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Divisible Good Auctions with Asymmetric Information: An Experimental Examination

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Abstract

An experimental approach is used to compare bidding behavior and auction performance in uniform-price and discriminatory auctions when there is incomplete information concerning the common value of the auctioned good. In a symmetric information environment, the different auction formats provide the same average revenue. However, when information is asymmetric the discriminatory auction results in higher average revenue than the uniform-price auction. The volatility of revenue is higher in the uniform-price auctions in all treatments. The results, therefore, provide support for the use of the discriminatory format. Subject characteristics and measures of experience in recent auctions are found to be useful in explaining bidding behavior.

I. Introduction

Divisible good or multi-unit auctions are an important market mechanism for a variety of goods around the world. Most countries use an auction mechanism as the primary market for their government's debt. In some countries initial public offerings of equity and/or corporate bonds are made via auction. Goods ranging from gold to electricity, from drilling rights to emission permits, are sold in divisible good auctions. The practical importance of these auctions and the pivotal role

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effective governmental borrowing has played around the globe in the struggle to overcome the recent financial crisis serve as reminders of the importance of developing our understanding of this market mechanism.

The choice of pricing rules in divisible good auctions across different environments remains an open question. The most commonly used mechanisms are the discriminatory and the uniform-price auctions. In uniform-price auctions, units of the good are awarded for bids at or above the market clearing price, and bidders pay the market clearing price for all units awarded. In discriminatory auctions, units are also awarded for bids at or above the market clearing price; however, the bid price is paid for all units awarded. The divisible good auction literature has identified a trade-off between a less severe winner's curse (in the uniform-price relative to the discriminatory auction) and collusive-seeming behavior or bid shading (more prominent in the uniform-price auction) as primary considerations in the revenue comparison for these auctions. However, theoretical comparison of the standard divisible good auctions is complicated by the existence of multiple equilibria. Back and Zender (1993) and Wang and Zender (2002) examine the nature of the equilibria and discuss difficulties associated with the standard comparisons.[1] Empirically, there are limited and conflicting results concerning the relative attractiveness of the different auctions.[2] In practice, even in the relatively simple realm of government debt auctions, different countries use different auctions (see Brenner, Galai, and Sade (2009)).

This study uses a laboratory experiment to compare auction performance and bidding behavior in uniform-price and discriminatory auctions of a good with a common value, multi-unit demands, and incomplete (symmetric and asymmetric) information concerning the value of the auctioned good.[3] Previous experimental work has examined divisible good auctions in which the value of the good is publicly known prior to the auction (e.g., Goswami, Noe, and Rebello (1996), Sade, Schnitzlein, and Zender (2006a), (2006b)). The theory of divisible good auctions indicates that the differential susceptibility of the 2 types of auctions to the strategic aspects of bidding will be highlighted in treatments when information is symmetric. An examination of the adjustment for the winner's curse and the relative ability of these auctions to extract bidders' private information will be highlighted when information is asymmetric.

We examine standard measures of auction performance (average revenue, volatility of revenue, and allocations) and bidding behavior (the elasticity of bid

[1] Back and Zender (2001) and Kremer and Nyborg (2004) examine features of auctions that may limit or eliminate certain equilibria in uniform-price auctions; however, these features are not commonly employed. Recently Rostek, Weretka, and Pycia (2010) provide interesting characterizations of the differences between uniform-price and discriminatory auctions by limiting attention to linear equilibria. The restriction to linear equilibria has, however, been demonstrated to be problematic (see Wang and Zender (2002)).

[2] Compare Simon's (1994) finding that the discriminatory auctions raised more revenue for the U.S. Treasury than the uniform-price auctions to the results in Umlauf (1993) or Tenorio (1993), who find the reverse in other markets. Furthermore, Hortacsu and McAdams (2010) find that a change from the discriminatory auction for Turkish treasuries to a uniform-price auction would not significantly alter revenue.

[3] For a review of the experimental economics papers investigating single unit and multiple unit auctions, see Kagel (1997) and Kagel and Levin (2008).

schedules and the adjustment for the winner's curse). We also examine how ex ante bidder characteristics such as confidence, gender, and education affect bidding and auction outcomes. Finally, the effect of subject experience is examined in 2 ways: the experience gained within a session as well as the effect of experience in a prior session.

An important difference between the approach taken in this paper and some of the experimental literature is that the complexity of the space of possible equilibria for the auctions does not allow us to compare actual behavior to equilibrium bidding behavior (or even a qualitatively similar family of equilibrium behaviors[4]). Rather, the theory is used to generate qualitative descriptions of how behaviors under alternate auction pricing rules will differ, and the empirical results examine these descriptions in order to inform the debate concerning the choice of auction mechanism.[5]

Our main results are summarized as follows: Consistent with the predicted behavior, on average, bidders make a greater allowance for the winner's curse and submit more elastic bid schedules in discriminatory auctions than in uniform-price auctions. Under symmetric information, the evidence suggests that the different auction formats have the same average revenue. However, when information is asymmetric, the discriminatory auction results in significantly higher revenue. Furthermore, the volatility of revenue is higher in uniform-price auctions and there is, on average, no difference in the auction's ability to extract bidders' private information or in the symmetry of allocations across the formats. The findings regarding revenue volatility, allocations, and the ability of the mechanism to extract bidders' private information support the use of discriminatory auctions, particularly when asymmetric information is an important consideration.

Subjects become more adept at bidding as they gain experience, both within the inexperienced sessions (when subjects have had no prior experience) and between the inexperienced and experienced sessions (when subjects have participated in a prior session).[6] Average bidder profit is negative for the inexperienced sessions; however, profits improve over the inexperienced sessions (i.e., profits are higher in later auctions). Average profit is near 0 in the experienced sessions, and there is improvement in per auction profit within the sessions, particularly under asymmetric information.

We also explore the impact of bidder characteristics and experiential variables within a session on strategies and outcomes. A growing financial literature documents individuals' overconfidence about their abilities.[7] The "above the average (median)" effect (examined in this paper) occurs when agents think (or predict) their own abilities are better, on average (median), than an unbiased statistical estimator would predict. For example, when Svenson (1981) asked

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[4]See, for example, Sade et al. (2006a) (examining Back and Zender (2001)) or Engelbrecht-Wiggans, List, and Reiley (2006) (examining Engelbrecht-Wiggans and Kahn (1998)).

[5]An example of this approach in an asset market context is Bloomfield, O'Hara, and Saar (2005).

[6]For a discussion of learning in experiments, see Sunder (1997).

[7]This literature relates overconfidence either to "miscalibration" or the "above the average" effect. Miscalibration refers to the tendency of individuals to overestimate the accuracy of their knowledge.

subjects to compare their driving ability to that of a group of peers, 70%–80% of subjects rated themselves as above the median in ability.[8]

Before (after) each session, subjects were asked to estimate the probability their performance would be (was) above the median performance for that session. We are therefore able to investigate the relation between confidence level, bidding behavior, and performance. While there is a large amount of dispersion in confidence, on average about half of the subjects identified themselves as being above the median in expected performance, indicating no general level of overconfidence. However, we find that subjects' estimates of their abilities are not well calibrated; subjects identifying themselves as being more confident before a session displayed no difference in performance or bidding behavior relative to those with less confidence.

Given the nature of the uncertainty and information in the experiment, it should not be the case that past realizations of private signals relative to realized values affect future strategies. However, in the asymmetric information sessions, we find that (controlling for the level of past profits) subjects who observe signals lower (higher) than the realized value of the good in previous auctions tend to increase (decrease) the level of their bids relative to their received signals in later auctions. The random nature of signals and values implies that this adjustment is inconsistent with the idea that Bayesian behavior is common knowledge among the subjects. Interestingly, this common adaptive behavior leads to lower subsequent profits.

This paper is organized as follows: Section II presents the theoretical foundations and develops the empirical hypotheses. Section III describes the experiment. Section IV presents the empirical analysis. Section V concludes. The Appendix contains a glossary of variables used in the statistical tests.[9]

II. Theory

A. Divisible Good Auction Theory

In divisible good or multi-unit auctions a seller offers multiple units of a good for sale via an auction. Bidders submit multiple price-quantity pairs as bids. The submission of bid schedules or "demand curves" as bids (rather than a single price) is a complicating aspect of the theory of bidding in multi-unit auctions.[10] An important consequence of this complication is the presence of multiple equilibria in these auctions. For a given set of parameter values, a continuum of Nash equilibria exist, differentiated by the extent to which bidders exert their strategic advantage or "market power" in each of the equilibria. Wang and Zender (2002)

[8]Overconfidence has been widely documented in health care (Larwood (1978)), managerial skill (Larwood and Whittaker (1977)), and business success (Camerer and Lovallo (1999)). In the finance literature Glaser and Weber (2007) find that overconfidence is associated with a higher level of trading for online investors.

[9]An Internet Appendix (www.jfqa.org) contains the instructions provided to the subjects, illustrations of the computer interface, and a copy of the post-experiment questionnaire.

[10]See, for example, Back and Zender (1993), Ausubel, Cramton, Pycia, Rostek, and Weretka (2011), and Wang and Zender (2002).

provide theoretical results based on assumptions that are comparable to the experimental environment considered here. They study equilibrium bidding behavior in uniform-price and discriminatory auctions for a perfectly divisible good with a common value. The multi-unit bid schedules are continuous, and the environment is characterized by symmetric and asymmetric information. Risk-neutral and risk-averse bidders are considered. The precise nature of bidder utility functions and the existence and extent of risk-averse behavior in the auctions have a material impact on the functional forms of the equilibria. As these are inherently unobservable, we cannot compare the functional form of the equilibrium bid schedules with the subject's observed behavior. The theory, however, does provide qualitative descriptions of bidding behavior that can be used to formulate empirical hypotheses.

Wang and Zender (2002) show that there is a tension between information revelation and strategic behavior in the equilibrium bidding strategies in these auctions. The impact of strategic behavior is most dramatically illustrated by considering their results under symmetric information. Under symmetric information, in both the uniform-price and the discriminatory auctions the equilibrium bid schedules have an intercept (the price for 0 quantity or the "level" of the bid schedule) equal to the expected resale value of the good. The elasticity of the bid schedule determines the extent of the strategic advantage employed by the bidders for each of the possible equilibria. In the discriminatory auction, the only equilibrium bid schedules are perfectly elastic, indicating that no strategic advantage can survive in equilibrium (Wang and Zender, Cor. 3.2). In the uniform-price auction (for a given set of parameter values), there is a continuum of equilibria (Wang and Zender, Cor. 3.1). Intuitively, if all bidders in a uniform-price auction submit very inelastic bid schedules, the aggregate bid schedule will also be very inelastic, and the expected stop-out price[11] will be very low. A low expected stop-out price provides an incentive for a bidder to deviate and attempt to capture additional units of the good. However, the inelasticity of the aggregate bid schedule implies that any deviation used by a bidder to capture additional quantity sharply increases the stop-out price, raising the price paid for all units and causing the deviation to be unprofitable. As a limiting case in the uniform-price auction, it is an equilibrium for bidders to submit perfectly elastic bid schedules. Therefore, in almost all equilibria of the uniform-price auction with symmetric information and risk-neutral bidders, bidder profits are higher and the seller's revenue is lower than that in the unique equilibrium of the discriminatory auction (Wang and Zender, Prop. 3.3).

The extreme contrast between the different mechanisms is tempered when bidders are risk averse; however, the qualitative comparisons remain the same. Risk aversion combined with uncertainty in the value of the good cause bidders in a discriminatory auction to bid less aggressively. Proposition 3.6 in Wang and Zender (2002) indicates that due to the greater strategic advantage available in the equilibria of the uniform-price auction and its effect on competition,

[11]The stop-out price is the highest price for which the aggregate quantity bids (at or above that price) equals or exceeds the available supply.

the stop-out price and the seller's revenue are larger in the discriminatory auction than in "most"[12] equilibria of the uniform-price auction.

With asymmetric information, the nature of the equilibrium bid schedules becomes richer. The bidders' strategic advantage in uniform-price auctions is balanced by a greater adjustment for the winner's curse in the discriminatory auction. The intercept of the equilibrium bid schedules in both the uniform-price and the discriminatory auctions equals the expected value of the auctioned good given a bidder's private signal and the information concerning other bidders' signals revealed by "winning" the "1st unit." In other words, the intercepts of the equilibrium bid schedules capture the standard notion of the winner's curse (Wang and Zender (2002), eq. 19). The elasticity of equilibrium bid schedules is determined by the level of risk aversion, the extent to which the bidders employ their strategic advantage, and adjustments for the "champion's plague" (see Ausubel (2004)). The champion's plague is an extension of the winner's curse in auctions with multi-unit demand (loosely, if winning a unit conveys bad news, winning many units conveys very bad news). The expected stop-out price and revenue, under asymmetric information, are influenced by the extent to which bidders employ their strategic advantage, risk aversion, and the adjustments for the winner's curse/champion's plague. There is, therefore, no generic revenue ranking for the 2 auctions under asymmetric information.

With asymmetric information, the intercepts of continuous bid schedules reflect the bidders' allowance for the winner's curse. All other points on the bid schedule will, in equilibrium, also contain adjustments for the champion's plague. The precise nature of the adjustments for larger quantities is specific to the particular equilibrium. However, the difference between expected resale value given a bidder's private signal and the intercept of that bidder's submitted bid schedule will provide a measure of the bidder's adjustment for the winner's curse. It will, therefore, be interesting to examine how this measure is affected by the pricing rule, subject's experience, as well as other subject characteristics and the feedback (gains or losses) from prior auctions in the session.

B. Empirical Implications

The theory described above provides qualitative descriptions of equilibrium bidding behavior and auction outcomes that can be tested empirically. In particular, we are able to examine the nature of individual bid schedules, stop-out prices, revenue, allocations, and the winner's curse. The empirical hypotheses include:

i) With symmetric information, relative to resale value, the stop-out price and the seller's revenue are expected to be weakly higher in the discriminatory auctions than in the uniform-price auctions. With asymmetric information, there is no clear prediction concerning the level of revenue, profits, or the stop-out price across the auction formats.

[12]With a large enough number of bidders, there exist equilibria of the uniform-price auction (if bidders fail to employ their strategic advantage) for which the expected seller's revenue and the expected stop-out price are larger in the uniform-price auction than in the discriminatory auction. However, as under risk neutrality, for the majority of the parameter space the discriminatory auction generates higher expected revenue.

ii) In all treatments, the volatility of the seller's revenue is expected to be higher in uniform-price auctions.

iii) In the asymmetric information treatments, the stop-out price and the seller's revenue should be positively related to resale value. Because the private signals jointly determine resale value, the strength of the relation between resale value and revenue (or stop-out price) measures the auction's ability to extract the bidders' private information.

iv) Allocations are expected to be more symmetric in the symmetric information treatments than in the asymmetric information treatments.

v) Bids are expected to be positively related to private signals; therefore, allocations should be "partially efficient" in the asymmetric information treatments in the sense that the bidders receiving the highest signals should receive the largest allocations.

vi) Reflecting the bidders' use of their strategic advantage, bid schedules are expected to be more inelastic in the uniform-price auctions than they are in the discriminatory auctions.

vii) In the asymmetric information treatments, the allowance for the winner's curse is expected to be positive, increasing in the level of the received signal, and greater in the discriminatory auctions than in the uniform-price auctions.

III. Experimental Design

In each session, bidders participated in a sequence of auctions for a divisible good. In each auction, subjects submitted bid schedules at computer terminals. Monetary values were denominated in an experimental currency referred to as "lab dollars" (L$). Prior to every auction, the resale value of each unit of the good (called widgets) was determined randomly, and subjects received a signal useful in updating the prior distribution governing value. The signals were either constrained to be common (symmetric information) or allowed to differ across bidders (asymmetric information). A bidder's payoff in an auction was calculated as the sum, over units allocated to that bidder, of the difference between the resale value and the price paid for that unit. Bidders were not allowed to communicate before or during the sessions nor were they given information concerning any other bidder's bids or allocations.

Each experimental session involved a cohort of 5 subjects, and each cohort participated in a single experimental treatment. Table 1 summarizes the implementation of the experiment. The typical session was made up of a sequence of 20 auctions. Senior undergraduate and MBA students from 2 universities were employed as subjects. All had at least 1 course in finance, as well as courses in statistics and economics.

We examine 4 treatments differing on 2 dimensions: the pricing mechanism and the allocation of information. Specifically, we compare uniform-price and discriminatory auctions in an uncertain, common value environment when bidders have either symmetric or asymmetric information concerning the value of

TABLE 1

Experimental Design: Subjects and Cohorts

The experiment consists of 75 sessions split between 2 auction mechanisms, 2 information structures, and 2 experience levels. In each session a cohort of 5 subjects bid together in 20 sequential auctions (in 1 session there were 15 auctions due to time constraints).

Auction Type	Information Structure	Experience Level	No. of Sessions	Total Auctions
Uniform-price	Symmetric information	Inexperienced	11	220
Uniform-price	Symmetric information	Experienced	7	140
Uniform-price	Asymmetric information	Inexperienced	14	275
Uniform-price	Asymmetric information	Experienced	7	140
Discriminatory	Symmetric information	Inexperienced	10	200
Discriminatory	Symmetric information	Experienced	7	140
Discriminatory	Asymmetric information	Inexperienced	12	240
Discriminatory	Asymmetric information	Experienced	7	140

the good. Seventeen sessions of discriminatory auctions with symmetric information (10 with inexperienced subjects and 7 with experienced subjects (subjects who had participated in a session of the same treatment)) and 18 (11 inexperienced and 7 experienced) sessions of uniform-price auctions with symmetric information were conducted. Nineteen sessions of discriminatory auctions with asymmetric information (12 inexperienced and 7 experienced) and 21 sessions of uniform-price auctions with asymmetric information (14 inexperienced and 7 experienced) were conducted.[13] To minimize the impact of subjects who did not fully understand the task, subjects with losses in excess of the initial endowment in their inexperienced sessions were not invited to participate as experienced subjects. Analysis shows that these subjects did not exhibit learning within the inexperienced session.[14] We expect this type of parsing of the subject pool would occur naturally in the markets we are ultimately interested in. We stress that our "experienced" subject pool includes many with losses in the 1st session. Our intention was to screen based on learning facility rather than bidding aggressiveness, although we recognize that perfectly disentangling the 2 effects is not possible.

In each auction, 26 units were offered for sale. Subjects were allowed to bid for as much or as little of the supply as they desired. Subjects were allowed to submit step function bid schedules for any integer quantity in the interval [0, 26] at each integer price in the interval [L$10, L$30]. The aggregate quantity demanded on each bid schedule was limited to 26 units. Once all subjects had submitted a bid schedule in a given auction, the computer aggregated the bids and determined the stop-out price for that auction. All bids submitted at prices above the stop-out price were winning bids, and any necessary rationing at the stop-out price was done on a pro-rata basis (fractional allocations were allocated). In uniform-price auctions the stop-out price was the unique price paid for all allocated units, and in discriminatory auctions the price paid on all winning bids was the bid price. Auctions were conducted using custom designed software. The software graphed individual bid schedules as subjects initiated the bidding process and provided

[13] See Table 1 for further details of the different treatment implementations.

[14] Losses are higher in sessions with asymmetric information. To avoid introducing a bias across mechanisms, we exclude the same number of subjects (9) from the both types of auctions in these sessions.

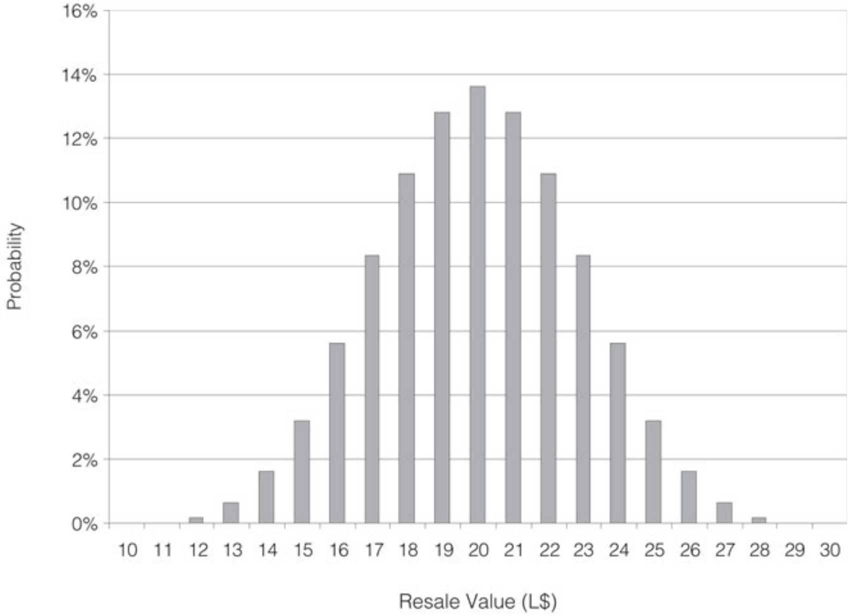
historical information pertaining to each subject's bidding, matched with the profit and the portion of total supply received for each prior auction.

In the symmetric information sessions it was public knowledge that all subjects received the same signal regarding resale value. Resale value was drawn from a discrete, uni-modal distribution (see Figure 1) over the integers in the

FIGURE 1

Resale Value Distribution (signal = 20)

Figure 1 depicts the posterior distribution of resale value in an asymmetric information auction given that a private signal with a value of 20 has been received. This is also the prior distribution of resale value in the symmetric information auctions.



Resale Value (L$)	Probability Resale Value Equals	Probability Resale Value Lower Than	Probability Resale Value Higher Than
10	0.0%	0.0%	100.0%
11	0.0%	0.0%	100.0%
12	0.2%	0.0%	99.8%
13	0.6%	0.2%	99.2%
14	1.6%	0.8%	97.6%
15	3.2%	2.4%	94.4%
16	5.6%	5.6%	88.8%
17	8.3%	11.2%	80.5%
18	10.9%	19.5%	69.6%
19	12.8%	30.4%	56.8%
20	13.6%	43.2%	43.2%
21	12.8%	56.8%	30.4%
22	10.9%	69.6%	19.5%
23	8.3%	80.5%	11.2%
24	5.6%	88.8%	5.6%
25	3.2%	94.4%	2.4%
26	1.6%	97.6%	0.8%
27	0.6%	99.2%	0.2%
28	0.2%	99.8%	0.0%
29	0.0%	100.0%	0.0%
30	0.0%	100.0%	0.0%

interval [L$10, L$30]. The distribution was symmetric, with a mean of L$20 and a standard deviation of L$2.8. For purposes of comparison, resale value was kept constant auction by auction across pricing rules for each level of experience (i.e., the same sequence of random draws for resale value was used for all symmetric information sessions with the same experience level).

Under asymmetric information, prior to each auction each subject observed a private signal drawn from the integers in the interval [L$18, L$22]. Each signal allowed that bidder to identify a posterior distribution governing resale value (depicted numerically and graphically in the instructions). In each auction, the resale value of all units was uniquely determined by the received signals. For each signal received by a subject, the difference between that signal and 20 was computed. Resale value was the sum of these differences across all subjects plus 20. This implied that each subject had a posterior distribution with the same variance but (typically) a different mean.[15] The distribution of resale value in the symmetric information sessions was equivalent to the posterior distribution facing a subject receiving a signal of 20 in an asymmetric information auction (see Figure 1). Again, for purposes of comparison, resale value and the signals received by subjects auction by auction were held constant across auction types for sessions with the same level of experience.

At the start of each experimental session, subjects were seated in a conference room, given 30–40 minutes with the written instructions, and had an opportunity to ask clarifying questions. The instructions explained the auction rules and the basis on which cash payments would be made, and they included images introducing the subjects to the software. Subjects were given a quiz to confirm their understanding of the bidding and allocation rules, and the session only began after all 5 subjects were able to get a perfect score on the quiz.

Subjects were not allowed to communicate with each other before or during the sessions, minimizing the possibility that any collusive behavior can be attributed to subject interaction. In addition, the layout of the computer lab prevented each subject from seeing the screen of any other subject. Subjects were informed that such behavior was contrary to the auctions rules, ensuring that bidding behavior remained private knowledge. To maintain subjects' privacy, at the completion of the final auction in each session, each subject's screen automatically reverted to a blank screen and subjects were paid individually in a side room.

Subjects were paid a US$5 upfront participation fee as well as "winnings" based on their total profit. Each subject was given an initial endowment of L$250. Gains and losses from each auction were added to this endowment. Subjects were allowed to go bankrupt, allowed to bid when bankrupt, and encouraged to continue in an attempt to recover their losses. To mitigate extreme behavior in bankruptcy, as in Bloomfield et al. (2005), at the beginning of each session subjects were informed that they would receive an additional random endowment at

[15]This structure, therefore, does not generate the difficulties associated with the "wallet game" (see Klemperer (1998)). However, as noted above, there are a vast number of equilibria in the bidding game.

the end of the session.[16] The exchange rate between L$ and US$ (the currency in which subjects were paid) was US$ = L$20. Payments to subjects averaged US$19.27. Experimental sessions with inexperienced subjects lasted an average of approximately 90 minutes, while sessions with experienced subjects lasted an average of 30–45 minutes.

IV. Experimental Results

We assess the experimental outcomes along the following dimensions: bidding strategies, stop-out prices, bidder profits, seller's revenue, and the nature of allocations.

A. Auction Basics

Summary statistics are provided in Table 2. We report means, medians, and standard deviations for a variety of variables from the experimental sessions to provide information concerning bidding behavior and auction outcomes for the

TABLE 2

Descriptive Statistics of Auction Outcomes and Individual Bidding Behavior

Means, medians, and standard deviations are shown in the first 3 rows, respectively; number of observations is shown in row 4 in square brackets; and *, **, and *** to the right of the uniform-price statistics show that the difference in means, medians, and standard deviations between pricing subsample pairs are significantly different at the 90%, 95%, and 99% levels, respectively. The difference in means between the 2 pricing subsamples is assessed using independent group t-statistic tests, adjusting standard errors and degrees of freedom for equal and unequal variances between the 2 subsamples, as needed. Difference in medians between the 2 pricing subsamples is assessed using the Wilcoxon 2-sample test. Tests for differences in variance between the 2 pricing subsamples are conducted using the Folded F method. Variable definitions can be found in the Appendix.

			Inexperienced Subjects				Experienced Subjects			
			Symmetric Information		Asymmetric Information		Symmetric Information		Asymmetric Information	
Variables	Statistics	All Sessions	Unif. Price	Disc. Price	Unif. Price	Disc. Price	Unif. Price	Disc. Price	Unif. Price	Disc. Price
Seller's revenue per auction	Mean	538.08	553.09**	529.99	560.62	554.01	514.97	516.52	512.57	523.87
	Median	533.76	547.53*	530.62	548.29	554.47	516.94	521.12	516.94	524.65
	Std. dev.	30.58	26.55	20.20	43.34***	15.18	14.69	14.07	13.95	16.32
	N	[75]	[11]	[10]	[14]	[12]	[7]	[7]	[7]	[7]
Stop-out price per auction	Mean	20.42	21.27***	19.75	21.56**	20.60	19.81	19.50	19.71	19.67
	Median	20.24	21.06***	19.94	21.09*	20.62	19.88	19.59	19.88	19.94
	Std. dev.	1.22	1.02	0.76	1.67***	0.57	0.56	0.57	0.54	0.67
	N	[75]	[11]	[10]	[14]	[12]	[7]	[7]	[7]	[7]
Average price paid per widget per auction	Mean	20.70	21.27**	20.38	21.56	21.31	19.81	19.87	19.71	20.23
	Median	20.53	21.06*	20.41	21.09	21.33	19.88	20.04	19.88*	20.29
	Std. dev.	1.17	1.02	0.78	1.67***	0.58	0.56	0.54	0.54	0.65
	N	[75]	[11]	[10]	[14]	[12]	[7]	[7]	[7]	[7]
Number of bidders with positive allocation per auction	Mean	4.98	4.98	4.98	4.99	4.94	4.99	5.00	4.99	4.95
	Median	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00	5.00
	Std. dev.	0.08	0.04	0.04	0.03***	0.16	0.02***	0.00	0.02***	0.13
	N	[75]	[11]	[10]	[14]	[12]	[7]	[7]	[7]	[7]
Herfindahl index of allocations (per auction)	Mean	0.43	0.40	0.40	0.49	0.49	0.31	0.36	0.45	0.49
	Median	0.42	0.39	0.36	0.46	0.48	0.30	0.36	0.43	0.46
	Std. dev.	0.10	0.07	0.08	0.14***	0.05	0.04	0.07	0.08	0.10
	N	[75]	[11]	[10]	[14]	[12]	[7]	[7]	[7]	[7]

(continued on next page)

[16]The random endowment was drawn from a discrete uniform distribution with a mean of L$100.

TABLE 2 (continued)

Descriptive Statistics of Auction Outcomes and Individual Bidding Behavior

			Inexperienced Subjects				Experienced Subjects			
			Symmetric Information		Asymmetric Information		Symmetric Information		Asymmetric Information	
Variables	Statistics	All Sessions	Unif. Price	Disc. Price	Unif. Price	Disc. Price	Unif. Price	Disc. Price	Unif. Price	Disc. Price
Individual bidder profit per auction	Mean	–4.19	–6.92***	–2.30	–8.88	–7.52	0.09	–0.22	1.18*	–1.08
	Median	–2.12	–4.16***	–0.67	–3.38*	–6.01	0.45	–0.17	1.28**	–0.98
	Std. dev.	11.41	9.35**	6.96	20.66***	7.97	3.58	4.57	4.63	5.84
	N	[375]	[55]	[50]	[70]	[60]	[35]	[35]	[35]	[35]
Elasticity of individual bid schedules at the bidder's signal per auction	Mean	–13.43	–10.24***	–15.65	–11.12***	–13.57	–13.37***	–18.04	–12.62***	–16.82
	Median	–13.85	–10.17***	–16.52	–10.59***	–13.11	–14.08***	–19.09	–15.38***	–17.79
	Std. dev.	4.88	4.58	4.25	3.88	3.24	5.55***	2.32	6.30***	2.87
	N	[363]	[55]	[48]	[70]	[58]	[34]	[31]	[35]	[32]
Highest price bid by individual bidders in an auction	Mean	20.86	22.31***	20.10	21.84***	20.65	20.89***	19.72	20.30**	19.69
	Median	20.59	22.53***	20.03	21.50***	20.65	20.65***	19.82	20.18	19.71
	Std. dev.	1.62	1.88***	1.09	1.63***	0.89	1.40***	0.78	1.54***	0.75
	N	[375]	[55]	[50]	[70]	[60]	[35]	[35]	[35]	[35]
Units bid for by individual bidders in an auction	Mean	24.05	24.49	23.84	24.56	24.21	23.58	23.85	24.03	23.04
	Median	26.00	25.94	26.00	26.00	26.00	26.00	25.94	26.00	26.00
	Std. dev.	4.14	3.03**	4.02	3.07***	4.42	4.69	4.41	4.68	5.68
	N	[375]	[55]	[50]	[70]	[60]	[35]	[35]	[35]	[35]
Number of prices at which individual bidders submitted bids in an auction	Mean	3.76	4.38**	3.72	4.39***	3.45	3.98***	2.75	3.55	3.10
	Median	3.65	4.00*	3.50	3.95***	3.47	3.41***	2.24	3.65	3.18
	Std. dev.	1.65	1.78	1.59	1.73**	1.28	1.95**	1.32	1.24	1.42
	N	[375]	[55]	[50]	[70]	[60]	[35]	[35]	[35]	[35]
Expected resale value conditional on a bidder's signal less the highest price bid by that bidder in the auction	Mean	–0.87	–2.31***	–0.10	–1.87***	–0.68	–0.89***	0.28	–0.30**	0.31
	Median	–0.59	–2.53***	–0.03	–1.47***	–0.59	–0.65***	0.18	–0.06*	0.24
	Std. dev.	1.65	1.88***	1.09	1.66***	0.96	1.40***	0.78	1.59***	0.89
	N	[375]	[55]	[50]	[70]	[60]	[35]	[35]	[35]	[35]

4 auction types (uniform-price with symmetric information, discriminatory with symmetric information, uniform-price with asymmetric information, and discriminatory with asymmetric information) with inexperienced as well as experienced subjects. All analysis was performed ignoring the first 3 auctions in each session so the results are not clouded by early extreme outcomes or behavior driven by subjects' unfamiliarity with the experiment.[17] To be as conservative as possible regarding standard errors, when comparing between treatments for auction-level variables, we first calculate a mean using each auction in a session and then use the session means as the unit of observation to perform *t*-tests.[18] When comparing bidder-level variables we first calculate a session-level mean for each bidder and use this mean as the unit of observation for that bidder.

As presented in Table 2, the seller's average revenue across all treatments is L$538.08, the average stop-out price is L$20.42, and the average price paid is L$20.70. Comparing these values with the average resale value, L$20, given

[17]Nearly all of the results are robust to alternative rules to establish the cutoff point of the excluded data. The exception is that increasing the cutoff to the first 5 auctions in each session causes some of the results regarding learning within a session to become insignificant.

[18]For robustness, we also performed a nonparametric randomization test as well as an analysis of variance on auction-level data with cluster robust standard errors. The results are nearly identical and are not reported.

26 units sold in each auction, these figures are consistent with the average bidder loss of L$4.19. These results indicate that on average, across all treatments, bids were "too high."

The "levels" of the bid schedules may be compared using the bidders' highest bid or their highest bid relative to observed signal. Under asymmetric information, the latter measure captures the allowance for the winner's curse. Consistent with the empirical hypotheses, Table 2 shows both measures are significantly higher in the uniform-price than the discriminatory auctions, for all 4 treatment categories.

Also consistent with the empirical hypotheses, bid schedules in the uniform-price auctions are more inelastic[19] than those in discriminatory auctions. For example, in the uniform-price auction with symmetric information, the average elasticity of individual bid schedules measured at the level of the bidders' signal is -10.24 in the inexperienced sessions and -13.37 in the experienced sessions. For the discriminatory auctions with symmetric information, the average elasticity of the bid schedules is -15.65 in the inexperienced sessions and -18.04 in the experienced sessions. In the asymmetric information sessions, the differences are smaller but remain highly significant.

The average maximal demand (total demand per bid schedule) ranges from 23.04 to 24.56, indicating that the coverage ratio (aggregate demand at a price of 10 relative to supply) is large in all auctions. The median maximal demand is always very close to 26, indicating that bidders commonly bid for the entire supply. Average maximal demand tends to be lower in the experienced relative to the inexperienced sessions; however, this is not true for all types of auctions, nor is the difference economically meaningful.

Subjects tended to submit multiple price/quantity pairs as bids. Across all auctions, the mean (median) number of distinct prices included in individual bid schedules is 3.76 (3.65). The average number of prices included in bid schedules is higher in the uniform-price auctions than in the discriminatory auctions. Only in the asymmetric information auctions with experienced subjects is the difference insignificant.

Finally, note that, on average, the allocations in the auctions are quite symmetric. The median number of bidders receiving a positive allocation in the auctions is 5 and the average is very close to 5. The minimum number of bidders in an auction to receive a positive allocation is 3, and this occurs in only 1 auction of 1 session. The average Herfindahl index of the allocations (the sum across bidders of squared percentage allocations, for which a value of 0.20 identifies perfect symmetry) indicates more symmetric allocations in the symmetric information sessions and in the experienced sessions. However, none of the differences are significant.

[19]Formally, the bid schedules are step functions. Therefore, at any price bid elasticity is not well defined. The variable *elasticity of individual bid schedules at the bidder's signal* is calculated by dividing the percentage change in cumulative demand exhibited by that bidder over the percentage change in price, as we move from the bidder's signal in that auction to the next higher price available on the bid schedule. Whenever the signal in an auction is outside a bidder's pricing range, this variable is not well defined for that bidder in that auction. The same occurs if the bidder does not submit any bids in that auction.

The broad averages reported in Table 2 highlight significant differences in bidding between uniform-price and discriminatory auctions. This is true in the symmetric and asymmetric information sessions with inexperienced and experienced bidders. This finding verifies the caution that a change in pricing rules will result in "a radical change in bidding behavior," raised by many scholars evaluating the choice over auction pricing mechanisms (see, e.g., Kahn, Cramton, Porter, and Tabors (2001)).

B. Symmetric Information

Table 3 examines the variables of interest in a regression context to control for factors that may explain bidding and outcomes in the symmetric information auctions. Each column reports the results of a regression in which the dependent variable is identified in the column heading. The independent variables are auction-type dummy variables, realized resale value, and the natural logarithm of

TABLE 3

Linear Regressions of Auction Outcomes: Symmetric Information Environment

In Panel A of Table 3, the headings in columns 1–7 identify the corresponding regression's dependent variable. Clustered standard errors are estimated in regressions 1–3 to adjust for correlated residuals among observations within the same experimental session and in regressions 4–7 to adjust for correlated residuals among observations within the same experimental session and among those generated by the same subject. In Panel B, the numbers present the *t*-statistics of the null hypothesis shown in column 1, adjusting standard errors for correlated residuals among observations within the same experimental session in regressions 1–3 and for correlated residuals among observations within the same experimental session and among those generated by the same subject in regression 4–7. In Panel A, *, **, and *** denote significance of coefficient at the 90%, 95%, and 99% levels, respectively; and in Panel B, *, **, and *** denote rejection of the null hypothesis at the 90%, 95%, and 99% levels, respectively. Variable definitions can be found in the Appendix.

Panel A. Ordinary Least Squares Regressions of Auction Outcomes within a Symmetric Information Environment

	Seller's Revenue	Stop-Out Price	Average Price Paid per Widget	Bidder Profits	Maximum Individual Bid	Elasticity of Bidder Demand at Signal	Individual Allocation
Independent Variables	1	2	3	4	5	6	7
UP_Inexp	576.91***	22.09***	22.19***	−23.39***	23.38***	−11.03***	5.20***
UP_Exp	512.53***	19.60***	19.71***	3.30*	21.62***	−16.11***	5.20***
DP_Inexp	554.06***	19.79***	21.31***	−18.81***	21.11***	−11.09***	5.20***
DP_Exp	502.67***	18.74***	19.33***	5.27**	20.01***	−17.35***	5.20***
Resale Value	−0.02	0.00	0.00		−0.02*	0.00	0.00
UP_Inexp × Auction	−9.84	−0.38	−0.38	6.90***	−0.30	0.37	0.00
UP_Exp × Auction	1.18	0.05	0.05	−1.35	−0.16	1.38***	0.00
DP_Inexp × Auction	−9.94***	−0.05	−0.38***	6.92***	−0.28**	−1.58**	0.00
DP_Exp × Auction	5.96	0.28	0.23	−2.30*	0.02	−0.13	0.00
No. of obs.	595	595	595	2,975	2,967	2,172	2,975
Adj. R^2	1.00	1.00	1.00	0.04	0.99	0.83	0.53

Panel B. Tests of Hypotheses Concerning the Regressions in Panel A

	Seller's Revenue	Stop-Out Price	Average Price Paid per Widget	Bidder Profits	Maximum Individual Bid	Elasticity of Bidder Demand at Signal	Individual Allocation
Null Hypothesis (H_O)	1	2	3	4	5	6	7
UP_Inexp = UP_Exp	2.11**	2.11**	2.11**	−4.57***	2.48**	2.33**	0.00
UP_Inexp = DP_Inexp	0.73	1.88*	0.73	−0.76	3.28***	0.03	0.00
UP_Exp = DP_Exp	0.58	1.36	0.58	−0.64	3.11***	0.41	0.00
DP_Inexp = DP_Exp	2.83***	1.44	2.83***	−7.21***	2.23**	2.09**	0.00
UP_Inexp = 20					5.68***		
UP_Exp = 20					4.22***		
DP_Inexp = 20					3.16***		
DP_Exp = 20					0.03		

auction number interacted with the auction-type dummy variables (to capture learning within a session). Regressions 1–3 are estimated at the auction level, and standard errors are estimated adjusting for correlation in residuals within the same experimental session. Regressions 4–7 are estimated at the auction-bidder level and standard errors are estimated adjusting for correlation within the same session and bidder.

The dependent variable in regression 1 of Table 3 is seller's revenue. The coefficient estimates on the auction-type dummy variables, with the test statistics in Panel B, show that at the beginning of the inexperienced sessions, average revenue in the uniform-price (L$576.91) and discriminatory (L$554.06) auctions are not significantly different. The estimated coefficient on the interaction between the inexperienced discriminatory dummy variable and auction number is significantly negative (−9.94). This indicates that revenue falls significantly throughout the discriminatory auction session with inexperienced bidders. The estimated coefficient on the interaction term between the inexperienced uniform-price dummy variable and auction number (−9.84) is only slightly smaller in absolute terms but, due to greater volatility, is not significant. Thus, while revenue in the different auctions was similar at the beginning of the inexperienced sessions, subjects in discriminatory auctions learn to bid more effectively. With experienced subjects, revenue is indistinguishable across the auction types at the beginning of the sessions, and there is no significant evidence of learning within the experienced sessions for either type of auction. For both types of auctions, we see that initially, revenue is significantly lower in the experienced sessions than in the inexperienced sessions.

These results are mirrored in regression 3 (average price paid) and regression 4 (average bidder profit) of Table 3. Consider bidder profits (regression 4). The coefficient estimates on the auction-type dummy variables for inexperienced uniform-price (−23.39) and inexperienced discriminatory (−18.81) are significantly negative but (see Panel B) not significantly different. The interaction terms (with auction number) show estimated coefficients of 6.90 and 6.92 (both significant at the 1% level) for the inexperienced uniform-price and inexperienced discriminatory auctions, respectively. Thus, inexperienced bidders lose money in the early auctions but see a significant increase in profits within the sessions. In both types of auctions, initial bidder profits are significantly larger for experienced bidders than for inexperienced bidders.

Regression 2 of Table 3 reports results using the stop-out price as the dependent variable. The stop-out price is initially significantly higher in the inexperienced uniform-price sessions than in the inexperienced discriminatory sessions (L$22.09 vs. L$19.79), and there is no significant evidence of learning across the auctions in these sessions. In the experienced sessions, the initial stop-out price is not statistically different across the auction types, and there is again no significant evidence of learning.

Regression 5 (intercept) and regression 6 (elasticity) of Table 3 characterize the bidding strategies. Consistent with predictions, for both experienced and inexperienced bidders, initially the highest bids on bid schedules submitted in discriminatory auctions are significantly lower than those on bid schedules submitted in uniform-price auctions. Comparing the inexperienced to the experienced sessions, in both types of auctions, the bid schedules submitted by experienced bidders are at significantly lower levels than those submitted by inexperienced bidders. In the inexperienced sessions for both types of auctions, the highest bids decrease over the session (significantly so in the discriminatory auctions). There is no significant evidence of change in the level of the bid schedules across the auctions of the experienced sessions.

The elasticity of bid schedules submitted in the uniform-price and the discriminatory auctions are initially indistinguishable for both inexperienced and experienced bidders. The differences in averages reflected in Table 2 are explained by learning within the sessions. In the inexperienced sessions the bid schedules submitted in the discriminatory auctions become significantly more elastic as the sessions progress. In contrast, in the experienced sessions, in the uniform-price auctions the bid schedules become significantly more inelastic. Comparing the inexperienced to the experienced sessions, the bid schedules initially submitted in the experienced sessions are significantly more elastic than those in the inexperienced sessions.

Finally, as expected with symmetric information, individual allocations (regression 7 of Table 3) are very symmetric, with no differences across auction types. Naturally, the average allocation is 5.20 in each type of auction. Furthermore, none of the other independent variables has a significant coefficient estimate. As a robustness test, we estimate the same regression using squared individual allocations as the dependent variable to highlight differences from the average. Identical conclusions are reached.

The results show that while bidding behavior differs significantly across auction types, there is little evidence that auction outcomes differ. There is marked improvement in bidding within the inexperienced sessions, and this improvement is greater in the discriminatory auctions. The results also show that, in general, experienced bidders exhibit bidding behavior that corresponds with the empirical hypotheses.

C. Asymmetric Information

A main motivation for this study is the examination of the effect of asymmetric information on bidding behavior and auction outcomes in the different auctions. As discussed above, theory provides expectations as to the level of the bid schedules. Under symmetric information, the level or highest price bid on equilibrium bid schedules should be based upon the (common) conditional expected resale value of the good. In the asymmetric information case, the highest bid price on an individual bid schedule should reflect the expected resale value conditional on that bidder's private signal and the information concerning other bidders' signals revealed by the realization of that price as the stop-out price. Thus, examining the level of the bid schedules will allow us to examine adjustments for the winner's curse. Theory also suggests that, as under symmetric information, the equilibrium bid schedules submitted in the uniform-price auctions will be more inelastic than those submitted in the discriminatory auctions. Finally, we are able to examine the extent to which the pricing mechanisms are able to extract private information from the subjects and use it in establishing auction prices.

Panel A of Table 4 contains the results of regression analysis using data generated by the asymmetric information sessions and shows findings similar to those in Tables 2 and 3 regarding outcomes across the auction types. Inexperienced bidders overbid on average. Consider bidder profits for inexperienced bidders. Fitting regression 4 at the sample mean values of the statistically significant independent variables, inexperienced bidders in uniform-price auctions see an average *loss* of L$7.58 (−58.38 + 20(2.54)) in the 1st auction. Similarly, inexperienced bidders in discriminatory auctions see an average *loss* of L$9.30 (−60.10 + 20(2.54)) in the 1st auction of a session. Contrary to the findings under symmetric information, there is only weak evidence of learning within the inexperienced sessions of the discriminatory auctions and no significant evidence of learning within the inexperienced sessions of the uniform-price auctions.

TABLE 4

Linear Regressions of Auction Outcomes: Asymmetric Information Environment

In Panel A of Table 4, the headings in columns 1–7 identify the corresponding regression's dependent variable. Clustered standard errors are estimated in regressions 1–3 to adjust for correlated residuals among observations within the same experimental session and in regressions 4–7 to adjust for correlated residuals among observations within the same experimental session and among those generated by the same subject. In Panel B, the numbers present the *t*-statistics of the null hypothesis shown in column 1, adjusting standard errors for correlated residuals among observations within the same experimental session in regressions 1–4 and for correlated residuals among observations within the same experimental session and among those generated by the same subject for regressions 5–7. In Panel A, *, **, and *** denote significance of coefficient at the 90%, 95%, and 99% levels, respectively; and in Panel B, *, **, and *** denote rejection of the null hypothesis at the 90%, 95%, and 99% levels, respectively. Variable definitions can be found in the Appendix.

Panel A. Ordinary Least Squares Regressions of Auction Outcomes within a Symmetric Information Environment

	Seller's Revenue	Stop-Out Price	Average Price Paid by Bidders	Bidder Profits	Elasticity of Bidder Demand at Signal	Exp. Res. Value Cond. on Signal Less Highest Bid	Individual Allocation
Independent Variables	1	2	3	4	5	6	7
UP_Inexp	500.86***	19.20***	19.25***	−58.38***	19.07***	−10.31***	−30.83***
UP_Exp	465.66***	17.85***	17.90***	−60.10***	10.04***	−8.04***	−30.54***
DP_Inexp	531.50***	19.26***	20.43***	−64.43***	17.70***	−10.18***	−30.61***
DP_Exp	490.22***	18.34***	18.89***	−64.63***	11.01***	−7.97***	−30.74***
Resale Value	2.15***	0.09***	0.08***		−0.03	0.03***	−0.44***
Signal				2.54***	−1.39***	0.39***	2.23***
UP_Inexp × Auction	7.50	0.29	0.29	−0.58	−0.70	0.07	0.07
UP_Exp × Auction	1.68	0.06	0.06	4.43***	2.32**	−0.22	−0.05
DP_Inexp × Auction	−8.52	−0.16	−0.33	2.53*	−1.34**	0.53***	−0.01
DP_Exp × Auction	−3.88	−0.16	−0.13	5.38***	0.25	0.00	0.05
No. of obs.	672	672	672	3,326	2,286	3,310	3,326
Adj. R^2	0.99	0.99	0.99	0.06	0.82	0.28	0.53

Panel B. Tests of Hypotheses Concerning the Regressions in Panel A

	Seller's Revenue	Stop-Out Price	Average Price Paid by Bidders	Bidder Profits	Elasticity of Bidder Demand at Signal	Exp. Res. Value Cond. on Signal Less Highest Bid	Individual Allocation
Null Hypothesis (H_o)	1	2	3	4	5	6	7
UP_Inexp = UP_Exp	1.85*	1.84*	1.85*	0.15	1.99**	−1.54	−0.09
UP_Inexp = DP_Inexp	−1.18	−0.06	−1.18	0.50	0.28	−0.10	−0.07
UP_Exp = DP_Exp	−2.08**	−0.98	−2.18**	0.42	−0.22	−0.05	0.07
DP_Inexp = DP_Exp	1.94*	1.15	1.88*	0.02	1.39	−1.83*	0.04

Experienced bidders performed better in the asymmetric information treatments. Using the fitted values as above, we see that with asymmetric information, experienced bidders in the uniform-price auctions initially lose L$9.30, while those in the discriminatory auctions initially lose L$13.84. However, the experienced bidders exhibit significant improvement within both the uniform-price and discriminatory auction sessions. The estimated coefficients on the interaction between auction type and auction number are 4.43 for the uniform-price and 5.38 for the discriminatory auctions; both are highly significant. The most significant evidence of learning in the asymmetric information sessions is the improvement in bidder profits across the experienced sessions. This difference from the symmetric information case may be due to the increased complexity introduced by asymmetric information. Consistent with these results, Table 2 indicates that revenue and average price paid are significantly lower in the experienced sessions of both types of auction relative to the corresponding inexperienced sessions.

Within the inexperienced sessions of the asymmetric information treatments, the initial seller's revenue in the uniform-price and discriminatory auctions are statistically indistinguishable. In the experienced sessions, initial revenue in the uniform-price auctions is significantly lower than in the discriminatory auctions. This finding is consistent with the notion that experienced bidders in the uniform-price auctions exploit more of their strategic advantage. Support for this conclusion is presented in Table 2, which indicates that inexperienced and experienced bidders in uniform-price auctions with asymmetric information use significantly more inelastic bid schedules than do bidders in discriminatory auctions. Furthermore, regression 5 shows that controlling for the level of individual signals and learning within the sessions, the differences in elasticity are initially insignificant, but that experienced bidders in the uniform-price auctions submit (significantly) more inelastic bid schedules as these sessions progress, while there is no significant change in the elasticity of the bid schedules submitted in the discriminatory auctions across the experienced sessions.

In regression 6 of Table 4, the dependent variable is expected resale value conditional on a bidder's signal less the highest price bid submitted by that bidder, a measure of the adjustment for the winner's curse. For inexperienced subjects, this quantity is initially negative for both types of auctions (−L$1.91 for uniform-price auctions and −L$1.78 for discriminatory auctions, evaluating the significant regressors at the sample mean), indicating that bidders are not making a proper adjustment for the winner's curse.[20] This regression also shows that inexperienced subjects in the discriminatory auctions with asymmetric information make significantly positive adjustments across auctions within the inexperienced sessions. Experienced subjects' bid schedules contain, on average, a positive adjustment for the winner's curse. While the coefficients on the auction-type dummy variables are negative, they are smaller in absolute value than for inexperienced sessions, resulting in a positive average adjustment for the winner's curse (0.36 in uniform-price and 0.43 in discriminatory auctions) when we evaluate the significant regressors (signal and resale value) at their sample means. Finally, there is a significantly positive coefficient on the signal received by each subject in each auction, indicating that a relatively larger adjustment for the winner's curse was associated with higher realized signals.

[20]Their behavior in this respect is similar to that of inexperienced subjects under symmetric information, where the maximum individual bid is on average higher than L$20.

Regression 7 examines allocations. There are no significant differences in average allocation across auction types or as sessions progress. Allocations are, however, not symmetric. The source of the asymmetry is that allocations are strongly responsive to the value of an individual bidder's signal (the estimated coefficient is 2.23, significant at the 1% level), holding resale value constant. Regression 7, therefore, provides support for the "partial efficiency" of the allocations; a greater portion of the supply goes to bidders with the highest valuation. Conversely, controlling for signal, there is a significantly (1% level) negative relation (-0.44) between resale value and allocation, indicating that, for a given signal received by a bidder, the higher are the other private signals (in aggregate), the lower is that bidder's allocation.

In addition to providing an indication of subjects' ability to bid effectively in auctions with asymmetric information, regressions 2 and 3 of Table 4 provide information concerning the ability of the auction mechanisms to extract the bidders' private information. The informational structure in the market is such that, in the aggregate, the information possessed by the bidders is perfectly revealing of the resale value. Thus, the extent to which the stop-out price and the average price paid by bidders in the auctions reflect ex post resale value is a measure of the mechanism's ability to extract the bidder's private information. The estimated coefficients of 0.09 on resale value in the stop-out price regression 2 and 0.08 in the average price paid regression 3 are both positive and highly significant.

Untabulated robustness results show that for both the stop-out price and the average price paid regressions, in both the inexperienced and the experienced sessions, estimated coefficients on interactions between the auction-type dummy variables and resale value are all significantly positive, indicating that the stop-out price and average price paid are positively related to resale value regardless of auction type or subject experience. The response of both measures of price to value is weaker in the inexperienced sessions than in the experienced sessions for both the uniform-price (0.07 vs. 0.10) and the discriminatory auctions (0.07 vs. 0.12); however, the difference is significant only for the discriminatory auctions. Holding the level of experience constant, there are no significant differences in these coefficients across auction types. The evidence indicates that the auctions' ability to extract bidders' private information is enhanced with bidder experience, but that this ability does not differ across pricing rules.

Generally, the results in the asymmetric information sessions show that bidding behavior and auction outcomes from the experienced sessions conform to the empirical hypotheses. Experienced bidders in both types of auctions make allowances for the winner's curse. Consistent with the empirical hypotheses, bid schedules submitted in the uniform-price auctions are more inelastic than those submitted in the discriminatory auctions. Also consistent with the predictions, with experienced bidders, the seller's revenue is initially significantly lower in the uniform-price auctions than in the discriminatory auctions, and there is no significant learning across the experienced sessions of either type of auction. Finally, the auction types appear to be indistinguishable with respect to allocations across the bidders and their abilities to extract bidders' private information.

D. Experience

By examining the fixed pool of subjects that participated in both the inexperienced and the experienced sessions, we can examine the impact of a prior session's experience on bidding behavior. Table 5 reports the results of regressions at the bidder level in each auction, holding the subject pool constant across the inexperienced and the experienced sessions. In regression 1, where the average price paid is the dependent variable, the estimated coefficients show that average price paid declines with experience. Panel B indicates that all the comparisons across experience levels are statistically significant, except for the comparison between inexperienced and experienced bidders in discriminatory auctions under symmetric information.

TABLE 5

Individual Bidding Behavior and Auctions Outcomes: Fixed Subject Pool

In Panel A of Table 5, the headings in columns 1–4 identify the corresponding regression's dependent variable. Clustered standard errors are estimated to adjust for correlated residuals among observations within the same experimental session and among those generated by the same subject. Bidding behavior and auction outcome data of inexperienced subjects who do not eventually participate in an experienced session are excluded from these regressions. That is, data for 104 subjects who participated in an experimental session but who did not make it to a 2nd experienced session were excluded. Only the data for the 132 subjects who eventually participated in an experienced session were used. In Panel B, the numbers present the *t*-statistics of the null hypothesis in column 1, adjusting standard errors for correlated coefficients among observations within the same experimental session and among those generated by the same subject. Here, *, **, and *** denote significance of coefficient at the 90%, 95%, and 99% levels, respectively. Variable definitions can be found in the Appendix.

Panel A. Ordinary Least Squares Regressions of Bidding Behavior and Auction Outcomes

	Average Price Paid by Bidders	Bidder Profits	Elasticity of Bidder Dem. at Signal	Exp. Res. Value Cond. on Signal Less Highest Bid
Independent Variables	1	2	3	4
Symm_UP_Inexp	19.21***	−68.47***	16.13***	−9.31***
Symm_UP_Exp	17.93***	−64.12***	14.05***	−8.10***
Symm_DP_Inexp	18.42***	−63.94***	10.19**	−7.00***
Symm_DP_Exp	17.99***	−64.43***	9.24**	−6.94***
Asym_UP_Inexp	19.49***	−67.58***	14.99***	−8.73***
Asym_UP_Exp	17.83***	−63.01***	14.02***	−7.52***
Asym_DP_Inexp	19.41***	−68.75***	12.91***	−7.69***
Asym_DP_Exp	18.35***	−65.24***	10.07**	−6.91***
Resale Value	0.05***		0.00	0.01
Signal	0.06***	2.95***	−1.39***	0.34***
Auction	−0.07	2.16***	0.42*	0.11
No. of obs.	4,588	4,588	3,195	4,575
Adj. R^2	1.00	0.03	0.85	0.22

Panel B. Tests of Difference of Regression Coefficients in Panel A

	Average Price Paid by Bidders	Bidder Profits	Elasticity of Bidder Dem. at Signal	Exp. Res. Value Cond. on Signal Less Highest Bid
Null Hypothesis (H_o)	1	2	3	4
SymmUPInexp = SymmUPExp	2.26**	−0.40	0.36	−0.77
SymmDPInexp = SymmDPExp	0.77	0.04	0.17	−0.04
AsymUPInexp = AsymUPExp	3.19***	−0.42	0.18	−0.83
AsymDPInexp = AsymDPExp	1.95*	−0.33	0.50	−0.52

In regression 2 of Table 5 (bidder profits) the coefficient estimates indicate that profits rise with experience for all types of auctions; however, none of these differences is statistically significant. These findings are consistent with those reported in Table 4 for the asymmetric information sessions. Table 3, however, indicates a significant increase in profits from experience under symmetric information for both auction types.

The point estimates of the coefficients in regression 3 (elasticity of individual bid schedules, measured at the level of the bidder's signal) and regression 4 (the adjustment for the winner's curse) in Table 5 indicate that subjects tend to lower their bid schedules and make them more elastic as they gain experience. However, as Panel B of Table 5 shows, none of the differences in the level or elasticity of the bid schedules between experienced and inexperienced sessions is statistically significant.

Similar to the results discussed in Section IV.C, regression 1 in Table 5 (average price paid) shows a positive and significant coefficient on resale value, indicating that both auction mechanisms are able to extract the bidder's private information. An untabulated alternate specification in which the auction-type dummy variables are interacted with resale value was used to examine the degree to which the different mechanisms are able to extract the bidder's private information. The results are numerically identical to those reported in Section IV.C, again indicating that the uniform-price and discriminatory auctions are equivalent in their ability to extract bidders' private information and that this ability is enhanced with bidder experience.

E. Subject Characteristics

Panel A of Table 6 presents descriptive statistics for subject characteristics. Here, 24% of subjects were graduate students and 69% were male. As the tests of differences in means and medians show, there is no significance difference in the proportion of graduate to undergraduate students between any of the treatments. With the exception of our inexperienced cohorts with symmetric information, in which a significantly higher percentage of males participated in the uniform-price auctions than in the discriminatory auctions, the same assertion can be made about the proportion of male to female subjects.

We also solicit indications of pre- and post-experiment confidence levels from each subject. Pre-experiment confidence is a subject's assessment, prior to a session, of the probability that his/her performance will be above that of the median of subjects participating in that session. Post-experiment confidence is the subject's assessment of this probability after the session has been completed.

The average level of pre-experiment confidence of inexperienced subjects (initial confidence) is 51%, which is not significantly different from the neutral prediction of 50%. If we restrict the sample to subjects that participate in 2 sessions, the confidence measure prior to their inexperienced session averages 50.2%. We therefore do not find any indication of systematic over or under preconfidence in inexperienced subjects.

Although initial confidence is neutral, there is substantial variation across subjects; the standard deviation equals 0.21. Consistent with many other studies,[21] initial confidence in male subjects (53.1%) is significantly higher than

[21] Croson and Gneezy (2009) is a general survey of experimental studies of gender differences in risk and competitive preferences. They cite numerous studies consistent with this result.

TABLE 6

Bidder Behavior and Subject Characteristics

In Panel A of Table 6, the means, medians, and standard deviations are shown in the first 3 rows, respectively. Number of observations is shown in row 4 in square brackets. In Panel B, the headings in columns 1–5 identify the corresponding regression's dependent variable. Clustered standard errors are estimated in regressions 1–4 to adjust for correlated residuals among observations within the same experimental session and among those generated by the same subject and in regression 5 to adjust for correlated residuals among observations within the same experimental session. In Panel A, *, **, and *** denote that differences in means, medians, and standard deviations between pricing subsample pairs are significantly different at the 90%, 95%, 99% levels, respectively; and in Panel B, *, **, and *** denote significance of coefficient at the 90%, 95%, and 99% levels, respectively. Variable definitions can be found in the Appendix.

Panel A. Descriptive Statistics of Subject Characteristics

			Inexperienced Subjects				Experienced Subjects			
			Symmetric Information		Asymmetric Information		Symmetric Information		Asymmetric Information	
Variables	Statistics	All Sessions	Unif. Price	Disc. Price	Unif. Price	Disc. Price	Unif. Price	Disc. Price	Unif. Price	Disc. Price
Dummy graduate student	Mean	0.24	0.20	0.10	0.29	0.25	0.23	0.14	0.37	0.34
	Median	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Std. dev.	0.43	0.41**	0.30	0.46	0.44	0.43	0.36	0.49	0.48
	N	[370]	[54]	[50]	[66]	[60]	[35]	[35]	[35]	[35]
Dummy male student	Mean	0.69	0.80**	0.62	0.64	0.65	0.80	0.63	0.71	0.69
	Median	1.00	1.00**	1.00	1.00	1.00	1.00	1.00	1.00	1.00
	Std. dev.	0.46	0.41	0.49	0.48	0.48	0.41	0.49	0.46	0.47
	N	[374]	[54]	[50]	[70]	[60]	[35]	[35]	[35]	[35]
Pre-probability	Mean	0.51	0.51	0.50	0.51	0.52	0.55	0.50	0.54	0.49
	Median	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50
	Std. dev.	0.21	0.20	0.23	0.23	0.20	0.18	0.22	0.21	0.21
	N	[353]	[54]	[48]	[59]	[55]	[35]	[35]	[33]	[34]
Post-probability	Mean	0.44	0.40	0.43	0.43	0.40	0.50	0.44	0.57*	0.46
	Median	0.50	0.50	0.50	0.50	0.40	0.50	0.50	0.50	0.50
	Std. dev.	0.26	0.27	0.29	0.25	0.23	0.23	0.29	0.22	0.28
	N	[357]	[51]	[50]	[65]	[57]	[32]	[34]	[34]	[34]

Panel B. Bidder Behavior Regression Controlling for Subject Characteristics

	Average Price Paid by Bidders	Bidder Profits	Elasticity of Bidder Dem. at Signal	Exp. Res. Value Cond. on Signal Less Highest Bid	Post-Experiment Confidence
Independent Variables	1	2	3	4	5
Symm_UP_Inexp	19.840***	−60.812***	18.239***	−10.560***	−3.563***
Symm_UP_Exp	18.562***	−57.767***	16.385***	−9.464***	−3.537***
Symm_DP_Inexp	19.044***	−57.663***	13.661***	−8.434***	−3.515***
Symm_DP_Exp	18.645***	−58.595***	11.415***	−8.288***	−3.557***
Asym_UP_Inexp	20.167***	−62.952***	17.497***	−10.146***	−3.537***
Asym_UP_Exp	18.432***	−56.337***	16.606***	−8.951***	−3.443***
Asym_DP_Inexp	19.838***	−61.431***	14.472***	−8.912***	−3.548***
Asym_DP_Exp	18.925***	−57.417***	12.003***	−8.162***	−3.519***
Signal	0.090***	2.251***	−1.436***	0.397***	
Auction	−0.333**	5.678***	−0.142	0.174	1.237***
Pre-probability	−0.282	4.828	1.909	−0.234	0.566***
Dummy male student	−0.160	−1.605**	−0.370	−0.124	0.012
Dummy graduate student	0.106	−0.073	−1.040	0.409***	0.024
Previous cumulative profits	−0.004***	0.092***	−0.016***	0.005***	
Negative cash balance dummy	−0.038	4.485	−2.717*	0.180	−0.179***
Signal extremity	−0.008*	−0.473***	0.122***	−0.038***	0.005
Dummy male × Prev. cum. profits	0.001**	−0.050**	0.004	−0.002**	
Dummy grad. × Prev. cum. profits	0.001	−0.046***	−0.005	0.000	
Pre-probability × Auction	0.37	−1.70	−0.61	0.26	
No. of obs.	5,971	5,971	4,224	5,950	340
Adj. R^2	1.00	0.12	0.83	0.32	0.810

that in female subjects (45.5%, $p = 0.03$). There are no significant differences in initial confidence by student type (graduate vs. undergraduate), experiment location (experiments were conducted at 2 universities), mechanism (uniform price vs. discriminatory), or information structure (symmetric vs. asymmetric).[22]

F. Subject Characteristics and Bidding Behavior

Panel B of Table 6 presents the results of regressions, similar to those in Table 5, based on data gathered from all subjects. We include subject characteristics (male, graduate student) and experiential explanatory variables to examine the extent to which these variables affect bidding behavior. Previous Cumulative Profits measures, for each auction, the cumulative profit earned by that subject in all prior auctions of the session. Negative Cash Balance Dummy is a variable that takes the value 1 if the subject's cash balance at the end of the previous auction is negative. Signal Extremity measures the extremity of the bidder's signal accumulated over the last 3 auctions. For each bidder in each auction, signal extremity represents the difference between the realized resale value and the received signal. Positive values of this variable indicate that the subject has, on average, observed signals below the realized resale value in recent auctions.[23] Finally, we include pre-experiment confidence as an explanatory variable.

Given the substantial variation in initial confidence, we first examine whether subjects are well calibrated: whether confidence prior to a session predicts performance. Regressions 1–4 in Panel B of Table 6 indicate that this is not the case. The dependent variables are the average price paid, bidder profits, the elasticity of bid schedules, and the expected resale value conditional on the observed signal less the highest bid price. Confidence is an insignificant explanatory variable in regressions 1–4; more confident bidders do not pay a significantly lower price, nor do they earn significantly higher profits. The estimated coefficients indicate that more confident bidders tend to bid more aggressively (less of an adjustment for the winner's curse and more inelastic bid schedules); however, the estimates are not statistically significant.

Examining bidder characteristics, the significantly negative coefficient (-1.065) on Dummy Male in regression 2 of Table 6 indicates that male subjects experience lower profits relative to female. Regressions 1, 3, and 4, however, indicate that the average price paid and the level and elasticity of the bid schedules do not differ by gender. This contradiction may be explained by males' response to previous profits. The significant coefficients in regressions 1, 2, and 4 for the interaction between the Dummy Male and Previous Cumulative Profits suggest that after male subjects realize greater cumulative profits, they bid more aggressively, submitting bid schedules with smaller adjustments for the winner's curse and ultimately paying higher average prices and realizing lower profits. An alternative hypothesis is that male subjects are less risk averse than are female subjects.

[22]Moore and Cain (2007) provide evidence that people believe they are below average in difficult skill-based tasks. The lack of a significant difference in initial confidence by mechanism or information structure is therefore indirect evidence that subjects do not perceive the treatments to differ in difficulty.

[23]Using signal extremity for the last auction or the cumulative signal extremity for all previous auctions provides the same qualitative results.

Bidders that are less risk averse will, all else being equal, submit bid schedules at a higher level than will more risk-averse bidders. The coefficient in regression 4 on Dummy Male is indeed negative but insignificant.

The estimated coefficient on Dummy Graduate Student in regression 4 of Table 6 reports that graduate students tend to make larger adjustments for the winner's curse than do undergraduate students. This could be a reflection of a greater understanding of the auction environment or a reflection of a greater level of risk aversion. As regression 2 shows, the difference in these adjustments does not translate into higher profits. The significant coefficient estimate in regression 2 for the interaction between Dummy Graduate Student and Previous Cumulative Profits suggests that as graduate students accumulate greater profits, they tend to realize lower profits in subsequent auctions relative to undergraduate students. This may indicate that graduate students become overly cautious as they act to protect existing gains.

The experiential variables, Previous Cumulative Profit and Signal Extremity, have significant impacts on subsequent bidding and performance. Panel B of Table 6 indicates that, on average, as bidders achieve higher cumulative profits they bid less aggressively, making greater adjustments for the winner's curse and submitting more elastic bid schedules. These adjustments have a significantly positive impact on subsequent profits.

Signal Extremity measures the extent to which a subject has observed signals that were not equal to the realized resale value in the 3 most recent auctions. Under the informational structure of this experiment, if Bayesian updating on the part of all bidders is common knowledge, subjects would not alter their bidding strategies based on the observed relation between their signal and the realized resale value.

Signal Extremity is, however, a significant explanatory variable for the level and elasticity of subsequent bid schedules, as well as for subsequent realizations of average price paid and bidder profits. Regressions 1–4 in Panel B of Table 6 show, on average, that as subjects observe signals below (above) the realized resale value in recent auctions, they tend to bid more (less) aggressively, raising (lowering) the level of their bid schedules and making them more (less) inelastic. Bidder profits have a significantly negative relation to signal extremity, suggesting that this adaptation is self-defeating. The observed change could be due to subjects' attempts to anticipate the behavior of other bidders in subsequent auctions. However, it seems more likely that the response to past profitability of strategies is a more direct way to identify that type of updating. Alternatively, such an adjustment in strategies would make sense in a real-world context in which bidders are attempting to update their strategies based on signals of unknown precision. The explanation for this behavior may be that subjects do not understand the nature of the uncertainty in the experiment and there is consequently a failure in Bayesian updating following observations of signals and resale values that appear consistently different.

Finally, regression 5 in Panel B of Table 6 examines post-experiment confidence. The results indicate that post-experiment confidence is positively related to pre-experiment confidence, consistent with an updating process. While cumulative profits are not significantly related to post-experiment confidence, the estimated coefficient on the negative cash dummy variable indicates that if a subject ends the experiment with negative profits, there is a significant downward adjustment in confidence.

V. Conclusion

This paper presents the results of an experiment in decision making under uncertainty. In each experimental session subjects participated in a series of auctions for a divisible good in which the common value of the good was uncertain. In some sessions it was common knowledge that all subjects received the same information concerning resale value, while in other sessions subjects received different signals of resale value. We find that the strategies employed by the subjects in our experiments qualitatively match the equilibrium strategies suggested by the theory of divisible good auctions.

The evidence from the experienced sessions provides support for the use of the discriminatory auction, particularly when information is distributed asymmetrically across bidders. With experienced bidders, average revenue is not significantly different across the 2 auction types when information is symmetric but is significantly higher in the discriminatory auction when information is asymmetric. More importantly, in all treatments, the volatility of revenue is lower in discriminatory auctions, and there is no significant difference in allocations or the ability of the auction to extract the bidders' private information across the auction types. These findings are consistent with Brenner et al.'s (2009) result that the use of the uniform-price auction as a mechanism for selling government debt is most prevalent in countries with highly developed financial markets. Our support for the use of the discriminatory auction is contrary to the conclusions of Friedman (1960), McAfee and McMillan (1987), and Milgrom (1989) that the uniform-price auction would result in higher revenue.

Subjects become more adept at bidding in the auctions as they gain experience, both within the inexperienced sessions and between the inexperienced and the experienced sessions. For example, bidder profits are negative on average over the inexperienced sessions. This improves over the inexperienced sessions, as profits are higher in the later auctions of these sessions than they are in the earlier auctions. In turn, average profits are near 0 or marginally positive in the experienced sessions. In accord with empirical hypotheses, experienced bidders submit more elastic bid schedules in discriminatory auctions than in the corresponding uniform-price auctions.

We also explore the impact of bidder characteristics and experiential variables on bidder strategies and auction outcomes. Most interestingly, higher previous profits appear to promote more cautious bidding and higher subsequent profits. Furthermore, subjects in the asymmetric information sessions that observe signals lower than the realized resale value in previous auctions tend to increase the level of their bids relative to their received signals in future auctions. The random nature of signals and values in the experiment makes this adaptation in strategies something of a puzzle.

A topic for future research is to examine the impact of an increase in the number of bidders on these results. The auction literature has identified encouraging bidder participation as a top priority in auction design, and this is an important and interesting issue that seems ideally suited for investigation within the experimental laboratory.

Appendix. Variable Definitions

Glossary of variables used in the statistical tests conducted throughout the study, from Table 2 through Table 6, presented in alphabetical order.

Asym_DP_Exp is a dummy variable that takes a value of 1 when a discriminatory auction is conducted with experienced subjects in an asymmetric information environment, and 0 otherwise. Subjects are deemed to be experienced if they have all participated previously in at least 1 auction under identical treatment settings.

Asym_DP_Inexp is a dummy variable that takes a value of 1 when a discriminatory auction is conducted with inexperienced subjects in an asymmetric information environment, and 0 otherwise.

Asym_UP_Exp is a dummy variable that takes a value of 1 when a uniform-price auction is conducted with experienced subjects in an asymmetric information environment, and 0 otherwise. Subjects are deemed to be experienced if they have all participated previously in at least 1 auction under identical treatment settings.

Asym_UP_Inexp is a dummy variable that takes a value of 1 when a uniform-price auction is conducted with inexperienced subjects in an asymmetric information environment, and 0 otherwise.

Auction is a variable used to control for intersession learning effects and is given by the natural logarithm of the auction number within a session, which ranges from 1 to 20.

Average elasticity of individual subjects' bid schedule per auction is obtained by first calculating the ratio of the percentage change in cumulative demand exhibited by an individual bidder over the percentage change in price, as we move up the price grid from the lowest price at which the bidder submitted a bid to the highest price at which the bidder submitted a bid, and then averaging those ratios over the number of prices in the observed bid-range. In any given auction, this variable is not well defined for bidders who did not submit any bids in that auction.

Average price paid per widget per auction equals seller revenue per auction divided by 26, the number of units auctioned.

Change in Pre-Experiment Confidence measures, for subjects who participated in more than 1 session, the difference between Pre-Experiment Confidence (i.e., Pre-Probability) before the 2nd session and Pre-Experiment Confidence before the 1st session.

DP_Exp is a dummy variable that takes a value of 1 when a discriminatory auction is conducted with experienced subjects, and 0 otherwise. Subjects are deemed to be experienced if they have all participated previously in at least 1 auction under identical treatment settings.

DP_Inexp is a dummy variable that takes a value of 1 when a discriminatory auction is conducted with inexperienced subjects, and 0 otherwise.

Dummy Graduate Student is a variable that takes a value of 1 if the subject participating in a session is a graduate student, and 0 otherwise.

Dummy Male Student is a variable that takes a value of 1 if the subject participating in a session is a male student, and 0 otherwise.

Elasticity of individual bid schedules at the Bidder's Signal per auction is obtained for each bidder in an auction by dividing the percentage change in cumulative demand exhibited by that bidder over the percentage change in price, as we move from the bidder's signal in that auction to the next higher price available in the price grid.

Whenever the signal in an auction is outside a bidder's pricing range, this variable is not well defined for that bidder in that auction. The same occurs if the bidder does not submit any bids that auction.

Expected resale value conditional on a bidder's signal less the highest price bid by that bidder in the auction is just the signal received by a bidder in an auction minus the highest price bid by that bidder in the auction, as defined below. The signal for all auctions conducted under the symmetric information setting is assumed to be L$20, the unconditional expected resale value of the widgets. Whenever a bidder decided not to acquire a signal in an asymmetric information auction, the signal was assumed to be L$20. For those bidders who decided not to participate in an auction or submitted no bids in an auction, the variable is undefined.

Herfindahl index of allocations (per auction) is computed by adding the square of the fraction of the total supply of widgets that each of the bidders obtained in an auction.

Highest price bid by individual bidders in an auction shows the highest price in the grid (from L$10 to L$21) at which each individual bidder submitted a bid in an auction. For those bidders who decided not to participate in an auction or submitted no bids in an auction, the variable is not well defined.

Individual bidder allocation per auction represents the number of widgets each individual bidder was allotted in each auction.

Individual bidder profit per auction is the laboratory dollar value of the difference between an individual bidder's ending balance (without incorporating early show-up fee and the final random adjustment) and the beginning balance of L$250. That is, individual bidder profit per auction captures exclusively the trading profits an individual bidder was able to generate.

Negative Cash Balance Dummy is a dummy variable that takes the value 1 if the subject's cash balance at the end of the previous auction is negative, and 0 otherwise.

Number of bidders with positive allocation per auction shows how many bidders participated in an auction and succeeded in obtaining any amount of widgets (even a fraction of a widget).

Number of prices at which individual bidders submitted bids in an auction shows the number of different prices at which each individual bidder in an auction submitted bids for any positive amount of widgets. Whenever a bidder submitted a bid for multiple widgets at a particular price, that price is only counted once.

Payment Rank measures the performance rank each bidder obtained in a given session. The ranks are measured from 1 to 5, where a rank of 1 is assigned to the top performing bidder in a session and a rank of 5 is assigned to the worst performing bidder in a session.

Performance Payment is the laboratory dollar payment each subject obtained in a session, excluding the early show-up fee, and the initial (L$250) and final random endowments. That is, this variable measures only the trading profits each bidder generated during a session.

Post-Probability (Post-Experiment Confidence) is the subject's assessment once an experimental session has concluded of the probability (%) that his/her performance will be above the median (top 50%) of all those subjects who participated in that experimental session.

Pre-Probability (Pre-Experiment Confidence) is the subject's assessment before an experimental session begins of the probability (%) that his/her performance will be above the median (top 50%) of all those subjects who participate in that experimental session.

Previous Cumulative Profits measures, for each bidder in each auction, the cumulative profit earned by that bidder in all prior auctions of that session.

Prior Experience Dummy is a dummy variable that takes a value of 1 when a session is conducted with experienced subjects, and 0 otherwise.

Resale Value is the common, random liquidation value of all widgets purchased by bidders in an auction. For each auction, this resale value is randomly drawn from a discrete distribution with a support in the interval [L$10, L$30], with increments of L$1. The distribution is symmetric with a mean of L$20 and a standard deviation of L$2.8.

Seller's revenue per auction is the sum of the revenue collected (in L$) by the seller across the 26 widgets auctioned.

Signal represents the informative signal (an integer ranging from L$18 to L$22) concerning the resale value of the widgets that each bidder in an asymmetric environment auction receives before each auction. While in the asymmetric information auctions, each bidder received a (potentially) different, but equally informative signal, in the symmetric information sessions it was common knowledge that all subjects received the same signal (namely, L$20).

Signal Extremity measures, for each bidder and each auction in a session (beginning with auction 4), the extremity of the bidder's signal accumulated over the last 3 auctions. For each auction, the extremity of the bidder's signal represents the difference between the realized resale value of the widgets and the signal received by the subject about the widgets' resale value that auction. Positive values of this variable indicate the extent to which the subject has, on average, observed signals below the realized resale value in the recent sequence of auctions.

Stop-out price per auction is the highest price (in L$) at which the cumulative demand for widgets in an auction equals or exceeds the 26 widgets auctioned.

Symmetric Information Dummy is a dummy variable that takes a value of 1 when an auction is conducted within a symmetric information environment, and 0 otherwise.

Symm_DP_Exp is a dummy variable that takes a value of 1 when a discriminatory auction is conducted with experienced subjects in a symmetric information environment, and 0 otherwise. Subjects are deemed to be experienced if they have all participated previously in at least 1 auction under identical treatment settings.

Symm_DP_Inexp is a dummy variable that takes a value of 1 when a discriminatory auction is conducted with inexperienced subjects in a symmetric information environment, and 0 otherwise.

Symm_UP_Exp is a dummy variable that takes a value of 1 when a uniform-price auction is conducted with experienced subjects in a symmetric information environment, and 0 otherwise. Subjects are deemed to be experienced if they have all participated previously in at least 1 auction under identical treatment settings.

Symm_UP_Inexp is a dummy variable that takes a value of 1 when a uniform-price auction is conducted with inexperienced subjects in a symmetric information environment, and 0 otherwise.

Units bid for by individual bidders in an auction shows the number of widgets each individual bidder requested in an auction. Since each bidder could request anywhere between 0 and 26 widgets, the variable could take any value in between those 2 figures, including 0 and 26.

Uniform-Price Dummy is a dummy variable that takes a value of 1 when an auction is conducted using a uniform-price mechanism, and 0 otherwise.

UP_Exp is a dummy variable that takes a value of 1 when a uniform-price auction is conducted with experienced subjects, and 0 otherwise. Subjects are deemed to be experienced if they have all participated previously in at least 1 auction under identical treatment settings.

UP_Inexp is a dummy variable that takes a value of 1 when a uniform-price auction is conducted with inexperienced subjects, and 0 otherwise.

References

Ausubel, L. M. "An Efficient Ascending-Bid Auction for Multiple Objects." *American Economic Review*, 94 (2004), 1452–1475.

Ausubel, L. M.; P. Cramton; M. Pycia; M. Rostek; and M. Weretka. "Demand Reduction, Inefficiency and Revenues in Multi-Unit Auctions." Working Paper, University of Wisconsin (2011).

Back, K., and J. F. Zender. "Auctions of Divisible Goods: On the Rationale for the Treasury Experiment." *Review of Financial Studies*, 6 (1993), 733–764.

Back, K., and J. F. Zender. "Auctions of Divisible Goods with Endogenous Supply." *Economics Letters,* 73 (2001), 29–34.

Bloomfield, R.; M. O'Hara; and G. Saar. "The 'Make or Take' Decision in an Electronic Market: Evidence on the Evolution of Liquidity." *Journal of Financial Economics*, 75 (2005), 165–199.

Brenner, M.; D. Galai; and O. Sade. "Sovereign Debt Auctions: Uniform or Discriminatory." *Journal of Monetary Economics*, 56 (2009), 267–274.

Camerer, C., and D. Lovallo. "Overconfidence and Excess Entry: An Experimental Approach." *American Economic Review*, 89 (1999), 306–318.

Croson, R., and U. Gneezy. "Gender Differences in Preferences." *Journal of Economic Literature*, 47 (2009), 448–474.

Engelbrecht-Wiggans, R., and C. Kahn. "Multi-Unit Auctions with Uniform Prices." *Economic Theory,* 12 (1998), 227–258.

Engelbrecht-Wiggans, R.; J. A. List; and D. H. Reiley. "Demand Reduction in Multi-Unit Auctions with Varying Numbers of Bidders: Theory and Evidence from a Field Experiment." *International Economic Review,* 47 (2006), 203–231.

Friedman, M. *A Program for Monetary Stability*. New York: Fordham University Press (1960).

Glaser, M., and M. Weber. "Overconfidence and Trading Volume." *Geneva Risk and Insurance Review,* 32 (2007), 1–36.

Goswami, G.; T. Noe; and M. Rebello. "Collusion in Uniform-Price Auctions: Experimental Evidence and Implications for Treasury Auctions." *Review of Financial Studies*, 9 (1996), 757–785.

Hortacsu, A., and D. McAdams. "Mechanism Choice and Strategic Bidding in Divisible Good Auctions: An Empirical Analysis of the Turkish Treasury Auction Market." *Journal of Political Economy,* 118 (2010), 833–865.

Kagel, J. "Auctions: A Survey of Experimental Research." In *The Handbook of Experimental Economics,* J. Kagel and A. Roth, eds. Princeton, NJ: Princeton University Press (1997).

Kagel, J., and R. Levin. "Auctions: A Survey of Experimental Research 1995–2008." In *The Handbook of Experimental Economics,* Vol. II, J. Kagel and A. Roth, eds. Princeton, NJ: Princeton University Press (2008).

Kahn, A.; P. Cramton; R. Porter; and R. Tabors. "Uniform Pricing or Pay-as-Bid Pricing: A Dilemma for California and Beyond." *Electricity Journal*, 14 (2001), 70–79.

Klemperer, P. "Auctions with Almost Common Values: The 'Wallet Game' and Its Applications." *European Economic Review,* 42 (1998), 757–769.

Kremer, I., and K. Nyborg. "Underpricing and Market Power in Uniform-Price Auctions." *Review of Financial Studies,* 17 (2004), 849–877.

Larwood, L. "Swine Flu: A Field Study of Self-Serving Biases." *Journal of Applied Social Psychology*, 8 (1978), 283–289.

Larwood, L., and W. Whittaker. "Managerial Myopia: Self-Serving Biases in Organizational Planning." *Journal of Applied Psychology,* 62 (1977), 194–198.

McAfee, R. P., and J. McMillan. "Auctions and Bidding." *Journal of Economic Literature,* 30 (1987), 699–738.

Milgrom, P. "Auctions and Bidding: A Primer." *Journal of Economic Perspectives*, 3 (1989), 3–22.

Moore, D. A., and D. M. Cain. "Overconfidence and Underconfidence: When and Why People Underestimate (and Overestimate) the Competition." *Organizational Behavior and Human Decision Processes*, 103 (2007), 197–213.

Rostek, M.; M. Weretka; and M. Pycia. "Design of Divisible Good Markets." Working Paper, University of Wisconsin (2010).

Sade, O.; C. Schnitzlein; and J. F. Zender. "Competition and Cooperation in Divisible Good Auctions: An Experimental Examination." *Review of Financial Studies*, 19 (2006a), 195–235.

Sade, O.; C. Schnitzlein; and J. F. Zender. "When Less (Potential Demand) Is More (Revenue): Asymmetric Bidding Capacities in Divisible Good Auctions." *Review of Finance*, 10 (2006b), 389–416.

Simon, D. "The Treasury's Experiment with Single-Price Auctions in the Mid-1970s: Winner's or Taxpayer's Curse?" *Review of Economics and Statistics,* 76 (1994), 754–760.

Sunder, S. "Experimental Asset Markets: A Survey." In *The Handbook of Experimental Economics,* J. Kagel and A. Roth, eds. Princeton, NJ: Princeton University Press (1997).

Svenson, O. "Are We All Less Risky and More Skillful Than Our Fellow Drivers?" *Acta Psychologica*, 47 (1981), 143–148.

Tenorio, R. "Revenue-Equivalence and Bidding Behavior in a Multi-Unit Auction Market: An Empirical Analysis." *Review of Economics and Statistics*, 75 (1993), 302–314.

Umlauf, S. "An Empirical Study of the Mexican Treasury Bill Auction." *Journal of Financial Economics*, 33 (1993), 313–340.

Wang, J. J. D., and J. F. Zender. "Auctioning Divisible Goods." *Economic Theory*, 19 (2002), 673–705.