Entry into Auctions: An Experimental Analysis

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Abstract

This paper investigates entry decisions into first and second price auctions using an experimental design to extract information on willingness-to-pay to enter (WTE). We find that subjects tend to overpay to enter both auction formats. In particular, if the subjects believe they will be bidding against bidders following the risk-neutral Nash strategy, their WTE is greater than the optimal risk-neutral amount 97% of the time for first-price auctions (FPA) and 90% for second-price auctions (SPA). If they believe that they are bidding against subjects who bid as do the other subjects, they submit a WTE that is too high 92% of the time for FPA and 69% of the time for SPA. We also find, in line with previous studies, significant overbidding in both the FPA and SPA. We then investigate whether introducing risk aversion (RA) or "joy of winning" (JOY) can explain the joint observation of over-entry and overbidding. In particular, using *bid data alone*, we structurally estimate three models, one allowing RA only, one allowing for JOY only and one allowing for both RA and JOY. While a model with JOY alone overestimates WTE, we find that RA alone can explain 38% of WTE but a model with both RA and JOY (where RA is estimated using FPA bids, and JOY is estimated using SPA bids) can explain 65% of WTE. Moreover, JOY appears to explain nearly all of the of the male WTE but only 44% of the female WTE.

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1 Introduction

From a mechanism design perspective, it is important to understand the determinants of entry and their effect on behavior in auctions. This concern may be greater when agents are heterogenous, potentially in multiple dimensions. In many economic contexts, the choice of participating in different market mechanisms is available to individuals interested in purchasing an object. For example, one can buy the object at a posted price in a store or participate in an online auction. Within auctions themselves, there is considerable variety along many dimensions, such as the type of auction mechanism (e.g. first-price, second-price, Dutch, open auction), the number of bidders, the distribution of valuations, the availability of information, the presence of an outside option, etc. The pool of participants in real-life auctions is "selected" and the sample of bidders who choose to participate in a certain auction may have different traits and behave differently than if a random sample of individuals were asked to participate in that auction. While the theoretical auction literature has addressed the endogeneity of entry (see for example Levin and Smith (1994)), only recently have the empirical (see, for example, Athey et al. (2004) or Bajari and Hortaçsu (2003)) and experimental auction literatures begun to confront this issue. One exception in the experimental literature is Lucking-Reiley (2005), which itself points out that the vast majority of the experimental auction literature fixes the number of auction participants. Given that there is considerable individual heterogeneity across dimensions such as risk-aversion, competitiveness, rationality or experience, it is likely that auctions with different characteristics will attract different types of participants, which may change equilibrium predictions on bidding and the seller's expected revenue. This paper presents a series of laboratory experiments aimed at better understanding the determinants of auction entry. We document willingness-to-enter into auctions that greatly exceeds risk neutral expected payoffs from these auctions. We then seek to explain this over-entry phenomenon, considering different types of preferences.[1] We find support for a model that includes "joy of winning" which refers to an extra utility received from winning the object in an auction.

Our experimental design is based on the elicitation of subjects' willingness to enter an auction and their bids upon entry, across different auction types. In each round of the experiment, participants are asked to report the maximum amount they would be willing to pay to enter into that round's auction (WTE), where they will compete with computerized "virtual" bidders for an object. The type of auction format and the amount of information available about the auction varies, as will be explained in detail in the experimental design section. We use the Becker-DeGroot-Marschak procedure to elicit the WTE in an incentive compatible way: after subjects report their maximum WTE, a random entry cost is drawn, and if this cost falls below the stated WTE, the subject enters the auction. If the entry cost is above the WTE, then she stays out and receives a fixed payoff.

We find substantial over-entry into auctions. In a context where they believe they are competing against virtual bidders, subjects are willing to pay "too much" to enter, as often as 97% of the time in first-price auctions (FPA) and 90% of the time in second-price auctions (SPA).We also analyze

[1] Another paper which seeks to further develop the relationship between entry, bidding behavior and individual characteristics is Palfrey and Pevnitskaya (2008).

the WTE by dropping the assumption that bidders believe that they are bidding against virtual bidders and assuming instead that they believe they are actually bidding against bidders who bid like they do. Using the subjects' empirical bid distribution, we show that bidders still are willing to enter too often, and would do better by stating a lower WTE. In fact, their entry can be rationalized against this bid distribution only 8% of the time for FPA and 31% for SPA. Each of these results on over-entry provide scope for a "joy of winning" (JOY) effect to enter the model of auction participation and bidding behavior.

Like other experimental studies, we also find evidence for overbidding in the bid data. In the second-price auction, the well-known dominant strategy is that bidders ought to bid their values regardless of risk attitudes. However, over 50% of the time subjects bid more than their assigned value, and when they overbid, they do so by a large amount: on average they bid 27% more than their valuation. Also, on average, men are more likely to overbid in these auctions than women by 11%. The overbidding results in the SPA suggest a place for JOY in models of bidding behavior as well.

Another piece of evidence for a potential JOY effect comes from a feature of our experiment which allows subjects to select into auctions. Palfrey and Pevnitskaya (2008) show that in models with risk aversion (RA) alone, more selected samples of bidders ought to bid more aggressively, i.e. bid a lower fraction of their valuation, in first price auctions. The intuition is that because the participants that entered the auction (which incorporates a risky payoff) had a higher tolerance for risk, they will behave consistently with this risk-loving profile when they bid by bidding more aggressively. Our data generate the opposite result. When looking at first price auctions, we measure how selected a sample is in multiple ways and show that bidders who had a higher willingness-to-participate in auctions do not bid more aggressively, and, if anything, bid a greater percentage of their valuation. This finding can be rationalized by incorporating JOY at the entry stage, since the subjects' outside option of not entering is receiving a fixed payoff from which any JOY effect will be absent.[2]

As suggested above, to justify our findings on over-entry and overbidding, we present a model that incorporates both JOY and RA in bidders' choice of whether to enter an auction and how they ought to bid following entry. Functional form assumptions on the way JOY enters the model are necessary, but we can incorporate a wide range of functional forms, not just additive (as has been done elsewhere in the literature–see Cooper and Fang (2008)). In practice, we use additive and multiplicative functional forms to include JOY in our model. We then seek to rationalize what we have previously referred to as "over-entry" using the model. We show that including JOY along with RA is vital in matching the observed entry behavior, and that it appears to play a greater role in driving men's entry decisions than women's. We use bidding in SPA to identify a JOY parameter, since the dominant bidding strategy in this auction is to bid one's value regardless of risk attitude. We then use the bidding data in FPA to estimate a RA parameter conditional on JOY. Then, we seek to explain subjects' stated WTE using models that incorporate RA alone, JOY alone, and

[2]Below we explain why our design may generate conflicting results with those in Palfrey and Pevnitskaya (2008).

both RA and JOY. While a model with JOY alone overestimates WTE, we find that RA alone can explain 38% of WTE but a model with both RA and JOY (where RA is estimated using FPA bids, and JOY is estimated using SPA bids) can explain 65% of WTE. Moreover, JOY appears to explain nearly all of the of the male WTE but only 44% of the female WTE.

It is important to note here that while economists have only recently begun to explore joy of winning in auctions, companies using auctions, such as eBay, seem to have long known about this effect. This is evident from commercials and slogans such as eBay's promotional activity touting that "It's better when you win it" in auctions and that their site helps to "Make shopping exciting" and encourages its customers to "Shop victoriously."
footnoteeBay commercials and promotional activity, 2007.Emphasizing the excitement of winning is a strategy often used to lure potential auction participants into entering auctions, rather than buying the item elsewhere at a fixed price, which is very similar to the decision problem faced by the subjects in our experiment.

The organization of the paper is as follows: section 2 reviews the relevant literature, section 3 explains the experimental design, section 4 presents evidence of RA and JOY in the subjects' behavior, section 5 presents our modeling attempt to include and then estimate JOY and RA and section 6 concludes. All tables, figures and derivations appear at the end.

2 Related Literature

The current paper is related to two main strands within the large experimental literature on auctions: studies on the determinants of bidding, and studies on self-selection. Our experiment explores the effects of the number of bidders, the amount and timing of information about the number of bidders and valuation for the object, as well as individual characteristics such as gender and prior experience with auctions in real life in both FPA and SPA contexts, and is one of the first few papers to look at how factors such as these affect self-selection into auctions.

A large body of literature about the FPA has focused on explaining overbidding in FPA (compared to the risk-neutral Nash equilibrium), and factors such as risk-aversion (e.g. Cox et al. (1988)), misjudgments of winning probabilities (Dorsey and Razzolini (2003), Issac and James (2000), Armantier and Treich (2006)), and anticipated regret (Engelbrecht-Wiggans and Katok (2005), Filiz-Ozbay and Ozbay (2007)) have been put forward. Using field data, Lee and Malmendier (2008) find that bidders bid more than the price they could purchase an item for and attribute this effect to a "lack of attention" to the fixed price. Additional utility derived from winning an auction have been proposed as a source of overbidding. Focusing on the "joy of winning" an auction as a potential explanation for the overbidding, Goree et al. (2005), find that in a first price auction the explanation fits the data well, but not as well as a quantal response equilibrium risk-aversion model. Joy of winning has also been proposed by Cooper and Fang (2008) as the source of the common observation of overbidding in SPA. We explore joy of winning jointly with risk-aversion in both FPA and SPA contexts in the current paper.

Regarding the effect of the number of bidders on bidding, early experimental tests were provided by Dyer et al. (1989) and Kagel and Levin (1993), who found quite strong support for the theoretical comparative statics predictions related to changes in the number of bidders in the FPA. A more recent study by Issac et al. (2007) explores bidding in both FPA and SPA when the number of bidders is unknown, and finds that there is significant heterogeneity in bidding in the FPA but not in the SPA. A modest amount of overbidding in the FPA is observed, which is attributable to risk-aversion, but risk-aversion is unable to account for all the observed heterogeneity in bidding. Our paper focuses on studying the effects of uncertainty and compares different informational conditions on bidding, and therefore is related to the more general literature on the effects of information in auctions as well. Two relevant papers in this regard are Andreoni et al. (2007) and Chen et al. (2007). The former analyzes bidding under different amounts of information about rivals' types, and the latter studies the effects of ambiguity about valuation distributions on bidding, with the finding that ambiguity leads to higher bids.

There are significantly fewer papers on endogenous entry and selection, although this area has been attracting considerable attention recently. Papers that model entry have used one of two approaches (see Kagel and Levin (2008)): the first assumes that the entry cost is incurred before the subject learns about her valuation, and the second assumes that the subject knows this information before deciding on entry. Our paper makes this distinction a treatment variable. In the FPA context, Palfrey and Pevnitskaya (2008) study bidding behavior when the number of entrants in an auction is endogenously determined, and the subjects do not know their valuation at the point of entry. The main result is that when the outside option is better, that is, when the sample that ends up entering the auction is more "selected", bidding will be consistent with lower risk-aversion. They also find evidence for excess entry, however, which is difficult to reconcile with the risk-averse bidder model used to explain overbidding. There are also a few papers which have focused on direct comparisons of entry into first-price and ascending auctions. Ivanova-Stenzel and Salmon (2004) directly compare the willingness-to-pay to enter the two types of auctions for subjects who have experience with both formats. They document a strong preference for ascending auctions when the two auctions have same entry cost, but also find that subjects are not willing to pay "enough" to enter into the ascending auction, considering its ex-post profitability relative to the first-price auction. The authors propose a model that posits the same degree of risk-aversion in entry and bidding to explain the data. In a further study (Ivanova-Stenzel and Salmon (2008)), they test and refute loss aversion and the dynamic properties of the ascending auction (as opposed to submitting sealed bids) as other possible explanations. Engelbrecht-Wiggans and Katok (2005), in a series of small experiments, also find that subjects have a preference for the oral ascending auction, but that they underestimate the expected earnings from ascending auctions relative to first-price auctions.

In terms of individual characteristics, gender is an important factor that has been highlighted in some auction studies as well as in studies of related settings that involve competition and/or choice under uncertainty. Chen et al. (2005) find that women bid significantly higher and earn significantly less than men in FPA, consistent with an explanation based on higher risk-aversion. They find, on the other hand, that bidding is not significantly different for women and men in the SPA. Given that gender has been found to affect selection into competitive and risky institutions (e.g. Niederle and Vesterlund (2007)), our experiment, by manipulating the availability of information as well as the auction format, could provide important implications for how auction institutions should be designed, especially when the object sold is gender-targeted. Another relevant characteristic that can affect bidding and entry is real-life bidding experience. One paper that is related to this issue is by Garratt et al. (2008), who test for bidding in SPA using experienced eBay participants, and find that they might bring "incorrect" bidding heuristics from their actual experience over to the laboratory. The current paper elicits information on how familiar subjects are with auction institutions using a post-experiment questionnaire and uses this as a control in the analysis of bidding and entry.

Finally, our paper is tied to a growing literature on issues of selection in experiments more generally. Work on improving our understanding of the role that selection plays in well-known experimental contexts includes but is not limited to: Lazear et al. (2006) (dictator games), Bohnet and Kubler (2005) (prisoner's dilemma), Camerer and Lovallo (1999) (entry games), Eriksson et al. (2006) (tournaments and incentivized contracts) and obviously Palfrey and Pevnitskaya (2008) (auctions).

3 Experimental Design

The experiment is designed to study entry and bidding, using (1) the type of auction and (2) the amount of information available about the type of auction as treatment variables. The auctions, in turn, differ with respect to auction format (FPA and SPA) and the number of bidders. We first start with the basic building blocks of the experiment that is common to all treatments and then describe the treatments in detail.

3.1 Design Features Consistent Across Treatments

Each round of the experiment consists of two stages: the entry stage and the bidding stage. The entry stage elicits subjects' maximum willingness-to-pay (WTE) to enter into the auction, using a Becker-DeGroot-Marschak (BDM) mechanism (Becker et al. (1964)). This mechanism works as follows: at the beginning of a round, subjects are given information about the type of auction in which they will participate during that round. The type of auction and the amount of information provided about the auction are treatment variables, as will be explained below. Subjects are then asked to submit the maximum entry cost they would be willing to incur in order to enter the auction. The actual entry cost is selected by the computer randomly from an interval, and a subject enters the auction only if her maximum WTE is greater than or equal to this randomly chosen entry cost. The subjects know that this is the entry mechanism. With this mechanism, it is optimal for subjects to reveal their true WTE, because the stated WTE does not determine how much the subject actually pays to enter, only whether she enters the auction or not. Subjects are not informed of the actual entry cost, and only know whether they will participate or not.

In the event that the subject does not participate in the auction, she receives a fixed endowment in that round, and the round is over for her. If she participates, she receives the same endowment, plus any profit she makes in the auction after paying the entry cost. In all auctions, the winner is the highest bidder. The winner's profit is equal to her valuation minus her own bid in the FPA, and her valuation minus the second highest bid in the SPA. Before the auction starts, subjects know their valuation and possibly other information about the type of auction (again, how much information about the auction is revealed before bidding starts is a treatment variable). After this, the subject is asked to submit a bid, and the round ends. At the end of each round, all subjects are given information on whether they won or not (if they entered), and their total earnings in that round.

The auctions used in the experiment are all independent private value auctions, where valuations are drawn uniformly from the distribution $[25, 100]$. The entry costs are drawn from [0, 25]. The distribution of entry costs is such that 20% of the time the entry cost would be zero, and 80% of the time it would be a number between 0 and 25 with equal chance.[3] Subjects who end up participating in the auction bid against "virtual bidders", and not against other subjects.[4] In each round, auction participants face either 2 or 4 virtual bidders. The virtual bidders are programmed to bid according to risk-neutral Nash equilibrium (NE) strategies in all the auctions.

3.2 Treatments

For each auction institution (FPA and SPA), we have 8 treatments that differ in the amount and type of uncertainty inherent in the auction. The sources of uncertainty are: (1) the subject's own valuation and (2) the number of bidders in the auction. The uncertainty about one's own valuation is only present at the entry stage: subjects always learn their valuations before bidding and sometimes know their valuation at the point of entry decision as well. For the number of bidders, we consider cases where:

Case 1 the number of competing bidders is known at the entry stage

Case 2 the number of competing bidders is known to be equally likely to be 2 and 4 at the entry stage and the realization is revealed to the subject before bidding

Case 3 the number of competing bidders is known to be equally likely to be 2 and 4, but the realization is not revealed to the subject before bidding

Case 4 the probabilities of 2 or 4 competing bidders are not known at the entry stage and are never revealed. In fact, the actual probabilities are that 2 and 4 bidders are equally likely.[5]

[3]This was done in order to be able to gather enough data on bidding with a non-selected sample. Notice that this manipulation does not affect the incentive-compatibility of the BDM mechanism used to elicit WTE's.

[4]We do this is in order to study the effect of uncertainty about the number of bidders on auction entry in a controlled way.

[5]This case is meant to capture the effect of ambiguity in entry and bidding.

Notice that the labeling of the cases is increasing in the amount of uncertainty subjects face about the number of competing bidders they will face. Thus, a treatment is a defined by two uncertainties: (*See valuation at entry stage, Case j, j=1, 2, 3, 4*).

At Entry Stage:	First Price Auction				Second Price Auction			
Value Known	C1	C2	C3	C4	C1	C2	C3	C4
Value Unknown	C1	C2	C3	C4	C1	C2	C3	C4
N	486	552	503	552	402	353	385	400

The experimental design has both within-subject and between-subject elements: the auction format (first price or second price) is held constant within a session, but in each round within a session, subjects are presented with a randomly-drawn treatment from the 8 treatments.

The experiments were conducted at the California Social Science Experimental Laboratory (CASSEL) at UCLA, using undergraduate students as subjects.[6] A total of five sessions were run, and 69 subjects participated. Three of these were FPA sessions (41 subjects), and 2 were SPA (28 subjects). 35 participants were male, 34 female. Each subject participated in only one session. A session consisted of 60 rounds, except for one session which proceeded exceptionally slowly and only 36 rounds could be completed. Ten of the 60 rounds were randomly picked by the computer to be compensated, and subjects' payoffs were equal to the sum of their payoffs in these selected rounds.[7]

After the instructions were read, participants played 3 practice rounds before starting to play for real rewards. Sessions lasted roughly an hour and a half. We gave the subjects a survey at the end of the experiment, which asked questions about subjects' prior experience with auctions and about their bidding strategies and also collected some demographic information.[8] Earnings in the experiment were denominated in "points". The exchange rate between points and dollars was 0.04. In addition to earnings from the experiment, subjects were paid a show-up fee of $5. Total earnings averaged around $20, and participants were paid in cash, in private, after the experiment ended.

4 A Role for JOY and RA?

This section presents evidence that subjects over-enter into and overbid in auctions, which suggests that incorporating JOY and RA jointly into models of bidding and self-selection can be useful for explaining the observed behavior.

[6] The experiment was computerized using z-tree (Fischbacher (1998)), by Avinash Bhardwaj.

[7] The subjects knew that this would be the payout rule and this was done to prevent wealth effects during the experiment.

[8] The survey questions as well as the instructions for the FPA can be found in the Appendix.

4.1 Over-Entry

The data provide evidence for over-entry, which may be justified by a JOY effect. Recall that each participant knows that if they stay out of the auction they will automatically receive their endowment. However, by entering the auction they have the ability to potentially earn more than this, and the greater a subject's valuation, the greater should be her willingness to enter the auction. To begin our analysis of the rationality of entry, we compare the stated maximum WTE with theoretical benchmarks. In order to do this, we use data on the actual bidding of the individual subject in conjunction with her WTE for that auction.

Assuming that the individual knows how she will bid once she enters, the perceived probability of winning at the point of entry can be inferred using the actual bids, for subjects who end up entering.[9] Using the cdf of the valuation distribution and the bidding strategy of the virtual bidders, this probability is given by the following equations. When the number of bidders (N) is known at the point of entry, in the FPA we have:

$$Pr(win)_N = \begin{cases} Pr(b_i > \frac{N-1}{N}(v) + \frac{v_l}{N}))^{N-1} = F(\frac{Nb_i - v_l}{N-1})\ ^{N-1} \text{ if } \frac{Nb_i - v_l}{N-1} \leq v_h \\ 1 \text{ otherwise.} \end{cases} \tag{1}$$

When the number of bidders is unknown at the point of entry and will never be observed, but its distribution is known (case 3), we have:[10]

$$Pr(win) = \begin{cases} 0.5[\Pr(win)_3)] + 0.5[\Pr(win)_5] \text{ if } \quad \frac{Nb_i - v_l}{N-1} \leq v_h \text{ for all } N \in \{3,5\} \\ 0.5 + [\Pr(win)_5] \quad \text{ if } \frac{3b_i - v_l}{2} > v_h \text{ and } \frac{5b_i - v_l}{4} \leq v_h \\ 1 \text{ otherwise.} \end{cases} \tag{2}$$

Theoretically, when a risk-neutral subject i knows her valuation at the point of entry, her maximum WTE should equal her expected payoff in the auction. Therefore, we can calculate the optimal WTE by:

$$WTE_i = \Pr(win)(v_i - b_i) \tag{3}$$

If we then classify the subjects who are willing to pay more than the optimal WTE as over-entering, we find that subjects over-enter the FPA 97.18% of the time. When we add the observations for the case with ambiguity as well, with the assumption that subjects assign equal chance to the two possible numbers of bidders in this case, this over-enty result does not change.

An important point to note in the above analysis is the assumption of risk-neutrality for the potential entrant. Notice, however, that if the subject is instead risk-averse, she would be more likely to shy away from entry into the auction, which suggests that the actual rate of over-entry may

[9]Notice that this strategy cannot be directly applied to case 2, since the number of bidders is unknown at the point of entry but known at the point of bidding, and therefore actual bids cannot be used to rationalize the quoted maximum entry fee in that particular round for that subject. Cases 3 and 4 do not suffer from this because no new information is revealed prior to bidding.

[10]Notice that these formulas would hold for the case with ambiguity (case 4) also, assuming that under ambiguity, subjects assign a 50% chance to the number of bidders being 2 or 4.

be even higher. The risk-neutral case given above therefore provides a lower bound for over-entry observed in the FPA.

For the SPA, since virtual bidders follow the dominant strategy of bidding own value, the probability of winning with a bid b is equal to

$$F(b)^{N-1} = \left(\frac{b - v_l}{v_h - v_l}\right)^{N-1} \tag{4}$$

Expected payment in the auction for a bidder with valuation v_i who bids b_i is then given by:

$$E(\max(v_{j\neq i}|\, v_i \geq v_j)) = \left(\frac{N-1}{N}\right) b_i + \frac{v_l}{N} \tag{5}$$

Given this, defining over- and under-entry in the same way as we do for FPA, we find that in 90.12% of the cases, subjects overpay to enter auctions.

Having found that in most cases subjects are willing to overpay to enter auctions, we then analyze how much the stated WTE's exceed the theoretical benchmarks we calculate. We find a significant difference here between the two auction institutions: the amount that subjects are willing to overpay, on average, constitutes 29.1% of their valuation in the FPA, as opposed to 17.5% in the SPA (the difference is statistically significant, with p-value < 0.00). Another interesting difference is with respect to gender: while there is no difference in the overpayment propensity across the genders in the SPA (women's average overpayment fraction is 18.8% whereas men's is 16.6%), women's maximum WTE in the FPA imply an overpayment of 32.3% of valuation (as opposed to men's 25%). This gender difference in the FPA is again statistically significant (p-value = 0.011).

A caveat to the previous analysis is that bidders believe they are competing against virtual bidders who are playing NE strategies. Suppose instead that bidders believe that they are competing against bidders who bid as they do. We can again test whether bidders are over-entering by examining the rationality of their WTE when measured against the empirical bid distribution generated by the subjects in the experiment. To perform this analysis, using our nonparametric estimate of $\beta_{g,k}$, we first compute our estimate of the bid a bidder would have made in the event that their WTE was below the realized entry cost. To do so we compute a nonparametric estimate of the bidding function $\beta_{g,k}(v), g \in \{male, female\}$ and $k \in \{FPA, SPA\}$ for each gender in each auction format.[11,12] We then use this function to predict the bid for auctions that the subject was not forced to participate in. That is, let $\widehat{H_{g,k}(b)}$ be the empirical bid distribution pertaining to each gender in each auction format. Then, by simulating S auctions from the relevant bid distribution we can calculate the frequency with which each participant's stated WTE was *ex ante* rational. Table 1 displays the results. Consistent with the findings when the assumption was that participants believed themselves to be competing against virtual bidders, the subjects over-enter. When pooling first-price and second-price auctions, subjects over-enter 84% of the time, but in

[11] Note that we could do this by just using the "free entry" auctions where everyone was allowed to participate.

[12] In practice we use a fifth order polynomial in a bidder's value, conditional on gender and the number of bidders in the auction to estimate $\beta_{g,k}$.

second price auctions, this is less drastic, with participants over-entering only 69% of the time. In first price auctions, however, the over-entry is much more pronounced. Subjects over-enter approximately 90% of the time when they are competing against two other bidders (N=3) and 95% of the time when they know they will compete against four other bidders ($N = 5$).

4.2 Overbidding

In this section we present results on overbidding, which may again be explained by a JOY effect. The first piece of evidence of overbidding comes from our analysis of bidding in second price auctions.

Second price auctions are a clear case where JOY can be isolated because risk attitude does not affect the dominant strategy of bidders. This is because the dominant strategy is for bidders to bid their own value regardless of risk attitude. Therefore, overbidding in this case is defined as a subject bidding more than their assigned valuation. We have 28 subjects who participated in the second price auctions. Table 2 summarizes the bidding data from these sessions. The average bid is greater than the average randomly assigned valuation for the object, with overbidding occurring 53% of the time, and this is statistically significant at the 1% level (p-value of 0.000). In terms of the magnitude of this effect, conditional on overbidding, the size of the overbid is significant. When bidders overbid, they tend to overbid by 27% of their assigned valuation. To investigate further drivers of this overbidding, Table 3 presents results from a probit model of the event of overbidding on various individual characteristics, including gender and experience in previous auctions such as eBay. The table displays estimated coefficients, controls for within-subject correlation in errors, includes period dummies of length five and includes treatment fixed effects where appropriate. It is clear that males are more likely to overbid by approximately 30%. Even this fairly coarse test illustrates the potential for JOY to affect bidding behavior. Also note that the tendency to overbid does not seem to diminish as the experiment progresses, suggesting that the story is not one tied to a misperception of the probability of winning. If it were, we might expect to see this overbidding reduced over time.

To probe more deeply for a JOY effect on bidding behavior in second price auctions, we also investigate bidding determinants. Table 4 displays OLS results of the fraction of a subject's value that she bid as a function of her value and other demographic controls. The table pools all treatments together and includes treatment controls, but each specification was also tested within treatment with no real change to the results. As evident in Table 4, men bid a greater percent of their valuation and across genders this fraction declines with the level of a subject's value. There is also evidence that a subject is less likely to overbid, the more experience she has with bidding on eBay. Other self-proclaimed attributes from the end of experiment survey do not appear to determine bidding behavior. Taking the results from bidding in second price auctions together, there is evidence of overbidding, potentially stemming from JOY, and that this effect may be greater in men than in women.

The next piece of evidence that there may be scope for JOY to enter the model of bidding behavior comes from our analysis of first price auctions. Given that we have data on auctions where there are differences in the strength of selection, an interesting question is how bidding behavior differs according to one's willingness-to-pay to enter into auctions. Palfrey and Pevnitskaya (2008) study a similar question by varying the outside option available to the subjects. We therefore compare bids in the FPA across entry cost, in order to analyze the effects of the strength of the selection. A higher realized entry cost means that the sample will be more selected, since only the bidders who were willing to pay a lot for entering will have entered. Palfrey and Pevnitskaya find that bidders who choose to enter FPA when the outside option is higher are more risk-loving, and therefore bid more aggressively in the auction. This implies that bids will be lower when the sample is more "selected". In our framework, this would correspond to the hypothesis that bidding should be more aggressive when realized entry costs are higher. We test this hypothesis in Table 5.[13]. The first regression (Column 1) regresses bidding as a percent of valuation in the "Palfrey-Pevnitskaya case"[14] on the number of bidders, gender and bidding experience, as well as entry cost. This regression yields a positive and significant effect of the cost of entry, and the effects of gender, number of bidders and their interaction are significant. Thus we see that auctions for which the entry cost draw was higher leads to bidders bidding a greater percentage of their valuation. While this appears to contradict the findings in Palfrey and Pevnitskaya (2008), it is important to note that the subjects in our experiment do not learn the actual entry cost at the time of bidding. Thus, a closer comparison is when we control for the stated maximum willingness-to-pay, and when we do this, we do not find a significant effect of selection on bidding.[15] Controlling for selection through the direct inclusion of each subject's stated maximum willingness-to-pay for the auction does not change the results much since the direction of the effect of selection is opposite to that proposed by existing work, although the effect is not statistically significant (Column 2). In each of the specifications, we now see that men bid a greater percentage of their valuation than women once the selection effect is controlled for. We also see that men respond less to increased competition than women, and that the selection effect has a marginally lower impact on their bidding behavior than on women's.

We now extend this analysis to the other cases. We run similar regressions for all the cases where the number of bidders is ultimately observed before bidding, and control for selection using the entry cost (Columns 3 and 4). We continue to find that more selected samples bid less aggressively (a higher percentage of their valuation), contrary to the existing hypothesis. This is robust to our differing measures of selection. Taken with the first result that bidders overbid in second price auctions, these results of the absence of the "selection" effect lead us to posit that JOY of winning, combined with RA, can play an important role in determining bidding behavior.

There is also evidence in Table 5 that knowing the number of competitors at the entry stage leads to a more conservative bidding strategy, even though the number of bidders are known at the time of bidding. Also, learning there are two, as opposed to four other bidders before one bids,

[13]We calculate robust standard errors, clustered by subject, in all columns

[14]This case corresponds to the configuration where subjects do not observe either their valuation or the number of bidders at the entry stage, but learn both before bidding.

[15]While men tend to bid a greater percentage of their valuation, the effect of a more selected sample is diminished for them.

but after one enters, leads to a less aggressive bidding strategy. This is in contrast to not knowing one's valuation at the time of entry, which has no residual impact on bidding behavior once it is known. Taken as a whole, this may be suggestive of a "spite" motive.[16] One might think that the spite motive is identified by cases where the bidder knows she has a low value before entering, enters anyway and then learns she is competing against four bidders as opposed to two. We can check this by comparing the percent of one's valuation bid when one knows she has a low value but enters anyway in Case 2 when there turn out to be four other bidders as compared to Case 1 when she knew there would be four other bidders at the entry stage. This test is complicated by risk aversion. All else being equal, the chance of facing two bidders in a first price auction should encourage more risk averse bidders to enter the auction than when they knew they would face four bidders. However, this effect would also cause the bidding conditional on learning that there are four bidders to be greater than when it was pre-announced that there would be four bidders. Thus, there are two effects moving bidders to bid a greater percentage of their valuation in this subset of Case 2 as compared to Case 1. However, when comparing the percent of one's value bid in these two events, as is seen in Table 6, we see that bidders do not tend to increase their bid by a statistically significant amount when they learn they are competing against four bidders as opposed to two. Furthermore, the effect doesn't appear to depend on the bidders' holding low values, something implied by the spite motive.

These results on overbidding, taken in conjunction with the results on over-entry, provide further support for including JOY along with RA in models of bidding. It has long been suggested that risk aversion alone may not completely explain the frequently observed tendency to overbid in auctions (Kagel (1995)). In line with this, we now turn towards positing a model that relies on both RA and JOY in order to justify the results presented thus far.

5 Model and Structural Estimation

In this section we augment the standard auction framework to incorporate JOY and RA in a model of entry into, and bidding in, independent private value first price auctions. This is a model of Case 1, where the subjects learn their values prior to entering the auction. In the first stage, the bidder learns her value v, which is drawn from a distribution $F(v)$, and makes a decision about her maximum willingness-to-pay, WTE, in order to enter a first price auction where she will compete against $N-1$ bidders. Then a random number ϕ will be drawn and if $\phi < WTE$, the subject enters the auction and places bid b for the object. The subject knows she will participate against risk neutral bidders who know they are facing $N-1$ bidders all of whom draw their values from $F(v)$. Regardless of whether or not she wins the auction, she pays ϕ out of a budget E. If $\phi > WTE$ (ties happen with zero probability) the subject keeps E. The bidder's von Neumann-Morgenstern utility function is $u(\cdot)$, with $u'(\cdot) > 0$, $u''(\cdot) < 0$ and $u(0) = 0$

We introduce two parameters into the model: risk aversion and joy of winning. Let α be the

[16] See Andreoni et al. (2007) or Cooper and Fang (2008) for example.

risk aversion parameter. Below we work with a parameterized version of $u(\cdot;\alpha)$. Let θ denote a bidder's "joy of winning" such that conditional on winning the object the consumer now enjoys a value $\hat{v} = h(v;\theta)$, with $\frac{\partial h(\cdot)}{\partial v} \geq 0$ for all θ and $\frac{\partial h(\cdot)}{\partial \theta} \geq 0$ for all v.

The equilibrium choices that we are interested in are the subjects' choice of WTE and b, conditional on entry. We begin with the second stage, where the bidder has already entered and is selecting her optimal bid, b^*. At the point of bidding, the bidder views the entry cost as sunk when she chooses her bid b^* so that:

$$b_i^* = \text{argmax}_{b_i}\ u\left(h(v;\theta) - b_i;\alpha\right)\Pr[Win|b_i, N, F(v)] \tag{6}$$

where $\Pr[Win|b_i]$ is the probability that the bidder will win if she submits bid b_i given that she faces $N-1$ other bidders who are playing the risk neutral Nash Equilibrium strategy when values are drawn from $F(v)$. A closed form solution for the optimal bid is derived for the parameters used in the experiment in the Appendix.

At the first stage, the bidder must choose her maximum willingness-to-pay to enter the auction, WTE_i. This choice will trade off the benefit of staying out of the auction and receiving E for sure with the possibility of winning an auction where the monetary gain could exceed E. Let the expected profit of the bidder with value v bidding b when she pays an entry cost ϕ, faces $N-1$ other bidders with values drawn from $F(v)$ and preferences defined by α and θ be $\mathrm{E}\left[\Pi(v, b; \phi, N, F(v), \alpha, \theta)\right]$. In equilibrium, knowing her bid conditional on entry will be $b_i^*(v)$ (dropping the dependence on parameters for a moment), the bidder will choose her maximum willingness-to-pay, WTE_i^* such that:

$$E = \mathrm{E}\left[\Pi(b_i^*(v); WTE_i^*, N, F(v), \alpha, \theta)\right] \tag{7}$$

We observe T_1 first price auctions and T_2 second price auctions. This section uses only data from Case 1 where bidders observed their valuation at the entry stage. We now seek to explain subjects' tendency to over-enter into auctions in a risk-neutral environment with no joy of winning, using the above model. To do so, we will need estimates of θ and α. We will use bidding in second price auctions to generate estimates of θ and bidding in first price auctions for estimates of α. However, because we do not observe the same subject bidding in both first and second price auctions, we assume that $\theta_i = \theta$ and $\alpha_i = \alpha\ \forall i$. In practice, we allow for subjects with different characteristics D_i to have different α and θ.[17] At this point we parameterize the function $h(\cdot)$ in the following ways:

Additive $h(v;\theta) = v + \theta$

Multiplicative $h(v;\theta) = v\theta$

This parameterization is important for pinning down JOY, as will be seen below.

We begin by assuming that we know θ. Having presented evidence of overbidding in first price auctions, we now illustrate the way it identifies RA given estimates of JOY. Using the parameterized

[17] In practice we let D include whether the subject was male or female.

version of the model which was employed in the experiment, (importantly, that bidders have CRRA preferences and that $F(v)$ is uniform over $[v_L, v_H]$), we know (see Equation 9 in the Appendix):

$$b_i = \frac{\alpha v_L + h(v_i;\theta)(N-1)}{\alpha + N - 1} \tag{8}$$

This bidding function forms a mapping between a subject's value and her bid given her RA and JOY parameters. Therefore, for any θ, we can estimate α using nonlinear least squares. Note that if we believed there were no JOY effect, i.e. $h(v;\theta) = v$, then we could still use bidding data in first price auctions to generate an estimate of α. Let $\widehat{\alpha}$, $\widehat{\alpha(\theta_A)}$ and $\widehat{\alpha(\theta_M)}$ denote the estimates of α assuming no JOY, additive JOY and multiplicative JOY, respectively.

We now turn to forming estimates of θ which were assumed to be known when estimating α. Having presented evidence of overbidding in second price auctions, we now illustrate the way it identifies JOY given parametric assumptions regarding $h(v;\theta)$. If the value to the bidder of winning the auction is given by $h(v;\theta)$, then the dominant strategy in the second price auction to bid $b = h(v;\theta)$. Therefore, for known $h(v;\theta)$, if we observe (v_i, b_i) for some bidder i in a second price auction, $\theta = h^{-1}(b_i; v_i)$. Exploiting the two previously mentioned functional forms for $h(\cdot)$, we form estimates $\widehat{\theta_A}$ and $\widehat{\theta_M}$ (for additive and multiplicative JOY, respectively) using bidding in second price auctions by: $\widehat{\theta}_l = \frac{1}{T_2}\sum_{i=1}^{T_2} h_l^{-1}(b_i; v_i), l = A, M$.

Before using these parameters to predict entry behavior into auctions, we present our parameter estimates. We begin by showing our estimates of JOY in Table 7. It is clear that men are found to display a greater JOY than women whether JOY is modeled as additive or multiplicative. This is consistent with the patterns of overbidding in the second price auctions we presented earlier. Our estimates of RA appear in Table 8. The results are consistent with risk averse bidders and the well-known result, even after controlling for JOY, that women are more risk averse than men.

With estimates of θ and α in hand, we can estimate the optimal willingness-to-pay to enter the first price auctions in an attempt to rationalize the over-entry observed in the data. To do so, for each observed value and bid, we find the WTE that solves equation 7 given the estimates of α and θ. Let $\widehat{WTE}$, $\widehat{WTE(\theta_A)}$ and $\widehat{WTE(\theta_M)}$ denote the estimates of WTE assuming no JOY, additive JOY and multiplicative JOY, respectively.

Table 9 displays the results of this estimation procedure under various assumptions. The first column shows the results when we have only RA affecting bidders. The second and third allow only JOY to affect bidders. The fourth and fifth allow both RA and JOY to affect bidders.[18] The table displays 95% confidence intervals for the estimated WTE as a fraction of valuation. These are bootstrapped for the cases with JOY. It is clear that a model without JOY cannot explain the over-entry of bidders and that the model without RA overestimates participants' willingness-to-participate substantially. This suggests that including both RA and JOY should be important in matching the observed WTE as a fraction of valuation and this is substantiated in the fourth and fifth columns. When we incorporate JOY and RA, we move much closer to the observed

[18] If we look only at auctions where $\phi = 0$, so that all subjects enter, the results are very similar, suggesting that selection is not driving much of the results.

participation. When we include JOY we explain almost all of the over-entry observed by men but still leave 53% of the over-entry of women unexplained. Even with no within-subject variation in auction format (FPA vs. SPA) behavior, the model incorporating JOY, either as additive or multiplicative, does a much better job of rationalizing the over-entry.

While the fit of the model is better when we incorporate both RA and JOY, we are now interested in how the residuals from the predicted WTE vary as a function of valuation. Figure 1 plots these residuals as a function of valuation. The curves are fifth order polynomials fitting the plotted data. That the curve increases in valuation when we ignore JOY (the first panel) suggests that JOY indeed ought to be included to match this pattern. The second and third panels illustrate that we are predicting too high a willingness-to-enter when we ignore RA. The fourth and fifth panels suggest that while we have not fit the data perfectly, the remaining residuals may be attributable to a "joy of participation" or some other effect which is independent of valuation, as the curve does not increase in valuation.

6 Conclusion

To the extent that a mechanism designer believes there is heterogeneity among agents, she should be concerned with the potential differential impact her design may have on agents of varying types. This paper aims at providing evidence that such concerns are valid in the context of auctions. In this paper we focus on bidders' decisions to enter auctions or to opt out and receive a fixed payment. In one of the few experimental studies to focus on entry into auctions, we document severe over-entry. Relative to risk neutral payoffs, bidders over-enter first price auctions 97% of the time and second price auctions 90% of the time. We also document the well-known tendency of subjects to overbid. We then seek to explain such behavior through a combination of risk aversion and "joy of winning". We show reduced form facts consistent with the presence of both, and then turn to a structural model in an attempt to fit the observed entry and bidding behavior of subjects. We show that a model incorporating "joy of winning" alongside risk aversion does a better job in matching the observed entry behavior than a model lacking the joy of winning" To our knowledge, this is the first study to propose "joy of winning" to explain not only bidding behavior, but also endogenous entry behavior. Furthermore, we show that adding "joy of winning" seems to match male entry behavior better than that of females. Still, there is unexplained variation in observed entry behavior that we believe may be explained by a "joy of participation" effect, but more research should be brought to bear on this matter.

Appendix

$F(v)$ is Uniform$[v_L, v_H]$. Conditional on entry, the optimal bidding rule in a first price auction for a bidder with CRRA preferences, i.e. $U(x;\alpha) = x^{\alpha}$ facing $N-1$ other risk bidders *who are submitting bids of the form:* $b = \frac{N-1}{N}v + \frac{v_L}{N}$ is solved by:

$$\begin{aligned}
\Pi &= max_{b_i}(h(v_i;\theta) - b_i)^{\alpha} Pr[Win|b_i] \\
&= max_{b_i}(h(v_i;\theta) - b_i)^{\alpha} Pr\left[\frac{Nb_i - v_L}{N-1} > max_{j\neq i}\{v_j\}\right] \\
&= max_{b_i}(h(v_i;\theta) - b_i)^{\alpha} \left(\frac{Nb_i - v_L}{(N-1)(v_H - v_L)} - \frac{v_L}{v_H - v_L}\right)^{N-1} \\
&= max_{b_i}(h(v_i;\theta) - b_i)^{\alpha} \Phi(b)^{N-1}
\end{aligned}$$

where $\Phi(b) = \frac{Nb - v_L}{(N-1)(v_H - v_L)} - \frac{v_L}{v_H - v_L}$.

The associated First Order Condition:

$$\begin{aligned}
0 &= -\alpha(h(v_i;\theta) - b_i)^{\alpha-1}\Phi(b)^{N-1} + (h(v_i;\theta) - b_i)^{\alpha}(N-1)\Phi(b)^{N-2}\frac{N}{(v_H - v_L)(N-1)} \\
&\Longleftrightarrow \\
0 &= -\alpha\Phi(b) + (h(v_i;\theta) - b_i)\frac{N}{v_H - v_L} \\
&\Longleftrightarrow \\
0 &= -\alpha\,(b - v_L) + (h(v_i;\theta) - b_i)(N-1) \\
&\Longleftrightarrow \\
b_i^* &= \frac{\alpha v_L + h(v_i;\theta)(N-1)}{\alpha + N - 1}
\end{aligned} \tag{9}$$

Thus, for any set of parameters we have the equilibrium mapping between bidder values and submitted bids.

Instructions

Welcome to CASSEL. This is an experiment on decision-making. Your earnings in the experiment will depend partly on your decisions, and partly on chance. You will receive a $5 show-up fee for your participation, plus the amount you earn during the experiment. You will be paid privately, in cash, at the end of the experiment. You are under no obligation to tell anyone how much you have earned. Throughout the experiment, you will be assigned a subject ID number and your name will never be associated with your decisions. Please listen to the instructions carefully. If you have any questions, please raise your hand.

The earnings in this experiment are denominated in experimental points, which will be converted to dollars at the end of the experiment. The exchange rate between experimental points and dollars is 0.04, meaning that every experimental point corresponds to 4 cents. The experiment will consist of 60 rounds. At the end of the experiment, 10 of the rounds will be selected randomly by the computer, and you are going to be paid according to your decisions in those rounds. Each of the rounds is equally likely to be picked, and has a chance to determine your payoffs, so you should take every round seriously.

In each round of this experiment, you will be given an initial monetary endowment of 25 points, and you will be faced with the decision of whether or not to enter into an auction for a virtual object. In each round, you will be randomly assigned a valuation for that rounds object by the computer, denominated in terms of experimental points. This valuation determines the worth of the object to you, and is picked randomly between 25 and 100, with each value in that interval being equally likely. The auction will be conducted among you and a certain number of computerized virtual bidders. These bidders are robot bidders who also have randomly drawn valuations for the item, from the same distribution as yours ([25, 100]). They are programmed to bid rationally (to maximize their expected earnings) given their valuation. The number of robot bidders will be either 2 or 4, and may change from round to round (from auction to auction). If you end up participating in the auction in any given round, your earnings in the auction will be determined as follows:

You will be the winner of the auction if your bid was the highest bid among the competitors. If this happens, you will receive earnings in the amount of (your valuation-your bid).

If you are not the winner of the auction (meaning that you did not have the highest bid among the competitors), you will receive zero earnings from the auction.

Entry into the auction will typically entail an entry fee. This fee will be drawn randomly from [0, 25], and will be subtracted as a payment from your round earnings, should you end up participating in that rounds auction. Depending on whether you participate in the auction or not, your final earnings in each round will be as follows:

If you enter into the auction and win (that is, if you were the highest bidder):

Your earnings=(Your valuation your bid)-auction entry cost + your per-round endowment

If you enter into the auction and lose:

Your earnings= Your per-round endowment entry cost

If you do not enter into the auction:

Your earnings=Your per-round endowment

Do you have any questions up to this point?

Now, we will explain the type of auctions and the entry process in more detail. The decisions that you will be asked to make in each round are as follows:

1. After being given some information about that rounds auction and the worth of the item to you, you will be asked to state the maximum entry fee that you would be willing to pay to enter into that rounds auction. That is, you will be asked to give a threshold fee, above which you would not wish to enter the auction, and below which you would choose to enter the auction by paying the fee.

As mentioned before, the actual fee that you are going to pay will be determined by a random draw by the computer. After you state your maximum fee, the computer will draw a number from the interval [0,25]. If this randomly selected fee happens to be lower than the maximum fee you stated you are willing to pay, you will enter into the auction, and pay the randomly selected fee.

If this randomly selected fee happens to be above your threshold fee, you will not enter the auction, and will not pay any entry cost.

Notice that this mechanism is equivalent to you saying I will enter at this cost or I will not enter at this cost to all possible entry costs ranging from 0 to 25. The actual cost is then determined by the computer, and your decision of whether to enter or not at this cost is implemented.

Please notice that with this structure, there are no incentives to misreport the maximum fee that you are willing to pay. Because, your stated maximum entry fee does not affect the randomly chosen entry fee at all. Does it make sense to say that you are willing to pay a lower fee than you are actually willing to pay? No. Suppose that you are truly willing to pay at most 15 points for entry, but stated that you were willing to pay only up to 10. If the randomly chosen fee happens to be 12, for example, you will end up not participating in the auction, although in fact you would have liked to. Likewise, does it make sense to say that you are willing to pay a higher fee than you are actually willing to pay? No. If, for example, you are truly willing to pay up to 15 points and you stated 20, and if the randomly selected fee is 17, you would end up entering into the auction and would have to pay a fee (17) that is more than what you are in fact willing to pay. So, it is always in your best interest to make a truthful statement about the maximum entry fee you would be willing to pay.

Please notice that if you end up entering into the auction, you will be bidding against virtual (robot) bidders. These bidders do not have entry costs. Think about this as an auction where either 2 or 4 bidders have already decided to participate, and they are in a room waiting for the auction to start. You are basically faced with potentially purchasing a ticket to enter into this auction with these bidders, and deciding at what price ranges you would be willing to purchase this ticket.

2. According to the above mechanism, if you end up entering into the auction, you will be asked to make a bid. If you do not enter the auction, the round ends.

To reiterate the earnings calculations,

If you enter into the auction and win (i.e. you were the highest bidder in the auction):

Your payoff=(Your valuation your bid)-entry cost + your per-round endowment

If you enter into the auction and lose:

Your payoff= Your per-round endowment entry cost

If you do not enter into the auction:

Your payoff=Your per-round endowment

As we mentioned before, there will be a total of 60 rounds. 10 rounds of this will be randomly picked to count for payoffs, and your end-of-experiment earnings will be the sum of your payoffs from these auctions.

Types of Auctions

Finally, we will give you some information about the types of auctions you will be faced with.

There will be several different types of auctions in the experiment that differ in how much information is available about the auction. In each round, the computer will randomly draw one of these auction types and present it to you. You will know the type of the auction, and you will tell the computer the maximum entry fee you would be willing to pay to enter such an auction.

Information about Your Valuation

Type 1: In this setting, your valuation for the item is unknown to you at the time of your auction entry decision. You will only know that it is drawn from the interval 25 to 100, and you will make a decision based on this knowledge. You will, however, always learn your valuation before you bid.

Type 2: In this setting, your valuation for the item is known to you at the time of auction entry decision.

Information about the Number of Bidders:

Type 3: In this setting, you know the number of bidders you will be competing against when you make your entry decision.

Type 4: In this setting, you do not know the number of competing bidders when you make your entry decision, just that it is equally likely to be 2 or 4 (not including yourself). In this auction, you will learn the actual number of bidders if you enter, before you bid.

Type 5: In this setting, you do not know the number of bidders when you make your entry decision, just that it is equally likely to be 2 or 4 bidders. In this auction, if you enter, you will not learn the number of bidders before you make your bid either.

Type 6: In this setting, you do not know the number of bidders when you make your entry decision, and do not even know how likely it is to be 2 or 4. And if you enter the auction, you will not learn how many bidders you will be competing against either.

Now, we will start running the study. Please pull out your dividers now, and click the z-leaf icon on your desktop. You will see, once the program starts, that the program has assigned you a subject number. Please make sure to note this number on your record sheet. Also, we will be playing 3 practice rounds at the start of the experiment to familiarize you with the program. These practice rounds do not count for your earnings. If at any point in the experiment you have questions, please raise your hand and we will assist you.

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Table 1: Over-Entry into Auctions: Competing Against Similar Bidders

Case	Mean	Std. Dev.
OVERALL	0.161	0.368
SECOND PRICE	0.316	0.467
FIRST PRICE, N=3	0.109	0.313
FIRST PRICE, N=5	0.058	0.235

This table displays the percentage of times bidders were *ex ante* rational in their WTE measure under the assumption that they thought they were competing against bidders like themselves.

Table 2: Bidding in Second Price Auctions

Variable	Mean	Median	Std. Dev.	p25	p75
BID	68.65	70.00	24.35	50.00	90.00
VALUATION	64.54	65.00	21.40	46.00	84.00
OVERBID	0.53	1.00	0.50	0.00	1.00
PERCENTAGE OVERBID	0.28	0.15	0.32	0.06	0.38

This data come from second price auctions with 13 females and 15 males.

Table 3: Overbidding in Second Price Auctions

	(1)	(2)	(3)	(4)	(5)
VALUATION	0.0002	0.0006	0.003	-.002	0.0005
	(0.003)	(0.007)	(0.004)	(0.005)	(0.004)
MALE	0.801**	0.954**	0.609	1.030**	0.802*
	(0.395)	(0.422)	(0.432)	(0.429)	(0.437)
EXPERIENCE	-.467	-.880	-.010	-.188	-.870
	(0.599)	(0.602)	(0.71)	(0.564)	(0.623)
RISK	-.354*	-.441***	-.296	-.631***	-.257
	(0.197)	(0.164)	(0.22)	(0.221)	(0.216)
COMPETITIVE	-.048	0.124	-.072	-.091	-.141
	(0.229)	(0.209)	(0.262)	(0.245)	(0.229)
HOWOFTEN	0.173	0.359	0.026	0.322	0.024
	(0.277)	(0.284)	(0.322)	(0.294)	(0.283)
PERIOD	-.019	-.014	0.038	0.027	-.088*
	(0.022)	(0.061)	(0.096)	(0.061)	(0.046)
CONSTANT	2.105	0.356	-1.347	2.189	5.401*
	(1.962)	(4.024)	(5.538)	(1.525)	(3.083)
CASE DUMMIES	YES	N/A	N/A	N/A	N/A
PERIOD DUMMIES	YES	YES	YES	YES	YES
CONSTANT	0.806	1.348	0.383	0.051	1.224
	(1.285)	(1.389)	(1.734)	(1.475)	(1.424)
N	805	226	177	188	209
Pseudo R^2	0.0892	0.0753	0.1741	0.1363	0.1248
CASES	ALL	1	2	3	4

The table displays results from a probit model of whether the subject bid more than his value in the second price auction.
In all specifications standard errors are clustered by subjects.
All specifications include 5-period-length dummies and subject survey responses.
*, **, *** imply significance at the 10%, 5% and 1% level, respectively.

Table 4: Bidding in Second Price Auctions

	(1)	(2)	(3)	(4)
VALUE	-.004***	-.004***	-.004***	-.004***
	(0.001)	(0.001)	(0.001)	(0.001)
MALE	0.119*	0.119*	0.118*	0.118*
	(0.066)	(0.066)	(0.066)	(0.067)
EXPERIENCE	-.193*	-.194*	-.192*	-.192*
	(0.101)	(0.101)	(0.101)	(0.101)
RISK	-.004	-.003	-.004	-.003
	(0.033)	(0.033)	(0.033)	(0.033)
COMPETITIVE	-.028	-.029	-.028	-.029
	(0.037)	(0.036)	(0.036)	(0.036)
HOWOFTEN	0.031	0.031	0.031	0.031
	(0.042)	(0.041)	(0.042)	(0.042)
PERIOD	-.001	-.001	-.001	-.001
	(0.0007)	(0.001)	(0.0007)	(0.001)
CASE DUMMIES	NO	NO	YES	YES
PERIOD DUMMIES	NO	YES	NO	YES
CONSTANT	1.379***	1.398***	1.368***	1.387***
	(0.249)	(0.275)	(0.249)	(0.276)
N	805	805	805	805
R^2	0.11	0.114	0.111	0.115

The dependent variable is the fraction of value bid by subjects in second price auctions.
In all specifications standard errors are clustered by subjects.
All specifications include subject survey responses.
PERIOD DUMMIES are dummies of period length 5.
Each regression was also done by case and no interesting additional results were found.
*, **, *** imply significance at the 10%, 5% and 1% level, respectively.

Table 5: The Selection Effect on Bidding in First Price Auctions

	(1)	(2)	(3)	(4)
ENTRYCOST	0.009***		0.006***	
	(0.003)		(0.002)	
MAXENTRYFEE		0.006		0.003
		(0.005)		(0.004)
MALE	0.199***	0.243**	0.089**	0.073
	(0.06)	(0.117)	(0.04)	(0.082)
FOURBIDDERS	0.15***	0.147***	0.077***	0.067**
	(0.05)	(0.048)	(0.029)	(0.028)
CASE 1			0.036**	0.037**
			(0.018)	(0.017)
MALE×FOURBIDDERS	-.193***	-.192***	-.038	-.028
	(0.063)	(0.065)	(0.038)	(0.037)
MALE×ENTRYCOST	-.009		-.005*	
	(0.007)		(0.003)	
MALE×MAXENTRYFEE		-.005		-.001
		(0.007)		(0.004)
FOURBIDDERS×CASE 1			-.085***	-.084***
			(0.028)	(0.027)
EXPERIENCE	-.071	-.064	0.012	0.011
	(0.062)	(0.063)	(0.051)	(0.052)
RISK	0.026	0.023	-.002	-.001
	(0.017)	(0.017)	(0.013)	(0.014)
COMPETITIVE	0.018*	0.016	0.012	0.012
	(0.01)	(0.014)	(0.012)	(0.012)
HOWOFTEN	0.006	0.002	-.044	-.046
	(0.038)	(0.04)	(0.037)	(0.037)
PERIOD	-.004	-.003	-.002	-.001
	(0.013)	(0.014)	(0.006)	(0.006)
SEEVALUATION			-.002	0.00009
			(0.015)	(0.016)
PERIOD DUMMIES	YES	YES	YES	YES
CONSTANT	0.454***	0.421***	0.924**	0.86*
	(0.089)	(0.128)	(0.415)	(0.456)
Cases	1	1	1 and 2	1 and 2
Obs.	153	153	622	622
R^2	0.174	0.155	0.082	0.07

The dependent variable is the fraction of value bid by subjects.
The first two columns use only case 1 when bidders can't see their valuations; the rest use cases 1 and 2.
In all specifications the standard errors are clustered by subject.
PERIOD DUMMIES are dummies of period length 5.
*, **, *** imply significance at the 10%, 5% and 1% level, respectively.

Table 6: Potential for Spite Motive

	Case 1		Case 2		
	Mean	Std. Dev.	Mean	Std. Dev.	t-stat
All v	0.799	0.295	0.844	0.327	-1.103
v <62	0.803	0.405	0.852	0.494	-0.468

This table displays the percentage value bid when bidders end up facing four bidders and knew their value at the entry stage.

Table 7: JOY Estimates from Bidding in Second Price Auctions

	Pooled	Men	Women
$\widehat{\theta_A}$	4.229	4.813	3.472
$\widehat{\theta_M}$	1.093	1.105	1.078

The table displays the implied “joy of winning” parameters from second price auctions.

Table 8: RA Estimates from Bidding in First Price Auctions with and without JOY

	RA Only	RA and Additive Joy	RA and Multiplicative Joy
	$\widehat{\alpha}$	$\widehat{\alpha(\theta_A)}$	$\widehat{\alpha(\theta_M)}$
Pooled	0.602	0.735	0.755
Men	0.621	0.825	0.843
Women	0.591	0.666	0.667

The table displays the estimated implied risk parameters from first price auctions for different assumptions about the presence and form of JOY, assuming CRRA preferences.

Table 9: WTE as a fraction of Valuation Estimates for First Price Auctions with and without JOY

	Actual	RA Only	Additive Joy	Multiplicative Joy	RA and Additive Joy	RA and Multiplicative Joy
		$\widehat{WTE}$	$\widehat{WTE(\theta_A)}$	$\widehat{WTE(\theta_M)}$	$\widehat{WTE(\alpha, \theta_A)}$	$\widehat{WTE(\alpha, \theta_M)}$
Pooled	0.2664	0.1021	0.4008	0.4035	0.1642	0.1770
		[.1020, .1023]	[.3975, .4041]	[.3998, .4074]	[.1522, .1771]	[.1616, .1944]
Men	0.2569	0.1091	0.4104	0.4119	0.2269	0.2420
		[.1088, .1095]	[.4004, .4165]	[.4056, .4184]	[.1927, .2668]	[.2026, .2847]
Women	0.2728	0.098	0.3913	0.3912	0.1285	0.1290
		[.0979, .0984]	[.3875, .3955]	[.3872, .3955]	[.1186, .1393]	[.1182, .1413]

The table displays the mean of the implied WTE from first price auctions for different assumptions about the presence and form of JOY, assuming CRRA preferences.

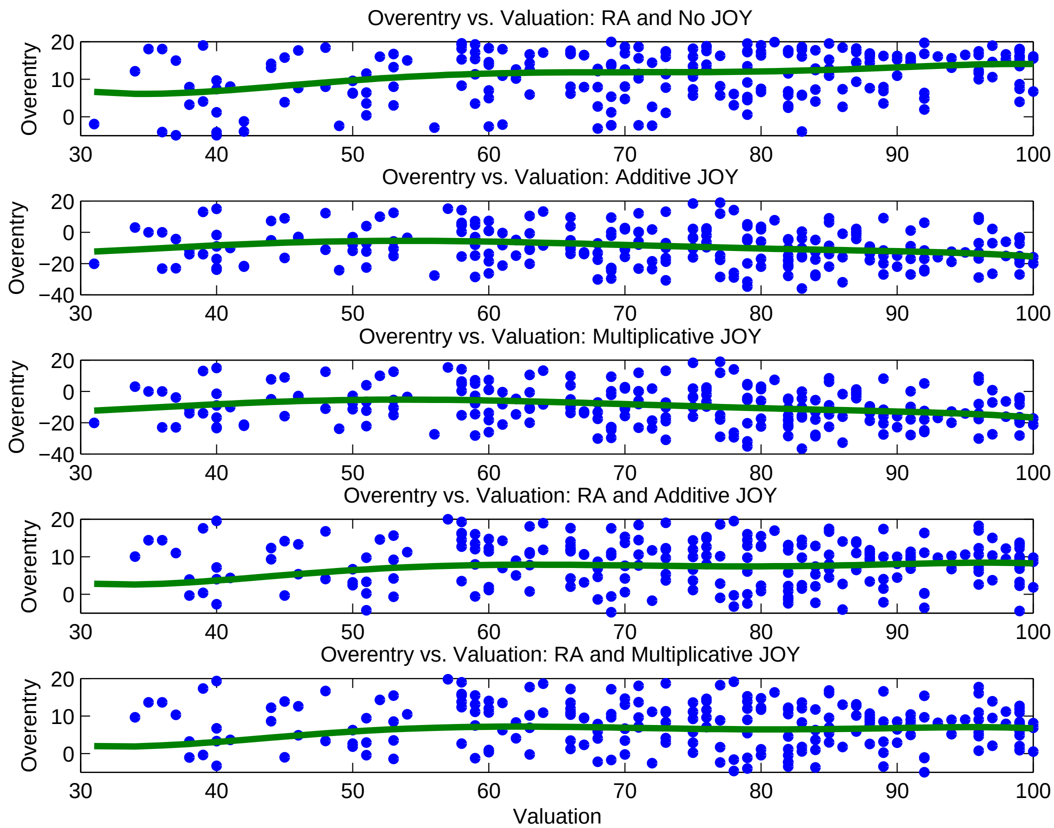

Figure 1: Plot of (WTE-$\widehat{WTE}$) as a function of value for various models.