Bidding Behavior in Pay-to-Bid Auctions: An Experimental Study*

Michael Caldara†
Department of Economics
University of California, Irvine

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Abstract

This paper experimentally studies the pay-to-bid auction format and compares average revenues in the discrete time simultaneous decision model to average revenues in the continuous time setting experienced in pay-to-bid auctions on the internet. For both of the group sizes studied, 3 and 5, there is no difference in the average revenues between the two environments. However, there is significant over-bidding, as has been observed in pay-to-bid auctions on the internet, for both group sizes and this over-bidding depends on the number of participants. Over-bidding decreases with experience, and strategic sophistication plays a large role in the outcomes of individuals. Some of the least successful subjects cease auction participation all together, suggesting that the pay-to-bid auction mechanism can only sustain revenues above the value of the prize as long as new inexperienced participants can be attracted.

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†3151 Social Science Plaza, Irvine, CA, 92697-5100, mcaldara@uci.edu.

1 Introduction

In recent years, a peculiar new auction format, the "pay-to-bid" auction (or "penny" auction), has surfaced on the internet. The auction format boasts average revenues well in excess of the value of the prize (e.g., Thaler 2009, Platt, Price and Tappen 2010, Augenblick 2011) and yet tens if not hundreds of individuals willingly participate in each new auction. This is in sharp contrast to the standard game theoretic prediction (e.g., Hinnosaar 2010, Platt et al 2010, Augenblick 2011) that average revenues will equal at most the value of the prize. An apparent key to the auction format's success is its ability to effectively exploit behavioral biases while still enticing new participants to join. This enticement stems from the generally great deal offered to the high bidder (i.e., a High Definition Television for \$24.36, a \$200 gift card for \$17.45, a Blu-ray player for \$1.71). It is the participants as a collective whole that lose, as the auctioneer collects a small non-refundable bid fee each time a bid is placed. In this example taken from a popular pay-to-bid auction website, the three auctions raised \$2654.72 and retail price of the items was 779.98. With such lopsided outcomes it is no wonder the auction has been called "the evil stepchild of game theory and behavioral economics" (Gimein 2009).

The pay-to-bid auction, which has similarities to the dollar auction (Shubik 1971), the war of attrition (e.g., Smith 1974, Fundenberg and Tirole 1986) and the all-pay auction (e.g., Krishna and Morgan 1997, Baye, Kovenock and de Vries 1996), is distinguished by the following features: Participants choose between bidding and not bidding. When a participant bids, the auction price increases by a small fixed increment and that participant is charged a non-refundable fee. The participant can bid multiple times during the auction, but must pay the non-refundable fee *each* time she bids. When there is no time left on the countdown clock, the *last* participant to bid wins the prize and pays the end auction price. Whenever a bid is placed in the last few seconds, a small amount of time (i.e., 15 or 20 seconds) is added to the countdown clock. Thus, the auction can be in the "last few seconds" indefinitely (several hours is common).

It is clear from the structure of this auction that it is rife with the opportunity to make mistakes. The bid fees are a sunk cost, the monetary commitment of the active participants grows in small increments as the auction progresses, decisions must be made in a short window of time, and each decision to not bid risks losing the auction. Since the fees from past bids are lost forever, participants might fall victim to the sunk cost fallacy. If we try to model these sunk costs with prospect theory and loss aversion (e.g., Kahneman and Tversky 1979; 1991; 1992, Thaler 1980), excess revenues can be explained by risk seeking behavior in small losses (bid fees) from the reference point (the participant's initial wealth).[1] The growing monetary commitment of active participants may lead to further escalation of commitment as these participants try to dig themselves out of a hole. For instance, participants may be better able to rationalize unsuccessful bids through further bidding (e.g., Staw 1981, Wong, Kwong and Ng 2008). Additionally, the negative emotions that participants may encounter in this adversarial setting have been shown to increase the likelihood of escalation (e.g., Wong, Yik and Kwong 2006, Tsai and Young 2010) although if the participants are able to predict future regret (e.g., Wong and Kwong 2007, Ku 2008a), learn not to escalate from prior experience (e.g., Ku 2008b) or set a mental budget to limit participation (e.g., Heath 1995), this effect may be mitigated. Lastly, the short time between decisions may lead to mistakes due to limited cognition (e.g., Simon 1976).

While it is easy to develop a list of behavioral phenomena such as the sunk cost fallacy, escalation of commitment, bounded rationality, and loss aversion, that *could* explain the excess revenues of pay-to-bid auction websites, it is difficult to determine theoretically whether these biases *are* driving excess revenues, and if so, which of these biases are the most salient. A variety of alternative theories have been proposed that can also explain excess revenues, including: Information asymmetries and imperfect information (e.g., Byers, Mitzenmacher and Zervas 2010), risk loving preferences (e.g., Platt et al 2010), shill bidding (e.g., Platt et al 2010, Byers et al 2010), and signalling strategies (e.g., Augenblick 2011,

[1] Alternatively, Augenblick (2011) shows a similar result by explicitly modelling naive sunk cost fallacy in pay-to-bid auctions.

Byers et al 2010). Furthermore, evidence from field data highlights the important influence that individual heterogeneities have on individual outcomes. Both strategic sophistication and experience (Wang and Xu 2011)[2], and reputation and signalling behavior (Goodman 2011) have been shown to play a role in individual auction outcomes. While all of the above findings are plausible explanations for the excess revenues of pay-to-bid auction websites, this analysis is complicated by the complexity of the pay-to-bid auction format. For the sake of simplicity and tractability, the baseline pay-to-bid auction theory of (Augenblick 2011, Hinosaar 2010, and Platt et al 2010) makes many abstractions. But until the theoretical model is better understood, we have no way of knowing whether the game modelled by the baseline theory bears any resemblance to the game being played by the participants on the pay-to-bid auction websites.

I seek to bridge this gap with the experimental method. By examining bidding behavior in pay-to-bid auctions in a controlled laboratory setting, I can test both the game modelled in the baseline theory, and a game that is closer to what is played on pay-to-bid auction websites in an environment where many of the confounding factors present in field data have been removed (i.e., imperfect information, asymmetries, unknown risk preferences, censored data). While this is the first paper to experimentally study the pay-to-bid auction format, this work fits into a large body of experimental work on contests (e.g., Millner and Pratt 1991, Davis and Reilly 1998, Potters, de Vries and van Winden 1998, Gneezy and Smorodinsky 2006, Herrmann and Orzen 2008, Amaldoss and Rapoport 2009, Horish and Kirchkamp 2010, Muller and Schotter 2010, Sheremeta 2010; 2011, Sheremeta and Price 2011) and auctions (e.g., Coppinger, Smith and Titus 1980, Cox, Roberson and Smith 1982, Cox, Smith and Walker 1988, Kagel and Levin 1993).

Much of the contest literature has found evidence of over-bidding in lottery and all-pay contests. As the pay-to-bid auction is a type of dynamic contest, we might expect to observe some over-bidding as well. Of key interest is the *cause* of any over-bidding, and whether

[2] Wang and Xu use an adaptation of Camerer, Ho and Chong (2004) that is especially suited for measuring sophistication in pay-to-bid auctions.

this over-bidding persists as subjects gain experience. For example, Sheremeta (2011) finds evidence that mistakes play a role in over-bidding, Amaldoss and Rapoport (2009) attribute this over-bidding to strategic sophistication, Gneezy and Smorodinsky (2006) find that over-bidding depends on the number of players, and Herrmann and Orzen (2008) link over-bidding with spiteful preferences. It is also possible that the dynamic nature of the pay-to-bid auction may turn this result on it's head, as Horish and Kirchkamp (2010) do find over-bidding in the static all-pay auction, but find under-bidding in the dynamic war of attrition (despite the theoretical similarities). In addition, there is evidence that experience diminishes over-bidding in the all-pay auction (e.g., Davis and Reilly 1998), and so we might expect any over-bidding to diminish with time. It is unclear whether sunk cost fallacy will play an important role in this setting. The fee structure of pay-to-bid auctions will clearly generate sunk costs, and so we might expect to observe sunk cost fallacy as has been observed in more general settings (e.g., Arkes and Blumer 1985) but other studies find the effect to be small (e.g., Friedman, Pommerenke, Lukose, Milam and Huberman 2007) and the results of Sheremeta (2010) for multi-stage contests are inconsistent with sunk cost fallacy all together.

Building off this previous literature, I test bidding behavior in pay-to-bid auctions using a 2×2 design. The two key treatment variables are the number of auction participants ($n = 3$ or $n = 5$) and the strategy space (discrete rounds with simultaneous bid decisions as in the baseline theory or continuous time with instantaneous feedback as in a pay-to-bid auction on the internet). I control for many of the confounding factors in internet pay-to-bid auctions by holding the remaining auction parameters constant, providing full information, and making the participants symmetric. The main observations of interest are average revenue under each treatment condition, the determinants of individual auction outcomes, and the presence of behavioral biases. In line with the previous literature, I find persistent over-bidding that tapers off with time. Auction revenues in the $n = 5$ treatment are significantly greater than auction revenues in the $n = 3$ treatment, consistent with the bidder mistakes hypothesis. I find no difference between the auction revenues under the discrete rounds treatment and the auction revenues under the continuous time treatment, suggesting that the game modelled in the baseline theory is capturing many of the key strategic considerations present in a pay-to-bid auction on the internet. Risk aversion has the predicted effect on number of bids placed relative to risk neutral participants, but the results for risk seeking participants are inconclusive. I find strategic sophistication to be a strong determinant of individual auction outcomes. I observe the use of signalling strategies, but not generally with success. This ineffectiveness may be in part to the shortened auction lengths and symmetries built in to the experiment design. Another key finding is that many less successful participants cease participation entirely over the course of the session. The findings that overbidding decreases with experience and less successful participants learn to leave supports the hypothesis of Wang and Xu (2011) that pay-to-bid auction websites profit from a "revolving door of new bidders". For a fixed pool of participants, it does not appear that the pay-to-bid auction format can generate sustained revenues in excess of the value of the prize.

2 Baseline Theory

2.1 The Model

I first summarize the theoretical models presented in Augenblick (2011), Hinnosaar (2010), and Platt et al (2010). These closely related models can be used to characterize the symmetric equilibrium in a pay-to-bid auction. Each work models the pay-to-bid auction as a full information extensive form game, but a main point of departure between the three models is how to handle the possibility of ties. Platt et al assume the round ends immediately when a bid is placed and that potential bidders' decisions of when to act are distributed without atoms throughout each period. This treatment is conceptually closest to the continuous time setting in which the probability of a tie is zero and the round advances as soon as a bid is placed. Augenblick achieves a similar result by allowing multiple bids to be placed in a round and accepting one bid at random. This treatment, in which the bid fee is only paid if the bid is accepted, has the advantage of being easier to test in the laboratory while providing an equivalent solution concept. Hinnosaar also allows multiple bids to be placed in a round but in his model all bids are accepted and the high bidder is selected at random. This treatment differs from the other two models by adding the possibility of paying a bid fee without becoming the high bidder.

Hinnosaar's treatment captures an important consideration that participants face in a pay-to-bid auction. While the auctions do take place in continuous time where the probability of a tie is zero, it is quite common for a situation to arise where multiple bids are placed in a small window of time. For example, if a bidder is not trying to signal, a good strategy is to wait until the last possible second to place a bid. If several bidders are following this strategy then it is common for bids to be placed within a fraction of a second of one another. In this case, the actual order of bids will determine the high bidder, but from the perspective of a participant with a limited reaction time the order in which the bids are placed will appear random and the timing of the bids will appear to be simultaneous. Thus when placing a bid, the participant must consider the possibility of becoming the high bidder at an auction price multiple increments higher than the current auction price. Additionally, the participant must also consider the possibility of being charged a bid fee and then being immediately outbid by another bid that would have been placed anyway. These situations do not occur in the Augenblick or Platt et al treatments, but they may affect bidding behavior in practice. For this reason, and since the Hinnosaar model is also easy to test in the laboratory, my treatment will utilize the Hinnosaar approach to tie-breaking. [3]

The baseline model is as follows. A single item is put up for auction. A non-participating auctioneer conducts the auction and a non-participating seller commits to sell the item at the end auction price. Any revenues generated by the auction will be divided in some manner between the auctioneer and the seller. There are $n \geq 2$ participants in the auction,

[3] This analysis makes no judgement as to which model should be preferred for other applications. A natural downside of the Hinnosaar model is that the symmetric equilibrium does not have an analytical solution and must instead be solved numerically using backwards induction. As this analysis is primarily concerned with revenue rather than the nature of the equilibria that are played, this downside is not problematic for my purposes.

indexed by $i \in \{1, 2, ..., n\}$, who share a known common value Π for the item. The number of participants n is fixed throughout the auction and n is known to all participants. The auction is conducted over a series of discrete rounds, indexed by $t \in \{0, 1, 2, ...\}$. In all rounds $t > 0$, exactly one of the n participants is designated as the "high bidder", a title that is awarded based on the outcome of the prior round, and the remaining $n - 1$ participants are designated as "non-leaders." The auction starts in round $t = 0$ at initial price $P_0 \geq 0$ with no high bidder.

In a given round t, non-leaders simultaneously choose between bidding and not bidding. The high bidder does not participate in the round. If a participant chooses to bid, the auction price increases by the price increment $\varepsilon > 0$, the participant pays a non-refundable bid fee of C ($\varepsilon < C < \Pi - \varepsilon$), and the participant gains a chance to become next round's high bidder. The high bidder is chosen at random from the set of all bidders and so the chance that this participant will become next round's high bidder is $\frac{1}{k}$ where k is the number of bids placed in the round. If a participant chooses not to bid, this participant does not pay the non-refundable bid fee, but also does not have a chance of becoming the next round's high bidder. If all non-leaders pass in round $t > 0$, then the auction ends and the high bidder wins the item at price P_t. If all non-leaders pass in round $t = 0$, then the auction ends and the seller keeps the item.

To simplify notation, define $c = \frac{C}{\varepsilon}$, $p_t = \frac{P_t - P_0}{\varepsilon}$, and $\pi = \frac{\Pi - P_0}{\varepsilon}$. Let m denote the number of non-leading participants, $q(p_t)$ denote the probability of a non-leader bidding at price p_t, $V(p_t)$ denote the continuation value of the auction for a non-leader p_t, and $V^*(p_t)$ denote the continuation value of the auction for the high bidder at p_t. Hinnosaar (2010) shows that the risk neutral symmetric Markov perfect equilibrium is recursively characterized by (1) and (2) below (time subscripts dropped).[4]

[4] Markov perfection (e.g., Maskin and Tirole 2001) requires that $q(\cdot)$ depend only on payoff relevant-past events. In this context, all payoff relevant information is captured by the current price p_t, whether a player is the high bidder or a non-leader, and the continuation values $V(p_t)$ and $V^*(p_t)$. History dependent strategies such as signalling or cooperation are not considered.

$$V(p) = \max \left\{ \begin{array}{c} \sum_{k=0}^{m-1} \left[\binom{m-1}{k} q(p)^k (1-q(p))^{m-1-k} \left(\frac{V^*(p+k+1)+kV(p+k+1)}{k+1} \right) \right] - c, \\ \sum_{k=1}^{m-1} \left[\binom{m-1}{k} q(p)^k (1-q(p))^{m-1-k} V(p+k) \right] \end{array} \right\} \quad (1)$$

$$V^*(p) = (1-q(p))^m (\pi - p) + \sum_{k=1}^{m} \left[\binom{m}{k} q(p)^k (1-q(p))^{m-k} V(p+k) \right] \quad (2)$$

Denote the first and second arguments of the max function by A and B respectively. Argument A is the expected continuation value of bidding with certainty given the bid probabilities of others. Argument B is the expected continuation value of not bidding given the bid probabilities of others. For $q(p_t)$ to be a part of the equilibrium bidding strategy it must satisfy one of 3 conditions:

1. $q(p_t) = 1$ and $A \geq B$

2. $q(p_t) = 0$ and $A \leq B$

3. $q(p_t) \in (0, 1)$ and $A = B$

This equilibrium is not in general unique and so there may be multiple $q(p_t)$ which satisfy one of these conditions for a given p_t. By utilizing the fact that $V(p_t) = 0$ for $\pi - p_t < 0$ this system can be solved numerically using backwards induction. The equilibrium symmetric bid strategies for the parameters I use in the experiment can be found in Table A1. Three key results from Hinosaar (2010) are presented in Theorem 1 below. I refer the reader to his paper for further details.

Theorem 1 *(Hinnosaar 2010) Let $E(R)$ denote the expected auction revenue conditional on sale in the symmetric risk neutral Nash equilibrium characterized by (1) and (2). Then $E(R)$ has the following properties:*

(i) $E(R) \leq \Pi$

(ii) if $q(p) < 1, \forall p$, *then* $E(R) = \Pi$

(iii) for some values of the auction parameters $E(R) < \Pi$

This theorem suggests that expected revenue in the symmetric risk neutral nash equilibrium should equal *at most* the value of the item. This is a weaker statement than can be made in the framework of Augenblick (2011) and Platt et al (2010) in which expected revenue equals the value of the item.

With such a complicated solution concept which must be solved numerically using backwards induction it seems unreasonable to expect that human subjects will naturally arrive at the symmetric equilibrium even if they are all risk neutral. After all, there are also many asymmetric equilibria that can be played. What can be said about expected revenue in general? As it turns out, the proof of Theorem 1 does not require the symmetry assumption and instead makes use of the fact that $V(p) = 0$ for $q(p) \in [0, 1)$. This leads to the following corollary:

Corollary 1 *In any asymmetric risk neutral nash equilibrium characterized by (1) and (2), the expected auction revenue conditional on sale* $E(R)$ *has the following properties:*

(i) $E(R) \leq \Pi$

(ii) if $q_i(p) < 1, \forall i, p$*, then* $E(R) = \Pi$

(iii) for some values of the auction parameters $E(R) < \Pi$

Proof. Any strategy combination $q_i(p) < 1, \forall p$ assigns a positive probability to participant i never bidding. This strategy will yield 0 with certainty. Since a participant will only use a mixed strategy when she indifferent between her strategy choices, when $q_i(p) \in (0, 1)$ this strategy must yield 0 in expectation. Thus, $V_i(0) = 0$. When $q_i(p) < 1, \forall i, p$, $V_i(0) = 0, \forall i$. This implies that $E(R) = \Pi$ when $q_i(p) < 1, \forall i, p$. Since $q_i(p) = 1$ only when $V_i(p) > 0$, it follows that $E(R) \leq \Pi$ and that $E(R) < \Pi$ in equilibria which involve a participant bidding with certainty. ■

Corollary 1 leads to another natural question. For any set of auction parameters (n, π, c, ε) does at least one equilibrium exist such that $E(R) = \Pi$? We know this will be the case when $q_i(p) < 1, \forall i, p$, but this condition need not be satisfied for all auction parameters.

When restricting attention to Markov perfect equilibria, this condition cannot in general be satisfied. Consider the case where $m = 2$, the symmetric bid function $q(p_t) = 1$ for some t, and suppose that $q(p_t) = 1$ is the only symmetric strategy that satisfies conditions 1-3 above. Suppose the symmetry restriction is dropped, and that participant i deviates to $q_i(p_t) \neq 1$. Participant $-i$'s best response is still $q_{-i}(p_t) = 1$ as $V_{-i}(p_t) > 0$ for all strategies $q_i(p_t)$. But by similar logic, when $q_{-i}(p_t) = 1$, participant i's best response is $q_i(p_t) = 1$. Thus no symmetric or asymmetric strategy exists in this case such that $q_i(p) < 1, \forall i, p$. For larger values of m it is more likely that a Markov perfect equilibrium will exist such that $E(R) = \Pi$. First, as m increases, the degree of the polynomials in (1) and (2) increase, leading to more possible symmetric solutions for which $q(p) < 1$. Second, since participants are indifferent between bidding and not bidding at any symmetric solution $q(p) \in (0, 1)$, for $m > 2$ there are also equilibria where a subset of the non-leaders choose symmetric mixed strategies and the remaining non-leaders choose $q(p) = 0$. These additional asymmetric equilibria give even more solutions for which $q_i(p) < 1, \forall i$.

When the Markov perfect and subgame perfect restrictions are removed, it is easy to see that equilibria exist such that $E(R) = \Pi$ for an arbitrary (n, π, c, ε). Pick any strategy set s such that the expected continuation value for all players at time zero equals zero and such that $E(R) = \Pi$. Now define the strategy s_i^* which is: play strategy s_i until some player $j \neq i$ deviates from s_j and then bid with probability 1 until $\pi - p_t \leq 0$. The strategy set s^* constitutes a nash equilibrium where $E(R) = \Pi$.

Due to the complexity of the symmetric equilibrium, it seems unreasonable to expect that human subjects in a laboratory would naturally arrive at this particular equilibrium. Furthermore, since there always exist equilibria such that $E(R) = \Pi$ and never exist equilibria such that $E(R) > \Pi$ under risk neutrality, I use Π as a conservative baseline prediction to compare against average revenue in my experiment sessions. If instead the assumed equilibrium is such that $E(R) < \Pi$ then this would only serve to exaggerate any difference between the theoretical prediction and the empirical result in the case of overbidding.

Another important consideration is the effect of risk preferences on expected revenue. Platt et al (2010) show in their model of pay-to-bid auctions that when participants are symmetrically risk averse expected revenue decreases, and when the participants are symmetrically risk loving expected revenue increases. As the Hinnosaar approach to tie-breaking merely shifts probability to states where the participant has bid but does not become the high bidder and since the continuation value of these states is generally zero, this finding also applies to the above model. This leads to the following theorem.

Theorem 2 *(Platt et al 2010) Let $E(R)$ denote the expected auction revenue conditional on sale in the symmetric nash equilibrium characterized by (1) and (2). Then $E(R)$ has the following properties:*

(i) $E(R) < \Pi$ *when participants are symmetrically risk averse*

(ii) $E(R) > \Pi$ *when participants are symmetrically risk loving*

To summarize the predictions from the baseline theory: given any full information pay-to-bid auction where participants make bidding decisions simultaneously in a series of discrete rounds by maximizing expected utility, we can expect revenue to be no greater than the value of the item unless the participants are sufficiently risk seeking in aggregate.

2.2 Reasons Why The Baseline Model Might Fail

Since the profit margins of pay-to-bid auction websites are empirically estimated to be much greater than zero (e.g., Augenblick 2011, Platt et al 2010), it is clear that the baseline model is failing to capture an important factor that is relevant in a real pay-to-bid auction. Several additional theories have been proposed in an attempt to explain this discrepancy between the theoretical prediction of zero profits and the empirical estimate of positive profits. I summarize these theories below:

1. Information asymmetries and imperfect information (Byers et al 2010)

2. Risk loving preferences (Platt et al 2010)

3. Shill bidding (Platt et al 2010, Byers et al 2010)

4. Signalling strategies (Augenblick 2011, Byers et al 2010)

5. Sunk cost fallacy (Augenblick 2011)

The baseline model assumes perfect information about the auction parameters (n, π, c, ε), and that all participants face the same auction parameters. However, only the bid increment ε is known with certainty. First, in a pay-to-bid auction on the internet, the presence of a participant is only known when that participant submits a bid. Also, if a prior bidder hasn't placed a bid in a while, it is hard to tell whether or not that bidder has left the auction. Thus participants must estimate the number of participants n when determining the optimal bidding strategy. Second, participants need not have a common value for the item, and so the exact value that each bidder attaches to the item may not be known. Third, since many pay-to-bid auction websites regularly have auctions for "bid packs", it is possible for some bidders to face a lower cost of bidding than others, and again the exact cost each bidder paid per bid may not be known to the other participants. Suppose that $n-1$ participants believe that all n participants face the auction parameters (n, π, c, ε), but that 1 participant knows she faces a higher value π' or a lower cost c' and this participant knows the beliefs of the other participants. Byers et al (2010) show that so long as the $n-1$ other participants do not realize the asymmetry this will increase expected revenue $E(R)$. In addition, they show that when participants systematically underestimate the number of other participants n this will increase expected revenue $E(R)$.

The baseline model also assumes that participants are risk neutral. If instead the participants are risk loving, this would increase expected revenue. As pay-to-bid auction participants are faced with relatively low winning probabilities and seemingly random auction outcomes with high rewards, these auctions do have the feel of a lottery. Thus it is plausible that risk lovers would be drawn to pay-to-bid auction websites by the thrill of winning, and that risk averse and risk neutral individuals would learn to avoid the websites due to the losses generally incurred by participants. This selection story, suggested by Platt et al (2010), may help to explain the large profits of pay-to-bid auction websites.

Another possible explanation for these large profits is the presence of shill bidders. A shill bidder is a participant who is employed by the seller to bid at key points in the auction to keep the auction alive and increase average revenues. Platt et al (2010) show that when a shill bidder is present and attempts to blend in by playing the optimal bidding strategy, expected revenue is unchanged. There will be more bids when the shill bidder is present, but since the shill bidder is not charged bid fees and cannot actually buy the item this increase in bids does not affect revenue. However, as Byers et al (2010) point out, if the shill bidder deviates from the optimal strategy by overbidding at key points, this will increase expected revenue so long as the auction participants cannot detect the shill bidder's behavior.

Both Augenblick (2011) and Byers et al (2010) note how signalling behavior may increase expected revenue. Suppose participant i employs the strategy: bid with certainty no matter what the price ($q_i(p) = 1, \forall p$). Then the best response of all participants $j \neq i$ is to never bid ($q_j(p) = 0, \forall p$). This asymmetric equilibrium, which exists for all choices of the auction parameters (n, π, c, ε), results in participant i winning the item after a single bid for a profit of $\Pi - C - \varepsilon$. As this sort of equilibrium is quite favorable for participant i, participant i might try to signal this strategy by bidding with high frequency and by immediately outbidding any opponents rather than waiting until the end of a round to place a bid as is ordinarily preferred. If participant i is successful in implementing this strategy, then expected revenue will decrease substantially. However, if multiple participants attempting to play this strategy enter into a game of chicken, the resulting bidding war may serve to increase auction revenue.

Augenblick (2011) also suggests that sunk cost fallacy may help to explain the large profits of pay-to-bid auction websites. In the above model, participants only care about the marginal cost of bidding versus the marginal benefit of bidding. The total amount that a participant has spent previously in the auction does not enter into the calculation. This should be the case from a normative perspective, as it is still worthwhile to place a bid whenever the marginal benefit of bidding exceeds the marginal cost of bidding. However, it is possible that participants do take their prior auction expenditures into account when formulating bidding decisions. Augenblick shows that when participants experience regret from placing bids that do not win the auction and when these participants naively underestimate their future regret, this will increase auction revenue.

Another possibility is that the participants we observe in internet pay-to-bid auctions are boundedly rational or computationally limited and that these limitations are driving the profits of auction websites. The optimal bidding strategy is quite complex, can vary substantially depending on the auction parameters, and must be solved numerically through backwards induction. Even if the auction participants knew the formula used to calculate the optimal bidding strategy and all participants resolved to use it, the participants would not generally have time to calculate the optimal bidding strategy as there are only a few seconds between rounds. For participants to be able to play the optimal bidding strategy it would require that each participant had worked out the optimal bid probabilities ahead of time or that each participant have access to a bid probability calculator. This scenario is implausible. The more likely scenario is that a population of symmetric participants participating in a series of identical pay-to-bid auctions might learn over time to bid as if the symmetric equilibrium was being played. If this were the case and if new participants had a tendency to bid more frequently than optimal, expected revenue would increase in the short run, until behavior converged to the equilibrium level. This dynamic is consistent with the findings of Wang and Xu (2011) who observe in bid level auction data that pay-to-bid auction websites profit from a "revolving door" of new participants and lose money to experienced participants.

2.3 How the Experimental Method Can Help

As described in the previous section, attempts to reconcile the baseline theory's prediction of no profit for the seller with empirical estimates of large profits for the seller have led to several theoretically founded explanations. While each of these explanations is plausible, we must turn to empirical evidence to determine the true cause of this discrepancy. Field data is of limited use for these purposes as the baseline theory makes many abstractions from the strategic environment of a real pay-to-bid auction on the internet.[5] For example, the number of participants is not generally known, participants may have different valuations for the item and may face different bid costs, the auctions are conducted in continuous time rather than discrete rounds, and since the user ID of the high bidder is made public knowledge, bidder reputation and signalling strategies may be a factor. The presence of these confounding factors makes direct comparison to the theory difficult.

On the other hand, in a controlled laboratory experiment I can exactly replicate the strategic environment developed in the baseline theory to better differentiate between the possible causes of large profits for the seller. I ensure there are no information asymmetries by providing full information about the auction parameters. By drawing from a large and diverse subject pool, I am unlikely to get a sample of risk lovers. I also measure risk preference, and find that my subjects are predominately risk averse and risk neutral. In addition, shill bidders are no longer a possibility and I can keep the identity of the high bidder anonymous to discourage the use of signalling strategies.

These controls allow me to ask my primary questions of interest: (1) What is the average revenue of a pay-to-bid auction when conducted in the simpler setting that is assumed in the baseline theory? (2) Does this average revenue depend on the number of known participants

[5] This is not to say that field data isn't useful for other purposes. For instance, the analyses of Wang and Xu (2011) and Goodman (2011) shed light on important factors that can affect participant outcomes such as experience, sophisticiation, reputation, and signalling behavior.

n? (3) does the abstraction from continuous time to discrete rounds affect average revenue? In answering these questions I hope to identify some of of the reasons why the revenues of pay-to-bid auction websites are much higher than the theory would suggest.

3 Experiment Design

3.1 Basics

I conducted 5 experiment sessions with a total of 162 subjects. The sessions took place during November of 2011 and January of 2012 in a computer laboratory at a large public university. The experiment was programmed and conducted with the software z-Tree (Fischbacher 2007). Subjects were students who had previously registered to be in the laboratory subject pool, and were recruited by E-mail solicitation. Subjects were not allowed to participate in more than one session.

In each session, subjects participated in a series of pay-to-bid auctions. Parameters were held the same across auctions, but the treatment variables, the number of observed bidders n and the strategy space, were varied between sessions. I utilize a between subjects design rather than a within subjects design to ensure an adequate number of trials for behavior to converge in case of learning effects. As can be seen in Table 1, there were a large number of groups for each treatment condition and so it is unlikely that my results are driven by sampling variation. Consistent with this claim, the two sessions conducted for the Discrete-5 treatment yielded statistically identical revenue per auction.

Subjects earned $1.00 for each 1.00 of experimental currency earned during the session. In addition, subjects received $2.00 at the beginning of the session to prevent bankruptcy, as well as a payment for showing up. The amount of this show up payment ranged from $0.25 to $12.25 and was determined based on a subject's preference over three lotteries and based on the outcome of the selected lottery. Over the course of the experiment, subjects participated in a total of 1 practice auction and 8 real auctions. The average take-home amount was approximately $20 for 80 minutes of participation.

3.2 A Single Auction

Subjects are randomly assigned to a group of n participants at the beginning of each auction and shown a "start" screen with information on the auction parameters. The auction is for a commodity with common value $\Pi = 2.00$. The auction starting price P_0, bid increment ε, and bid fee C are 0.00, 0.10 , and 0.15 respectively. Subjects begin the auction with an endowment (referred to in the software as "bank account") of 1.50, which is sufficient to ensure the subjects are never budget constrained during the auction. After each subject indicates she is ready by pressing the "start" button, the auction begins. In an auction round, the subjects choose between bidding and not bidding. The auction continues until no bids are placed in a round, or until $\Pi - P_t \leq 0$, since winning the auction ceases to be profitable in this range. At the conclusion of the auction, the high bidder receives the common value of the commodity less the end auction price. The resulting profit for the high bidder is given by $\Pi - P_t \equiv 2.00 - 0.10 \times (total\ \#\ of\ bids)$. In addition, each participant (including the high bidder) receives the residual value of her bank account as profit at the end of the auction. To test whether the losing bidders cease to participate over time, the subjects are paid for *each* auction, rather than a randomly selected auction as is commonly done when trying to induce one-shot game behavior.

3.3 A Single Auction Round

Each round begins with 15 seconds on the countdown clock and the countdown begins immediately. During a round, the subjects choose between bidding and not bidding. Subjects can place a bid at any time by pressing the "Bid" button. If a subject does not press the "Bid" button, then no bid is placed. Placing a bid costs 0.15 and increments the auction price by 0.10. The round ends when the countdown clock reaches zero and, in the continuous time treatments, whenever a bid is placed. At the end of a round, both the choices that were made and the outcome of the round are revealed. If a subject places a bid in a round, that subject becomes the next round's high bidder. The high bidder is not allowed to bid while she retains this title, but receives the commodity at the end auction price if no more bids are placed. If multiple bids are placed in a round, then the high bidder is chosen at random from the set of participants who placed a bid in this round.

3.4 Number of Observed Participants

One key treatment variable is the number of observed participants n. The baseline theory suggests that expected revenue will not depend on the the number of observed participants, as a participant will adjust her probability of bidding to account for the number of other participants. However, this may not be the case in practice. For example, Gneezy and Smorodinsky (2006) find that over-bidding is increasing in the number of players. If participants are bad at adjusting the probability of bidding to account for the number of other participants, this could be one reason why pay-to-bid auction websites have revenue in excess of the value of the prize. I use two levels of the number of observed participants, $n = 3$ and $n = 5$. Since the high bidder does not participate in the round, there are $n - 1$ participants after the first round. Thus $n = 3$ is the smallest group size that can accommodate multiple participants in the later rounds of the auction. I choose $n = 5$ as the other level of the number of observed participants to double the number of participants in the later rounds of the auction relative to $n = 3$. In addition, if average revenue differs between auctions with $n = 3$ and $n = 5$, then we would expect this difference to exist for larger spreads of the number of observed participants n, so the results from this case are quite general.

3.5 Strategy Space

Another key treatment variable is the strategy space. The baseline theory assumes that participants act simultaneously in a series of discrete rounds, but pay-to-bid auctions on the internet are conducted in continuous time. While the baseline model can be adjusted to accommodate multiple rounds per bidding period, any Markov perfect equilibrium (i.e., no signalling) will only have bidding in the final round of a bidding period. Thus, the abstraction from continuous time to simultaneous rounds should not theoretically affect auction revenue.

However, anyone watching a live pay-to-bid auction would see almost immediately that bids are regularly placed at times other than the last second. Wang and Xu (2011) find evidence in auction data that different levels of bidder sophistication play a role in this behavior. In addition, Goodman (2011) finds evidence of signalling behavior in auction data, suggesting that non-Markovian equilibria are played. These deviations from equilibrium behavior in the baseline theory may have an effect on the revenue and so it is possible that differences in the strategy space can explain why pay-to-bid auction sites have revenues in excess of the value of the prize.

To test for this possibility I vary the strategy space between sessions. In one treatment, the subjects make decisions simultaneously in *discrete rounds* as modeled in the baseline theory, and in the other treatment, the subjects make decisions in *continuous time* as they would in a pay-to-bid auction on the internet. In the discrete rounds treatment, subjects have 15 seconds to decide between bidding and not bidding and the outcome of these decisions is not revealed until the countdown clock reaches 0. Since the timing of a bid has no strategic value in this context and bids are revealed simultaneously, this treatment is equivalent to the game modelled in the baseline theory. In addition, no identifiers are given to the subjects in this treatment so as to not encourage the use of Markov strategies (signalling strategies in particular). Omitting the identity of the bidder(s) each round makes it more difficult to use these Markov strategies effectively, and so the strategies played are more likely to conform with the strategies analyzed in the baseline theory. In the continuous time treatment, subjects also have 15 seconds to decide between bidding and not bidding, but now the outcome of the bid decision is revealed and the clock is reset as soon as a bid is placed. Here the timing of a bid does have strategic value as information is revealed instantaneously. The subjects are given identifiers in this treatment to allow for Markov strategies to be played.

3.6 Measuring Risk Preferences

Risk preferences may affect the bid probabilities used in equilibrium, and thus may affect expected revenue. For instance, Platt et al (2010) show that when the pay-to-bid auction participants are risk-seeking, expected revenue may be greater than the value of the prize. To account for the effect these risk preferences have on expected revenue, I elicit the subjects risk preferences at the end of the experiment session. With this measure of risk aversion, I then categorize the subjects as risk averse, risk neutral, or risk loving. The lotteries are designed with simplicity in mind, in accordance with the method of Eckel and Grossman (2008). In particular the lotteries involve two outcomes, each with 50% probability, and the lotteries are increasing linearly in standard deviation.

Each subject is asked to select her preferred show-up payment from a set of three possible lotteries. The lotteries are presented in a random order to ensure there is no ordering bias to the selections. One lottery gives \$7 with probability 100%, the second lottery gives \$10.25 with probability 50% and \$4.25 with probability 50%, and the third lottery gives \$12.25 with probability 50% and \$0.25 with probability 50%. This decision is framed in the context of a choice of show up payment so that subjects will view the lottery payoffs separately from prior earnings in the experiment. If this is the case, then a subject with constant relative risk aversion (CRRA) coefficient greater than 0.4 should prefer the first lottery, a subject with CRRA coefficient less than -0.4 should prefer the third lottery, and a subject with CRRA between -0.4 and 0.4 should prefer the second lottery. Thus, the first lottery will generally appeal to risk averse subjects, the second lottery will generally appeal to risk neutral subjects, and the third lottery will generally appeal to risk loving subjects. If a subject does take her prior earnings into account when making her selection, this will serve to increase the range of coefficients for which she prefers the "risk neutral" lottery, making the measure more crude. Regardless of which case occurs, so long as the subjects are consistent in how they evaluate these lotteries (i.e., they all generally do not account for prior earnings or they all generally do account for prior earnings), this approach will appropriately categorize subjects.

The most risk averse subjects be categorized as risk averse, the most risk loving subjects be categorized as risk loving, and the subjects in between will be categorized as risk neutral.

3.7 Sessions

I conducted 5 sessions in total, utilizing a 2×2 factorial design to test these treatment conditions. In each session, the subjects participated in a total of 1 practice auction and 8 real auctions. The auction parameters were held fixed across auctions, but the treatment parameters varied across sessions. In the first session, denoted "Discrete3", bid decisions were made in a series of simultaneous rounds and there were 3 participants per auction. In the second and third sessions, denoted "Discrete5-1" and "Discrete5-2", bid decisions were made simultaneously in a series of discrete rounds and there were 5 participants per auction. The Discrete5 treatment was split over two sessions because the computer laboratory could not accommodate the desired number of groups in a single session. In the fourth session, denoted "Continuous3", bid decisions were made in continuous time and there were 3 participants per auction. In the fifth session, denoted "Continuous5", bid decisions were made in continuous time and there were 5 participants per auction.

At the end of each session, subjects chose their preferred show up payment and then answered a short questionnaire. The questionnaire asked a variety of demographic questions (i.e., age, academic status, courses taken, gender, and major), and asked how the subject decided when to bid and when not to bid. This information is summarized in Table 1.

3.8 Hypotheses

I develop three testable hypotheses based on the predictions of the baseline theory.[6]

Hypothesis 1 *For all treatments, average revenue* $\bar{R}$ *will be less than or equal to the value of the item* Π. *(*$\bar{R} \leq \Pi$*)*

As shown in Theorem 1 and Corollary 1, expected revenue $E(R)$ should be no more than

[6] In formulating Hypotheses 1 and 2, I assume that the participants are not risk loving in aggregate. I later show that this is the case.

the value of the item Π. This result does not depend on the number of participants n and it does not depend on the strategy space.

Hypothesis 2 *For both group sizes ($n = 3, 5$), average revenue in the discrete round sessions $\bar{R}_d$ will equal average revenue in the continuous time sessions $\bar{R}_c$. ($\bar{R}_d = \bar{R}_c$)*

The baseline theory suggests that in the continuous time setting participants will wait until the last moment to place a bid. When this is the case, bids are placed *almost* simultaneously and the order of the bids *seems* random. Thus equilibrium play in the continuous time setting should be identical to equilibrium play in the discrete round setting and average revenue should be the same.

Hypothesis 3 For both group sizes ($n = 3, 5$), *risk averse individuals will bid the least on average, risk loving individuals will bid the most on average, and risk neutral individuals will be somewhere in between.*

The baseline theory suggests that expected revenue will be lower when participants are risk averse and higher when participants are risk loving. Ultimately this manifests itself as a decrease in the aggregate number of bids when participants are risk averse and an increase in the number of bids when participants are risk loving. Thus, we would expect risk averse individuals to bid the least, risk loving individuals to bid the most, and risk neutral individuals to bid a middling amount.

4 Results

4.1 Hypothesis 1

For each auction in which at least one bid was placed, I record the revenue of this auction in dollars. Auctions in which no bids are placed are excluded as the item is not sold in these cases. This yields average revenue conditional on sale, which can be directly compared to the revenue predictions of the baseline theory. Average revenue is reported by session and auction number in Table 2. Average revenues in the Discrete3, Discrete5-1, Discrete5-2, Continuous3, and Continuous5 sessions are \$2.22, \$3.10, \$3.02, \$2.32, and \$2.94 respectively.

As the Discrete5-1 and Discrete5-2 sessions each experienced the same treatment, I first test whether average revenue is the same between these sessions. When comparing the average revenue from each of these session, I cannot reject the null hypothesis of equal means (p-value 0.85). Thus I pool the data from these sessions in the remaining hypothesis tests. The resulting average for the Discrete5 treatment is \$3.07. For all treatments, I test whether average revenue is less than or equal to the \$2 value of the item. I reject this hypothesis at the 0.01 level for the Discrete5 and Continuous5 treatments, and at the 0.05 level for the Continuous3 treatment. I cannot reject that average revenue in the Discrete3 treatment is less than or equal to \$2 (p-value 0.12).

The above analysis casts doubt on Hypothesis 1, but it does not take into account the possibility of learning over time. As can be seen in Figure 1, there is substantial variability in the average revenue across auction trials but average revenue tends to lie above the \$2 value of the item, especially in early auctions. I do not find a significant trend in the Discrete3, Continuous3, and Discrete5-2 sessions, but I do find a significant downward trend in the Discrete5-1 and Continuous5 sessions (0.1 level) suggesting that subjects may learn to correct initial over-bidding with experience. To accommodate this possibility, I also test Hypothesis 1 using the last four auctions from each treatment. I identify the last four auctions as a natural breakpoint by comparing the average revenue from the first four auctions to average revenue from the last four auctions in the Discrete5-1 and Continuous5 sessions. In both sessions I find that average revenue in the last four auctions is lower, rejecting the null hypothesis at the 0.1 level and 0.05 level respectively. Average revenues in the last four auctions of the Discrete3, Discrete5, Continuous3, and Continuous 5 treatments are \$2.15, \$2.93, \$2.23, and \$2.49 respectively. For all treatments, I test whether average revenue in the last four auctions is less than or equal to the \$2 value of the item. I reject this hypothesis at the 0.01 level for the Discrete5 treatments, and at the 0.05 level for the Continuous5 treatment. I cannot reject that average revenues in the Discrete3 and Continuous3 treatments are less than or equal to \$2 (p-values 0.14 and 0.29).

As average revenues in the treatments with 5 participants are significantly greater than the value of the item even in the later auctions in the session, Hypothesis 1 is *rejected*. Subjects exhibit a persistent bias towards over-bidding. This bias becomes less severe as subjects gain experience, but it does not disappear even with moderate levels of experience. Also, the aggregate effect of this bias depends on the number of participants n. For both the discrete round and continuous time treatments, I find that average revenue is greater when $n = 5$ than when $n = 3$. I reject the null hypothesis that $\bar{R}_5 \leq \bar{R}_3$ at the 0.01 level for the discrete round treatment and at the 0.05 level for the continuous time treatment. This finding may help to explain why pay-to-bid auction websites have such large average profits. These auctions generally have a large number of bidders and so even a small individual bias towards over-bidding may lead to a lot of over-bidding in aggregate.

It is also worth noting that these revenue estimates are a lower bound on the true bias towards over-bidding. In this experiment, participants were not allowed to bid once the auction price reached \$2. This limit was reached in 42 of the 336 auctions I conducted (18 of which occurred in the one of the last four auctions) even though any bid placed after the price reached \$1.80 was guaranteed to lose money. This suggests that participants may have been willing to bid past \$2 if given the opportunity. While this behavior is seemingly irrational, it is consistent with findings in other experimental settings (e.g., Gneezy & Smorodinsky 2006, Herrmann & Orzen 2008).

4.2 Hypothesis 2

For both levels of the number of participants n, I compare average revenue in the discrete round treatment to average revenue in the continuous time treatment. In both cases, I cannot reject the null hypothesis that average revenue is the same across the two treatments (p-values 0.68 for $n = 3$ and 0.67 for $n = 5$). I interpret this as *confirming* Hypothesis 2. This finding is encouraging as it suggests that the abstraction from continuous time to discrete rounds does not fundamentally change the auction dynamics (at least when using the Hinnosaar 2010 model). Thus, further efforts to develop the theory of pay-to-bid auctions can still make headway using this simpler framework.

4.3 Hypothesis 3

I code each participant as risk averse, risk neutral, or risk loving based upon the participant's preferred lottery. In total, 69 subjects measured as risk averse, 74 subjects measured as risk neutral, and 19 subjects measured as risk loving. I then compute the average number of bids placed by the participants in each class of risk preferences. As can be seen in Figure 2, the average number of bids placed by risk averse, risk neutral, and risk loving participants in the $n = 3$ treatments is 18.9, 25.2, and 19.0 respectively. Risk neutral is significantly greater than risk averse (0.01 level) and risk loving (0.1 level). The average number of bids placed by risk averse, risk neutral, and risk loving participants in the $n = 5$ treatments is 16.6, 18.7, and 16.3 respectively. In this case, risk neutral is not significantly greater than risk averse (p-value 0.16) or risk loving (p-value 0.23). As expected, risk averse participants bid less than risk neutral participants, but surprisingly risk seeking participants also bid less than risk neutral participants. I see no theoretical justification as to why risk seeking participants would bid less than risk neutral participants. One possibility is that the mean of this relatively small sample of risk lovers is not indicative of the population mean. Another possibility is that the risk loving category is capturing some unobservable factor in addition to risk loving preferences. For example, the 8 risk loving subjects from the continuous time treatments measure as less sophisticated on average than the other subjects (although not significantly so).

As the hypothesized relationship holds for risk averse and risk neutral subjects, but not for risk loving subjects, my finding for Hypothesis 3 is *inconclusive*.

4.4 Individual Outcomes

Wang and Xu (2011) and Goodman (2011) use the timing of bids to show that factors such as sophistication and signalling behavior can have a large impact on individual auction outcomes. Key to both analyses is the strategic value of the timing of a bid in the continuous time setting. In general, when a participant is not trying to signal, the optimal time to place a bid is at the last moment. This way, if some other participant places a bid early, the participant who waited can avoid paying the bid fee. On the other hand, if a participant is trying to signal strength or aggression, placing a bid as soon as possible sends the strongest signal. Bidding in the middle of the clock is strategically inferior by both criteria. For this reason, Wang and Xu use proportion of middle bids as a proxy for strategic sophistication. They show that a lower proportion of middle bids is associated with higher profits, suggesting that strategic sophistication plays a role in individual outcomes. Goodman finds that participants who effectively employ signalling strategies tend to fare better than participants who do not signal in pay-to-bid auctions on the internet. This suggests that a participant's perceived strength and aggression may play a role in individual auction outcomes. In my setting, since each participant is symmetric, signals of strength are not credible. However, signals of aggression may still be credible, and so I test for the effect of these signals.

Following the method of Wang and Xu, I use proportion of middle bids as a proxy for sophistication. I classify a bid as a "middle bid" if it is placed from the 5th second to the 12th second of the 15 second countdown clock. I chose this range conservatively based on the bid timing histograms illustrated in Figure 3a and Figure 3b. As reported in Table 3 and illustrated in Figure 4, I find strong evidence supporting the relationship between strategic sophistication and individual outcomes. Proportion of middle bids has a strong negative correlation with net earnings, as defined by total earnings less initial endowment across all auctions. This relationship is significant at the 0.01 level for the $n = 3$ treatment, and at the 0.1 level for the $n = 5$ treatment. The least squares estimates suggest that a 1% increase in the proportion of middle bids is accompanied by an average \$0.04 to \$0.08 reduction in net earnings. Furthermore, I find no statistically or economically significant relationship between the proportion of middle bids and number of bids (p-values 0.96 and 0.76) so this finding is robust to the frequency of bids.

As described by Goodman (2011), "bidding runs" and "bid speed" are two potential ways in which a participant could try to signal aggression. A bidding run is when a participant places multiple bids in a row. For the purposes of this analysis, I consider any bidding run of length 3 or greater to be a potential signal. At most, 20 bids will be placed in any given auction, and so a run of length 3 makes up a large proportion of the total bids in an auction. In my data set, runs are most commonly of length 3 or 4 but sometimes are as long as 10. One complication is that a bidding run may not always be intended as a signal. We might also observe a bidding run if two participants enter into a bidding war or if a participant succumbs to sunk cost fallacy. To be conservative, I only consider a participant as having used a signalling strategy if that participant has at least one bidding run in the session and also uses bid speed to signal. Bid speed is the timing of a bid on the countdown clock. Earlier bids generally send a signal of aggression, although as Goodman notes when a bid is recorded at the 15 second mark it is difficult to determine whether this is a fast bid or a result of simultaneous bids in the prior round. For this reason, and due to the relatively high proportion of bids that are placed at the 1 second mark and the 15 second mark, I only code a participant as using the fast bid signal if that participant places more early bids (first 4 seconds) than late bids (last 3 seconds).

In total, 8 out of 39 subjects in the Continuous3 treatment and 6 out of 35 subjects in the Continuous5 treatment engaged in signalling behavior. As the goal of signalling in this context is to discourage the participation of other bidders, and there are less participants per auction in the Continuous3 treatment, we might expect that participants who signalled in the Continuous3 treatment fared better than participants who signalled in the Continuous5 treatment. I find this to be the case. Participants who signalled in the Continous3 treatment averaged net earnings of $-\$0.37$ which is significantly greater (0.1 level) than the $-\$2.10$ average net earnings of participants who signalled in the Continuous5 treatment. Relative to their counterparts who did not signal, participants who signalled did not fare very well. Participants who did not signal in the Continuous5 treatment averaged net earnings of $-\$0.84$

which is significantly greater (0.1 level) than the average net earnings of the participants who signalled in this treatment. Participants who did not signal in the Continuous3 treatment averaged net earnings of \$0.04 which is greater, but not significantly so (p-value 0.32), than the average net earnings of the participants who signalled in this treatment. As reported in Table 4, the actual effect of signalling is unclear. When controlling for the number of bids placed, signalling has a positive but insignificant effect on net earnings in the Continuous3 treatment. However, participants who signalled placed 9 more bids on average than participants who did not signal, and net earnings are decreasing in the number of bids placed. If these excess bids can be attributed to the cost of signalling, it appears that signalling was not an effective strategy.

The apparent ineffectiveness of signalling in this setting is not entirely surprising. In designing this experiment, I have abstracted away from three important factors that could make signalling effective in a pay-to-bid auction on the internet. First, in an effort to generate more data, I chose the auction parameters so that an auction would last no more than 20 rounds. In many pay-to-bid auctions on the internet, the auction could last for thousands of rounds, giving participants much more leeway to signal through bidding runs. For example, bidding run of length 50 sends a much more effective signal than a bidding run of length 3. Thus, as a consequence of the auction parameters I have chosen, it is more difficult to signal through bidding runs. In addition, in this setting all participants have equal endowments and are aware that they have equal endowments. This rules out the possibility that the signalling party is a strong participant with a large endowment that will muscle out the competition, a possibility that likely adds to the effectiveness of signalling in pay-to-bid auctions on the internet. Even if participants have different intrinsic levels of aggression, the signalling strategies that can be employed in this setting lend limited credibility. It is not very costly for an intrinsically passive participant to signal aggression with fast bids and a bidding run of length 3 or 4. Lastly, participants are assigned new identifiers at the beginning of every auction. This precludes the possibility of a participant building a reputation across auctions, a possibility that may aid in the effectiveness of signalling in pay-to-bid. So, while I find that signalling is not effective in the setting of this experiment, this does not rule out the possibility that signalling is effective in pay-to-bid auctions on the internet. In fact, evidence suggests that signalling is quite effective in the internet setting (e.g., Goodman 2011).

4.5 Attrition

As suggested by Wang and Xu (2011), persistently unsuccessful participants may learn to stop participating all together. To test for this possibility, I analyze each subject's participation decisions. If a subject places at least one bid within an auction, then it is clear that this subject participated in the auction. On the other hand, if a subject does not bid in an auction, this may or may not mean the subject participated in the auction. We only observe when a subject *does* bid and not when a subject *would* bid under the right circumstances. The latter is the criterion of interest in this analysis. To avoid over-estimating the level of attrition, I consider the decision not to participate to be irreversible. Thus, I code any subject who has bid at least once during the session (only 4 out of 162 subjects never placed a bid) as participating in every auction up until the point where they never bid again. So if a subject bid once in the first auction, and once in the eighth auction, then I consider this subject to have participated in every auction in the session. On the other hand, if a subject does not place any bids in the seventh and eighth auctions, then I consider this subject to have participated in the first 6 auctions. This measure will limit the bias towards over-estimating attrition, although it is still subject to error in the later auctions of the session since we do not observe what would have happened had the session continued. As can be seen in Figure 5, the first instance of attrition occurred in the fourth auction, and by the eighth auction 32 out of the 158 participating subjects had ceased participation. All 32 subjects who ceased to participate had cumulative losses at the time that they stopped participating. For each auction, I compare the cumulative net earnings of the subjects who ceased participation at the time of this auction to the cumulative net earnings of the subjects who continued to participate at the time of this auction. In all cases, the average cumulative net earnings of the non-participants were lower than the average cumulative net earnings of the participants. This difference is not significant for auctions 4, 5, and 6 (possibly due to the small sample size), significant at the 0.05 level for auction 7, and significant at the 0.01 level for auction 8. Across all auctions, non-participants averaged $0.94 less in cumulative net earnings than participants. This finding is in strong support Wang and Xu's hypothesis. I observe that persistent money losers do cease to participate and cease participation at a relatively high rate.

5 Conclusion

The main take away from this study is that the large profits of pay-to-bid auction websites can be explained simply through mistakes, and inexperience. While it is certainly possible that information asymmetries, imperfect information, risk preferences, and signalling strategies may further increase revenues, none of these dynamics are needed to observe over-bidding. Thus, the simple setting used in the baseline theory of Augenblick (2011), Hinnosaar (2010), and Platt et al (2010) captures the essence of the strategic environment of a pay-to-bid auction. Consistent with Wang and Xu (2011), I find that the symmetric equilibrium concept is the main deficiency in the current theory. There is substantial heterogeneity in the strategies employed by participants and these participants vary greatly in terms of strategic sophistication. While the population as a whole may slowly approach the equilibrium outcome where average revenue equals the value of the item, the path it takes to get there in no way resembles symmetric equilibrium play. Thus even with symmetric agents, the symmetric equilibrium is no more meaningful empirically than any of the many asymmetric equilibria (other than analytical convenience). Furthermore, a combination of learning and the long run attrition of less successful participants threatens the sustainability of the pay-to-bid auction as a mechanism to generate revenues above the value of the auctioned item. These excess revenues will only last as long as the pay-to-bid auction websites can attract new, inexperienced bidders.

APPENDIX

[To be added later]

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Table 1: Session Information

Session	Number of subjects	Number of groups	Percent male*	Percent with 1+ statistics courses*	Major*						Average take-home earnings**
					Percent Business or Economics	Percent Psychology or Cognitive Science	Percent Other Social Science, Sociology, Criminology	Percent Physical Science / Engineering	Percent Life Science / Biology / Public Health	Percent Humanities or Undecided/ undeclared	
All	162	42	47%	57%	22%	7%	15%	27%	23%	6%	$20.16
Simultaneous3	33	11	39%	61%	30%	6%	18%	21%	18%	6%	$20.57
Simultaneous5-1	35	7	34%	60%	29%	11%	11%	31%	17%	0%	$19.43
Simultaneous5-2	20	4	60%	75%	25%	15%	30%	10%	20%	0%	$19.03
Continuous3	39	13	56%	41%	21%	0%	8%	36%	23%	13%	$21.46
Continuous5	35	7	49%	57%	9%	9%	14%	26%	34%	9%	$19.71

Notes: * denotes information obtained from the questionnaire. ** includes the show up payment

Table 2: Average Revenue by Session and Auction Trial

Session	Auction Trial 1	2	3	4	5	6	7	8	**Total**
All	$ 3.10	2.47	2.98	2.47	2.93	2.05	2.52	2.22	**$ 2.59**
Simultaneous3	$ 2.25	2.17	3.00	1.63	3.04	2.41	1.75	1.78	**$ 2.22**
Simultaneous5-1	$ 4.14	2.70	3.38	3.42	3.39	1.83	2.96	2.60	**$ 3.10**
Simultaneous5-2	$ 1.58	3.19	3.25	2.83	4.31	2.42	2.92	3.17	**$ 3.02**
Continuous3	$ 2.88	2.13	2.96	1.67	2.50	1.96	2.54	1.94	**$ 2.32**
Continuous5	$ 4.29	2.93	2.54	3.82	2.32	1.86	3.11	2.68	**$ 2.94**

Notes: Auctions in which the item was not sold are excluded.

Figure 1: Average Revenue by Session and Auction Trial

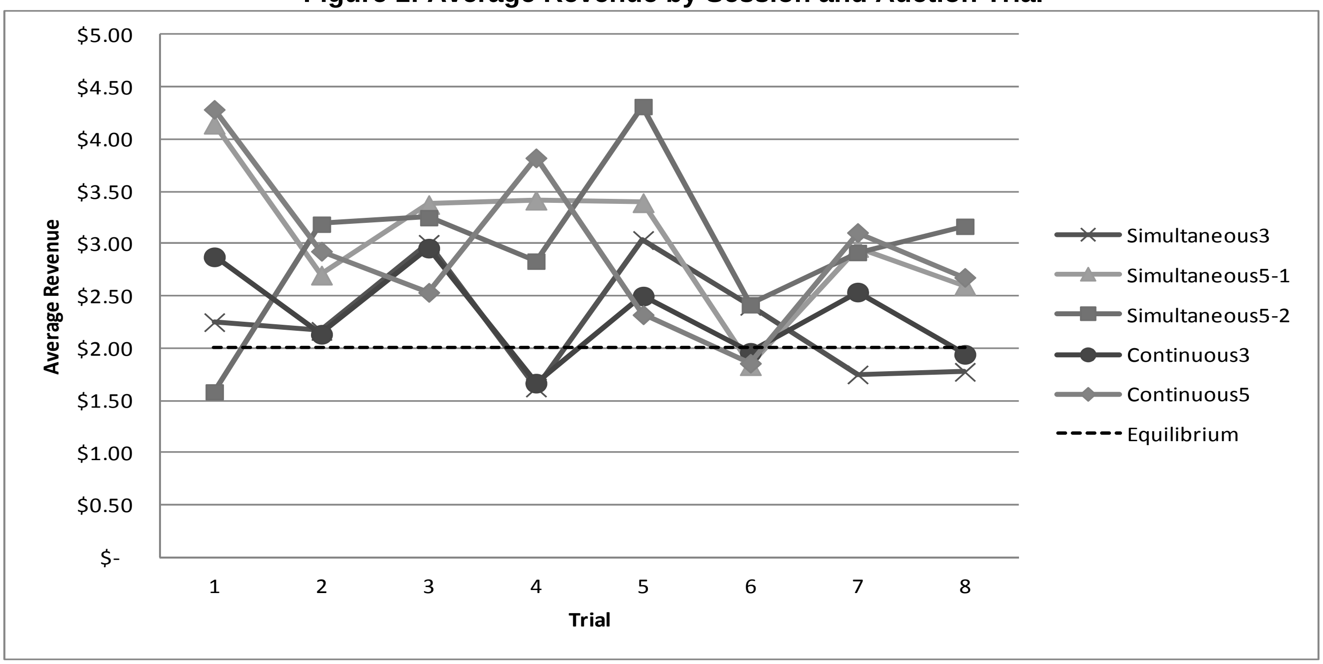

Table 3: Strategic Sophistication Regressions

	Dependent Variable: Net Earnings				Dep Var: % Middle Bids	
	n=3		n=5		n=3	n=5
	(1)	(2)	(3)	(4)	(5)	(6)
% Middle Bids	-8.421***	-8.476***	-4.075*	-3.755*		
	(2.680)	(2.483)	(2.364)	(2.171)		
# of Bids		-0.087**		-0.088**	-0.0001	0.001
		(0.033)		(0.033)	(0.002)	(0.003)
Constant	0.953**	3.033***	-0.501	1.160	0.121**	0.128**
	(0.451)	(0.884)	(0.459)	(0.753)	(0.055)	(0.057)

Notes: *significant at 0.1 level, **significant at 0.05 level, ***significant at 0.01 level.

Table 4: Signalling Regressions

	Dependent Variable: Net Earnings				Dep Var: # of Bids	
	n=3		n=5		n=3	n=5
	(1)	(2)	(3)	(4)	(5)	(6)
Signal	-0.412	0.357	-1.259	-0.486	8.343**	9.862**
	(0.893)	(0.911)	(0.804)	(0.833)	(3.438)	(3.789)
# of Bids		-0.092**		-0.078**		
		(0.040)		(0.035)		
Constant	0.044	2.076**	-0.841**	0.502	22.032***	17.138***
	(0.404)	(0.970)	(0.333)	(0.675)	(1.557)	(1.569)

Notes: *significant at 0.1 level, **significant at 0.05 level, ***significant at 0.01 level.

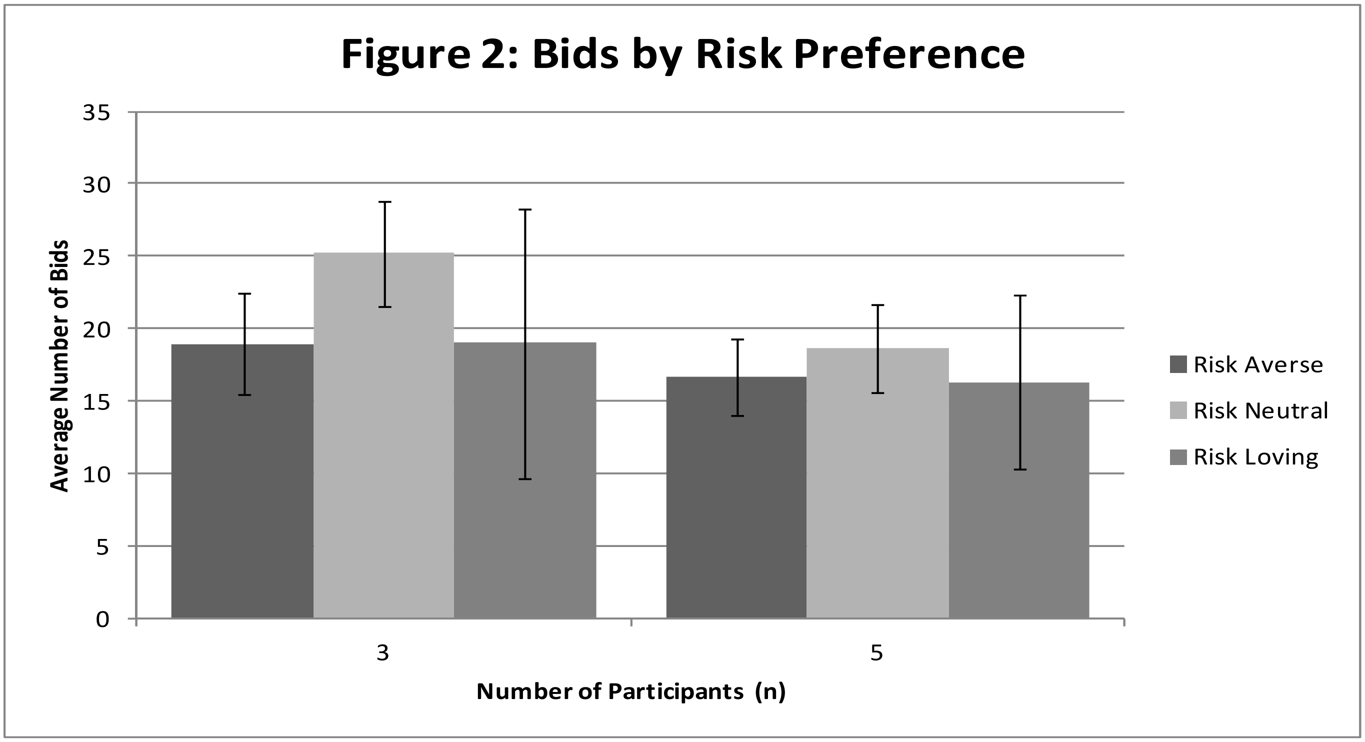
Figure 2: Bids by Risk Preference
35
30
25
20
15
10
5
0
Average Number of Bids
3
5
Number of Participants (n)
Risk Averse
Risk Neutral
Risk Loving

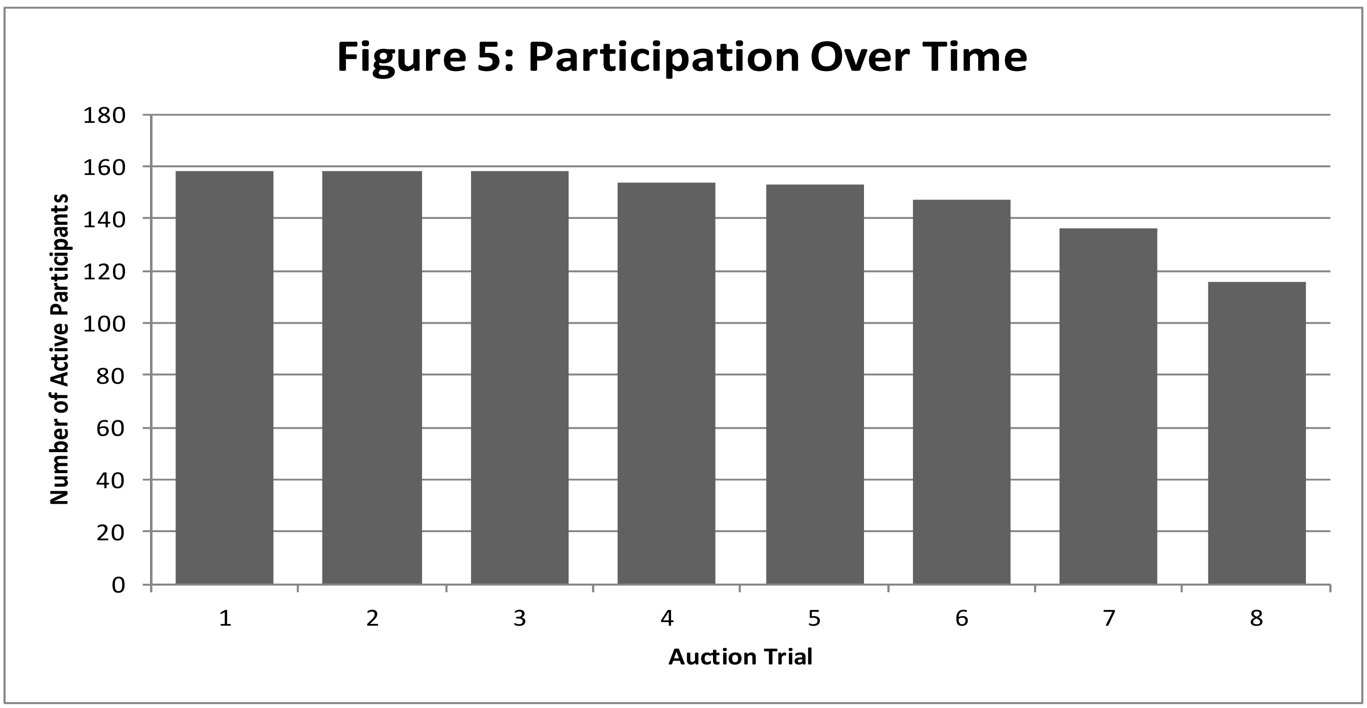
Figure 5: Participation Over Time
180
160
140
120
100
80
60
40
20
0
Number of Active Participants
1
2
3
4
5
6
7
8
Auction Trial

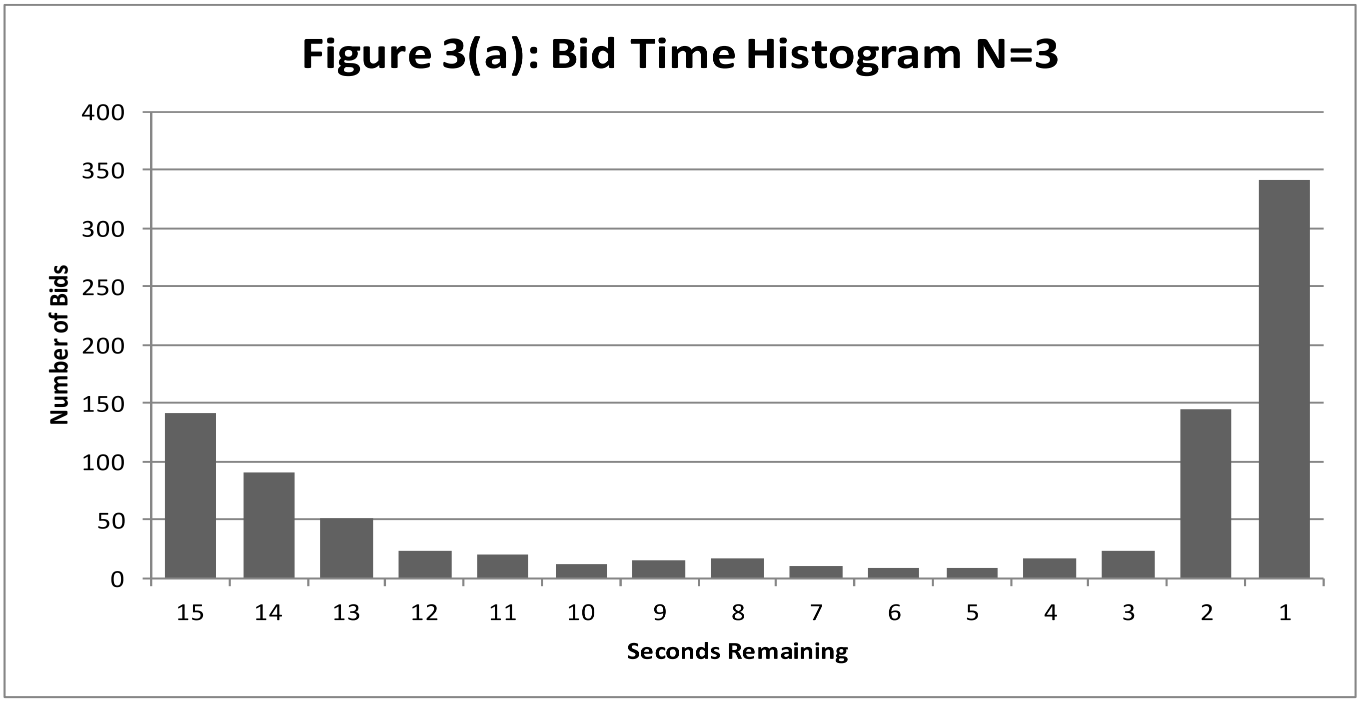
Figure 3(a): Bid Time Histogram N=3
Number of Bids
400
350
300
250
200
150
100
50
0
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
Seconds Remaining

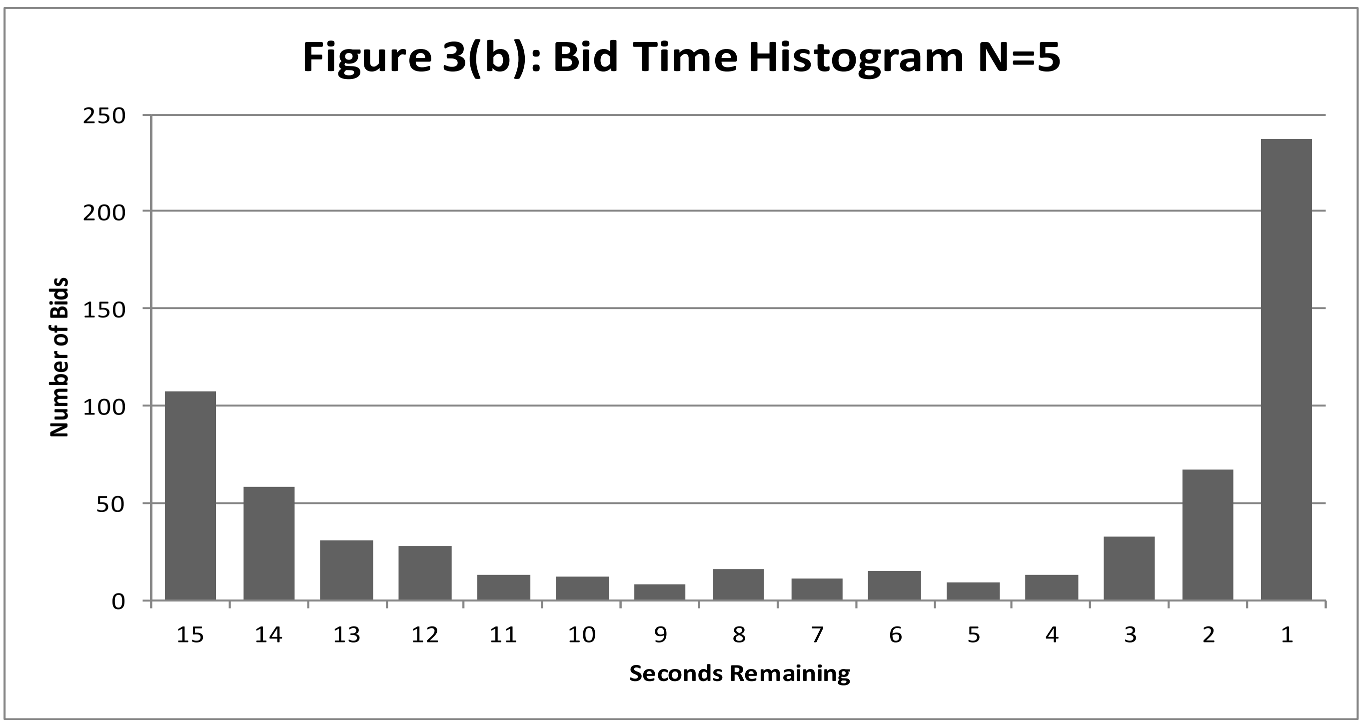
Figure 3(b): Bid Time Histogram N=5
Number of Bids
250
200
150
100
50
0
15
14
13
12
11
10
9
8
7
6
5
4
3
2
1
Seconds Remaining

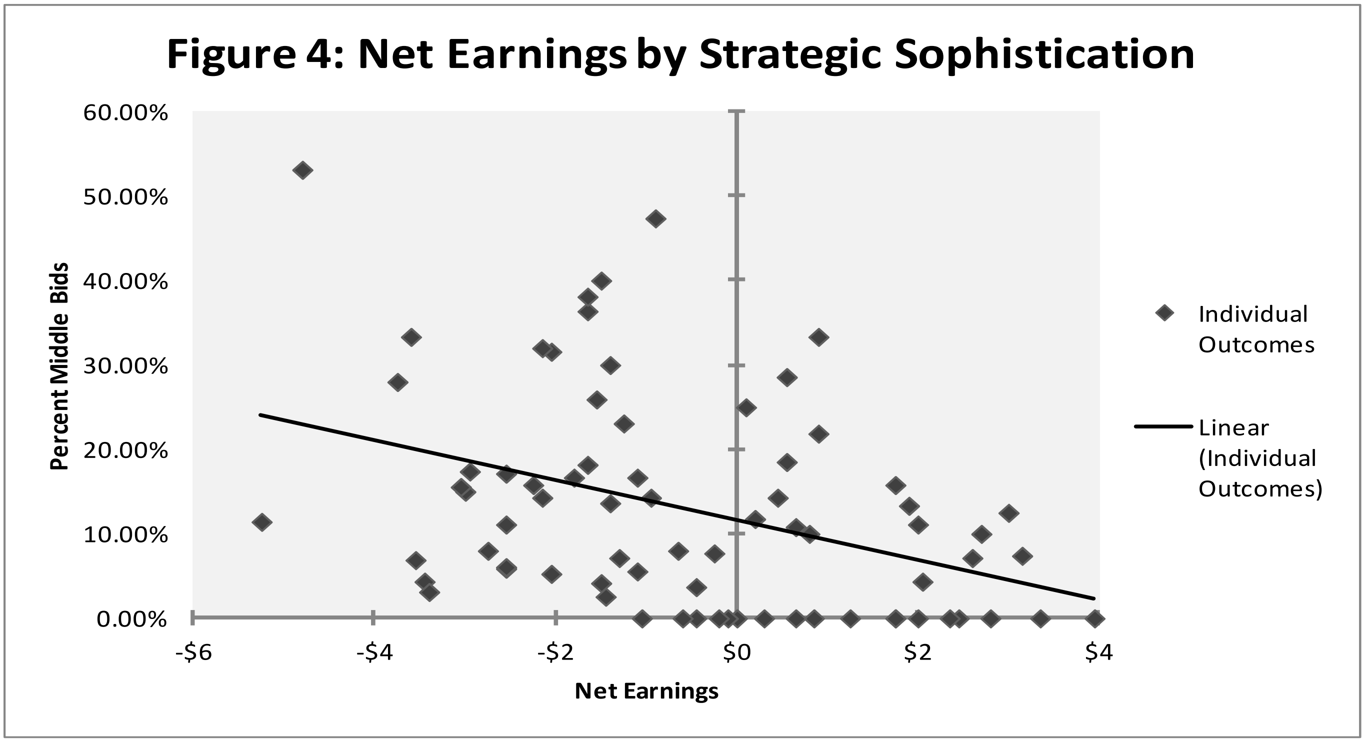
Figure 4: Net Earnings by Strategic Sophistication
60.00%
50.00%
40.00%
30.00%
20.00%
10.00%
0.00%
Percent Middle Bids
-$6
-$4
-$2
$0
$2
$4
Net Earnings
Individual Outcomes
Linear (Individual Outcomes)