Asymmetric Information in Contests: Theory and Experiments[1]

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Abstract

This paper considers imperfectly discriminating contests and all-pay auctions with asymmetric information. In our design one bidder observes an informative signal as to the realized common value of the good. The other bidder holds only public information; she knows the distribution from which the value of the prize is drawn. We characterize the equilibrium in a common value all-pay auction with this type of information asymmetry. Theory suggests that such asymmetric information yields information rents for the informed bidder and reduces the expected revenue of the seller. We report the results of experimental tests of these theoretical predictions.

1 Introduction

In a contest a set of economic agents expend unrecoverable effort to increase the probability of obtaining a good. One of the contestants wins the contest and gets the good. In a perfectly discriminating contest, also known as an all-pay auction, the contestant who expends the most effort wins the contest with certainty. In an imperfectly discriminating contest, an increase in effort relative to the other contestants increases the probability of winning, but no contestant wins the contest with certainty. The applications of such games are abundant and diverse. Contests are used to model research and development, elections, sports, labor markets and many more.

The theoretical analysis of contests is a vast and burgeoning literature which traces its roots to Tullock (1967). A survey of this literature can be found in Konrad (2009). An important topic in this literature is the role of asymmetric information. However, the literature concerning asymmetric information in contests is quite small. Wärneryd (2003) analyses a two player imperfectly discriminating contest in which one contestant is informed of the common but uncertain value of the good prior to bidding, while the other contestant knows only the distribution from which this value was drawn. In this framework, revenue decreases relative to the cases in which neither, or both, contestants are informed regarding the realized value of the good.. The informed contestant is better off in expectation than in either of these symmetric information cases, and the uninformed contestant is worse off in expectation. Rentschler (2010) extends these results in a two period model with more than two contestants. In the first round information is symmetric; no contestant holds information regarding the common and uncertain value of the good, beyond the distribution from which it is drawn. The winner of the first contest privately observes the value of the good in the first contest, and this value serves as a noisy signal regarding the value of the good in the second contest. The results in Wärneryd (2003) extent to this generalized case. Further, the increased incentive to win the first contest is sufficient to increase aggregate effort relative to the case in which information is symmetric in both contests.

In a related paper, Hurley and Shogren (1998) analyze a two player contest in which one contestant knows the other's valuation of the good, while the informed contestant's valuation is private information. They find that such an information asymmetry reduces the uninformed contestant's probability of winning. Fu (2006) considers a model in which contestants are asymmetrically informed and endogenously choose the order in which they choose their respective bids. In this model the uninformed contestant chooses to move first, and effort expenditures are reduced relative to a simultaneous move game. Prior to this paper, the role of asymmetric information in perfectly discriminating contests has not been analyzed theoretically.

This paper experimentally examines the role of asymmetric information in incomplete information contests, both perfectly and imperfectly discriminating. In our experimental design two contestants, or bidders, simultaneously submit bids, in an effort to obtain a good.[1] This good has a common but uncertain value. We vary the contest success function between perfectly discriminating (all-pay auction), and imperfectly discriminating (lottery contest). We also vary the information structure of the game. In the symmetric information structure, neither bidder holds any private information regarding the value of the good. In the asymmetric information structure one bidder observes a noisy signal regarding the value of this good, while the other does not. We also examine an all-pay auction in which each bidder observes a private signal, which allows us to compare our results to those of Grosskopf (2010), which experimentally analyses first-price auctions under these three information structures.

We also characterize the Nash equilibrium in an asymmetric information all-pay auction; one contestant receives a noisy estimate regarding the common and uncertain value of the good, while the other contestant does not. We find that aggregate effort falls in expectation relative to the case in which neither bidder observes a signal. Further, the informed contestant is better off relative to this symmetric information case, while the uninformed contestant has an expected payoff of zero.

[1] In the contest literature players are typically called contestants. In the all-pay auction literature, players are typically called bidders, and their effort expenditures are refered to as bids. Throughout the body of the paper we refer to players as bidders, and effort expenditures as bids. Our experimental instructions also used this terminology to frame the game.

Our experimental analysis yields several interesting results. First, information asymmetry reduces revenue in all-pay auctions. However, this in not the case in lottery contests; we are unable to reject revenue equivalence. We also find that the symmetric information all-pay auctions yields higher revenue that the symmetric information lottery contest. Interestingly, when there is asymmetric information, this does not hold. That is, we are unable to reject revenue equivalence between all-pay auctions and lottery contests when there is asymmetric information.

We also find, in both all-pay auctions and lottery contests, that the informed bidder is better off than the uninformed bidder. Additionally in both all-pay auctions and lottery contests, the informed bidder in the asymmetric information environment is better off than bidders in the symmetric information environment; the informed bidder earns a positive information rent. In accordance with theory, the uninformed bidder in the asymmetric information lottery contest is worse off than bidders in the symmetric information lottery contest. Also in accordance with theory, the uninformed bidder in the asymmetric information all-pay auction is not worse off than bidders in the symmetric information all-pay auction; we are unable to reject payoff equivalence between these two types of bidders. We also find that bidders in the symmetric information lottery contest are better off than bidders in the symmetric information all-pay auction. Additionally, we are unable to reject payoff equivalence between uninformed bidders in all-pay auctions and lottery contests, as well as payoff equivalence between informed bidders in all-pay auctions and lottery contests. This observation provides additional insight into the revenue equivalence between the two asymmetric information environments

We also compare bidding behavior to a strategy above which a bidder is guaranteed to earn negative payoffs, provided the other bidder is bidding according to the Nash equilibrium. We call such a bidding strategy a break-even bidding strategy. Such a threshold is of interest, since experimentalists have observed that bidders in contests often overbid relative to Nash predictions and go bankrupt as a result. Bidding above a break-even bidding strategy is analogous to falling victim to the winner's curse, which has been widely observed in the experimental auction literature.[2] We observe that informed bidders in the asymmetric information environments are much more prone to bid above this break-even bidding strategy than are uninformed bidders in the asymmetric or symmetric information environments. This is consistent with the findings of Grosskopf *et al.* (2010), which experimentally analyses the effect of asymmetric information in first-price, sealed-bid, common-value auctions. As mentioned above, to further aid comparison of our data to that of Grosskopf *et al.* (2010) we ran sessions in which bidders participate in a series of all-pay auctions and both bidders privately observe a signal (the signals are independent, conditional on the realized value of the good). While we do not have theoretical predictions for this game, bidding above a break-even bidding strategy is much more prevalent than in

[2] For an overview of this literature see Kagel and Levin (2002).

the symmetric information all-pay auctions in which neither bidder observed a signal.[3] As such, we can confidently say that asymmetric information is not the determining factor in informed bidders bidding above the break-even bidding strategy.

We also find evidence that men bid less than women regardless of the contest success function or the information structure of the game. In asymmetric information lottery contests, women learned to decrease their bids faster than men, such that by the final periods behavior had converged. This accelerated learning of women was not significant for bidders with symmetric information, or bidders in all-pay auctions with symmetric or asymmetric information.

Most of the existing experimental literature regarding contests and all-pay auctions study complete information environments. That is, each bidder's valuation of the good is common knowledge. Miller and Pratt (1989), examines lottery contests with complete information and find significant overbidding. Miller and Pratt (1991) finds that bidding is decreasing in risk aversion in complete information, common-value lottery contests. Davis and Reilly (1998) and Potters *et al.* (1998) both examine lottery contests and all-pay auctions in a complete information and common value context, and find that the all-pay auction generates more revenue than lottery contests. Rapoport

[3]The break even bidding-strategy in the all-pay auction in which each bidder observes a private signal is defined under the assumption that bidders employ a monotonically increasing bid function.

and Amaldoss (2004) experimentally examine all-pay auctions with complete information, a common-value good, and binding budget constraints. They find that behavior is consistent with equilibrium predictions at the aggregate, but not individual, level. Gneezy and Smorodininsky (2006) study common-value all-pay auctions with complete information and find dramatic overbidding relative to Nash predictions.

The experimental literature regarding contests with incomplete information is surprisingly small. Noussair and Silver (2006) study all-pay auctions in an independent private value environment. They find that this all-pay auction yields more revenue than predicted by theory, as well as yielding more revenue than the analogous first-price, sealed-bid auction. Barut *et al. (2002)* examines an independent private value all-pay auction with multiple units of the good, and find that bidder's overbid relative to the Baysian equilibrium. To the best of our knowledge, this is the first experimental analysis of perfectly or imperfectly discriminating contests with asymmetric information.

The remainder of the paper is organized as follows. Section 2 describes our experimental design. Section 3 contains the theoretical predictions. Section 4 provides our experimental results. Section 5 contains the conclusion. Appendix A contains the theoretical derivations of the Nash equilibrium of all-pay auctions with asymmetric information in a general environment. Appendix B contains the derivations of theoretical predictions using the distributions and parameters used in our design, Appendix C contains experimental results regarding all-pay auctions in which each bidder holds private information, and Appendix D provides a sample set of instructions.

2 Experimental Design

We employ a between-subject design which varies the game between an all-pay auction (perfectly discriminating contest) and a lottery contest (imperfectly discriminating contest) and varies the information observed by bidders prior to placing their bids. This design is summarized in Table 1. Participants engage in either a series of common-value, two-player all-pay auctions or lottery contests. Within a group of ten, participants are randomly and anonymously matched into pairs at the beginning of each session. Each bidder submits a bid, which must be paid. In all-pay auction sessions the bidder who submits the highest bid wins the all-pay auction and receives the good (in the event of equal bids, both bidders have a 50% chance of obtaining the good). In lottery contest sessions the probability that a bidder obtains the good is her proportion of the sum of bids. Participants are randomly and anonymously rematched after each round. This process is repeated for thirty rounds.[4][5]

In each all-pay auction or lottery contest a good with a common but uncertain value is available. The common value, x, is a realization of the random variable X, which is uniformly distributed with support $[25, 225]$. The realized value of the good is not observed by bidders before placing their bids. The distribution of X is common knowledge. Prior to placing their bid, bidders may privately observe a signal, which is drawn from a uniform distribution with support $[x - 8, x + 8]$. The treatments of our experimental design are as follows.

1. *Symmetric information all-pay auction (SAP).*—Participants engage in 30 all-pay auctions. In each of these all-pay auctions neither bidder observes any information regarding x beyond the distribution of X. As such, no bidder holds any private information, and information is symmetric.

2. *Asymmetric information all-pay auction (AAP).*—Participants engage in 30 all-pay auctions. In each of these all-pay auctions one of the bidders is randomly chosen to be the informed bidder, who privately observes a signal. This signal, z_I, is drawn from a uniform distribution

[4] Since matching of participants occured within groups of ten, and thirty rounds were conducted, participants were inevitably matched together more than once. However, participants were anonymously matched such that they were unable to build a reputation. Further, each session was ususally run with twenty or thirty participants, and participants were not informed that they would only interact within a group of ten.

[5] In one of the contest sessions, there are only 29 rounds.

with support $[x - 8, x + 8]$. The other bidder does not observe a signal; all the information available to them was common knowledge. Since the informed bidder is randomly determined in each auction, bidders change roles throughout each session.

3. *Symmetric information lottery contest (SLC).*—Participants engage in 30 lottery contests auctions. Neither bidder observes any information regarding x beyond the distribution of X. As such, no bidder holds any private information, and information is symmetric.

4. *Asymmetric information lottery contest (ALC).*—Participants engage in 30 lottery contests auctions. One of the bidders is randomly chosen to be the informed bidder, who privately observes a signal. This signal, z_I, is drawn from a uniform distribution with support $[x - 8, x + 8]$. The other bidder does not observe a signal; all the information available to them was common knowledge. Since the informed bidder is randomly determined in each auction, bidders change roles throughout each session.

In each of these treatments, the information structure is common knowledge. That is, if a bidder observes a signal, this fact, as well as the distribution from which the signal is drawn, is common knowledge. At the conclusion of each auction each bidder observes both bids, the earnings of both bidders, their own balance and, if applicable, the private signal(s) (par-

Table 1: Experimental design

Between-subject design		
	All-pay auctions.	Lottery contests
Symmetric information	5 groups of 10	5 groups of 10
Asymmetric information	5 groups of 10	5 groups of 10

ticipant numbers are suppressed).[6]

Examining two-bidder games makes sense because in all-pay auctions with asymmetric information the equilibrium bid function of the informed bidder does not depend on the number of bidders. The expected payoffs of these bidders (and hence, expected revenue) also do not depend on the number of bidders. Since we are interested in the role of information, we leave the test of these comparative statics to future research. Second, existing experimental analysis on all-pay auctions with symmetric information examines games with more than two bidders. Thus, our SAP treatment provides insight not already found in the literature.

All sessions were run at the Economic Research Laboratory (ERL) at Texas A&M University, and our participants were matriculated undergraduates of the institution. The sessions were computerized using z-Tree (Fischbacher 2007). Participants were separated by dividers such that they can not interact outside of the computerized interface. They were provided with

[6] Armantier (2004) finds that the ex post observation of bids, earnings and signals "homogenizes behavior, and accelerates learning toward the Nash equilibrium" in common-value first-price auctions when all bidders observe a signal.

instructions, which were read aloud by an experimenter.[7] After they instructions were read, questions were answered privately. Each participant then individually answered a set of questions to ensure understanding of the experimental procedure; their answers were checked by an experimenter who also answered any remaining questions. Participants were provided with a history sheet which allowed them to keep track of bids, earnings and. if applicable, signal(s) in each round. Each session lasted approximately two hours. Each participant began with a starting balance of $20 to cover any losses; no participant went bankrupt. At the end of all rounds, each participant was paid their balance, as well as a show-up fee of $5. The bids, signals and values were all denominated in Experimental Dollars (ED), which were exchanged for cash at a rate of 160ED/$1. The average payoff was $25.57, with a range of $9.44 to $33.62.

3 Theoretical Predictions

A set of risk neutral players $\mathbf{N} \equiv \{1, 2\}$ compete for a good with a common but uncertain value. The value of the good is a realization of the random variable X, which is uniformly distributed on $[25, 225]$. This distribution function is commonly known. The expected value of $X = E(X) = 125$. Player $i \in \mathbf{N}$ chooses an unrecoverable bid, $b_i \in \mathbb{R}_+$ at a cost of $C_i(b_i) = b_i$

[7] The instructions for the ALC treatment are found in Appendix C. Instructions for the remaining treatments are available upon request.

in an effort to obtain the good. These bids are chosen simultaneously, and players do not observe the value of x before choosing b_i. Players are not budget constrained; the strategy space of each player is $\mathbb{R}_+$. The vector of bids is $\mathbf{b} \equiv \{b_1, b_2\}$. Further, $\mathbf{b}_{-i} \equiv \mathbf{b} \backslash b_i$ and $\mathbf{N}_{-i} \equiv \mathbf{N} \backslash i$.

The function $p_i : \mathbb{R}_+ \rightarrow [0, 1]$ maps $\mathbf{b}$ into the probability that contestant i will receive the good. This function is typically called the contest success function in the contest literature. Different functional forms of p_i have been studied in the literature. Depending on the functional form of p_i a contest may be characterized as either a perfectly discriminating contest or an imperfectly discriminating contest. In a perfectly discriminating contest, p_i as is given by

$$p_i = \begin{cases} 1 & \text{if} \quad b_i = \max\{b_1, b_2\} \\ \\ 0 & \text{if} \quad b_i = \max\{b_1, b_2\} \\ \\ \frac{1}{2} & \text{if} \qquad b_1 = b_2. \end{cases}$$

Note that in such a perfectly discriminating contest the bidder with the highest bid obtains the good with certainty. Since bids are unrecoverable, this perfectly discriminating contest is equivalent to a first-price, sealed-bid, all-pay auction. Indeed, this game is typically referred to as an all-pay auction. As this terminology is prevalent throughout the literature, we adopt it.

In an imperfectly discriminating contest the bidder with the highest bid does not obtain the good with certainty. Skaperdas (1996) axiomises a class of imperfectly discriminating contest success functions. A special case of this class is

$$p_i = \begin{cases} \frac{b_i}{b_1+b_2} & \text{if} \quad \max\{b_1, b_2\} > 0 \\ \\ \frac{1}{2} & \text{if} \quad \max\{b_1, b_2\} = 0, \end{cases}$$

which characterizes a lottery contest. Notice that each bidder's probability of obtaining the good is proportional to the revenue generated by the contest. Also, when $b_i = b_j = 0$ then each bidder has an equal probability of obtaining the good. However if both bidders were to bid nothing, there is an incentive to bid an arbitrarily small amount and win the good with certainty. Thus this boundary case does not arise in equilibrium. As such, any assumption regarding this case would serve equally well. This particular contest success function is widely utilized throughout the experimental literature regarding contests. To aid in the comparability of our result with this literature we utilize it as well.

3.1 All-Pay Auctions

3.1.1 Symmetric Information All-Pay Auctions (SAP)

In a SAP auction, neither bidder holds private information. The distribution from which the value of the good is drawn is common knowledge. Assuming risk neutral bidders, this is strategically equivalent to an all-pay auction with complete information in which $E(X)$ is the common value of the good. The equilibria of all-pay auctions with complete information are completely characterized in Baye *et al.* (1996). In a two-bidder all-pay common-value auction with complete information, there is a unique, symmetric, risk neutral Nash equilibrium. In this equilibrium, both bidders employ a mixed strategy with support on $[0, 125]$. The distribution function of this equilibrium mixed strategy is given by

$$K(b_i) = \frac{b_i}{125}.$$

where b_i is the bid of bidder i.

Notice that zero is an element of the support of this mixed strategy, which implies that the bidders have an expected payoff of zero for every bid in that support. That is $E\left(\Pi^{SAP}\right) = 0$. The expected revenue generated by this equilibrium is $E\left(R^{SAP}\right) = E(X) = 125$.

Break-even Bidding Strategy in SAP Suppose that bidder j were to employ the equilibrium mixed strategy described above. Bidder i then has an expected payoff of zero for any $b_i \in [0, 125]$. For any $b_i > 125$, bidder i has a negative expected payoff in expectation. As such, $\rho^{SAP} = 125$ is a break-even bidding strategy; any bid above 125 guarantees a negative payoff in expectation.

3.1.2 Asymmetric Information All-Pay Auctions (AAP)

One of the bidders observes a signal, z_I, prior to bidding; we refer to this bidder as the informed bidder. This signal is a realization of the random variable Z_I which is uniformly distributed on $[x - 8, x + 8]$. The distribution function of Z_I is denoted as F_{Z_I}. The other bidder, who we refer to as the uninformed bidder, does not observe a signal. She only knows the distribution of X, Z_I and the fact that the informed bidder will observe a realization of Z_I.

This model is similar to the one in Engelbrecht-Wiggans *et al.* (1983), which studies this information structure in the context of a first-price, sealed-bid auction. The primary difference is that the low bidder must also pay her bid. The model found in Engelbrecht-Wiggans *et al.* (1983) is experimentally tested in Grosskopf *et al.* (2010).

The equilibrium for this model is derived for general joint distribution of X and Z_I in Appendix A. For the distributions and parameters employed in our experimental design the risk neutral Nash equilibrium bid function for the informed bidder is given by

$$\beta\left(z_I\right)=\begin{cases}\frac{(z_I+58)(z_I-17)^2}{19200} & \text{if} \quad z_I\in[17,33)\\ \\ z_I+g\left(z_I\right) & \text{if} \quad z_I\in[33,217)\\ \\ \frac{151683z_I-z_I^3+24z_I^2-21595738}{19200} & \text{if} \quad z_I\in[217,233],\end{cases}$$

where $g\left(z_I\right)=\frac{3z_I^2-1200z_I-1811}{1200}$ is the nonlinear portion of the informed AAP bidder's equilibrium bid function when $z_I\in[33,217)$.[8]

The uninformed bidder mixes on the interval $[0,125]$, where the probability that she bids b is

$$\begin{aligned}J\left(b\right) &= \text{Prob}\left[\beta\left(Z_I\right)\leq b\right]\\ &= F_{Z_I}\left(\beta^{-1}\left(b\right)\right).\end{aligned}$$

The derivation of $J\left(b\right)$ can be found in Appendix B. Note that the uninformed bidder will not bid more than 125 in equilibrium, because this would ensure negative expected profits upon winning the auction. Further, note that $J\left(b\right)$ indicates that the distribution of bids of the uninformed bidder is identical to that of the informed bidder. As such, the ex ante probability that the uninformed bidder will obtain the good is equal to the ex ante

[8]This definition of $g\left(z_I\right)$ is for notational convenience; we utilize this notation when estimating bid functions.

probability that the informed bidder will obtain the good.

Since, in equilibrium, the uninformed bidder employs a mixed strategy, it must be the case that the expected payoff of any bid in the support of this strategy yields the same expected payoff. As above, the fact that zero is in the support of the uninformed bidder's equilibrium bidding strategy implies that the ex ante expected payoff of the uninformed bidder, $E\left(\Pi_U^{AAP}\right)$, is zero.

Let $q\left(z_I\right) \equiv E\left(X \mid z_I\right)$. Since $q\left(z_I\right)$ is monotonically increasing in z_I, the distribution function of this random variable is $F_{Z_I}\left(q^{-1}\left(\cdot\right)\right)$, where $q^{-1}\left(\cdot\right)$ is the inverse of $q\left(\cdot\right)$. The expected payoff of the informed bidder, when z_I is observed, is $\Pi_I^{AAP}\left(z_1\right) = \int_{25}^{q(z_I)} F_{Z_I}\left(q^{-1}\left(s\right)\right) ds$. This yields

$$\Pi_I^{AAP}\left(z_I\right) = \begin{cases} \frac{\left(z_I - 17\right)^3}{38400} & \text{if} \quad z_I \in [17, 33) \\ \frac{1811 + 3 z_I \left(z_I - 50\right)}{1200} & \text{if} \quad z_I \in [33, 217) \\ \frac{12015737 - 143667 z_I + 699 z_I^2 - z_I^3}{38400} & \text{if} \quad z_I \in [217, 233]. \end{cases}$$

Integrating over $\Pi_I^{AAP}\left(z_I\right)$ with respect to F_{Z_I} yields the ex ante expected profit of the informed bidder, $E\left(\Pi_I^{AAP}\right) = 33.23$. We refer to this as the informed bidder's information rent in an AAP auction. This large information rent is largely due to the fact that the upper bound of the support of the uninformed bidder's equilibrium mixed strategy is 125. The ex ante expected revenue of an AAP auction, $E\left(R^{AAP}\right)$, is equal to $E\left(X\right) - E\left(\Pi_I^{AAP}\right) -$

$E\left(\Pi_U^{AAP}\right) = 91.77.$

Interestingly, the expected payoffs of both bidders in this AAP auction are exactly the same as in the analogous first-price sealed-bid auction. These results extend to a more general model, the proof of which is found in Appendix A.

Break-even Bidding Strategy in AAP For the informed bidder the break-even bidding strategy is the bid which satisfies

$$F_{Z_I}\left(\beta^{-1}(b)\right) E\left(X \mid z_I\right) - b = 0.$$

Since the uninformed bidder will never bid above $E(X) = 125$ in equilibrium, when $z_I \geq 125$, $b = E(X \mid z_I)$ is the break-even bid. For brevities sake, we do not include the derivations of the break-even bidding strategy when $z_I < 125$. These derivations can be found in Appendix B.

For the uninformed bidder, the break-even bidding strategy is $\rho_U^{AAP} = 125$. The reasoning behind this is similar to that of SAP bidders. Namely, for any bid less or equal to 125, the expected payoff is zero. To obtain a negative expected payoff, the uninformed bidder must bid more than 125.

3.2 Lottery Contests

3.2.1 Symmetric Information Lottery Contests (SLC)

If both bidders hold only public information, the distribution of X is the only information regarding x available to bidders before placing their bids. Assuming risk neutral bidders, the well known unique equilibrium of this game is for each bidder to bid $\frac{E(X)}{4} = 31.25$.[9]. The revenue generated by this equilibrium, $E\left(R^{SLC}\right)$, is simply the sum of the bids, which is 62.5. The expected payoff of each bidder is $E\left(\Pi^{SLC}\right) = 31.25$, which is equal to the equilibrium bid.

Notice that bidders earn a positive payoff in equilibrium, despite holding no private information. Further the $E\left(R^{SLC}\right)$ is half of $E(X)$. Contrasting this with the revenue prediction of the analogous all-pay auction, $E\left(R^{SAP}\right) = 125$, we see that a SLC generates half the revenue of a SAP, in equilibrium.

Break-even Bidding Strategy in SLC The break-even bidding strategy of bidder i in a SLC bidder is the b_i which satisfies

$$\frac{b_i}{b_i + 31.25} E(X) - b_i = 0.$$

That is, the break-even bidding strategy of a SLC bidder is $\rho^{SLC} = 93.75$. This break-even bidding strategy is defined assuming the other bidder is

[9] This well known result can be found in Cornes and Hartly (2005). The derivations of this equilibrium is found in Appendix B.

bidding according to the Nash equilibrium. Notice that if the other bidder were to bid more than the Nash equilibrium bid, as is often observed, the bid which ensures an expected payoff of zero is lower than 93.75. As such, this measure of overbidding is conservative, given the behavior typically observed in lottery contest experiments.

3.2.2 Asymmetric Information Lottery Contests (ATC)

One bidder observes a private signal before placing her bid. We refer to this bidder as the informed bidder. The signal is a realization of Z_I which is uniformly distributed on $[x-8, x+8]$ The distribution of Z_I is F_{Z_I}. The other bidder holds no private information, and we refer to this bidder as the uninformed bidder. Rentschler (2009) provides the unique, risk neutral Nash of this game.[10] The equilibrium bid function of the informed bidder is:

$$\zeta^{ALC}(z_I) = \begin{cases} 0 & \text{if} \quad z_I \in [17, 25.74) \\ \sqrt{14.68\,(z_I + 33)} - 29.37 & \text{if} \quad z_I \in [25.74, 33) \\ \sqrt{29.37 z_I} - 29.37 m\,(z_I) & \text{if} \quad z_I \in [33, 217) \\ \sqrt{14.68\,(z_I + 217)} - 29.37 & \text{if} \quad z_I \in [217, 233], \end{cases}$$

[10]The derivations of this Nash equilibrium bidding strategy, as well as the equilibrium payoff and expected revenue predictions for the distributions used in our experimental design are found in Appendix B.

where $m(z_I) = \sqrt{29.37 z_I} - 29.37$ is the nonlinear portion of $\zeta^{ALC}(z_I)$ when $z_I \in [33, 217)$.[11]

The equilibrium bid of the uninformed bidder, rounded to the nearest cent, is $b_U = 29.37$. Integrating $\zeta^{ALC}(z_I)$ over Z_I yields the ex ante expected bid of the informed bidder, $E\left(\zeta^{ALC}(z_I)\right) = 29.37$.

Notice that, in expectation, the informed bidder and the uniformed bidder bid the same amount. Also, notice that if the informed bidder observes a value of z_I such that $E(X \mid z_I) < 29.37$, the informed bidder will bid zero. When $E(X \mid z_I) < 29.37$, the informed bidder has no incentive to bid; submitting a positive bid in such a circumstance yields negative expected profits. An interesting consequence of this observation is that, ex ante, the uniformed bidder is expected to obtain the good with a higher probability than the informed bidder.

The expected payoff of the informed bidder, when he observes z_I, is given by

$$\Pi_I^{ALC}(z_I) = \begin{cases} 0 & \text{if} \quad z_I \in [17, 25.74) \\ \frac{z_I + 91.74}{2} - 2\sqrt{14.685(z_I + 33)} & \text{if} \quad z_I \in [25.74, 33) \\ z_I + 29.3663 - 2\sqrt{29.37 z_I} & \text{if} \quad z_I \in [33, 217) \\ \frac{z_I + 275.74}{2} - 2\sqrt{14.685(z_I + 217)} & \text{if} \quad z_I \in [217, 233]. \end{cases}$$

[11] This definition of $m(z_I)$ is done for notational convenience. We will utilize this notation when estimating bid functions.

The ex ante expected payoff of the informed bidder is $E\left(\Pi_I^{ALC}\right) = 36.92$. The expected payoff of the uninformed bidder is $E\left(\Pi_U^{ALC}\right) = 29.72$. The ex ante expected revenue of an ALC is $E\left(R^{ALC}\right) = 58.74$.

Note that $E\left(\Pi_I^{ALC}\right) > E\left(\Pi^{SLC}\right)$. This is a result of the private information held by the informed bidder. As such, we refer to $E\left(\Pi_I^{ALC}\right) - E\left(\Pi^{SLC}\right) > 0$ as the informed bidder's information rent in an ALC. This is a measure of the value of observing a private signal in a lottery contest.

3.2.3 Break-even Bidding Strategy in ALC

The break-even bidding strategy of an informed ALC bidder, when she observes z_I is the largest b_I that satisfies

$$\frac{b_I}{b_I + 29.37} E\left(X \mid z_I\right) - b_I = 0.$$

That is, the break-even bidding strategy of the informed ALC bidder is

$$\rho_I^{ALC}\left(z_I\right) = \begin{cases} 0 & \text{if} \quad z_I \in [17, 25.74) \\ \frac{z_I + 33}{2} - 29.37 & \text{if} \quad z_I \in [25.74, 33) \\ z_I - 29.37 & \text{if} \quad z_I \in [33, 217) \\ \frac{z_I + 217}{2} - 29.37 & \text{if} \quad z_I \in [217, 233]. \end{cases}$$

For the uninformed bidder in an ALC, the break-even bidding strategy is the bid that satisfies

$$E\left(\frac{b_U}{b_U+\zeta^{ALC}(z_I)}X\right)-b_U=0.$$

That is, the break-even bidding strategy for the uninformed bidder in an ALC is $\rho_U^{ALC}=90.17$.

3.3 Testable Hypotheses

Revenue predictions of all-pay auctions and lottery contests are not invariant to the information structure. The ex ante expected revenue predictions of each treatment where we have theoretical predictions are found above. Notice that $E\left(R^{ALC}\right)<E\left(R^{SLC}\right)<E\left(R^{AAP}\right)<E\left(R^{SAP}\right)$. When one bidder observes a signal, she is expected to earn an information rent which reduces expected revenue relative to the case where neither bidder observes a signal. Also, holding the information structure constant, all-pay auctions are expected to generate more revenue than lottery contests. These hypotheses are summarized in Table 2.

Since all-pay auctions and lottery contests are constant sum games between the seller and the bidders, revenue and bidder payoffs are closely related. When there is an information asymmetry as in our experimental design, the decrease in revenue relative to the symmetric information structure in which neither bidder observes a signal must improve the expected payoffs

Table 2: Revenue ranking in decreasing order

Information structure	**Ex ante expected revenue**
SAP	125
AAP	91.77
SLC	62.50
ALC	58.74

Table 3: Ranking of ex ante expected bidder payoffs in decreasing order

Bidders	**Ex ante expected payoffs**
ALC-Informed	36.92
AAP-Informed	33.23
SLC	31.25
ALC-Uninformed	29.72
SAP	0
AAP-Uninformed	0

of at least one bidder. Who gets this decrease in revenue, the informed bidder, the uninformed bidder or both? There are a number of predictions with regards to bidder payoffs which we test. The ex ante expected payoffs of bidders are found above. Notice that, $E\left(\Pi_U^{AAP}\right) = E\left(\Pi_i^{SAP}\right) < E\left(\Pi_U^{ALC}\right) < E\left(\Pi_i^{SLC}\right) < E\left(\Pi_I^{AAP}\right) < E\left(\Pi_I^{ALC}\right)$. These hypotheses are summarized in Table 3.

Since $E\left(\Pi_U^{AAP}\right) = E\left(\Pi_i^{SAP}\right)$, a bidder who does not observe a private signal in an all-pay auction has an expected profit of zero, regardless of whether or not the other bidder observes a signal. This implies that, in equilibrium, the ex ante expected payoff of a bidder who observes a signal in an all-pay auction is a measure of the value of that signal, given the information structure. That is, an informed bidder's ex ante expected payoff represents the expected information rent associated with the signal in an all-pay auction.

Since $E\left(\Pi_U^{ALC}\right) > 0$, $E\left(\Pi_I^{ALC}\right)$ is not the expected value of observing a signal in a lottery contest. This value, or information rent, is given by $E\left(\Pi_I^{ALC}\right) - E\left(\Pi_i^{SLC}\right)$. Notice that the expected information rent obtained by an informed bidder is greater in an all-pay auction than in a lottery contest.

4 Experimental Results

4.1 Revenue

Table 4 reports summary statistics of revenue. Average predicted revenue was calculated using the realized value of the signal(s) and x. As a result, the predictions where there is an informed bidder differs slightly from the ex ante revenue predictions. Note, however, that the revenue ranking remains the same.

There are six revenue ranking predictions, which we test using the non-parametric robust rank order test on session-level data.[12] Predictions are borne out between SAP and AAP auctions; we find support for the prediction that

[12] The critical values of the robust rank order test are found in Feltovich (2003).

Table 4: Revenue aggregated across all rounds and sessions

Treatment	**Average observed revenue (standard deviation)**	**Average predicted revenue (standard deviation)**
SAP	119.09	125.00
	(65.77)	(0.00)
AAP	95.23	88.24
	(69.31)	(29.80)
SLC	96.76	62.50
	(44.44)	(0.00)
ALC	95.97	56.13
	(56.83)	(14.65)

$E\left(R^{SAP}\right) > E\left(R^{AAP}\right)$ (robust rank-order test, $\acute{U} = 2.36$, $p < 0.048$). Further, we find strong support for the predictions that $E\left(R^{SAP}\right) > E\left(R^{SLC}\right)$ (robust rank-order test, $\acute{U} = 7.19$, $p = 0.008$) and $E\left(R^{SAP}\right) > E\left(R^{ALC}\right)$ (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$).[13]

We are, however, unable to reject equivalence between $E\left(R^{SLC}\right)$ and $E\left(R^{ALC}\right)$ (robust rank order test, $\grave{U} = -0.09$, $n.s.$). That is, our data indicates that the presence of asymmetric information does not reduce revenue in lottery contests, contrary to theory.

Interestingly, we are also unable to reject equivalence between $E\left(R^{AAP}\right)$ and $E\left(R^{SLC}\right)$ (robust rank order test, $\grave{U} = -0.09$, $n.s.$). Likewise, we are

[13] The highest average revenue observed within a group of ten participants in any ALC session is lower than the lowest average reveune observed within a group of ten participants any SAP session. As such, the test statistic of the robust rank order test is not defined. We denote such a test statistic as $\acute{U} = n.d.$.

unable to reject equivalence between $E\left(R^{AAP}\right)$ and $E\left(R^{ALC}\right)$ (robust rank order test, $\grave{U} = -0.09$, $n.s.$). This observed revenue equivalence between the asymmetric information all-pay auction and the asymmetric information lottery contest is surprising, given the magnitude of the difference in the theoretical predictions. The revenue in lottery contests, regardless of the information structure is much higher than predicted. As such, the observed revenue equivalence between the ALC, SLC and AAP treatments is largely the result of significant overbidding on the part of bidders in lottery contests.

4.2 Bidder Payoffs

Table 5 provides summary statistics regarding bidder payoffs. Average predicted payoffs are calculated using the signals observed by participants. Notice that, on average, the only bidders who have positive payoffs when not observing a signal are bidders in symmetric information lottery contests.

We find, in keeping with theoretical predictions, that informed AAP bidders earn significantly more than uninformed AAP bidders (sign test, $w = 46$, $p < 0.001$)[14] and SAP bidders (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$). That is, informed AAP bidders earn a significant information rent by virtue

[14] In the asymmetric information treatments (AAP and ALC), participants switched roles throughout the experiment. To test the prediction that informed bidders in asymmetric information structures have greater expected profits than their uninformed counterparts, the average payoff of a participant when she was informed was matched with the average payoff of that same participant when she was uninformed, for a total of 50 matched pairs. As such, the test of these predictions are within subject.

Table 5: Bidder payoffs aggregated over all rounds and sessions

Bidders	**Average observed payoffs (standard deviation)**	**Average predicted payoffs (standard deviation)**
SAP	−1.72	0
	(62.77)	(0)
AAP-Informed	26.38	27.29
	(59.50)	(27.70)
AAP-Uninformed	−6.08	0
	(44.06)	(0)
SLC	9.39	31.25
	(68.58)	(0)
ALC-Informed	22.72	31.20
	(60.96)	(26.85)
ALC-Uninformed	−3.16	29.72
	(54.68)	(0)

of holding private information. As predicted by theory, we are unable to reject that SAP bidders and uninformed AAP bidders have equal payoffs (robust rank-order test, $\acute{U} = 0.669$, $n.s.$). So, a bidder who does not observe a signal is not made worse off when the other bidder does. This implies that the positive information rent obtained on average by informed AAP bidders is extracted from the seller.

Informed ALC bidders have higher payoffs than uninformed ALC bidders (sign test, $w = 45$, $p < 0.001$) and SLC bidders (robust rank-order test, $\acute{U} = 7.188$, $p = 0.008$). Uninformed ALC bidders earn less than SLC bidders (robust rank-order test, $\acute{U} = 2.859$, $p = 0.028$). So informed ALC bidders earn a significant information rent. Unlike all-pay auctions, uninformed bidders in asymmetric information lottery contests are worse off than if neither bidder were informed. That is, the information rent that accrues to informed ALC bidders is extracted, at least in part, from the uninformed bidder.

These results have interesting implications in terms of the value of information in contests, and are in line with theoretical predictions. In particular, a bidder in a SAP auction is not worse off if the other bidder were to observe a signal, and would have no incentive to expend resources to prevent such an information asymmetry. The same does not hold true in lottery contests. An interesting question for further research would be whether or not an uninformed bidder would be willing to pay to observe a signal that has been observed by the other bidder. Theory predicts that a bidder in an all-pay auction would be indifferent, while a bidder in a lottery contest would be willing to expend resources to eliminate the information asymmetry.

As predicted by theory, SLC bidders have higher payoffs than SAP bidders (robust rank-order test, $\acute{U} = 7.188$, $p = 0.008$). Interestingly, we are unable to reject that informed ALC bidders and informed AAP bidders have equal payoffs (robust rank-order test, $\acute{U} = 0.435$, *n.s.*). Likewise, we are unable to reject that uninformed ALC bidders and uninformed AAP bidders have equal payoffs (robust rank-order test, $\acute{U} = 0.473$, *n.s.*). This yields additional insight into the observed revenue equivalence between the ALC and AAP treatments. In particular, it seems that the observed revenue equivalence between the AAP and ALC treatments is simply because bidders, both informed and uninformed, are equally well off under all-pay auctions and lottery contests; the change in contest success function does not change the welfare of bidders in an asymmetric information structure. Note that this does not hold when neither bidder observes a signal. The imperfectly discriminating contest success function actually makes bidders better off than the perfectly discriminating contest success function.

Lastly, we find that SAP bidders have lower payoffs than informed ALC bidders (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$), and are unable to reject that SAP bidders and uninformed ALC bidders have equal payoffs (robust rank-order test, $\acute{U} = 0.473$, $n.s.$). We find that SLC bidders have higher payoffs than uninformed AAP bidders (robust rank-order test, $\acute{U} = 7.188$, $p = 0.008$), and that SLC bidders have lower payoffs than informed AAP bidders (robust rank-order test, $\acute{U} = 4.20$, $p < 0.028$).

4.3 Break-even Bidding

In standard auctions, the bidders who do not win the auction do not expend any money; their payoff from losing the auction is zero. As such, a bid above the break-even bidding strategy is a bid above the expected value of the good, conditional on winning the auction. In the experimental auction literature it is widely observed that inexperienced bidders bid above the break-even bidding strategy when they observe a private signal. Such bidders are said to fall victim to the winner's curse.[15] This finding is very robust, and has been observed in many different auction formats. However, Grosskopf *et al.* (2010) finds that bidders who do not observe a private signal in a first-price, sealed-bid auction are much less prone to fall victim to the winner's curse than bidders who do observe a private signal. This finding is true of informed bidders who face informed opponents, and bidders who do not.

In contests, bidders must pay their bid whether or not they obtain the good. As a result, the break-even bidding strategy in a contest (the bid above which a bidder has a negative expected payoff, given that the other bidder is bidding according to equilibrium) is substantially less than the expected value of the good, conditional on obtaining the good. Prior to this paper, experimental analysis of contests have often observed significant overbidding, even in very simple environments. The benchmark against which this overbidding has been measured is the Nash equilibrium predictions. While we do compare behavior to Nash predictions, we are interested in whether bidders in common-value contests with incomplete information overbid such that they guarantee themselves negative expected payoffs, as bidders in standard auctions do. We are also interested in the role of observing a private signal on this overbidding. Does observation of such a signal make bidders more prone to bid above the break-even bidding strategy?

Table 6 contains summary statistics regarding when bidders bid above

[15] See Kagel and Levin (2002) for an introduction to this literature.

the break-even bidding strategy, aggregated across all rounds and sessions. There are several things worth noting. First, on average, bidders who observe a signal (i.e. informed bidders in the asymmetric information treatments) bid above the break-even bidding threshold much more frequently than bidders who do not observe a signal. Second, the proportion of informed AAP and informed ALC bidders who bid above the break-even bidding threshold is actually greater than the proportion such winning bids that fall above the break-even threshold. This is largely due to the fact that for low signal values, the break-even bidding strategy for informed bidders is quite low. As such, for low signal values a bidder may bid above the break-even strategy, and still be unlikely to obtain the good. Third, notice that informed AAP bidders win almost 70% of the time. Theory predicts that the informed and uninformed AAP bidders have an equal probability of obtaining the good. Further, the informed ALC bidder wins just over 50% of the time, while theory predicts that the uninformed ALC bidder has a higher ex ante probability of obtaining the good.

Figure 1 illustrates how the bidders' propensity to bid above the break-even bidding strategy varies as they gain experience. Note that as bidders gain experience the frequency with which they bid more than their break-even bidding strategy decreases. This is most pronounced for bidders who do not observe a signal. Also, the bidders who do observe a signal are much more likely to bid more than their break-even bidding strategy than uninformed

Table 6: Bidding above the break-even bidding strategy aggregated across all rounds and sessions

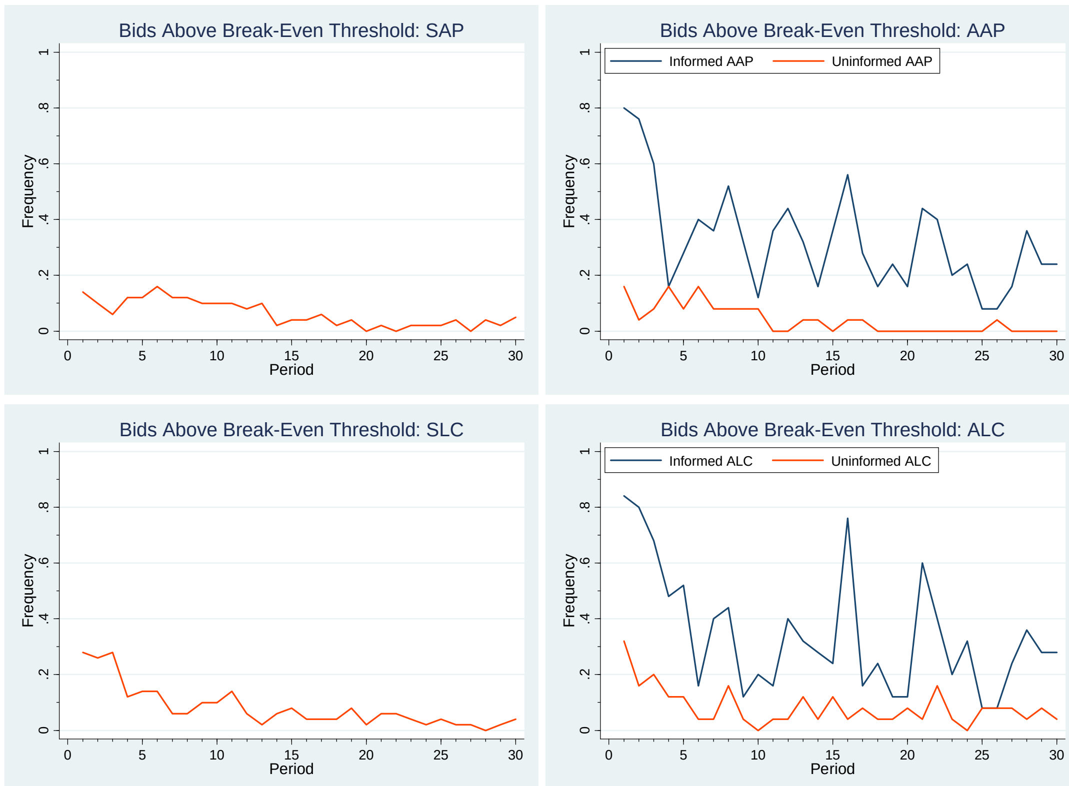
	Frequency bid exceeds break-even bid:		Frequency the informed bidder wins
Bidders	**All bidders**	**Winning bidders**	
SAP	6.2%	12.1%	NA
	(93/1490)	(90/745)	NA
AAP-Informed	32.7%	30.4%	69.2%
	(245/750)	(158/519)	(519/750)
AAP-Uninformed	4%	11.3%	NA
	(30/750)	(26/205)	NA
SLC	8.1%	12.1%	NA
	(122/1500)	(91/750)	NA
ALC-Informed	34.3%	32.8%	50.7%
	(257/750)	(168/512)	(380/750)
ALC-Uninformed	8.3%	16%	NA
	(62/750)	(38/238)	NA

NA = not applicable.

The decimal numbers in parentheses are standard deviations.

The fractions in parentheses are relative frequencies.

Figure 1: Frequency of bids above the break-even bidding strategy by period



bidders. Indeed, in the last periods, many informed bidders bid continue to bid above this break-even bidding threshold. In contrast, uninformed bidders, regardless of whether or not they face an informed bidder, have stopped bidding above this threshold almost entirely.

This interesting result is consistent with the behavior observed in Grosskopf (2010) in the context of first-price, sealed-bid auctions; informed bidders are much more likely to bid above a break-even bidding strategy than are uninformed bidders. As such, our data acts as a robustness test of the results of

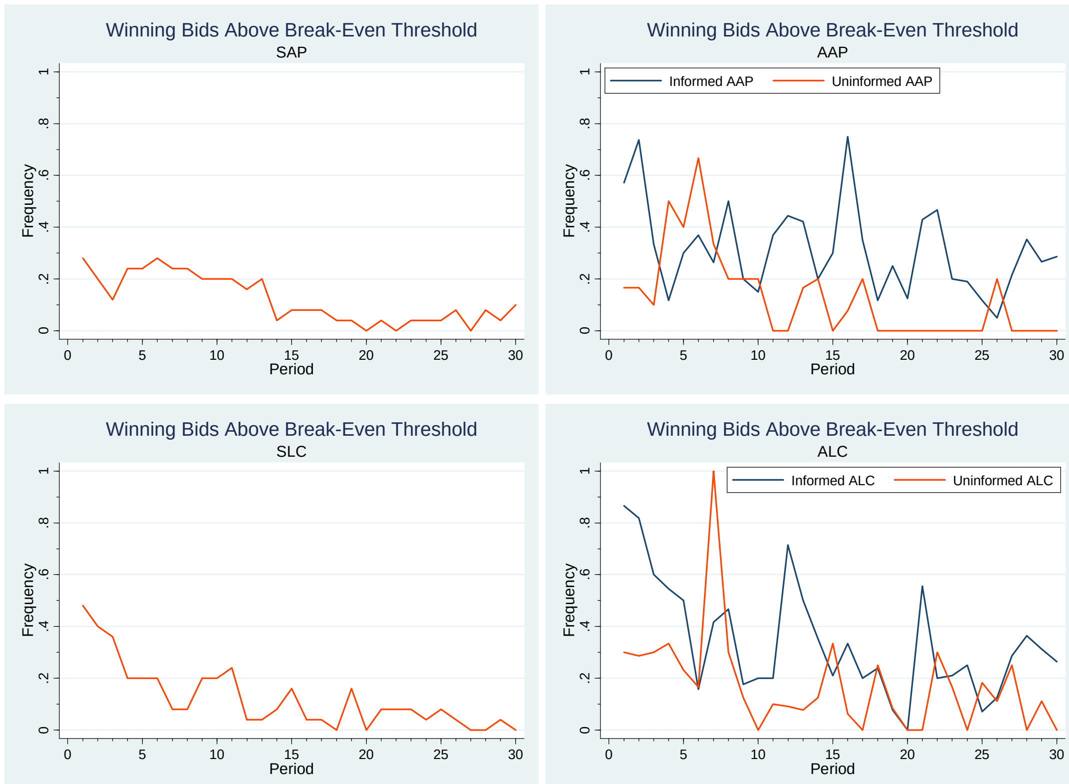
Grosskopf (2010). We have now observed this bidding behavior in three separate games: first-price auctions, all-pay auctions and lottery contests. As before, we interpret this behavior as overconfidence on the part of informed bidders; informed bidders are overconfident regarding the value of observing a private signal, and bid accordingly.[16] In Appendix C, behavior when both bidders in an all-pay auction observe a signal is analyzed. The same pattern emerges; these informed bidders are much more prone to bid above the break-even bidding threshold than are bidders in an all-pay auction who do not observe a signal.

This behavior is particularly interesting in the context of contests, because a bidder who loses must still pay her bid. As a result, there are two ways in which a bid may result in negative payoffs. First, an informed bidder may bid more than the value of the good, and end up with a negative payoff despite obtaining the good. Second, the informed bidder may not obtain the good, and still be forced to pay her bid. This is in contrast to first-price auctions, in which the only way a bidder may end up with a negative payoff is by obtaining the good by bidding more than its value.

Figure 2 illustrates how the frequency with which winning bidders bid more than the break-even bidding strategy changes as bidders gain experience. Here, the analysis is less clear. This is largely attributable to the

[16] Alexander Pope first addressed this hypothesis by writing: "A little learning is a dangerous thing; drink deep, or taste not the Pierian spring: there shallow draughts intoxicate the brain, and drinking largely sobers us again."

Figure 2: Frequency of winning bids above the break-even bidding strategy by period



fact that uninformed bidders who won when facing an informed bidder were likely to have bid more than the break-even bidding threshold in order to do so, while the other uninformed bidders typically bid conservatively and lost as a result. Spikes in the proportion of winning bids of uninformed AAP or ALC bidders who bid above the break-even bidding threshold reflect this. However, in later periods is it clear that informed winning bidders are much more prone to bid above the break-even bidding threshold.

Figure 3: The difference between observed bids and break-even bids depending on the signal

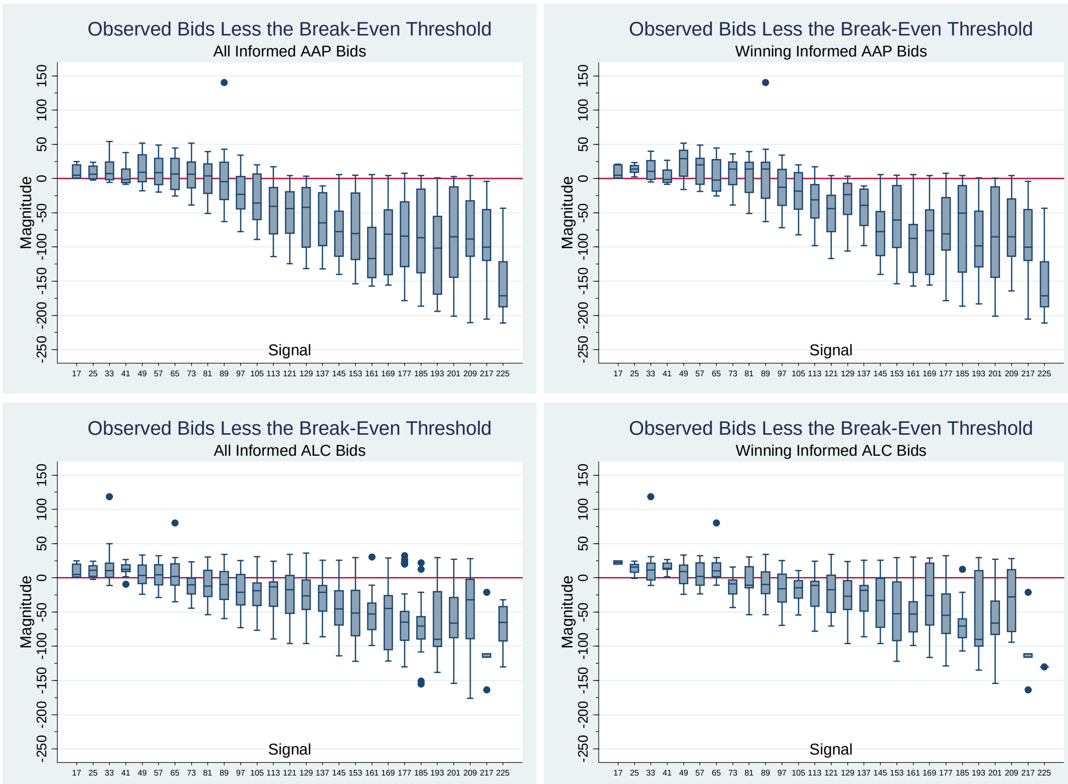


Figure 3 contains box plots which illustrate how the magnitude of the difference between observed bids and the break-even bidding threshold depends on the signal observed by informed bidders. Interestingly, for small signal values, this magnitude is larger than for large signals. This is true of all informed bids, as well as winning informed bids. This is a consequence of the fact that these bidders are facing uninformed opponents. Since an uninformed bidder is unlikely to bid a large amount, an informed bidder who observes a high signal is likely to win the contest, even if she bids much less than the value of the good. Taking this into account reduces her bid relative to the break-even bidding threshold.

Notice that the range of the difference between observed bids and the break-even bidding threshold increase with signal size. This is a result of the fact that for low signal values, the range of rationalizable bids is smaller than when the observed signal is high. An informed bidder knows that the value of the good will never exceed her signal by more than eight. Further, she cannot bid less than zero. These bounds, or course, expand in the signal size, and the range of bidding behavior expands as well.

Lastly, notice that for large signal values very few informed AAP bidders bid more than the break-even bidding threshold. In contrast, a non-trivial number of informed ALC bids fall above this threshold, for all but the highest signals. In spite of this, recall that we are unable to reject payoff equivalence between informed AAP and informed ALC bidders.

4.4 Bidding

We now compare the bidding behavior of participants across bidder types. Several interesting observations arise. First, we find that informed AAP bidders bid more than uninformed AAP bidders (sign test, $w = 45$, $p < 0.001$).[17] This result is contrary to theory; the distribution of Nash equilibrium bids

[17] The average uninformed bid of a participant is paired with the average informed bid of the same participant. As such, there are 50 observations for this test.

for the informed AAP bidder is the same as that of the uninformed AAP bidder. In lottery contests. we find that, contrary to theory, informed ALC bidders are bidding more than uninformed ALC bidders (sign test, $w = 45$, $p < 0.001$). Theory predicts that, ex ante, the expected bid of an uninformed ALC bidder is equal to that of an informed ALC bidder (recall that the realized signals in our design reduce the average predicted bid of informed ALC bidders slightly). These two results, of course, are consistent with the hypothesis that the observation of a private signal induces a bidder to increase her bid, on average.

Comparing the behavior of bidders who do not observe signals yields interesting results. SAP bidders bid more than uninformed AAP bidders (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$).[18] Likewise, SLC bidders bid more that uninformed ALC bidders (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$). That is, in all-pay auctions and lottery contests, uninformed bidders bid less if their opponent observes a signal than if they do not. This is interesting, in light of the fact that a SAP bidder is not significantly worse off than if her opponent were to observe a signal, while a SLC bidder is significantly better off than if her opponent were to observe a signal. While uninformed AAP bidders are able to reduce their bids relative to SAP bids such that they avoid a reduced payoff, uninformed ALC bidders are not.

[18] Since both SAP and uninformed AAP bidders are predicted to employ a mixed strategy in equilibrium, we also employ a two sample Kolmogorov-Smirnov equaltiy of distributions test, in which the average uninformed bid of an individual participant is the unit of observation. The null is strongly rejected (Kolmogorov-Smirnov test, $D = 0.400$, $p = 0.001$).

This is largely due to the fact that bidders in lottery contests have a positive expected payoff regardless of the whether they, or their opponent, observe a signal. In all-pay auctions, uninformed bidders have an expected payoff of zero, regardless of the information structure. As such, SLC bidders have something to lose if their opponent were to observe a signal; SAP bidders do not.

We are unable to reject the hypothesis that SAP and informed AAP bidders bid the same amount (robust rank-order test, $\acute{U} = 0.341$, $n.s.$). This result runs contrary to theory, because informed AAP bidders are expected to bid less in equilibrium than SAP bidders. Similarly, in lottery contests we find that informed ALC bidders bid more than SLC bidders (robust rank-order test, $\acute{U} = 2.064$, $p = 0.048$), which is also contrary to theory; informed ALC bidders are, ex ante, predicted to reduce their bids relative to SLC bids. That informed bidders do not bid less than their symmetric information counterparts suggests that informed bidders are not taking advantage of the fact that their uninformed opponents are predicted to reduce their bids in response to the asymmetric information, and may be overbidding relative to Nash predictions as a result. This assertion is tested explicitly below.

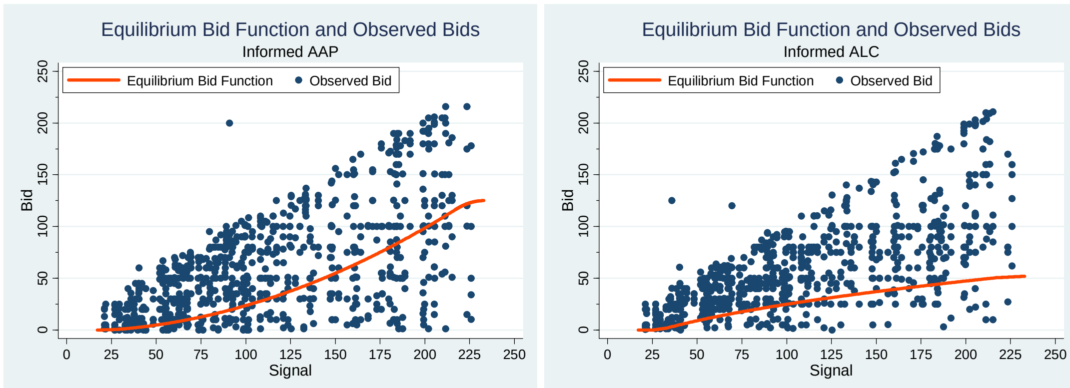
In addition, we are unable to reject the hypothesis that informed AAP bidders and informed ALC bidders bid the same amount (robust rank-order test, $\acute{U} = 0.088$, $n.s.$). Likewise, we are unable to reject the hypothesis that uninformed AAP bidders and uninformed ALC bidders bid the same amount (robust rank-order test, $\acute{U} = -0.258$, *n.s.*). Recall that we are also unable to reject payoff equivalence between informed AAP and informed ALC bidders, as well as between uninformed AAP and uninformed ALC bidders. Furthermore, we are unable to reject revenue equivalence between these two asymmetric information treatments. Consequently, these results are not surprising.

Lastly, SAP bidders bid more than SLC bidders (robust rank-order test, $\acute{U} = 7.188$, $p = 0.008$). This result is consistent with theory. Likewise, it is consistent with the existing literature. For example, Potters *et al.* (1998) find that bidders in all-pay auctions bid more than bidders in lottery contests.

4.5 Nash Equilibrium

We now turn to the question of how bidders bid relative to the Nash equilibrium predictions. Table 7 contains summary statistics regarding observed and predicted bids, using data aggregated across all rounds and sessions. Average Nash equilibrium bids are calculated using realized signals, rather than ex ante predictions. When Nash predictions involve mixed strategies, the expected value and standard deviation of the mixed strategy are reported. Notice that in the case of all-pay auctions, both SAP and uninformed AAP bidders bid below Nash predictions, on average. In stark contrast, informed AAP bidders bid a staggering 385.48% above Nash predictions, on average. Furthermore, informed ALC bidders overbid relative

Figure 4: Equilibrium bid functions and observed bids



to Nash predictions much more than SLC or uninformed ALC bidders on average, although all bidders in lottery contests overbid.

Also of interest is the fact that bidders do bid positive amounts, even when uninformed. This is of particular interest for uninformed bidders in all-pay auctions because for every bid in the support of their respective mixed strategies, they have an expected payoff of zero. As such, uninformed bidders are, in equilibrium,.indifferent between the Nash equilibrium mixed strategy, and bidding zero with probability one. Indeed, uninformed AAP bidders had negative payoffs on average, but submitted positive bids 73.86% of the time.

Figure 4 plots the equilibrium bid functions of informed bidders against a scatterplot of the observed bids. Notice that a great many bids lie on the 45° line, for both informed AAP and informed ALC bidders. This indicates that some bidders are naive, in that they simply bid their signal. Further,

Table 7: Bids relative to the Nash equilibrium aggregated over all rounds and sessions

Bidders	Average bid	Average Nash equilibrium bid	Average percent over Nash	Frequency of positive bids
SAP	59.54	62.5[a]	−4.73%	90.13%
	(46.50)	(36.08)	(0.74)	(1353/1490)
AAP-Informed	61.11	38.49	385.48%	98.40%
	(50.54)	(34.55)	(20.54)	(738/750)
AAP-Uninformed	34.13	45.89[a]	−25.63%	73.86%
	(42.99)	(36.85)	(0.94)	(554/750)
SLC	48.38	31.25	54.81%	94.20%
	(30.38)	(0.00)	(0.97)	(1413/1500)
ALC-Informed	61.02	26.53	229.95%	99.73%
	(44.30)	(14.59)	(6.83)	(748/750)
ALC-Uninformed	34.95	29.37	19.00%	89.47%
	(33.69)	(0.00)	(1.15)	(671/750)

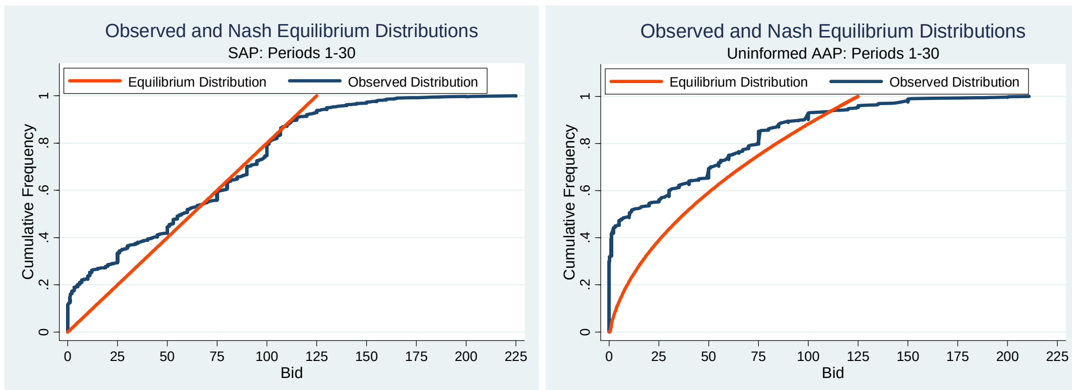
[a]This is the expected value of the equilibrium mixed strategy.
The decimal numbers in parentheses are standard deviations.
The fractions in parentheses are relative frequencies.

most bids lie above the equilibrium bid function, indicating that informed bidders tend to overbid relative to the Nash equilibrium.

For bidders whose Nash equilibrium bidding strategy is pure, we compare bidding behavior using the nonparametric sign test. Accordingly, we find that informed AAP bidders overbid relative to Nash predictions (sign test, $w = 41$, $p < 0.001$).[19] Further, informed ALC bidders overbid relative

[19]The unit of observation in this and subsequent sign tests is the average bid of an individual participant. That is, the bid of an individual participant averaged over all periods relative to the Nash equilibrium bid averaged over all periods. There are then 50 observations.

Figure 5: SAP and Uninforrmed AAP cumulative distribution (all periods)



to Nash predictions (sign test, $w = 48$, $p < 0.001$). As described above, these informed bidders are prone to bidding in excess of the break-even bidding strategy. This measure of overbidding is looser than Nash equilibrium predictions. As such, it is hardly surprising to find that informed bidders overbid relative to equilibrium. However, we also find that SLC bidders overbid relative to Nash predictions (sign test, $w = 41$, $p < 0.001$). This is in contrast to the results of Grosskopf *et al.* (2010), which found bidding in first-price auctions was significantly below Nash predictions when neither bidder observed a signal. In lottery contests, then, observation of a signal increases the magnitude of overbidding, rather than swinging a bidder to overbidding from underbidding as in first-price auctions.

We are unable to reject that uninformed ALC bidders bid according to the Nash equilibrium (two-tailed sign test, $w = 27$, $p = 0.6718$).[20] That is,

[20] If we assume that participant's bids are independent over time, such that there are 750 observations, we find that uninformed ALC bidders underbid relative to Nash predictions, although this result is only marginally significant (sign test, $w = 397$, $p = 0.0582$).

the only bidders in lottery contests who bid according to Nash predictions are uninformed ALC bidders.

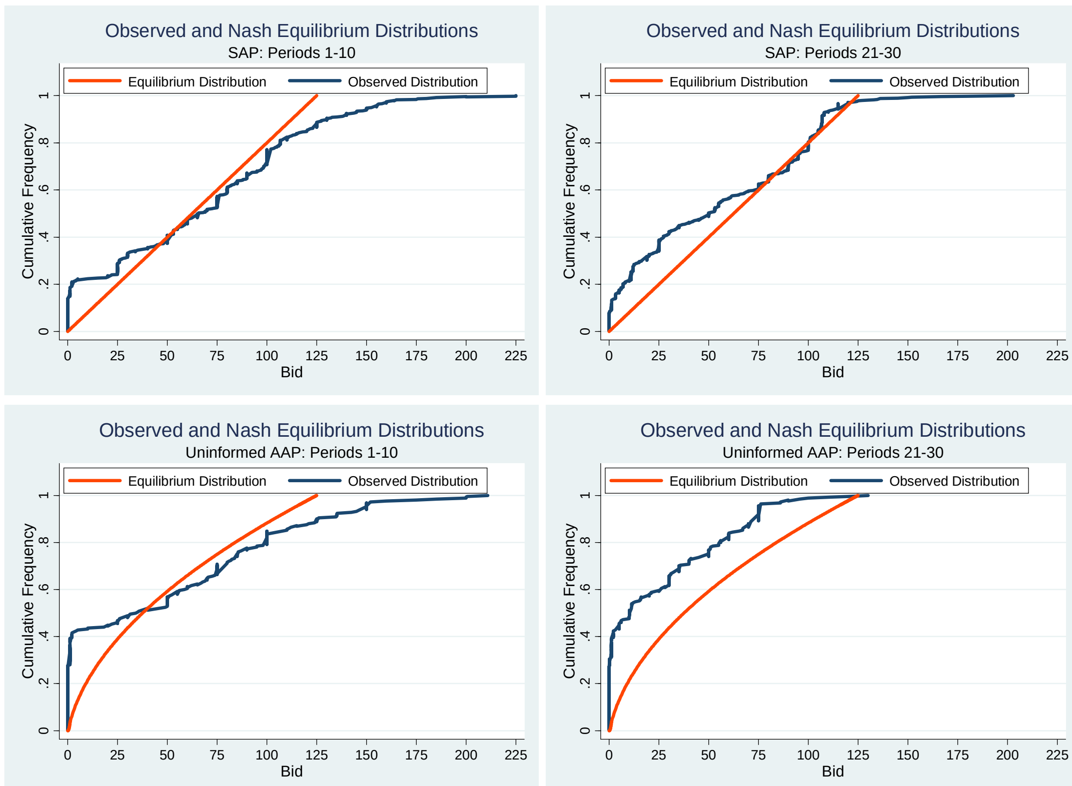
Next, recall that there are two types of bidders whose Nash equilibrium involves a mixed strategy: SAP and uninformed AAP bidders. The support for both of these equilibrium mixed strategies is $[0, 125]$. As such, we do not have point predictions for these bidders. Comparing the expected value of the equilibrium mixed strategy with the average bid tells us that, on average, uninformed AAP bidders are underbidding. The same is true of SAP bidders, although the difference is small. To test whether observed distribution of bids is consistent with the CDF of the equilibrium mixed strategies, we employ the nonparametric Kolmogorov–Smirnov test. We reject the hypothesis that the observed distribution of uninformed AAP bids is equal to that of the equilibrium mixed strategy (Kolmogorov–Smirnov test, $D = 0.1943$, $p = 0.0459$).[21] However, we are unable to reject the hypothesis that the observed distribution of SAP bids is equal to that of the equilibrium mixed strategy (Kolmogorov–Smirnov test, $D = 0.1030$, $p = 0.6630$).[22]

Figures 5 and 6 yield additional insight. Figure 5 plots the empirical cumulative distribution of bids in all periods against the distribution function of the equilibrium mixed strategy for both SAP and uninformed AAP

[21] The unit of observation is the average uninformed AAP bid of an individual participant.

[22] If we assume that an individual participant's bids are independent over time, such that there are 1490 independent observations, then the Null is strongly rejected (Kolmogorov–Smirnov test, $D = 0.8013$, $p < 0.001$).

Figure 6: SAP and Uninforrmed AAP cumulative distribution (periods 1-10 and 21-30)



bidders. For SAP bidders, there are more bids at both tails than predicted by theory. However, for uninformed AAP bidders, the empirical distribution is almost entirely to the left of the Nash distribution, save for several bids in at the right tail. Figure 6 restricts attention to the first and last ten periods. In the first ten periods, both uninformed AAP and SAP bidders have more bids on the right tail than predicted. However, in the last ten periods the empirical distribution of SAP bids has shifted dramatically to the left, such that the equilibrium mixed strategy lies almost entirely to the right of the empirical distribution. The change is even more dramatic for uninformed AAP bidders. In the last ten rounds the empirical distribution is far to the left of the equilibrium distribution. Clearly, as SAP and uninformed AAP bidders gain experience they reduce their bids such that, on average, they are underbidding.

The above analysis of uninformed AAP and SAP bids relies on aggregated data. Of interest is whether or not an individual participant is mixing at all, regardless of the distribution. Examining the behavior of bidders over time clearly demonstrates that they are not. A participant in a SAP session bids her modal bid 32.48% of the time. While the equilibrium distribution function for SAP bidders is continuous on $[0, 125]$, SAP bids are integers 69.93% of the time, and are multiples of five 49.4% of the time. For uninformed AAP bidders, an individual bids her modal uninformed AAP bid 44.00% of the time. Uninformed AAP bids are integers 81.07% of the time, and multiples of five 61.73% of the time. Clearly, these bidders are not mixing continuously. The fact that the modal bids are submitted so frequently suggests that they are not mixing at all.

4.6 Estimating Bid Functions

In estimating bid functions, we employ a random effects Tobit estimation to control for correlation of participant behavior over time, and the fact that bids were restricted to be within the interval $[0, 225]$. We restrict our attention to observations in which the observed signal (or the signal that a bidder would have observed had she been informed) is in the interval $[33, 217)$, where the majority of observations lie.

The specification for bidders who do not observe a signal (SAP, SLC, uninformed AAP, and uninformed ALC bidders) is given by

$$b_{it} = \beta_0 + \beta_1 z_{it} + \beta_2 M_i + \beta_3 \ln(1+t) + \alpha_i + \epsilon_{it},$$

where b_{it} is participant i's bid in period t, z_{it} is the (unobserved) signal of participant i in period t, M_i is equal to one if participant i is a male, and $\ln(1+t)$ captures learning.[23] This specification is estimated separately for each type of uninformed bidder, for a total of four such estimations. Recall that SAP and uninformed AAP bidders are predicted to employ a mixed strategy in equilibrium. We justify our estimation of bid functions for these bidders by noting that the data demonstrates that these bidders are not mixing. We include z_{it} as a test of whether or not the signal which would have been observed by the bidder if she were informed has any explanatory value. In each contest (there are 150 contests in each group of ten contestants) a realization of the good was drawn, as well as two signals, which are independent conditional on the realized value of the good. These same realizations were used for each group of ten participants, for all treatments (these are the

[23] Since period defines the panel, it cannot be included as a covariate. The inclusion of $\ln(1+t)$ captures learning. Moreover, since $\ln(1+t)$ is nonlinear in t, it takes account of diminishing returns to learning.

same realizations used in Grosskopf *et al.* (2010)). As such, in SAP and SLC sessions, neither bidder in any given contest observed the signal that was "assigned" to them. In AAP and ALC treatments, one of the bidders was randomly chosen to observe one of the signals. The other bidder did not observe one, although there was one "assigned" to them. We also ran sessions with all-pay auction in which both bidders observed the signal that was "assigned" to them. For SAP, SLC, uninformed AAP and uninformed ALC bidders, the (unobserved) signal that was assigned to them should not have any predictive power concerning bidding behavior. Inclusion of this signal as a covariate tests this assertion.

Following Casari *et al.* (2007), we also employ specifications which interact gender and learning. Casari *et al.* (2007) finds that women initially bid more than men, but that they learn faster than men such that bidding behavior quickly converges. We are interested in whether or not this observation holds in the context of contests. The specification for uninformed bidders which includes gender and learning interaction is given by

$$b_{it} = \beta_0 + \beta_1 z_{it} + \beta_2 M_i + \beta_3 \ln(1+t) + \beta_4 M_i \cdot \ln(1+t) + \alpha_i + \epsilon_{it}.$$

For informed AAP bidders, the specification without the gender and learning interaction is given by

$$b_{it} = \beta_0 + \beta_1 z_{it} + \beta_2 M_i + \beta_3 \ln(1+t) + \beta_4 g(z_{it}) + \alpha_i + \epsilon_{it},$$

where $g(z_{it})$ is the nonlinear portion of the informed AAP equilibrium bid function when $z_{it} \in [33, 217)$. Furthermore, the informed AAP specification with the gender and learning interaction is given by

$$b_{it} = \beta_0 + \beta_1 z_{it} + \beta_2 M_i + \beta_3 \ln(1+t) + \beta_4 M_i \cdot \ln(1+t) + \beta_5 g(z_{it}) + \alpha_i + \epsilon_{it}.$$

Similarly, when estimating bid functions for informed ALC bidders, the specification without the gender and learning interaction is

$$b_{it} = \beta_0 + \beta_1 z_{it} + \beta_2 M_i + \beta_3 \ln(1+t) + \beta_4 m(z_{it}) + \alpha_i + \epsilon_{it},$$

where $m(z_{it})$ is the nonlinear equilibrium bid function of informed ALC bidders when $z_{it} \in [33, 217)$. By including both z_{it} and $m(z_{it})$, we are testing whether informed ALC bidders bid according to a linear function of their signal, or whether they bid according to the nonlinear bid function, as predicted by theory. With the gender and learning interaction the specification is

$$b_{it} = \beta_0 + \beta_1 z_{it} + \beta_2 M_i + \beta_3 \ln(1+t) + \beta_4 M_i \cdot \ln(1+t) + \beta_5 m(z_{it}) + \alpha_i + \epsilon_{it}.$$

Lastly, we jointly estimate bid functions. Without the gender and learning interaction the specification is

$$
\begin{aligned}
b_{it} &= \beta_0 + \beta_1 z_{it} + \beta_2 M_i + \beta_3 \ln(1+t) \\
&+\beta_4 IAAP_{it} + \beta_5 UAAP_{it} + \beta_6 SLC_{it} + \beta_7 IALC_{it} + \beta_8 UALC_{it} \\
&+\beta_9 IAAP_{it} \cdot z_{it} + \beta_{10} UAAP_{it} \cdot z_{it} + \beta_{11} SLC_{it} \cdot z_{it} \\
&+\beta_{12} IALC_{it} \cdot z_{it} + \beta_{13} UALC_{it} \cdot z_{it} + \beta_{14} IAAP_{it} \cdot M_i \\
&+\beta_{15} UAAP_{it} \cdot M_i + \beta_{16} SLC_{it} \cdot M_i + \beta_{17} IALC_{it} \cdot M_i \\
&+\beta_{18} UALC_{it} \cdot M_i + \beta_{19} IAAP_{it} \cdot \ln(1+t) + \beta_{20} UAAP_{it} \cdot \ln(1+t) \\
&+\beta_{21} SLC_{it} \cdot \ln(1+t) + \beta_{22} IALC_{it} \cdot \ln(1+t) + \beta_{23} UALC_{it} \cdot \ln(1+t) \\
&+\beta_{24} IAAP_{it} \cdot g(z_{it}) + \beta_{25} IALC_{it} \cdot m(z_{it}) + \alpha_i + \epsilon_{it},
\end{aligned}
$$

where $IAAP_{it}$ is a dummy variable for informed AAP bidders, $UAAP_{it}$ is a dummy for uninformed AAP bidders, SLC_{it} is a dummy for SLC bidders, $IALC_{it}$ is a dummy variable for informed ALC bidders, and $UALC_{it}$ is a dummy variable for uninformed ALC bidders. When the gender and learning interaction, the joint specification is

$$
\begin{aligned}
b_{it} &= \beta_0 + \beta_1 z_{it} + \beta_2 M_i + \beta_3 \ln(1+t) \\
&+\beta_4 IAAP_{it} + \beta_5 UAAP_{it} + \beta_6 SLC_{it} + \beta_7 IALC_{it} + \beta_8 UALC_{it} \\
&+\beta_9 IAAP_{it} \cdot z_{it} + \beta_{10} UAAP_{it} \cdot z_{it} + \beta_{11} SLC_{it} \cdot z_{it} + \beta_{12} IALC_{it} \cdot z_{it} \\
&+\beta_{13} UALC_{it} \cdot z_{it} + \beta_{14} IAAP_{it} \cdot M_i + \beta_{15} UAAP_{it} \cdot M_i \\
&+\beta_{16} SLC_{it} \cdot M_i + \beta_{17} IALC_{it} \cdot M_i + \beta_{18} UALC_{it} \cdot M_i \\
&+\beta_{19} IAAP_{it} \cdot \ln(1+t) + \beta_{20} UAAP_{it} \cdot \ln(1+t) + \beta_{21} SLC_{it} \cdot \ln(1+t) \\
&+\beta_{22} IALC_{it} \cdot \ln(1+t) + \beta_{23} UALC_{it} \cdot \ln(1+t) \\
&+\beta_{24} IAAP_{it} \cdot M_i \cdot \ln(1+t) + \beta_{25} UAAP_{it} \cdot M_i \cdot \ln(1+t) \\
&+\beta_{26} SLC_{it} \cdot M_i \cdot \ln(1+t) + \beta_{27} IALC_{it} \cdot M_i \cdot \ln(1+t) \\
&+\beta_{28} UALC_{it} \cdot M_i \cdot \ln(1+t) + \beta_{29} IAAP_{it} \cdot g(z_{it}) \\
&+\beta_{30} IALC_{it} \cdot m(z_{it}) + \alpha_i + \epsilon_{it},
\end{aligned}
$$

Table 8 contains estimated bid functions without the gender and learning interaction, and Table 9 contains estimated bid functions with the gender and learning interaction.

Notice that, as expected, the (unobserved) signal is not significant in the estimated bid functions of SAP, SLC, uninformed AAP and uninformed ALC bidders. Conversely, the (observed) signal is highly significant in the estimated bid function of informed AAP and informed ALC bidders. In-

Table 8: Estimated bid functions without gender interaction (standard errors in parentheses)

	SAP	Informed AAP	Uninformed AAP	SLC	Informed ALC	Uninformed ALC	Joint
z_{it}	0.015	0.415***	−0.015	−0.012	0.613***	0.016	0.014
	(0.024)	(0.092)	(0.035)	(0.015)	(0.199)	(0.025)	(0.019)
$\ln(1+t)$	−5.535***	−22.824***	−20.490***	−7.893***	−12.980***	−4.975**	−5.672***
	(1.842)	(1.964)	(2.720)	(1.138)	(1.648)	(2.126)	(1.479)
M_i	−17.982***	−7.340***	−2.030	10.729***	−11.351***	−8.687***	−17.323***
	(2.646)	(2.941)	(4.064)	(1.690)	(2.479)	(2.789)	(2.215)
$g(z_{it})$	–	−0.379	–	–	–	–	–
		(0.230)					
$m(z_{it})$	–	–	–	–	−0.301	–	–
					(0.772)		
$IAAP_{it}$	–	–	–	–	–	–	−30.837***
							(10.913)
$UAAP_{it}$	–	–	–	–	–	–	2.734
							(8.080)
SLC_{it}	–	–	–	–	–	–	−17.079***
							(6.532)
$IALC_{it}$	–	–	–	–	–	–	−39.189***
							(8.617)
$UALC_{it}$	–	–	–	–	–	–	−29.935***
							(7.993)
$IAAP_{it} \cdot z_{it}$	–	–	–	–	–	–	0.400***
							(0.100)
$UAAP_{it} \cdot z_{it}$	–	–	–	–	–	–	−0.029
							(0.033)
$SLC_{it} \cdot z_{it}$	–	–	–	–	–	–	−0.027
							(0.027)
$IALC_{it} \cdot z_{it}$	–	–	–	–	–	–	0.598**
							(0.253)
$UALC_{it} \cdot z_{it}$	–	–	–	–	–	–	−0.004
							(0.033)
$IAAP_{it} \cdot \ln(1+t)$	–	–	–	–	–	–	−17.139***
							(2.564)
$UAAP_{it} \cdot \ln(1+t)$	–	–	–	–	–	–	−14.253***
							(2.565)
$SLC_{it} \cdot \ln(1+t)$	–	–	–	–	–	–	−2.300
							(2.084)
$IALC_{it} \cdot \ln(1+t)$	–	–	–	–	–	–	−7.311***
							(2.557)
$UALC_{it} \cdot \ln(1+t)$	–	–	–	–	–	–	0.767
							(2.556)
$IAAP_{it} \cdot M_i$	–	–	–	–	–	–	9.944***
							(3.788)
$UAAP_{it} \cdot M_i$	–	–	–	–	–	–	15.588***
							(3.804)
$SLC_{it} \cdot M_i$	–	–	–	–	–	–	28.465***
							(3.045)
$IALC_{it} \cdot M_i$	–	–	–	–	–	–	5.986
							(3.789)
$UALC_{it} \cdot M_i$	–	–	–	–	–	–	8.686**
							(3.752)
$IAAP_{it} \cdot g(z_{it})$	–	–	–	–	–	–	−0.381
							(0.245)
$IALC_{it} \cdot m(z_{it})$	–	–	–	–	–	–	−0.294
							(0.976)
Constant	78.789***	49.037***	81.644***	62.947***	40.498***	49.629***	79.658***
	(5.728)	(9.280)	(8.632)	(3.595)	(5.758)	(6.538)	(4.599)
Observations	1450	710	750	1460	710	750	5830
Left Censored	143	9	196	85	2	79	514
Right Censored	2	0	0	0	0	1	3
Log Likelihood	−7116.064	−3546.939	−3140.289	−6782.575	−3454.378	−3441.625	−27703.290

*Significant at the 0.10 level.
**Significant at the 0.05 level.
***Significant at the 0.01 level.

Table 9: Estimated bid functions with gender interaction (standard errors in parentheses)

	SAP	Informed AAP	Uninformed AAP	SLC	Informed ALC	Uninformed ALC	Joint
z_{it}	0.016	0.418***	−0.017	−0.012	0.638***	0.016	0.014
	(0.024)	(0.092)	(0.035)	(0.015)	(0.198)	(0.025)	(0.019)
$\ln(1+t)$	−4.106	−26.202***	−23.722***	−9.549***	−19.347***	−9.205***	−4.002**
	(2.591)	(3.282)	(4.441)	(1.854)	(2.731)	(3.258)	(2.080)
M_i	−10.462	−20.805*	−15.349	3.854	−37.162***	−26.001**	−8.606
	(9.884)	(10.895)	(15.085)	(6.305)	(9.191)	(10.443)	(7.930)
$M_i \cdot \ln(1+t)$	−2.885	5.233	5.135	2.656	9.944***	6.687*	−3.368
	(3.681)	(4.078)	(5.600)	(2.347)	(3.411)	(3.887)	(2.954)
$g(z_{it})$	–	−0.371	–	–	–	–	–
		(0.230)					
$m(z_{it})$	–	–	–	–	−0.401	–	–
					(0.768)		
$IAAP_{it}$	–	–	–	–	–	–	−17.630
							(13.667)
$UAAP_{it}$	–	–	–	–	–	–	13.976
							(11.512)
SLC_{it}	–	–	–	–	–	–	−8.031
							(8.964)
$IALC_{it}$	–	–	–	–	–	–	−18.186
							(11.866)
$UALC_{it}$	–	–	–	–	–	–	−14.653
							(11.307)
$IAAP_{it} \cdot z_{it}$	–	–	–	–	–	–	0.403***
							(0.100)
$UAAP_{it} \cdot z_{it}$	–	–	–	–	–	–	−0.031
							(0.033)
$SLC_{it} \cdot z_{it}$	–	–	–	–	–	–	−0.027
							(0.027)
$IALC_{it} \cdot z_{it}$	–	–	–	–	–	–	0.622**
							(0.253)
$UALC_{it} \cdot z_{it}$	–	–	–	–	–	–	−0.004
							(0.033)
$IAAP_{it} \cdot \ln(1+t)$	–	–	–	–	–	–	−22.204***
							(4.071)
$UAAP_{it} \cdot \ln(1+t)$	–	–	–	–	–	–	−18.505***
							(4.021)
$SLC_{it} \cdot \ln(1+t)$	–	–	–	–	–	–	−5.807*
							(3.169)
$IALC_{it} \cdot \ln(1+t)$	–	–	–	–	–	–	−15.386***
							(4.047)
$UALC_{it} \cdot \ln(1+t)$	–	–	–	–	–	–	−5.136
							(4.013)
$IAAP_{it} \cdot M_i$	–	–	–	–	–	–	−12.312
							(14.066)
$UAAP_{it} \cdot M_i$	–	–	–	–	–	–	−3.782
							(14.125)
$SLC_{it} \cdot M_i$	–	–	–	–	–	–	12.120
							(11.356)
$IALC_{it} \cdot M_i$	–	–	–	–	–	–	−28.695**
							(14.122)
$UALC_{it} \cdot M_i$	–	–	–	–	–	–	−17.367
							(14.046)
$IAAP_{it} \cdot M_i \cdot \ln(1+t)$	–	–	–	–	–	–	8.631
							(5.256)
$UAAP_{it} \cdot M_i \cdot \ln(1+t)$	–	–	–	–	–	–	7.476
							(5.250)
$SLC_{it} \cdot M_i \cdot \ln(1+t)$	–	–	–	–	–	–	6.315
							(4.229)
$IALC_{it} \cdot M_i \cdot \ln(1+t)$	–	–	–	–	–	–	13.372
							(5.247)
$UALC_{it} \cdot M_i \cdot \ln(1+t)$	–	–	–	–	–	–	10.066*
							(5.231)
$IAAP_{it} \cdot g(z_{it})$	–	–	–	–	–	–	−0.375
							(0.245)
$IALC_{it} \cdot m(z_{it})$	–	–	–	–	–	–	−0.395
							(0.976)
Constant	75.050***	57.826***	90.265***	67.162***	57.033***	60.523***	75.288***
	(7.453)	(11.524)	(12.725)	(5.176)	(8.059)	(9.102)	(5.985)
Observations	1450	710	750	1460	710	750	5830
Left Censored	143	9	196	85	2	79	514
Right Censored	2	0	0	0	0	1	3
Log Likelihood	−7115.757	−3546.116	−3139.862	−6781.935	−3450.154	−3440.149	−27697.128

*Significant at the 0.10 level.
**Significant at the 0.05 level.
***Significant at the 0.01 level.

terestingly, in the joint specifications, the coefficient on signal is larger for informed ALC bidders than for informed AAP bidders. Also of interest is the fact that the nonlinear part of the informed AAP bidder's bid function $(g(z_{it}))$ is not significant. A similar result is found for informed ALC bidders; the coefficient of the signal is positive and highly significant, and the nonlinear informed ALC bidder's bid function $(m(z_{it}))$ in not significant. As such, it is clear that informed bidder's bid function is linear in their signals, contrary to theory.

Interestingly, the results regarding learning differ substantially across treatments, when we do not include the gender and learning interaction. In SAP auctions, participants learn relatively slowly to reduce their bids as they gain experience. The same holds for SLC bidders. The fact that SLC bidders learn slowly is surprising, since they are, on average, bidding more than equilibrium predictions. However, as discussed above, SLC bidders are typically not bidding more than the break-even bidding strategy. As such, most SLC bidders are earning positive payoffs on average. These average positive payoffs are less likely to reduce bidding behavior than negative payoffs.

In stark contrast, informed AAP and informed ALC bidders learn to reduce their bids much faster than SAP and SLC bidders. We attribute this to the fact that these informed bidders are much more prone to bid above the break-even bidding strategy than are uninformed bidders. The resulting negative payoffs provides a strong incentive for these bidders to reduce their bids. It is important to recall that when informed bidders observe a high signal, they bid above the break-even bidding strategy infrequently. When they observe a small signal, the probability of obtaining the good is small, because the uninformed bidder cannot take the low value of the good into account when choosing her bid. If the informed bidder does not take this into account by, in some sense, ceding the contest to the uninformed bidder she is likely to bid such that she loses the contest and still must pay her bid. This process is, for the most part, the mechanism through which informed bidders learn to reduce their bids. Notice that this allows the average payoff of the informed bidders to be quite high (since they are likely to earn a substantial payoff for high signal values), while still facing negative payoffs which induce learning that is quicker than that of uninformed bidders.

Also, notice that uninformed AAP bidders learn to reduce their bids faster than SAP bidders, but uninformed ALC bidders do not. This is attributable to the fact that, on average, uninformed AAP bidders quickly learn that when they obtain the good, it is because the informed AAP bidder has observed that it is low valued. This induces the uninformed AAP bidders to reduce their bids faster than SAP bidders, who do not face this "winner's curse." On the other hand, an uninformed ALC bidder has a positive probability of obtaining the good, regardless of the informed ALC bidder's bid, provided she has submitted a positive bid of her own.[24] As such, un-

[24] Note that this argument neglects the boundary case in which neither bidder submits

informed ALC bidders often obtain the good, and earn a substantial payoff in the process. Consequently, they have less incentive to reduce their bids than the uninformed AAP bidders.

Interestingly, when we do not include the gender and learning interaction, there are significant gender differences. In particular, notice that women bid more than men everywhere except in symmetric information lottery contests (although the magnitude of this difference is quite small in the case of uninformed AAP bidders). Clearly this fact is not simply a consequence of the imperfectly discriminating contest success function; women bid more than men in asymmetric information lottery contests, regardless of whether or not they are informed.

Notice that when we include the gender and learning interaction, it is not significant in all-pay auctions, regardless of the information structure. Indeed, inclusion of this interaction renders the gender dummy insignificant for SAP and uninformed AAP bidders, and only marginally significant for informed AAP bidders. Further, note that when we include the gender and learning interaction, the gender dummy in the SLC treatment is also no longer significant.

In contrast, note that inclusion of this gender and learning interaction does not render the gender dummy insignificant for ALC bidders, regardless of whether or not they are informed. Indeed, the magnitude of the coef-

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a positve bid. As this case does not arise in our data, there is no need to consider it.

ficients has increased. Also, the gender and learning interaction itself is significant for informed and uninformed ALC bidders. That is, we find that in asymmetric information lottery contests, women bid more than men, but also learn faster. This result does not extend to other treatments.

5 Conclusion

We have experimentally examined the role of asymmetric information in two types of contests: all-pay auctions and lottery contests. In particular, we examine these contests in a common-value environment in which there is uncertainty regarding the value of the good. We employ a 2×2 between subject design which varies the information structure of the game and the contest success function. In the symmetric information structure, neither bidder observes a signal regarding the value of the good; both bidder know only the distribution from which the value is drawn. In the asymmetric information structure, one of the bidders is randomly chosen to privately observe a signal in the form of a noisy estimate of the value of the good. The other bidder does not observe a signal, and holds no private information. The two contest success functions we utilize in our design represent opposite extremes of discrimination. At one end, there is perfectly discriminating contest success function, which allocates the good to the bidder with the highest bid with certainty. At the other, there is the lottery contest success function which allocates the good to each bidder with probability equal to her proportion of the sum of bids.

In addition to the 2×2 design outlined above, we also ran sessions in which participants played a series of all-pay auctions where both bidders observe a private signal. While we do not have theoretical predictions for this game, behavior in this environment is of interest in light of the fact that bidders who observe a signal in first-price auctions are much more prone to bid above their break-even bid, regardless of whether or not their opponent observed a signal (Grosskopf *et al.* 2010). As such, we ran these additional sessions to compare behavior in all-pay auctions to behavior in first-price auctions.

Perhaps the most interesting result is that bidders in asymmetric information treatments who observe a signal are much more prone to bid above their break-even bidding strategy than are bidders who do not observe a signal. Similarly, we find that when both bidders in an all-pay auction observe a signal, they are much more likely to bid above their break-even bidding strategy than are bidders who do not observe a signal. As such, the results of Grosskopf *et al.* (2010) do extend to all-pay auctions.

We also find that when neither bidder observes a signal, all-pay auctions generate more revenue than lottery contests. Consequently, bidders in such all-pay auctions earn more than bidders in lottery contests, on average. Interestingly the same does not hold when information is asymmetric. We are unable to reject revenue equivalence between asymmetric information all-pay auctions and asymmetric information lottery contests. Further, we are unable to reject payoff equivalence between uninformed bidders in these two asymmetric information games. Likewise, we are also unable to reject payoff equivalence between the informed bidders in these asymmetric information games.

Another interesting result we find is that, in asymmetric information lottery contests, women bid significantly more than men in early periods, but learn at a faster rate than men such that behavior converges in later periods. This result does not extend to the other treatments.

Our results suggest several questions which provide avenues for future research. First, what induces informed bidders to overbid so dramatically? Is it that the information is privately observed? Second,.what happens to behavior as the quality of the signal decreases? Third, does the observed revenue equivalence in the asymmetric information treatments extend to other games? Lastly, how much are bidders willing to pay for a signal? Could a seller increase revenue by selling signals?

6 Appendix A

This appendix supplies a general proof of the equilibrium in an AAP auction:

In a first price sealed bid auction, each bidder submits a bid, and the highest bid wins with certainty. In the first price all-pay auction, every bidder must pay his/her bid.

Consider the first-price all-pay auction where the value of the prize has a common, but uncertain, value. This value, X, has the distribution function $H(x)$, with support contained in $[0, \infty)$ It is assumed that $E(X) < \infty$. Let there be two risk neutral bidders, one of whom observes an informative signal, Z, regarding the value of the good prior to bidding. The other bidder knows only the distributions from which both these random variables are drawn. Let $V = E(X \mid Z)$, and let $F(v)$ denote the distribution function of V, which is assumed to be absolutely continuous. Let the informed bidder be bidder one, and the uninformed bidder be bidder two.

Proposition 1 *The following strategies characterize an equilibrium in this game:*
Bidder one bids:

$$\zeta(v) = F(v) E(V \mid V \leq v).$$

Bidder two mixes on the interval $[0, E(V)]$*, where the probability that she bids* x *is:*

$$G(x) = Prob\left[F(v)\, E(V \mid V \le v) \le x\right].$$

Proof. *Note that if both bidders bid according to the strategy outlined above, and bidder two bids $x \in [0, E(V)]$, and wins, her expected payoff will be:*

$$\begin{aligned} & E(V \mid \zeta(V) < x) - x \\ = \; & \frac{\zeta\left(\zeta^{-1}(x)\right)}{F\left(\zeta^{-1}(x)\right)} - x \\ = \; & \frac{x}{F\left(\zeta^{-1}(x)\right)} - x. \end{aligned}$$

Further, if bidder two bids x and loses, her payoff is $-x$. Thus, the expected payoff of bidding x is:

$$\begin{aligned} E(U_2) &= \left(\frac{x}{F\left(\zeta^{-1}(x)\right)} - x\right) Prob\,(x \;\; wins) - x\,(1 - Prob\,(x \;\; wins)) \\ &= \left(\frac{x}{F\left(\zeta^{-1}(x)\right)} - x\right) Prob\,(\zeta(V) < x) - x\,(1 - Prob\,(\zeta(V) < x)) \\ &= \left(\frac{x\,Prob\,(\zeta(V) < x)}{F\left(\zeta^{-1}(x)\right)} - x\right) \\ &= 0. \end{aligned}$$

Thus, the uninformed bidder is indifferent over the interval $[0, E(X_0)]$. Now consider the case in which the informed bidder bids $\zeta(z)$ when he observes v. If the uninformed bidder is following the equilibrium strategy outlined above, *then the expected payoff for the informed bidder is:*

$$\begin{aligned} E(U_1) &= G(\zeta(z))\,v - \zeta(z) \\ &= Prob(\zeta(V) \leq \zeta(z))\,v - \zeta(z) \\ &= Prob(V \leq z)\,v - \zeta(z) \\ &= F(z)\,v - \zeta(z) \end{aligned}$$

Differentiating this with respect to z *yields:*

$$\begin{aligned} & f(z)\,v - \frac{d}{dz}\zeta(z) \\ = \; & f(z)\,v - \frac{d}{dz}F(z)\,E(V \mid V \leq z) \\ = \; & f(z)\,v - \frac{d}{dz}\int_0^z t\,dF(t) \\ = \; & f(z)\,v - zf(z) \\ = \; & f(z)\,(v - z) \end{aligned}$$

Notice that bidding where $v \neq z$ *diminishes the expected payoff of the informed agent, and so he should bid* $\zeta(v)$*.* ■

Proposition 2 *In equilibrium, the informed bidder"s ex ante expected payoff is*

$$\int_0^\infty (1 - F(z))\,F(z)\,dz.$$

Proof. When an informed bidder bids z, he wins with probability $F(z)$.

His payoff is thus

$$\begin{aligned}
\Pi_1(z) &= F(z)v - \zeta(z) \\
&= F(z)v - F(v)E(V \mid V \leq v) \\
&= F(z)v - F(z)v + \int_0^z F(t)\,dt \\
&= \int_0^z F(t)\,dt.
\end{aligned}$$

Integrating this over z gives us

$$\begin{aligned}
E(\Pi_1) &= \int_0^\infty \int_0^z F(t)\,dt f(z)\,dz \\
&= \int_0^\infty F(z)\left(\int_z^\infty f(t)\,dt\right)dz \\
&= \int_0^\infty (1 - F(z))F(z)\,dz.
\end{aligned}$$

■

7 Appendix B

7.1 Preliminaries

The common value of the available good, X, is drawn from a uniform distribution on the interval $[\underline{x}, \overline{x}]$. The realization of this value, x, is not observed by the two bidders before placing their bids. However, the distribution from which it is drawn is common knowledge.

In asymmetric information treatments, the informed bidder observes an estimate of the realized value of the good. This estimate is the realization of X plus an error term X_I. This error term is $U(-\delta, \delta)$, and is independent of X. That is, the estimate is a realization of $Z_I = X + X_I$.(We denote the distribution function of Z_I as F_{Z_I}). Throughout, we use f_A to denote the density function of the random variable A. A joint density function will be denoted as $f(\mathbf{x})$ where the vector $\mathbf{x}$ indicates the random variables to which $f(\mathbf{x})$ pertains.

Since Z_I is simply the sum of independent random variables, it's density function is easily calculated. To do so, we use the following, well known, formula:

$$\begin{aligned} f_{Z_I}(z_I) &= \int_{-\infty}^{\infty} f_X(z_I - x) f_X(x)\,dx \\ &= \int_{-\delta}^{\delta} f_X(z_I - x) f_X(x)\,dx. \end{aligned}$$

This becomes a piecewise linear function:

$$f_{Z_I}(z_I) = \begin{cases} \int\limits_{-\delta}^{z_I - \underline{x}} \left(\frac{1}{2\delta(\overline{x}-\underline{x})}\right) dx = \frac{z_I+\delta-\underline{x}}{2\delta(\overline{x}-\underline{x})} & \text{if} \quad z_I \in [\underline{x}-\delta, \underline{x}+\delta) \\ \int\limits_{-\delta}^{\delta} \left(\frac{1}{2\delta(\overline{x}-\underline{x})}\right) dx = \frac{1}{(\overline{x}-\underline{x})} & \text{if} \quad z_I \in [\underline{x}+\delta, \overline{x}-\delta) \\ \int\limits_{z_I-\overline{x}}^{\delta} \left(\frac{1}{2\delta(\overline{x}-\underline{x})}\right) dx = \frac{\delta - z_I + \overline{x}}{2\delta(\overline{x}-\underline{x})} & \text{if} \quad z_I \in [\overline{x}-\delta, \overline{x}+\delta]\,. \end{cases}$$

The distribution function of Z_I is

$$F_{Z_I}(c) = \begin{cases} \int\limits_{\underline{x}-\delta}^{c} \frac{z+\delta-\underline{x}}{2\delta(\overline{x}-\underline{x})} dz & \text{if} \quad c \in [\underline{x}-\delta, \underline{x}+\delta) \\ \int\limits_{\underline{x}-\delta}^{\underline{x}+\delta} \frac{z+\delta-\underline{x}}{2\delta(\overline{x}-\underline{x})} dz + \int\limits_{\underline{x}+\delta}^{c} \frac{1}{(\overline{x}-\underline{x})} dz & \text{if} \quad c \in [\underline{x}+\delta, \overline{x}-\delta) \\ \int\limits_{\underline{x}-\delta}^{\underline{x}+\delta} \frac{z+\delta-\underline{x}}{2\delta(\overline{x}-\underline{x})} dz + \int\limits_{\underline{x}+\delta}^{\overline{x}-\delta} \frac{1}{(\overline{x}-\underline{x})} dz + \int\limits_{\overline{x}-\delta}^{c} \frac{\delta-z+\overline{x}}{2\delta(\overline{x}-\underline{x})} dz & \text{if} \quad c \in [\overline{x}-\delta, \overline{x}+\delta]\,. \end{cases}$$

This reduces to:

$$F_{Z_I}(c) = \begin{cases} \frac{(c-\underline{x}+\delta)^2}{4\delta(\overline{x}-\underline{x})} & \text{if} \quad c \in [\underline{x}-\delta, \underline{x}+\delta) \\ \frac{c-\underline{x}}{(\overline{x}-\underline{x})} & \text{if} \quad c \in [\underline{x}+\delta, \overline{x}-\delta) \\ \frac{\overline{x}-\underline{x}-\delta}{(\overline{x}-\underline{x})} + \frac{(\overline{x}+3\delta-c)(c-\overline{x}+\delta)}{4\delta(\overline{x}-\underline{x})} & \text{if} \quad c \in [\overline{x}-\delta, \overline{x}+\delta]. \end{cases}$$

It is easy to check that the joint density function of X and Z_I is given by:

$$f(x, z_I) = \frac{1}{2\delta(\overline{x}-\underline{x})}.$$

The density function of X given the realized value of Z_I is:

$$f_X(x \mid z_I) = \begin{cases} \frac{1}{z_I+\delta-\underline{x}} & \text{if} \quad z_I \in [\underline{x}-\delta, \underline{x}+\delta) \\ \frac{1}{2\delta} & \text{if} \quad z_I \in [\underline{x}+\delta, \overline{x}-\delta) \\ \frac{1}{\delta-z_I+\overline{x}} & \text{if} \quad z_I \in [\overline{x}-\delta, \overline{x}+\delta]. \end{cases}$$

7.2 Equilibrium Bidding in SAP

Theorem 1 in Baye *et al.* (1996) demonstrates that in any Nash equilibrium of this game, the expected payoff of both bidder's is zero, and that both bidders randomize continuously on $[0, E(X)]$. In a symmetric equilibrium, this implies that for any $b_i \in [0, E(X)]$

$$\Pi_i^{SAP}(b_i) = K(b_i)E(X) - b_i = 0$$

where $K(\cdot)$ is the distribution function of the symmetric equilibrium mixed strategy. Thus,

$$K(b_i) = \frac{b_i}{E(X)}.$$

Since both bidders have expected payoffs of zero, the expected revenue of this auction is $E(X)$.

7.3 Equilibrium Bidding in AAP

Appendix A provides the unique equilibrium of this game. In this equilibrium, when the informed bidder observes z_I he/she bids according to the function

$$\begin{aligned}\beta(z_I) &= F_{z_I}(z_I)E(E(X \mid Z_I) \mid Z_I \leq z_I) \\ &= \int_{\underline{x}-\delta}^{z_I} E(X \mid Z_I = s) f_{Z_I}(s)\,ds.\end{aligned}$$

When $z_I \in [\underline{x} - \delta, \underline{x} + \delta)$, this is

$$\begin{aligned}\beta(z_I) &= \int_{\underline{x}-\delta}^{z_I} \left(\frac{\underline{x} + s + \delta}{2}\right)\left(\frac{s + \delta - \underline{x}}{2\delta(\overline{x} - \underline{x})}\right) ds \\ &= \frac{(2\underline{x} + z_I + \delta)(z_I - \underline{x} + \delta)^2}{12\delta(\overline{x} - \underline{x})}.\end{aligned}$$

When $z_I \in [\underline{x}+\delta, \overline{x}-\delta)$ this is

$$\begin{aligned}\beta(z_I) &= \int_{\underline{x}-\delta}^{\underline{x}+\delta} \left(\frac{\underline{x}+s+\delta}{2}\right)\left(\frac{s+\delta-\underline{x}}{2\delta(\overline{x}-\underline{x})}\right) ds + \int_{\underline{x}+\delta}^{z_I} s\left(\frac{1}{(\overline{x}-\underline{x})}\right) ds \\ &= \frac{3z_I^2+\delta^2-3\underline{x}^2}{6(z_I-\underline{x})}.\end{aligned}$$

When $z_I \in [\overline{x}-\delta, \overline{x}+\delta]$ this is

$$\begin{aligned}\beta(z_I) &= \int_{\underline{x}-\delta}^{\underline{x}+\delta} \left(\frac{\underline{x}+s+\delta}{2}\right)\left(\frac{s+\delta-\underline{x}}{2\delta(\overline{x}-\underline{x})}\right) ds + \\ &\quad \int_{\underline{x}+\delta}^{\overline{x}-\delta} s\left(\frac{1}{(\overline{x}-\underline{x})}\right) ds + \\ &\quad \int_{\overline{x}-\delta}^{z_I} \left(\frac{\overline{x}+s-\delta}{2}\right)\left(\frac{\overline{x}+\delta-s}{2\delta(\overline{x}-\underline{x})}\right) ds. \\ &= \frac{2\overline{x}^3+(z_I-\delta)^3+6\underline{x}^2\delta-3\overline{x}^2(z_I+\delta)}{12\delta(\overline{x}-\underline{x})}\end{aligned}$$

That is, the equilibrium bid function for the informed bidder in AAP auctions is

$$\beta(z_I) = \begin{cases} \frac{(2\underline{x}+z_I+\delta)(z_I-\underline{x}+\delta)^2}{12\delta(\overline{x}-\underline{x})} & \text{if} \quad z_I \in [\underline{x}-\delta, \underline{x}+\delta) \\ \frac{3z_I^2+\delta^2-3\underline{x}^2}{6(z_I-\underline{x})} & \text{if} \quad z_I \in [\underline{x}+\delta, \overline{x}-\delta) \\ \frac{2\overline{x}^3+(z_I-\delta)^3+6\underline{x}^2\delta-3\overline{x}^2(z_I+\delta)}{12\delta(\overline{x}-\underline{x})} & \text{if} \quad z_I \in [\overline{x}-\delta, \overline{x}+\delta]. \end{cases}$$

In equilibrium, the uninformed bidder will mix on the interval $[0, E(X)]$

according to the following distribution function:

$$\begin{aligned} J(b) &= \text{Prob}\left[\beta\left(Z_I\right) \leq b\right] \\ &= F_{Z_I}\left(\beta^{-1}(b)\right). \end{aligned}$$

So, the uninformed bidder will mix according using this distribution function:

$$J(b) = \begin{cases} \frac{\left(\beta^{-1}(b)-\underline{x}+\delta\right)^2}{4\delta(\overline{x}-\underline{x})} & \text{if} \quad b \in \left[\beta\left(\underline{x}-\delta\right), \beta\left(\underline{x}+\delta\right)\right) \\ \frac{\beta^{-1}(b)-\underline{x}}{(\overline{x}-\underline{x})} & \text{if} \quad b \in \left[\beta\left(\underline{x}+\delta\right), \beta\left(\overline{x}-\delta\right)\right) \\ \frac{4\delta(\overline{x}-\underline{x}-\delta)+\left(\overline{x}+3\delta-\beta^{-1}(b)\right)\left(\beta^{-1}(b)-\overline{x}+\delta\right)}{4\delta(\overline{x}-\underline{x})} & \text{if} \quad b \in \left[\beta\left(\overline{x}-\delta\right), \beta\left(\overline{x}+\delta\right)\right]. \end{cases}$$

The expected payoff of the informed bidder is given by:

$$\Pi_I^{AAP}\left(z_I\right) = \begin{cases} \frac{(z_I-\underline{x}+\delta)^3}{12\delta(\overline{x}-\underline{x})} & \text{if} \quad z_I \in \left[\underline{x}-\delta, \underline{x}+\delta\right) \\ \frac{3(\underline{x}-z_I)^2-\delta^2}{6(\overline{x}-\underline{x})} & \text{if} \quad z_I \in \left[\underline{x}+\delta, \overline{x}-\delta\right) \\ \frac{(\overline{x}-z_I+\delta)^3}{24\delta(\overline{x}-\underline{x})} + \frac{(\overline{x}+z_I-\delta)}{2} - \frac{(\overline{x}-\underline{x})}{2}. & \text{if} \quad z_I \in \left[\overline{x}-\delta, \overline{x}+\delta\right]. \end{cases}$$

The ex ante expected payoff of the informed bidder is

$$\begin{aligned} E\left(\Pi_I^{AAP}\right) &= \int_{\underline{x}-\delta}^{\overline{x}+\delta} \Pi_I^{AAP}\left(z_I\right) dz_I \\ &= \frac{5\left(\overline{x}-\underline{x}\right)^3 - 10\delta^2\left(\overline{x}-\underline{x}\right) + 8\delta^3}{30\left(\overline{x}-\underline{x}\right)^2}. \end{aligned}$$

For the parameters employed in our design, $E\left(\Pi_I^{AAP}\right) = 33.2301$. Recall that the uninformed bidder has an expected payoff of zero.

The ex ante expected revenue for the seller is found by subtracting the ex ante expected payoff of the informed bidder from the expected value of X. This yields

$$\begin{aligned} E\left(R^{AAP}\right) &= E\left(X\right) - E\left(\Pi_I^{AAP}\right) \\ &= \left(\frac{\overline{x}+\underline{x}}{2}\right) - \frac{5\left(\overline{x}-\underline{x}\right)^3 - 10\delta^2\left(\overline{x}-\underline{x}\right) + 8\delta^3}{30\left(\overline{x}-\underline{x}\right)^2}. \end{aligned}$$

For the parameter values used in our design $E\left(R^{AAP}\right) = 91.7699$.

7.4 Equilibrium Bidding in SLC

Recall that the probability that player i will obtain the good is given by:

$$p_i\left(b_i, b_j\right) = \begin{cases} \frac{b_i}{b_i+b_j} & \text{if} \quad \max\left\{b_i, b_j\right\} \neq 0 \\ \frac{1}{2} & \text{if} \quad b_i = b_j = 0 \end{cases}.$$

We assume that the marginal cost of bidding is constant and equal to one. Bidder i's seeks to maximize his expected payoff which is given by:

$$\Pi_i^{SLC} = p_i \left(b_i, b_j\right) E\left(X\right) - b_i.$$

This expenditure function is strictly concave in x_i given x_j. As discussed above, bidding zero is not an equilibrium strategy, so the best response is determined by the following first order condition:

$$\frac{b_j E\left(X\right)}{\left(b_i + b_j\right)^2} - 1 = 0.$$

Utilizing the fact that the bidders are symmetric, this yields the equilibrium bids of:

$$b_i = b_j = \frac{E\left(X\right)}{4}.$$

Using these equilibrium bids, we can easily calculate the equilibrium expected payoff of the bidders:

$$\begin{aligned}
\Pi_i^{SLC} &= p_{i2}\left(\frac{E\left(X\right)}{4}, \frac{E\left(X\right)}{4}\right) E\left(X\right) - \frac{E\left(X\right)}{4} \\
&= \frac{E\left(X\right)}{2} - \frac{E\left(X\right)}{4} \\
&= \frac{E\left(X\right)}{4}.
\end{aligned}$$

Revenue in this game is the expected value of the good less the expected payoffs of the bidders. Therefore, the expected revenue in this treatment, $E\left(R^{SLC}\right)$, is $\frac{E(X)}{2}$.

7.5 Equilibrium Bidding in ALC

This game is similar to the setup analyzed in [23]. However, in our design the informed bidder is not perfectly informed as to the value of the good. This game is a special case of the model analyzed in the last period of [20]. If $a(z) = \max(\underline{x}, z - \delta)$ and $b(z) = \min(\overline{x}, z + \delta)$, then the informed bidder's problem is:

$$\begin{aligned}
\Pi_I^{ALC}(z_I) &= \int_{a(z_I)}^{b(z_I)} \left(\frac{\zeta^{ALC}(z_I)}{\zeta^{ALC}(z_I) + b_U^{ALC}} \right) x f(x \mid z_I)\, dx - \zeta^{ALC}(z_I) \\
&= \left(\frac{\zeta^{ALC}(z_I)}{\zeta^{ALC}(z_I) + b_U^{ALC}} \right) E(X \mid z_I) - \zeta^{ALC}(z_I),
\end{aligned}$$

where b_U^{ALC} is the bid of the uninformed ALC bidder. As in the SLC, this function is strictly concave given the bid of the uninformed bidder. The first order condition is:

$$\frac{b_U^{ALC} E(X \mid z_I)}{\left(\zeta^{ALC}(z_I) + b_U^{ALC}\right)^2} - 1 = 0.$$

Any $\zeta^{ALC}(z_I) \geqslant 0$ makes this condition negative if $b_U^{ALC} > E(X \mid z_I)$. Thus, the best response function of the informed bidder is:

$$\zeta^{ALC}(z_I) = \begin{cases} \sqrt{b_U^{ALC} E(X \mid z_I)} - b_U^{ALC} & \text{if} \quad z_I \geq q^{-1}\left(b_U^{ALC}\right) \\ 0 & \text{if} \quad z_I < q^{-1}\left(b_U^{ALC}\right). \end{cases}$$

where $q(z) = E(X \mid z_I)$, and $q^{-1}(\cdot)$ is the inverse of $q(\cdot)$.

The uninformed bidder's problem is given by:

$$\Pi_U^{ALC} = \int_{\underline{x}-\delta}^{\overline{x}+\delta} \int_{\underline{x}}^{\overline{x}} \frac{b_U^{ALC}}{\zeta^{ALC}(z_I) + b_U^{ALC}} x f(x, z_I) dx dz_I - b_U^{ALC}$$

This yields the following first order condition:

$$\int_{\underline{x}-\delta}^{\overline{x}+\delta} \int_{\underline{x}}^{\overline{x}} \frac{\zeta^{ALC}(z_I)}{\left(\zeta^{ALC}(z_I) + b_U^{ALC}\right)^2} x f(x, z_I) dx dz_I - 1 = 0$$

Plugging in the informed bidder's best response function and simplifying characterizes the equilibrium in this game:

$$1 = \left(\frac{1}{\sqrt{b_U^{ALC}}}\right) \int_{q^{-1}\left(b_U^{ALC}\right)}^{\overline{x}+\delta} \sqrt{E\left(X \mid z_I\right)} f\left(z_I\right) dz_I - \left(1 - F_{Z_I}(q^{-1}\left(b_U^{ALC}\right))\right).$$

In our experimental design $b_U^{ALC} = 29.37$.

The uninformed bidder's expected payoff is given by:

$$E\left(\Pi_U^{ALC}\right) = \int_{\underline{x}-\delta}^{q^{-1}\left(b_U^{ALC}\right)} \int_{\underline{x}}^{\overline{x}} x f(x, z_I) dx dz_I + b_U^{ALC}\left(1 - F_{Z_I}(q^{-1}\left(b_U^{ALC}\right))\right).$$

For the parameter values employed in our experimental design, $E\left(\Pi_U^{ALC}\right) = 29.72$.

The expected payoff of the informed bidder when he/she observes an estimate $Z_I = z_I$ is given by:

$$\Pi_I^{ALC}(z_I) = \begin{cases} 0 & \text{if} \quad z < q^{-1}\left(b_U^{ALC}\right) \\ E(X \mid z_I) - 2\sqrt{b_U^{ALC} E(X \mid z_I)} + b_U^{ALC} & \text{if} \quad z \geq q^{-1}\left(b_U^{ALC}\right). \end{cases}$$

The ex ante expected payoff of the informed bidder is given by:

$$E\left(\Pi_I^{ALC}(z_I)\right) = \int_{q^{-1}\left(b_U^{ALC}\right)}^{\overline{x}+\delta} \int_{\underline{x}}^{\overline{x}} x f(x, z_I) dx dz_I - b_U^{ALC}\left(3 - F_{Z_I}\left(q^{-1}\left(b_U^{ALC}\right)\right)\right).$$

For the parameter values employed in our experiment, $E\left(\Pi_I^{ALC}(z_I)\right) = 36.92$.

The ex ante expected revenue in this treatment is found by adding the expected equilibrium bid of the informed ALC bidder and the equilibrium bid of the uninformed ALC bidder. In our experimental design this is $E\left(R^{ATC}\right) = 58.74$.

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8 Appendix C

8.1 Description

Symmetric information all-pay auction with private signals.(SAP-PRIV)— Participants engage in 30 all-pay auctions. In each of these all-pay auctions each bidder privately observes a signal. These signals, z_1 and z_2, are independently drawn from a uniform distribution with support $[x-8, x+8]$. In this treatment both bidders hold private information in the form of their signal. Information is symmetric in that each signal is an equally precise estimate of x. We do not have theoretical predictions for this treatment.[25] We include this treatment for comparison with the results of Grosskopf *et al.* (20010). Additionally, the susceptibility of bidders to bidding above the break-even bidding strategy in such an environment is of interest.

8.1.1 Break-even Bidding in SAP-PRIV

A long literature experimentally studies this information structure in the context of first-price, sealed-bid auctions.[26] It is well documented that when inexperienced bidders privately observe private signals they consistently fall victim to the winner's curse.[27] Further, Grosskopf *et al.* (2010) show that when inexperienced bidders in a first-price, sealed-bid auction do not observe a signal prior to bidding the winner's curse is almost completely eliminated. Including the SAP-PRIV information structure for all-pay auctions allows us to compare our results to those found in Grosskopf *et al.* (2010). Do bidders who observe signals in all-pay auction bid above the beak-even bidding strategy when their opponent also observes a signal?

As such, defining the break-even bidding strategy in the context of an all-pay auction when both bidder's observe private signals is important. If bidders bid according to a monotonically increasing bid function, then the

[25] As noted in Athey (2001), a common value all-pay auction with conditionally independent signals does not satisfy the single crossing property.

[26] See Kagel and Levin (2002) for a review of this literature.

[27] The winner's curse is defined as bidding above a break-even threshold, such that when a bidder wins an auction, they have negative expected profits.

bidder who observes the highest signal will win the auction. Thus, the expected value of the good, conditional on winning the all-pay auction is the same as the expected value of the good conditional on having the highest signal. So, if bidder i bids above, $E(X \mid z_i > z_j)$, the bidder will have a negative expected payoff, conditional on winning the auction. However, if the bidder were to lose the auction, she would still have to pay her bid. As such, the break-even bidding threshold, assuming the bidders are bidding according to a monotonically increasing bid function is any bid greater than $F(Z_j = z_i \mid Z_i = z_i) E(X \mid z_i > z_j)$.

When $z_i \in [\underline{x} - \delta, \underline{x} + \delta)$,

$$
\begin{aligned}
& F(Z_j = z_i \mid Z_i = z_i) E(X \mid Z_i = z_i > z_j) \\
= & \int_{\underline{x}-\delta}^{z_i} \int_{\underline{x}}^{z_j+\delta} x f_X(x, z_j \mid z_i) \, dx dz_j \\
= & \int_{\underline{x}-\delta}^{z_i} \int_{\underline{x}}^{z_j+\delta} x \frac{1}{2\delta (z_i + \delta - \underline{x})} dx dz_j \\
= & \left(\frac{z_i + \delta - \underline{x}}{4\delta} \right) \left(\frac{z_i + 2\underline{x} + \delta}{3} \right).
\end{aligned}
$$

When $z_i \in [\underline{x} + \delta, \overline{x} - \delta)$,

$$\begin{aligned}
& F(Z_j = z_i \mid Z_i = z_i) E(X \mid Z_i = z_i > z_j) \\
= & \int_{z_i - 2\delta}^{z_i} \int_{z_i - \delta}^{z_j + \delta} x f_X(x, z_j \mid z_i) \, dx dz_j \\
= & \int_{\underline{x} - \delta}^{z_i} \int_{\underline{x}}^{z_j + \delta} x \frac{1}{4\delta^2} dx dz_j \\
= & \frac{z_i}{2} - \frac{\delta}{6}.
\end{aligned}$$

When $z_i \in [\overline{x} - \delta, \overline{x} + \delta]$

$$\begin{aligned}
& F(Z_j = z_i \mid Z_i = z_i) E(X \mid Z_i = z_i > z_j) \\
= & \int_{z_i - 2\delta}^{z_i} \int_{z_i - \delta}^{z_j + \delta} x f_X(x, z_j \mid z_i) \, dx dz_j \\
= & \int_{z_i - 2\delta}^{\overline{x} - \delta} \int_{z_i - \delta}^{z_j + \delta} x \frac{1}{2\delta(\overline{x} + \delta - z_i)} dx dz_j + \int_{\overline{x} - \delta}^{z_i} \int_{z_i - \delta}^{\overline{x}} x \frac{1}{2\delta(\overline{x} + \delta - z_i)} dx dz_j \\
= & \frac{(z_i + 5\delta)(z_i - \delta) + \overline{x}(z_i + 5\delta) - 2\overline{x}^2}{12\delta}.
\end{aligned}$$

That is,

$$F(Z_j = z_i \mid Z_i = z_i) E(X \mid Z_i = z_i > z_j) = \begin{cases} \left(\frac{z_i + \delta - \underline{x}}{4\delta}\right)\left(\frac{z_i + 2\underline{x} + \delta}{3}\right) & \text{if} \quad z_i \in [\underline{x} - \delta, \underline{x} + \delta) \\ \frac{z_i}{2} - \frac{\delta}{6} & \text{if} \quad z_i \in [\underline{x} + \delta, \overline{x} - \delta) \\ \frac{(z_i + 5\delta)(z_i - \delta) + \overline{x}(z_i + 5\delta) - 2\overline{x}^2}{12\delta} & \text{if} \quad z_i \in [\overline{x} - \delta, \overline{x} + \delta]. \end{cases}$$

Table 10: Revenue aggregated across all rounds and sessions

Treatment	**Average observed revenue (standard deviation)**	**Average predicted revenue (standard deviation)**
SAP	119.09	125.00
	(65.77)	(0.00)
AAP	95.23	88.24
	(69.31)	(29.80)
SAP-PRIV	140.88	–
	(104.49)	
SLC	96.76	62.50
	(44.44)	(0.00)
ALC	95.97	56.13
	(56.83)	(14.65)

8.2 Experimental Results

8.2.1 Revenue

Table 10 contains summary statistics regarding revenue. Notice that SAP-PRIV auctions generate more revenue than any other treatment, on average.

We find dramatic results regarding revenue in all-pay auctions when both bidders observe a private signal. In particular, we find that revenue is greater than in any other treatment. Revenue in all-pay auctions where both bidders observe a private signal is greater than when neither bidder observes a signal (robust rank-order test, $\acute{U} = 3.086$, $p < 0.028$). Typically, auction theory predicts that bidders who hold private information earn a positive information rent, and reduce revenue relative to the case in which their information is unobserved or made public. Our data suggests that providing bidders with private information can increase revenue. This result is also observed in the context of first-price auctions in Grosskopf *et al.* (2010).

We also find that revenue in all-pay auctions when both bidders observe a private signal is greater than in asymmetric information all-pay auctions (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$). This is also true in lottery contests with symmetric (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$) and asymmetric (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$).information.

8.2.2 Bidder Payoffs

Table 11 contains summary statistics regarding bidder payoffs. Notice that SAP-PRIV bidders have the lowest payoffs, on average.

We find that informed AAP bidders earn more than SAP-PRIV bidders (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$). SAP bidders, who hold no private information, have payoffs significantly greater than SAP-PRIV bidders, who do hold private information (robust rank-order test, $\acute{U} = 2.564$, $p < 0.048$). This surprising result is consistent with the findings in Grosskopf *et al.* (2010) in which bidders in common-value, first price auctions earn higher payoffs when bidders do not observe private signals than when all bidders observe private signals. We also find that uninformed AAP bidders earn significantly higher payoffs than SAP-PRIV bidders (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$).

Table 11: Bidder payoffs aggregated over all rounds and sessions

Bidders	**Average observed payoffs (standard deviation)**	**Average predicted payoffs (standard deviation)**
SAP	−1.72	0
	(62.77)	(0)
AAP-Informed	26.38	27.29
	(59.50)	(27.70)
AAP-Uninformed	−6.08	0
	(44.06)	(0)
SAP-PRIV	−12.67	–
	(62.34)	
SLC	9.39	31.25
	(68.58)	(0)
ALC-Informed	22.72	31.20
	(60.96)	(26.85)
ALC-Uninformed	−3.16	29.72
	(54.68)	(0)

8.2.3 Break-even Bidding

Table 12 contains summary statistics regarding break-even bidding.

8.2.4 Bidding

We find that SAP-PRIV bidders bid more than SAP bidders (robust rank-order test, $\acute{U} = 2.361$, $p < 0.048$). We can not reject the hypothesis that SAP-PRIV bidders bid the same amount as informed AAP bidders (robust

Table 12: Bidding above the break-even bidding strategy aggregated across all rounds and sessions

Bidders	Frequency bid exceeds break-even bid: All bidders	Frequency bid exceeds break-even bid: Winning bidders	Frequency the high (or only) signal holder wins
SAP	6.2%	12.1%	NA
	(93/1490)	(90/745)	NA
AAP-Informed	32.7%	30.4%	69.2%
	(245/750)	(158/519)	(519/750)
AAP-Uninformed	4%	11.3%	NA
	(30/750)	(26/205)	NA
SAP-PRIV	62.87%	83.73%	58.67%
	(943/1500)	(628/750)	(440/750)
SLC	8.1%	12.1%	NA
	(122/1500)	(91/750)	NA
ALC-Informed	34.3%	32.8%	50.7%
	(257/750)	(168/512)	(380/750)
ALC-Uninformed	8.3%	16%	NA
	(62/750)	(38/238)	NA

NA = not applicable.

The decimal numbers in parentheses are standard deviations.

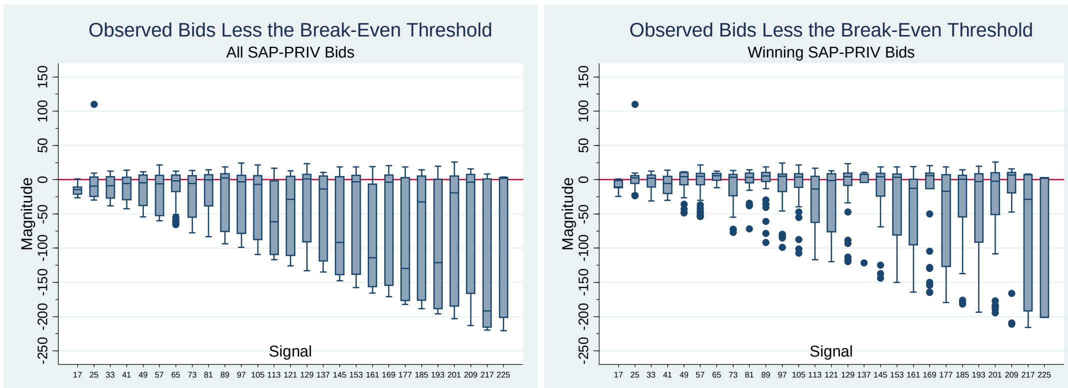
The fractions in parentheses are relative frequencies.

Table 13: Bids relative to the Nash equilibrium aggregated over all rounds and sessions

Bidders	**Average bid**	**Average Nash equilibrium bid**	**Average percent over Nash**	**Frequency of positive bids**
SAP	59.54	62.5[a]	−4.73%	90.13%
	(46.50)	(36.08)	(0.74)	(1353/1490)
AAP-Informed	61.11	38.49	385.48%	98.40%
	(50.54)	(34.55)	(20.54)	(738/750)
AAP-Uninformed	34.13	45.89[a]	−25.63%	73.86%
	(42.99)	(36.85)	(0.94)	(554/750)
SAP-PRIV	70.44	–	–	97.47%
	(63.84)			(1462/1500)
SLC	48.38	31.25	54.81%	94.20%
	(30.38)	(0.00)	(0.97)	(1413/1500)
ALC-Informed	61.02	26.53	229.95%	99.73%
	(44.30)	(14.59)	(6.83)	(748/750)
ALC-Uninformed	34.95	29.37	19.00%	89.47%
	(33.69)	(0.00)	(1.15)	(671/750)

[a]This is the expected value of the equilibrium mixed strategy.
The decimal numbers in parentheses are standard deviations.
The fractions in parentheses are relative frequencies.

Figure 7: The difference between observed bids and break-even bids depending on the signal



rank-order test, $\acute{U} = 0.853$, $n.s.$). SAP-PRIV bidders also bid more than uninformed AAP bidders (robust rank-order test, $\acute{U} = n.d.$, $p = 0.004$).

9 Appendix D

What follows is a sample set of instructions. Instructions for the remaining treatments are available upon request.

Introduction

Welcome. This experiment is about decision making in markets. The following instructions describe the markets you will be in and the rules that you will face. The decisions you make during this experiment will determine how much money you earn. If you make good decisions, you can earn a substantial amount of money. You will be paid in cash privately at the end of our experiment.

It is important that you remain silent and do not look at other people's work. If you have any questions, or need assistance of any kind, please raise your hand and an experimenter will come to you. If you talk, laugh, exclaim out loud, etc., you will be asked to leave and you will not be paid. We expect and appreciate your cooperation.

We will go over these instructions with you. After we have read the instructions, there will be time to ask clarifying questions. When we are done going through the instructions, each of you will have to answer a few brief questions to ensure everyone understands.

Overview

Our experiment will consist of 30 rounds. In each of these rounds, you will be randomly paired with another participant in today's experiment. Both of you will be buyers in a market. In each market, there will be a single unit of an indivisible good for sale. As a buyer, your task is to submit a bid for the purchase of the good. You will receive earnings based on the outcome of the market. This process will be repeated until all 30 rounds have been completed.

Determination of Your Earnings

Each participant will receive a showup fee of $5. In addition, each participant in this experiment will start with a balance of $3,200 "experimental dollars" (EDs). EDs will be traded in for cash at the end of the experiment at a rate of $\$160ED = \$1$. Your starting balance can increase or decrease depending on your payoffs in each round. That is, if you have a negative payoff in a round, this loss will be deducted from your balance. If you earn a positive payoff, this is added to your balance. You are permitted to bid more than your remaining balance. However, if after a round is completed your balance is less than or equal to zero, you will not be able to participate in any future rounds.

In each round, you and the other buyer in the market will submit a bid. Both of those bids will have to be paid, but only one of the buyers will receive the good. Each of the buyers has the following probability of receiving the good:

$$\frac{\text{(Own Bid)}}{\text{(Own Bid)+(Other's Bid)}}$$

Notice that if one a buyer submits a bid of zero, there is no chance of that buyer receiving the good; the other buyer will receive the good with certainty. If both buyers submit the same bid, then each of the buyers has a 50% chance of receiving the good.

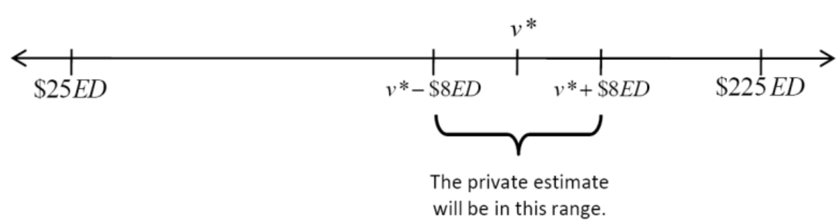
Notice that a buyer who receives the good can end up with a negative payoff, if he/she bids more than the good is worth. The buyer who does not receive the good will always have a negative payoff if their bid was greater than zero. No buyer is permitted to submit a bid that is lower than zero.

In each round, the value of the good, which we will denote as v^*, will not be known to the buyers. The value of this good will be between \$25ED

and \$225ED. Any value between \$25ED and \$225ED is equally likely to be chosen as v^*. The value of the good in any given round is independent of the value in any other round. That is, the value of the good in one round will not have *any* effect on the value of the good in a different round.

Private Information

In each market, one of the two buyers will be randomly chosen to receive some private information about the value of the good (you can think of this as flipping a coin to determine which of the buyers will receive this information, where the probability of the coin landing on each side is 50%). The person who receives the private information will be given an estimate of the value of the good. The estimate will be a randomly chosen number that is within \$8ED above or below the real value of v^* (see the illustration below). Any number between $v^* - \$8ED$, and $v^* + \$8ED$ is equally likely to be chosen as the private estimate. For example, if you receive a private estimate of \$125ED, then you know that v^* is between \$117ED and \$133ED, inclusive. It is possible for the estimate to be a value below \$25ED or above \$225ED, but the real value of v^* will always be between \$25ED and \$225ED.



Rounds

As mentioned before, there will be 30 rounds in this experiment. In each round there will be several markets going on simultaneously, with two buyers in each market. After each round you will be randomly paired with another participant in today's experiment. This random assignment is done *every round* so that two buyers will probably not be in the same market together for two consecutive rounds. Further, this pairing is anonymous. That is, if you are a buyer in a given market, you do not know which of the other participants in the experiment is the other buyer in that market. Remember that these different markets and rounds are independent from all others, and from one another. The bids and the value of the good and the private estimate in one market or round do not have any effect on other markets or rounds. Markets and rounds operate independently.

Summary

1. Each participant has a starting balance of $\$3,200ED$.

2. In every round, each participant will be a bidder in one market. Two participants are randomly assigned to a market in each round.

3. In each market each buyer gets $v^* - \text{(Own bid)}$ with probability $\left(\frac{\text{(Own Bid)}}{\text{(Own Bid)}+\text{(Other's Bid)}}\right)$, and gets $0-\text{(Own bid)}$ with the remaining probability $\left(1-\frac{\text{(Own Bid)}}{\text{(Own Bid)}+\text{(Other's Bid)}}\right)$. This payoff is added to the balance of each bidder (a bidder's balance will go down if the value is negative, and up if this value is positive).

4. The value of the good, v^*, is unknown. It is known that it is somewhere between $\$25ED$ and $\$225ED$. Every value between $\$25ED$ and $\$225ED$ is equally likely to be v^*.

5. One of the two bidders in each market is randomly chosen to receive a private estimate of v^*. This estimate is not observed by the other bidder in the market. This estimate is randomly drawn from the interval between $v^* - \$8ED$ and $v^* + \$8ED$, inclusive. Any number from this interval is equally likely to be chosen as the private estimate.

6. Every participant will receive the show-up fee of \$5. Additionally, each participant will receive his/her balance at the end of all 30 rounds, based on the $\$3,200ED$ beginning balance and earnings in each market.

7. If a participant's balance should become negative at any point during this experiment, he/she will not be permitted to participate in future rounds.

If you have any questions, raise your hand and one of us will come help you. Please do not ask any questions out loud.

Questions

Before we begin the experiment, we would like you to answer a few questions that are meant to review the rules of today's experiment. Please raise your hand once you are done, and an experimenter will attend to you.

1. How many buyers are in each market? ____________

2. Who pays their bid in each market, the bidder who gets the good, the bidder who doesn't get the good, or both? ____________

3. The private estimate must be within what range of v^*? ____________

4. Are you allowed to bid more than your current balance? ____________

5. For each market, how many buyers get to see the estimate of v^*? ____________

6. If the bid of a buyer who receives the good in a market is \$152.10ED, and the value of the good is revealed to be \$200.90ED, what is the winner's payoff for that market? ____________

7. What would the earnings from question six have been if the value of the good had been \$25.90ED? ____________

8. If Buyer 1 bids \$150.00ED, and Buyer 2 bids \$200.00ED, and the value of the good is revealed to be \$220.75ED, what are the payoffs for Buyer 1 and Buyer 2 if Buyer 2 receives the good? ____________

9. What would the earnings from question eight have been if Buyer 1 received the good? ____________