Auctions with endogenous participation and an uncertain number of bidders: experimental evidence [1]

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Abstract

Attracting bidders to an auction is a key factor in determining revenue. We experimentally investigate revenue equivalence predictions between first-price and English clock auctions with endogenous entry. Potential bidders observe their value and then decide whether or not to incur a cost to enter. We also investigate the revenue implications of informing bidders of the number of entrants. Our results suggest that the optimal choice for an auction designer who wishes to maximize revenue is a first-price auction with uninformed bidders.

JEL Classifications: D44, D80.

Keywords: auctions, revenue equivalence, endogenous entry, experiments, bidding.

1 Introduction

In practice, an auction designer needs to attract potential bidders who face an opportunity cost of participating and often an explicit cost of preparing a bid. If entry decisions differ across auction mechanisms, this will affect revenue. Given this, what auction format should an auction designer choose if she wishes to maximize revenue?[1] Upon choosing an auction format, an auction designer also must decide whether or not to reveal the number of entrants. Should she make this information common knowledge before bids are placed?

We experimentally investigate these questions in independent private value environments where potential bidders observe both their private value and a common opportunity cost of participating prior to entry. We vary the auction format between first-price and English clock auctions on a within-subject basis. Additionally, we vary whether or not bidders observe the number of entrants prior to placing their bids on a between subject basis.

We find that, regardless of whether or not bidders are informed of the number of entrants prior to placing their bids, first-price auctions generate more revenue than English clock auctions. However, the effect of informing bidders differs across auction format. In English clock auctions, revenue is increased by informing bidders, and the opposite is true in first-price auctions. As such, our results suggest that an auction designer should opt for a first-price auction with uninformed bidders is she wishes to maximize revenue.

Our findings contribute to the literature on endogenous entry into auctions. This literature can

[1] The revenue equivalence theorem addresses this question for independent private value auctions with an exogenous number of bidders. It states that bidders are indifferent between standard auction formats, and thus that any such format will generate the same expected revenue (see e.g. (Vickrey 1961), (Myerson 1981) or (Heydenreich, Müller, Uetz, and Vohra 2009)). However, this theorem has not fared well in laboratory studies. In particular, a robust finding of the experimental literature is that first-price auctions generate more revenue, on average, than English clock or second-price auctions (see e.g. (Cox, Roberson, and Smith 1982),(Kagel and Levin 1993)). This is a result of persistent overbidding in first-price auctions, which drives revenue above equilibrium predictions.

be categorized based on whether potential bidders observe private information about the value of the good before or after making a costly entry decision. Most of the early theoretical analysis focuses on the case where signals regarding value are revealed only after incurring the cost of entry. In such an environment potential bidders are unable to use such signals to self-select into the auction.[2] Without private information, equilibrium entry is either asymmetric and deterministic ((McAfee and McMillan 1987), (Engelbrecht-Wiggans 1993)) or symmetric and stochastic ((Engelbrecht-Wiggans 1987), (Levin and Smith 1994), (Smith and Levin 1996), (Ye 2004), (Li and Zheng 2009)).

We are interested in the case where potential bidders observe their private signal regarding the value before making entry decisions and entry costs are common knowledge.[3] In such environments, entry depends on the private value signals.[4] The most relevant theoretical analysis is (Menezes and Monteiro 2000).[5] They examine symmetric equilibria in first and second-price auctions, with a homogenous and common knowledge entry cost. Potential bidders are predicted to enter if their private value is (weakly) above a threshold. In equilibrium, this threshold does

[2]Some variations allow for private information on dimensions other than value to be observed prior to entry. (Pevnitskaya 2004) allows for heterogeneous levels of risk aversion, where an individuals degree of risk aversion is private information. (Cox, Dinkin, and Swarthout 2001) study common-value auctions where bidders learn their private opportunity cost prior to making an entry decision; after they make their entry decision, they observe their private signal for the common value and submit bids. In (Moreno and Wooders 2011), participation costs are private information and are independently drawn from a common distribution.

[3]The case in which both bidders valuations and participation costs are both private information has also been studied theoretically. (Green and Laffont 1984) and (Cao and Tian 2009) both investigate this case for second-price auctions.

[4]Much of the attention in this theoretical literature has focused on second-price auctions, as bidders who enter have a weakly dominant strategy to bid their valuation. (Campbell 1998) identifies conditions on the distribution of values which guarantees the existence of asymmetric equilibrium in second-price auctions when the participation cost is the same for all potential bidders. (Tan and Yilankaya 2006), (Miralles 2008) and (Cao and Tian 2008) also examines second-price auctions in this environment but allows for asymmetric bidders. Note that in second-price auctions equilibrium entry decisions will not depend on whether or not the number of bidders is revealed, as subsequent equilibrium bids are independent of the number of bidders. (Cao and Tian 2010) analyzes the case of homogenous and common knowledge participation costs in independent private value first-price auctions, and finds conditions on the distribution of values which guarantee the existence of an asymmetric equilibrium.

[5]Other theoretical papers which analyze similar environments include (Samuelson 1985), (Stegeman 1996) and (Lu 2009).

not vary across auction format. Nor does it depend on whether or not the number of bidders is announced prior to bids being placed. Further, expected revenue is predicted not to depend on information structure or auction format. Our design experimentally tests these results, although we examine English clock in place of the second-price auction.

Despite the important theoretical progress that has been made, there is relatively little empirical or experimental work on entry in auctions. The existing empirical literature largely focuses attention on the case in which bidders only learn their value after they have incurred their participation cost.[6] (Reiley 2005) reports the results of a field experiment in which the reserve price for online sealed-bid auctions for collectible trading cards was varied. Bidders in the auction do not know the actual number of bidders they faced. The data offer support for the prediction that potential bidders enter the auction stochastically. [7] (Roberts and Sweeting 2013)use data from timber auctions to estimate parameters which are then used to show that a sequential entry and bidding process may yield more revenue than a game with simultaneous entry followed by an auction. As yet, this model has not been tested experimentally.

A related experimental approach has been to analyze an environment where first-price and English clock auctions directly compete for a fixed pool of potential bidders. It is important to note that in such an environment the opportunity cost of participating in a particular auction format is the expected payoff of the other format. Thus entry into an auction format is costly, but the cost is

[6](Smith and Levin 2002) experimentally examines the entry decisions of potential bidders in which the subsequent (first-price common-value) auction was simulated. They find support for the symmetric equilibrium in which potential bidders randomize between entering and not entering. (Palfrey and Pevnitskaya 2008) reports the results of an experiment which demonstrates that potential bidders with relatively high degrees of risk aversion do self-select into a first-price auction. Additionally, they find that, contrary to theory, the average payoff of those who enter the auction is less than the opportunity cost of entry.

[7]Interestingly, the data are interpreted assuming that potential bidders observe their private value only after making a costly entry decision, although it seems likely that potential bidders in this naturally occurring environment know their values beforehand.

endogenous based on the beliefs of the auctions' expected payoffs. Beliefs regarding such payoffs depend on beliefs about how many bidders the alternate format will have, as well as believed bidding behavior, which are not observed. In (Ivanova-Stenzel and Salmon 2008a) potential bidders choose between entering an English clock or first-price auction prior to observing their value, and without knowing ex ante how many bidders they would face in either format. They find that entry into the English clock auction is higher, and that the higher number of bidders is sufficient to offset the overbidding in first-price auctions, so that revenue is equivalent.[8] (Ivanova-Stenzel and Salmon 2011) examines a similar environment, except that potential bidders observe their values prior to choosing an auction format. Revenue equivalence is also observed, as well as a self-selection effect in which potential bidders with low values tend to sort into first-price auctions, while those with high values tend choose English clock auctions. In both of these experiments, bidders are informed of the number of bidders prior to placing bids, and it is, by design, impossible for an entrant to be the only bidder in any given auction.

This is the first paper that experimentally examines auctions with costly and endogenous participation where bidders have to choose whether to participate or not in the auction after observing their private values and the common cost of participation. Our approach focuses directly on the question of optimal auction format and information structure for an auction designer who wishes to maximize revenue, taking opportunity costs of participation and endogenous entry into account. By not having auction formats (and information structures) compete head-to-head for bidders, we are able to cleanly access their implications for revenue, holding all else constant. This approach is of practical importance, especially when an auction designer seeks to auction off a good for which

[8]Note that the addition of a bidder to one format is necessarily the loss of a bidder for the other in such an environment. Given that payoffs are typically observed to be higher in English clock auctions when entry is exogenous, it is perhaps not surprising that higher entry into them is observed such that payoffs are approximately equalized between the formats.

there are no close substitutes.

The remainder of the paper is organized as follows. Section 2 provides the theoretical predictions underlying our experimental design. Section 3 describes our experimental protocols and design. Section 4 contains the results, and Section 5 concludes.

2 Theoretical predictions

A set of risk neutral players $N \equiv \{1, ..., n\}$ are potential bidders in an auction for a single unit of an indivisible good. The seller's valuation of the good is 0, and this is common knowledge. Potential bidder i's value is denoted as v_i, and is an independently drawn realization of the random variable V, with continuous and differentiable distribution F, density f and support on $[0, v_H]$. There is an opportunity cost of entering the auction, $c \in (0, v_H)$. This opportunity cost is common to all potential bidders and is common knowledge. Each potential bidder i must decide, after observing both v_i and c, whether or not to enter the auction. We denote as m the number of potential bidders who forgo c and enter, and refer to them as bidders. We call bidders informed if m is made common knowledge prior to bids being placed, and uninformed if it is not. Following (Menezes and Monteiro 2000) we consider symmetric equilibria in which potential bidders use a threshold entry rule. In particular, we consider symmetric equilibria in which a potential bidder only enters the auction if their value is (weakly) greater than some threshold. Symmetric perfect Bayesian Nash equilibrium in such environments was first determined in (Menezes and Monteiro 2000).[9]

Suppose that the entry threshold associated with opportunity cost c is given by v_c. Then each bidder updates her beliefs regarding the values of any other bidders. The value of any other bidder

[9]Relevant derivations for the equilibria can be found in Appendix C and in (Menezes and Monteiro 2000).

is then taken to be an independent draw from

$$F(v \mid v \geq v_c) = \frac{F(v) - F(v_c)}{1 - F(v_c)}, \tag{1}$$

with positive density on $[v_c, v_H] \subset [0, v_H]$.

Note that if bidders are uninformed, then, in addition to updating beliefs regarding values, bidders must form beliefs regarding the number of bidders in the auction based on v_c. Since values are independent draws, and a potential bidder i only enters if $v_i \geq v_c$, the probability that $m < n$ other bidders enter is $\left(\frac{m!}{(n-m-1)!}\right) F(v_c)^{n-m-1} (1 - F(v_c))^m$.

In what follows, we first analyze equilibrium bidding behavior in the auction conditional on the existence of an entry threshold, and then specify this entry threshold based on the bidding behavior.

2.1 First-price auctions with informed bidders

Consider the case of informed bidders in a first-price auction. Denote the entry threshold in this environment as v_ω. Since m is common knowledge and all potential bidders only participate if $v_i \geq v_\omega$, this auction is a standard independent private values auction with values being drawn from $F(v \mid v \geq v_c)$. Equilibrium bidding behavior is well known in such auctions.[10] The symmetric equilibrium bid function is given by

$$\beta(v_i) = \begin{cases} 0 & m = 1 \\ v_i - \left(\frac{\int_{v_\omega}^{v_i} (F(t) - F(v_\omega))^{m-1} dt}{(F(v_i) - F(v_\omega))^{m-1}}\right) & m > 1. \end{cases} \tag{2}$$

[10]See e.g. (Milgrom and Weber 1982).

Notice that if $m = 1$ then the bidder bids zero, and obtains the good being auctioned at a price of zero.

2.2 First-price auctions with uninformed bidders

Now consider a first-price auction in which bidders are uninformed. Denote the entry threshold in this environment as v_α. In this case, bidders are no longer able to condition their bids on m, and form their beliefs regarding the number of bidders they face based on the value of v_α. The symmetric equilibrium bid function is given by

$$\gamma\left(v_i\right) = \frac{\int_{v_\alpha}^{v_i} \left(n-1\right) tF\left(t\right)^{n-2} f\left(t\right) dt}{F\left(v_i\right)^{n-1}}. \tag{3}$$

This equilibrium function closely resembles that of the analogous first-price auction with exogenous entry in which all n potential bidders bid in the auction. In particular, rather than integrating from 0 to v_i as with the exogenous entry case, the lower limit of integration is v_α. This accounts for the fact that any bidder with a value less than v_α will not enter the auction. Note that this implies that bidders are shading their bids more in the case of endogenous entry.

2.3 English clock auctions with informed bidders

In the English clock auction with informed bidders, we denote the entry threshold as v_θ. In this environment bidders abandon the auction once the price reaches their value. That is, the symmetric equilibrium bid function is given by $\rho\left(v_i\right) = v_i$. Note that this bid function does not depend on m. In the event that $m = 1$ the sole bidder employs the same equilibrium bid function. However, the bidder would obtain the good at a price of zero since the auction would end immediately.

2.4 English clock auctions with uninformed bidders

In the English clock auction with uninformed bidders, we denote the entry threshold as v_δ. When bidders are uninformed in an English clock auction, the symmetric equilibrium bid function is also $\rho(v_i) = v_i$. This is because in English clock auctions, regardless of how many bidders there are in the auction, abandoning the auction at a price equal to your value is weakly dominant.[11] As such, whether or not m is common knowledge is irrelevant to equilibrium bidding behavior.

2.5 Revenue equivalence

(Menezes and Monteiro 2000) find that the symmetric equilibrium entry threshold does not depend on whether or not bidders are informed and is invariant between second-price and first-price auctions. Since second-price auctions are strategically equivalent to English clock auctions, it follows that this result holds for English clock auctions as well.[12] This means that in our setup $v_\omega = v_\alpha = v_\theta = v_\delta$. We denote this common equilibrium entry threshold as v_c.

The symmetric equilibrium entry threshold is the value for which the potential bidder is indifferent between participating in the auction and staying out. Since the symmetric equilibrium bid functions are monotonically increasing, a bidder with $v_i = v_c$ will only obtain the good with positive probability if she is the only bidder. In an English clock auction, the price in the auction with only one bidder is zero. In a first-price auction, such a bidder bids zero in equilibrium. Thus, the expected profit of such a bidder is $v_c F(v_c)^{n-1}$. Setting this expected payoff equal to c implicitly defines v_c as

$$v_c F(v_c)^{n-1} = c. \tag{4}$$

[11] Note that in the game being considered here, an equilibrium bid function does not constitute a strategy, since there is more than one information set for each player.

[12] See Appendix C for the relevant derivations.

In a related result, (Menezes and Monteiro 2000) find that ex ante expected revenue also does not vary between second-price and first-price auctions regardless of whether or not the bidders are informed. Once again, the strategic equivalence of second-price auctions and English clock auctions implies that this result also extends to English clock auctions. This expected revenue is given by:

$$R = n\left(n-1\right)\int_{v_c}^{v_H}\left(1-F\left(t\right)\right)tF\left(t\right)^{n-2}f\left(t\right)dt. \tag{5}$$

This revenue equivalence is an important extension of the well-known revenue equivalence result with a fixed and exogenous set of bidders.[13] Importantly, this result suggests that when entry is endogenous, both potential bidders and the auctioneer are indifferent between bidders being informed or not. An interesting question that we leave for future research is allowing only a subset of bidders to be informed.

Revenue equivalence implies payoff equivalence across the four environments we consider. The expected payoff of an informed bidder with value v_i who knows that there are m bidders is given by

$$\pi_i\left(v_i \mid m\right) = \begin{cases} v_i & if\ m = 1 \\ \frac{\int_{v_c}^{v_i}\left(F(y)-F(v_c)\right)^{m-1}dy}{\left(1-F(v_c)\right)^{m-1}} & if\ m > 1. \end{cases} \tag{6}$$

The expected payoff of a bidder with value v_i but who is uninformed is given by,

$$\pi_i\left(v_i\right) = \begin{cases} c & if\ v_i < v_c \\ v_cF\left(v_c\right)^{n-1} + \int_{v_c}^{v_i}F\left(t\right)^{n-1}dt & if\ v_i \geq v_c. \end{cases} \tag{7}$$

Note that $\pi_i\left(v_i\right)$ is also the expected payoffof entering the auction for a potential bidder with value

[13]See e.g. (Myerson 1981) or (Heydenreich, Müller, Uetz, and Vohra 2009).

v_i in any of the four environments considered.

3 Experimental design and protocols

In each experimental session, twelve subjects are randomly and anonymously sorted into groups of three. Each group of three subjects comprises a set of potential bidders in an auction for a single unit of an indivisible good, and the number of potential bidders is common knowledge. Bidder valuations are independent draws from a discrete uniform distribution on $\{0, 1, ..., 100\}$, and are private information. The opportunity cost of participating in the auction, c, is common to all potential bidders, and is common knowledge. It is drawn from a discrete uniform distribution on $\{1, 2, ..., 20\}$. At the beginning of each period, each potential bidder observes their value and c. Potential bidders then simultaneously decide whether or not to forgo c and enter the auction.

If a potential bidder decides not enter the auction, she receives c and must wait until that periods auction concludes (assuming that at least one potential bidder enters). To mitigate boredom as a driver of entry into the auction, subjects who choose not to enter the auction automatically get a chance to play tic-tac-toe against the computer.[14] If a potential bidder enters the auction, then she forgoes the payment of c, and her payoff for the period is determined by the outcome of the auction.

Once the auction is complete each subject observes whether or not she obtained the good, the number of bidders in the auction, the price at which the good was sold, and her earnings. Each subject is shown all the observed bids (ordered from largest to smallest).[15] The same feedback is

[14] In equilibrium tic-tac-toe always results in a draw. As such, we think it unlikely that subjects will opt to not participate in the auction in order to play tic-tac-toe. Subjects who play tic-tac-toe can play repeatedly against the computer until the auction for that period ends. They are told the results of each game, but are informed that these results do not affect their payoffs.

[15] In English clock auctions the strategy of the bidder who obtains the good is not observed, and so was unable to be

Table 1: Summary of experimental design

Information structure	Leading auction format	Number of sessions
Informed	First-price	5
Uninformed	First-price	5
Informed	English clock	4
Uninformed	English clock	5

given to all subjects, regardless of whether or not they entered the auction.[16] At the end of the period, subjects are randomly and anonymously re-matched into different groups. This process is repeated for forty-eight periods.

We use a 2x2 design where we vary the auction format on a within-subject basis and the information structure on a between-subject basis. In nine sessions bidders are informed; in the remaining ten sessions, bidders are uninformed. In addition, we vary the auction format every twelve periods (so that subjects have two twelve period blocks of each auction format) in each session. To control for order effects, we vary which auction format is observed first. In particular, in ten sessions, subjects are potential bidders in a series of twelve first-price auctions, then in a series of twelve English clock auctions, and so on. In the remaining nine sessions subjects are first potential bidders in a series of twelve English clock auctions, then in a series of twelve first-price auctions and so on. This experimental design is summarized in Table 1. In what follows we refer to first-price auctions with informed bidders as the FPI treatment, and first-price auctions with uniformed bidders as the FPU treatment. Analogously, we refer to English clock auctions with informed bidders as the ECI treatment, and English clock auctions with uninformed bidders as the ECU treatment.

Subjects also participate in a risk elicitation task that resembles (Holt and Laury 2002). How-

shown to the subjects.

[16] Homogenizing feedback is intended to reduce the possibility that the outcome of the auction has different effects on the behavior of those who enter and those who do not.

ever, rather than choosing between two lotteries in each of ten choices, as in (Holt and Laury 2002), subjects choose between a certain payoff and a lottery.[17] Since potential bidders had to choose between a certain payoff of c and an uncertain payoff from an auction, this risk elicitation procedure is more closely related to the task we seek to explain than the standard (Holt and Laury 2002) measure. In particular, if subjects are uncertainty adverse, the risk elicitation procedure we employ will control for this, whereas the measure from (Holt and Laury 2002) would not. To control for order effects, we vary the order in which subjects participate in the risk elicitation task.[18] The results of this task are not determined until the end of the session, in order to eliminate wealth effects.

Sessions were run at the Centro Vernon Smith Economía Experimental at the Universidad Francisco Marroquín.[19] Subjects were predominantly undergraduates of Universidad Francisco Marroquín, although some subjects were students at surrounding universities. Subjects were recruited using ORSEE ((Greiner 2004)). The computer interface was programmed in z-Tree ((Fischbacher 2007)).

All subjects were seated at computer terminals for the duration of the experiment. These terminals have dividers to prevent subjects from interacting outside of the computer interface. Once

[17]Subjects are all shown video instructions for this risk elicitation task. For the translated content (from the original Spanish) of this video, as well as the table of choices, see the Appendix B.

[18]In eleven sessions, this was done at the beginning of the session, and in the other eight it was done at the end.

[19]In addition to the nineteen sessions we report, three sessions were run in which the data is unusable. In one, a subject had previously participated; in the other two we encountered software problems. We also ran four sessions in which bidders in the auction were informed of the number of bidders, but this information was not (in our view) sufficiently salient. In particular, many bidders in first-price auctions were submitting positive bids when they were the only bidder, despite being able to obtain the good with a bid of zero (an English clock auction automatically ends at a price of zero if there is only one bidder). We modified the software so that when there was only one bidder in a first-price auction (and bidders were informed of the number of bidders) this bidder was reminded that she could obtain the good with a bid of zero. While this information was presented in the instructions, we were concerned that the possibility of obtaining a good at a price of zero was confusing for some subjects. Even after implementing this change, some subjects who were the only bidders in first-price auctions (and were aware of this) submitted positive bids. The data from these four sessions is not included in the analysis for the sake of brevity. However, the results of this analysis are available upon request.

seated, subjects were shown video instructions (they were also provided with a hard copy of the instructions).[20] This video contains screen shots of the computer interface in order to familiarize subjects with the environment. Once the video was completed, subjects were asked to complete a quiz to ensure comprehension. Any remaining questions were then answered in private.

At the end of the experiment the outcome of the risk elicitation task was determined publicly using a ten sided die. Afterwards, subjects completed a post-experimental survey and were paid in private. Each session lasted for approximately one and a half hours. Subjects were paid a $Q20 \approx US\$2.50$ show-up fee. All other monetary amounts in the experiment were denominated in experimental pesos ($E\$$), which were exchanged for Quetzals at a rate of $E\$7.5 = Q1$. Subjects began the experiment with a starting balance of $E\$75$ to cover potential losses. The average payoff was $Q120$, with a minimum of $Q44$ and a maximum of $Q178$.[21]

4 Results

4.1 Revenue

We first investigate the revenue equivalence predictions. Table 2 contains summary statistics for both observed and predicted revenue in all four treatments. Figure 1 illustrates the same. We find that first-price auctions generate more revenue than English clock auctions. This is true both when bidders are informed (sign test, $w = 9$, $p = 0.002$) and when bidders are uninformed (sign test, $w = 10$, $p = 0.001$).[22]

[20] A copy of the instructions (translated from the original Spanish) for sessions with uninformed bidders can be found in Appendix A.

[21] To contextualize these amounts, lunch can be purchased on Universidad Francisco Marroquín's campus for $Q25$.

[22] Our non-parametric tests use average results from each session as observations.

Table 2: Summary statistics for revenue

Treatment	Observed revenue	Predicted revenue
FPI	41.98	36.19
	(32.55)	(5.96)
FPU	46.65	36.23
	(25.81)	(5.94)
ECI	33.71	36.27
	(30.18)	(5.92)
ECU	30.93	36.23
	(29.18)	(5.94)

Notes: Table contains means with standard deviations in parentheses.

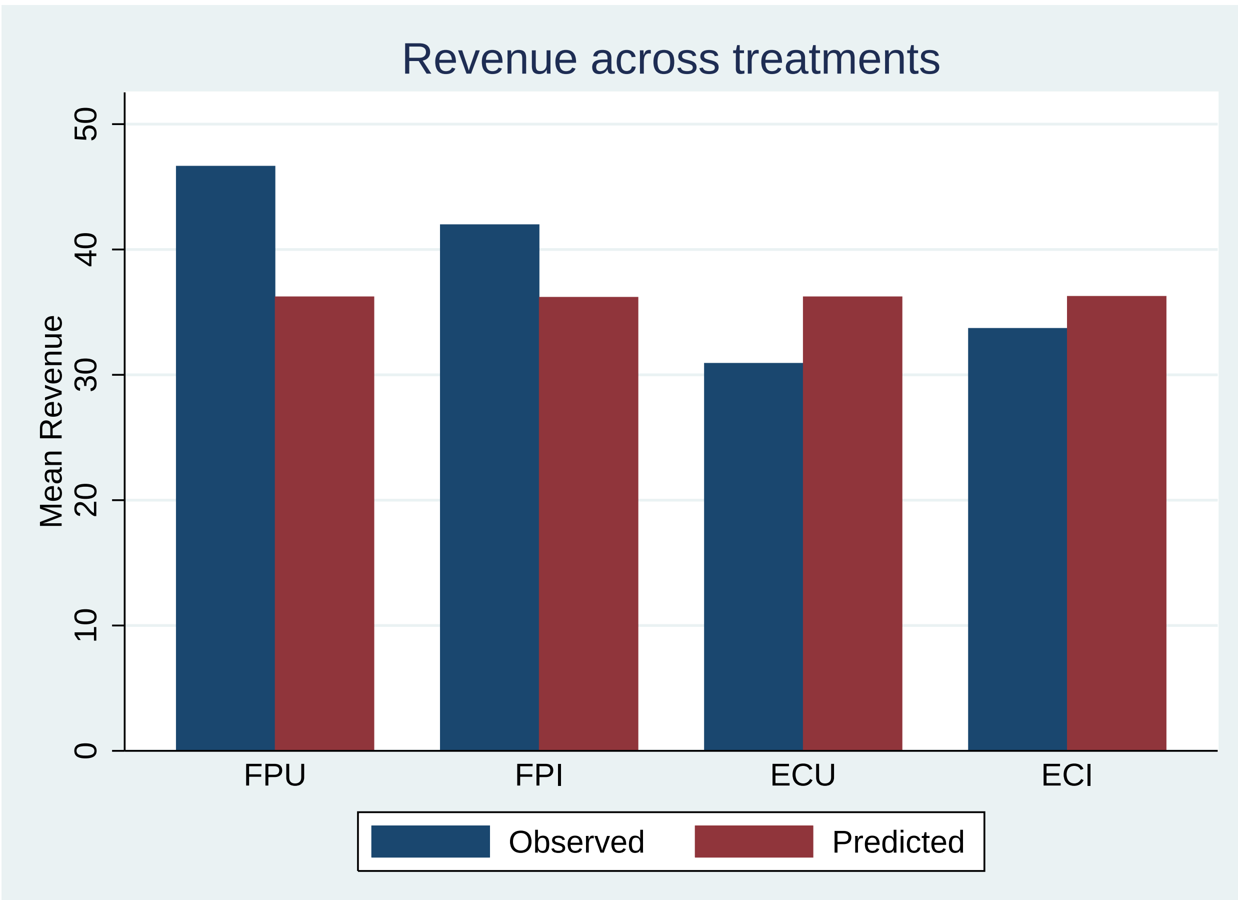

Figure 1: Revenue by information structure and auction format (Intended to be color in both web and print versions)

Interestingly, the role of information differs across auction formats. In first-price auctions, revenue is higher when bidders are uninformed (robust rank order test, $\acute{U} = 3.254$, $p < 0.01$)

while in English clock auctions revenue is higher when bidders are informed (robust rank order test, $\acute{U} = 1.904$, $p < 0.05$).[23]

Higher revenue with uninformed bidders in first-price auctions is also observed in (Dyer, Kagel, and Levin 1989) where bidders face uncertainty regarding the number of bidders in the auction, but do not make entry decisions. However, in their environment, theory predicts higher revenue with uninformed bidders, and in ours, revenue equivalence is predicted. Given that, regardless of information structure, English clock auctions have a weakly dominant strategy of bidding your value, the fact that information structure matters is counterintuitive. In what follows, we will explore whether or not differences in entry explain the observed revenue differences.

Figure 2 provides further insight into our revenue results by illustrating how revenue differs across treatments by the observed number of bidders. The fact that first-price auctions generate more revenue when bidders are uninformed is largely driven by auctions in which there is a single bidder. When bidders are uninformed, they bid, and pay, positive amounts. This is more than enough to counter the fact that in cases in which $m \geq 2$, revenue is slightly higher when bidders are informed on average. Note that theory predicts that revenue will be higher in first-price auctions when bidders are uninformed and $m = 1$. However, theory predicts that revenue will be lower in the uninformed case when $m \geq 2$, such that the ex ante prediction is revenue equivalence. As such, the direction of our revenue result is in line with theory, although the magnitudes are not.

As in first-price auctions, when $m \geq 2$, revenue is lower in English clock auctions when bidders are uninformed. Note that, when $m = 1$, English clock auctions end at a price of zero, so the $m = 1$ case does not offset the reduction in revenue when there are multiple uninformed

[23] Since the asymptotic p-value in the robust rank order test is not a good approximation when there are less than twelve observations in both samples, we rely on critical values calculated by (Feltovich 2003). As such, we are not able to report exact p-values.

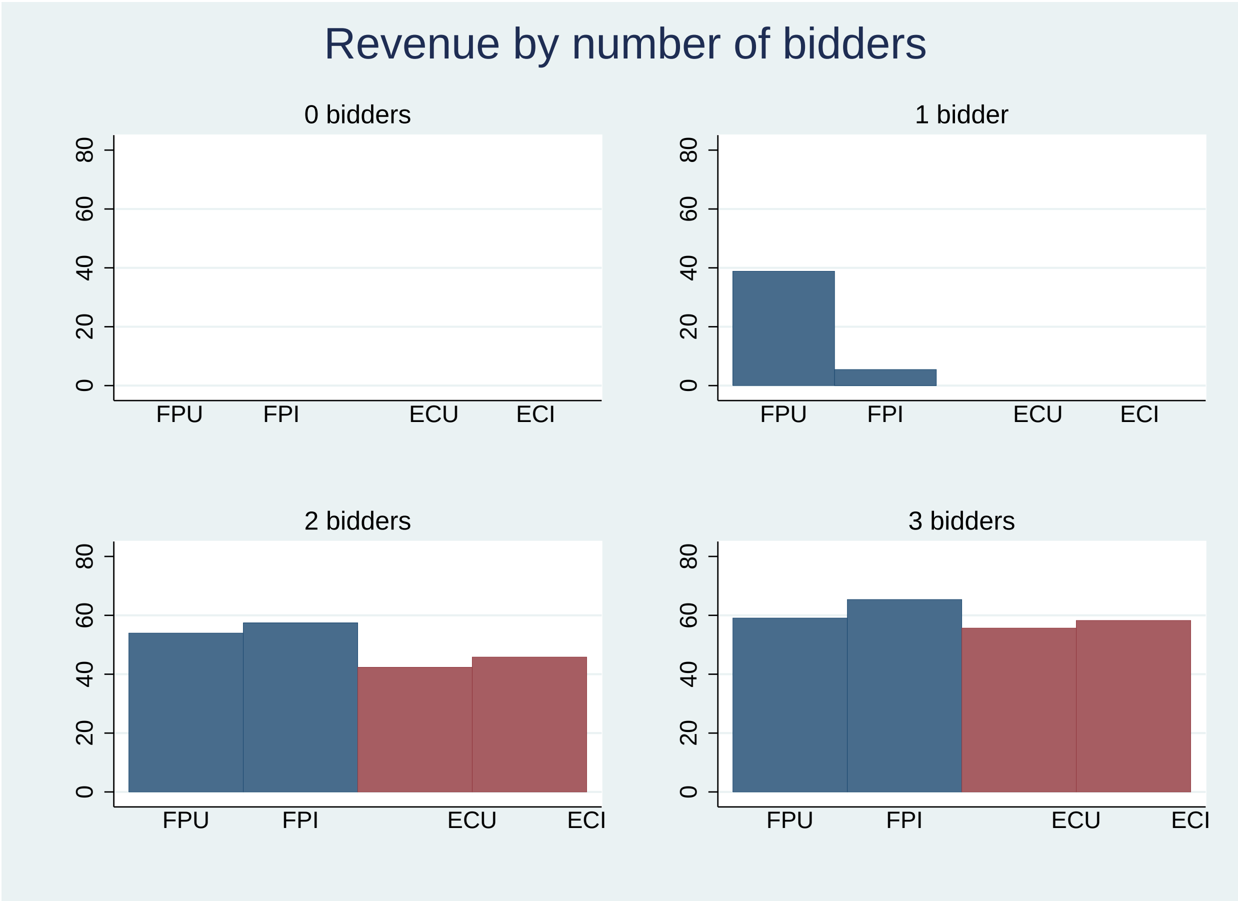

Figure 2: Revenue by number of bidders (Intended to be color in both web and print versions)

bidders.

To further understand the determinants of revenue, we compute OLS estimates of revenue, with standard errors clustered at the session level. The dependent variable is observed revenue in auction j. As the main independent variables we have auction format ($FP_j = 1$ if auction j is a first-price auction, and 0 otherwise, with $EC_j = 1 - FP_j$) and information structure ($Informed_j = 1$ if bidders in auction j are informed and 0 otherwise) interacted with auction format. In addition, we control for both the number of bidders in each auction (m_j), and the opportunity cost of entry (c_j). Table 3 presents estimates of three alternative specifications: the first is as just described. The second specification includes additional experimental controls: experience ($ln(t + 1)$, where t is the

Table 3: OLS estimates of revenue

	All 48 periods		Last 24 periods
	(1)	(2)	(3)
FP_j	15.362***	15.363***	11.044***
	(1.431)	(1.417)	(2.183)
$Informed_j \cdot FP_j$	-2.743**	-2.742**	-2.694*
	(0.834)	(0.802)	(1.076)
$Informed_j \cdot EC_j$	1.073*	1.100*	0.262
	(0.485)	(0.461)	(0.394)
m_j	23.148***	23.109***	23.681***
	(0.76)	(0.749)	(0.772)
c_j	0.218**	0.212**	0.123
	(0.068)	(0.069)	(0.116)
$ln(t+1)$		-0.675	-2.846
		(0.433)	(3.224)
$FirstFormat_j$		-0.556	0.405
		(1.058)	(1.132)
$RiskOrder_j$		1.261	0.527
		(0.929)	(1.008)
$Constant$	-13.896***	-11.644***	-1.927
	(1.662)	(2.957)	(12.871)
Observations	3647	3647	1824
Number of clusters	19	19	19
Adjusted R^2	0.542	0.542	0.593

Standard errors (in parentheses) clustered to allow for intra-session correlation.
$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

period in which auction j occurs), order effects for the two auction formats ($FirstFormat_j = 1$ if the potential bidders saw first-price auctions first, and 0 otherwise), and the order of the risk elicitation task ($RiskOrder_j = 1$ if the risk elicitation task came before the auctions, and 0 otherwise). In the third specification we restrict attention to the last 24 periods of the experiment.

In line with non-parametric tests, note that the coefficient for first-price auctions is positive and highly significant. Further, the magnitude of this coefficient is quite large, although it is lower if only the last 24 periods are used in the estimation. Note that revenue is reduced in first-price auctions when bidders are informed, and that the reverse is true in English clock auctions.

As illustrated in Figure 2 the regression results confirm that m_j is positively related to revenue. Interestingly, the coefficient for c_j is positive and significant. Since a higher c_j should reduce the number of bidders in the auction, intuition suggests that this coefficient would be negative. However, m_j constant, an increase in c_j will mean that those who opt to enter are likely to have a higher value, which tends to increase revenue. Note that if we restrict attention to the second half of the experiment, this coefficient is no longer significant. These results are robust to controlling for experience, and for order effects.

We now compare observed revenue against predictions. In first-price auctions, revenue is greater than predicted. This is true both when bidders are informed (sign test, $w = 9$, $p = 0.002$) and when bidders are uninformed (sign test, $w = 10$, $p = 0.001$). However, the opposite is true for English clock auctions both when bidders are informed (sign test, $w = 7$, $p = 0.0898$) and when bidders are uninformed (sign test, $w = 10$, $p = 0.001$).

Deviations from predicted revenue may be driven by entry behavior, bidding behavior, or both. To determine the extent to which each of these possible explanations drive the observed deviations, we estimate via OLS the deviation in revenue. Our dependent variable is the difference between observed and predicted revenue, where the predicted revenue assumes both Nash entry and bidding behavior and is conditional on the realized values of the potential bidders. Our independent variables are over-entry, defined as the difference between the observed number of bidders (m_j) and the predicted number of bidders (m_j^e), and the deviation in the price at which the good is sold (p_j) from the predicted price conditional on m_j (p_j^e).[24] In addition we add controls for order effects ($FirstFormat_j$ and $RiskOrder_j$) and bidder experience ($ln(t + 1)$). We run separate regressions

[24]Notice that $p_j - p_j^e$ is not the same as the revenue deviation, since p_j^e is the predicted price conditional on actual entry, rather than the ex ante predicted price.

Table 4: OLS estimates of revenue deviations from Nash predictions in first-price auctions

	FPI		FPU	
	All 48 periods	Last 24 periods	All 48 periods	Last 24 periods
	(1)	(2)	(3)	(4)
$m_j - m_j^e$	13.982***	14.193***	3.827***	4.848**
	(0.504)	(0.848)	(0.506)	(1.051)
$p_j - p_j^e$	0.549***	0.316	1.009***	0.985***
	(0.081)	(0.155)	(0.025)	(0.029)
$ln(t+1)$	-2.016**	11.396	0.535	4.025*
	(0.596)	(8.066)	(0.557)	(1.464)
$FirstFormat_j$	1.080	-3.266	-0.736	-3.480**
	(1.239)	(2.921)	(0.683)	(0.967)
$RiskOrder_j$	0.939	0.579	-1.544	-2.140**
	(1.001)	(1.460)	(0.728)	(0.604)
$Constant$	4.897*	-36.423	-4.013	-12.261*
	(2.011)	(25.426)	(2.275)	(3.966)
Observations	864	432	960	480
Clusters	9	9	10	10
Adjusted R^2	0.318	0.272	0.749	0.763

Standard errors (in parentheses) clustered to allow for intra-session correlation.
$^{*}p < 0.05, ^{**} p < 0.01, ^{***} p < 0.001$

for each treatment, and include specifications for all auctions and auctions in the last half of the experiment (the last 24 periods).

Table 4 reports the results for first-price auctions. The coefficients for both excess entry and price deviations conditional on observed entry are positive and highly significant, for both FPI and FPU auctions. However, the magnitude for price deviations is very small. Rather, revenue deviations seem to depend on the number of excess bidders. This suggests that excess entry is the primary driver of the higher than predicted revenue in first-price auctions. Further, the magnitude of the coefficient for excess entry is much higher in FPI auctions than for FPU auctions. This is largely because in FPI auctions, m_j is observed by bidders. If there is over-entry, Nash bid predictions (for those bidders who were predicted to enter) involves less bid shading than if entry corresponded to predictions. That is, if there is an excess bidder in a FPI auction, then the corresponding price prediction (equilibrium bid of the bidder with the highest valuation) increases. This in turn, decreases the magnitude of the price deviation for a given observed price. The same is not true for FPU auctions, as m_j is not observed, and so the equilibrium bid of a bidder is independent of the number of actual (excess) bidders. Note that if the set of actual entrants is not equal to the predicted entrants in an FPU auction, then the price prediction may change. In particular, in some cases the potential bidder with the highest valuation does not enter. In others, bidders enter, when none were predicted to enter.

Table 5 presents the estimates of revenue deviations for English clock auctions. In contrast to the results for first-price auctions, for both ECI and ECU auctions the coefficient for excess entry is not significant. The coefficients for price deviations, conditional on observed entry, are significant and positive. Since submitting a bid equal to value is a weakly dominant bidding strategy regardless of the number of bidders, this result is surprising. Since observed revenue in both ECI and EU auctions is, on average, less than predicted revenue, this result can be interpreted as the last bidder who abandons the auction doing so at a price slightly below her value, on average.

Our data clearly rejects the hypotheses of revenue equivalence across auction formats and information structures. In particular, FPU generates the most revenue followed by FPI, ECI and then ECU. These results seem to be driven primarily by entry decisions in first-price auctions, and bidding behavior in English clock auctions.

Our results differ significantly from those of (Ivanova-Stenzel and Salmon 2008a) and (Ivanova-Stenzel and Salmon 2011).[25] They observe higher entry into English clock auctions such that rev-

[25] In (Ivanova-Stenzel and Salmon 2008a) potential bidders observe their value after making their entry decision and in (Ivanova-Stenzel and Salmon 2011) potential bidders observe their value prior to their entry decision. They find that revenue equivalence is robust to this change.

Table 5: OLS estimates of revenue deviations from Nash predictions in English clock auctions

	ECI		ECU	
	All 48 periods	Last 24 periods	All 48 periods	Last 24 periods
	(1)	(2)	(3)	(4)
$m_j - m_j^e$	0.271	0.245	1.481	1.349
	(0.999)	(0.813)	(1.361)	(1.314)
$p_j - p_j^e$	0.568***	0.520***	0.490***	0.509***
	(0.023)	(0.041)	(0.028)	(0.034)
$ln(t+1)$	-1.941	-13.087**	-0.204	-19.830**
	(0.977)	(3.205)	(0.941)	(6.093)
$FirstFormat_j$	-1.335	-7.489***	-2.081	-11.167***
	(0.683)	(1.303)	(1.534)	(2.248)
$RiskOrder_j$	-0.055	-0.956	0.986	-0.218
	(0.460)	(0.700)	(1.116)	(1.537)
$Constant$	24.715***	74.196***	15.096**	101.816**
	(3.564)	(13.264)	(4.356)	(25.633)
Observations	863	432	960	480
Clusters	9	9	10	10
Adjusted R^2	0.295	0.251	0.250	0.261
Bayesian Information Criteria	7986.156	4021.579	8871.447	4472.388

Standard errors (in parentheses) clustered to allow for intra-session correlation.
$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

enue equivalence is observed. As such, it is important to understand how differences between their designs and ours drive these results.

First, in their designs, a fixed pool of potential bidders must choose between an English clock and a first-price auction. Note that in such an environment higher entry into English clock auctions will, on average, increase revenue, while simultaneously decreasing revenue in first-price auctions. In our design, higher entry in a given auction format would likely increase its revenue, but would not affect the revenue of the other format.

Second, in both (Ivanova-Stenzel and Salmon 2008a) and (Ivanova-Stenzel and Salmon 2011), a potential bidder knows that there will always be at least two bidders in either auction format and bidders are always informed. We find that informing bidders decreases revenue in first-price auctions and increases revenue in English clock auctions. As such, considering only the informed case is more likely to result in revenue equivalence.

Third, in our design, c is exogenous and common knowledge. In both (Ivanova-Stenzel and Salmon 2008a) and (Ivanova-Stenzel and Salmon 2011) the opportunity cost of participating in a given format is the expected payoff of the alternative format, which is endogenously determined. (Ivanova-Stenzel and Salmon 2004) find that potential bidders are not willing to pay a higher entry fee for English clock auctions that would equalize expected payoffs between the two formats (in an environment in which there would be two bidders in either format, and value is observed after entry).[26] Given that in our design potential bidders enter the auction when their willingness to pay (given their value) is weakly greater than c, the low willingness to pay for English clock auctions observed in (Ivanova-Stenzel and Salmon 2004) could contribute to the lack revenue equivalence in our data.

It is also important to note that (Engelbrecht-Wiggans and Katok 2005), in an experiment very similar to (Ivanova-Stenzel and Salmon 2011), find that higher entry into English clock entry is not sufficient to offset higher bidding in first-price auctions, such that revenue is higher in first-price auctions.

4.2 Payoffs

Predictions and results for payoffs closely mirror those of revenue. We first consider payoffs for the entire game (as opposed to only those of bidders). When the auction format is English clock,

[26](Ivanova-Stenzel and Salmon 2008b) find that loss-aversion and impatience to end an English clock auction cannot explain this low willingness to pay for English clock auctions.

payoffs are higher. This is true both when bidders are informed (sign test, $w = 8$, $p = 0.0195$) and when bidders are uninformed (sign test, $w = 10$, $p = 0.001$). As with revenue, the effect of information structure on payoffs differs by auction format. When bidders are informed, payoffs are higher in first-price auctions (robust rank order test, $\acute{U} = 5.367$, $p < 0.001$) and lower in English clock auctions (robust rank order test, $\acute{U} = 1.474$, $p < 0.10$).

Relative to theory, payoffs are lower than predicted in first-price auctions, both when bidders are informed (sign test, $w = 9$, $p = 0.002$) and when they are uninformed (sign test, $w = 10$, $p = 0.0010$). However, in English clock auctions we are unable to reject that payoffs are equal to their predictions both when bidders are informed (sign test, $w = 5$, n.s.) and when they are uninformed (sign test, $w = 5$, n.s.).[27]

We now restrict attention to bidders. Table 6 contains summary statistics of bidder payoffs and predicted bidder payoffs, both total, and net of c. Figure 3 illustrates observed and predicted payoffs of bidders, net of c. Note that predictions vary across treatment, since these are predicted payoffs conditional on observed entry. We find that payoffs are higher in English clock auctions, both when bidders are informed (sign test, $w = 9$, $p = 0.002$) and uninformed (sign test, $w = 10$, $p = 0.001$). In first-price auctions, bidders are better off when they are informed (robust rank order test, $\acute{U} = 6.706$, $p < 0.001$). In English clock auctions, we cannot reject that bidder payoffs are equal (robust rank order test, $\acute{U} = 1.297$, n.s.).

Bidder payoffs are higher than predicted in English clock auctions in both the informed (sign test, $w = 8$, $p = 0.0391$) and uninformed case (sign test, $w = 8$, $p = 0.0547$). When bidders are informed in first-price auctions payoffs are lower than predicted (sign test, $w = 10$, $p = 0.001$). However, we cannot reject that payoffs are equal to predictions in FPI auctions (sign test, $w = 4$,

[27]n.s. indicates that the test is not significant at conventional levels.

Table 6: Summary statistics for payoffs

Treatment	Observed payoffs of bidders	Predicted payoffs of bidders	Observed payoffs of bidders less c	Predicted payoffs of bidders less c
FPI	11.91	12.02	2.43	4.84
	(22.94)	(22.41)	(21.90)	(8.46)
FPU	9.57	17.18	-0.08	4.89
	(15.41)	(11.04)	(15.25)	(8.40)
ECI	17.23	13.35	7.49	4.86
	(27.26)	(22.93)	(26.56)	(8.36)
ECU	18.46	17.15	8.78	4.80
	(27.77)	(10.96)	(27.03)	(8.35)

Notes: Table contains means with standard deviations in parentheses.

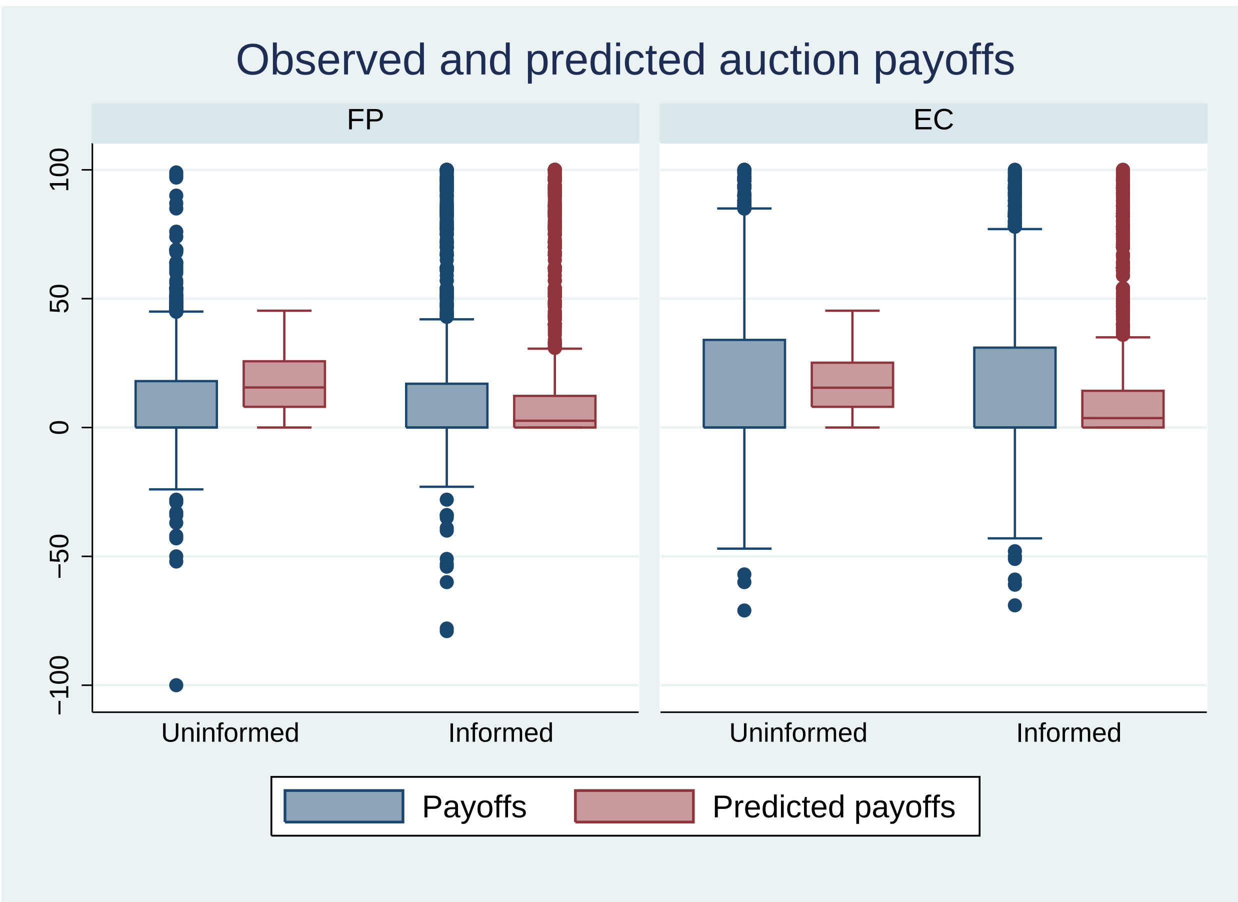

Figure 3: Payoffs by information structure and auction format (Intended to be color in both web and print versions)

n.s.).

Theory predicts that the expected payoff of a potential bidder with $v_i = v_c$ is c. If $v_i > v_c$, then the expected payoff of entering the auction is greater than c. As such, determining whether bidder payoffs exceed c is of interest. It particular, do bidders, on average, earn payoffs that merit entry? We find that in FPU auctions, this is not the case (sign test, $w = 5$, n.s.). However, in FPI auctions, bidder payoffs are significantly higher than c (sign test, $w = 9$, $p = 0.002$). This is also true in ECU (sign test, $w = 10$, $p = 0.001$) and ECI auctions (sign test, $w = 9$, $p = 0.002$).

4.3 Efficiency

In most of the literature on single unit auctions with independent private values, allocative efficiency is predicted to be perfect, since, in equilibrium, the bidder with the highest value will always obtain the good, and there is no opportunity cost of bidding in the auction. However, efficiency considerations are more complex when entry is endogenous with opportunity costs of participation. In particular, if no potential bidders enter the auction, then the good remains with the auctioneer (who is assumed to have a value of zero). In equilibrium this occurs if all potential bidders have values less than v_c. As such, efficiency is not always predicted to be perfect. We first consider allocative efficiency, which is the percentage of possible surplus actually realized, neglecting efficiency concerns about c. The measure of allocative efficiency that we use is given by

$$\frac{v_{winner}}{v_{max}} \tag{8}$$

where v_{winner} is the value of the person who obtained the good (possibly the auctioneer), and v_{max} is the highest value from among the potential bidders.

We call the efficiency measure which accounts for efficiency losses due to multiple potential bidders forgoing c and entering the auction total efficiency. It is measured by

$$\frac{(v_{winner} - mc) - min(v_{min} - nc, 0)}{max\,(v_{max} - c, 0) - min(v_{min} - nc, 0)}. \tag{9}$$

Note that if $v_{max} < c$, then the efficient outcome is for no potential bidder to enter. If $v_{max} \geq c$, then the efficient outcome is for only the potential bidder with the highest value to enter, and to obtain the good. Each additional bidder causes an efficiency loss of c, with no gain in allocative efficiency. In equilibrium, of course, any potential bidder with a value weakly above v_c is predicted to enter. As such, predicted total efficiency is likely to be lower than allocative efficiency. Note that, as the number of potential bidders increases, expected total efficiency will decrease, while predicted allocative efficiency will increase. In our design, the number of potential bidders is constant. An interesting question that we leave for future research is the effect on total and allocative efficiency of increasing the number of potential bidders.

Table 7 contains summary statistics regarding both allocative and total efficiency. Notice that predicted allocative efficiency is low relative to the case of exogenous entry. This indicates that there are a non-negligible number of auctions in which no potential bidders are predicted to enter. This is not surprising given that there are only three potential bidders for any given auction, and that c can be as high as 20. Also note that predicted total efficiency is not dramatically different from predicted allocative efficiency. This is also a result of the low number of potential bidders. Efficiency losses due to more than one potential bidder entering are predicted to be minimal.

Notice that allocative efficiency is, on average, higher than predicted in all four treatments.

Table 7: Summary statistics for efficiency

Treatment	Observed allocative efficiency	Predicted allocative efficiency	Observed total efficiency	Predicted total efficiency
FPI	0.861	0.855	0.830	0.854
	(0.347)	(0.352)	(0.183)	(0.179)
FPU	0.879	0.854	0.846	0.852
	(0.327)	(0.353)	(0.170)	(0.182)
ECI	0.899	0.853	0.851	0.850
	(0.302)	(0.354)	(0.168)	(0.184)
ECU	0.885	0.854	0.850	0.852
	(0.319)	(0.353)	(0.168)	(0.182)

Notes: Table contains means with standard deviations in parentheses.

However, in all cases, this is not statistically significant.[28] Allocative efficiency is able to be higher than predicted because of the entry decisions of potential bidders. Since allocative efficiency is zero when no potential bidders enter the auction, excess entry, which we observe, will tend to increase it. Total efficiency will account for such efficiency gains from excess entry, while also accounting for the efficiency losses from additional potential bidders forgoing c.

Contrary to theory allocative efficiency is greater in English clock auctions than in first-price auctions when bidders are informed, although the result is only marginally significant (sign test, $w = 7$, $p = 0.090$). Since first-price auctions are typically observed to have lower efficiency when entry is exogenous and the number of bidders is known, this is in line with the existing literature. However, when bidders are uninformed we cannot reject that allocative efficiency is equal between first-price and English clock auctions (sign test, $w = 6$, n.s.). Further, we cannot reject that information structure does not affect allocative efficiency for both first-price auctions (robust rank order test, $\acute{U} = 0.707$, n.s.) and English clock auctions (robust rank order test, $\acute{U} = 0.913$, n.s.).

Turning our attention to total efficiency, we find it is greater in English clock auctions when

[28]The corresponding test statistics are: FPI (sign test, $w = 5$, n.s.), FPU (sign test, $w = 7$, n.s.), ECI (sign test, $w = 8$, $p = 0.020$) and ECU (sign test, $w = 7$, n.s.) auctions.

bidders are informed (sign test, $w = 8$, p=0.0195) but are unable to reject that total efficiency is equal between the two formats when bidders are uninformed (sign test, $w = 5$, n.s.). In first-price auctions total efficiency is higher when bidders are uninformed (robust rank order test, $\acute{U} = 2.096$, $p < 0.05$). However, information structure does not affect total efficiency in English clock auctions (robust rank order test, $\acute{U} = 0.388$, n.s.). We are unable to reject that total efficiency is in line with predictions for all treatments except FPI auctions, where total efficiency is significantly less than predicted.[29]

These results are significant from an auction design standpoint. An auction designer may be concerned with increasing both efficiency and revenue. Our results suggest that FPU auction ought to be preferred in such a case, as it generates the highest revenue, while maintaining allocative efficiency.

4.4 Bidding behavior

Bidding behavior in auctions has been studied extensively in the literature. In English clock auctions, bidders tend to bid their values, as predicted, when the number of bidders is sufficiently large.[30] In first-price auctions, however, bidders tend to overbid relative to risk-neutral Nash predictions (see e.g. (Kagel and Levin 1993)). A variety of hypotheses have been proposed to explain this overbidding including risk aversion ((Cox, Smith, and Walker 1983), (Cox, Smith, and Walker 1988)), a non-monetary joy of winning ((Cox, Smith, and Walker 1992) and (Holt and Sherman 1994)), quantal response equilibrium ((Goeree, Holt, and Palfrey 2002)), and cognitive hierarchy

[29]The corresponding test statistics are: FPI (sign test, $w = 9$, $p = 0.002$), FPU (sign test, $w = 5$, n.s.), ECI (sign test, $w = 5$, n.s.) and ECU (sign test, $w = 5$, n.s.).

[30]See e.g. (Coppinger, Smith, and Titus 1980), who find that prices are approximately equal to the second highest value in English clock auctions with both six and nine bidders. However, when there are only three bidders, they find that the price is below the second highest value.

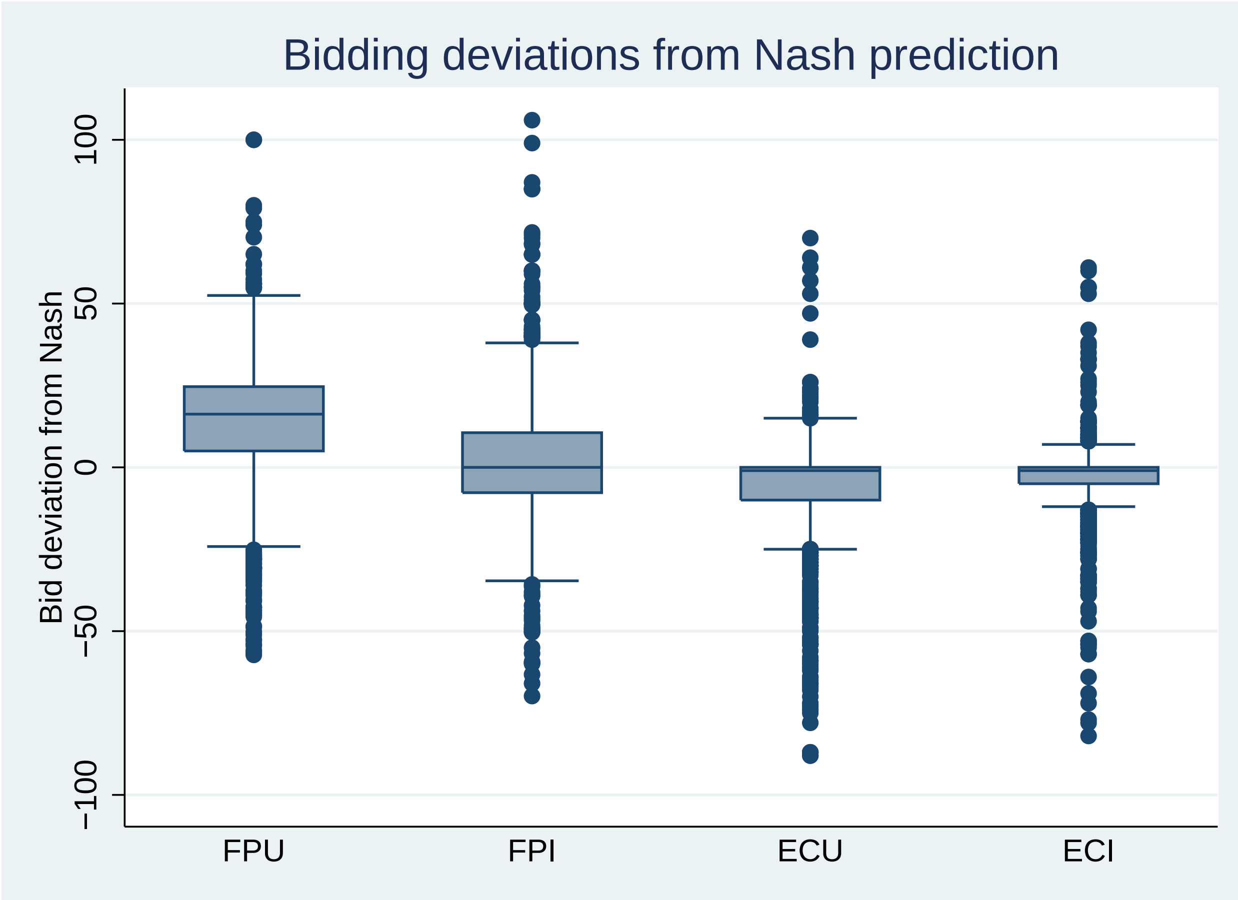

Figure 4: Bid deviations from predictions by information structure and auction format (Intended to be color in both web and print versions)

models such as level-k ((Crawford and Iriberri 2007)).

The main focus of this paper is testing revenue equivalence predictions with endogenous entry, so we do not structurally estimate models to determine what combination of these explanations best fits our data. Rather, we focus on how bidding varies by information structure and auction format to determine the robustness of results with an exogenous number of bidders to these treatment variables. Figure 4 illustrates bidding relative to predictions across all four treatments using boxplots.

Table 8 contains summary statistics regarding both predicted and observed bids. Since in English clock auctions, the winning bid is not observable, we split between the winning bid and the

Table 8: Summary statistics for bidding conditional on observed entry behavior

Treatment	Observed bids of auction winner	Predicted winning bids	Observed bids of auction losers	Predicted losing bids
FPI	47.112	43.503	34.117	33.146
	(30.775)	(31.083)	(18.954)	(28.701)
FPU	51.241	33.427	29.531	19.085
	(22.281)	(20.315)	(19.067)	(19.208)
ECI	-	(71.493)	47.126	50.872
		(21.350)	(22.549)	(23.225)
ECU	-	71.022	43.437	50.969
		(22.168)	(22.908)	(23.284)

Notes: Table contains means with standard deviations in parentheses.

losing bids for all four treatments. We find that bids in first-price auctions are significantly above predictions for both the informed (sign test, $w = 9$, $p = 0.002$) and uninformed case (sign test, $w = 10$, $p = 0.001$). Further, in first-price auctions, bid deviations above Nash predictions are higher when bidders are uninformed: (robust rank order test, $\acute{U} = undefined$, $p < 0.01$).[31] Note that in cases where $m = 1$, any bid above zero exceeds Nash predictions in FPI auctions, and such bids are observed in some cases. This will, of course, tend to drive up overbidding in FPI auctions relative to FPU auctions, where the predicted bid is positive when $m = 1$.

For English clock auctions, observed bids are less than predicted despite the presence of a weakly dominant bidding strategy. Again, this observation holds for both the informed (sign test, $w = 9$, $p = 0.002$) and uninformed (sign test, $w = 10$, $p = 0.001$) case. In addition, information structure matters. Observed bids in English clock auctions are further from Nash predictions when bidders are uninformed: (robust rank order test, $\acute{U} = 4.398$, $p < 0.05$). In this case this means that observed bids in ECU auctions are further below bidder valuations than in ECI auctions. Thus, it is not surprising that revenue is observed to be higher in ECI auctions.

[31] The test statistic is undefined because the lowest average bid deviation in FPU auctions is bigger than the biggest average bid deviation in FPI auctions.

Since the Nash prediction to bid your value is a weakly dominant strategy in English clock auctions, the observed underbidding is puzzling. However, it is important to note that in (Coppinger, Smith, and Titus 1980) underbidding in English clock auctions with three bidders was observed.[32]

4.5 Entry decisions

The entry decisions of potential bidders are particularly interesting in that they yield some insight into bidder preferences regarding auction format, and information structure. Table 9 contains summary statistics regarding observed and predicted entry decisions split into three value regions. In region one, the value observed by a potential bidder was $v_i < v_{c=1}$, so that entry, regardless of the value of c, was not predicted. In region two $v_i \in [v_{c=1}, v_{c=20}]$, so that whether or not entry was predicted depended on the value of c. In region three, $v_i > v_{c=20}$, so that, regardless of c potential bidders were predicted to enter the auction. Note that these three regions do not vary with information structure or auction format.

Note that in region one, where potential bidders are predicted not to enter, we see substantial entry across both auction formats and information structures. Likewise, in region two, entry is well above predictions in all treatments. Since in region three all potential bidders are predicted to enter, any deviation will produce under-entry. However, it is important to note that the over-entry in regions one and two are sufficient to keep overall entry significantly above predictions in all treatments.[33] It is important to note that, despite the observed over entry, bidders earn more than c,

[32](Coppinger, Smith, and Titus 1980) hypothesize that the observed underbidding is due to tacit collusion. In our data, such collusion is unlikely, given that subjects are randomly re-matched after each period, and were not permitted to communicate. Further, in any given session, subjects participate in both English clock and first-price auctions. If bidders manage to coordinate on a collusive bidding strategy in English clock auctions, they would do the same in first-price auctions. (Coppinger, Smith, and Titus 1980) do not observe underbidding for larger number of bidders, which suggests that investigating the effect of increasing the number of potential bidders is an important extension of the current paper. This extension is investigated in (Aycinena, Bejarano, and Rentschler 2013).

[33]The relevant test statistics are: FPI (sign test, $w = 9$, $p = 0.002$), FPU (sign test, $w = 10$, $p = 0.001$), ECI (sign

Table 9: Summary statistics for entry

Treatment/region	Observed entry decision	Predicted entry decision
Region 1		
FPI	0.272	0.000
	(0.446)	(0.000)
FPU	0.249	0.000
	(0.433)	(0.000)
ECI	0.231	0.000
	(0.422)	(0.000)
ECU	0.249	0.000
	(0.433)	(0.000)
Region 2		
FPI	0.592	0.321
	(0.492)	(0.467)
FPU	0.567	0.320
	(0.496)	(0.467)
ECI	0.578	0.318
	(0.494)	(0.466)
ECU	0.556	0.320
	(0.497)	(0.467)
Region 3		
FPI	0.849	1.000
	(0.358)	(0.000)
FPU	0.854	1.000
	(0.353)	(0.000)
ECI	0.863	1.000
	(0.344)	(0.000)
ECU	0.851	1.000
	(0.356)	(0.000)

Table contains means with standard deviations in parentheses.
In region 1 v_i is such that, regardless of c, entry is not predicted.
In region 2 v_i is such that whether or not entry is predicted depends on c.
In region 3 v_i is such that, regardless of c, entry is predicted.

on average, in all treatments except FPU auctions.

Figure 5 further illustrates observed entry. Notice that entry does not differ substantially between auction formats or information structures, regardless of region.[34] Indeed, we are unable

test, $w = 9$, $p = 0.002$) and ECU (sign test, $w = 10$, $p = 0.001$).

[34] Note that our experimental design has low power to evaluate entry according to theory because we cannot observe their entry thresholds, only their entry decissions for a given value and outside option. (Aycinena, Bejarano, and

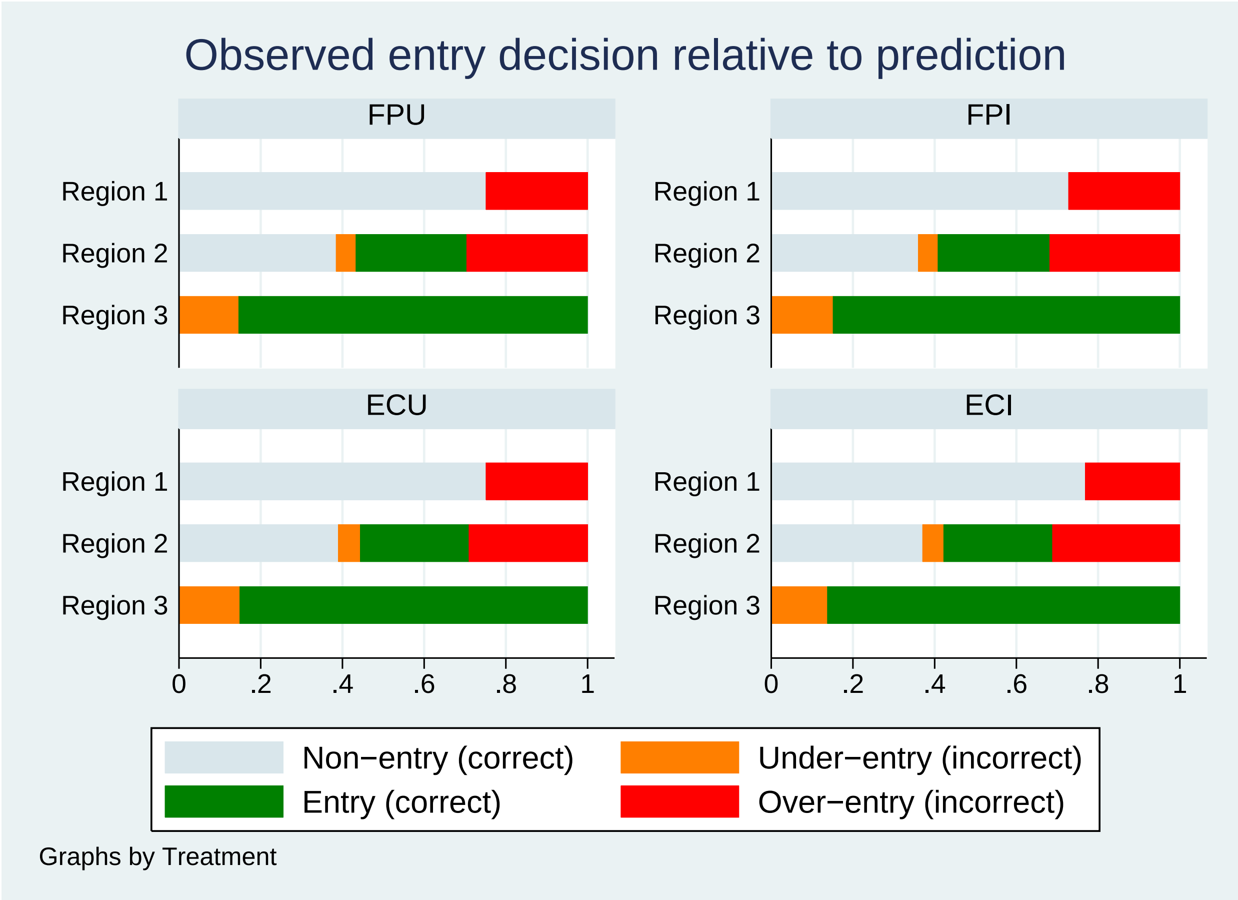

Figure 5: Observed entry relative to theory (Intended to be color in both web and print versions)

to reject that entry is equal between auction formats, both when bidders are informed (sign test, $w = 5$, n.s.) and uninformed (sign test, $w = 4$, n.s.). Likewise, information structure does not affect entry for both first-price (robust rank order test, $\acute{U} = 0.822$, n.s.) and English clock auctions (robust rank order test, $\acute{U} = 0.922$, n.s.). These results are robust to restricting attention to region two.

This is in contrast to the result of (Ivanova-Stenzel and Salmon 2011), who found that potential bidders with higher values were more likely to enter English clock auctions, while those with low values were more likely to enter first-price auctions. However, potential bidders in (Ivanova-

Rentschler 2013) uses a Becker-DeGroot-Marschack mechanism to evaluate threshold entry strategies.

Stenzel and Salmon 2011) had to choose to enter one format or the other. In our setup, a potential bidder with a high value was likely to enter, regardless of the format, and a potential bidder with a low value was likely not to enter, regardless of format. To further investigate whether or not entry decisions differ across auction formats by value, we divide region two (where entry decisions are predicted to depend on value and c) in to three sections. We find that entry does not differ between auction formats for values in the top third of region two for both informed (sign test, $w = 6$, n.s.) and uninformed (sign test, $w = 6$, n.s.) bidders. Similar results hold for the bottom third of region two for informed (sign test, $w = 5$, n.s.) and uninformed (sign test, $w = 6$, n.s.) bidders. As such, we find no evidence of the high-low divide reported in (Ivanova-Stenzel and Salmon 2011).

The fact that entry does not differ across the four treatments is predicted by theory. However, given that observed payoffs are higher in English clock auctions, it is puzzling that we do not observe higher entry into them. However, such behavior is not atypical. (Ivanova-Stenzel and Salmon 2004) finds that potential bidders are not willing to pay a higher entry fee for English clock auctions which would make the expected payoff of the two formats approximately equal (in an environment in which there would be two bidders in either format, and value is observed after entry). Further, (Engelbrecht-Wiggans and Katok 2005) observes that the willingness to pay to enter an English clock auction is equal to that of first-price auctions (with five potential bidders). They hypothesize that potential bidders have a difficult time determining the expected payoffs of the auction formats.

We also report probit estimates of individual level entry decisions, with standard errors clustered at the session level. Our dependent variable is the observed entry decision. We control for auction format ($FP_{it} = 1$ if bidder i is in an first-price auction in period t, and zero otherwise, with ($EC_{it} = 1 - (FP_{it})$ and information structure ($Informed_i = 1$ when potential bidder i is in a session with informed bidders, and zero otherwise) interacted with auction format. Additionally, we control for value (v_{it}) and entry cost (c_{it}) observed by bidder i in period t. We also control for experience ($ln(t+1)$), gender ($Male_i$ is equal to one for men, and zero for women), risk preferences ($SafeChoices_i$, the number of safe options potential bidder i chose in the risk preference elicitation task) and order effects ($RiskOrder_i$ and $FirstFormat_i$). Regression results are presented in Table 10, with three alternative specifications.

Notice that, consistent with the nonparametric tests, the coefficients on the auction format and the information structure interactions with auction format are not statistically significant. As predicted, we find that a higher value increases the probability of entering the auction. Also, as the opportunity cost of participation increases, the probability of entry decreases, as predicted by theory. In regression specification two, we explore whether value affects entry decisions differently according to auction format, and find no evidence for it ($\chi^2 = 0.08$, n.s.).

Bidder experience plays a role, in that as potential bidders become more experienced, they are less likely to enter. Since we observe, on average, over-entry, this is interpreted as potential bidders moving in the direction of equilibrium as they gain experience. This result is robust to looking only at the last 24 periods.

The coefficient on risk attitudes is both significant and negative, indicating that more risk-averse potential bidders are less likely to enter the auction. This is in line with our expectations, and suggests that bidders self-select into the auction not only by value, but also by risk attitudes.[35] We find no evidence of gender effects on entry, and order effects are not significant, with the exception of the order in which the risk elicitation task was performed in the experiment, if we

[35] Such self-selection into auctions by risk attitudes has also been observed in (Palfrey and Pevnitskaya 2008). In their experimental design, potential bidders only observe their value after entry, so that self-selection is driven only by risk attitudes. In our design, value is observed prior to entry, so self-selection in multidimensional.

Table 10: Probit estimates of determinants of entry (reporting marginal effects)

	All 48 periods		Last 24 periods
	(1)	(2)	(3)
FP_{it}	0.009	0.018	0.009
	(0.012)	(0.029)	(0.019)
$Informed_i \cdot FP_{it}$	0.009	0.009	0.013
	(0.007)	(0.007)	(0.012)
$Informed_i \cdot EC_{it}$	0.007	0.007	0.016
	(0.006)	(0.006)	(0.010)
v_{it}	0.010***		0.012***
	(0.000)		(0.000)
$v_{it} \cdot FP_{it}$		0.010***	
		(0.000)	
$v_{it} \cdot EC_{it}$		0.010***	
		(0.000)	
c_{it}	-0.034***	-0.034***	-0.036***
	(0.001)	(0.001)	(0.002)
$ln(t+1)$	-0.024**	-0.024**	-0.067*
	(0.008)	(0.008)	(0.032)
$Male_i$	0.025	0.025	0.028
	(0.028)	(0.028)	(0.034)
$SafeChoices_i$	-0.021***	-0.021***	-0.025**
	(0.006)	(0.006)	(0.008)
$FirstFormat_i$	-0.022	-0.022	-0.026
	(0.011)	(0.011)	(0.018)
$RiskOrder_i$	-0.022	-0.022	-0.040*
	(0.012)	(0.012)	(0.019)
Observations	10944	10944	5472
Clusters	19	19	19
Log Likelihood	-5103.052	-5102.938	-2310.619
Pseudo R^2	0.299	0.299	0.372
Bayesian information criterion	10308.411	10317.483	4715.920

$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

restrict attention to the second half of the experiment.

5 Conclusion

We empirically address the question of the optimal auction format in an environment with endogenous entry. Potential bidders observe both their private value and the common opportunity cost of entry before making their entry decision. We vary the auction format between first-price and English clock on a within-subject basis. In addition, we investigate whether or not the seller should inform bidders of the number of entrants prior to bids being placed. This is varied on a between-subject basis.

Theory suggests that both of these questions are irrelevant, as neither the information structure, nor the auction format should affect revenue. However, we find that first-price auctions generate more revenue, regardless of information structure. Further, the effect of information structure differs across auction formats. Specifically, revenue is higher in first-price auctions when bidders are uninformed, and the opposite is true for English clock auctions. As such, our results suggest that an auctioneer who wishes to maximize revenue should opt for a first-price auction and should not reveal the number of participating bidders.

Although we find that entry in all four treatments is higher than predicted by theory, we cannot reject that entry is equal among them, despite the fact that bidders are better off in English clock auctions. The fact that higher payoffs in English clock auctions does not induce higher entry is similar to the results found in (Engelbrecht-Wiggans and Katok 2005). Possible explanations for this behavior include overconfidence in first-price auctions and difficulty in discerning expected payoffs across auction formats. These results suggest a need for further research. Why does entry not increase with expected payoffs?

Consistent with the experimental literature with an exogenous number of bidders, we find that bids in first-price auctions exceed Nash predictions. In contrast, in English clock auctions, bids tend to be slightly less than predicted. This underbidding in English clock auctions is itself somewhat puzzling, given that the Nash bid is a weakly dominant bidding strategy. However, it is important to note that such underbidding in English clock auctions has been observed in (Coppinger, Smith, and Titus 1980), in an environment with three bidders. In our design there are three potential bidders, so that the maximum number of bidders is also three.

In addition to the contribution to practical auction design, our paper has contributed to the literature on endogenous entry in auctions. However, further research is needed on auctions with endogenous entry when bidders learn their value prior to making costly entry decisions. In particular, in our design we are only able observe whether a potential bidder enters the auction or not, thus allowing only for a very coarse test on entry thresholds across auction formats. It would be valuable to be able to observe the threshold value that a bidder employs for a given opportunity cost of entry. This would allow a more precise analysis of entry decisions than our data allows.

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