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 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.

JEL Classifications: D44, D80.

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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 mechanism.[1]

Of course, the revenue generated depends on the behavior of bidders 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 overbidding 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. 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."

Furthermore, revenue may depend on whether or not bidders know the actual number of entrants when formulating their bids. This is especially true when potential bidders hold information regarding the value of the good when they decide to enter the auction, as potential bidders may use this information to select into the auction. This could also affect bidding behavior since if a bidder sees a large number of entrants, she may infer that they value the asset highly and adjust her bidding 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.

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 if she

[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).

wishes to maximize revenue.

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. Rather, more aggressive bidding in first-price auctions raises it's revenue relative to that of English clock auctions, regardless of information structure. In first-price auctions bidding is more aggressive when bidders are uninformed, which results in higher revenue.

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.[3]

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.[4] 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.[5]

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 unable to use their signals to self-select into the auction.[6] The empirical literature has also focused on the case in which bidders only learn their value after entry. Examples include Smith and Levin (2002), Palfrey and Pevnitskaya (2008), and Reiley (2005).[7]

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

[3]For a theoretical analysis of bidding in auctions with an uncertain number of bidders see e.g., Matthews (1987), McAfee and McMillan (1987), 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.

[4]See e.g., Menezes and Monteiro (2000).

[5]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 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).

[6]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). 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).

[7]Roberts and Sweeting (2013) uses 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.

closely the theoretical analysis in Menezes and Monteiro (2000).[8] They provide symmetric equilibria in first and second-price auctions, with a homogeneous and commonly known entry cost.[9] 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.

Extending the theoretical analysis of auctions by endogenizing the entry decisions of potential bidders leaves the predictions of the revenue equivalence theorem intact. Since this theorem does not fare well in laboratory studies, whether or not the relative payoffs of bidders across environments affect entry decisions such that revenue is approximately equalized is of particular interest for practical auction design.

Environments where potential bidders know their value prior to making costly entry decisions into auctions are common. Sellers often distribute information relevant to the valuation of the good being auctioned in such a way that it is available to potential bidders prior to incurring meaningful costs (such as preparing legal paperwork, traveling to the auction house, formulating a bid, etcetera). An interesting example is the Nairobi Coffee Exchange, which sends samples of each lot to each potential bidder ahead of the weekly auction. Another such example is Rapaport Auctions, which holds single stone diamond auctions in which the stones are certified, and catalogs of the available diamonds are made available prior to the auctions. Further, as noted in Sakata and Xu (2010), in US highway procurement auctions the Department of Transportation releases considerable information regarding the project in advance of the auction.

Our results are relevant to environments in which the seller need not compete for bidders against alternative sellers. 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.[10] We are interested in scenarios where the seller is either auctioning a (relatively) unique good, or does not need to compete

[8]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, as bidders who enter have a weakly dominant strategy to bid their valuation, e.g., Campbell (1998), Tan and Yilankaya (2006), Miralles (2008) and Cao and Tian (2008). 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.

[9]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) .

[10]There is also a literature in which multiple sellers of homogeneous goods compete for bidders via auction format rather than price. Theoretical analysis of such an environment can be found in Peters and Severinov (1997) and McAfee (1993). Related experimental analysis can be found in Ivanova-Stenzel and Salmon (2008a), Ivanova-Stenzel and Salmon (2004), Ivanova-Stenzel and Salmon (2008b), and Ivanova-Stenzel and Salmon (2011). Peters and Severinov (2006) analyses the case in which sellers employ second-price auctions, but compete via reserve prices. Anwar et al. (2006) uses data from e-Bay auctions to test the predictions of this model.

for bidders in a meaningful way. Examples of such relevant environments abound, and tend to be large in scale. 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.

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 Section 5 concludes.

2 Theoretical predictions

A set of 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 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 an 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. The price paid is the bid submitted. 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 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.[11] 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 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 $\left(\frac{(n-1)!}{(n-r-1)!r!}\right) F(v_c)^{n-r-1}(1 - F(v_c))^r$.

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 $G_c(v)$.

Since, when $m = 1$ the sole bidder can win with a bid of zero, we need only solve the case where $m \geq 2$. Denote the symmetric equilibrium bidding function as β_m. Assuming that the other $m-1$ bidders bid according to β_m, the expected payoff of bidder i with $v_i \geq v_c$ who bids $b \neq \beta_m(v_i)$, with $b \geq \beta_m(v_c)$, is given by

$$\pi_i^{FPI}(b, v_i|m) = G_c\left(\beta_m^{-1}(b)\right)^{m-1}(v_i - b).$$

[11] 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. As our focus here is on revenue ranking, we leave this for future research.

To maximize this expected payoff, we take the partial derivative with respect to b, set it equal to zero. Since β_m is an equilibrium bid function, the bid which maximizes bidder i's profit must be $b = \beta_m(v_i)$. Rearranging yields the differential equation

$$\frac{d}{dv_i}\beta_m(v_i)\left(G_c(v_i)\right)^{m-1} = (m-1)\left(G_c(v_i)\right)^{m-2}\left(g_c(v_i)\right)(v_i).$$

Integrating both sides and using the initial condition $\beta_m(v_c) = v_c$ yields

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

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 a 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 expected payoff of bidder i with value $v_i \geq v_c$ who bids $b \neq \gamma(v_i)$, such that $0 < b < \gamma(v_c)$ would only obtain the good if there were no other bidders in the auction. In this event, a bid of $b = 0$ would result in a strictly higher expected payoff. The expected payoff of a bidder who bids $b \neq \gamma(v_i)$ such that $b \geq \gamma(v_c)$ is given by

$$\pi_i^{FPU}(b, v_i) = F\left(\gamma^{-1}(b)\right)^{n-1}(v_i - b).$$

Maximizing this expected payoff, we take the partial derivative with respect to b, set it equal to zero and use the fact that, if γ is an equilibrium, then the bid which maximizes bidder i's profit must be $b = \gamma(v_i)$, so that $\gamma^{-1}(b) = v_i$. This leaves us with the differential equation

$$(n-1)\,F(v_i)^{n-2}f(v_i)\frac{1}{\gamma'(v_i)}(v_i - \gamma(v_i)) - F(v_i)^{n-1} = 0.$$

Solving, and using the initial condition $\gamma(v_c) = v_c$, we find that

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

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 with 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.[12] 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.

Note that this implies that the expected revenue of these three environments is simply the expected second highest valuation of those potential bidders with a valuation weakly above v_c. This is given by

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

In the remaining case of FPU auctions, bidders update their beliefs regarding the (unobserved) number of bidders, and are, on average, correct. Expected revenue is simply the highest equilibrium bid of those

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

with values weakly above v_c:

$$\int_{v_c}^{v_H} \left(\frac{\int_{v_c}^{x} (n-1) F(t)^{n-2} f(t) (t) \, dt}{F(x)^{n-1}} \right) nF(x)^{n-1} f(x) \, dx.$$

Simplifying this expression, and changing the order of integration leaves us with

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

Therefore, revenue equivalence holds in all of the environments we study. This revenue equivalence is an important extension of the well-known revenue equivalence result with a fixed and exogenous set of bidders. Importantly, this result suggests that when entry is endogenous, both potential bidders and the auctioneer are indifferent between bidders being informed or not.[13]

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 $\{1, 2, ..., 20\}$. The same realization of c is used for all four groups in the period. In each period the realized value of c is independently determined.[14] 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.

We opted to examine the simple case in which the opportunity cost of entry is the same across potential bidders and common knowledge to simplify the assessment of expected payoffs of entry for potential bidders. This simplicity is an asset to our design, since the experiments reported in Engelbrecht-Wiggans and Katok (2005) suggests that potential bidders may have a difficult time ascertaining the relative payoffs of different auction formats.

If a potential bidder decides not enter the auction, she receives c and must wait until the next period

[13]The expected payoff of bidders in the informed and uninformed cases can be found in Appendix A.

[14]Table 12 in Appendix E contains a breakdown of the number of times in a session each possible realizations of c is used, as well as the corresponding frequencies. Table 13 in Appendix E shows the number of potential bidders we observe in each treatment for each possible realization of c.

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

begins. To mitigate boredom, subjects who choose not to enter the auction automatically get a chance to play tic-tac-toe against the computer.[15] If a potential bidder enters the auction, 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).[16] The same feedback is given to all subjects, regardless of whether or not they entered the auction. 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. At the end of the period, subjects are randomly and anonymously re-matched into different groups. That is, groups are not fixed during the experiment. A total of forty-eight periods are completed.

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.[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

[15]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. This pastime was used in all periods and sessions, so any effect on behavior would be symmetric across treatments.

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

[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 Appendix B.

standard Holt and Laury (2002) measure. In particular, if subjects are uncertainty averse, 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. Our experimental design is summarized in Table 1.[19]

Sessions were run at the Centro Vernon Smith Economía Experimental at the Universidad Francisco Marroquín.[20] 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 seated, subjects were shown video instructions (they were also provided with a hard copy of the instructions).[21] 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

[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] One of the strengths of our design is that, since we varied the order experimental tasks within sessions, we are able to test and control for order effects in our analysis. In the regressions reported in the manuscript, we include a control ($FirstFormat_i$) for which auction format a subject was exposed to first, as well as a control ($RiskOrder_i$) for whether or not the risk task was done at the beginning or at the end of the experiment. Several of the order dummy variables are significant in our regressions, demonstrating the value of varying the order of experimental tasks. We also test for order effects on entry and bidding using the robust rank order test. We find that the order of the risk elicitation task does affect entry (robust rank order test, $\acute{U} = 1.754$, $p < 0.10$), although this result is only marginally significant. All other non-parametric regarding order effects tests are insignificant at conventional levels.

[20] 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.

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

$E\$75$ 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, and their earnings from the risk elicitation task. The average payment was $Q120$, with a minimum of $Q44$ and a maximum of $Q178$.[22]

4 Results

Since the behavior of different subjects 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.[23] In our analysis of revenue, we include auctions in which no bidder entered, so that revenue is zero. We do this because, in practice, a seller may not be able to attract any bidders, and this possibility may determine the optimal choice of auction format or information revelation policy. Table 2 contains summary statistics for both observed and predicted revenue in all four treatments.[24] Since we are averaging at the individual auction level, and including auctions in which no bidder entered, the reported standard deviations are quite high.

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, $w = 10$, $p = 0.001$). This seems to be driven by the observed bidding behavior in the two formats, since entry does not differ by format. We will discuss this in more detail below.

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

Our data clearly rejects the hypothesis of revenue equivalence across auction formats and information structures. In particular, 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 a first-price auctions, and should not inform bidders. Given that English clock and ascending auctions are much more commonly used on auction

[22]To contextualize these amounts, lunch can be purchased on Universidad Francisco Marroquín's campus for $Q25$, and student workers in the library earn $Q24$ an hour.

[23]The results for payoffs mirror those of revenue. In the interest of brevity, we therefore relegate a discussion of these results to Appendix C. A discussion of efficiency is in Appendix D.

[24]Table 14 in Appendix E contains summary statistics broken down by the number of observed bidders.

Table 2: Summary statistics for revenue

Treatment	Observed revenue	Predicted revenue
FPI	41.986	36.194
	(32.548)	(5.963)
FPU	46.651	36.231
	(25.813)	(5.943)
ECI	33.714	36.269
	(30.178)	(5.924)
ECU	30.927	36.231
	(29.176)	(5.943)

Notes: Table contains means with standard deviations in parentheses.

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 Salmon (2004) show that potential bidders prefer English clock to first-price auctions. Thus, all else equal, a seller would be better off choosing an English clock auction. However, 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. As discussed in the introduction, environments such as this tend to be large in scale. Examples include government timber auctions, privatization of state-owned assets, pollution permits, infrastructure procurement auctions, and auctions for highly valued pieces of art.

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 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 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

Table 3: OLS estimates of revenue

	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

Notes: Standard errors (in parentheses) clustered at the session level.
$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

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 revenue is reduced in first-price auctions when bidders are informed. 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. 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. Since the effect of an additional bidder differs across treatments, despite entry being approximately the same across treatments it is worth investigating the extent to which each of these possible explanations drive the observed deviations. To do so, we estimate via OLS the deviations in revenue. Our dependent variable is the standardized 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 standardized 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 standardized difference between the price at which the good is sold (p_j) and the predicted price conditional on m_j (p_j^e). 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. In addition we add controls for order effects ($FirstFormat_j$ and $RiskOrder_j$) and bidder experience ($ln(t+1)$). We run separate regressions 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 standardized excess entry and standardized price deviations conditional on observed entry are positive and significant, for both FPI and FPU auctions. However, the coefficient corresponding to price deviations in FPI auctions is no longer significant when attention as restricted to the second half of the experiment. Further, note that in FPI auctions the magnitude of the coefficient of excess entry is larger than that of the price deviations, especially in the second half. This suggests that excess entry plays a larger role in determining revenue deviations in FPI auctions. Note that this difference is statistically only marginally significant, although it is significant at the 5% level when attention is restricted to the second half. In FPU auctions, note that while excess entry does positively affect revenue deviations, the effect of bid deviations is much larger, and that the corresponding

Table 4: OLS estimates of standardized 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)
$z(m_j - m_j^e)$	0.475***	0.485***	0.111***	0.141**
	(0.018)	(0.030)	(0.015)	(0.033)
$z(p_j - p_j^e)$	0.353***	0.217	0.616***	0.607***
	(0.048)	(0.096)	(0.013)	(0.013)
$ln(t+1)$	-0.075*	0.456	0.029	0.098
	(0.024)	(0.313)	(0.021)	(0.064)
$FirstFormat_j$	0.037	-0.132	-0.031	-0.114*
	(0.049)	(0.115)	(0.024)	(0.036)
$RiskOrder_j$	0.036	0.025	-0.053	-0.075**
	(0.040)	(0.057)	(0.027)	(0.019)
$Constant$	0.310**	-1.364	-0.116	-0.226
	(0.080)	(0.974)	(0.083)	(0.189)
Observations	864	432	960	480
Clusters	9	9	10	10
Adjusted R^2	0.329	0.277	0.787	0.808
Tests of coefficients				
$z(m_j - m_j^e) = z(p_j - p_j^e)$	0.051	0.043	0.000	0.000

Notes: Standard errors (in parentheses) clustered at the session level.
$^*p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$
$z(\cdot)$ indicates the z-score of a variable.
For the tests of coefficients, p-values of a two-sided test of equality are reported.

coefficients are statistically different. As will be discussed below, these results are largely driven by the fact that, on average, bid deviations in FPI auctions are small, and bid deviations in FPU auctions are relatively large.

Table 5 presents the estimates of standardized revenue deviations for English clock auctions. Recall that in this case, the dependent variable is often negative, since we observe lower revenue than expected for English clock auctions on average. For both ECI and ECU auctions the coefficients for both standardized excess entry and standardized price deviations are positive and significant. While the coefficients corresponding to excess entry are larger in all cases, the magnitudes of these differences are small, and the corresponding coefficients are not statistically different.

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)
$z(m_j - m_j^e)$	0.311***	0.278***	0.328***	0.351***
	(0.021)	(0.041)	(0.031)	(0.033)
$z(p_j - p_j^e)$	0.229***	0.192*	0.241***	0.279***
	(0.041)	(0.062)	(0.024)	(0.032)
$ln(t+1)$	0.040	0.968	0.103*	0.862
	(0.036)	(0.451)	(0.036)	(0.452)
$FirstFormat_j$	0.018	0.370*	-0.044	0.286
	(0.040)	(0.143)	(0.061)	(0.132)
$RiskOrder_j$	0.019	-0.021	0.042	-0.011
	(0.036)	(0.031)	(0.045)	(0.057)
$Constant$	-0.288	-4.146	-0.462*	-3.658
	(0.163)	(1.845)	(0.172)	(1.820)
Observations	863	432	960	480
Clusters	9	9	10	10
Adjusted R^2	0.119	0.077	0.151	0.117
Tests of coefficients				
$z(m_j - m_j^e) = z(p_j - p_j^e)$	0.129	0.258	0.106	0.213

Notes: Standard errors (in parentheses) clustered at the session level.
$^{*}p < 0.05,^{**} p < 0.01,^{***} p < 0.001$
$z(\cdot)$ indicates the z-score of a variable.
For the tests of coefficients, p-values of a two-sided test of equality are reported.

4.2 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 6 contains summary statistics regarding observed and predicted entry decisions split into three value regions. In region one, the value of a potential bidder was $v_i < v_{c=1} = 21.54$, so that the equilibrium expected payoff of entering the auction was less than one. Thus, regardless of the realized value of c, entry was not predicted. In region three $v_i > v_{c=20} = 58.48$, so that the equilibrium expected payoff of entering the auction was higher than c for a potential bidder, regardless of the realized c. In region two $v_i \in [v_{c=1}, v_{c=20}]$, so that whether or not entry was predicted depended on the realized c. Note that these three regions do not vary with information structure or auction format.

In region one we see substantial entry across both auction formats and information structures. In region three we see lower entry than predicted by theory in all auction formats and information structures. Notice

Table 6: 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.

however that any deviation from theoretical entry in region two (region three) will result in over-entry (under-entry). However, the magnitude of over-entry in region one is greater than that for under-entry in region three. Likewise, in region two, entry is well above predictions in all treatments. Thus, the over-entry in regions one and two are sufficient to keep overall entry significantly above predictions in all treatments.[25]

The reasons for observed over-entry are unclear and we cannot rule out the possibility that boredom with the pastime for non-entrants is a factor. However, over-entry is not uncommon in experimental set-

[25]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 6 in Appendix E illustrates this.

tings (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. Lastly, it is important to note that, despite the observed over-entry, bidders earn more than c, on average, in all treatments except FPU auctions.

Figure 1 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.[26] Notice that, for all treatments, observed entry is declining in c, indicating that as the opportunity cost of entry increases, entry into the auction declines. Interestingly, entry does not differ substantially between auction formats or information structures. 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.). These results are robust to restricting attention to region two, in which entry is predicted to depend on the realized value and c.

The implications of the entry equivalence we observe is striking. In particular, we find that that neither the choice of auction format nor the choice of information revelation policy will attract more bidders. Note however that our experimental design has low power to evaluate entry, because we cannot observe the entry thresholds, only entry decisions for a given value and outside option.[28] 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.[29]

[26] Since potential bidders know both c and their value when they make entry decisions, both of these variables are of interest. Figure 1 illustrates average entry by c. Figure 5 in Appendix E illustrates average entry by value. Probit regressions reported in Table 7 examine the effect of both c and value on entry, all else constant.

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

[28] Aycinena et al. (2016) uses a Becker-DeGroot-Marschack mechanism to directly elicit threshold entry strategies.

[29] 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. This is perhaps why English auctions (or very similar formats) are predominantly used on auction websites such as e-bay. 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.

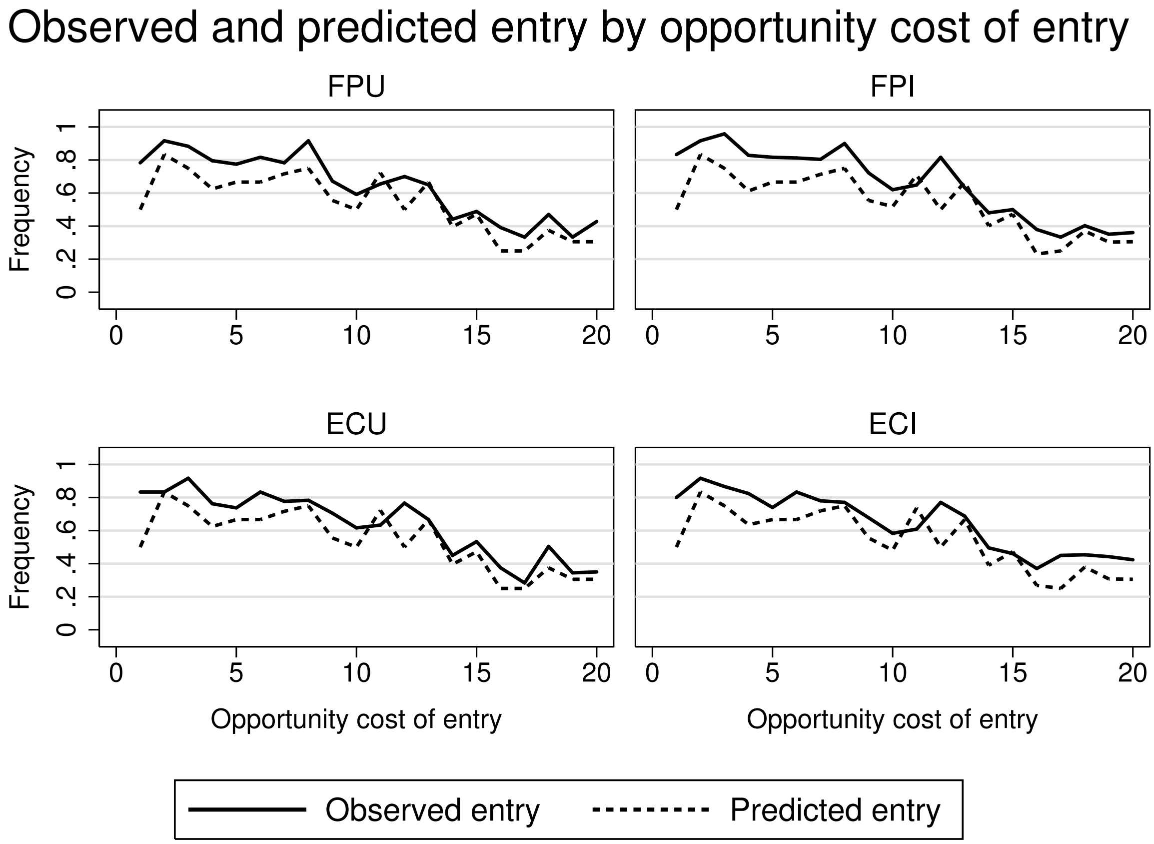

Figure 1: Observed entry relative to theory

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) into 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 that the high-low divide reported in Ivanova-Stenzel and Salmon (2011) is present in the environment we study.

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 $Informed_i$. Regression results are presented in Table 7, with three alternative specifications.[30]

Notice that, consistent with the non-parametric tests, the coefficients on the auction format and the information structure interactions with auction format are not 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.[31] 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.[32] 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 has also been observed in a different environment 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.

[30]Table 15 in Appendix E contains results without the lagged number of bidders.

[31]Notice that the magnitude of the marginal effect corresponding to c_{it} is approximately three 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.

[32]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.

Table 7: 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	10716	10716	5472
Clusters	19	19	19
Log Likelihood	-4889.182	-4888.754	-2291.386
Pseudo R^2	0.313	0.313	0.377

Notes: Standard errors (in parentheses) clustered at the session level.
$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

4.3 Bidding behavior

Bidding behavior in auctions has been studied extensively in the literature. In English clock auctions, bidders tend to bid their values in accordance with theory.[33] In first-price auctions, however, bidders tend to overbid relative to risk-neutral Nash predictions (Kagel and Levin, 1993). A variety of hypotheses have been proposed to explain this overbidding including risk aversion (Cox et al., 1983, 1988), a non-monetary joy of winning (Cox et al., 1992; Holt and Sherman, 1994), regret aversion (Engelbrecht-Wiggans and Katok, 2007; Filiz-Ozbay and Ozbay, 2007; Engelbrecht-Wiggans and Katok, 2009), quantal response equilibrium (Goeree et al., 2002), and a level-k model of bidding (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. However, the addition of endogenous entry, and the predictions of the aforementioned hypotheses in this initial stage, does offer some valuable insight into which of these hypotheses could organize our data.

Figure 2 illustrates the absolute deviation of bids from predicted bids across all four treatments by the number of observed bidders using boxplots. Notice that in English clock auctions we exclude auctions with a single bidder. This is because the auction ends automatically at a price of zero in this case. Note also that in English clock auctions the bid of the winning bidder is not observed. 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 losing bids for all four treatments.

Bids in first-price auctions are above predictions for both the informed (sign test, $w = 9$, $p = 0.002$) and uninformed case (sign test, $w = 10$, $p = 0.001$).[34] However this difference is larger for the uninformed case (robust rank order test, $\acute{U} = undefined$, $p < 0.01$).[35] As Figure 2 illustrates, the magnitude of bid deviations in FPU auctions is substantially higher than in FPI auctions. 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 uncommon and lower than in FPU. Note also that overbidding in FPI auctions is much closer to zero than in FPU auctions.

[33] See e.g., Coppinger et al. (1980), who find that prices are approximately equal to the second highest value in English clock auctions.

[34] Regressions which test whether or not bids in first-price auctions correspond to theory are in Table 18 in Appendix E. The estimates are consistent with the results of the non-parametric tests.

[35] 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.

One possible explanation of the bid deviations in first-price auctions is that bidders are simply responding optimally to the over-entry in the first stage of the game. However, if this were the case, they would reduce their bids relative to the equilibrium bid predictions (which assume equilibrium entry behavior), which is the opposite of what we observe.

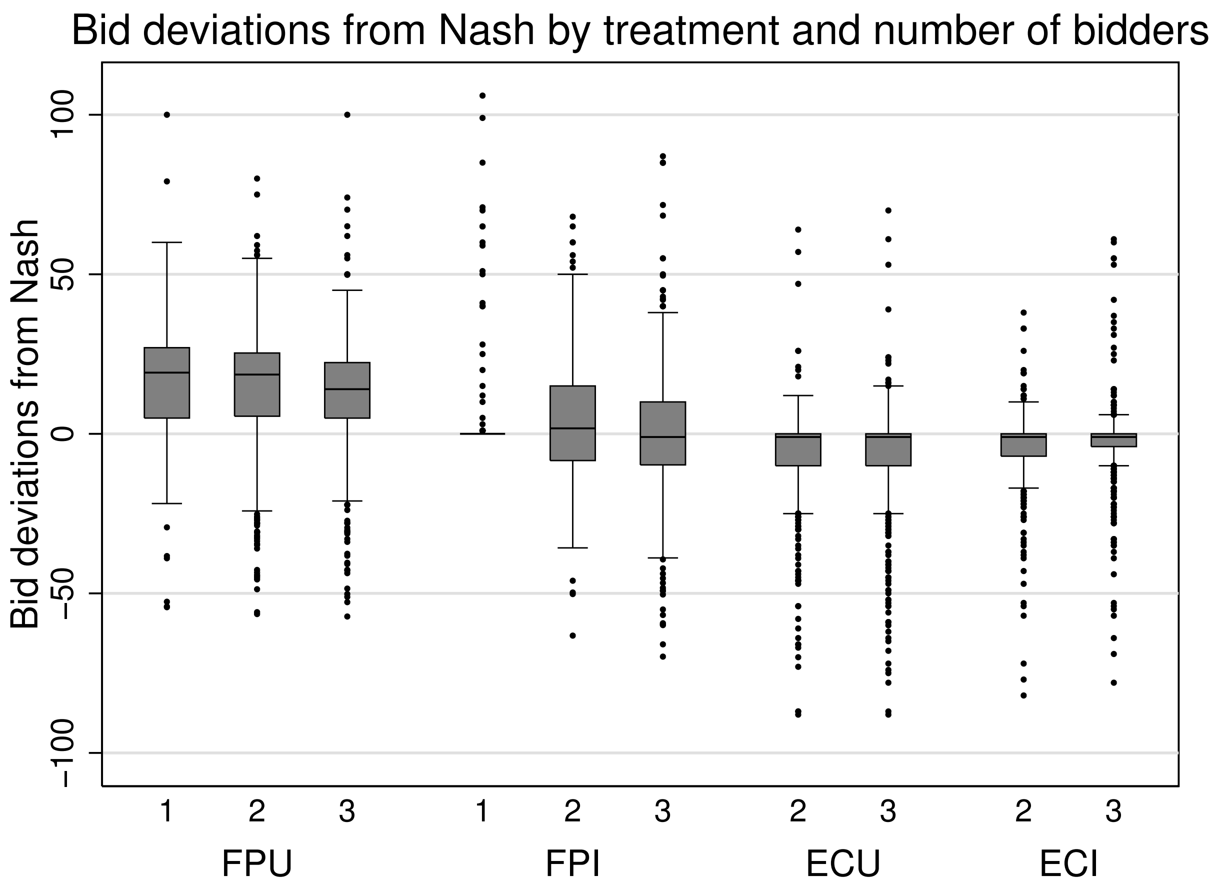

Figure 2: Absolute bid deviations from Nash predictions by treatment and number of bidders.

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.

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, $w = 9, p = 0.002$)

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	29.53	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)

Notes: Table contains means with standard deviations in parentheses.

and uninformed (sign test, $w = 10$, $p = 0.001$) case.[36] In addition, information structure matters. Observed bids in English clock auctions are further from Nash predictions when bidders are uninformed: (robust rank order test, $\acute{U} = 4.398$, $p < 0.05$).[37] In this case this means that observed bids in ECU auctions are further below bidder valuations than in ECI auctions. It is unlikely that collusion drives observed bidding behavior in English clock auctions, 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.

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, as illustrated in Figure 2, that the median level of bid deviations is close to zero (for both ECI and ECU auctions, the median bid deviation is -1.), and that the magnitude of bid deviations is typically quite small. 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 underbidding is less pronounced than suggested by the non-parametric tests. This is shown in Figure 3 which contains kernel estimates of bid deviations by auction format.

If potential bidders had a non-monetary joy of winning, entry and bidding in first-price auctions would

[36]Regressions which test whether or not bids in English clock auctions correspond to theory are in Table 19 in Appendix E. The estimates are consistent with the results of the non-parametric tests.

[37]Referring to Table 8, note that losing bidders in ECU auctions are abandoning the auction sooner than losing bidders in ECI auctions. One possibility is that bidders in English clock auctions abandon the auction early if they don't expect to win. If when a bidder believes she faces more bidders she gives up hope of winning and abandons the auction earlier, a ECI bidder who faced two other bidders may abandon the auction earlier than a ECI bidder who knew she faced one other bidder. Further, if ECU bidders who face only one bidder over-estimate the number of opposing bidders, they may abandon the auction earlier. This could be a potential mechanism for why information reduces revenue in English clock auctions. Table 17 in Appendix E breaks down bids by the number of bidders. Note that in both ECI and ECU auctions losing bids are closer to equilibrium when there are three bidders. As such, this hypothesis is unlikely. This is further illustrated in Figure 2.

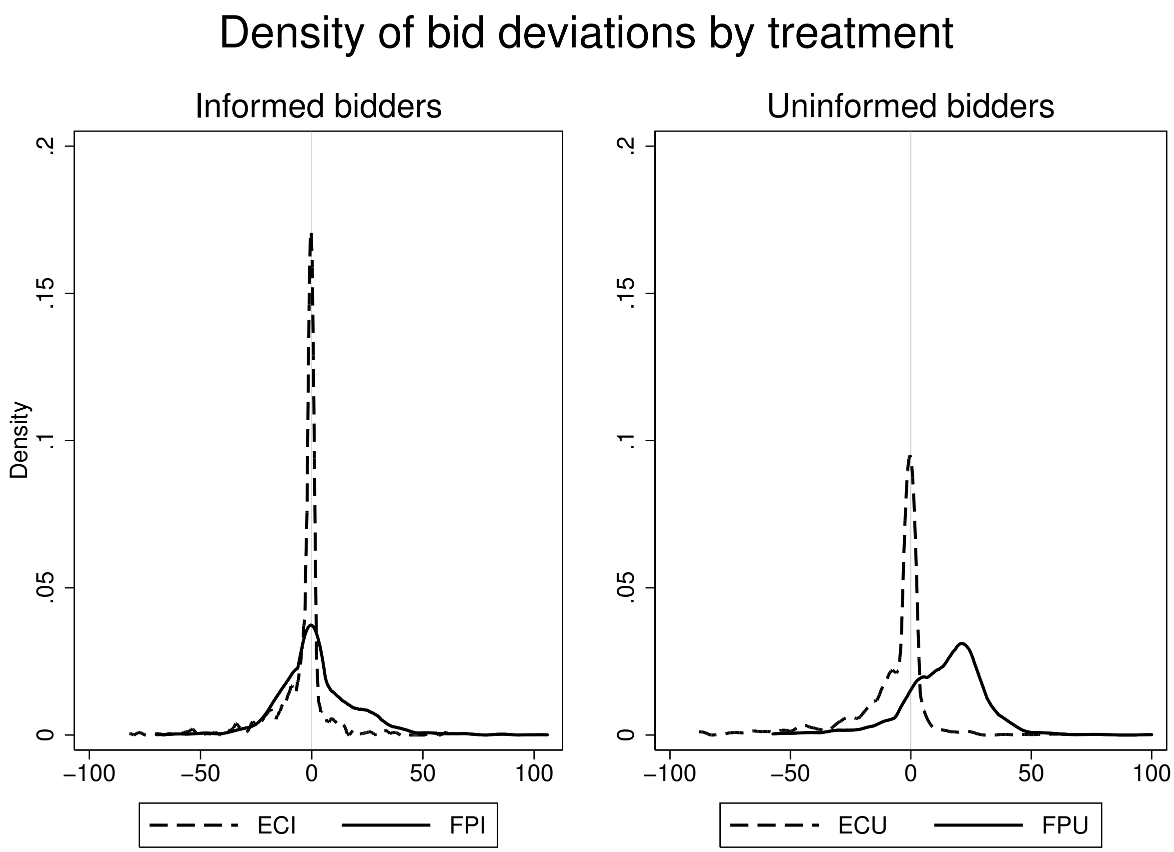

Figure 3: Kernel estimates of bid deviations.

exceed predictions, which is consistent with our observations. However, the same would be true for English clock auctions. Since we do not observe over-bidding in English clock auctions, this explanation also fails to explain our data. This is especially true since we vary the auction format on a within-subject basis, so that we observe bidding behavior of the same participants in both auction formats.[38]

To further investigate the determinants of bids conditional on observed entry, we estimate bids 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 7. 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

[38]While it is beyond the scope of the current paper, our data suggests that investigating quantal response equilibrium, cognitive hierarchy models, or truncated quantal response equilibrium (Rogers et al., 2009) in such environments would be promising avenues for future research.

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 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 9. Note that 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.

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.

Interestingly, 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. One possible explanation for this is that, since we do not observe the bids of winning bidders, the observed bids tend to be from those with relatively low values. Such bidders may be entering the auction in the hope that they are the only entrant, at which point they would win the auction at a bid of zero. When this does not occur, believing that they are unlikely to win the auction, they may choose to simply abandon the auction.

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.[39] Our data does not support such opposing effects. In both cases, a higher entry costs reduces bids. One possible explanation for the fact that informed bidders do not increase their bids is that bidders are falling victim to the sunk cost fallacy. As c_{it} goes up, they have sacrificed more to participate, and may be unwilling to bid aggressively as this would reduce their earnings conditional on winning the auction relative to the sunk c_{it}. However, note that we observe the opposite sign for informed bidders in English clock auctions (although this is not significant in the second half of the experiment).

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. It would be interesting to observe whether this trend continues as additional experience is acquired. This is one of the extensions explored in Aycinena et al. (2016), as all participants in these experiments previously participated in sessions for the current paper.

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.

[39]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.

Table 9: OLS estimates of bids conditional on observed entry

	First-price		English clock	
	All 48 periods	Last 24 periods	All 48 periods	Last 24 periods
	(1)	(2)	(3)	(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

Notes: Standard errors (in parentheses) clustered at the session level.
$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

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.

When the number of bidders is exogenous revenue in first-price auctions is significantly higher than in English clock auctions, and as a result bidder payoffs are higher in the latter. Consequently, there is reason to suspect that when entry is endogenous potential bidders would be more likely to enter an English clock auction, such that revenue between the two would be approximately equal. Indeed, this is what Ivanova-Stenzel and Salmon (2008a) finds when the two auction formats compete head-to-head for the same set of potential bidders so that an additional bidder for an English clock auction is necessarily one less bidder for the first-price auction. In practice, this result is relevant to cases in which multiple sellers of homogeneous goods compete for bidders using auction format, as on eBay.com. We are interested in environments in which the seller need not compete for bidders directly against different auction formats with similar goods, but for whom the choice of auction format and information structure may affect the generated revenue via the entry decisions and bidding behavior. Examples of such environments include government auctions of natural resources, infrastructure procurement auctions, auctions for pollution permits, auctions to sell state owned assets, and art auctions among others.

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. 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. Note that the result that revenue is higher in first-price auctions when bidders are uninformed is also observed in Dyer et al. (1989).

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.[40] These results suggest a need for further research.

In addition to the contribution to practical auction design, our paper contributes 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. As such, we are not able to observe the exact entry threshold employed by potential bidders.

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A Equilibrium payoffs and revenue

We know that threshold entry, in all four environments we study must satisfy $c = v_c F(v_c)^{n-1}$.

A.1 FPI auctions

The equilibrium bid function when $m \geq 2$ is given by

$$\beta_m(v_i) = \frac{1}{\left(\frac{F(v_i)-F(v_c)}{1-F(v_c)}\right)^{m-1}} \int_{v_c}^{v_i} (m-1)\left(\frac{F(t)-F(v_c)}{1-F(v_c)}\right)^{m-2}\left(\frac{f(t)}{1-F(v_c)}\right)(t)\,dt$$

for $m \geq 2$. Integrating by parts and simplifying yields

$$\beta_m(v_i) = v_i - \frac{\int_{v_c}^{v_i}(F(t)-F(v_c))^{m-1}\,dt}{(F(v_i)-F(v_c))^{m-1}}.$$

Notice that if $m = 1$, the sole bidder can obtain the good with a bid of zero. Plugging the equilibrium bid function into the payoff function shows that the equilibrium payoff of a bidder with value $v_i \geq v_c$ and $m > 1$ is given by

$$\pi_i^{FPI}(\beta_m(v_i), v_i|m) = \int_{v_c}^{v_i}\left(\frac{F(t)-F(v_c)}{1-F(v_c)}\right)^{m-1} dt.$$

The expected payoff of entering the auction for a potential bidder who observes an opportunity cost of c, and has value $v_i \geq v_c$ is

$$\pi_i^{FPI}(\beta_m(v_i), v_i) = v_i F(v_c)^{n-1} + \sum_{m=2}^{n}\left(\frac{(n-1)!}{(n-m)!(m-1)!}\right)(v_i - \beta_m(v_i))(F(v_i)-F(v_c))^{m-1} F(v_c)^{n-m}.$$

Plugging in the equilibrium bid function leaves us with

$$\pi_i^{FPI}(\beta_m(v_i), v_i) = v_i F(v_c)^{n-1} + \sum_{m=2}^{n}\left(\frac{(n-1)!}{(n-m)!(m-1)!}\right)\left(\int_{v_c}^{v_i}(F(t)-F(v_c))^{m-1}\,dt\right) F(v_c)^{n-m}.$$

A.2 FPU auctions

The equilibrium bid function is given by

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

Plugging the equilibrium bid function into the expected payoff function and integrating by parts shows that the equilibrium payoff of a bidder with value $v_i \geq v_c$ is given by

$$\pi_i^{FPU}\left(\gamma\left(v_i\right),v_i\right)=v_cF\left(v_c\right)^{n-1}+\int_{v_c}^{v_i}F\left(t\right)^{n-1}dt.$$

Note that this is also the expected payoff of a potential bidder who enters the auction when she observes an opportunity cost of c, and has value $v_i \geq v_c$, since bidders are uninformed.

A.3 ECI and ECU auctions

Whether or not bidders are informed, equilibrium bidding does not change: $\rho\left(v_i\right)=v_i$.

The equilibrium expected payoff of a bidder in an ECI auction with $v_i \geq v_c$ who observes that there are $m > 1$ bidders is given by

$$\pi_i^{ECI}\left(\rho\left(v_i\right),v_i|m\right)=G\left(v_i\right)\left(v_i-\left(\frac{1}{G\left(v_i\right)}\right)\int_{v_c}^{v_i}tg\left(t\right)t\right).$$

Integrating by parts, plugging in G_c, and simplifying yields

$$\pi_i^{ECI}\left(\rho\left(v_i\right),v_i|m\right)=\int_{v_c}^{v_i}\left(\frac{F\left(t\right)-F\left(v_c\right)}{1-F\left(v_c\right)}\right)^{m-1}dt.$$

Thus, the equilibrium expected payoff of entering an ECI auction for a potential bidder with value $v_i \geq v_c$ is given by

$$\pi_i^{ECI}\left(\rho\left(v_i\right),v_i\right)=v_iF\left(v_\theta\right)^{n-1}+\sum_{m=2}^{n}\left(\frac{(n-1)!}{(n-m)!(m-1)!}\right)\left(\int_{v_c}^{v_i}\left(F\left(t\right)-F\left(v_c\right)\right)^{m-1}dt\right)F\left(v_c\right)^{n-m}.$$

Note that the equilibrium expected payoff of a potential bidder in an ECU auction with value $v_i \geq v_c$ is given by

$$\pi_i^{ECU}\left(\rho\left(v_i\right), v_i\right) = v_i F\left(v_c\right)^{n-1} + \int_{v_c}^{v_i}\left(v_i - t\right)\left(n-1\right) F\left(t\right)^{n-2} f\left(t\right) dt.$$

Integrating by parts and simplifying leaves us with

$$\pi_i^{ECU}\left(\rho\left(v_i\right), v_i\right) = v_c F\left(v_c\right)^{n-1} + \int_{v_c}^{v_i} F\left(t\right)^{n-1} dt.$$

B Instructions

This appendix contains the instructions, translated from the original Spanish, when the number of bidders who chose to enter the auction in not revealed to bidders before they place their bids.

SLIDE No.1

Introduction

- The following instructions explain to you how you can earn money. The amount of money that each participant earns may vary considerably depending on the decisions made.
- Participants will interact only through computers. If anyone disobeys the rules, we will terminate the experiment and will ask you to leave without any earnings.

SLIDE No.2

Earnings in the experiment

- The amounts in the experiment are denominated in Experimental Pesos (E$).
- Each participant will start the experiment with a balance of E$75. The profits (or losses) are added (or subtracted) to the balance.
- At the end of the experiment, we will convert your accumulated balance to Quetzales (Q1 = E$7.5), and we will pay it in cash.

SLIDE No.3

Overview

- The experiment will have 48 rounds. In each round, you and 2 other participants will be potential buyers in an auction (in some rounds in Auction A and in other rounds in Auction B). Each participant will decide between getting a FIXED AMOUNT or participating in the auction.

- If you participate, you will not receive the FIXED AMOUNT, but you could earn money if you buy the good at a price lower than what it actually is worth.
- If you do not participate in the action, you will receive the FIXED AMOUNT as payment for not participating.

SLIDE No.4

Value

- Each potential buyer will know his value of the good to be auctioned, but the potential buyer will not know how much the good is valued by the other 2 potential buyers.
- The VALUE of the good for each buyer will be between E$0 and E$100, and it will be determined randomly. (All the values between 0 and 100 have the same probability in being designated).
- The VALUE of each buyer shall be independent from the others; the VALUE is not related (and probably will be different) to the VALUE of the others.

SLIDE No.5

- The earnings you can get (if you purchase the good in the auction) depend on its VALUE, and the Price that you pay for the good. If the Price you pay is lower than its VALUE, you will earn the difference.
- VALUE - Price = Earnings
- If the Price you pay is greater, you will lose money. If you do not buy the good, you will not earn or lose any money.

SLIDE No.6

Fixed Amount

- In each round, participants can choose between receiving the FIXED AMOUNT or participating in the auction.
- At the beginning of each round, a FIXED AMOUNT between E$1 and E$20 will be randomly determined. (All amounts between E$1 and E$20 are equally likely to be designated).

- The FIXED AMOUNT will be the same for all participants. That is, in each round all potential buyers will have the same FIXED AMOUNT, but probably a different VALUE.

SLIDE No.7

Participation Decision

- At the beginning of the round, each potential buyer will see how much the good is worth to him (its VALUE) and the FIXED AMOUNT. Then the potential buyer will decide whether to participate or not in the auction.
- If you choose not to participate, you will receive the FIXED AMOUNT.
- If you choose to participate, you will have the option to earn money if you buy the good at a lower price than its VALUE. You will NOT know how many participants are in the auction before it starts.

SLIDE No.8

Auctions

- In some rounds, the good is sold in Auction A, and in others in Auction B. At the beginning of each round, all participants will know which auction will be used to determine who buys the good. (The type of auction used in each round will be the same for all).

SLIDE No.9

Auction A

- Each potential buyer that participates in the auction will see the starting price of E$0, which will increase by E$1 every 0.65 seconds, and may indicate at each price if he is willing to continue in the auction and buy the good, or if he wishes to abandon the auction and not buy the good.
- The person who has not abandoned the auction after everybody else has will buy the good. The Price which the buyer will pay will be equal to the price at which the last person abandoned the auction.
- If you are the only participant in the auction, you will automatically buy the good at a price of 0.

SLIDE No.10

Example for Auction A

- Example: Suppose that your value is 65. If the other two people abandon the auction at 27 and 60 and you are still in the auction, you will buy the good and pay the price (60). Your profit in this round would be (65 - 60 =) 5.
- If you leave the auction you do not buy the good, and you will have neither earnings nor losses.

SLIDE No.11

Auction B

- Each potential buyer that participates in the auction will make an Price Offer.
- The person that submits the highest Price Offer will buy the good. (In case of a tie between two or more offers, the buyer will be determined randomly). The buyer will pay the Price equal to his Offer.
- If you are the only participant in the auction, you will buy the good with any offer you submit, even with an offer of 0. However, you will NOT know if you are the only participant in the auction; you will not know if there are 0, 1 or 2 other participants besides yourself).

SLIDE No.12

Example for Auction B

- Example: Suppose that your value is 65. If your offer is 61 and the other participants submit offers of 28 and 59, you will buy the good and pay the price (61). Your profit in this round would be (65 - 61 =) 4.
- If your offer is not the highest one, you will not buy the good, and you will have neither earnings nor losses.

SLIDE No.13

Earnings in the Auction

- The earnings of the buyer is the difference between the VALUE and the Price:
- VALUE - Price = Earnings.
- Note that you will lose money if you buy the good at a Price higher than its VALUE.
- Those who do not buy the good will have earnings of 0.

SLIDE No.14

Not Participating in the Auction

- If you choose not to participate you will obtain the FIXED AMOUNT.
- While the auction is being held, you can automatically make use of a pastime: Tic-tac-toe.
- You will play against the computer and you will win if you can place 3 of the symbols (X) in a straight line (horizontal, vertical or diagonal).
- Your results in this pastime will not affect your earnings.

SLIDE No.15

Rounds

- The experiment will have 48 rounds. In each round, the participants will be randomly reassigned in groups of 3; that is, you will NOT be participating with the same people in all rounds.

SLIDE No.16

Summary

- The experiment consists of a series of rounds, where you and other 2 people will be potential buyers of a good. Before each round, everyone will know the auction being used to determine who will buy the good (Auction A or Auction B). In each round, you will decide:
    1. If you will participate or not.
    2. If you decide to participate, you will have to determine the price that you are willing to pay or offer.

SLIDE No.17

Summary

- If you decide not participate in the auction, you will obtain the FIXED AMOUNT.
- If you participate in the auction, you can earn money by buying the good at a price lower than its value.
- Earnings (if you buy the good) = VALUE - Price.

- Earnings (if you do not buy the good)=E$0.
- Earnings (if you do not participate) = FIXED AMOUNT.

Once the participants finish watching the video which contains the instructions, they are asked to answer the following questions to ensure understanding:

1. Suppose that in a round is the VALUE AMOUNT FIXED 50 and is 14. How much is the FIXED AMOUNT VALUE and for 2 other potential bidders in that round?
2. Suppose that in a period your VALUE is 22 and the FIXED AMOUNT is 6. You buy the good and the price is 38. What are your earnings in this round?
3. Suppose your VALUE in a round is 78 and the FIXED AMOUNT is 12. You do not participate in the auction, and the price is 60. What are your earnings?
4. Suppose your VALUE in a round is 47 and the FIXED AMOUNT is 7. You participate in the auction, the price is 60, but you do not buy the good. What are your earnings?

B.1 Instructions for the risk elicitation task

This appendix contains the instructions, translated from the original Spanish, for the risk elicitation task. The decision sheet provided to subjects can be found in Figure 4.

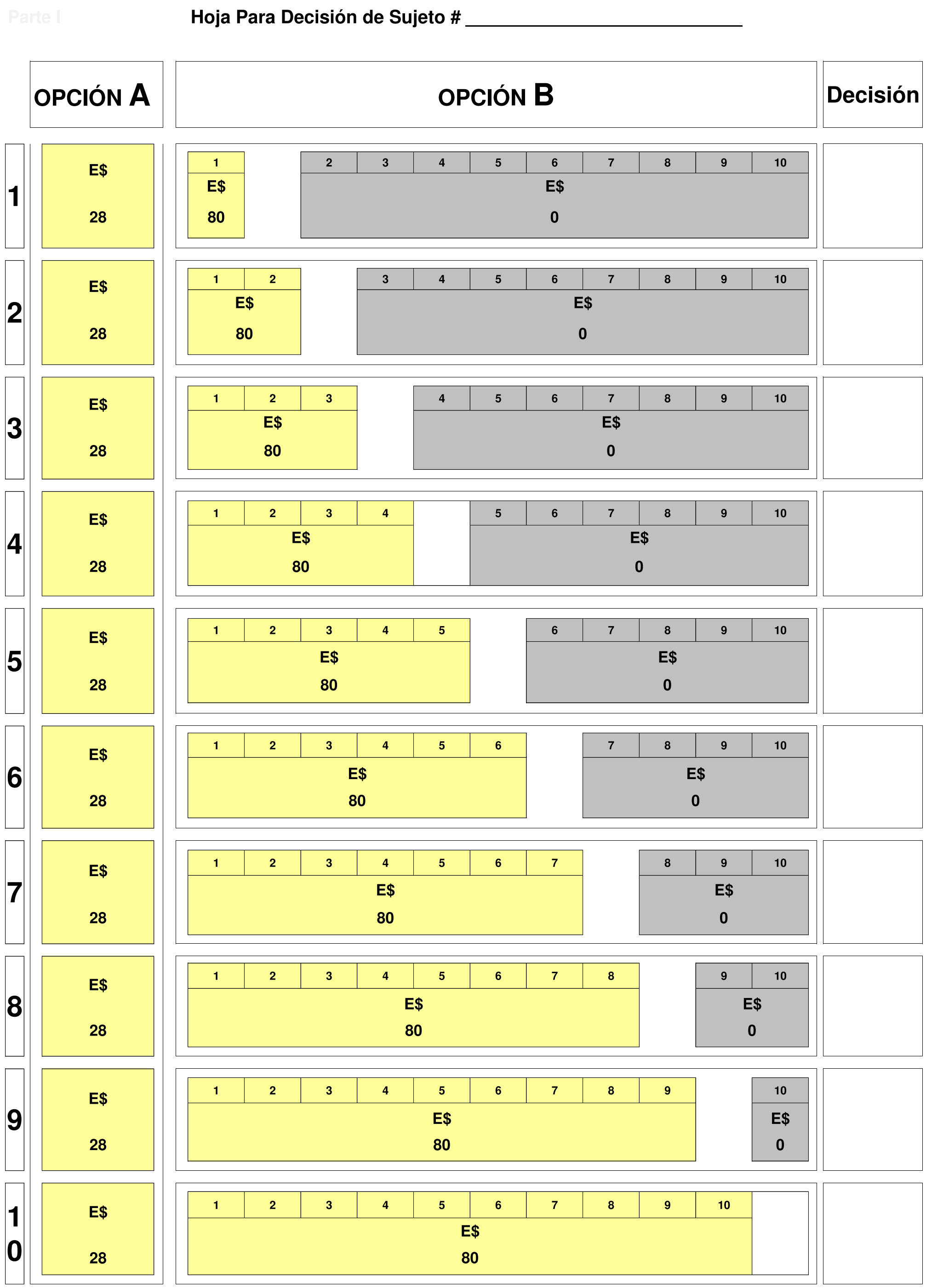
SLIDE No.1

Welcome. You will be participating in a decision-making experiment. These instructions will explain to you how you may earn money. If you have any questions during these instructions, please raise your hand and we will address them in private. As of right now, it is very important not to talk or try to communicate in any way with the other participants. If you disobey the rules, we will have to end the experiment and ask you to leave without any payment.

SLIDE No.2

Your decision sheet shows 10 rows of decisions. Each of them is a selection between two options, Option A and Option B. Option A represents a fixed payment; unlike Option B, whose payment depends on the throw of a 10-sided die.

SLIDE No.3 Now, please look at the first row at the top of the decision sheet. Option A pays $E\$28.00$. Option B pays $E\$80.00$ if the die lands on the number 1, but if the dice lands in any number between 2 and



Parte I Hoja Para Decisión de Sujeto # ____________________

	OPCIÓN A	OPCIÓN B	Decisión
1	E$ 28	1: E$ 80 — 2 3 4 5 6 7 8 9 10: E$ 0	
2	E$ 28	1 2: E$ 80 — 3 4 5 6 7 8 9 10: E$ 0	
3	E$ 28	1 2 3: E$ 80 — 4 5 6 7 8 9 10: E$ 0	
4	E$ 28	1 2 3 4: E$ 80 — 5 6 7 8 9 10: E$ 0	
5	E$ 28	1 2 3 4 5: E$ 80 — 6 7 8 9 10: E$ 0	
6	E$ 28	1 2 3 4 5 6: E$ 80 — 7 8 9 10: E$ 0	
7	E$ 28	1 2 3 4 5 6 7: E$ 80 — 8 9 10: E$ 0	
8	E$ 28	1 2 3 4 5 6 7 8: E$ 80 — 9 10: E$ 0	
9	E$ 28	1 2 3 4 5 6 7 8 9: E$ 80 — 10: E$ 0	
10	E$ 28	1 2 3 4 5 6 7 8 9 10: E$ 80	

Figure 4: Decision sheet used in the risk elicitation task

10 it pays $E\$0.00$. The other decisions are similar, except that as you move down the table, the probability of the higher payment for Option B increases. In fact, for row 10, the last one, the option pays $E\$80.00$ with certainty so that you will have to choose between $E\$28.00$ and $E\$80.00$. Only one of the 10 rows determines your earnings. You will choose one option for each of the 10 rows and write it in the right

column.

SLIDE No.4

After you have made all your selections, we will throw the 10-sided die to select the row that will determine your earnings. (Obviously, each decision row has the same probability of being chosen.)

SLIDE No.5

If for the decision row that will determine your earnings you chose option A, you will earn $E\$28.00$. If for that row you chose option B, we will throw the die a second time to determine your earnings. Remember you have to choose an option for each decision row. Now, please write your name and student ID number on the decision sheet.

C Results for payoffs

As mentioned in the results section, 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, 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.). Since we see both overbidding and over-entry in first-price auctions, this is not surprising. In English clock auctions, the reduction in payoffs resulting from over-entry is offset by the slight reduction in bidding. One might expect that higher payoffs in English clock auctions would result in higher entry such that payoffs (and consequently revenue) are equalized between the two formats. However, recall that, even when we restrict attention to the second half of the experiment, there is no difference in entry behavior. This suggests that either potential bidders have a difficult time discerning the differences in expected payoffs between the formats, or that their entry decisions are not solely driven by financial considerations. To analyze this

Table 10: 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	11.913	12.017	2.431	4.835
	(22.943)	(22.406)	(21.896)	(8.455)
FPU	9.574	17.178	-0.075	4.886
	(15.409)	(11.042)	(15.248)	(8.398)
ECI	17.231	13.345	7.493	4.862
	(27.263)	(22.927)	(26.555)	(8.358)
ECU	18.461	17.141	8.776	4.804
	(27.768)	(10.957)	(27.034)	(8.345)

Notes: Table contains means with standard deviations in parentheses.

question in more detail, we would need cleaner measurements of willingness to pay for each auction format. This extension is considered in Aycinena et al. (2016).

We now restrict attention to payoffs of bidders. Table 10 contains summary statistics of bidder payoffs and predicted bidder payoffs, both total, and net of c. 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, $w = 8$, $p = 0.0547$). This reflects the slight underbidding we observe in English clock auctions. Not surprisingly, 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, $w = 4$, n.s.). This result implies that the reduction in overall payoffs in FPI auctions is due to over-entry, rather than by bidding behavior.

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, if we restrict attention to the second half of the experiment, this is no longer the case. In the remaining treatments, bidder payoffs are significantly higher than c.[41]

[41] The corresponding test statistics are FCI: sign test, $w = 9$, $p = 0.002$; ECU: sign test, $w = 10$, $p = 0.001$; ECI: sign test, $w = 9$, $p = 0.002$.

D Results for 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 consider three notions of efficiency. The first, which we call selection efficiency, is equal to one if the potential bidder with the highest value enters the auction, and is otherwise equal to zero. This is of practical concern in auction design, since whether a particular environment successfully attracts the bidder with the highest value may affect revenue.

We also consider allocative efficiency, which is the percentage of possible surplus actually realized, neglecting efficiency concerns about c. This measure is important, as an auction designer may not be concerned about the efficiency consequences of c, since the cost of entry does not go to the seller.[42] The measure of allocative efficiency that we use is given by

$$\frac{v_{winner}}{v_{max}} \tag{1}$$

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.

Lastly, we call the normalized efficiency measure which accounts for efficiency losses due to potential bidders forgoing c and entering the auction total efficiency. It is measured by

$$\frac{(v_{winner} - mc) - min(v_{min} - nc, 0)}{max\,(v_{max} - c, 0) - min(v_{min} - nc, 0)}. \tag{2}$$

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. Note

[42]This would not be the case if c represented an entry fee for the auction.

further that this efficiency measure is normalized to take into account the observed efficiency relative to the worst possible outcome: the allocation to v_{min} with all potential bidders entering the auction, as long as $v_{max} < nc$ -if $v_{max} > nc$, the worst possible outcome would be that no bidder enters.[43]

Table 11 contains summary statistics regarding selection, allocative and total efficiency. Since we observe over-entry, one might expect selection efficiency to be higher than predicted, since this would reduce the number of cases in which no potential bidder enters the auctions. However, cases in which potential bidders with lower values enter while the potential bidder with the highest value does not are common enough that the reverse is true. This difference is significant in all but FPU auctions.[44] Further, selection efficiency is not affected by information structure in first-price auctions(robust rank order test, $\acute{U} = 0.407$, n.s.) or English clock auctions (robust rank order test, $\acute{U} = -1.020$, n.s.). Likewise, it is not affected by auction format when bidders are informed (sign test, $w = 6$, n.s.) or uninformed (sign test, $w = 5$, n.s.).

Note 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 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. The higher the number of potential bidders, the larger the efficiency losses from entry.

Table 11: Summary statistics for efficiency

Treatment	Observed selection efficiency	Predicted selection efficiency	Observed allocative efficiency	Predicted allocative efficiency	Observed total efficiency	Predicted total efficiency
FPI	0.792	0.855	0.861	0.855	0.830	0.854
	(0.406)	(0.352)	(0.347)	(0.352)	(0.183)	(0.179)
FPU	0.806	0.854	0.879	0.854	0.846	0.852
	(0.395)	(0.353)	(0.327)	(0.353)	(0.170)	(0.182)
ECI	0.814	0.853	0.899	0.853	0.851	0.850
	(0.390)	(0.354)	(0.302)	(0.354)	(0.168)	(0.184)
ECU	0.792	0.854	0.885	0.854	0.850	0.852
	(0.406)	(0.353)	(0.319)	(0.353)	(0.168)	(0.182)

Notes: Table contains means with standard deviations in parentheses.

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

[43]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.

[44]The corresponding test statistics are FPI: sign test, $w = 9$, $p = 0.002$; FPU: sign test, $w = 6$, n.s.; ECI: sign test, $w = 7$, $p = 0.035$; ECU: sign test, $w = 9$, $p = 0.011$.

all cases, this is not statistically significant.[45] This is driven by the excess entry observed in all treatments; in particular, over-entry reduces the number of cases in which there are no entrants. 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.).

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.). When bidders are informed total efficiency is greater in English clock auctions (sign test, $w = 8$, p=0.0195). Yet, when they are uninformed we are unable to reject that total efficiency is equal between the two formats (sign test, $w = 5$, n.s.). We are also 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.[46]

[45]The corresponding test statistics are FPI: sign test, $w = 5$, n.s.; FPU: sign test, $w = 7$, n.s.; ECI: sign test, $w = 8$, n.s.; ECU: sign test, $w = 7$, n.s..

[46]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., ECU: sign test, $w = 5$, n.s..

E Additional tables and figures

Table 12: Frequency and number of observations of each realization of c within each session

Possible realizations of c	Frequency	Number of observations
1	0.021	1
2	0.021	1
3	0.021	1
4	0.083	4
5	0.083	4
6	0.021	1
7	0.104	5
8	0.021	1
9	0.063	3
10	0.042	2
11	0.063	3
12	0.021	1
13	0.021	1
14	0.083	4
15	0.063	3
16	0.042	2
17	0.021	1
18	0.083	4
19	0.063	3
20	0.063	3

Table 13: Number of potential bidders in each treatment for each possible realization of c

Possible realizations of c	FPI	FPU	ECI	ECU
1	48	60	60	60
2	60	60	48	60
3	48	60	60	60
4	204	240	228	240
5	240	240	192	240
6	48	60	60	60
7	276	300	264	300
8	60	60	48	60
9	144	180	180	180
10	108	120	108	120
11	168	180	156	180
12	60	60	48	60
13	60	60	48	60
14	204	240	228	240
15	144	180	180	180
16	108	120	108	120
17	48	60	60	60
18	216	240	216	240
19	168	180	156	180
20	180	180	144	180

Table 14: Summary statistics for revenue

Treatment	Observed revenue	Predicted revenue
$m = 1$		
FPI	5.459	28.665
	(17.802)	(21.056)
FPU	38.857	26.875
	(25.240)	(20.200)
ECI	0.000	27.906
	(0.000)	(20.602)
ECU	0.000	26.792
	(0.000)	(20.225)
$m = 2$		
FPI	57.435	37.607
	(19.706)	(17.334)
FPU	53.962	39.601
	(19.947)	(16.870)
ECI	45.823	39.881
	(22.385)	(16.681)
ECU	42.317	39.738
	(22.815)	(17.188)
$m = 3$		
FPI	65.372	45.466
	(17.729)	(13.802)
FPU	59.083	45.596
	(16.890)	(13.670)
ECI	58.260	44.337
	(19.753)	(14.694)
ECU	55.668	45.454
	(19.267)	(13.368)
$m \in \{0, 1, 2, 3\}$		
FPI	41.986	36.194
	(32.548)	(5.963)
FPU	46.651	36.231
	(25.813)	(5.943)
ECI	33.714	36.269
	(30.178)	(5.924)
ECU	30.927	36.231
	(29.176)	(5.943)

Notes: Table contains means with standard deviations in parentheses. Predicted revenue is the Nash equilibrium revenue of the auctions in which the specified number of bidders is observed. Thus, the predicted number of bidders may not be the same as the observed number of bidders.

Table 15: Probit estimates of determinants of entry without lagged number of bidders (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

Notes: Standard errors (in parentheses) clustered at the session level.
$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

Table 16: 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

Table 17: Summary statistics for bidding conditional on observed entry behavior by number of bidders

Treatment	Observed bids of auction winner	Predicted winning bids	Observed bids of auction losers	Predicted losing bids
One bidder ($m = 1$)				
FPI	5.459	0.000	-	-
	(17.802)	(0.000)		
FPU	38.857	22.948	-	-
	(25.240)	(20.916)		
Two bidders ($m = 2$)				
FPI	57.435	53.165	31.305	28.355
	(19.706)	(22.922)	(18.494)	(28.272)
FPU	53.963	34.305	28.173	17.744
	(19.947)	(19.323)	(19.402)	(19.254)
ECI	-	74.260	45.963	50.805
		(19.622)	(22.274)	(24.075)
ECU	-	73.521	42.317	50.306
		(20.059)	(22.815)	(23.559)
Three bidders ($m = 3$)				
FPI	65.372	63.735	35.573	35.627
	(17.729)	(16.492)	(19.042)	(28.632)
FPU	59.083	41.852	30.384	19.928
	(16.890)	(16.438)	(18.821)	(19.147)
ECI	-	75.533	47.911	50.917
		(19.178)	(22.722)	(22.653)
ECU	-	76.838	44.183	51.411
		(18.320)	(22.960)	(23.112)

Notes: Table contains means with standard deviations in parentheses.
Since an English clock auction ends automatically when there is only one bidder, we exclude this case.

Table 18: Random effects estimates of the responsiveness to bids in first-price auctions to theoretical predictions conditional on observed entry

	FPI		FPU	
	All 48 periods	Last 24 periods	All 48 periods	Last 24 periods
	(1)	(2)	(3)	(4)
Equilibrium bid	0.928***	0.917***	0.667***	0.584***
	(0.021)	(0.019)	(0.014)	(0.040)
m_{it}	-3.231***	-0.316	-1.293*	-0.588
	(0.787)	(0.644)	(0.548)	(0.934)
$ln(t+1)$	-1.110	-6.069	-4.004***	-19.947***
	(0.711)	(5.110)	(0.851)	(5.767)
$Male_i$	-2.902	-2.122	-3.747	-4.852*
	(1.556)	(1.871)	(2.227)	(1.893)
$SafeChoices_i$	0.586	0.604	2.239***	2.094**
	(0.738)	(0.852)	(0.461)	(0.765)
$FirstFormat_i$	0.151	1.856	-0.271	3.779
	(0.789)	(1.829)	(2.191)	(3.111)
$RiskOrder_i$	0.673	-0.738	-1.520	-1.516
	(1.330)	(1.171)	(2.093)	(2.373)
$Constant$	9.828*	18.425	33.915***	87.854***
	(4.722)	(14.136)	(5.614)	(20.251)
Observations	1161	586	1296	645
Clusters	9	9	10	10
R^2 of overall model	0.622	0.747	0.350	0.280

Notes: Standard errors (in parentheses) clustered at the session level.
$^{*}p < 0.05,^{**}p < 0.01,^{***}p < 0.001$

Table 19: Random effects estimates of the responsiveness to bids English clock auctions to theoretical predictions conditional on observed entry

	ECI		ECU	
	All 48 periods	Last 24 periods	All 48 periods	Last 24 periods
	(1)	(2)	(3)	(4)
Equilibrium bid	0.785***	0.611***	0.894***	0.796***
	(0.044)	(0.040)	(0.037)	(0.081)
m_{it}	2.172*	0.461	1.758**	0.519
	(1.000)	(1.093)	(0.668)	(1.616)
$ln(t+1)$	3.686*	7.408***	17.402**	10.411
	(1.495)	(1.553)	(5.342)	(5.972)
$Male_i$	1.202	0.847	1.455	0.611
	(1.852)	(2.224)	(1.651)	(1.943)
$SafeChoices_i$	-0.499	1.243*	0.686	1.821**
	(0.654)	(0.542)	(0.538)	(0.682)
$FirstFormat_i$	3.429*	4.392*	4.069*	0.934
	(1.349)	(1.898)	(1.812)	(2.153)
$RiskOrder_i$	0.316	-0.958	-0.278	-2.193
	(0.845)	(1.843)	(0.723)	(2.584)
$Constant$	-12.869*	-20.348*	-73.667**	-39.513
	(6.124)	(8.110)	(23.890)	(22.363)
Observations	509	559	264	283
Clusters	9	10	9	10
R^2 of overall model	0.453	0.320	0.713	0.487

Notes: Standard errors (in parentheses) clustered at the session level.
$^{*}p < 0.05, ^{**}p < 0.01, ^{***}p < 0.001$

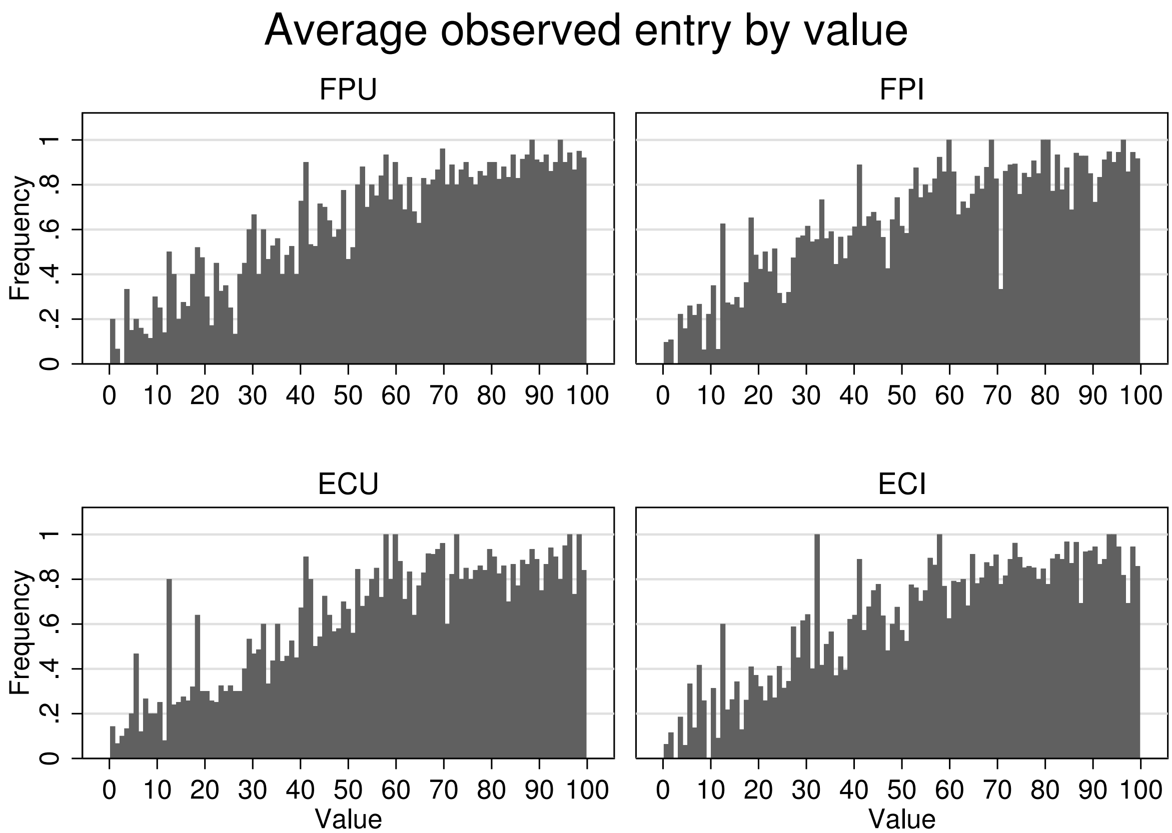


Figure 5: Observed entry by value

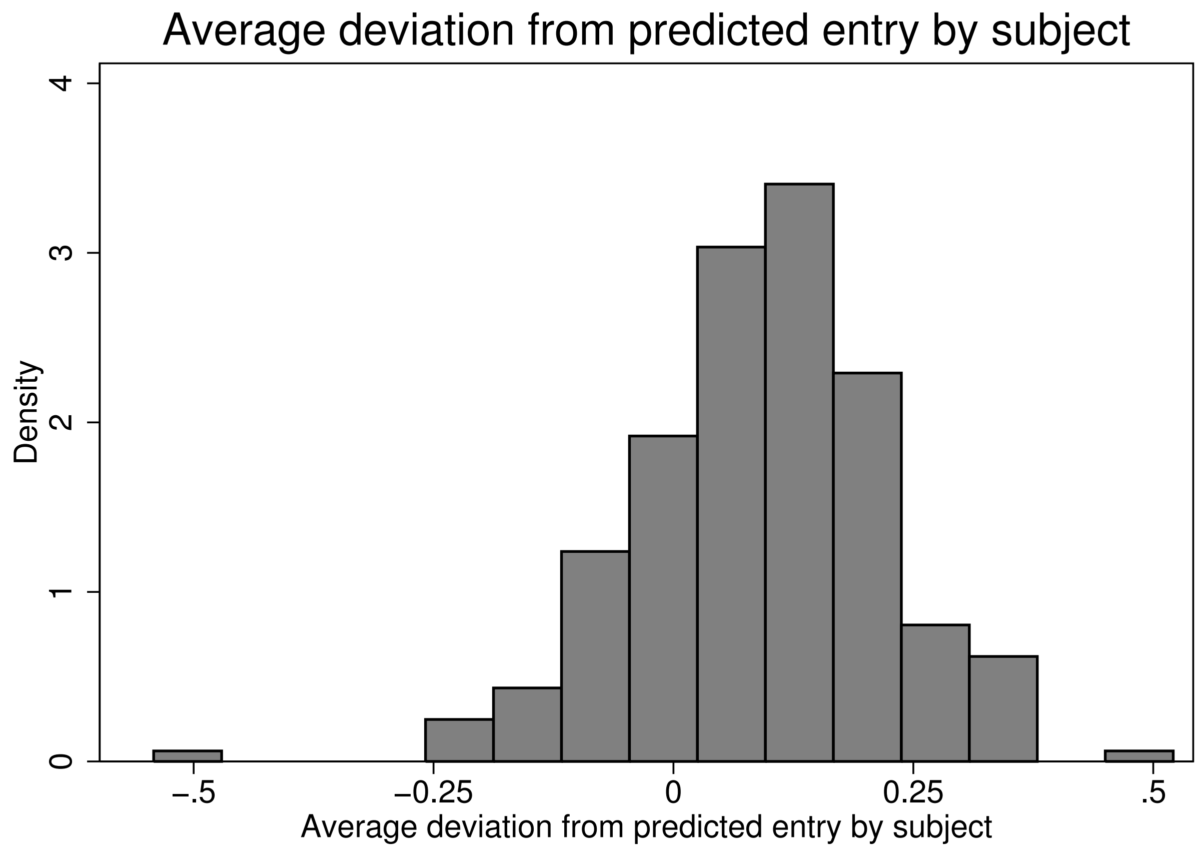


Figure 6: Average deviation from predicted entry by subject. Over-entry is denoted as one, predicted entry as zero, and under-entry as negative one.