	0.52	1.00	0.36	0.20	0.43	0.49	0.22
UC6	0.49	0.25	0.32	0.31	0.34	0.23	0.07	0.22	0.32	0.41	0.17	0.20	0.41	0.41	0.30	0.11
UC7	0.13	0.19	0.33	0.53	0.17	0.38	0.33	0.05	0.33	0.29	0.29	0.23	1.00	0.49	0.34	0.23
UC8	0.18	0.33	0.50	0.33	0.06	0.16	0.33	0.28	0.41	0.63	0.33	0.33	0.50	0.33	0.34	0.15
Mean	0.31	0.31	0.42	0.45	0.46	0.43	0.25	0.39	0.42	0.50	0.48	0.39	0.60	0.53	0.42	0.23
STD	0.14	0.18	0.29	0.29	0.33	0.28	0.11	0.23	0.16	0.23	0.36	0.24	0.31	0.26	0.24	
C1	0.05	0.09	0.13	0.15	0.13	0.12	0.13	0.09	0.08	0.12	0.06	0.12	0.08	0.08	0.10	0.03
C2	0.15	0.15	0.14	0.13	0.09	0.07	0.11	0.14	0.12	0.11	0.15	0.20	0.10	0.15	0.13	0.03
C3	0.14	0.14	0.04	0.20	0.15	0.20	0.10	0.08	0.12	0.12	0.15	0.20	0.11	0.11	0.13	0.05
C4	0.15	0.11	0.13	0.10	0.12	0.12	0.11	0.06	0.07	0.14	0.11	0.13	0.11	0.14	0.11	0.02
C5	0.16	0.13	0.14	0.17	0.14	0.17	0.14	0.09	0.20	0.15	0.10	0.20	0.05	0.14	0.14	0.04
C6	0.14	0.11	0.13	0.12	0.07	0.12	0.13	0.11	0.15	0.15	0.06	0.14	0.04	0.06	0.11	0.04
C7	0.11	0.14	0.09	0.12	0.11	0.13	0.11	0.11	0.08	0.14	0.10	0.13	0.15	0.14	0.12	0.02
Mean	0.13	0.12	0.11	0.14	0.12	0.13	0.12	0.10	0.12	0.13	0.10	0.16	0.09	0.12	0.12	0.03
STD	0.04	0.02	0.03	0.03	0.03	0.04	0.02	0.03	0.05	0.02	0.04	0.04	0.04	0.03	0.03	

Table 7: The relationship between the MCP and the bid price

Panel A. UC treatment

Rank	Quantity-weighted bid price	*t-stat*
1 (highest)	1.48	*7.99*
2	-1.58	*-7.67*
3	-2.99	*-13.31*
4 (lowest)	-4.68	*-13.71*
Market Clearing Price	0.83	

Panel B. C treatment

Rank	Quantity-weighted bid price	*t-stat*
1 (highest)	3.17	*15.49*
2	0.58	*2.33*
3	-1.49	*-6.86*
4	-2.39	*-11.38*
5	-3.64	*-11.87*
6 (lowest)	-4.92	*-9.66*
Market Clearing Price	-0.24	

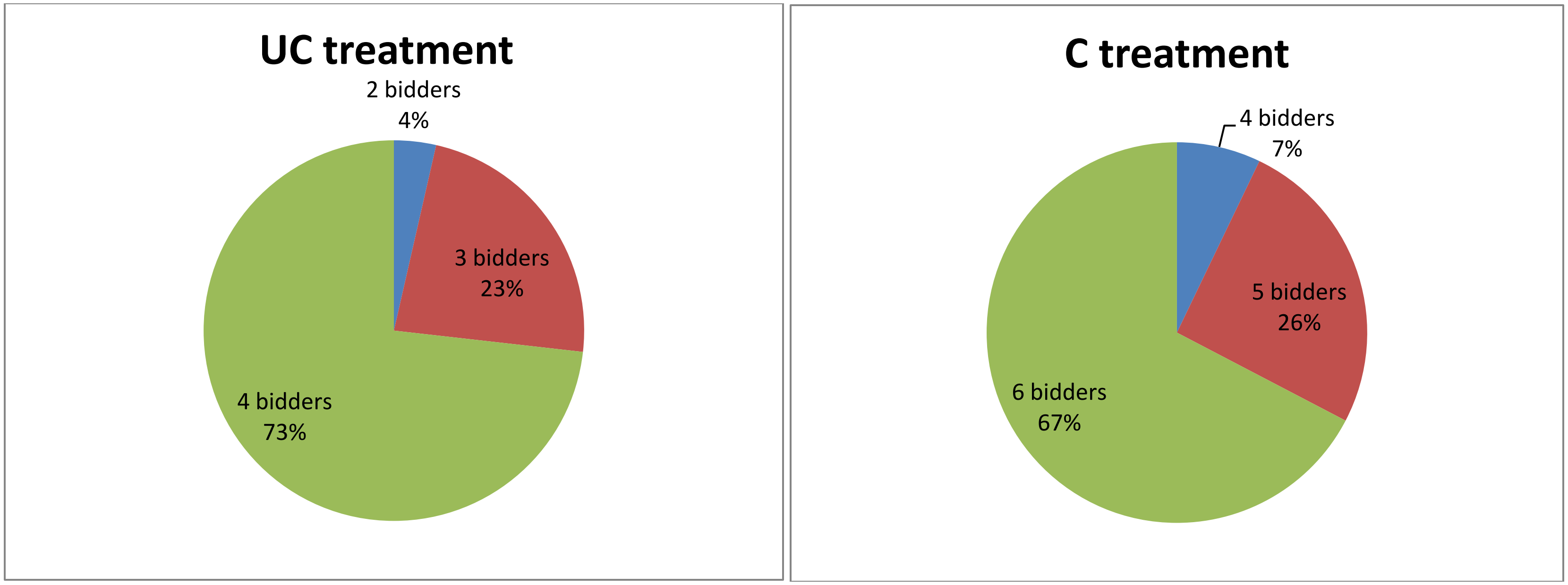

Figure 1: Auction distribution by the number of bidders who submitted price-quantity pairs
Note: This figure shows the percentage of auctions under each treatment in which a given number of subjects submitted more than one price-quantity combination.

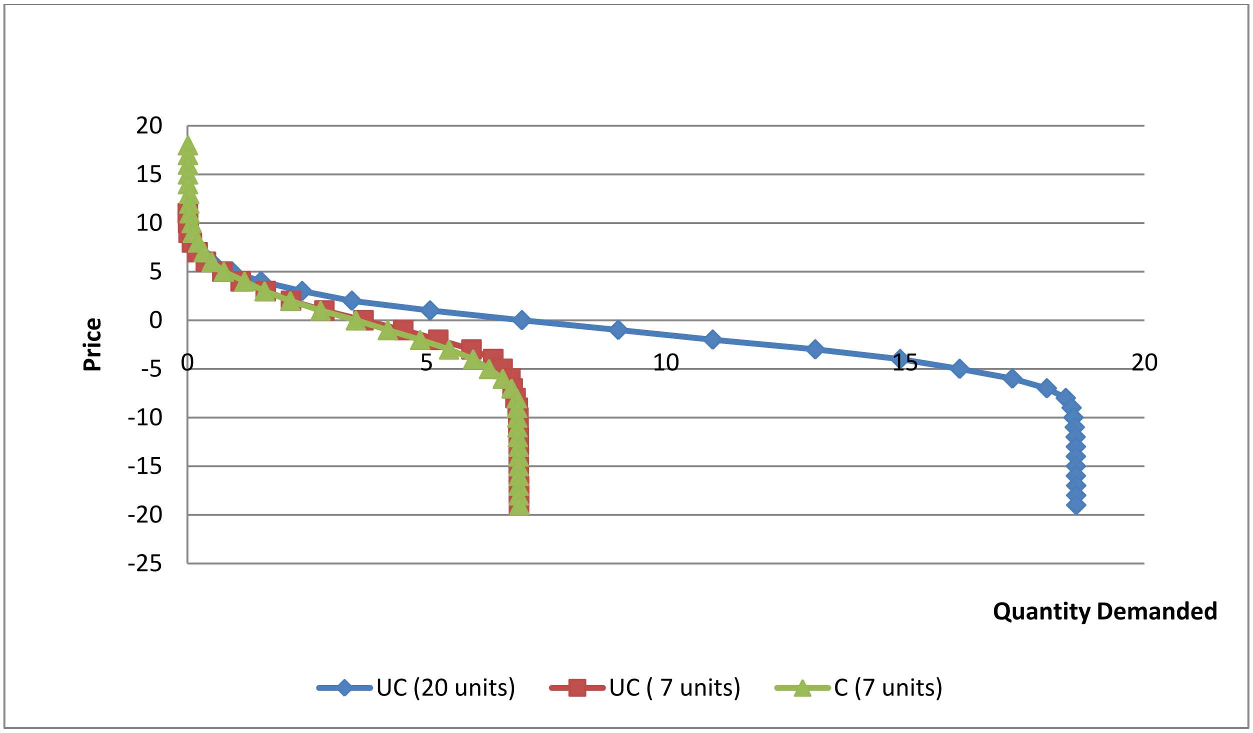

Figure 2: Demand curve
Note: The demand is at bidder's auction level. The true asset value is normalized to zero.

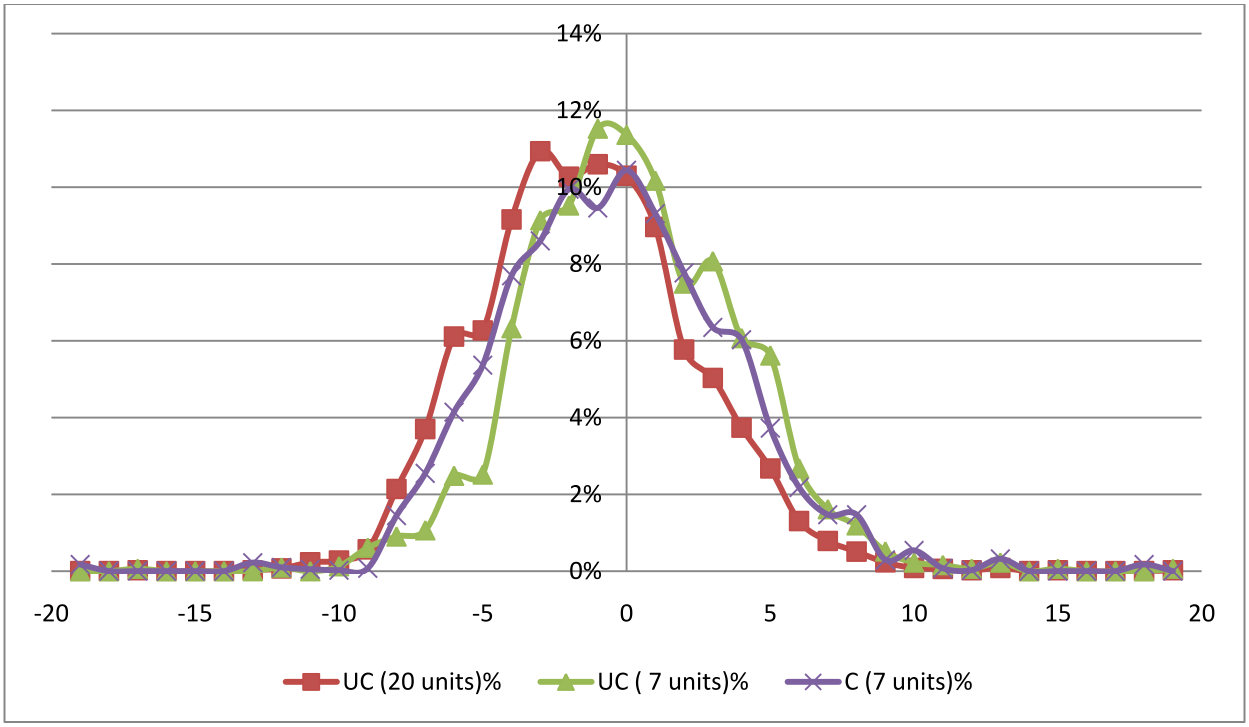

Figure 3: Bids distribution for average bidder in one auction
NOTE: This figure shows the quantity demanded distribution at each bidding price level for both UC and C treatments. We include UC (7 units) for comparison purpose. The true asset value is zero. The percentage of quantity demanded at a certain price level is calculated by obtaining each bidder's mean auction quantity demanded at that price level, then dividing the mean auction quantity demanded by mean auction total quantity demanded), and then averaging all the bidders' percentage of quantity demanded at that price level.

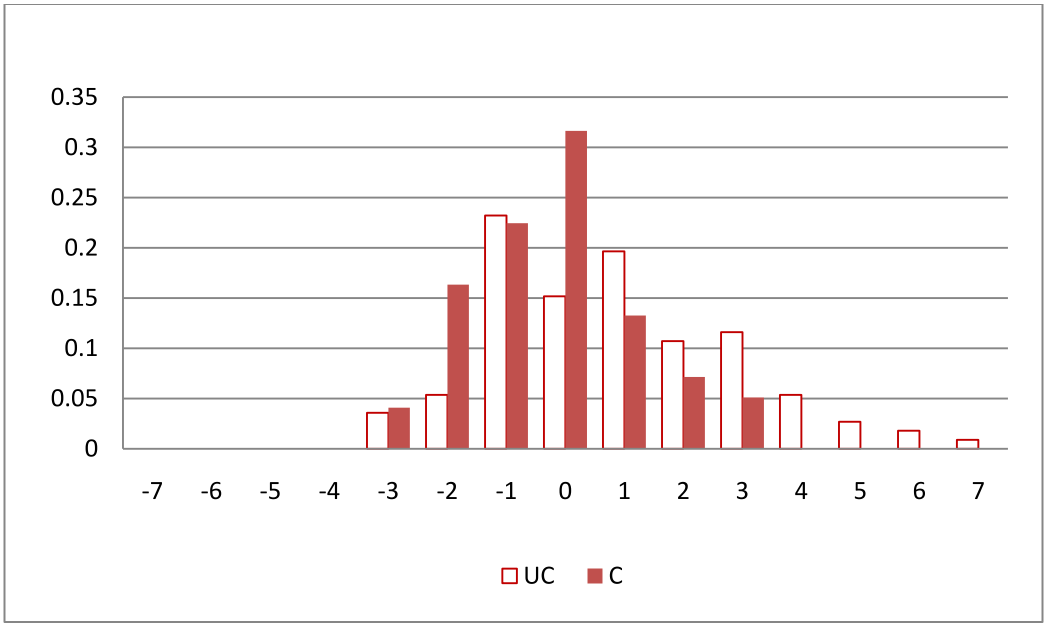

Figure 4: Distribution of auctions by the market clearing price

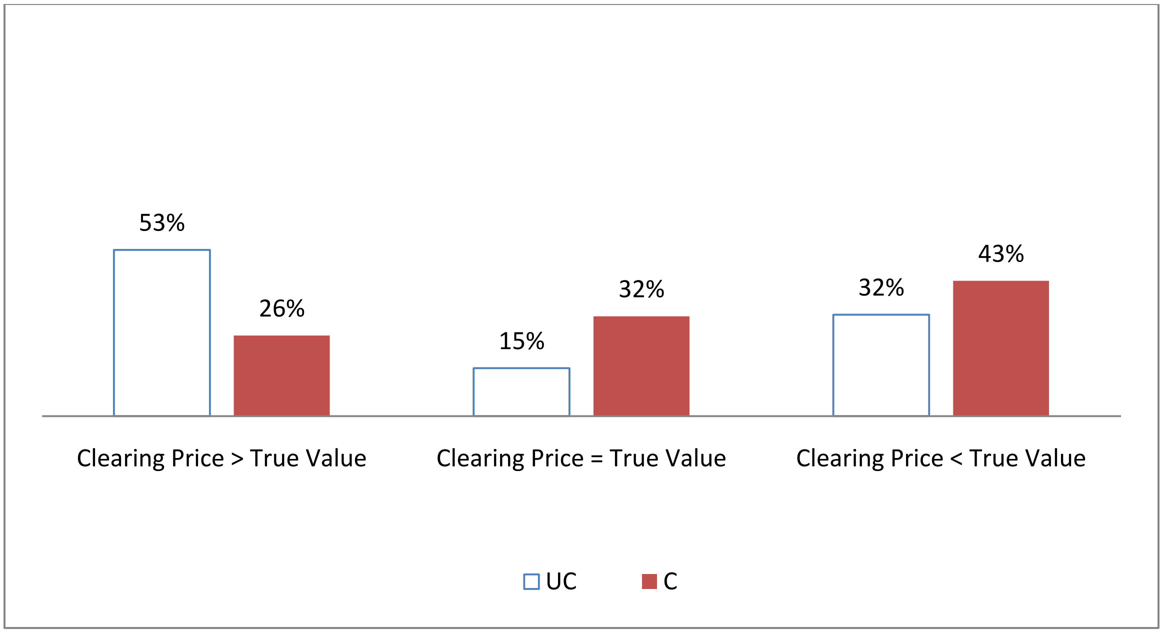

Figure 5: Distribution of auctions by the relationship between the market clearing price and the true value

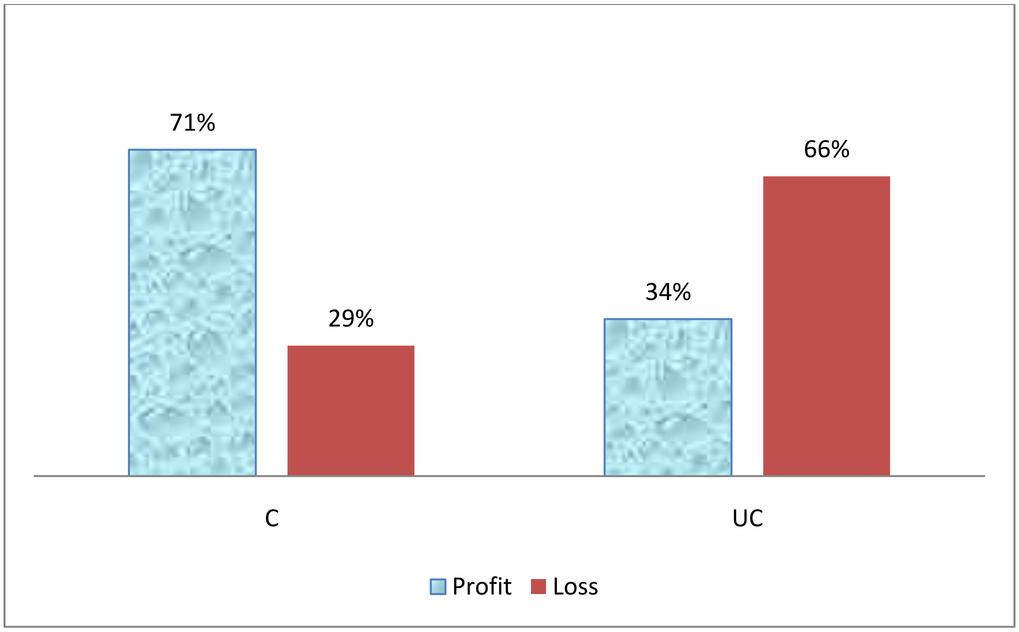

Figure 6: Distribution of bidders by session profit/loss

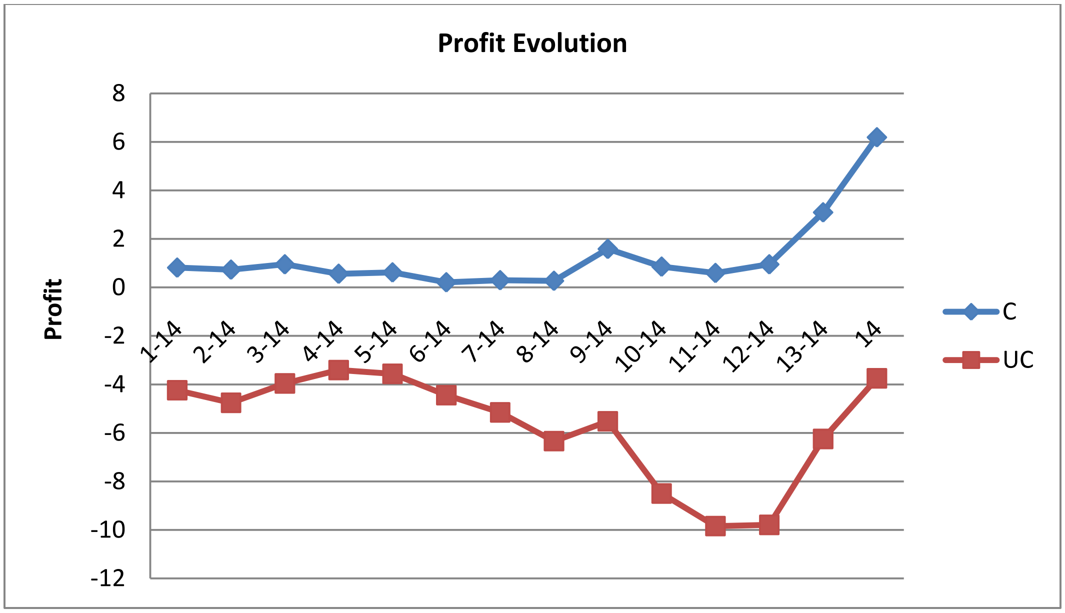

Figure 7: Profit evolution

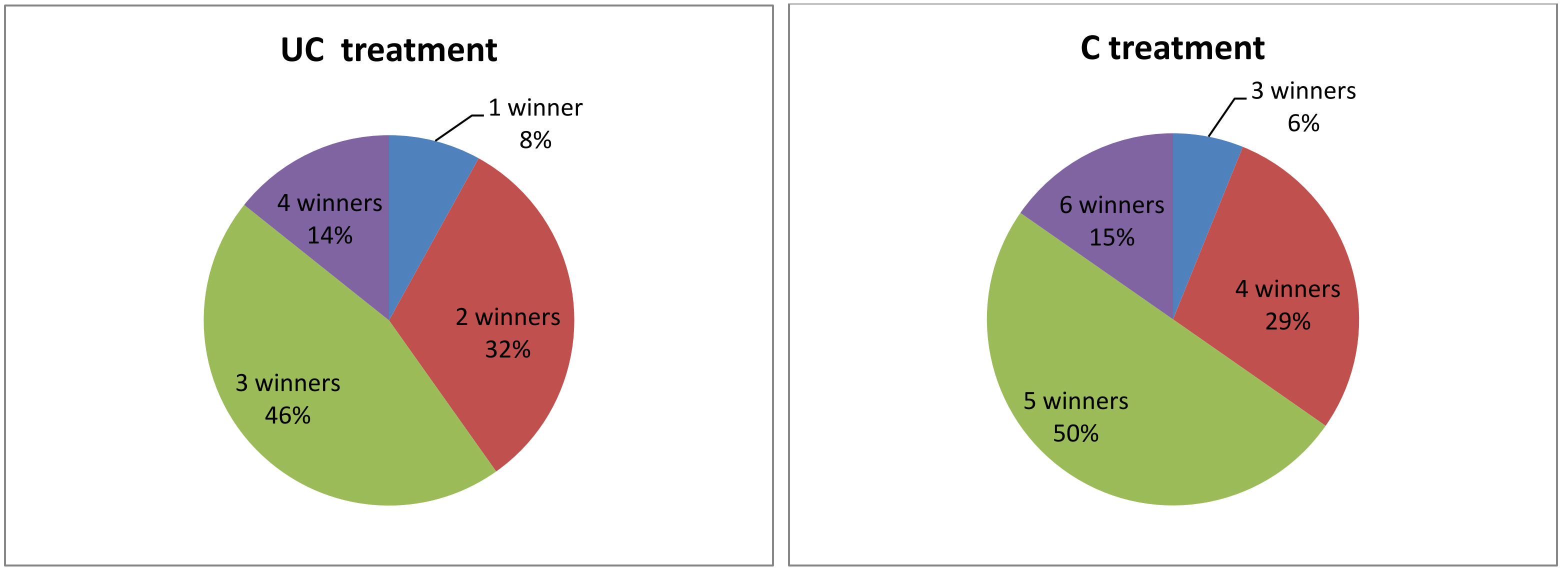

Figure 8: Auction distribution by the number of bidders receiving allocation

ESSAY 2: MULTI-UNIT AUCTIONS WITH NONCOMPETITIVE BIDDING: AN EXPERIMENTAL EXAMINATION

2.1 Introduction

Auction is an important selling mechanism in the competitive markets where market participants hold diverse information about the intrinsic value of the auctioned items. In the financial market, auction has become a prevalent procedure for government debt issuance. However, it is rarely used in the equity Initial Public Offering (IPO) market where the estimation of the intrinsic value is more difficult. The auction approach has been tested in many countries in the 1980s, but it was gradually replaced by the bookbuilding and fixed price offer methods. Currently auctioned IPOs can be found only in a few countries and in none of these countries auction has become the dominant procedure.

The academic literature has advanced arguments for the potential reasons why auction is unpopular in the IPO market. Ausubel (2002) contributes the unpopularity of the auction to the pressure from investment banks to use bookbuilding since the profits from using bookbuilding is enormous, which is around 7 percent of the issue proceeds. Jagannathan and Sherman (2006) and Sherman (2005) provide different view. They show that auctions were abandoned long before the bookbuilding was introduced from the United States and it was even replaced by the fixed price offer in which the fees could be even lower. They argue that auction is particularly vulnerable to two serious problems in an IPO setting: the winner’s curse and the free riding problem. The winner’s curse problem applies when the value of the auctioned item is the same to all the bidders but bidders hold differential information about the intrinsic value. Theoretically the winner’s curse problem can be overcome by shading bids, but bidders usually find it more difficult to adequately adjust the winner’s curse when the number of participants in the auction is unpredictable. Therefore, the winner’s curse deters the participation of investors. Among the potential participants, retail investors face the strongest winner curse because they are uninformed due to no resources to gather information. The second problem – the free rider problem arises because the standard IPO auction does not reward those who costly gather information or truly reveal information. Some investors, especially retail investors, have incentives to free ride by submitting extremely high bids as a bidding strategy to get shares without paying information acquisition cost. Degeorge, Derrien and Womack (2008) study the 19 U.S. IPOs completed by WR Hambrecht +Co through OpenIPO auction mechanism and find that retail investors are the major body of free riders.

The auction literature shows that mechanism design matters. Since the traditional IPO auction is vulnerable to two major problems, a natural question arises: can the inherent drawbacks be overcome by design modification which improves the performance of the auction by encouraging more participation, enforcing competitive results, promoting accurate pricing?

In seek of how to overcome the two problems that confront the standard IPO auction, we find that the U.S treasury has the practice of using a noncompetitive bidding mechanism to attract retail investors to participate. This noncompetitive bidding mechanism ensures less sophisticated and budget-constrained retail investors to acquire a certain amount of shares at the market price, which creates an opportunity for retail investors to “free ride” in spite of their information disadvantage. In the IPO market, the information gathering process is more costly and the winner's curse that investors face is much stronger than in the Treasury auction. Therefore, we predict that adding a noncompetitive bidding mechanism will affect the entry and bidding decisions of market participants, especially those unsophisticated retail investors. Allowing them to submit noncompetitive bids can reduce the winner's curse and their incentives to free ride because they can now "free ride" by submitting market order. As a result, the investor base will broaden. In addition, the auction price is expected to be more accurate since competitive bids contain less noise when most of the uninformed retail bidders do not participate in the competitive bidding.

So far, no empirical work has been done to examine the role of the noncompetitive mechanism yet. No existing equity IPO models have incorporated this mechanism. Back and Zender's (1993) Treasury auction model shows that the equilibrium stop-out price is monotonically increasing with noncompetitive demand, but this model is built on a lot of assumptions. Therefore, due to the lack of equilibrium models, we use laboratory experiments to examine the impact of incorporating a noncompetitive bidding option on auction results and bidding behaviors. Laboratory auction markets are a useful tool for understanding relative performance because they permit the controlled manipulation of the rules and procedures that constitute an auction mechanism. We also exploit the laboratory setting in order to control information sets, and to allow strategic dimensions.

Our experiment design includes two treatments: NC treatment (a uniform-price auction with noncompetitive bidding option) and C treatment (a standard uniform-price auction where all bids are competitive). Important features of the bidding environment include endogenous entry, costly information acquisition, and bidders with different bidding capacity. We impose two bidder types in the experiment: large bidder and small bidder. This design is motivated by the observation that in the financial markets there are two types of investors: retail investors and institutional investors. They differ in their size and bidding capacity. Retail investors are usually informally disadvantaged. In the experiment, the bidder type is exogenously determined. Once knowing his bidder type, each bidder then can make decisions on whether or not to participate, whether or not to purchase information, and how to submit bids. These bidding features simulate the real world IPO market and allow us to investigate how bidders make decisions in different market mechanism.

In our experiment, we restrict the auction pricing rule to be uniform rather than discriminatory, because in the United States the SEC prohibits issuers from selling shares to investors at different prices. A large body of theoretical work [for example, Vickery (1961), Friedman (1960), and Milgrom (2004)] suggests uniform pricing rules reduce the winner's curse in the common value auction and encourage competition. We also employ pro rata rationing rule rather than the traditional rationing rule that gives allocation priority to the bids above the stop-out price. Kremer and Nyborg (2004a) and Damianov (2005) show that rationing of all bids at and above the stop-out price can reduce underpricing in a uniform-price auction. This pro rata rationing rule is used in French IPO auction (see Derrien and Womack (2003)).

The main insight of this paper is that the major problems that confront the traditional IPO auction can be mitigated by improving the mechanism design. This research compliments recent work that studies alternative IPO auction mechanisms. For example, Ausubel (2004) proposes an ascending multi-unit auction. Manelli, Sefton, and Wilner (2006) experimentally compare the Ausubel ascending auction with the Vickrey auction and show that the revenue generated in the Ausubel auctions are higher than the Vickrey auction in a common value setting.

Our main results are as follows. We find that the auction incorporated with a noncompetitive bidding option provides better performance with higher revenue, and lower pricing volatility and lower price error than the standard auction. In a costly information acquisition setting, we find significant underpricing in both treatments, but underpricing is less severe in the NC treatment. The noncompetitive bidding option significantly increase small investors' participation rate and allocation, and reduces small bidders' incentives to free ride by submitting extremely high bids. Bidding is more conservative in the NC treatment. However, the force of reduced supply on increasing the market clearing price is much stronger than the force of lowered bidding aggressiveness on reducing the market clearing price. As a result, the market clearing price in the NC treatment is higher. In both treatments, large bidders earn significantly higher profits than small bidders. Information purchase increases large bidder's profit but reduces small bidder's profit. The pricing accuracy is significantly related to the treatment and the number of information purchase.

The plan of the paper is as follows. In section II we review the relevant literatures. In section III we explain the experimental design, in section IV we discuss our results, in session V we further discussion about our results, and in section VI we conclude.

2.2 Literature Review

An auction with noncompetitive bidding system has been used in the U.S Treasury auctions. According to *the Joint Report on the Government Securities Market* (1992), the Treasury permits noncompetitive bidding in order to make it easier for smaller, less sophisticated bidders to participate. Theoretical IPO literature (Bennouri and Falconieri (2006) and Malakhov (2007)) have shown that increasing the participation of uninformed bidders generates more revenues to the issuer because it lowers the informational rent paid to the informed bidders. The noncompetitive bidding mechanism provides an opportunity for small investors to “free ride” by submitting noncompetitive bids and receiving shares at the market price, which reduces the winner’s curse they face and mitigate the free ride problem. Theoretical study of the noncompetitive bidding in a common value auction includes Back and Zender (1993). Their Treasury auction model shows the equilibrium stop-out price increases monotonically with the random noncompetitive demand. The noncompetitive demand reduces the supply but also creates an uncertainty on the competitive supply. The expected stop-out price in a setting when there is uncertainty in the supply is higher than in a fixed supply setting. In a private paradigm, Engelbrecht-Wiggans (1996) models a multi-unit auction with noncompetitive sales with symmetric information. His model shows that at equilibrium, some buy noncompetitively while others bid in the auction, and the seller benefits from allowing noncompetitive sales. Engelbrecht-Wiggans and Katok (2006) study a procure procedure which involves a hybrid mechanism which combines an English auction with noncompetitive contracts. Their experimental study indicates that the hybrid mechanisms increase competition through removing some supply from the auction market.

In the mechanism design, we employ a uniform pricing rule. There are practical and theoretical reasons. According to the regulation of the U.S Securities and Exchanges Committee, investors should pay the same price for the new issued shares. Vickrey (1961) states that an auction should be structured so that the price paid by the player is as independent of his bids as possible, which will encourage competition. Milgrom (2004, pg 256) explains the uniform auction is frequently adopted in practice because it reduces price risk. Friedman (1960) claims that a uniform-price auction reduces the effect of the winner's curse problem therefore encouraging competitive bidding. Sade, Schnitzlein, and Zender (2006a) find in a laboratory experiment that uniform pricing auction in a multi-unit common value setting generates higher revenues than does a discriminatory auction. Bennouri and Falconieri (2006) show that the optimal IPO auction is a uniform-price auction.

Although a uniform pricing auction can enforce competition, the seminal paper by Wilson (1979), extended by Back and Zender (1993) shows that there are often multiple equilibria when a uniform-price auction is employed. These multi-unit auction models are built on multiple assumptions. Recent studies [Kremer and Nyborg (2004a, b), Sade, Schnitzlein, and Zender (2006a,b), Back and Zender (2001), and Damianov (2005)] have investigated whether the underpricing equilibria still hold if some assumptions are relaxed or some reasonable features are considered. These examinations includes changing demand functions from continuous to discrete, changing the rationing rule, considering bidder characteristics, and introducing endogenous supply. All these studies show that the set of underpricing equilibria can be eliminated or reduced. Kremer and Nyborg (2004b) argue that when bidders are allowed to submit discrete demand schedules or when there exist a minimal price tick and a minimal quantity multiple, underpricing can be reduced or even eliminated. Kremer and Nyborg (2004a) study the role of a rationing rule and show that rationing of all bids at and above the stop-out price leads to better outcomes for the seller in a uniform-price auction. Sade, Schnitzlein, and Zender (2006b) find that asymmetry in bidders' capacity constraints plays an important role in inhibiting collusion and promoting competitive outcomes in multi-unit common value auctions. Sade, Schnitzlein, and Zender (2006a) demonstrate that in their experimental setting, bidders do not play the standard collusive-seeming strategies in the uniform-price auction. These results imply that collusion may not be a serious problem in the IPO market since investors in the new issuance markets are asymmetric in many aspects such as bidding capacities. The endogenous supply or uncertainty of supply will also reduce the set of underpricing equilibria [see Back and Zender (2001) and Damianov (2005)]. Damianov (2005) finds that endogenous supply with a pro rata rationing rule eliminates underpricing in the uniform-price auction. In our study, to limit the degree of underpricing, we adopt the pro rata rationing and build asymmetric bidding capacity into the auction mechanism. The result of these studies suggests that a well designed multi-unit uniform-price auction can enforce competitive results.

2.3 Experiment Design and Procedure

2.3.1 Experimental Design Overview

Each experiment session consists of a series of periods in which 30 shares of stock are sold to 8 potential investors. There are 4 small investors and 4 large investors. In each period, each subject is randomly assigned as either large investor or small investor. A large investor can bid for up to 15 shares while a small investor can bid for up to 3 shares. This design is motivated by the observation that in the equity IPO market there are typically two groups of investors: institutional investors, who are better informed of the firm value and retail investors who are relatively uninformed. Typically, the two groups would also face different budget constraints so their bidding capacity differs. Before each auction begins, each bidder receives his bidder type. He then makes an entry decision. If he decides not to participate, he will receive L$1 nonparticipation payment, which represents the return of investing in the risk free asset while giving up the bidding opportunity. For those who participate in the bidding, they have an option to purchase information about the true asset value. We include this feature in the experiment since gathering costly information about the fundamental value of the firm is a key characteristic of the equity IPO market. Once a bidder purchases information, he will receive a signal, which narrows the intrinsic value within the range of L$3 above or below the true value. The information cost is L$3.

We conduct experiments under two treatments. The first treatment is NC treatment (a uniform-price auction with noncompetitive bidding option). The second treatment is C treatment (a standard uniform-price auction, where only competitive bids are allowed). In the C treatment, each participant submits only competitive bids while in the NC treatment, each participant is allowed to submit both noncompetitive and competitive bids. In the NC treatment, we impose restrictions on both the noncompetitive supply and the individual noncompetitive demand. The noncompetitive supply is 10 shares and the individual noncompetitive demand cannot exceed 3 shares. We impose restrictions on noncompetitive supply because it is necessary to maintain a large pool of competitive bids to determine a price. If the noncompetitive supply is set too high, the price will be distorted since it only represents a very small proportion of market demand. If the noncompetitive supply is set too low, it will eliminate the role of the noncompetitive bidding. In the experiment, the supply available for the competitive bidders is not disclosed. This design is motivated by the research work of Back and Zender (2001) and Damianov (2005), who suggest that the uncertainty of the supply in the multi-unit auction will benefit the issuer. In both treatments, the competitive bidding is conducted in a common value uniform-pricing auction where the intrinsic value is randomly selected from the interval of [L$12, L$28]. The distribution of the true value is common knowledge. The true value is unknown to all the bidders before auction begins and is revealed to all the bidders when the auction is completed. Once all the bidders finish submitting bids, software will determine whether the auction is successful or not; if market demand exceeds market supply, auction is successful. Then the software will calculate the market clearing price and allocate shares to the winning bidders. If market demand is less than market supply, auction fails and no shares will be distributed.

Next, we discuss the details about how the market clearing price and the allocation is determined when the auction is successful. Following is the notation we use for the explanation of the allocation rule.

p	stop-out price (market clearing price)
n	the number of participants
d_i^{NC}	bidder *i*'s noncompetitive demand
d_i^{C}	bidder *i*'s cumulative competitive demand at stop-out price *p*
D^{NC}	market noncompetitive demand
D^{C}	market cumulative competitive demand at stop-out price p
q_i^{NC}	bidder *i*'s noncompetitive allocation
q_i^{C}	bidder *i*'s competitive allocation
q_i	bidder *i*'s total allocation
ω	nonparticipation payment
c	information cost

If the realized total noncompetitive demand (D^{NC}) is equal or less than 10, the noncompetitive allocation for each bidder is the exact number of shares he submits (d_i^{NC}). If D^{NC} is greater than 10 shares, we will allocate the 10 shares to the winning bidders by pro rata rationing rule. Therefore, the noncompetitive allocation for bidder *i* is

$$q_i^{NC} = \begin{cases} \dfrac{d_i^{NC}}{D^{NC}} \times 10 & if \quad D^{NC} > 10 \\ d_i^{NC} & if \quad D^{NC} \leq 10 \end{cases}.$$

When the total noncompetitive demand is greater than 10, the competitive supply is 20. When the total noncompetitive demand is less than or equal to 10, the competitive supply will be the difference of the total supply 30 and the total noncompetitive demand D^{NC}. The stop-out price *p* is the highest price at which the market cumulative competitive demand equals or exceeds the total competitive supply. The market cumulative competitive demand at stop-out price p is D^C, which is the sum of all bidders' cumulative competitive demand at p ($D^C = \sum_{i=1}^{n} d_i^C$). Bidder i's competitive allocation q_i^C is

$$q_i^C = \begin{cases} \dfrac{d_i^C}{D^C} \times 20 & if \quad D^{NC} > 10 \\ \dfrac{d_i^C}{D^C} \times (30 - D^{NC}) & if \quad D^{NC} \le 10 \end{cases}.$$

Bidder i's total allocation in the NC treatment is the sum of noncompetitive allocation and competitive allocation, which is

$$q_i = q_i^{NC} + q_i^C = \begin{cases} \dfrac{d_i^{NC}}{D^{NC}} \times 10 + \dfrac{d_i^C}{D^C} \times 20 & if \quad D^{NC} > 10 \\ d_i^{NC} + \dfrac{d_i^C}{D^C} \times (30 - D^{NC}) & if \quad D^{NC} \le 10 \end{cases}.$$

In the C treatment, bidder i's total allocation q_i equals to q_i^C, which is calculated as $\dfrac{d_i^C}{D^C}$. The following table summarizes the allocation rules for a successful auction.

	NC treatment		C treatment
	$D^{NC} > 10$	$D^{NC} \le 10$	
Bidder i's total allocation q_i	$\dfrac{d_i^{NC}}{D^{NC}} \times 10 + \dfrac{d_i^C}{D^C} \times 20$	$d_i^{NC} + \dfrac{d_i^C}{D^C} \times (30 - D^{NC})$	$\dfrac{d_i^C}{D^C} \times 30$

In both treatments, bidder i 's profit π_j in auction j, j=1…18, is calculated as follows:

$$\pi_i = \begin{cases} \varpi & participation = No \\ q_i \times (p - v) & participation = Yes \quad purchase = No \\ q_i \times (p - v) - c & participation = Yes \quad purchase = Yes \end{cases}$$

2.3.2 Parameter Values and Variable Distributions

In our experiment, the monetary unit employed is the laboratory dollar (L$). To convert laboratory dollars to $US, the exchange rate is 0.04. Each bidder starts with the same initial cash balance of L$500. At the end of experiment, each subject receives an additional random payment ranging from $US1 to $US5. The random additional payment is designed to enhance experimental control when bidders have low balances.

There are three draws of the true values for three levels of subject experience. Bidder type and information structure are held constant. The private information is randomly selected from the integer range [-3, +3]. The signal value is the true value plus the private information. Each bidder's role as small bidder or large bidder is randomly assigned, conditional on that there are 4 small bidders and 4 large bidders in each auction and in each session each subject is assigned as small bidder in 9 auctions and as large bidder in 9 auctions. There are 18 auctions for each session.

2.3.3 Subjects and Procedures

We conducted a total of 14 sessions, with 7 sessions for each treatment. Each session consists of 18 auctions, with a cohort of 8 subjects. The experiment was programmed and conducted with z-Tree software (Fischbacher 2007). In May, June, and October of 2009, we recruited graduate and undergraduate students who had previous auction experiment experience at the University of Central Florida. The majority of the subjects were undergraduates of the College of Business Administration. Subjects' level of experience includes inexperienced, experienced, and twice-experienced. In the "inexperienced" session, the subjects were first time participants. In the "experienced" session, the subjects participated in the experiment for the second time. In the "twice-experienced" session, the subjects were participating for the third time.

At the beginning of each session, subjects were given written instructions. The instructions explained the auction rules, the basis on which cash payments would be made, and included the bidding interface that introduce the subjects to the software used to conduct the experiment. The experimenter read the instructions to the subjects, and subjects were then given the opportunity to ask questions. Each subject was then assigned to a computer terminal. After each auction finishes, each subject learns the market clearing price, the true value, his allocation, his profit, and his cash balance. The interface stores historical auction results. Each auction is independent, with the exception of cash balances. The profit (loss) is carried over from period to period. Over the course of experiment, subjects are not allowed to communicate with each other.

2.4 Experimental Results

We examine the experimental results focusing on the following outcomes: participation rate, information purchase behavior, bidding strategies, market clearing price, profit, and allocation.

2.4.1 Basic Statistics

Table 8 presents basic statistics about auction results for both treatments. To simplify the data analysis, we normalize the true value in each auction to zero. Therefore, the market clearing price after shifting the true value to zero actually indicates the deviation of the market clearing price from the true value. In both treatments, the market clearing price is significantly lower than the true asset value, indicating significant underpricing occurs. The degree of underpricing in the NC treatment (L$0.69) is less severe than in the C treatment (L$1.21). The nonparametric test shows that the difference of underpricing in both treatments is significant at 10 percent level. We use the standard deviation of market clearing prices to proxy for price volatility and find that the price in the NC treatment is relatively less volatile. However, the difference of the price volatility across treatments is not statistically significant. Another performance indicator we examine is price error, which is defined as the difference of the market clearing price and the true asset value, in absolute value. We find that the price error in the NC treatment is significantly lower ($p=0.07$), indicating more accurate pricing. These three performance indicators suggest that the auction with noncompetitive bidding option performs better than the standard auction with significantly higher market clearing price and lower price error.

2.4.2 Participation Rate and Information Purchase Behavior

Table 9 presents statistics about the participation rate. The participation rate of small (large) bidders is the number of small (large) bidders who choose to participate in the auction divided by the total number of small (large) bidders, which is 4 in each auction. In both treatments, the participation rate of large bidders is significantly higher than that of small bidders. In the NC treatment, the participation rate of large bidders is 98% and 85% for small bidders. In the C treatment, the participation rate is 95% for the large bidders and only 74% for the small bidders. Comparing both treatments, we find that the small bidders in the NC treatment have significantly higher participation rate than in the C treatment. The difference in the mean of the participation rate of small bidders is 11% (t=3.03). Comparing large bidders' participation rate in both treatments, we find there is no significant difference. This result shows that the incorporation of a noncompetitive bidding option increases small bidders' incentives to participate.

Table 10 shows the data for information acquisition. The subject pool excludes the non-participants. The purchase rate of potential participants is the number of bidders who purchased information divided by the total number of participants. We find that in both treatments, large bidders are more likely to purchase information than small bidders. In the NC treatment, the information purchase rate for large bidders is 83%, but only 7% for small bidders. In the C treatment, the rate for large bidders is 74% and 14% for small bidders. The difference is statistically significant at 1% level. Comparing the information acquisition behavior across treatments, we find small bidders in the NC treatment are less willing to purchase information than in the C treatment. It seems that the noncompetitive bidding option increases small bidders' incentives to free ride by submitting noncompetitive bids with no need to purchase costly information. In contrast, large bidders in the NC treatment are more willing to purchase information than in the C treatment.

2.4.3 Noncompetitive Bidding

Table 11 displays the demand data. We first examine individual bidder's total demand. In the C treatment, on average, a small bidder demands 2.98 shares while a large bidder demands 14.78 shares. In the NC treatment, an average small bidder demands 2.99 shares while an average large bidder demands 14.39 shares. There is no significant difference in the total demand across treatments for both groups.

We next examine the noncompetitive demand for the NC treatment. The total demand is 64.49 in each auction, with 14% from noncompetitive demand, and 86% from competitive demand. Small bidders submit more noncompetitive bids than competitive bids. On average, 58% of a small bidder's total demand is noncompetitive demand, which suggests that with the option of noncompetitive bidding, small bidders prefer to submit noncompetitive bids to secure shares. The large bidders submit both noncompetitive and competitive bids. But their noncompetitive demand (1.28) is even lower than that of small bidders (1.73).

2.4.4 Competitive Bidding

Next we examine how bidders submit competitive bids. We follow the moment analysis by Keloharju, Nyborg, and Rydqvist (2005). The quantity-weighted bid price (the first moment) and the standard deviation (the second moment) are shown in Table 12. The weighted bid price shows the bidding aggressiveness while the standard deviation indicates the degree of bids spreading. $\{(p_{ijk,} q_{ijk})\}_{k=1}^{m}$ represents the demand schedule submitted by bidder *i* in auction *j*, where *m* is the number of bids bidder *i* submitted. p_{ij} is the quantity-weighted bid price for bidder *i* in auction j, which is calculated by $p_{ij} = \sum_{k=1}^{m} w_{ijk} p_{ijk}$, where $w_{ijk} = \frac{q_{ijk}}{\sum_{k=1}^{m} q_{ijk}}$. The standard deviation is calculated as $\sigma_{ij} = \sqrt{\sum_{k=1}^{m} w_{ijk} (p_{ijk} - p_{ij})^2}$.

The result shows that large bidders in the NC treatment bid relatively less aggressively than in the C treatment, though the mean difference is not statistically significant. The weighted bid price for the large bidder in the NC treatment is -L$1.62 and -L$1.24 in the C treatment. We further split the large bidders into two groups: those who purchased information and those who did not purchase information. We found the large bidders with information purchase shaded their bids significantly more than those who did not purchase information. In the NC treatment, the average weighted bid price for large bidders with information purchase is -L$1.79 while -L$0.66 for those without information purchase. In the C treatment, the weighted bid price for those who purchased information is -L$1.44 while -L$0.43 for those who did not purchase information. The explanation of this result is that information cost is one important element for bidders to build their bidding strategies.

Now we examine the bidding strategies of small bidders. We split small bidders in the NC treatment into two groups: those whose competitive bids are positive and those whose competitive bids are zero. For those who did not submit competitive bids, we cannot calculate his weighted bid price. Table 12 Panel B shows that in the NC treatment the average weighted bid price for small bidders with information purchase is -L$0.60 and -L$1.10 for those without information purchase. In Table 12 Panel D, the weighed bid price for small bidders with information purchase is -L$0.59 but L$4.48 for those who did not purchase information. The result shows that small bidders in the C treatment submit very high bids, especially for those who did not purchase information. This result is consistent with the empirical findings of Degeorge, Derrien and Womack (2008) that small bidders submit extremely high bids to free ride in the U.S. auctioned IPOs.

The standard deviation is an indicator of the dispersion of bids. The result shows large and small bidders who did not purchase information in the C treatment spread out more bids than those in the NC treatment. This indicates the bidding strategies of those bidders who face the strongest winner's curse.

2.4.5 Market Clearing Price

In this section, we compare the market clearing price across the treatments. The mean market clearing prices are reported in Table 8. Figure 9 shows the distribution of auctions by the market clearing price. Figure 10 shows the distribution of auctions by the relationship between the market clearing price and the true value. Table 13 reflects regression results pertaining to determinants of the market clearing price and price error.

Table 8 reports the mean market clearing price. The result shows that the market clearing prices in both treatments are significantly lower than the true asset value. The degree of underpricing is significantly lower in the NC treatment than in the C treatment. Figure 9 shows the distribution of auctions by the market clearing price. We find there are more auctions in both treatments with market clearing prices below the true asset values. The market clearing price in the C treatment is relatively more volatile than in the NC treatment since there are more auctions with extreme market clearing prices. Figure 10 displays the distribution of auctions by the relationship between the market clearing price and the true value. In the NC treatment, 28% of the auctions saw a market clearing price higher than the true value. In the C treatment, only 17% of the auctions have a market clearing price higher than the true value. There are more auctions in the C treatment (64%) than in the NC treatment (53%) in which the market clearing price is less than the true value.

Table 13 examines the determinants of market clearing price and price error. We find that the market clearing price is significantly related to the dummy variable *NC treatment* and the average signal, indicating the market clearing price in the NC treatment is significantly higher than in the C treatment and the level of market clearing price is increasing with the level of average signal. We use two variables to measure the price error. The first is the absolute value of the difference of the market clearing price and the true asset value. The second variable is the absolute value of the difference of the market clearing price and the average signal. The independent variables are *NC treatment* (1 for NC treatment and 0 for C treatment), *signal accuracy*, *the number of signals*, *inexperienced* (1 for inexperienced session and 0 for experienced and twice-experienced sessions), and *experienced* (1 for experienced session and 0 for inexperienced and twice-experienced sessions). There are two measurements for signal accuracy. *Signal accuracy 1* is the difference of the mean of signals purchased by all bidders and the true value, in absolute value. *Signal accuracy 2* is the standard deviation of all the signals purchased by bidders. The regression result shows that price error is significantly related to the number of signals. When there are more signals in the auction, the price is more accurate and price error is significantly lower. When we use the absolute value of the difference of the market clearing price and the average signal to measure the pricing error, we find that the coefficient for the dummy variable *NC treatment* is significant at the 1% level, indicating the price error in the NC treatment is significantly lower than in the C treatment.

2.4.6 Profit and Allocation

Bidder's profits display the same pattern for both treatments. Large bidders earn higher profits than small bidders. The auction profit for an average large bidder in the NC treatment is L$2.04, and L$1.13 for an average small bidder. In the C treatment, an average large bidder earns L$6.29 while an average small bidder earns L$1.20. In both treatments, large bidders who purchased information earn significantly higher profits (L$3.03 in the NC treatment and L$8.15 in the C treatment) than those who did not purchase information (-L$0.81 in the NC treatment and L$3.03 in the C treatment). In contrast, small bidders who did not purchase information earn higher profits than those who purchased information. The average uninformed small bidder's profit is L$1.34 in the NC Treatment and L$1.57 in the C treatment. However, for small bidders who purchased information, the average profit is -L$2.09 in the NC treatment and -L$1.74 in the C treatment. Therefore, it is difficult for small bidders to cover the information cost. Across the treatment, large bidders in the standard auction earn significantly higher profits than those large bidders in the auction with noncompetitive bidding option. This is due to the lower market clearing price in the C treatment.

Figure 11 shows the distribution of bidders by profit or loss. Bidders in the C treatment are more likely to make money. The percentage of small bidders with a profit is 75% in the C treatment while 21% in the NC treatment. The percentage of large bidders with profit in the C treatment is 83% but 69% in the NC treatment.

Table 12 also reports the allocation information. The pattern is very clear. A large bidder receives significantly more shares than a small bidder since the large bidder has a higher bidding capacity. We further find that the incorporation of the noncompetitive bidding option greatly improves a small bidder's allocation. An average small bidder gets 2.06 shares in the NC treatment but 1.78 shares in the C treatment. The difference is statistically significant (t=2.53). The large bidders in the NC treatment receive significantly fewer shares than in the C treatment. An average large bidder receives 5.99 shares in the NC treatment and 6.55 shares in the C treatment. Including a noncompetitive bidding option helps small bidders to win more shares and therefore reduce large bidders' allocation. On average, a small bidder's allocation in the NC treatment is significantly higher than in the C treatment.

Table 14 reports the total allocation data. The result shows that the noncompetitive bidding mechanism removes 29% of the supply from the total supply. On average, 9 shares are allocated to the noncompetitive bidders and 21 shares are allocated to the competitive bidders.

2.5 Discussion

In the previous analysis we find that bidders in the C treatment bid more aggressively than in the NC treatment, especially for small bidders. This indicates that small bidders in the standard auction are more likely to free ride by submitting high bids. With the noncompetitive bidding option, small bidders do not need to submit extremely high competitive bids to secure shares. Rather, they can just submit noncompetitive bids to ensure an allocation.

Then an interesting question arises: Why do both large and small bidders in the NC treatment bid less aggressively than in the C treatment but the market clearing price in the NC is higher than in the C treatment? The reason lies in the mechanism effect of the noncompetitive demand on the market clearing price. In our experiment, the market clearing price is determined by the highest price at which the cumulative demand exceeds or is equal to the total supply. When the total supply is reduced by 30% due to the noncompetitive demand, the market clearing price is indirectly increased. The force of reducing supply on increasing the market clearing price is much stronger than the force of lowered bidding aggressiveness on reducing the market clearing price. Therefore, the market clearing price in the NC treatment is still higher than in the C treatment.

2.6 Conclusion

This paper uses economic experiments to evaluate design features of a uniform-price auction in a setting relevant for the issuance of new securities. The experimental design features include: different bidding capacities, endogenous entry, costly information acquisition, and uncertainty in the intrinsic value. We find significant underpricing in both treatments but the underpricing in the NC treatment is less severe. Incorporation of a noncompetitive bidding option generates better auction results, including higher market clearing price, lower price volatility, and lower pricing error. Including the noncompetitive bidding option also attracts more small investors to participate and they receive significantly more shares. By examining the bidding data, we find that including the noncompetitive bidding option allows small bidders to secure shares by submitting noncompetitive bids rather than submitting extremely high bids in a standard auction. Therefore, it reduces the incentives of small investors to free ride and makes the price less volatile. Including the noncompetitive bidding option reduces the bidding aggressiveness, but the effect of reducing the market clearing price is largely offset by the effect of increasing the market clearing price through removing some supply by noncompetitive bidding. The impact of the force of removing supply on the market clearing price is much stronger than the force of reducing bidding aggressiveness. Therefore, the market clearing price is higher in the NC treatment. By examining the profit and allocation data, we find that in both treatments, large bidders earn higher profits and receive significantly more shares than small bidders. Information acquisition has an impact on the bidder's profit. It increases large bidders' profits but reduces small bidders' profits. Information acquisition also affects information efficiency. The pricing accuracy is increasing in the rate of information acquisition.

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Table 8: Experimental sessions and summary statistics

The price error is the difference of the market clearing price and the true value, in absolute value. The t-statistics significant at the 10%, 5%, and 1% level are indicated with *, **, and *** respectively. The nonparametric test is two-sample Fisher-Pitman permutation test for equality of means. The *p*-value is two-tailed *p*-value.

Date	Treatment	Session	Experience	# of bidders	# of auctions	Market clearing price (True value is normalized to 0)				Price error
						Mean	**Max**	**Min**	**Std**	
5/19/2009	NC	1	Inexperienced	8	18	-0.22	2	-4	2.10	1.78
5/20/2009	NC	2	Inexperienced	8	18	-0.89	1	-5	1.45	1.22
5/27/2009	NC	3	Experienced	8	18	-0.89	3	-3	1.91	1.78
5/28/2009	NC	4	Experienced	8	18	-0.28	2	-5	2.02	1.50
6/2/2009	NC	5	Twice-experienced	8	18	-0.83	1	-3	1.10	1.06
6/15/2009	NC	6	Inexperienced	8	18	-1.67	3	-6	2.28	2.22
10/6/2009	NC	7	Inexperienced	8	18	-0.06	3	-3	1.89	1.50
mean				**8**	**18**	***-0.69***	***2.14***	***-4.14***	***1.82***	***1.58***
t-stat						*-3.30* **	*6.30* ***	*-9.02* ***	*11.81* ***	*10.78* ***
5/21/2009	C	1	Inexperienced	8	18	-1.22	3	-5	1.90	1.78
5/29/2009	C	2	Inexperienced	8	18	-1.94	2	-5	1.92	2.29
6/1/2009	C	3	Experienced	8	18	-0.61	4	-7	2.87	2.28
6/3/2009	C	4	Experienced	8	18	-0.72	6	-4	2.11	1.50
6/4/2009	C	5	Twice-experienced	8	18	-1.61	1	-5	1.50	1.72
6/16/2009	C	6	Inexperienced	8	18	-1.17	5	-4	2.41	2.06
10/13/2009	C	7	Inexperienced	8	18	-1.17	4	-6	2.55	2.06
mean				**8**	**18**	***-1.21***	***3.57***	***-5.14***	***2.18***	***1.95***
t-stat						*-6.86* ***	*5.50* ***	*-12.73* ***	*12.49* ***	*17.36* ***
Difference						***0.52***	***-1.43***	***1.00***	***-0.36***	***-0.38***
t-stat						*1.88* *	*-1.95* *	*1.63*	*-1.54*	*-2.03* *
Nonparametric test (*p*-value)						*0.08*	*0.11*	*0.19*	*0.15*	*0.07*

Table 9: Participation rate

The participation rate of small (large) bidders is the number of small (large) subjects who choose to participate divided by the total number of small (large) subjects, which is 4. The t-statistics significant at the 10%, 5%, and 1% level are indicated with *, **, and *** respectively.

Session	Number of participants			Number of nonparticipants			Participation rate			*Difference (Small-Large)*	*t-stat*
	Small	**Large**	**Total**	**Small**	**Large**	**Total**	**Small**	**Large**	**Total**		
NC1	3.7	3.8	7.6	0.3	0.2	0.4	93%	96%	94%		
NC2	3.2	4.0	7.2	0.8	0.0	0.8	81%	100%	90%		
NC3	3.4	4.0	7.4	0.6	0.0	0.6	86%	100%	93%		
NC4	3.6	4.0	7.6	0.4	0.0	0.4	89%	100%	94%		
NC5	3.7	4.0	7.7	0.3	0.0	0.3	92%	100%	96%		
NC6	2.7	3.6	6.3	1.3	0.4	1.7	68%	90%	79%		
NC7	3.4	4.0	7.4	0.6	0.0	0.6	85%	100%	92%		
Mean	**3.4**	**3.9**	**7.3**	**0.6**	**0.1**	**0.7**	**85%**	**98%**	**91%**	***-13%***	***-3.79*** ***
C1	3.1	3.7	6.7	0.9	0.3	1.3	76%	92%	84%		
C2	2.8	3.4	6.2	1.2	0.6	1.8	71%	85%	78%		
C3	2.9	4.0	6.9	1.1	0.0	1.1	72%	100%	86%		
C4	2.8	4.0	6.8	1.2	0.0	1.2	69%	100%	85%		
C5	2.8	4.0	6.8	1.2	0.0	1.2	71%	100%	85%		
C6	3.3	3.7	6.9	0.7	0.3	1.1	82%	92%	87%		
C7	3.0	3.9	6.9	1.0	0.1	1.1	75%	99%	87%		
Mean	**3.0**	**3.8**	**6.8**	**1.0**	**0.2**	**1.2**	**74%**	**95%**	**85%**	***-21%***	***-7.66*** ***
Difference(NC-C)	**0.4**	**0.1**	**0.5**	**-0.4**	**-0.1**	**-0.5**	**11%**	**3%**	**7%**		
t-stat	***3.03*** ***	***1.04***	***2.79*** ***	***-3.03*** ***	***-1.04***	***-2.79*** ***	***3.03*** ***	***1.04***	***2.79*** ***		

Table 10: Information purchase rate

For each auction, we count the number of information buyers for small (large) bidder group. Then we average these numbers across 18 auctions to get the mean of the number of small (large) buyers for that particular session. The purchase rate for the small (large) bidder group in each session is the average number of small (large) buyers by the average number of small (large) participants. The t-statistics significant at the 10%, 5%, and 1% level are indicated with *, **, and *** respectively.

Session	**# of buyers**			**# of participants**			**Purchase rate**			***Difference (Small-Large)***	***t-stat***
	Small	**Large**	**Total**	**Small**	**Large**	**Total**	**Small**	**Large**	**Total**		
NC1	0.7	3.2	3.9	3.7	3.8	7.6	17.9%	84.1%	51.5%		
NC2	0.2	3.5	3.7	3.2	4.0	7.2	5.2%	87.5%	50.8%		
NC3	0.2	3.0	3.2	3.4	4.0	7.4	6.5%	75.0%	43.3%		
NC4	0.2	3.3	3.5	3.6	4.0	7.6	4.7%	83.3%	46.3%		
NC5	0.0	3.4	3.4	3.7	4.0	7.7	0.0%	84.7%	44.2%		
NC6	0.1	2.5	2.6	2.7	3.6	6.3	4.1%	69.2%	41.2%		
NC7	0.3	3.7	4.0	3.4	4.0	7.4	8.2%	93.1%	54.1%		
Mean	**0.2**	**3.2**	**3.5**	**3.4**	**3.9**	**7.3**	**6.8%**	**82.6%**	**47.4%**	***-76%****	***-20.70***
C1	0.6	3.1	3.7	3.1	3.7	6.7	20.0%	84.8%	55.4%		
C2	0.6	1.9	2.6	2.8	3.4	6.2	21.6%	57.4%	41.1%		
C3	0.1	2.6	2.6	2.9	4.0	6.9	1.9%	63.9%	37.9%		
C4	0.2	2.8	3.1	2.8	4.0	6.8	8.0%	70.8%	45.1%		
C5	0.0	4.0	4.0	2.8	4.0	6.8	0.0%	100.0%	58.5%		
C6	1.1	2.8	3.9	3.3	3.7	6.9	33.9%	77.3%	56.8%		
C7	0.2	2.5	2.7	3.0	3.9	6.9	7.4%	63.4%	39.2%		
Mean	**0.4**	**2.8**	**3.2**	**3.0**	**3.8**	**6.8**	**13.7%**	**74.2%**	**47.8%**	***-60%****	***-8.36***
Difference (NC-C)	**-0.2**	**0.4**	**0.2**	**0.4**	**0.1**	**0.5**	**-6.9%**	**8.4%**	**-0.3%**		
t-stat	***-1.03***	***1.46***	***0.79***	***3.03***	***1.04***	***2.79***	***-1.30***	***1.34***	***-0.10***		

Table 11: Demand

Each auction is an observation. NC demand - noncompetitive demand; C demand - competitive demand.

	Average demand by small bidder in one auction					**Average demand by large bidder in one auction**					**Total demand in one auction**				
session	NC demand	C demand	total	NC demand%	C demand%	NC demand	C demand	total	NC demand%	C demand%	NC demand	C demand	Total demand	NC demand%	C demand%
NC1	1.73	1.27	3.00	58%	42%	1.25	13.55	14.79	8%	92%	9.17	56.83	66.00	14%	86%
NC2	2.07	0.93	3.00	69%	31%	1.69	12.79	14.49	12%	88%	9.94	54.17	64.11	16%	84%
NC3	1.75	1.25	3.00	58%	42%	1.49	12.96	14.44	10%	90%	9.39	56.22	65.61	14%	86%
NC4	1.64	1.34	2.98	55%	45%	1.33	12.46	13.79	10%	90%	9.00	54.61	63.61	14%	86%
NC5	1.61	1.39	3.00	54%	46%	1.86	12.93	14.79	13%	87%	9.44	56.89	66.33	14%	86%
NC6	1.74	1.23	2.96	59%	41%	0.44	12.97	13.40	3%	97%	6.17	50.28	56.44	11%	89%
NC7	1.56	1.40	2.96	53%	47%	0.90	14.10	15.00	6%	94%	8.22	61.11	69.33	12%	88%
Mean	**1.73**	**1.26**	**2.99**	**58%**	**42%**	**1.28**	**13.11**	**14.39**	**9%**	**91%**	**8.76**	**55.73**	**64.49**	**14%**	**86%**
C1			3.00					15.00					64.17		
C2			2.94					14.60					58.17		
C3			3.00					14.42					66.33		
C4			2.94					14.97					68.06		
C5			3.00					14.99					68.44		
C6			2.98					14.57					63.22		
C7			3.00					14.92					67.83		
Mean			**2.98**					**14.78**					**65.17**		

Table 12: Bidding data

The analyzed bidding data excludes the failed auction (C2 Aution3). In order to calculate the weighted bid price and standard deviation of the bid price, we exclude those bidders who submitted zero bids. Each auction is an observation. (***: 1% significance level; **: 5% significance level; *: 10% significance level.)

Panel A: NC treatment-Large bidder

Treatment	Bidder Type	Information Purchase	# of observations	Weighted bid price	Std	Profit	Allocation	NC demand	C demand	Total demand	# of price-quantity pairs
NC1	Large	Yes	18	-1.95	1.36	0.61	5.90	1.30	13.51	14.81	3.94
NC2	Large	Yes	18	-1.35	1.05	3.35	6.50	1.81	13.15	14.96	3.90
NC3	Large	Yes	18	-2.81	1.78	4.97	5.53	1.51	13.01	14.53	3.95
NC4	Large	Yes	18	-1.12	1.30	-0.06	6.11	1.19	13.51	14.70	3.59
NC5	Large	Yes	18	-2.30	1.95	2.02	5.96	1.75	13.25	15.00	3.78
NC6	Large	Yes	18	-1.73	1.51	11.60	7.09	0.10	14.44	14.53	5.14
NC7	Large	Yes	18	-1.27	0.98	-1.31	5.56	0.96	14.04	15.00	3.37
Mean				**-1.79**	**1.42**	**3.03**	**6.09**	**1.23**	**13.56**	**14.79**	**3.95**
NC1	Large	No	10	0.02	1.06	-5.87	6.36	1.15	13.35	14.50	4.15
NC2	Large	No	9	-2.77	1.20	1.18	3.07	1.00	10.22	11.22	3.67
NC3	Large	No	15	-1.56	1.20	-2.01	6.34	1.43	12.57	14.00	4.67
NC4	Large	No	9	2.91	4.18	0.97	6.17	1.83	11.28	13.11	2.17
NC5	Large	No	11	-3.22	8.10	4.53	5.05	2.73	12.27	15.00	2.27
NC6	Large	No	13	-2.01	2.19	5.70	5.91	1.14	10.04	11.18	4.97
NC7	Large	No	5	1.99	2.66	-10.19	7.57	0.00	15.00	15.00	6.00
Mean				**-0.66**	**2.94**	**-0.81**	**5.78**	**1.33**	**12.10**	**13.43**	**3.99**
NC1	Large	Yes + No	18	-1.67	1.28	-0.30	5.92	1.25	13.55	14.79	3.93
NC2	Large	Yes + No	18	-1.53	1.08	2.80	6.01	1.69	12.79	14.49	3.89
NC3	Large	Yes + No	18	-2.57	1.64	3.06	5.77	1.49	12.96	14.44	4.15
NC4	Large	Yes + No	18	-0.52	1.69	-0.66	5.97	1.30	13.19	14.49	3.38
NC5	Large	Yes + No	18	-2.39	2.85	2.30	5.79	1.88	13.13	15.00	3.50
NC6	Large	Yes + No	18	-1.66	1.70	9.07	6.72	0.44	12.97	13.40	5.18
NC7	Large	Yes + No	18	-1.01	1.12	-1.98	5.73	0.90	14.10	15.00	3.57
Mean				**-1.62**	**1.62**	**2.04**	**5.99**	**1.28**	**13.24**	**14.52**	**3.94**

Panel B: NC treatment-small bidder

Treatment	Information Purchase	NC bids	# of observations	Weighted bid price	Std	Profit	Allocation	NC demand	C demand	Total demand	# of price-quantity pairs
NC1	Yes	NC=3	3			-4.00	2.82	3.00	0.00	3.00	
NC2	Yes	NC=3	1			-3.00	2.73	3.00	0.00	3.00	
NC3	Yes	NC=3	1			3.00	3.00	3.00	0.00	3.00	
NC7	Yes	NC=3	1			-3.00	2.50	3.00	0.00	3.00	
Mean						***-1.75***	***2.76***	***3.00***	***0.00***	***3.00***	
NC1	Yes	NC=0,1,2	8	-1.34	0.03	-2.58	1.07	0.31	2.69	3.00	1.06
NC2	Yes	NC=0,1,2	2	1.75	0.25	-4.27	2.49	1.50	1.50	3.00	1.50
NC3	Yes	NC=0,1,2	3	-1.00	0.27	-0.06	2.52	0.00	3.00	3.00	1.67
NC4	Yes	NC=0,1,2	3	-1.33	0.54	0.03	0.97	0.00	3.00	3.00	2.33
NC6	Yes	NC=0,1,2	2	-0.50	0.00	-3.00	2.31	1.50	1.50	3.00	1.00
NC7	Yes	NC=0,1,2	3	-1.17	0.44	-2.38	0.62	0.33	2.67	3.00	2.00
Mean				**-0.60**	**0.26**	**-2.04**	**1.66**	**0.61**	**2.39**	**3.00**	**1.59**
NC1	Yes	NC=0,1,2,3	9			-3.42	1.41	0.89	2.11	3.00	
NC2	Yes	NC=0,1,2,3	3			-3.85	2.57	2.00	1.00	3.00	
NC3	Yes	NC=0,1,2,3	3			0.33	2.71	0.50	2.50	3.00	
NC4	Yes	NC=0,1,2,3	3			0.03	0.97	0.00	3.00	3.00	
NC6	Yes	NC=0,1,2,3	2			-3.00	2.31	1.50	1.50	3.00	
NC7	Yes	NC=0,1,2,3	5			-2.63	0.87	0.80	1.60	2.40	
Mean						**-2.09**	**1.81**	**0.95**	**1.95**	**2.90**	
NC1	No	NC=3	16			0.07	2.54	3.00	0.00	3.00	
NC2	No	NC=3	16			2.28	2.30	3.00	0.00	3.00	
NC3	No	NC=3	15			1.77	2.39	3.00	0.00	3.00	
NC4	No	NC=3	16			1.26	2.52	3.00	0.00	3.00	
NC5	No	NC=3	18			1.58	2.27	3.00	0.00	3.00	
NC6	No	NC=3	11			5.73	3.00	3.00	0.00	3.00	
NC7	No	NC=3	18			0.13	2.84	3.00	0.00	3.00	
Mean						**1.83**	**2.55**	***3.00***	***0.00***	***3.00***	

Panel B: NC treatment-small bidder

Treatment	Information Purchase	NC bids	# of observations	Weighted bid price	Std	Profit	Allocation	NC demand	C demand	Total demand	# of price-quantity pairs
NC1	No	NC=0,1,2	16	1.17	0.64	0.21	1.78	0.71	2.29	3.00	1.95
NC2	No	NC=0,1,2	15	-1.62	0.41	0.85	1.33	0.87	2.13	3.00	1.90
NC3	No	NC=0,1,2	16	-1.24	1.17	0.89	1.55	0.76	2.24	3.00	2.15
NC4	No	NC=0,1,2	16	7.32	0.19	0.53	1.75	0.11	2.83	2.94	1.44
NC5	No	NC=0,1,2	18	2.32	0.94	1.41	1.70	0.45	2.55	3.00	1.75
NC6	No	NC=0,1,2	16	-2.53	0.55	2.97	1.88	1.06	1.90	2.96	1.60
NC7	No	NC=0,1,2	16	2.25	0.82	-0.13	1.53	0.24	2.76	3.00	1.64
Mean				**1.10**	**0.67**	**0.96**	**1.65**	**0.60**	**2.38**	**2.99**	**1.78**
NC1	No	NC=0,1,2,3	18			0.31	2.17	1.85	1.15	3.00	
NC2	No	NC=0,1,2,3	18			1.60	1.84	2.07	0.93	3.00	
NC3	No	NC=0,1,2,3	18			1.27	1.99	1.75	1.25	3.00	
NC4	No	NC=0,1,2,3	18			0.82	2.16	1.71	1.27	2.98	
NC5	No	NC=0,1,2,3	18			1.50	1.95	1.61	1.39	3.00	
NC6	No	NC=0,1,2,3	18			4.03	2.32	1.74	1.22	2.96	
NC7	No	NC=0,1,2,3	18			-0.16	2.17	1.64	1.36	3.00	
Mean						**1.34**	**2.09**	**1.77**	**1.22**	**2.99**	
NC1	Yes + No	NC=0,1,2,3	18			-0.34	2.11	1.73	1.27	3.00	
NC2	Yes + No	NC=0,1,2,3	18			1.42	1.87	2.07	0.93	3.00	
NC3	Yes + No	NC=0,1,2,3	18			1.22	2.05	1.75	1.25	3.00	
NC4	Yes + No	NC=0,1,2,3	18			0.64	2.08	1.64	1.34	2.98	
NC5	Yes + No	NC=0,1,2,3	18			1.50	1.95	1.61	1.39	3.00	
NC6	Yes + No	NC=0,1,2,3	18			3.93	2.32	1.74	1.23	2.96	
NC7	Yes + No	NC=0,1,2,3	18			-0.46	2.07	1.56	1.40	2.96	
Mean						**1.13**	**2.06**	**1.73**	**1.26**	**2.99**	

Panel C: C treatment-large bidder

Treatment	Bidder Type	Information Purchase	# of observations	Weighted bid price	Std	Profit	Allocation	Total demand	# of price-quantity pairs
C1	Large	Yes	18	-1.48	0.63	9.32	7.24	15.00	2.68
C2	Large	Yes	16	-1.48	1.82	12.99	8.39	14.81	3.12
C3	Large	Yes	18	-0.71	0.92	5.67	6.87	15.00	2.60
C4	Large	Yes	18	-0.47	2.22	3.56	6.94	15.00	3.26
C5	Large	Yes	18	-1.36	0.78	7.65	6.53	14.99	3.11
C6	Large	Yes	18	-1.90	1.21	8.01	7.02	14.68	3.61
C7	Large	Yes	18	-2.70	2.40	9.88	6.26	14.92	4.34
Mean				**-1.44**	**1.43**	**8.15**	**7.04**	**14.91**	**3.25**
C1	Large	No	8	0.20	3.69	1.69	7.48	15.00	5.44
C2	Large	No	14	-2.05	7.89	9.25	5.33	14.91	2.80
C3	Large	No	17	2.84	4.82	-2.11	5.99	13.51	4.75
C4	Large	No	15	-2.92	8.00	3.19	4.19	14.87	3.40
C6	Large	No	11	1.28	2.55	5.17	5.82	13.82	4.86
C7	Large	No	16	-1.93	2.97	1.08	5.49	14.81	5.16
Mean				**-0.43**	**4.99**	**3.04**	**5.72**	**14.49**	**4.40**
C1	Large	Yes + No	18	-1.31	1.03	7.29	7.09	15.00	3.01
C2	Large	Yes + No	17	-1.81	4.32	11.53	7.08	14.87	2.95
C3	Large	Yes + No	18	0.41	2.29	2.61	6.15	14.42	3.49
C4	Large	Yes + No	18	-1.06	3.90	2.91	6.13	14.97	3.29
C5	Large	Yes + No	18	-1.36	0.78	7.65	6.53	14.99	3.11
C6	Large	Yes + No	18	-1.20	1.52	6.13	6.83	14.57	3.95
C7			18	-2.36	2.62	5.94	6.07	14.92	4.60
Mean				**-1.24**	**2.35**	**6.29**	**6.55**	**14.82**	**3.48**

Panel D: C treatment-small bidder

Treatment	Bidder Type	Information Purchase	# of observations	Weighted bid price	Std	Profit	Allocation	Total demand	# of price-quantity pairs
C1	Small	Yes	9	-1.72	0.41	-1.41	1.11	3.00	1.94
C2	Small	Yes	9	1.52	1.65	0.96	1.58	3.00	1.50
C3	Small	Yes	1	1.33	0.47	-5.31	2.31	3.00	2.00
C4	Small	Yes	4	-2.42	0.12	-2.32	0.68	3.00	1.25
C6	Small	Yes	14	-2.23	0.79	-0.58	1.09	3.00	1.90
C7	Small	Yes	4	0.00	1.77	-1.76	1.92	3.00	1.25
Mean				**-0.59**	**0.87**	**-1.74**	**1.45**	**3.00**	**1.64**
C1	Small	No	18	3.34	1.79	0.87	1.53	3.00	1.66
C2	Small	No	17	6.90	2.53	4.42	2.08	2.90	1.37
C3	Small	No	18	6.36	1.88	-0.25	1.82	3.00	1.47
C4	Small	No	18	9.34	0.56	1.12	2.15	3.00	1.12
C5	Small	No	18	0.58	1.92	1.72	1.45	3.00	2.14
C6	Small	No	18	1.64	1.66	1.44	1.84	2.97	1.96
C7	Small	No	18	3.21	1.67	1.70	2.09	3.00	2.12
Mean				**4.48**	**1.72**	**1.57**	**1.85**	**2.98**	**1.69**
C1	Small	Yes + No	18	2.02	1.68	0.22	1.43	3.00	1.75
C2	Small	Yes + No	18	5.79	2.35	4.00	2.01	2.93	1.41
C3	Small	Yes + No	18	6.13	1.81	-0.31	1.82	3.00	1.48
C4	Small	Yes + No	18	8.39	0.50	0.50	1.97	3.00	1.13
C5	Small	Yes + No	18	0.58	1.92	1.72	1.45	3.00	2.14
C6	Small	Yes + No	18	0.56	1.26	0.75	1.66	2.98	1.94
C7	Small	Yes + No	18	3.03	1.71	1.51	2.08	3.00	2.07
Mean				**3.79**	**1.60**	**1.20**	**1.78**	**2.99**	**1.70**

Panel F: Comparison

Treatment	Bidder Type	Information Purchase	Weighted bid price	Std	Profit	Allocation	Total demand	# of price-quantity pairs
NC-C	Large	Yes + No	*-0.38*	*-0.73*	*-4.25*	*-0.57*	*-0.30*	*0.46*
t-stat			*-0.90*	*-1.29*	*-2.37*	*-2.66*	*-1.35*	*1.42*
					***	***		
NC-C	Large	Yes	*-0.35*	*-0.01*	*-5.13*	*-0.94*	*-0.12*	*0.71*
t-stat			*-0.95*	*-0.03*	*-2.56*	*-2.85*	*-1.33*	*2.29*
					***	***		***
NC-C	Large	No	*-0.23*	*-2.04*	*-3.86*	*0.06*	*-1.06*	*-0.42*
t-stat			*-0.18*	*-1.49*	*-1.45*	*0.09*	*-1.55*	*-0.61*
NC-C	Small	Yes + No			*-0.07*	*0.29*	*0.00*	
t-stat					*-0.09*	*2.53*		
						***		
NC-C	Small	Yes			*-0.35*	*0.36*		
t-stat					*-0.31*	*0.86*		
NC-C	Small	No			*-0.23*	*0.23*		
t-stat					*-0.32*	*1.92*		
NC-C	Small	Yes	*-0.01*	*-0.61*	*-0.31*	*0.21*	*0.00*	*-0.05*
t-stat			*-0.01*	*-2.08*	*-0.28*	*0.50*		*-0.19*
				*				
NC-C	Small	No	*-3.39*	*-1.04*	*-0.61*	*-0.21*	*0.00*	*0.08*
t-stat			*-1.95*	*-4.09*	*-0.93*	*-1.63*		*0.48*
			*	***				

Table 13: Determinants of market clearing price and price error

The dependent variables are market clearing price, |market clearing price-true value|, and |market clearing price-average signal|. |market clearing price-true value| and |market clearing price-average signal| measure the pricing error. The *NC treatment* is a dummy variable with 1 for the NC treatment and 0 for the C treatment. *Average signal* is the mean of the signal values purchased by all bidders. *Signal accuracy 1* is the difference of the mean of signals purchased by all bidders and true value, in absolute value. *Signal accuracy 2* is the standard deviation of all the signals purchased by bidders. *Inexperienced* is a dummy variable with 0 for experienced and super-experienced session and 1 for inexperienced session. *Experienced* is a dummy variable with 0 for inexperienced and super-experienced session and 1 for experienced session.

Dependent variable	**Market clearing price**	**Pricing error**			
		|market clearing price - true value|		**|market clearing price - average signal|**	
Intercept	-1.37***	2.93***	3.24***	3.22***	3.01***
t-static	*-3.95*	*6.41*	*7.25*	7.61	7.26
p-value	*0.00*	*0.00*	*0.00*	0.00	0.00
NC treatment	0.49**	-0.28	-0.26	-0.50***	-0.51***
t-static	*2.01*	*-1.59*	*-1.49*	-3.12	-3.12
p-value	*0.05*	*0.11*	*0.14*	0.00	0.00
Average signal	0.68***				
t-static	*5.51*				
p-value	*0.00*				
Signal accuracy1		0.09		-0.18	
t-static		*0.65*		-1.34	
p-value		*0.51*		0.18	
Signal accuracy2			-0.10		0.00
t-static			*-1.07*		*0.00*
p-value			*0.29*		*1.00*
# of signals		-0.40***	-0.42	-0.40***	-0.38***
t-static		*-4.16*	*-4.21*	*-4.57*	*-4.18*
p-value		*0.00*	*0.00*	*0.00*	*0.00*
Inexperienced	0.15	0.35	0.35	0.25	0.24
t-static	*0.42*	*1.36*	*1.37*	*1.07*	*1.02*
p-value	*0.68*	*0.18*	*0.17*	*0.29*	*0.31*
Experienced	0.58	0.13	0.12	0.22	0.24
t-static	*1.47*	*0.44*	*0.43*	*0.85*	*0.90*
p-value	*0.14*	*0.66*	*0.67*	*0.40*	*0.37*
R-square	*0.13*	*0.11*	*0.10*	*0.13*	*0.12*
# of observations	251	251	246	251	246

Table 14: Allocation

	Average allocation by small bidder in one auction					Average allocation by large bidder in one auction					Total allocation in one auction				
session	NC allocation	C allocation	total	NC allocation %	C allocation %	NC allocation	C allocation	total	NC allocation %	C allocation %	NC allocation	C allocation	Total allocation	NC allocation %	C allocation %
NC1	1.47	0.63	2.11	70%	30%	1.02	4.90	5.92	17%	83%	9.17	20.83	30.00	31%	69%
NC2	1.56	0.31	1.87	83%	17%	1.25	4.76	6.01	21%	79%	9.94	20.06	30.00	33%	67%
NC3	1.41	0.64	2.05	69%	31%	1.17	4.60	5.77	20%	80%	9.39	20.61	30.00	31%	69%
NC4	1.32	0.75	2.08	64%	36%	1.07	4.58	5.65	19%	81%	9.00	21.00	30.00	30%	70%
NC5	1.16	0.79	1.95	59%	41%	1.32	4.39	5.71	23%	77%	9.44	20.56	30.00	31%	69%
NC6	1.74	0.59	2.32	75%	25%	0.44	6.28	6.72	6%	94%	6.17	23.83	30.00	21%	79%
NC7	1.45	0.62	2.07	70%	30%	0.83	4.90	5.73	15%	85%	8.22	21.78	30.00	27%	73%
Mean	**1.44**	**0.62**	**2.06**	**70%**	**30%**	**1.01**	**4.92**	**5.93**	**17%**	**83%**	**8.76**	**21.24**	**30.00**	**29%**	**71%**
C1			1.43					7.09					30.00		
C2			2.01					6.07					30.00		
C3			1.82					6.15					30.00		
C4			1.95					6.13					30.00		
C5			1.45					6.53					30.00		
C6			1.66					6.83					30.00		
C7			2.08					6.07					30.00		
Mean			**1.77**					**6.41**					**30.00**		
Difference			**0.29**					**-0.48**					**0.00**		
t-stat			*2.58* ***					*-2.28* ***							

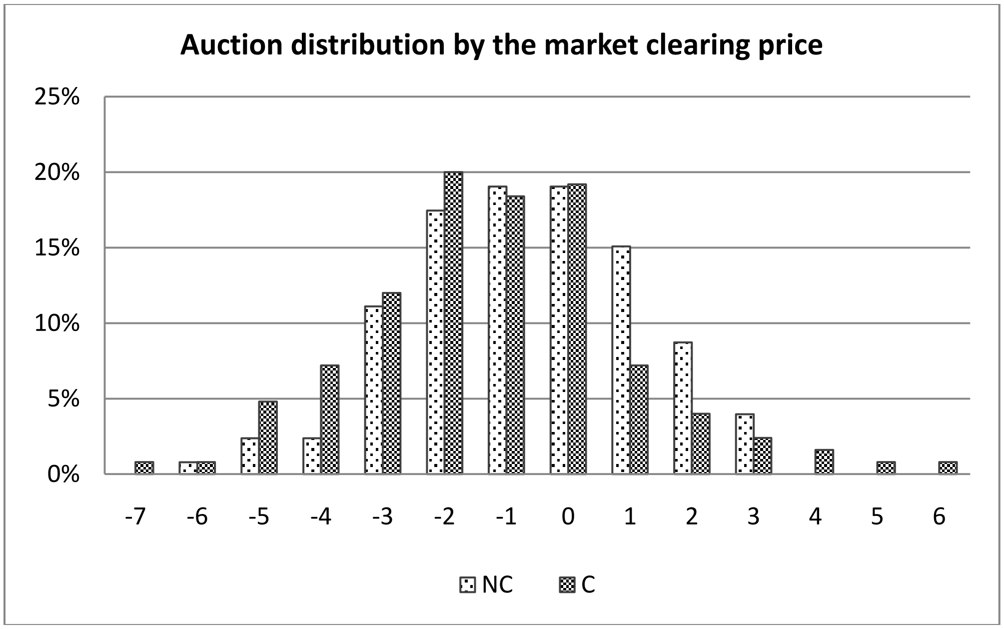

Figure 9: Auction distribution by the market clearing price

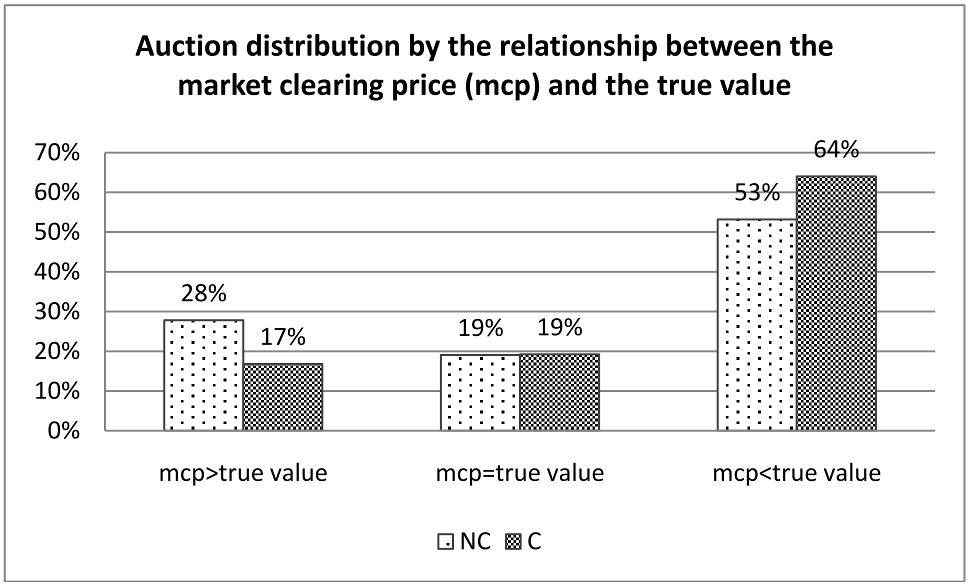

Figure 10: Auction distribution by the relationship between the MCP and the true value

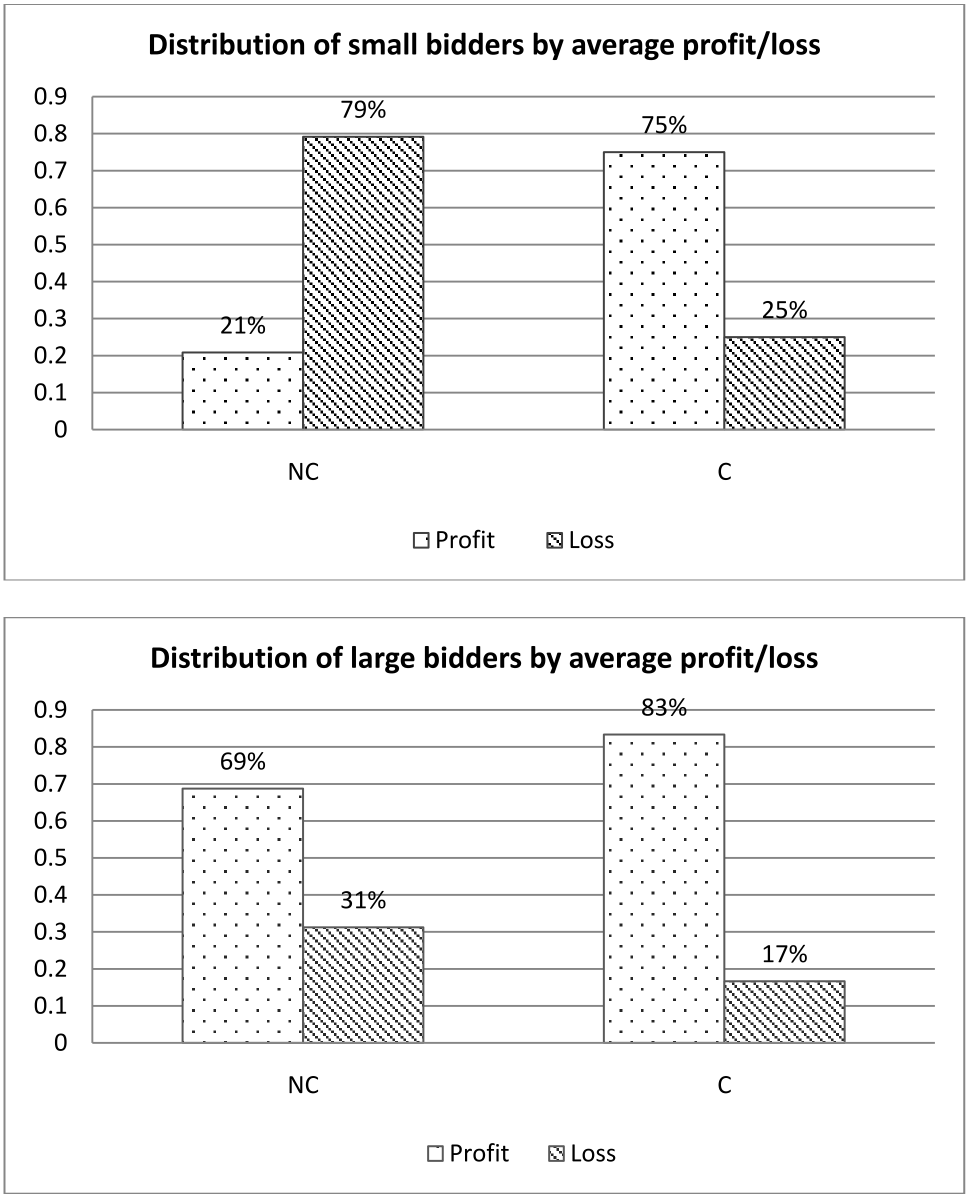

Figure 11: Auction distribution by profit/loss