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

Diego Aycinena[1] · Lucas Rentschler[2]

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Abstract Attracting bidders to an auction is a key factor in determining revenue. We experimentally investigate entry and bidding behavior in first-price and English clock auctions to determine the revenue implications of entry. Potential bidders observe their value and then decide whether or not to incur a cost to enter. We also vary whether or not bidders are informed regarding the number of entrants prior to placing their bids. Revenue equivalence is predicted in all four environments. We find that, regardless of whether or not bidders are informed, first-price auctions generate more revenue than English clock auctions. Within a given auction format, the effect of informing bidders differs. In first-price auctions, revenue is higher when bidders are informed, while the opposite is true in English clock auctions. The optimal choice for an auction designer who wishes to maximize revenue is a first-price auction with uninformed bidders.

Keywords Auctions · Revenue equivalence · Endogenous entry · Experiments · Bidding

JEL Classifications D44 · D80

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✉ Lucas Rentschler
lucas.rentschler@usu.edu

1 Facultad de Economía, Universidad del Rodario, Calle 12C No. 6-25, Bogotá, D.C., Colombia

2 Department of Economics and Finance, Utah State University, 3500 Old Main Hill, Logan, UT 84322, USA

1 Introduction

Consider a government official that seeks to privatize an asset via an auction. If the aim is to maximize the government's revenue, there are many practical issues to consider when choosing the rules of the auction (i.e., mechanism, information to be disclosed, etc.).[1] This is especially true if it is costly for bidders to participate and consequently the seller faces uncertainly about the number of bidders that a given set of rules can attract. As noted in Klemperer (2002), "[A] major area of concern of practical auction design is to attract bidders, since an auction with too few bidders risks being unprofitable for the auctioneer."

The revenue generated in an auction depends on entry decisions and bidding behavior in the chosen mechanism. A robust finding from the experimental literature is that, all else constant, first-price auctions generate more revenue than English clock auctions, largely due to persistent overbidding in the former.[2] This implies that bidder payoffs tend to be higher in English clock auctions. If potential bidders are able to anticipate this, one might expect that when given the choice, they would be more likely to enter an English clock auction, thus increasing its relative revenue. Will such entry decisions equalize the expected revenue of these two formats, or even cause the English clock auction to revenue dominate? The answer to this question is of practical concern to an auction designer who must consider whether or not a particular mechanism will appeal to potential bidders.

Furthermore, revenue may also depend on whether or not bidders know the actual number of entrants when formulating their bids. When potential bidders know their value of the good prior to deciding on entry, they may use this information to select into the auction. Thus, disclosing the number of entrants reveals information about the distribution of values of other participants. With this information, bidders can adjust their strategy accordingly.

Given these considerations, which mechanism and information revelation policy is optimal for the auction designer? We experimentally investigate these questions in independent private value environments where potential bidders know their value and a common opportunity cost of participating when they make their entry decisions. We vary the mechanism within subjects between first-price and English clock auctions. We vary whether or not bidders are informed of the number of entrants on a between subject basis.

In this paper we focus on the case of a small number of potential bidders because this is when the effect of attracting an additional bidder will have the largest effect

[1] The revenue equivalence theorem addresses the choice of mechanism 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) and Heydenreich et al. (2009).

[2] See e.g., Cox et al. (1982) and Coppinger et al. (1980).

on revenue. That is, the importance of the auction rules in determining revenue via entry decisions is highest when the number of potential bidders is low.[3,4]

Theory predicts revenue equivalence between these four environments. However, we find that, regardless of whether or not bidders are informed, first-price auctions generate more revenue than English clock auctions. Further, 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.

This failure of revenue equivalence is not driven by differences in entry. In fact, entry does not differ across auction format or information structure, although it exceeds risk-neutral predictions.[5] Rather, more aggressive bidding in first-price auctions raises it's revenue relative to that of English clock auctions, regardless of information structure.

In the first-price auction environments we study, homogeneously risk averse potential bidders will, in equilibrium, reduce entry and increase their bids relative to the risk-neutral equilibrium (Menezes and Monteiro 2000). Since we observe entry that exceeds the risk-neutral predictions, one of the contributions of this paper is to show that homogeneous risk aversion is not able to explain behavior.[6]

The fact that not revealing the number of bidders can increase revenue in first-price auctions has also been observed in Dyer et al. (1989). In this study, the number of bidders is uncertain, but not endogenous, and the result is explained by a model with risk-averse bidders.[7]

Previous papers have analyzed auctions with endogenous entry. However, most of the relevant theoretical literature focuses on the case where signals regarding value are revealed only after entry. In such an environment potential bidders are

[3] Auctions with few participating bidders are empirically relevant. For instance, in all outer continental shelf auctions for oil and gas run between 1954 and 1979, the modal number of participating bidders was one. These auctions attracted a single bidder 36.89% of the time, and two bidders 19.24% of the time.

[4] See e.g., Hendricks et al. (1987, 1989, 1993, 1994) and Hendricks and Porter (1988).

[5] The finding that entry exceeds risk neutral predictions is also observed in other auction settings. See e.g., Palfrey and Pevnitskaya (2008) and Smith and Levin (2002).

[6] We thank an anonymous reviewer for this point. A model with heterogeneous risk attitudes may be able to explain our data. Characterizing equilibrium in such an environment is particularly challenging, because potential bidders would self-select into auctions based on their value and their degree of risk aversion. Since we are primarily interested in the revenue ranking of the auction formats and information structures, we leave this for future research. For an analysis of heterogeneous risk preferences in first-price auctions in which potential bidders do not observe their value prior to entry, so that self-selection into auctions is determined by a single variable, see Pevnitskaya (2004). Palfrey and Pevnitskaya (2008) finds behavior in the lab consistent with heterogeneous risk-averse potential bidders.

[7] For a theoretical analysis of bidding in auctions with an uncertain number of bidders see e.g., Matthews (1987), McAfee and McMillan (1987b), Harstad et al. (1990) and Levin and Ozdenoren (2004). Isaac et al. (2012) experimentally examines both second and first-price auctions with an uncertain number of bidders, and argues that their data can be explained by a model with heterogeneous risk preferences.

unable to use their signals to self-select into the auction.[8] The empirical literature has also focused on the case in which bidders only learn their value after entry.[9]

In contrast, we study auctions in which potential bidders know their value before making their entry decisions. To the best of our knowledge, the only other paper to experimentally examine such an environment is Ivanova-Stenzel and Salmon (2011). However, their setup involves multiple auction formats which offer homogeneous goods, and are competing for a fixed pool of bidders. The environments we study mirrors closely the theoretical analysis in Menezes and Monteiro (2000).[10] They provide symmetric equilibria in first and second-price auctions, with a homogeneous and commonly known entry cost.[11] Potential bidders are predicted to enter if their private value (weakly) exceeds a threshold. In equilibrium, this threshold does not vary across auction format. Nor does it depend on whether or not the number of bidders is announced prior to bids being placed. Interestingly, theory predicts that neither the choice of auction format nor the information structure will affect expected revenue. Since the English clock auction is strategically equivalent to the second-price auction, there predictions carry over to the environments we study.

Our results are relevant to environments in which the seller need not compete for bidders against alternative sellers, or the seller is auctioning a relatively unique good. It is important to note that our motivation is not e-Bay and other online auction websites that allow sellers of homogeneous goods to compete for bidders by choice of auction format.[12] Examples of such relevant environments abound, tend to be large in scale, and it is common to observe a small number of bidders participating in these auctions. For example, there is a wide variety of government auctions to which our results would apply: timber auctions, infrastructure procurement auctions, auctions for pollution permits, and auctions of state owned assets. Examples from the private sector include real estate auctions and art auctions.

[8] Without private information, equilibrium entry is either asymmetric and deterministic (McAfee and McMillan 1987a; Engelbrecht-Wiggans 1993) or symmetric and stochastic (Engelbrecht-Wiggans 1987; Levin and Smith 1994; Smith and Levin 1996; Ye 2004; Li and Zheng 2009). Some variations allow for private information on dimensions other than value to be observed prior to entry. For example, potential bidders observe their participation costs in Cox et al. (2001) and Moreno and Wooders (2011), and observe their degree of (heterogeneous) risk aversion in Pevnitskaya (2004).

[9] Examples include Smith and Levin (2002), Palfrey and Pevnitskaya (2008), Reiley (2005) and Roberts and Sweeting (2013).

[10] Other theoretical papers which analyze similar environments include Samuelson (1985), Stegeman (1996), Lu (2009) and Cao and Tian (2010). When private values are observed prior to entry, most theoretical analysis has focused on second-price auctions e.g., Campbell (1998), Tan and Yilankaya (2006), Miralles (2008) and Cao and Tian (2008).

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

[12] There is also a literature in which multiple sellers of homogeneous goods compete for bidders via auction format. See Peters and Severinov (1997) and Preston McAfee (1993) for theoretical analysis of such an environment, and Ivanova-Stenzel and Salmon (2004, 2008a, b, 2011) for experimental analysis. Peters and Severinov (2006) analyses second-price auctions where sellers compete via reserve prices, and Anwar et al. (2006) uses e-Bay auctions data to test this model.

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

2 Theoretical predictions

A set of players $N \equiv \{1, \ldots, n\}$ 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 of obtaining the good 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 consider two auction formats: first-price auctions and English clock auctions. In a first-price auction, all bidders simultaneously submit bids, the highest of which wins the auction at a price set by the winning bid. In an English clock auction the price begins at zero, and continues to increase if excess demand exists. Bidders indicate their bid by abandoning the auction at the corresponding price. When there is only one bidder remaining in the auction it ends, and the remaining bidder wins. The price paid is the price at which the last bidder abandoned the auction. In both auction formats the payoff of all bidders who do not win the auction is zero.

Additionally, we consider environments where m is made common knowledge before bids are placed, and environments where it is not. When m is revealed we say that bidders are informed; when it is not we say that bidders are uninformed.

In what follows we refer to first-price auctions with informed bidders as FPI auctions, and first-price auctions with uniformed bidders as FPU auctions. Analogously, we refer to English clock auctions with informed bidders as ECI auctions, and English clock auctions with uninformed bidders as ECU auctions.

Following Menezes and Monteiro (2000) we consider symmetric equilibria in which risk-neutral potential bidders use a threshold entry rule, and the subsequent equilibrium bidding functions are monotonically increasing and differentiable.[13] In such an equilibrium, potential bidders only enter the auction if their value is (weakly) greater than some threshold. When the opportunity cost of entry is c, we denote the associated entry threshold as v_c. We will show that, in equilibrium, this entry threshold is the same in all the environments we study.

Since, in equilibrium, bid functions are monotonically increasing, the only way a potential bidder with a value of v_c can win the auction with positive probability is to be the sole entrant. This would result in a payoff of v_c since she would obtain the

[13] Equilibrium in a model in which symmetric potential bidders are risk averse would involve more aggressive bidding in first-price auctions, and a higher entry threshold. See Menezes and Monteiro (2000) for proof of this assertion. As will be discussed in the results section, this is not consistent with our data. A model in which potential bidders have heterogeneous risk preferences may be able to explain our data.

good at a price of zero. The probability of being the only bidder is given by $F(v_c)^{n-1}$. Thus, her expected payoff of entering the auction is $v_c F(v_c)^{n-1}$. Since the entry threshold is the value for which a potential bidder is indifferent between entering the auction or not, v_c must satisfy $c = v_c F(v_c)^{n-1}$. Crucially, notice that this condition is the same for both auction formats and both information structures.

Thus, conditional on having entered the auction, each bidder's value is an independent draw from

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

with positive density on $[v_c, v_H] \subset [0, v_H]$. We denote the density function associated with $G_c(v)$ as $g_c(v)$.

Note that v_c also allows potential bidders to form beliefs regarding how many others will enter the auction. In particular, the probability that $r \leq n-1$ other potential bidders enter is the same as the probability that r of them have values such that $v_i \geq v_c$, and the remaining $n-r-1$ potential bidders have values such that $v_i < v_c$. There are $\frac{(n-1)!}{(n-r-1)!r!}$ ways in which this could occur. Thus, the corresponding probability is given by $\left(\frac{(n-1)!}{(n-r-1)!r!}\right) F(v_c)^{n-r-1}(1 - F(v_c))^r$.

Below, we introduce the equilibrium bidding strategies in each of the four environments we study, and then discuss the predicted revenue equivalence. Detailed derivations of bidding functions and the expected payoff of bidders can be found in the online supplement.

2.1 First-price auctions with informed bidders

Consider the case of FPI auctions. Since m is common knowledge and all potential bidders only participate if $v_i \geq v_c$, this auction is a standard independent private values auction with values being drawn from $G_c(v)$.

When $m = 1$ the sole bidder can win with a bid of zero. When $m > 1$ the equilibrium bidding function is

$$\beta_m(v_i) = \frac{1}{G_c(v_i)^{m-1}} \int_{v_c}^{v_i} (m-1) G_c(t)^{m-2} g_c(t) t dt.$$

Note that this is simply the expected value of highest of the other bidder's values, conditional on bidder i's value being the highest.

2.2 First-price auctions with uninformed bidders

Now consider an FPU auction. 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 v_c. The equilibrium bidding function is given by

$$\gamma(v_i) = \frac{1}{F(v_i)^{n-1}} \int_{v_c}^{v_i} (n-1)F(t)^{n-2} f(t)(t)dt.$$

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 without forgoing c. In particular, rather than integrating from 0 to v_i as with the exogenous entry case, the lower limit of integration is v_c. This accounts for the fact that any bidder with a value less than v_c will not enter the auction. Note that this implies that bidders are shading their bids more in the case of exogenous entry.

2.3 English clock auctions with informed bidders

In the English clock auction wit informed bidders, bidders abandon the auction once the price reaches their value, as this is the weakly dominant bidding strategy. That is, the symmetric equilibrium bid function is given by $\rho(v_i) = v_i$. 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 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. As such, whether or not m is common knowledge is irrelevant to equilibrium bidding behavior.

2.5 Revenue equivalence

Since the equilibrium entry threshold v_c is common to all four environments we study, each bidder's valuation is an independent draw from $G_c(v)$. When bidders are informed, this means that the revenue equivalence theorem applies.[14] This revenue equivalence extends to English clock auctions with uninformed bidders because v_c is the same as when bidders are informed, and because the weakly dominant bidding strategy implies that equilibrium behavior is identical to the case of English clock auctions with informed bidders. Menezes and Monteiro (2000) shows that this revenue equivalence extends to the case of first-price auctions with uninformed bidders.

The expected revenue of these four environments is simply the expected second highest valuation of those potential bidders with a valuation weakly above v_c. This is given by

$$n(n-1) \int_{v_c}^{v_H} (1 - F(t))tF(t)^{n-2} f(t)dt.$$

[14] See e.g., Myerson (1981) and Heydenreich et al. (2009).

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 $\{0, 1, \ldots, 100\}$, 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 $\{1, 2, \ldots, 20\}$. The realized value of c is independently determined for each period. The same realization of c is used for all four groups in a period.[15] The same realizations of valuations and c are used in all sessions, to minimize session differences. At the beginning of each period, each potential bidders observes their value and c, and then decides 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 the next period begins. To mitigate boredom, subjects who choose not to enter the auction play tic-tac-toe against the computer.[16]

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).[17] The same feedback is given to all subjects, regardless of whether or not they entered the auction. Subjects are randomly re-matched in each of the 48 periods.

We use a 2×2 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.

Subjects also participate in a risk elicitation task that resembles Holt and Laury (2002). However, rather than choosing between two lotteries in each of ten choices, subjects choose between a certain payoff and a lottery. To control for order effects,

[15] Table 1 in the online supplement contains a breakdown of the number of times in a session each possible realizations of c is used.

[16] Subjects who do not enter can repeatedly play tic-tac-toe can play against the computer until the auction for that period ends. They know that results of each game do not affect their payoffs. Palfrey and Pevnitskaya (2008) investigates the effect on entry into first-price auctions of having non-entrants play a version of rock–paper–scissors against the computer. In their setup, bidders learn their value after entry, and are informed. They find that the use of rock–paper–scissors reduces, but does not eliminate, over-entry.

[17] In English clock auctions the winning bid is not observed.

Table 1 Summary of experimental design

	Risk elicitation first		Risk elicitation second	
	First-price first	English clock first	First-price first	English clock first
Informed	3 sessions	2 sessions	2 sessions	2 sessions
Uninformed	3 sessions	3 sessions	2 sessions	2 sessions

we vary the order in which subjects participate in the risk elicitation task.[18] Our experimental design is summarized in Table 1.

Sessions were run at Universidad Francisco Marroquín (UFM).[19] Subjects were predominantly UFM undergraduates, recruited using ORSEE (Greiner 2004). Subjects interacted through a computer interface programmed in z-Tree (Fischbacher 2007). They saw a video (and received a hard copy) of the instructions and were asked to complete a quiz to ensure comprehension.[20]

At the end of the experiment the outcome of the risk elicitation task was resolved. 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 ($E\$$). Subjects began the experiment with a starting balance of $E\$75$ to cover potential losses. Each subject was paid the sum of their show-up fee, their starting balance, their cumulative earnings from the 48 periods (E$14.01 on average each period), and their earnings from the risk

[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 two sessions, due to a problem with a parameter in the software, subjects received instructions for the incorrect treatment (Informed instead of Uninformed). In the other, a subject had participated in a previous session. The results we report are robust to including the data from this session, but we feel that it it better to exclude it so that our session-level data is independent. We also discard the data from the first four sessions we ran in which bidders in the auction were informed of the number of bidders, but this information was not (in our view) sufficiently salient. This is because when the only bidder in a FPI auction submits a positive bid, the interpretation is unclear. The environment in which subjects participate is a complex one, and it may not seem natural or intuitive to subjects that one can win an auction with a bid of zero. Our impression was that subjects who made positive bids in FPI auctions did so due to limited attention, memory, or salience. This was a cause for concern for two reasons: First, one treatment variable was revealing information about the number of bidders. If this information was not salient enough, our implementation of the treatment was weak. Second, this would affect the comparability of our results as it would artificially exacerbate the treatment differences in revenue between FPI and ECI auctions. Recall that in the ascending clock auction with only one bidder, the clock automatically stopped at a price of zero. After the first four sessions, we decided to omit these sessions to be conservative and not stack the deck against the ECI treatment. We then modified the software so that when there was only one bidder in an FPI (or ECI) auction, this bidder was reminded that she could obtain the good with a bid of zero. Although some single bidders in FPI still bid positive amounts, the frequency is lower and reduces in the second half. Following Roth (1994, p. 287), we feel it is important to openly disclose the process through which the data was collected.

[20] A copy of the instructions (translated from the original Spanish) for sessions with uninformed bidders, as well as instructions for the risk elicitation task, can be found in the online supplement.

Table 2 Summary statistics for observed and predicted revenue (pooling across number of bidders)

Treatment	Observed revenue	Predicted revenue
FPI	41.986	34.617
	(32.548)	(33.606)
FPU	46.651	35.582
	(25.813)	(19.755)
ECI	33.714	34.627
	(30.178)	(34.387)
ECU	30.927	34.500
	(29.176)	(34.388)

Table contains means with standard deviations in parentheses. Predicted revenue is the Nash equilibrium revenue of the auctions assuming equilibrium entry and bidding, conditional on the realized cost of entry and values of potential bidders. For both, observed and predicted revenue, summary statistics pool cases with all numbers of bidders

elicitation task. Earnings in E$ were exchanged at a rate of $E\$7.5 = Q1$. The average payment was $Q120$, with a minimum of $Q44$ and a maximum of $Q178$.[21]

4 Results

Since behavior within a session may not be independent, we take a conservative approach in our analysis. In particular, our non-parametric tests use average results from each session as our unit of observation. In all cases, results are robust to using individual level data. Additionally, in all reported regressions, standard errors are clustered at the session level to account for session effects.

4.1 Revenue

We first analyze our primary question of interest: the revenue ranking.[22] Recall that our focus is on environments in which the seller is auctioning a good with no close substitutes, and a relatively small number of potential bidders make costly entry decisions. In such environments, the marginal value of an extra bidder is high, and understanding how the number of self-selected bidders affects revenue is important. A seller will choose auction rules, and those rules may attract several, a single, or no bidders. Since we are interested in the expected revenue accounting for all these possibilities, we focus our revenue analysis by pooling across all possible number of participating bidders.

Our data clearly rejects the hypothesis of revenue equivalence across auction formats and information structures. Table 2 compares observed and predicted

[21] As reference, lunch can be purchased on UFM's campus for $Q25$, and student workers in the library earn $Q24$ an hour.

[22] The results for payoffs mirror those of revenue. In the interest of brevity, we therefore relegate a discussion of these results to the online supplement.

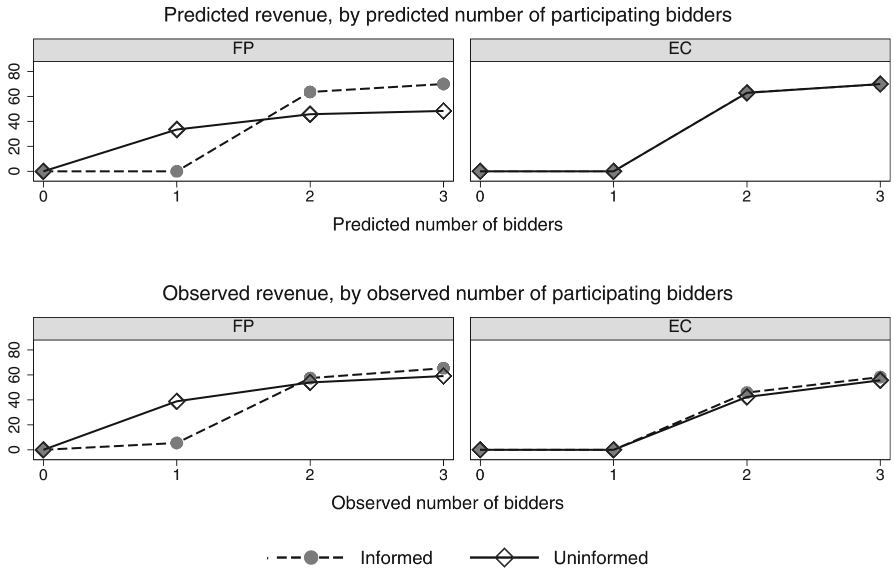

Fig. 1 Predicted and observed revenue by number of bidders

revenue across all four treatments. Note that revenue is higher than predicted in first-price auctions. This is true both when bidders are informed (sign test, $w = 9$, $p = 0.002$) and when bidders are uninformed (sign test, $w = 10$, $p = 0.001$). However, the opposite is true for English clock auctions when bidders are uninformed (sign test, $w = 9$, $p = 0.011$). If bidders are informed in English clock auctions, we cannot reject that revenue is equal to theory (sign test, $w = 6$, $p = 0.508$). Consequently, 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, $w = 10$, $p = 0.001$).[23]

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, $\acute{U} = 1.904$, $p < 0.05$).

Thus, we find that on average FPU auctions generates the most revenue followed by FPI, ECI and then ECU auctions. As such, our results suggest that a seller should opt for auction rules that use a first-price format and not provide information on number of bidders. Given that English clock and ascending auctions are much more commonly used on auction websites, this result may seem puzzling. However, such websites typically feature environments in which a variety of sellers are competing head-to-head for potential bidders. In such environments, Ivanova-Stenzel and

[23] The fact that first-price auctions generate more revenue than English clock auctions with a fixed number of bidders is well known. See e.g., Cox et al. (1982). Our result thus shows that this revenue ranking is robust to allowing potential bidders to choose to enter the auction after observing their value.

Table 3 Summary statistics for observed revenue by number of observed bidders

	$m = 1$	$m = 2$	$m = 3$	$m \in \{0, 1, 2, 3\}$
FPI	5.459	57.435	65.372	41.986
	(17.802)	(19.706)	(17.729)	(32.548)
FPU	38.857	53.962	59.083	46.651
	(25.240)	(19.947)	(16.890)	(25.813)
ECI	0.000	45.823	58.260	33.714
	(0.000)	(22.385)	(19.753)	(30.178)
ECU	0.000	42.317	55.668	30.927
	(0.000)	(22.815)	(19.267)	(29.176)

Table contains means with standard deviations in parentheses

Salmon (2004) show that potential bidders prefer English clock to first-price auctions. In the environments we study, the seller is offering a (relatively) unique good, and thus does not need to worry about alternative sellers who differentiate by auction format.

To understand what drives this empirical revenue ranking, we examine revenue by number of bidders. The top panel of Fig. 1 shows predicted revenue broken down by the predicted number of bidders. If a seller fails to attract any bidders, the auction fails and generates no revenue. In the case of $m = 1$, English clock auctions end with a price of zero, regardless of whether or not the bidder is informed. In first-price auctions, if $m = 1$ and the bidder is informed, their predicted bid is zero, but if the bidder is uninformed the predicted bid will be positive. Thus, FPU auctions are the only institution we study that are predicted to generate positive revenue when $m = 1$.

When we turn to the case where $m \geq 2$ in first-price auctions, the equilibrium bids of informed bidders are higher than that of uninformed bidders, all else constant. This is because informed bidders are aware of the level of competition in the auction, while uninformed bidders believe that they are the only bidder with positive probability. Thus, when $m \geq 2$ predicted revenue in FPI is greater than in FPU. In English clock auctions, predicted revenue does not differ by information structure, since bidding your value is a weakly dominant strategy.

As Table 3 and the bottom panel of Fig. 1 shows, we observe the predicted pattern of revenue in our data: FPU auctions generate more revenue than FPI auctions when $m = 1$ (robust rank order test, $\acute{U} = \textit{undefined}$, $p < 0.01$).[24] When $m \geq 2$, revenue in FPI auctions is greater than in FPU auctions (robust rank order test, $\acute{U} = 4.19$, $p < 0.05$).

Notice that the magnitude of the difference in revenue between FPI and FPU when $m \geq 2$ is much smaller than when $m = 1$.[25] This seems to account for the

[24] The test statistic is undefined because the lowest observation in FPU auctions is bigger than the largest observation in FPI auctions.

[25] Splitting the data into the cases where $m = 1$ and does not affect the results of non-parametric tests on revenue ranking except in the FPU and FPI case and the trivial case of English clock auctions with $m = 1$ (where the auction ends immediately at a price of zero).

overall differences in revenue. We will further explore the role of entry and bidding below, to better understand what drives our observed revenue ranking.

Our result that revenue is higher in first-price auctions when bidders are uninformed is not without precedent. Dyer et al. (1989) obtains similar results 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.

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) 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). We interact m_j with dummies for all four treatments to see if the effect of an additional bidder differs. Table 4 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 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. Note that relative to FPU revenue is reduced in FPI. The regression results confirm that m_j is positively related to revenue in all four treatments, and that the magnitude of this effect differs across treatments. Interestingly, the coefficient for c_j is positive and significant. Since a higher c_j may result in more cases in which no one enters the auction, intuition suggests that this coefficient would be negative (recall that auctions in which there are no bidders are included in our analysis). However, holding m_j constant, an increase in c_j may cause the winning bidder to bid more aggressively, since the higher c_j may mean that the winning bidder believes she faces a more aggressive distribution of opposing bids. When 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.

4.2 Entry decisions

Given the observed differences in revenue, it is important to examine to what extent they are driven by differences in entry. Further, the entry decisions of potential bidders are interesting in that they yield some insight into bidder preferences regarding auction format and information structure.

Table 5 contains a breakdown of the frequencies of each possible number of entrants in each environment we study. Interestingly, entry does not differ

Table 4 OLS estimates of revenue (pooling across number observed of bidders)

	All 48 periods		Last 24 periods
	(1)	(2)	(3)
FP_j	29.858***	29.840***	29.820***
	(2.185)	(2.138)	(2.333)
$Informed_j \cdot FP_j$	− 11.979***	− 11.961***	− 12.939***
	(1.015)	(1.036)	(1.063)
$Informed_j \cdot EC_j$	− 0.254	− 0.213	0.215
	(0.686)	(0.695)	(0.703)
$FPI_j \cdot m_j$	13.219***	13.189***	13.565***
	(0.347)	(0.345)	(0.307)
$FPU \cdot m_j$	16.498***	16.463***	15.744***
	(0.516)	(0.484)	(0.536)
$ECI_j \cdot m_j$	12.882***	12.850***	13.124***
	(0.253)	(0.253)	(0.286)
$ECU_j \cdot m_j$	24.357***	24.312***	26.279***
	(0.567)	(0.575)	(0.734)
c_j	0.221**	0.213**	0.118
	(0.060)	(0.060)	(0.105)
$ln(t+1)$		− 0.740	− 2.904
		(0.471)	(2.911)
$FirstFormat_j$		− 0.538	0.607
		(1.025)	(1.041)
$RiskOrder_j$		1.010	0.233
		(0.921)	(0.947)
Constant	− 16.140***	− 13.546***	− 6.385
	(1.129)	(2.862)	(11.307)
Observations	3647	3647	1824
Clusters	19	19	19
Adjusted R^2	0.557	0.558	0.617

Standard errors (in parentheses) clustered at the session level

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

Table 5 Frequencies of observed number of bidders by treatment

Treatment	$m = 0$	$m = 1$	$m = 2$	$m = 3$
FPI	0.109	0.227	0.338	0.326
FPU	0.090	0.262	0.362	0.288
ECI	0.079	0.262	0.38	0.28
ECU	0.089	0.268	0.368	0.276

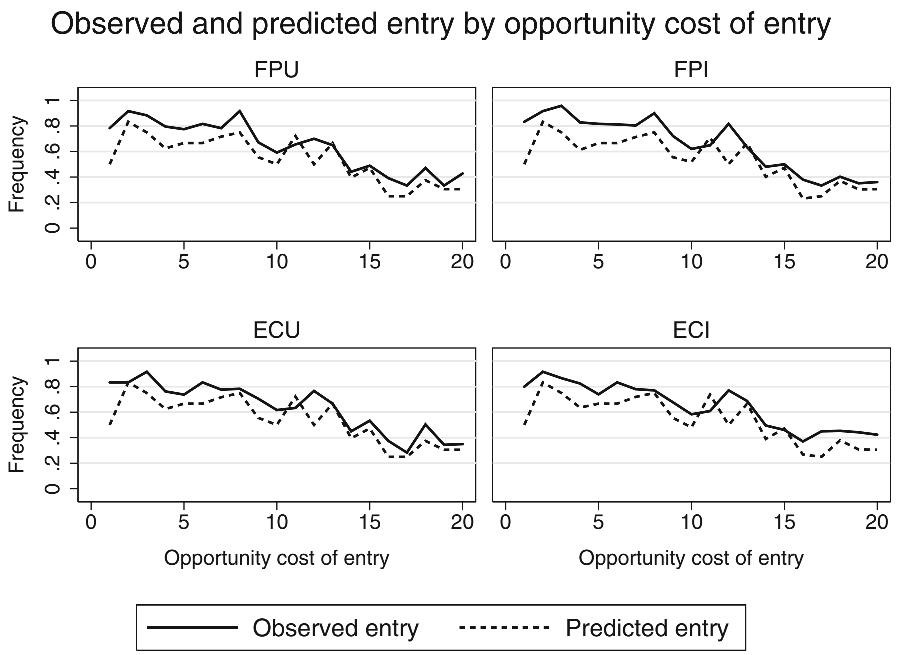

Fig. 2 Observed entry relative to theory

substantially between auction formats or information structures.[26] Indeed, we are unable 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.).[27] Likewise, information structure does not affect entry for both first-price (robust rank order test, $\acute{U} = 0.822$, n.s.) or English clock auctions (robust rank order test, $\acute{U} = 0.922$, n.s.).

Figure 2 further illustrates observed entry by showing the percentage of potential bidders who enter, and who are predicted to enter, for all possible values of c.[28] Entry is declining in c, indicating that as the opportunity cost of entry increases, entry into the auction declines.

Entry is significantly above predictions in all treatments.[29] The reasons for observed over-entry are unclear and we cannot rule out the possibility that boredom

[26] Using two sample Kolmogorov–Smirnov tests, we cannot find differences in the distribution for any pairwise treatment comparison: FPI versus FPU ($D = 0.0389$, n.s.); ECI versus ECU ($D = 0.0160$, n.s.); ECU versus FPU ($D = 0.0115$, n.s.); ECI versus FPI ($D = 0.0463$, n.s.).

[27] n.s. indicates that the test is insignificant at conventional levels.

[28] Since potential bidders know both c and their value when they make entry decisions, both of these variables are of interest. Figure 2 illustrates average entry by c. Figure 1 in the online supplement illustrates average entry by value. Probit regressions reported in Table 6 examine the effect of both c and value on entry, all else constant.

[29] The relevant test statistics are FPI: sign test, $w = 9$, $p = 0.002$, FPU: sign test, $w = 10$, $p = 0.001$, ECI: sign test, $w = 9$, $p = 0.002$ and ECU: sign test, $w = 10$, $p = 0.001$. There is some heterogeneity in entry behavior. While the majority of participants over-enter on average, several enter less than predicted. Figure 2 in the online supplement illustrates this.

Table 6 Probit estimates of determinants of entry (reporting marginal effects)

	All 48 periods		Last 24 periods
	(1)	(2)	(3)
FP_{it}	0.010	0.028	0.009
	(0.013)	(0.029)	(0.020)
$Informed_i \cdot FP_{it}$	0.018	0.019	0.041**
	(0.010)	(0.010)	(0.015)
$Informed_i \cdot EC_{it}$	0.014	0.014	0.045**
	(0.012)	(0.012)	(0.017)
v_{it}	0.010***		0.012***
	(0.000)		(0.000)
$v_{it} \cdot FP_{it}$		0.010***	
		(0.000)	
$v_{it} \cdot EC_{it}$		0.011***	
		(0.001)	
c_{it}	− 0.037***	− 0.037***	− 0.037***
	(0.001)	(0.001)	(0.002)
m_{it-1}	− 0.044***	− 0.044***	− 0.035***
	(0.007)	(0.007)	(0.010)
$m_{it-1} \cdot Informed_i$	− 0.004	− 0.004	− 0.014*
	(0.004)	(0.004)	(0.007)
$ln(t+1)$	− 0.013	− 0.013	− 0.067
	(0.009)	(0.009)	(0.035)
$Male_i$	0.030	0.030	0.029
	(0.029)	(0.029)	(0.035)
$SafeChoices_i$	− 0.023***	− 0.023***	− 0.026**
	(0.006)	(0.006)	(0.008)
$FirstFormat_i$	− 0.028*	− 0.028*	− 0.029
	(0.012)	(0.012)	(0.019)
$RiskOrder_i$	− 0.025	− 0.024	− 0.042*
	(0.013)	(0.013)	(0.020)
Observations	10,716	10,716	5472
Clusters	19	19	19
Log likelihood	− 4889.182	− 4888.754	− 2291.386
Pseudo R^2	0.313	0.313	0.377

Standard errors (in parentheses) clustered at the session level

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

with the pastime for non-entrants is a factor. However, over-entry is not uncommon in experimental settings (Palfrey and Pevnitskaya 2008; Camerer and Lovallo 1999; Goeree and Holt 2005; Fischbacher and Thoni 2008). Further the pastime is consistent in all sessions, so that any effect on entry should not affect comparisons across treatments.

The implications of the entry equivalence we observe is striking. In particular, we find no evidence that either the choice of auction format or the choice of information revelation policy will attract more bidders.[30] Since observed payoffs are higher in English clock auctions, it is puzzling that we do not observe higher entry in English clock formats. However, such behavior is not atypical. In a slightly different environment, 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. 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), despite higher payoffs in the English clock format. They hypothesize that potential bidders have a difficult time determining the expected payoffs of the auction formats.[31]

To explore the determinants of individual level entry decisions, we report probit estimates with standard errors clustered at the session level. Our dependent variable is the observed entry decision, taking a value of 1 if subjects decide to enter, and 0 otherwise. Our explanatory variables include the auction format ($FP_{it} = 1$ if bidder i is in an first-price auction in period t, and zero otherwise) 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 include 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 $FirstFormat_i$). Since feedback at the end of each period included the observed number of bidders, and this may help potential bidders to form accurate beliefs regarding the entry behavior of others, we also include the observed number of bidders in the previous period (m_{it-1}), and interact it with $Informed_i$.[32] Regression results are presented in Table 6, with three alternative specifications.[33]

Notice that, consistent with the non-parametric tests, the coefficients on the auction format and the information structure interactions with auction format are not

[30] Note however that our experimental design has low power to evaluate entry, because we cannot observe the entry thresholds of potential bidders. Aycinena et al. (2017) uses a Becker–DeGroot–Marschack mechanism to directly elicit threshold entry strategies and find no differences in entry thresholds between FPI and ECI.

[31] Our results on equality of entry across treatments differ considerably from those 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, our results are not directly comparable. In their setting potential bidders had to choose to enter one format or the other, since they study an environment in which multiple sellers of a homogeneous good compete for bidders via auction format, rather than price. Their result suggests that in such an environment, a seller may be able to attract bidders away from competitors by utilizing an English clock auction. However, in the environments we study, the seller need not compete against other sellers for bidders. As such, 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.

[32] Observing a large number of participants in the previous period may affect participation, regardless of the auction format. Note that m_{it-1} does not take into account changes in auction format which occurs three times over the course of the experiment. However, results are robust in terms of direction, statistical significance and magnitude of the coefficients, if we estimate models that drops the preceding period if a different auction format was used.

[33] Table 2 in the online supplement contains results without the lagged number of bidders.

statistically significant, although if we restrict attention to the second half of the experiment, the interactions become significant. As predicted, we find that a higher value increases the probability of entering the auction and that, as the opportunity cost of participation increases, the probability of entry decreases.[34] In regression specification two, we explore whether value affects entry decisions differently according to auction format, and find no evidence for this ($\chi^2 = 0.08$, 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, which suggests that there is still considerable learning during the second half of the experiment.[35] The lagged number of bidders reduces entry. Since we observe over-entry, this may be driven by potential bidders adjusting to the observed entry behavior. Notice that we find no gender effect in entry and the order of treatments played no role in our results.

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. Such self-selection into auctions by risk attitudes is consistent with Palfrey and Pevnitskaya (2008).

4.3 Bidding behavior

The observed differences in revenue across treatment are not explained by entry behavior. Thus, it is important to examine how bidding differs by auction format and information structure.[36]

Table 7 contains summary statistics regarding both predicted and observed bids.[37] Since in English clock auctions the winning bid is not observable, we split between the winning bid and the losing bids for all four treatments. Figure 3 contains kernel estimates of bid deviations by auction format.[38]

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[34] Notice that the magnitude of the marginal effect corresponding to c_{it} is approximately between 3.0 to 3.7 times as large as the marginal effect corresponding to v_{it}. If this is driven by expected payoffs, then one would expect that the return to an incremental increase in c_{it} is approximately three times that of an incremental increase in v_{it}. We find that the average increase in payoffs resulting from an incremental increase in v_{it} is 0.290. This is calculated by taking the average payoff at each possible value, and then taking the average change in payoff resulting from a one unit increase in value.

[35] An interesting avenue of research would be to examine, in the spirit of List and Lucking-Reiley (2002), the entry behavior of experienced market participants relative to neophytes to determine if experienced potential bidders entry less frequently.

[36] Bidding behavior has been studied extensively in the literature. In English clock auctions, bidders tend to bid their values in accordance with theory [see e.g., Coppinger et al. (1980)]. In first-price auctions, however, bidders tend to overbid relative to risk-neutral Nash predictions [see e.g., Kagel and Levin (1993)].

[37] Table 3 in the online supplement breaks down the summary statistics on bidding by the number of bidders in the auction.

[38] For English clock auctions, we are restricted to cases where $m \geq 2$.

Table 7 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	29.53	19.085
	(22.281)	(20.315)	(19.07)	(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)

Table contains means with standard deviations in parentheses of observed and predicted bids of auction participants. Predictions assume that a bidder believes that all other bidders (if any) are bidding according to Nash equilibrium, and that the bidders are best responding to those beliefs. These predicted bids are conditional on the realized c, the realized value of the bidder, and the realized number of bidders (if this is in a treatment where bidders are informed)

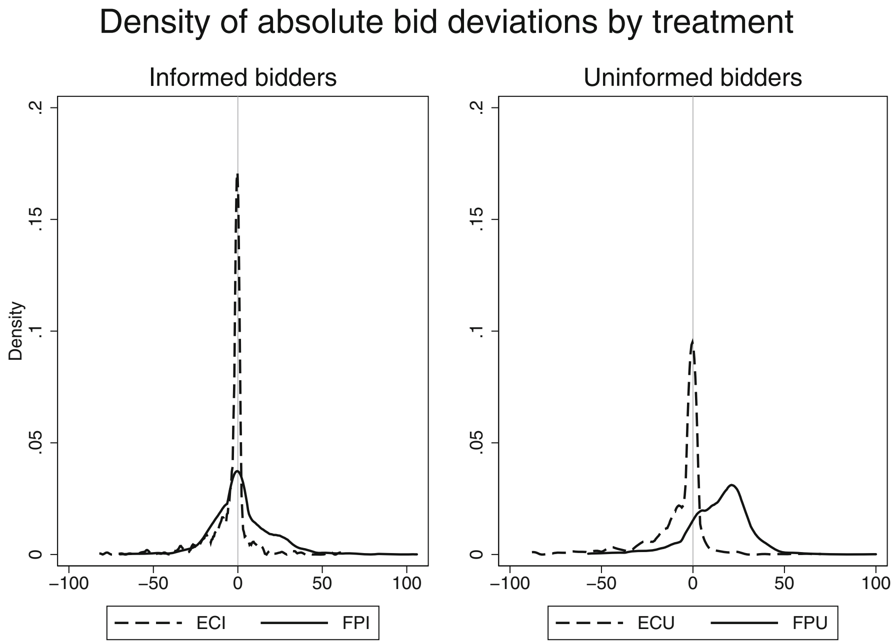

Fig. 3 Kernel estimates of absolute deviations of observed from Nash equilibrium bids

For English clock auctions, observed bids are less than predicted despite the presence of a weakly dominant bidding strategy.[39] This observation holds for both the informed (sign test, $w = 9$, $p = 0.002$) and uninformed (sign test, $w = 10$, $p = 0.001$) case.[40] In addition, information structure matters. Observed bids in English clock auctions are further from Nash predictions when bidders are uninformed: (robust rank order test, $\acute{U} = 4.398$, $p < 0.05$). This means that observed bids in ECU auctions are further below bidder valuations than in ECI auctions.

Since the Nash prediction to bid your value is a weakly dominant strategy in English clock auctions, the observed underbidding is puzzling. However,the magnitude of median bid deviations is typically quite small. For both ECI and ECU auctions the median bid deviation is -1. Further, positive bid deviations were less frequent than negative bid deviations. The end result of this is that the average bid is below Nash predictions, but the magnitude of underbidding is less pronounced than suggested by the non-parametric tests. This is reflected by the high mass of bid deviations around zero in Fig. 3.

Bids in first-price auctions are above predictions for both the informed (sign test, $w = 9$, $p = 0.002$) and uninformed case (sign test, $w = 10$, $p = 0.001$).[41] However this difference is larger for the uninformed case (robust rank order test, $\acute{U} = \textit{undefined}$, $p < 0.01$).[42] As Fig. 3 illustrates, the magnitude of bid deviations is substantially higher in FPU (right panel) than in FPI auctions (left panel). This can account for the revenue differences observed between FPU and FPI.

To further understand this difference in bid deviations, we examine them by number of bidders. Figure 4 illustrates the absolute deviation of bids from predicted bids across all four treatments by the number of observed bidders using boxplots. As the figure illustrates, the magnitude of bid deviations in FPU auctions is substantially higher than in FPI auctions, for any number of participating bidders. 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 $m = 1$. However, notice that overbidding in FPI auctions is typically less than in FPU.[43]

[39] It is unlikely that collusion drives underbidding in English clock auctions, given that subjects are randomly re-matched after each period, and were not able 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.

[40] Regressions which test whether or not bids in English clock auctions correspond to theory are in Table 4 of the online supplement. The estimates are consistent with the results of the non-parametric tests.

[41] Regressions which test whether or not bids in first-price auctions correspond to theory are in Table 5 in the online supplement. The estimates are consistent with the results of the non-parametric tests.

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

[43] Bid deviations in first-price auctions are not explained by optimal response to over-entry by bidders. If this were the case, entrants would reduce their bids relative to the equilibrium bid predictions (which assume equilibrium entry behavior), which is the opposite of what we observe.

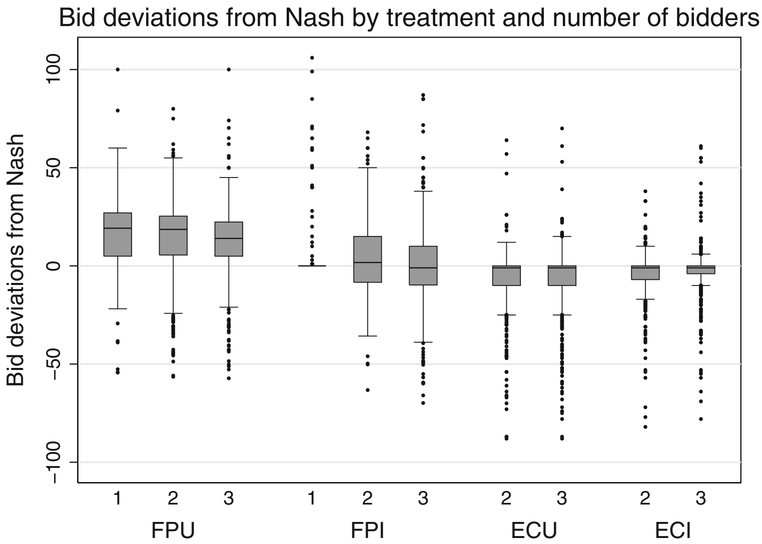

Fig. 4 Absolute deviations of observed from nash equilibrium bids, by treatment and number of bidders

It is also worth pointing out that our data is not consistent with equilibrium predictions in which potential bidders have a homogeneous degree of risk aversion. Such predictions involve an increased equilibrium entry threshold (so that entry is reduced) and an increase in bids relative to the risk neutral equilibrium. Consistent with the literature with a fixed number of bidders, we observe bids in excess of risk-neutral predictions. However, the fact that we also observe over-entry relative to the risk neutral predictions indicates that homogeneous risk aversion cannot explain our data.[44]

To further investigate the determinants of bids conditional on observed entry, we estimate determinants of bidding via OLS, and cluster errors at the session level. Since the strategic considerations between first-price and English clock auctions are quite different, we estimate separate regressions for each format. Further, we report regressions using both all periods and only those from the second half of the experiment. Most of the explanatory variables mirror those of the entry regressions reported in Table 6. In particular, we examine the role of information structure ($Informed_i = 1$ when potential bidder i is in a session with informed bidders, and zero otherwise, with $Uninformed_i = 1 - Informed_i$). We also include the number of bidders in the relevant auction (m_{it}), and interact this with information structure. Of course, when bidders are uninformed, we would expect this to be insignificant. Additionally we consider the role of both a bidders value (v_{it}) and the opportunity cost of entry (c_{it}), and interact these variables with information structure. For first-price auctions, we also include the square of value, to test for non-linearities in bid

[44] Palfrey and Pevnitskaya (2008) consider heterogeneous risk preferences in an environment where bidders learn their value after entry, and finds that heterogeneous risk attitudes are consistent with observed behavior.

Table 8 OLS estimates of bids conditional on observed entry

	First-price		English clock	
	All 48 periods (1)	Last 24 periods (2)	All 48 periods (3)	Last 24 periods (4)
$Informed_i \cdot v_{it}$	0.772***	0.920***	0.748***	0.866***
	(0.046)	(0.067)	(0.014)	(0.017)
$Uninformed_i \cdot v_{it}$	0.686***	0.866***	0.708***	0.827***
	(0.063)	(0.093)	(0.020)	(0.023)
$Informed_i \cdot v_{it}^2$	− 0.001	− 0.002***		
	(0.000)	(0.001)		
$Uninformed_i \cdot v_{it}^2$	0.000	− 0.002*		
	(0.001)	(0.001)		
$Informed_i$	− 39.654***	− 47.173***	− 3.554	− 2.215
	(3.575)	(4.986)	(4.310)	(4.469)
$Informed_i \cdot m_{it}$	7.424***	8.362***	2.201**	1.758*
	(0.414)	(0.552)	(0.690)	(0.729)
$Uninformed_i \cdot m_{it}$	0.062	− 0.692	1.820	1.624
	(0.563)	(0.761)	(0.947)	(0.997)
$Informed_i \cdot c_{it}$	− 0.382***	− 0.447***	0.178**	0.023
	(0.054)	(0.073)	(0.067)	(0.073)
$Uninformed_i \cdot c_{it}$	− 0.473***	− 0.609***	0.123	0.078
	(0.074)	(0.100)	(0.094)	(0.103)
$ln(t+1)$	− 2.458***	− 8.600*	4.074***	12.702***
	(0.351)	(3.356)	(0.459)	(3.377)
$Male_i$	− 2.875*	− 2.758*	0.485	0.598
	(1.127)	(1.226)	(1.064)	(1.058)
$SafeChoices_i$	1.127**	1.202**	0.624	1.126***
	(0.365)	(0.400)	(0.348)	(0.342)
$FirstFormat_i$	− 0.252	1.397	3.259**	2.711
	(1.115)	(1.605)	(1.076)	(1.509)
$RiskOrder_i$	0.632	− 0.189	0.027	− 0.518
	(1.102)	(1.194)	(1.042)	(1.032)
Constant	6.434	25.981*	− 18.089***	− 54.553***
	(3.550)	(11.378)	(4.241)	(14.580)
Observations	3399	1648	1694	819
Clusters	19	19	19	19
R^2	0.569	0.583	0.628	0.762

Standard errors (in parentheses) clustered at the session level

$*p < 0.05$; $**p < 0.01$; $***p < 0.001$

functions. Such non-linearity is not included in the English clock regressions, as bids are predicted to be linear in value. Lastly, we are also interested in how learning ($ln(t+1)$), 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 $FirstFormat_i$) affect bidding behavior. Results are reported in Table 8.[45]

Information structure only affects bidding behavior in first-price auctions, and informed bidders bid less than their uninformed counterparts, controlling for the observed number of bidders. The fact that information structure has no significant effect in English clock auctions is not surprising, given that bidding your value is a weakly dominant strategy.

When bidders are informed, the number of bidders increases bids in both first-price and English clock auctions. While such behavior is predicted in first-price auctions, in English clock auctions, this is surprising. However, note that the magnitude of this effect is relatively small. Not surprisingly, when bidders are not informed, the number of bidders has no effect on bidding.

Value is highly significant and positive in all cases. In first-price auctions the square of value is only significant in the second half of the experiment. The magnitude for English clock auctions is not equal to one, contrary to predictions.

Note that coefficient corresponding to the opportunity cost of entry is expected to have opposite signs in FPU and FPI auctions. When a bidder is informed, a higher cost of entry, holding the number of bidders fixed, increases the equilibrium bid. This is because the values of opposing bidders must exceed the higher entry threshold associated with the higher opportunity cost of entry. However, for an uninformed bidder a higher cost of entry also means that there are likely to be fewer bidders. In equilibrium, the effect of this reduction in the expected number of opposing bidders is large enough that uninformed bidders reduce their bids as a result.[46] Our data does not support such opposing effects. In both cases, a higher entry costs reduces bids.

The effect of bidder experience is negative for first-price auctions, but positive for English clock auctions. This is consistent with bidders moving closer to equilibrium predictions over time.

We also observe that men bid slightly less than women in first-price auctions, controlling for risk preferences, and no corresponding effect in English clock auctions. Similar results are reported in Chen et al. (2013) although the comparison is between first and second-price auctions. Further, increased risk aversion slightly increases bids, which is consistent with the literature. However, as noted above, risk aversion is not able to explain both bidding and entry behavior, and so is not a sufficient explanation for non-equilibrium behavior.

[45] The number of observations for English clock auctions is less than those for first-price auctions since we do not observe the bids of winning bidders in the former.

[46] Note that this does not affect the valuation of the predicted winning bidder, but does effect their equilibrium bids. It is, of course, possible that an increase in the opportunity cost of entry is large enough that the predicted winning bidder chooses not to enter the auction.

5 Conclusion

We empirically address the question of the optimal auction format in a private values 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.

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.

This revenue ranking is not driven by entry decisions. In fact, we find that although entry is higher than predicted by theory in all four treatments, we cannot reject that it 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.

Thus, the revenue ranking found in the bulk of the experimental literature on auctions (with endogenously determined number of bidders) stands: overbidding in first-price auctions results in higher revenue. Further, higher bids in FPU auctions relative to FPI auctions explains the difference in revenue across these two auctions. The result that revenue is higher in first-price auctions when bidders are uninformed is also observed in Dyer et al. (1989), and this result deserves more attention in practical auction design.

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