A Laboratory Comparison of Auctions and Sequential Mechanisms

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When bidders incur a cost to learn their valuations, bidder entry can impact auction performance. Two common selling mechanisms in this environment are an English auction, and a sequential bidding process. Bulow and Klemperer (2009) show, theoretically, that sellers should prefer the auction, because it generates higher expected revenues, while bidders should prefer the sequential mechanism, because it generates higher expected bidder profits. We compare the two mechanisms in a controlled laboratory environment, varying the entry cost, and find that, contrary to the theoretical predictions, average seller revenues tend to be the higher under the sequential mechanism, while average bidder profits are approximately the same. We identify three systematic behavioral deviations from the theoretical model: (1) bidders do not enter the auction 100% of the time, (2) in the sequential mechanism, bidders do not set pre-emptive bids according to the predicted threshold strategy, and (3) subsequent bidders tend to over-enter in response to pre-emptive bids by first bidders. We develop a model of noisy bidder entry costs that is consistent with these behaviors, and show that our model organizes the experimental data well.

Keywords: Auctions, Experimental Economics, Behavioral Mechanism Design.

1. Introduction

In this study we analyze a setting in which an asset or a contract is up for bid, and potential bidders must incur a cost prior to bidding, in order to learn their valuations. This setting is used in a number of contexts. For instance, in procurement activities, suppliers must commit significant resources to estimate the value of a contract up for bid. Similarly, in mergers and acquisitions, one firm must incur the due diligence cost to research the value of the other company. In any of these scenarios, the bid taker can choose from a number of mechanisms to award the asset to a bidder, and this decision is often portrayed as choosing between an auction and a negotiation (see Bulow and Klemperer (1996) and Bulow and Klemperer (2009)). Past empirical work suggests that bidders and sellers differ in terms of how they view auctions. For example, in a recent poll of private equity firms, 80 percent said that, when acting as sellers, they prefer running auctions. However, 90 percent of those same companies said that when they act as bidders, they prefer to avoid auctions (Stephenson, Jones and Di Lapigio 2006). Similarly, Warren Buffet, when describing the Berkshire Hathaway acquisition criteria in his 2008 annual report writes "We don't participate in auctions." (Berkshire Hathaway 2009).

An alternative to an auction is a negotiation, and while it is relatively straightforward to define and model an auction, a clear definition of a negotiation has proven elusive. Bulow and Klemperer (2009) defined a stylized sequential negotiation mechanism that captures two important features of a negotiation: potential bidders interact with the bid-taker one at a time, and different bidders may have different information about what has occurred in the negotiation so far. While the Bulow and Klemperer (2009) sequential mechanism undoubtedly has features that make it different from a real negotiation (most notably, it has a great deal more structure than a real negotiation, making it analytically tractable) the two features it does capture make it useful as a first step towards understanding the differences between auctions and negotiations.

Theoretical research supports the empirical findings that bid takers generally prefer auctions, while bidders prefer to avoid them, because auctions are generally revenue maximizing for bid-takers. In contrast, the sequential mechanism maximizes bidders' profits (see Fishman (1988), Bulow and Klemperer (2009), and references therein). Auctions force all bidders to incur entry costs and compete with each other simultaneously. This improves revenue for bid takers, but creates inefficiencies because some bidders incur entry costs unnecessarily. The sequential mechanism allows early bidders to circumvent the auction and set preemptive jump bids, which can deter future entry by competitors and allow the initial bidder to capture higher profits than they would in an auction. While both of these mechanisms have been studied in the theoretical literature, and were used in roughly 50% of public takeover activities in the 1990s, which represented over $1 trillion in deals (Boone and Mulherin 2007), they have not been compared in a controlled laboratory setting.

In this study we adapt a simple version of the Bulow and Klemperer (2009) model (see also Fishman (1988)) in which a single contract is up for bid, and two potential bidders must incur entry costs prior to learning their valuations. The two mechanisms we compare are an auction, in which the two bidders must make entry decisions simultaneously, and a Bulow and Klemperer (2009) sequential negotiation (we will call it *sequential mechanism* in the rest of the paper), in which the bidders make entry decisions sequentially, and the first bidder has an opportunity to signal her valuation by placing a pre-emptive jump bid. We test the predictions of the model in the controlled laboratory setting under two different cost of entry treatments. In the *Lowcost* treatment, the cost of entry is low so the expected differences in seller revenue and bidder profits are more modest than in the *Highcost* treatment where the relatively high cost of entry makes it easy for a first bidder to deter entry by a second bidder thus substantially lowering seller revenue in the sequential mechanism.

The objective of this study is to examine, using the controlled setting of an economics laboratory, whether bidder behavior is similar to theoretical predictions of the Bulow and Klemperer (2009) model that results in the conclusions that an English auction generates higher seller revenues and the sequential mechanism generates higher bidder profits. There are a number of reasons why this theoretical result may not translate into practice. For instance, past experimental work has shown that when bidders in auctions made bidding decisions without knowing their bidding status, behavior does not conform to standard game theoretic predictions (see Kagel (1995) for a survey of laboratory auction research). So bidders in sealed-bid first price auctions tend to bid more aggressively than they should, while bidders in English auctions quickly learn to follow the weakly dominant strategy. In our study, both bidders entry decisions, as well as the first bidder's pre-emptive bid decision in the sequential mechanism have the"sealed bid" flavor to them because bidders do not know their winning status that would result from their decisions. Similarly, the sequential mechanism model incorporates signaling behavior that assumes bidders are perfect optimizers who can make complex inferences and calculations related to entry decisions and preemptive bidding behavior. Issues of bounded rationality by bidders may affect their behavior and ultimately the normative predictions of revenue and profits for the two mechanisms (see Simon (1984) and Conlisk (1996) for summaries of bounded rationality models). By comparing the performance of the auction and the sequential mechanism in a controlled setting of a laboratory, with well-defined rules that match the Bulow and Klemperer (2009) model, we can test whether this model is a good predictor of actual behavior. Previous experimental work and the relative complexity of the environment studied, suggests that some deviations from theory is to be expected. The main objective of this study is ascertain whether these deviations are sufficient to reverse the normative predictions of the theory that a seller should prefer and auction whereas bidder should prefer a sequential mechanism.

Our main finding is that the preference of the two mechanisms for bidders and sellers is different from the theoretical prediction. We find that with high entry costs the sequential mechanism actually results in slightly higher seller revenues than does the auction, while average bidder profits continue to be similar. Therefore, our laboratory results indicate that it may well be that sellers should actually prefer sequential mechanisms over auctions, while bidders should be indifferent between the two. We find that the differences between our data and theoretical predictions result primarily from three behavioral phenomena. First, in the auction, bidders do not enter 100% of the time, as the standard theory predicts, thus driving its revenue slightly below that of normative benchmarks. Second, in the sequential mechanism, the first bidders set positive preemptive bids different from the standard theory. And, third, the second bidders enter the auctions more often than they should. This third result in particular, second bidder over-entry, drives the revenues in the sequential mechanism to be significantly higher than it should in theory.

We proceed to develop an alternative model of bidder behavior that better organizes our data. We show that if individual bidders derive some (random) benefit or cost from entering auctions,[1] we can generate predictions that are largely consistent with what we observe in the laboratory. We use structural modeling to fit this model to our data to illustrate that it predicts behavior better than the standard theory.

Besides Bulow and Klemperer (2009) and Fishman (1988) of which our experimental environment is specifically designed to match, the work of Roberts and Sweeting (2011) is most closely related to our work. In their paper they develop a model where bidders may have noisy estimates of their valuations prior to entering the auction. They show that this addition may also change the predictions of the standard theory and then estimate the model from USFS timber auctions data. In many ways, our concurrently developed models and experiments are complimentary in that they demonstrate the fragility of the Bulow and Klemperer (2009) results to many small but realistic changes to the model. Bernhardt and Scoones (1993) present a specific application of a sequential mechanism to wage offers. Arnold and Lippman (1995) compare an auction to a sequential process with information asymmetries, discounting, and costly search by sellers. Hirshleifer and Png (1989) also theoretical study a sequential bargaining process with two bidders, however, they assume that bidding itself is costly. In their setting, the sequential mechanism can generate higher revenue compared to an auction. A concept related to the preemptive bidding in the sequential mechanism is the notion of jump bidding in an English auction (a bidder places a bid greater than the minimum required increment) Avery (1998) models how bidders can use jump bidding to signal in ascending auctions in an attempt to keep other bidders out of

[1] The benefit could come from a variety of sources such as the joy of competing, or to overestimating the probability of winning the auction, to name a few possible sources. We do not specifically model the source of the cost or benefit. Rather our intent is to demonstrate that such factors might have a dramatic impact on both individual behavior and aggregate performance of the mechanism.

the auction, and as a result earn higher profits and differentiating the revenue results of an English auction from a sealed bid auction.

In addition to these theory papers, there are two important strands of related experimental literature. There is an experimental literature on jump bidding in ascending auctions documenting that jump bidding is commonly observed in practice. Isaac, Salmon and Zillante (2007) examine 41 spectrum auctions conducted by the FCC and find that sometimes as many as 40% of the bids are jump bids. Easley and Tenorio (2004) use data from 236 internet auctions and find that jump bidding is observed in over a third of their sample. Kwasnica and Katok (2007) observe that jump bidding in ascending auctions emerges as a way to decrease the auction duration in a treatment in which bidders have incentives to complete more auctions. However, Kwasnica and Katok (2007) do not find evidence that jump bidding is used for signaling.

In the next section we describe our experimental design along with standard theoretical predictions for both the auction and sequential mechanism. In Section 3 we present the results of all the treatments in our experiment. Following this, in Section 4 we present an alternative model that builds on the standard theory and show that it better describes our data using structural modeling techniques to estimate parameters. Lastly, in Section 5, we conclude our investigation with a summary and comment on future research.

2. Experimental Design

In all treatments two bidders compete to purchase a single indivisible object. We used two bidders to create the simplest possible environment in which the theory applies, thus giving the theory the best chance to be correct. Each subject in every treatment was randomly assigned the role of either a first or second bidder. In each round a first and second bidder were randomly matched together.[2] In the auction treatments, each round began with both bidders making their entry decisions privately and simultaneously. If both bidders entered the auction, they were then shown their own private values, and proceeded to compete for the item via an ascending clock auction in which the initial price was 0. The bidder who dropped out of the auction first lost the auction, and this drop-out price established the winning bid for the other bidder.

In the sequential mechanism (Seqmech) treatments, each round began with the first

[2] We called the two bidders "bidder A" and "bidder B" in the experiment to avoid any framing effects.

bidder of each pair deciding whether or not to enter the auction, and, if she chose to enter the auction, setting an initial preemptive bid for the auction. After the first bidder made these decisions, the second bidder then made her entry decision after observing the first bidder's preemptive bid. If both bidders entered the auction, then they competed for the item in an ascending clock auction in which the initial price corresponded to the first bidder's pre-emptive bid (please see the online appendix for sample instructions).

The private values for all bidders were integer values, uniformly distributed between 1 and 100, independent and identically distributed, in each round of all treatments. Each subject participated in a single treatment only, and each treatment included 30 rounds. To eliminate the possibility of losses, we provided each subject with an initial endowment of 20 laboratory dollars per round in all four treatments in our study.

In both the auction and sequential mechanism, we ran one set of treatments with an entry cost of 3 ($c = 3$), which we will refer to as Lowcost. In a second set of treatments we set the entry cost to 10 ($c = 10$), which we will refer to as Highcost. We varied the entry costs between treatments to help determine if any potential results were influenced by entry costs rather than the selling mechanism. Table 1 summarizes our design of the experiment and sample sizes. In each treatment, we ran 10 cohorts of 6 subjects, [3] where we will use the cohort as the main unit of statistical analysis in our Results section.

Table 1: Experimental design and number of participating cohorts.

Treatment	Auction	Seqmech	Total
Lowcost	10	10	20
Highcost	10	10	20
Total	20	20	80

Following the completion of each round of each treatment, we provided the following information to the bidders: who entered the auction, the outcome of any auction (the winning bid was 0 if a single bidder entered the auction), who won the object, and the resulting private profits.

In roughly half of the sessions we also administered a separate and independent second stage of the experiment. This second stage was comprised of the Holt and Laury (2002) risk aversion elicitation exercise, where subjects were required to select their preference between

[3] In each of the two Highcost treatments, we had one cohort of 8 and one cohort of 10, but all other cohorts consisted of 6 subjects.

10 lottery pairs. In each pair, the "safe" option, A, resulted in a payoff of either \$2.00 or \$1.60, and the "risky" option, B, resulted in either \$3.85 or \$0.10. In the first pair listed, the chance of the higher payoff of both options (\$2.00 and \$3.85) was 10%. In the second pair the chance of the higher payoff was 20%, in the third pair 30%, and so on (please see the Online Appendix for sample instructions, which includes a screenshot). We performed this separate stage to determine if any of our potential results could be attributed to risk aversion. In terms of our experimental procedure at the start of these sessions, subjects were informed that after they finished the 30 rounds of stage 1, there would be a second additional exercise. At this time, no details were provided for the second stage. Then, after all subjects completed all 30 rounds of the first stage, we distributed the instructions for the second stage, read them out loud, answered questions, and administered the exercise.[4]

We conducted all sessions at a large northeast U.S. university in the spring of 2010. Subjects in all four treatments were students, mostly undergraduates, from a variety of majors. Before each session subjects were allowed a few minutes to read the instructions themselves. Following this, we read the instructions aloud and answered any questions. Each individual was recruited through an online recruitment system where cash was the only incentive offered. Subjects were paid a \$5 show-up fee plus an additional amount that was based on their personal performance for all 30 rounds. Average compensation for the participants, including the show-up fee, was \$22. Each session lasted approximately 45 minutes and we programmed the software using the zTree system (Fischbacher 2007).

2.1 Predictions

Given our experimental parameters we begin by expressing bidder behavior, seller revenue and bidder profits for both the auction and sequential mechanism as predicted by the unique sequential perfect equilibrium identified in the more general model of Bulow and Klemperer (2009).[5]

Under both mechanisms, there are two potential bidders who must decide whether or not to pay a common cost c to learn their private valuations. Values are drawn independently from the continuous uniform distribution on 0 to 1.[6]

[4] We found no differences in the 30 rounds of data between these sessions and those where Stage 2 was omitted.

[5] The interested reader for is refered to Bulow and Klemperer (2009) for a more detailed development of the theoretical predictions in addition to the common equilibrium refinement (on out of equilibrium beliefs) that Bulow and Klemperer (2009) utilize to generate uniqueness of the equilbirium.

[6] In the actual experiment, valuations were drawn uniformly on the integer valuations between 1 and 100.

The timing of decisions under the two selling mechanisms are different. Under the sequential mechanism, the first bidder 'arrives' first and has the opportunity to pay the cost c to learn her value (v_1) and then enter the auction. We will denote the possibly mixed strategy between entry or not by the first bidder with the probability of entry of β_1 and not entry $1-\beta_1$. Contingent upon entry, the first bidder learns her valuation and has the opportunity to place a preemptive bid that might depend upon her valuation and is denoted by $p(v_1)$. The second bidder 'arrives' next and observes whether or not the first bidder entered and the preemptive bid. She then decides whether or not to enter and learn her valuation (v_2). We denote the possibly mixed entry strategy of the second bidder by $\beta_2(p)$, (enter) and $1-\beta_2(p)$ (not enter).[7] After the entry decision of the second bidder, the item is sold in an English auction with the starting price of either 0 (if the first bidder did not enter) or p if the first bidder entered. Assuming both bidders play the weakly dominant strategy of bidding up to their value in the auction, any auction with only one bidder will end at either 0 (in the event the first bidder did not enter but the second bidder did) or p (the first bidder enters but the second bidder does not). An auction with both bidders will proceed to the maximum of the second highest valuation of the two bidders ($\min\{v_1, v_2\}$) and the preemptive bid p.

The auction mechanism is similar except that the preemptive bid opportunity is not available to the first bidder. Therefore, in effect, both bidders simultaneously decide whether or not to enter and, after learning their valuations, compete in an English auction. As before, the English auction will progress to a price of 0 (only one bidder entered) or to the second highest valuation of the two entering bidders.

We first examine the equilibrium in the auction mechanism since it is easily derived from well-known auction results. The payoff table in Figure **??** depicts each player's (ex ante) expected profits from entry in the auction. Clearly, as long as $c < \frac{1}{6}$ it is a dominant strategy for both bidders to enter resulting in expected bidder profits of $\frac{1}{6} - c$, and a seller expected revenue of $\frac{1}{3}$.[8]

When comparing theoretical results with our experimental predictions, we simply divide the experimental results by 100. As is standard in experimental auction studies, we assume that the application of the continuous theory to a discrete implementation is sufficiently precise.

[7] The entry strategy of the second bidder can depend upon the preemptive bid strategy and the entry decision of the first bidder in different equilibria (e.g. $p(v)$ and β_1). For notational clarity, we do not include the observed and equilibrium entry decisions of the first bidder. It is obvious that, contingent upon non-entry by the first bidder, the second bidder will have a dominant strategy to always enter for the parameter values of c in our experiment.

[8] If $\frac{1}{3} \leq c < \frac{1}{2}$ there are multiple equilibria where only one bidder enters and the other does not resulting in a revenue of 0 for the seller. In this case, there is also a mixed strategy equilibrium. Bulow and Klemperer (2009) and we do not consider this case explicitly.

		Bidder 2	
		Enter	Not Enter
Bidder 1	Enter	$\frac{1}{6}-c,\ \frac{1}{6}-c$	$\frac{1}{2}-c,\ 0$
	Not Enter	$0,\ \frac{1}{2}-c$	$0,\ 0$

Figure 1: Payoff table from Auction Entry Stage.

Now consider the equilibrium in the sequential mechanism. The preemptive bidding strategy of the first bidder is the crucial element of the sequential mechanism since it allows for the first bidder to transmit information about her valuation to the second bidder, which might induce the second bidder to not enter. Note that the auction mechanism outcome can always be replicated by the first bidder entering and following a 'pooling' preemptive bidding strategy of always bidding zero (e.g. $p(v_1) = 0$ for all $v_1 \in [0, 1]$). On the other hand, a completely revealing preemptive bid strategy (e.g. $p(v_1)$ is an increasing continuous function of v_1) is not tenable since low valuing first bidders would want to mimic high valuing bidders who can discourage competition from the second bidder; the second bidder would *never* enter if she knew the first bidder's value was greater than $1 - \sqrt{2c}$. Therefore, the equilibrium preemptive bidding strategy is of a 'partially pooling' nature where low valuing bidders bid zero and all others bid a common preemptive bid. Bulow and Klemperer (2009) show that in the unique perfect sequential equilibrium (under a standard refinement on out of equilibrium beliefs) the first bidder selects a preemptive bid of 0 if her value is below the cut-off value v_s (called the *deterring value*), and p^* otherwise. In equilibrium, the preemptive bid p^* is chosen in a way that makes the second bidder indifferent between not entering and paying c to compete against a bidder whose value is above v_s. At the same time p^* is selected such that a first bidder with a value of v_s is indifferent between competing in the auction against the second bidder whose value if uniformly distributed on $[0, 1]$, or winning the auction outright with the bid of p^*.

Formally, the equilibrium preemptive bid has the following form:

$$p(v) = \begin{cases} 0 & v < v_s \\ p^* & v \geq v_s \end{cases} \tag{1}$$

where $p^* \leq v_s$ ensures individual rationality for the first bidder. Given this preemptive bid strategy, the second bidder can calculate her expected auction profits (denoted π_2^a) for each preemptive bid observed in equilibrium:[9]

$$\pi_2^a(p) = \begin{cases} \frac{(v_s)^2}{6} + \frac{1-v_s}{2} & p = 0 \\ \frac{(1-v_s)^2}{6} & p = p^* \end{cases} \tag{2}$$

To make preemptive bidding worthwhile, the second bidder must be induced to not enter whenever p^*. Assuming that the bidder will decide not to enter when she is indifferent between entry and not, we must have $\pi_2^a(p*) - c = 0$, or

$$\frac{(1-v_s)^2}{6} = c. \tag{3}$$

Note that, since $p^* \leq v_s$, the second bidder's expected auction profits only depends upon the cutoff value v_s so solving for v_s yields:

$$v_s = 1 - (6c)^{\frac{1}{2}} \tag{4}$$

When the second bidder enters the auction, The first bidder's (interim) auction profits depends upon the chosen level of the preemptive bid and is given by:

$$\pi_1^a(p, v_1) = \frac{v_1^2 - p^2}{2}. \tag{5}$$

The equilibrium is therefore found by selecting a p^* that ensures that low valuing first bidders (those with values below v_s) prefer a preemptive bid of 0 to p^*. Since Equation (5) is an increasing function of v_1, this is found by finding the p^* such that $\pi_1^a(0, v_s) = v_s - p^*$ where the right hand side is the certain profit from bidding a preemptive bid of p^* and therefore deterring entry by the second bidder . Given the value of v_s from Equation 4, the preemptive bid p^* is given by:

$$p^* = \frac{1}{2} - 3c \tag{6}$$

whenever $c < \frac{1}{6}$. Given the enhanced profitability of this preemptive bidding strategy, the first bidder will always enter ($\beta_1 = 1$).

Expected profits of both the bidders and the sellers can be calculated given the equilibrium and our parameterizations. Table 2 summarizes predicted seller revenue, bidder profits (net endowments), deterring values, preemptive bids, and efficiency for our experimental parameters. We define efficiency as the proportion of time the bidder with the highest valuation wins the item.

[9]More generally, the second bidder's expected auction profits from competition against a bidder whose values lie uniformly in the sub-interval of the original distribution given by $[\underline{v}, \overline{v}]$ is $\pi_2^a = \frac{(\overline{v}-\underline{v})^2}{6} + \frac{(1-\underline{v})(1-\overline{v})}{2}$.

Table 2: Experimental predictions based on actual value draws from the experiment.

Treatment		Auction	Seqmech
Lowcost ($c = 3$)	Seller Revenue	33.05	30.54
	First bidder Profit	14.23	16.15
	Second bidder Profit	13.80	13.45
	Deterring Value, v_s	-	57.57
	Preemptive Bid, p^*	-	41.00
	Efficiency	1.000	0.919
Highcost ($c = 10$)	Seller Revenue	33.56	17.98
	First bidder Profit	6.72	22.29
	Second bidder Profit	7.00	6.80
	Deterring Value, v_s	-	22.54
	Preemptive Bid, p^*	-	20.00
	Efficiency	1.000	0.678

Note that the Bulow and Klemperer (2009) theory predicts that the seller revenue is higher in the auction, and bidder expected profit (particularly the first bidder's profit) is higher under the sequential mechanism. Furthermore, the difference in seller revenue between the two mechanisms should be increasing in c; we intentionally selected the cost parameters such that the expected differences between the two mechanism was quite high in the Highcost treatment whereas the difference was smaller in the Lowcost treatment. Finally, the predicted deterring value and optimal preemptive bid are both decreasing in c.

3. Results

Table 3 summarizes average seller revenue, bidder profits, preemptive bids, and entry rates in the experiment.[10]

We can see from Table 3 that in both cost conditions, the sequential mechanism generates equal or higher revenue for the seller compared to the auction. Using the cohort average as the main statistical unit of analysis (we will follow this approach for all statistical tests in this section), we find that a one-sided t-test comparing the Auction and Seqmech revenue results

[10] We provide cohort level data for revenue in the Appendix.

Table 3: Summary of the data (standard errors in parenthesis).

Treatment		Auction	Seqmech
Lowcost ($c = 3$)	Seller Revenue	31.57 (0.85)	34.25 (1.30)
	First bidder Profit	14.58 (1.09)	11.57 (1.49)
	Second bidder Profit	14.00 (1.27)	12.58 (1.13)
	Preemptive Bid		7.97 (1.37)
	First bidder Entry Proportion	0.959 (0.013)	0.983 (0.009)
	Second bidder Entry Proportion	0.967 (0.015)	0.937 (0.022)
	Efficiency	0.888 (0.018)	0.900 (0.017)
Highcost ($c = 10$)	Seller Revenue	26.61 (0.76)	30.30 (1.39)
	First bidder Profit	8.15 (1.01)	7.36 (1.08)
	Second bidder Profit	9.33 (1.18)	9.24 (1.46)
	Preemptive Bid		10.24 (1.12)
	First bidder Entry Proportion	0.843 (0.032)	0.928 (0.025)
	Second bidder Entry Proportion	0.907 (0.020)	0.862 (0.034)
	Efficiency	0.823 (0.018)	0.841 (0.022)

in $p = 0.0158$ in Highcost, and $p = 0.0507$ in Lowcost.[11] This is counter to the predictions of the Bulow and Klemperer (2009) model, which predicts that the auction should generate higher seller revenues in both cost treatments. We also observe that the sequential mechanism has a slightly higher efficiency than the auction, although the differences are not significant for either cost condition.

Comparing Tables 2 and 3 we can also see that the auction, particularly in the Highcost treatment, generates seller revenue that is slightly below theoretical predictions (two-sided t-test Highcost $p < 0.001$ and Lowcost $p = 0.0578$). In our data we see that bidders in the auction do play the dominant strategy of bidding up to their values, so lower than predicted auction revenues are due to entry behavior.[12] Bidders enter the auction only 96.28% of the time in the Lowcost treatment, and 87.46% of the time in the Highcost treatment.Lower than 100% entry rates account for the auction's revenues being slightly below the predicted values, along with lower efficiencies, and suggest that bidders respond to the magnitude of the entry cost when making their entry decisions. We will explore alternative models for this

[11] A more conservative Mann-Whitney test results in $p = 0.0413$ in Costhigh and $p = 0.1304$ in Costlow).

[12] The second lowest value less the winning bid was, on average, -0.11 across all observations in all four treatments.

entry behavior in later sections.

Turning to the bidders' profits, the first bidders should fare better in the sequential mechanism than in the auction, as it provides them with the opportunity to set a preemptive jump bid, potentially deterring the second bidders from entering the auction. On the other hand, if the first bidders act optimally, second bidders earn the same average profits under the two mechanisms.

In the auction, both first and second bidder profits are largely in line with the predicted values (there is a slight increase in bidder profits in our data due to the entry decisions mentioned previously, however this does not cause any of these differences to be statistically significant). In the sequential mechanism, second bidder profits are also not statistically different from theoretical predictions. But first bidder profits in the sequential mechanism are far below theoretical predictions (two-sided t-test leads to $p < 0.0001$ in Highcost and $p < 0.0134$ in Lowcost). This last finding also results in first bidders' average profits being roughly the same between the auction and the sequential mechanism.

Thus far we have shown that the sequential mechanism results in higher seller revenues than an auction, which is contrary to the Bulow and Klemperer (2009) model. This higher profit for the seller is achieved primarily at the expense of the first bidder. Next, we examine both bidders' decisions in comparison to the equilibrium predictions of the Bulow and Klemperer (2009) to better understand the potential causes of these findings.

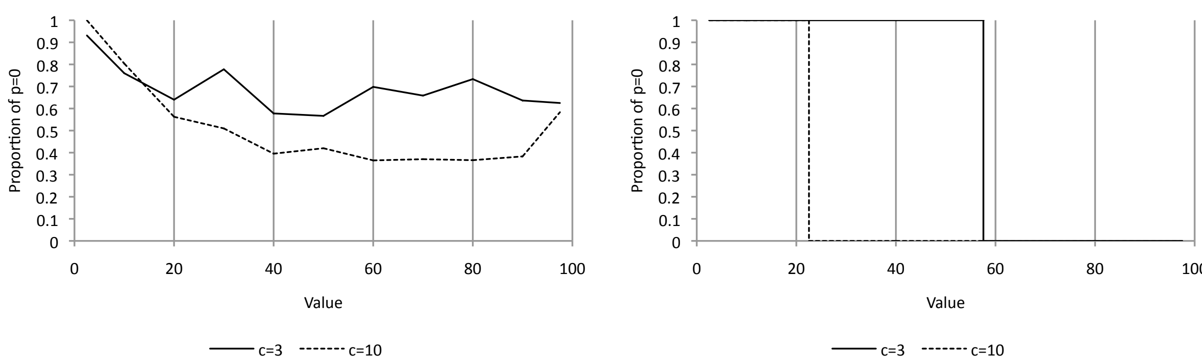

Figure 2: Proportion of preemptive bids equalling zero in our data (left panel) and in theory (right panel).

We begin by examining how first bidders set preemptive bids. In the Bulow and Klemperer (2009) model, first bidders follow a threshold strategy, shown in the right panel of Figure 2: first bidders should set the preemptive bid equal to 0 if their value is below v_s, and when their value is above v_s they should set the preemptive bid equal to p^*. The left panel of Figure 2 shows the proportion of preemptive bids set to zero in our data, as a function of value.[13] It is clear from Figure 2 that bidders do not follow the threshold strategy, but instead, their probability of setting a preemptive bid of zero decreases in value up to some point, and then levels off, never reaching a probability of zero.

Next we examine the magnitude of preemptive bids. The preemptive bids should follow a threshold strategy shown on the right panel of Figure 3, specifically, preemptive bids should be constant when $v \geq v_s$, and positive preemptive bids should be different for the two cost conditions. But in our data, summarized in the left panel of Figure 3, we see that the magnitude of positive preemptive bids increases in v linearly, and moreover, there is no discernible difference in the two cost conditions. We confirmed this formally with a random effect regression: the coefficient on v is positive and significant, the coefficient on $HIGHCOST$ is not significant, and neither is the coefficient on the interaction variable $v \times HIGHCOST$.

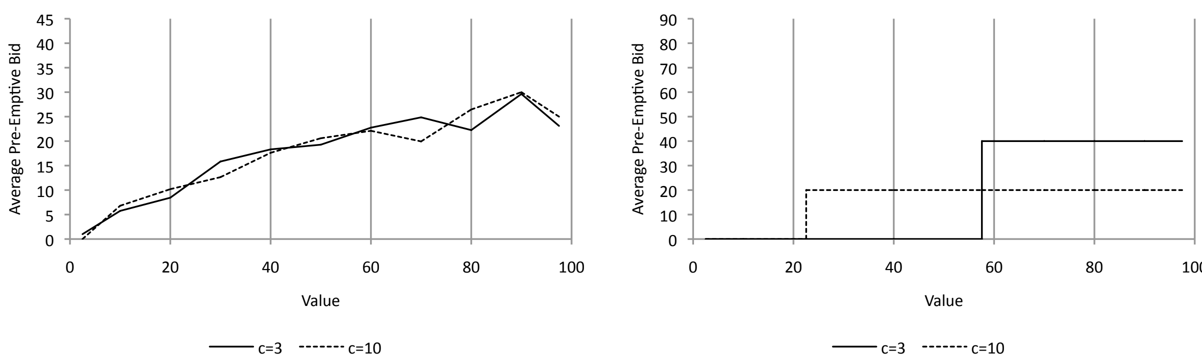

Figure 3: The magnitude of positive preemptive bids in our data (left panel) and in theory (right panel).

To summarize our conclusions about the behavior of first bidders in the sequential mechanism: first bidders enter the auctions less than 100% of the time. When they do enter, they do not follow the threshold strategy in regards to either their decision to place a positive preemptive bid, or to the magnitude of the preemptive bid. For low v's, first bidders' probability of entering a positive preemptive bid increases in value, and for high v's these probabilities reach a constant level, that is significantly below 100%. So first bidders are more likely to place preemptive bids when their v's are low, and are not likely enough to place positive preemptive bids when their v's are high. The size of the preemptive bid itself

[13] For all figures, we removed any observation where bidder 1 entered and set a preemptive bid equal to or above their value, this occurred 19 times out of all 1890 decisions by first bidders.

increases in v and does not depend on the entry cost. Overall, the first bidders' behavior does not resemble the Bulow and Klemperer (2009) model.

Moving on to the second bidder's behavior, as shown in the right panel of Figure 4, according to the theory, second bidders should always enter as long as the preemptive bid is below p^*, and should never enter as long as the preemptive bid is above p^*. The critical difference between how our second bidders enter and how the Bulow and Klemperer (2009) model says they should enter, is that they enter too often following high preemptive bids. Specifically, second bidders in the $c = 10$ condition should never enter when preemptive bids are above 20, and second bidders in the $c = 3$ condition should never enter when preemptive bids are above 41. However, as we can see from the left panel of Figure 4, second bidders enter quite frequently when faced with preemptive bids exceeding 20 and 40.The expected profitability of entry depends upon the beliefs of the second bidder about the first bidder's value given the observed preemptive bid. Since we know first bidders are not placing preemptive bids in accordance with the theory, it may not be irrational that second bidders are entering. Even under the most optimistic beliefs about the first bidder's value given a preemptive bid that $p = v_1 - c$, in the Highcost condition the second bidder would not want to enter after observing a preemptive bid of greater than 45.[14] As is evidenced by Figure 4, the entry rate for preemptive between 45 and 60 is quite high. We can also demonstrate over entry by second bidders empirically. In the Highcost (Lowcost) treatment, second bidders make losses on average whenever they enter following a preemptive bid of XX (YY) yet they continue to enter frequently after observing such preemptive bids (XX% Highcost, YY% Lowcost).[15] Second bidders also sometimes fail to enter for low preemptive bids, but this effect is not very large.[16]

In sum, our data suggest that the sequential mechanism generates the same or higher revenue to sellers when compared to the auction, and roughly the same profits to bidders. These results stem from three systematic behavioral deviations from the theory: (1) in the auction, subjects do not enter quite enough, especially when entry costs are high, (2)

[14]The belief that $p = v_1 - c$ is the most optimistic second bidder belief under the assumption that first bidders don't place preemptive bids that guarantee losses. Under the Lowcost condition the preemptive bid would have to be 72, which is rarely observed.

[15]Even in the second half of the 30 experimental periods, second bidder entry following these preemptive bids is common at XX% (Highcost) and YY% (Lowcost).

[16]It is worth noting that the number of observations across values in Figures 1 and 2 is quite constant. However, in Figure 3, the number of observations is right skewed so that the number of preemptive bids that were above 50, for example, only occurred roughly 1% and 2% in Lowcost and Highcost.

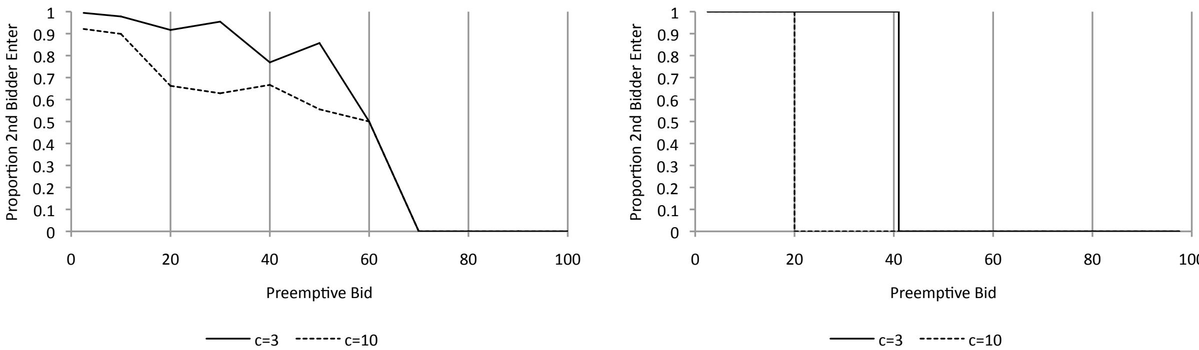

Figure 4: Entry proportion of second bidders in response to the preemptive bid in our data (left panel) and in theory (right panel).

in the sequential mechanisms, first bidders do not follow the threshold strategy in setting preemptive bids, and as a result they end up not setting preemptive bids frequently enough, and when they do set them, the size of the preemptive bid is positively correlated with the first bidder's value; and (3) in the sequential mechanism, second bidders enter even when first bidders set high preemptive bids.

3.1 Risk Aversion Analysis

Risk aversion has often been cited as a likely cause of deviations in observed auction behavior from that of the standard theory where risk neutrality is typically assumed ((Cox, Roberson and Smith 1982)). In this section, we attempt to determine if the observed behavior in our experiments is likely to be driven by risk aversion. We examine the issue both theoretically and experimentally.

As mentioned earlier, bidders failed to always enter under the auction mechanism. It is possible that such behavior may be the result of risk aversion. If players are sufficiently risk averse, there will exist two pure strategy Nash equilibria where 1 bidder enters and the other does not (since the non-entering risk averse bidder prefers the certain payoff of 0 versus the risky but positive expected payoff of participating in the auction versus another bidder). There will also be a mixed strategy equilibrium where both bidders enter with some probability. While this may rationalize behavior in the auction, these levels of risk aversion, however, contradict behavior in the sequential mechanism. If bidders are sufficiently risk averse to induce non-entry in the auction, it also mean that the equilibrium in the sequential mechanism will involve the first bidder entering and the second bidder (knowing that the their choice is between the certain payoff 0 and the risky expected profit associated with competing in a two person auction) not entering. Most importantly, the first bidders entry decision would be sufficient to deter entry by the second bidder and preemptive bidding would not be need. This behavior is obviously not consistent with the observed behavior in our experiment.[17]

As mentioned in the Section 2, in some of our treatments we had subjects complete a second stage of the experiment where we administered the Holt and Laury (2002) risk-aversion elicitation exercise. In this exercise, subjects were required to select their preference between 10 lottery pairs. In each pair, the "safe" option, A, resulted in a payoff of either \$2.00 or \$1.60, and the "risky" option, B, resulted in either \$3.85 or \$0.10. In the first pair listed, the chance of the higher payoff of both options (\$2.00 and \$3.85) was 10%. In the second pair the chance of the higher payoff was 20%, in the third pair 30%, and so on.

For each subject that completed the risk-aversion elicitation exercise, we calculated the number of times they selection option A. We use this as a proxy for risk aversion, where more selections of option A are linked to higher levels of risk aversion. We report logit regressions (with random effects) for the sequential mechanism with second bidder entry as the dependent variable in Table 4.[18]

In Table 4 we observe that the coefficient *SumA* is insignificant in both cost conditions.[19] However, note that the coefficient on *Jump* is negative and significant in both cost conditions. Combining this with our previous entry observations, it appears that subjects were somewhat deterred by higher preemptive bids, but not enough to coincide with the standard theoretical predictions. Therefore, considering that risk aversion is not a key driver in explaining second bidder entry decisions in the sequential mechanism, we now turn to a more formal model that may explain this behavior.

[17]Furthermore, an examination of the required levels of risk aversion under standard risk averse preferences needed to induce a mixed strategy equilibrium in the auction that matches our observed entry frequencies implies much higher levels of risk aversion than is typically observed experimentally. Also, it possible that a model of heterogeneity of risk aversion may generate results that are qualitatively similarly to the model that we develop in the proceeding section, but the parameter estimation provided suggests that at least some bidders would have to be assumed to be risk loving.

[18]For these regressions, we excluded those observations where the first bidder failed to enter.

[19]We ran a variety of different regressions on second bidder entry. In no regression was the coefficient on *SumA* significant.

Table 4: Regressions examining if risk aversion is related to entry by second bidders in the sequential mechanism.

Variable	Description	Lowcost	Highcost
Constant	Intercept	2.169 [1.811]	4.039*** [1.000]
SumA	Total number of "safe" options selected	0.393 [0.283]	-0.040 [0.174]
Period	Decision period	-0.006 [0.017]	0.017 [0.015]
Jump	Preemptive bid	-0.088*** [0.012]	-0.089*** [0.010]

Note: $^{***}p - value < 0.01$, $^{**}p - value < 0.05$, $^{*}p - value < 0.10$.

4. Modeling Bidding Behavior

The objective of this section is to develop a parsimonious and plausible model of bidder behavior that matches, at least qualitatively, the features of bidder behavior identified in Section 3. Primarily, we are asking the following question: Is there a model that deviates from the standard theory of Bulow and Klemperer (2009) in a realistic and minimal way that better organizes the experimental data?

As is typical with such an exercise, we could have varied the model in a number of (potentially complimentary) ways. We considered three possible types of changes to the theory of Bulow and Klemperer (2009). First, Bulow and Klemperer (2009) assume that bidders play a particular perfect sequential signaling equilibrium that is uniquely identified via a standard equilibrium refinement.[20] Without this refinement, there are a continuum of potential perfect sequential equilibria. One possibility in our data might be that player behavior is more closely approximated by some other equilibrium. There is a substantial literature examining whether signaling equilibria develop experimentally and the efficacy of various equilibrium refinements. For example, in the context of limit pricing Cooper, Garvin and Kagel (1997b) find that signaling equilibrium behavior will often develop. On the other

[20]See footnote 11 in Bulow and Klemperer (2009) for a description of the equilibrium refinement utilized.

hand, in the same context, equilibrium selections predicted by seemingly plausible refinement do not always present themselves in the data ((Cooper, Garvin and Kagel 1997a)). In these experiments, the signaling environment is typically must simple than the one studied here due to finiteness of both the type space and strategy spaces of the players. The complexity of the type and strategy spaces in the sequential mechanism and the ensuing continuum of potential other equilibria makes our experiment not amenable to a rigorous examination of whether other equilibria are chosen.

A second approach might be to abandon the perfect sequential equilibrium approach altogether in favor of another equilibrium concept that allows for potential more realistic behavior. Some possibilities might include an adaptive learning type model proposed by Cooper et al. (1997b) or the increasingly popular quantal response equilibrium model of McKelvey and Palfrey (1995) and extended to extensive form games with the AQRE model in McKelvey and Palfrey (1998). While these models have proven remarkably successful in explaining experimental data and, as we discuss below, there is a similarity between our proposed model and a simplified AQRE model, a full model of either adaptive learning or quantal response across all stages of the game has not proven to be readily tractable. In addition, an equilibrium concept that allows for noisy behavior in all stages of the game would, therefore, predict noisy behavior in the auction bidding phase whereas our data indicates that bidding behavior in the auction stage is remarkably consistent with standard theory.

The third approach, which we ultimately selected, is to propose changes to the underlying payoffs or structure of the game but to retain the perfect sequential equilibrium concept (with a similar refinement). This is a common approach taken by many *behavioral* models that seek to explain experimental data. For example, models of equity and reciprocity ((Bolton and OckenfelsO 2000)) have proven successful at explaining behavior in ultimatum, public good, and dictator games among others. Models that allow for regret ((Engelbrecht-Wiggans and Katok 2008)) are also consistent with experimentally observed bidding behavior in first-price auctions. In this context, Roberts and Sweeting (2011) demonstrate that a model that retains the same equilibrium concepts but assumes that players get a noisy signal of their valuation prior to entry is sufficient to substantially change predicted bidder behavior away from the partially pooling equilibrium identified by Bulow and Klemperer (2009) in favor an equilibrium where the preemptive bid function reveals the first bidder's valuation. The theory model we develop here shares a number of similarities with the approach concurrently developed by Roberts and Sweeting (2011).

The fact that we have chosen this third approach is not meant to exclude the other two approaches a potential explanations of our data. In deed, as it shown by Goeree, Holt and Palfrey (2002), it is often the case that many different modeling approaches can arrive at similar conclusions. It is possible also that a hybrid model that includes features such as learning would better organize our experimental data. However, the exercise here is not to identify the exact model of behavior but to look for a simple and tractable model that generates the observed behavior. The fact that so many models might arrive at similar conclusions further highlights the fragility of the Bulow and Klemperer (2009) normative result.

4.1 The Model

We develop a model of noisy bidder entry decisions. In particular, we assume that in addition to paying a cost c to enter and learn their values, each bidder (i) perceives an additional benefit/cost of ϵ_i for entry into the mechanism where ϵ_i is privately known by the bidder at the time of entry. We assume that ϵ_i is drawn independently from the normal distribution $N(\mu, \sigma)$. As is the case of the entry cost c, we assume the additional cost factor ϵ_i to be sunk at the time of entry decision so that it does not directly impact future decisions such as auction bidding strategies (for both bidders) or preemptive bidding strategies (for bidder 1).[21]

There are a number of justifications for the inclusion of such a term. Formally, these errors might be generated as some type of idiosyncratic cost or benefit element. In practice, we feel it is reasonable that in high value auctions, of the type where this model is probably most appropriate, such as mergers and acquisitions and procurement settings, that, in addition to the commonly known cost element, there might be idiosyncratic cost or benefit elements that are not known by the other participants. For example, a firm considering bidding on a procurement contract might decide not to spend the considerable effort required to put together a cost estimate (e.g. decide not to enter) because of internal issues within the firm. In the laboratory setting, this idiosyncratic cost element might come from more

[21]Our model can also be considered to be a restricted AQRE model of McKelvey and Palfrey (1998) where the noisy behavior is restricted to only occur in the entry decisions and not in the other stages of the game and the random unobserved error term is normally distributed. While most implementations of QRE models assume a logistic distribution of the error term, the general theory allows for many error distributions including the normal distribution.

psychic benefits or costs perceived by the experimental subjects. For example, a subject might prefer to avoid the cognitively difficult task of determining a proper bid and therefore decide not to enter the auction. On the other hand, a subject might perceive some benefit from 'getting in the game' and decide to enter despite potentially negative monetary rewards. Previous work by Katok and Kwasnica (2008) and Kwasnica and Katok (2007) has shown that bidder in auctions will often respond to other costs/benefits not directly induced via monetary incentives. Modeling noise as a random cost or benefit element may serve as a useful approximation to capture other behavioral issues, such as regret, social preferences, or errors in calculations of expected profitability. While these models might invite somewhat different function formulations, exploratory attempts to formally model these behavior yielded largely consistent results. The advantage of the approach we chose here is that the the fact that the additional cost term ϵ_i enters into the bidders' calculations in an additively separable manner makes the theory substantially more tractable. The fact that the term is sunk at the time of bidding meant that auction stage behavior would conform to theory as it does in the experiment.

Since the bidders in the sequential mechanism are asymmetric, it may well be reasonable for the noise terms of the two bidders to come from different distributions. One may argue that the first bidder's entry decision is simpler than the second bidder's, because he does not have to think about the pre-emptive bid, so it may well be that the first bidder's term comes from a distribution with μ close to zero, and a small σ. In contrast, the second bidder must interpret the first bidder's pre-emptive bid, and this complexity may well cause the second bidder's σ to be large. Knowing that failure to enter is sure to result in the first bidder earning higher profit may trigger some inequality aversion, and $\mu > 0$ may be a reasonable approximation for modeling it.[22]

We continue to assume values are distributed uniformly on 0 to 1. Since the payoff from non-entry is 0, a bidder will decide to enter only if

$$\pi_i^a - c + \epsilon_i \geq 0$$

where π_i^a is bidder i's expected profits from the auction. This, of course, means that a bidder will only enter if this extra term is sufficient large where $\epsilon_i^* = c - \pi_i^a$ represent the cutoff

[22] Modeling social preferences is beyond the scope of this paper.

between entry and not. The (ex ante) entry probability for a bidder is then given by

$$\begin{aligned}\beta_i &= \Pr(\epsilon_i \geq \epsilon_i^*) \\ &= 1 - \Pr(\epsilon_i \leq \epsilon_i^*) \\ &= 1 - \Phi\left(\frac{\epsilon_i^* - \mu}{\sigma}\right) \qquad (7)\end{aligned}$$

where $\Phi(\cdot)$ is the cdf of the standard normal distribution.

Let us first consider the impact of a noisy cost of entry on the equilibrium entry decisions of both players in the auction. Because both players are now entering with less than probability one, each bidder must consider the fact that they may be the sole entrant into the auction and, therefore, obtain a greater profitability.

Proposition 1 *In a symmetric equilibrium in the auction each bidder will enters if* $\epsilon_i \geq \frac{1}{3}\beta^* + c - \frac{1}{2}$ *resulting in expected entry probability* $\beta^* = \beta_1 = \beta_2$ *that is the solution to the following equation:*

$$1 - \beta^* = \Phi\left(\frac{\frac{1}{3}\beta^* + c - \frac{1}{2} - \mu}{\sigma}\right). \qquad (8)$$

Proof: Given the entry probability of the other bidder β_j, bidder i's expected payoff from the auction is

$$\begin{aligned}\pi_i^a &= \beta_j \frac{1}{6} + (1 - \beta_j)\frac{1}{2} \qquad (9) \\ &= \frac{1}{2} - \beta_j \frac{1}{3} \qquad (10)\end{aligned}$$

where the first term in Equation (9) is the expected profits to a bidder is a two-person auction and the second term is the expected profits in the event of non-entry by the other bidder so that the auction price is zero. Since the payoff from non-entry is zero, bidder i will enter only if

$$\frac{1}{2} - \beta_j \frac{1}{3} - c + \epsilon_i \geq 0$$

or

$$\epsilon_i \geq \beta_j \frac{1}{3} + c - \frac{1}{2}$$

which results in the following entry probability

$$\beta_i = 1 - \Phi\left(\frac{\frac{1}{3}\beta_j + c - \frac{1}{2} - \mu}{\sigma}\right). \qquad (11)$$

Since Equation (11) must hold for both bidder's in equilibrium, we have the equilibrium condition of the proposition. ∎

Next, consider the sequential mechanism. The key strategic variable is now the preemptive bid. We proceed by characterizing the necessary conditions for a revealing equilibrium with noisy entry decisions. In the appendix, we show following a similar approach to Roberts and Sweeting (2011) that the equilibrium identified is indeed the unique perfect sequential equilibrium under the D1 refinement (Banks and Sobel 1987, Cho and Kreps 1987), which is a common restriction placed upon out of equilibrium beliefs in signaling games. Let us suppose there exists a revealing preemptive bid function $p(v_1)$ with $p(v_1) \leq v_1$ for all v_1. Suppose that the bid function is differentiable and increasing everywhere so that $p'(v_1) > 0$. The boundary condition is that $p(0) = 0$. Let $v^{-1}(p)$ be the inverse preemptive bid function. Then, the second bidder's expected profit from the auction having observed a preemptive bid p is given by:

$$\pi_2^a(p) = \frac{(1 - v^{-1}(p))^2}{2},$$

which is simply the expected value of $(v_2 - v_1)$ conditional on $v_2 \geq v_1$. The cutoff value for entry is therefore given by $\epsilon_2^*(p) = c - \pi_2^a(p)$ and the ex ante entry probability of the second bidder, denoted now by $\beta_2(p)$, is given by Equation (7) with this expected term substituted into the equation. The first bidder's expected profit from the auction contingent upon entry by the second bidder is still given by Equation (5). The first bidder's expected profits from a particular preemptive bid level is therefore given by:[23]

$$\begin{aligned} \pi_1(p, v_1) &= \beta_2(p)\pi_1^a(p, v_1) + (1 - \beta_2(p))(v_1 - p) && (12) \\ &= \pi_1^a(p, v_1) + \Phi\left(\frac{[c - \pi_2^a(p)] - \mu}{\sigma}\right)[v_1 - p - \pi_1^a(p, v_1)] && (13) \end{aligned}$$

In order for the preemptive bid strategy to be an equilibrium it must be that the prescribed preemptive bid maximizing expected profits for a first bidder with that valuation or the necessary first order condition is given by:

$$\frac{\partial \pi_1(p, v_1)}{\partial p} = 0 \qquad (14)$$

$$\frac{\partial \pi_1^a(p, v_1)}{\partial p} - \phi(\gamma(p))\frac{\frac{\partial \pi_2^a(p)}{\partial p}}{\sigma}[v_1 - p - \pi_1^a(p, v_1)] - \Phi(\gamma(p))\left(1 + \frac{\partial \pi_1^a(p, v_1)}{\partial p}\right) = 0 \qquad (15)$$

where $\gamma(p) = \frac{\epsilon_2^* - \mu}{\sigma}$.

[23] Note that the c and ϵ_1 terms are dropped from these equations since they are sunk at the time of preemptive bid decision making. This is primarily done for notational simplicity when considering the first bidder entry decision.

Since,

$$\frac{\partial \pi_2^a(p)}{\partial p} = -(1 - v^{-1}(p))\frac{\partial v^{-1}(p)}{\partial p}$$

and

$$\frac{\partial \pi_1^a(p, v_1, e_2)}{\partial p} = -p$$

Equation (15) can be rewritten as follows:

$$-p + \phi\left(\gamma(p)\right) \frac{(1 - v^{-1}(p))\frac{\partial v^{-1}(p)}{\partial p}}{\sigma}\left[v_1 - p - \pi_1^a(p, v_1)\right] - \Phi\left(\gamma(p)\right)(1 - p) = 0.$$

If this is in equilibrium, then it must be that $v^{-1}(p) = v_1$ and utilizing the fact that $\frac{\partial v^{-1}(p)}{\partial p} = \frac{1}{p'(v_1)}$, we have that

$$-p + \phi\left(\gamma(p)\right)\frac{1}{p'(v_1)}\frac{1}{\sigma}\left(1 - v_1\right)\left[v_1 - p - \pi_1^a(p, v_1)\right] - \Phi\left(\gamma(p)\right)(1 - p) = 0.$$

Solving for $p'(v_1)$ we arrive at the following differential equation:

$$p'(v_1) = \frac{\phi\left(\gamma(p(v_1))\right)\frac{1}{\sigma}\left(1 - v_1\right)\left[\left(v_1 - p(v_1)\right)\left(1 - \frac{v_1 + p(v_1)}{2}\right)\right]}{p(v_1) + \Phi\left(\gamma(p(v_1))\left(1 - p(v_1)\right)\right)}. \tag{16}$$

While this differential equation does not readily admit an analytic solution, it can be solved for numerically. Let $p^*(v_1)$ be the solution to the differential Equation (16). Given this solution, we can now move to the earlier stage, where bidder one makes her entry decision. In order to treat both players symmetrically, we assume this decision to be noisy as well. Therefore, the first bidder's expected payoff from entry (e_1) is given by

$$\pi_1(e_1) = \int_{-\infty}^{\infty} \pi_1(p^*(v_1), v_1) f(v_1) dv_1 - c + \epsilon_1$$

where $\pi_1(p, v)$ is given by Equation (13). Using the fact that values continue to be distributed uniformly on 0 and 1, we have that

$$\pi_1(e_1) = \int_0^1 \pi_1(p^*(v_1), v_1) dv_1 - c + \epsilon_1.$$

Since the payoff from non-entry is 0, bidder one will decide to enter only if

$$\int_0^1 \pi_1(p^*(v_1), v_1) dv_1 - c + \epsilon_1 \geq 0.$$

This, of course, means that bidder one will only enter if

$$\epsilon_1 \geq c - \int_0^1 \pi_1(p^*(v_1), v_1) dv_1.$$

The (ex ante) entry probability for bidder one then is given by

$$\begin{aligned}
\beta_1 &= \Pr(\epsilon_1 \geq c - \int_0^1 \pi_1(p^*(v_1), v_1) dv_1) \\
&= 1 - \Pr(\epsilon_1 \leq c - \int_0^1 \pi_1(p^*(v_1), v_1) dv_1) \\
&= 1 - \Phi\left(\frac{[c - \int_0^1 \pi_1(p^*(v_1), v_1) dv_1] - \mu}{\sigma}\right) \qquad (17)
\end{aligned}$$

The entry probabilities of the two bidders β_1 Equation (17) and β_2 Equation (7) given the preemptive bid $p^*(v_1)$ characterize the equilibrium under noisy costly entry and can be utilized to calculate expected revenue and profit results for the seller and both bidders.

Note that this is in contrast to the result of the standard theory of Bulow and Klemperer (2009) where there exists a partially pooling equilibria. The reason that such an equilibrium fails to exist in our setting is that increases in the preemptive bid by the first bidder will always have a measurable impact on the likelihood of entry by the second bidder (by changing the cutoff level ϵ_2^*). This provides sufficient incentive for high valuing first bidders to attempt to differentiate themselves by placing a higher preemptive bid. In contrast, under the standard theory, any increase of bid beyond the one specified in the equilibrium will only have a negative impact for first bidders since the second bidder is already not entering for sure so a higher preemptive bid only increases the price that the first bidder will pay.

The model of noisy bidder cost of entry replicates many of the features observed in the experimental data. In the auction, bidders fail to enter all the time due to high idiosyncratic cost draws in our model. In the sequential mechanism, first bidders place preemptive bids that are positively correlated with their own value and, second bidders, having observed any preemptive bid still enter with a positive (ex ante) probability. Next, we proceed by using maximum likelihood estimation to identify parameters (distributions of ϵ_i) that best fit the observed experimental data.

4.2 Parameter Estimation

In this section we estimate the parameters that define the distribution of ϵ, (μ, σ), that best fit our experimental data. We use maximum likelihood estimation (MLE) for this purpose. We take a progressive approach to the estimation process, first fitting a common set of (μ, σ) across both institutions, the auction and the sequential mechanism, and then allowing (μ, σ)

to vary between the auction and the sequential mechanism, along with first and second bidders.

Let t denote a single decision period, $t = 1, ..., \mathcal{T}$ where $\mathcal{T}$ represents the total number of entry decisions made. If we assume a common (μ, σ) across institutions, then the joint likelihood function is given by:

$$L(\mu, \sigma) = \prod_{t \in \mathcal{T}} \left(\beta_2^{e2_t}(1-\beta_2)^{(1-e2_t)}\right) \; \left(\beta_1^{e1_t}(1-\beta_1)^{(1-e1_t)}\right)$$

$$\text{where } ei_t = \begin{cases} 1 & \text{If bidder } i \text{ enters in decision } t \\ 0 & \text{Otherwise} \end{cases}$$

Table 5 presents the MLE and log-likelihood (LL) results for our noisy entry model when μ and σ are fixed across both institutions, and when they are allowed to vary between the two mechanisms and first and second bidders. We have also provided the Bayesian information criterion (BIC) in this table, a function that penalizes models with extra parameters (as is the case when we allow μ and σ to vary) where a lower BIC value is preferred. BIC allows us to understand whether including additional parameters results in a more efficient fit.

Table 5: MLE and LL results for the noisy entry model.

Treatment	MLEs (μ,σ)	LL	BIC
Both Institutions	(0.39, 0.350)	-2,017	4,052
Auction	(-0.01, 0.08)	-1,026	4,011
Seqmech	(0.50, 0.41)	-961	
Auction	(-0.01, 0.08)	-1,026	3,975
Seqmech - First bidder	(0.02, 0.08)	-334	
Seqmech - Second bidder	(0.60, 0.54)	-600	

As one can see from Table 5, the estimation allowing parameters to vary between bidders is the best fit (based on the smallest BIC value). For this estimation, starting from the bottom, μ and σ are quite large for the second bidder, agreeing with our data that second bidders overenter with considerable noise. The first bidder, however, has a relatively low μ and σ, indicating a smaller benefit of entry along with less variability. This too agrees with our data, where first bidders consistently entered (and standard theory assumes an entry rate of 100%). The MLEs for the auction also seem to coincide with our data, where the fixed benefit of entry is actually slightly negative, $\mu = -0.01$, with $\sigma = 0.08$ accounting for the noise we see, pushing entry rates slightly below 100%. In short the MLEs, overall, agree with our experimental results.

We show the predicted seller revenue levels, based on the MLEs that vary between bidders, for the noisy entry model in Table 6. We see that the predicted revenues are close to the

Table 6: Comparison of institution revenue, between the experimental data and MLE predictions, for the noisy entry model, where the MLEs are allowed to vary across bidders.

	Actual		Predicted	
	Auction	Seqmech	Auction	Seqmech
Lowcost	31.57	34.25	30.72	33.01
Highcost	26.61	30.30	26.03	28.43

actual revenues we observe in our experiment, both in terms of the point predictions, and in terms of the qualitative comparison between the two institutions. Specifically, in line with our data and contrary to the Bulow and Klemperer (2009) theory, the noisy entry model predicts higher revenues under the sequential mechanism than under the auction.

5. Conclusion

Our paper is the first one to compare the performance of an auction and a sequential mechanism in a controlled laboratory setting. We design our experiments to closely match the setting in the Bulow and Klemperer (2009) model. We find that the average seller revenue in the auction is slightly lower than what the theory predicts, and the average sequential mechanism revenue is significantly higher, especially in the treatment with high entry costs.

These experiments demonstrate that individual behavior can vary significantly from the strong predictions of standard game theory. While individual variations from theoretical predictions are certainly not surprising, we demonstrate that those variations are sufficient to reverse the normative prescriptions of the theory.

The behavior we observe in our experiment differs from the model predictions in three ways. First, bidders do not enter the auction 100% of the time, causing auction revenues to be somewhat lower than predicted by the model. Second, in the sequential mechanism, we find that the first bidders do not set preemptive bids according to the threshold strategy. Instead, both the probabilities of setting positive preemptive bids, and the magnitudes of these bids increase with the first bidders' values. Third, second bidders in the sequential mechanism tend to over-enter in response to high preemptive first bidder bids. We find that it is the second bidder's over-entry that accounts for most of the difference between the sequential mechanism revenue we observe, and the revenue predicted by the Bulow and Klemperer (2009) model. We develop a new model that incorporates the noisy entry behavior and use MLE techniques to estimate model parameters for our data. We find that the model organizes our data reasonably well, in that it matches revenues fairly closely. While our model is quite consistent with the data, we recognize that there might be other behavioral factors that we have not accounted for (such as limited rationality regarding the informational content of the preemptive bid) that might also be playing a role in the experiments. Rather, our results are a warning that a mechanism designer might want to consider the robustness of their results to many possible behavioral phenomena. The formal incorporation of non-standard behavior into the design and selection of mechanism is, in our opinion, an exciting and challenging avenue for future research.

A normative implication of our study is that sequential mechanisms may well represent a viable alternative to auctions for a variety of applications. Not only do bidders prefer them, but they are actually better for the bid takers as well. In a setting with costly entry, sequential mechanisms are also more efficient than auctions, because fewer potential bidders end up paying the entry fees unnecessarily. Thus, further theoretical and empirical work is called for to better understand sequential mechanisms.

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A. Uniqueness of Equilibrium

In this section we proceed as do Roberts and Sweeting (2011) and use existing results on sequential equilbria of signaling games to verify that the revealing equilibrium identified in the Section 4.1 is indeed the unique perfect sequential equilibrium under the D1 refinement concerning out of equilibrium beliefs. The approach follows the prior theoretical work of Mailath (1987) and Ramey (1996), which essential establish that single crossing property is satisfied.

Slightly modifying the statement of the first bidders expected profit from Equation 13 to reflect that it is also a function of the chosen cutoff strategy ϵ_2^* of the second bidder, we have the following expression:

$$\pi_1(p, v_1, \epsilon_2^*) = \pi_1^a(p, v_1) + \Phi\left(\frac{\epsilon_2^* - \mu}{\sigma}\right)[v_1 - p - \pi_1^a(p, v_1)]\,. \tag{18}$$

It is sufficient to show that the following three properties hold for all $v_1 \in (0, 1]$:

1. $\frac{\partial \pi_1(p, v_1, \epsilon_2^*)}{\partial \epsilon_2^*} > 0$,
2. $\frac{\frac{\partial \pi_1(p, v_1, \epsilon_2^*)}{\partial p}}{\frac{\partial \pi_1(p, v_1, \epsilon_2^*)}{\partial \epsilon_2^*}}$ is monotonic in v_1, and
3. The cutoff strategy of bidder two ϵ_2^* is uniquely defined for any beliefs about the first bidder's values and, if the second bidder believes the first bidder's value is higher the cutoff move is favorable to the first bidder (e.g. ϵ_2^* increases meaning entry is less likely.

We show that each of these conditions are satisfied in turn.

1. Taking the appropriate partial derivative of Equation 18 we have the following:

$$\frac{\partial \pi_1(p, v_1, \epsilon_2^*)}{\partial \epsilon_2^*} = \phi\left(\frac{\epsilon_2^* - \mu}{\sigma}\right)\left[v_1 - p - \pi_1^a(p, v_1)\right]\frac{1}{\sigma}$$

   which is strictly greater than zero given that $\phi(\cdot)$ is the strictly positive density of the normal, $p < v_1$ for all $v_1 \in (0, 1]$ and $\sigma > 0$.

2. The partial derivative of Equation 18 with respect to p is given by:

$$\frac{\partial \pi_1(p, v_1, \epsilon_2^*)}{\partial p} = -p + \Phi\left(\frac{\epsilon_2^* - \mu}{\sigma}\right)[p - 1].$$

   Combining this with $\frac{\partial \pi_1(p,v_1,\epsilon_2^*)}{\partial \epsilon_2^*}$ from the previous part, we see that the only place were v_1 enters into the this ratio of partial derivatives is now in the $[v_1 - p - \pi_1^a(p, v_1)]$ in the denominator. Since the derivative of this term with respect to v_1 is given by $1 - v_1$ so is clearly monotonic on the relevant range, the ratio of partial derivative must also be monotonic.

3. Since for any beliefs about the first bidder's values the second bidders expected profits from the auction are well-defined and given by $\pi_2^a = E[v_2 - v_1 | v_2 \geq v_1]$. the cutoff term, which is determined by $\epsilon_2^* = c - \pi_2^a$ is uniquely defined. Further, since thinking that bidder one has a higher value will reduce π_2^a thereby increasing ϵ_2^* and making entry less likely, which is favorable to the first bidder all else equal.

B. Cohort Level Results

Table 7: Cohort level results for revenue.

Treatment	Cohort	Auction	Seqmech
Lowcost ($c = 3$)	1	33.63	29.86
	2	32.07	35.72
	3	29.99	36.31
	4	32.19	29.97
	5	34.18	39.98
	6	30.64	36.02
	7	25.27	38.53
	8	34.66	36.02
	9	30.87	27.30
	10	32.18	32.78
	Average	**31.57**	**34.25**
Highcost ($c = 10$)	1	25.65	30.73
	2	27.83	36.84
	3	25.61	34.78
	4	30.20	27.87
	5	26.38	22.99
	6	23.78	32.12
	7	30.70	28.14
	8	24.90	29.51
	9	23.90	25.39
	10	27.17	34.64
	Average	**26.61**	**30.30**