No Trade *

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Abstract

We investigate a common value bilateral bargaining model with two sided private information and no aggregate uncertainty. A seller owns an asset whose common valuation is a deterministic function of the two traders' private signals. We first establish a no-trade theorem for this environment, and proceed to study the effect of the asset valuation structure and the trading mechanism on extent to which asymmetric information induces individuals to engage in mutually unprofitable exchange. A laboratory experiment is conducted, where trade is found to occur between 19% and 35% of the time, and this depends in systematic ways on both the asset valuation function and the trading mechanism. Both buyers and sellers adapt their strategy to changes in the asset valuation function and to changes in the trading mechanism in clearly identifiable ways. An equilibrium model with naïve belief formation accounts for some of the behavioral findings, but open questions remain.

JEL classification: C78, C92, D82.

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1 Introduction

Understanding the effects of private information on pricing and volume of trade is central to the study of markets, especially markets for risky assets. In the present paper, we consider two simple trading mechanisms and three different kinds of assets in the context of a simple trading model. We investigate whether asymmetric information in this environment induces individuals to engage in exchange where trade is not mutually profitable. We find that it does, and study how the trading mechanisms and asset types affect the likelihood and terms of trade.

To study this problem, we analyze a two-person bargaining game with two-sided private information and no aggregate uncertainty. One individual (the seller) is endowed with one unit of an asset. Another individual (the buyer) can acquire it if both can agree on a price for the transaction. We consider a class of assets with a pure common value and each individual has a private signal about this value. The value of the asset is a deterministic function of the two signals, so if agents pool their information there is no residual uncertainty about the asset value. As a result, there cannot be trade for insurance or risk-sharing motives regardless of the risk attitudes of buyer and seller. Furthermore the information structure and the prior distribution of the states is common knowledge so there is no possibility of trade based on heterogeneous priors. The logic is similar to standard no-trade theorems: both agents cannot benefit from a trade, so accepting the other agent's terms implies that one's end of the deal cannot be ex-post favorable. However the actual structure of the model is somewhat different and does not allow us to directly apply existing results. Our first result is a no-trade theorem for this class of environment.

We then proceed to study the effect of the asset valuation structure and the trading mechanism on extent to which asymmetric information induces individuals to engage in mutually unprofitable exchange. A laboratory experiment is conducted, where trade is found to occur between 19% and 35% of the time, and this depends in systematic ways on both the asset valuation function and the trading mechanism.

Specifically, private signals are drawn independently from a commonly known distribution on a real interval, and the experiment considers three different valuation structures for how the common value is related to the underlying signals: the average of the signals; the minimum of the signals; and the maximum of the signals (hence forth referred to as the "ave", "min" and "max" asset values, respectively). Second, we compare exchange behavior under two trading mechanisms: a two stage mechanism where the seller sets a take-it-or-leave-it price which the buyer can accept or reject; and a simultaneous move double auction, where trade occurs at the seller's offer whenever the buyer's bid weakly exceeds it (henceforth referred to as the "price" and "auction" mechanisms). Hence, both the asset value structure and the mechanism for sharing this value between buyer and seller are varied in the experiment. To the extent that trade is observed in the experiment, this design provides an opportunity to identify possible explanations for observed non-equilibrium behavior, because the asset value affects the Nash equilibrium prices, bids, and offers (although not the outcome, which is always no-trade). By contrast, both trading mechanisms are strategically equivalent for the seller, in the sense that he should set identical prices in either case. Thus, theoretically we should see differences in behavior across asset types, but no differences across trading mechanisms.

Our first set of results relates to findings that are common to the different treatments. Contrary to the theoretical prediction, we always observe substantial trade, with probabilities ranging from 32% to 58% of the time when the buyer's signal exceeds the seller's signal depending on treatments.[1] Also, there is little evidence of learning by either buyers or sellers in this game, despite a significant number of rounds being played (20) and with feedback and experience in both roles, buyer and seller. Finally, under both trading mechanisms, sellers have net losses on average in the ave and max treatments and net gains in the min treatment. The combination of no learning and exploitation of subjects in one role by subjects in the other is surprising since individuals gain experience in both roles.

Our second set of results investigates more deeply the differences in behavior across treatments. Strategies of buyers and sellers *change across the asset valuation function*. In particular, seller prices and buyer bids both increase as we move from min to ave and from ave to max. Therefore, even though the exact numerical price levels are inconsistent with the theory and lead to trade, the qualitative changes in response to changes in asset values are quite intuitive and consistent with theory. Surprisingly however, behavior also *changes across mechanisms* in significant ways. In particular, buyers submit bids in the auction mechanism which are, on average, lower than the maximum offer prices they accept in the price mechanism. Theoretically there should be no difference. At the same time, prices posted by sellers are more responsive to their signal in the auction than in the price mechanism. In addition to these changes in pricing behavior, the extent to which behavior is inconsistent with Nash equilibrium has huge variation

[1] Not surprisingly, trade is rare when the seller's signal exceeds the buyer's signal.

across the three asset value functions, the two exchange mechanisms, and the trader roles (buyer/seller).

Finally, as an initial attempt to understand these findings, we consider an alternative model, the "cursed equilibrium" (Eyster and Rabin, 2005), where traders incorrectly believe that there is no relationship between the action and the private information of their rival. Traders with such erroneous beliefs are vulnerable to accepting or offering unfavorable terms of trade. We solve analytically the outcome of the game under the price mechanism and for the three value functions when all traders suffer this belief fallacy. We show that the buyers' acceptance decision, the sellers' price function and the trade frequencies predicted by the cursed equilibrium model all match up reasonably well with the data.

Related literature: Theory. Milgrom and Stokey (1982) and Tirole (1982) establish that, in equilibrium, rational individuals will not trade for purely informational reasons. More specifically, in a market context, if fully rational agents have common prior beliefs and the existing asset allocation is Pareto optimal (say, as the result of previous trading), then new private information to some or all agents in the economy will not induce trade. The logic is simple. Traders who receive private information have the marginal valuation for their asset allocation modified. However, without insurance or transaction motives for trading, every agent realizes that a transaction beneficial for someone must necessarily be detrimental for someone else. Thus, the acceptance of the terms of a trade is evidence that the deal must be unfavorable.[2]

Our framework is also related to the literature on bargaining with private information. In a private value setting with two-sided private information, it has been shown that trade occurs when the seller's valuation is sufficiently lower than the buyer's valuation. This means, in particular, that full efficiency cannot be achieved and that asymmetric information prevents the realization of some profitable trades.[3] In a common value setting with se-

[2] This "no-trade theorem" has been extended in a number of directions. For example, Morris (1994) identifies conditions under which no-trade occurs even if individuals have heterogeneous prior beliefs. Blume et al. (2006) show that the no-trade result applies to competitive markets if and only if markets are complete. Serrano-Padial (2007) demonstrates that it holds under a class of bilateral trading mechanisms.

[3] See for example Chatterjee and Samuelson (1983) in the context of a double auction and Myerson and Satterthwaite (1983) in a generalized bargaining game. Cramton et al. (1987) show that initial ownership is crucial to determine whether efficiency can be achieved. Radner and Schotter (1989) study in the laboratory the Chatterjee and Samuelson model of private values bargaining.

quential offers, Evans (1989) and Vincent (1989) show that one-sided private information also leads to inefficiently low trading. Instead, our experimental results imply *the opposite observation* for *actual* trading behavior: the introduction of asymmetric information leads to trade in contexts where we should observe none.

Related literature: Experiments. Constant sum bargaining games with two-sided private information, of which bargaining with common values is a special case, have rarely been studied in the laboratory. Exceptions are the *compromise game* (Carrillo and Palfrey, 2009), and the *betting game* (Sonsino et al. (2001), Sovic (2004), Rogers et al. (2009)). In these two experimental settings, subjects make binary choices. Both games exhibit the analogue of excessive trading (compromise and betting in their terminology). However, the sparseness of the strategy spaces in those settings (2×2 games) does not map easily into standard trading problems where prices play an important role, and are not rich enough models to explore systematic effects of different asset valuation structures and trading mechanisms.[4] In the richer bargaining environment studied in this paper, one can not only address that first question of whether subjects set the prices predicted by the theory, but can also identify in greater detail *how much* departure from the theory there is, how this depends on the asset valuation structure and the trading mechanism, and its different impact on buyer and seller profits.[5]

The trader incentives in our study share some similarities with the winner's curse problem for bidders in common value auctions (reviewed in Kagel and Levin, 2002) and the lemons problem of adverse selection markets (Akerlof 1970, Samuelson and Bazerman 1985). Under some conditions, players do not fully take account of the dependence of the actions of other players in the game on their private information, although these distortions often diminish with experience both through selection and learning (Kagel and Levin, 2002). Our two-sided asymmetric information setting delivers four novel implications related to these other problems. First, it shows that the

[4] The simplicity of the betting games also has a weakness in that the equilibrium predict "inaction" (no bets) independently of the subject's information, and hence equilibrium payoffs are also independent the private information. Thus, boredom could explain the bulk of the findings. This *does not* apply to our game where (i) subjects must select prices; (ii) the Nash equilibrium action depends on the subject's signal; (iii) equilibrium payoffs for the seller depends on both types; and (iv) subjects can earn substantial profits if they choose prices optimally.

[5] Very recently, a working paper has been circulated (Angrisani et al., 2009) reporting the results of a trading experiment that also uses our ave-auction treatment, but with aggregate uncertainty.

adverse selection problem does not depend on subjects being at a disadvantaged, fully uninformed position relative to a fully informed seller, as in the lemons problem. Second, with this double asymmetry, learning is limited even though subjects gain substantial experience in both roles. Third, the trading mechanism affects the extent to which subjects fall prey to the adverse selection problem, and it affects sellers behavior in fundamentally different ways from buyers. Fourth, the asset valuation structure, i.e., the mapping from signal profile to asset value, has strong and significant effects on non-equilibrium behavior; and as with the trading mechanism, the asset valuation structure affects buyers in different ways than sellers.

2 The model

The trading game can be formalized as follows. An asset is to be divided among two agents, 1 and 2. Agent 1, the seller, possesses the asset. Agent 2, the buyer, can acquire it if they mutually agree on a price. The asset has a common value to both agents, and each has a signal, denoted by s and b for the seller and buyer, respectively. The common value $v(s, b)$ is a commonly known and deterministic function of the signals, $s \in \mathcal{S} = [s_{\min}, s_{\max}] \subset \Re$ and $b \in \mathcal{B} = [b_{\min}, b_{\max}] \subset \Re$. There are many possible bargaining mechanisms that might apply in these environments. The simplest trade mechanism, and the one that we consider here, is one in which the seller sets a take-it-or-leave-it price, which is accepted or rejected by the buyer. A strategy for a seller is a measurable pricing function $P : \mathcal{S} \to \Re$ and a strategy for the buyer is a measurable acceptance function $A : \Re \to \{0, 1\}$ where 1 denotes "accept" and 0 denotes "decline". A natural alternative, which we also consider, is a seller-price double-auction, where seller and buyer simultaneously quote price and bid, and the transaction is executed at the seller's price if and only if the bid weakly exceeds the price. Here we analyze only the take-it-or-leave-it pricing mechanism, but the results of this section apply equally to the seller-price double-auction mechanism.

Denoting the seller's price by p, the payoffs in case of trade are given by:

$$\begin{aligned} \pi_1(s, b, p, 1) &= p \\ \pi_2(s, b, p, 1) &= v(s, b) - p \end{aligned}$$

The payoffs in case of no trade are given by:

$$\begin{aligned} \pi_1(s, b, p, 0) &= v(s, b) \\ \pi_2(s, b, p, 0) &= 0 \end{aligned}$$

In these mechanisms the total surplus $v(s,b)$ is fixed but the splitting rule (trading price) is endogenously determined. We assume s and b are private information for seller and buyer, respectively. More precisely, $s \in \mathcal{S}$ and $b \in \mathcal{B}$ with commonly known conditional distribution functions, $F_s(s \,|\, b)$ and $F_b(b \,|\, s)$, possibly different and possibly correlated. We assume strictly positive continuous densities $f_s(s \,|\, b)$ and $f_b(b \,|\, s)$ for all s and b. We also restrict attention to *monotone* value functions, i.e., for every signal pair (s,b), $\partial v(s,b)/\partial s \geq 0$ for all b and $\partial v(s,b)/\partial b \geq 0$ for all s. Last, we assume that the utility of the seller, $u_1(\pi_1)$, and the utility of the buyer, $u_2(\pi_2)$, are strictly increasing in their own payoffs, π_1 and π_2, that is, $u_1'(\pi_1) > 0$ and $u_2'(\pi_2) > 0$. These utility functions are not necessarily the same. Moreover, we allow for risk-averse and risk-loving utilities ($u_1'' \gtreqless 0$ and $u_2'' \gtreqless 0$).

This class of environments does *not* satisfy the conditions for no-trade described in Milgrom and Stokey (1982). In particular, the initial allocation is not Pareto optimal if the seller is more risk-averse than the buyer for all relevant levels of wealth. Therefore, we cannot apply existing no-trade theorems. Nevertheless, a no trade property can be proved, summarized in the proposition below.

Proposition. *In equilibrium, there is no trade except when both buyers and sellers are indifferent between trading and not. There is at most one price where trade can occur:* $p^* = v(s_{\min}, b_{\max})$*. Trade can occur at a pair* (s,b) *only if* $v(s,b) = v(s_{\min}, b_{\max})$*.*

Proof. To conserve notation, we consider only pure strategies in this proof, but the logic is identical for mixed strategies. Suppose there exists a price p, a subset $S_p \subseteqq \mathcal{S}$ and a subset $B_p \subseteqq \mathcal{B}$ such that for all $s \in S_p$ agent 1 offers the good at price p and for all $b \in B_p$ agent 2 accepts to trade at that price. Let $\overline{s} = \max_{s \in S_p}$ and $\underline{b} = \min_{b \in B_p}$. Agent 2 accepting p implies that:

$$
\begin{aligned}
\int_{s \in S_p} u_2(v(s,b) - p)\, dF_s(s \,|\, b, s \in S_p) \quad &\geq \quad u_2(0) \qquad\qquad \forall\, b \in B_p \\
&\Rightarrow \\
u_2(v(\overline{s}, \underline{b}) - p) \quad &\geq \quad u_2(0) \\
&\Rightarrow \\
p \quad &\leq \quad v(\overline{s}, \underline{b})
\end{aligned}
$$

Similarly, agent 1 offering p implies that:

$$\begin{aligned}
u_1(p) &\geq \int_{b\in B_p} u_1(v(s,b))dF_b(b\,|\,s, b\in B_p) \qquad\qquad \forall\, s\in S_p \\
&\Rightarrow \\
u_1(p) &\geq u_1(v(\overline{s},\underline{b})) \\
&\Rightarrow \\
p &\geq v(\overline{s},\underline{b})
\end{aligned}$$

Hence $p = v(\overline{s},\underline{b})$. But this implies that $u_1(v(\overline{s},\underline{b})) \geq \int_{b\in B_p} u_1(v(s,b))dF_b(b\,|\,s, b\in B_p)\ \forall\, s\in S_p$ and $\int_{s\in S_p} u_2(v(s,b) - v(\overline{s},\underline{b}))dF_s(s\,|\,b, s\in S_p) \geq u_2(0)\ \forall\, b\in B_p$. Therefore, $p = v(\overline{s},\underline{b}) = v(s,b)\ \forall\, s\in S_p$ and $\forall\, b\in B_p$. Moreover, p was chosen arbitrarily, which implies that in any equilibrium, trade occurs only when both buyer and seller are indifferent. Thus, for all (s,b,p) combinations, it must be that either there is no trade or $p = v(s,b)$. Because of monotonicity of v, this also implies that $p = v(s,\underline{b})$ for all $s < \overline{s}$, and $p = v(\overline{s},b)$ for all $b > \underline{b}$. Otherwise, if $p > v(s,\underline{b})$ for some $s < \overline{s}$, such a seller could offer p and make a profit, or if $p < v(\overline{s},b)$ for some $b > \underline{b}$, such a buyer could accept the trade at p and make a profit. Therefore, $v(s_{\min},\underline{b}) = p$ and $v(\overline{s},b_{\max}) = p$ where $s_{\min}$ and $b_{\max}$ are the lower and upper bounds of the support of seller and buyer types, respectively. However, by monotonicity, we have $p = v(s_{\min},\underline{b}) \leq v(s_{\min},b_{\max})$ and $p = v(\overline{s},b_{\max}) \geq v(s_{\min},b_{\max})$ hence $p = v(s_{\min},b_{\max})$. Note that if, at $(s_{\min},b_{\max})$, either $\partial v(s,b)/\partial s > 0$ or $\partial v(s,b)/\partial b > 0$, then the set of trading pairs in any equilibrium has zero measure. Also note, that for every equilibrium with trade, there is a payoff-equivalent equilibrium with the same seller pricing strategy where no type of buyer ever accepts. A similar proof extends this result to the seller-price double-auction. □

The intuition is straightforward, and is most easily described for the case where v is *strictly* monotone. In this case, trade can only occur in equilibrium between the least optimistic seller type, $s_{\min}$, and the most optimistic buyer type, $b_{\max}$, at a price equal to $v(s_{\min},b_{\max})$. There can of course be many equilibria, as there are many prices the seller can set that no buyer will accept. One example of such an equilibrium is where the seller uses the pricing rule:

$$P(s) = \begin{cases} v(s_{\min},b_{\max}) & \text{if } s = s_{\min} \\ v(s_{\max},b_{\max}) & \text{otherwise} \end{cases}$$

Along the equilibrium path, the buyer can either accept if and only if he is type $b_{\max}$ and the price is less than or equal to $v(s_{\min}, b_{\max})$, or reject at either price. Obviously there may be many sequential equilibria of this complicated signaling game, but all share this basic property. Notice that, at the stage where individuals can trade, each agent has incomplete information, but there is no residual uncertainty about the value of the asset (formally, $v(\cdot)$ is a deterministic function of s and b). Therefore, trading for insurance or risk-sharing motives is not possible, despite the possible differences in the agents' risk-tolerance. Because of their different private information, agents will hold different interim beliefs about the value of the asset. This could, in principle, generate trade. However any deal beneficial for one player must necessarily be harmful for the other. Because trade only occurs under mutual agreement, this is enough to break any deal except for the most extreme types, who are indifferent between trade and no trade.

The simplicity of the argument makes it also very robust: as long as we keep the deterministic and common value nature of the asset, extending the game in other dimensions will not change the no-trade outcome. In particular, allowing counter-offers, divisibility of the asset or more sophisticated trading mechanisms will not induce agents to trade. By contrast, it is also easy to see why the absence of residual uncertainty on the asset's value is important. Indeed, if this was not the case, incentives to trade for insurance or risk-sharing motives may be present after the revelation of information and could outweigh the adverse selection problem.[6]

3 The experiment

3.1 Implementation of the game in the laboratory

We specialize the environment for the laboratory in the following ways. First, the private information signals, s and b, are independent draws from identical, uniform distributions. For the asset value function, we obtain data for three cases: average of signals ($v(s, b) = \frac{s+b}{2}$), minimum of signals ($v(s, b) = \min\{s, b\}$), and maximum of signals ($v(s, b) = \max\{s, b\}$). For the trading mechanism, we obtain data for two cases: a take-it-or-leave-it price and a seller-price double-auction. When there is no trade, the payoff of the buyer is 0 and the payoff of the seller is $v(s, b)$ under either mechanism. In the experiment, we impose that u is linear, so when there is trade, the payoff

[6] To grasp the intuition, imagine the limit situation where s and b provides almost no information about the value of the asset. The adverse selection effect would be minimal so if the seller were more risk-averse than the buyer, they would both gain from trading.

of the buyer is the value of the asset minus the price paid, $v(s,b) - p$, and the payoff of the seller is the price p.

Under both mechanisms the action of the buyer determines only whether there is trade, so seller behavior should be the same in equilibrium in both mechanisms. Furthermore, the buyer bidding behavior in the auction mechanism should be isomorphic to their acceptance strategy in the price mechanism. Hence, the only real difference between the two mechanisms lies in the timing: sequential (price mechanism) vs. simultaneous (auction mechanism).

3.2 Experimental design and procedures

We conducted 12 sessions with a total of 146 subjects. The first 7 sessions were conducted at The Princeton Laboratory for Experimental Social Science (PLESS) in 2006 and 2007. Subjects were registered Princeton University students who were recruited by email solicitation. To expand the sample size, we conducted 5 more sessions at the California Social Science Experimental Laboratory (CASSEL) in 2009 with UCLA students also recruited by email solicitation. The protocols were identical in the Princeton and UCLA sessions. All interaction between subjects was computerized, using the open source software package, Multistage Games.[7] No subject participated in more than one session. In each session, subjects made decisions over 20 rounds. Each subject played exactly one game with one opponent in each round, with random rematching after each round.

At the beginning of each round, each subject was randomly assigned a role as either seller or buyer, and assigned a new signal, s or b. Signals were integer numbers drawn independently with replacement from a uniform distribution over $[0, 100]$. Each subject observed his own signal, but did not observe the opponent's signal. The distribution was common knowledge. The common value was computed as a deterministic function of the two signals, using either the average, minimum, or maximum. The value function was held constant within a session.[8]

In the price variant, the seller offered the asset for a price, p, which was limited to integer numbers in the range of possible values of the asset, $[0, 100]$. The buyer then decided whether to accept or reject the offer, and

[7]Documentation and instructions for downloading the software can be found at http://multistage.ssel.caltech.edu.

[8]The average treatments were framed as the sum of the two signals, rather than the average, to make the instructions simpler. This only results in a rescaling of strategies and payoffs.

payoffs for that round accrued accordingly. In the auction variant, buyer and seller simultaneously quoted bid and ask prices also limited to integer numbers in the range of possible values of the good. Trade occurred at the seller's price if and only if the bid weakly exceeded the ask price. In either case, players learned at the end of each round the signal and decision of their opponent. Finally, subject computer screens included a table with the history of behavior, signals, and outcomes in previous rounds.

At the beginning of each session, instructions were read by the experimenter standing on a stage in the front of the experiment room, which fully explained the rules, information structure, and computer interface.[9] After the instructions were finished, two practice rounds were conducted, for which subjects received no payment. After the practice rounds, there was a interactive computerized comprehension quiz that all subjects had to answer correctly before proceeding to the paid rounds. The subjects then participated in 20 paid rounds, with opponents, roles (seller or buyer), and signals randomly reassigned at the beginning of each round. The common value function and trading mechanism were held constant throughout all rounds of a session, and two sessions were conducted for each (Value, Mechanism) pair. Subjects were paid the sum of their earnings over the 20 paid rounds, in cash, in private, immediately following the session. Table 1 displays the details of the 12 sessions.

Session	# subjects	# Rounds	Location	Asset Value	Mechanism
1	12	20	PLESS	ave	price
2	14	20	PLESS	ave	price
3	12	20	PLESS	min	price
4	12	20	PLESS	max	price
5	12	20	PLESS	ave	auction
6	12	20	PLESS	min	auction
7	12	20	PLESS	max	auction
8	12	20	CASSEL	min	price
9	12	20	CASSEL	max	price
10	12	20	CASSEL	ave	auction
11	12	20	CASSEL	min	auction
12	12	20	CASSEL	max	auction

Table 1. Session details.

[9] A sample copy of the instructions is attached as an appendix.

4 Results

4.1 Aggregate behavior and payoffs

The first cut at the data consists of comparing the prices, frequency of trade and realized gains and losses of buyers and sellers in the different treatments, without conditioning on the actual draws of s and b. Table 2 shows average choices for the ave, min and max value functions under the price and auction mechanisms. In all tables, standard errors (clustered at the individual level when appropriate) are reported in parenthesis. Also, except where noted, we use standard t-test and use asterisks to identify estimates that are significantly different from 0 at the 10% level (*), 5% level (**), and 1% level (***).

Asset Value	ave		ave		min		min		max		max	
Mechanism	price		auction		price		auction		price		auction	
# observations	[260]		[240]		[240]		[240]		[240]		[240]	
Average seller price	61.5	(2.82)	58.3	(3.04)	51.6	(2.17)	56.4	(2.33)	82.3	(2.11)	76.4	(2.18)
Average buyer bid	—		45.3	(2.11)	—		28.5	(2.84)	—		51.4	(3.15)
Frequency of trade (%)	31.9		35.0		22.5		18.8		23.8		22.1	
Seller gain given trade	-4.6***	(1.43)	-2.3	(2.35)	1.1	(3.00)	5.6*	(2.98)	-5.2*	(2.74)	-9.4**	(3.40)
Seller gain	-1.5***	(0.52)	-0.8	(0.85)	0.2	(0.67)	1.0*	(0.54)	-1.2*	(0.69)	-2.1**	(0.80)
Gain if all traded	13.9	(2.82)	8.1	(2.51)	18.8	(2.18)	21.2	(1.99)	15.6	(2.70)	10.2	(2.48)

Table 2. Average choices and trade probabilities

Result 1 *There is substantial trade in all treatments.*

In approximately half of our observations, the buyer's signal is below the seller's signal. These are situations with essentially no chance for trade even with completely naïve behavior, implying a natural upper bound of 50% on the amount of trade. Yet we observe trade between 18.8% to 35.0% of the time, depending on the treatment. Since trade occurs around 10% of the time when $b < s$, it implies trade probabilities of 32% to 58% when $b > s$ (see Table 4 below for details).

Result 2 *Traders in the role of sellers lose money on average in the ave and max treatments and gain money on average in the min treatments.*

Sellers' offer prices would, on average, earn them non-negligible profits *if* buyer acceptance decisions were uncorrelated with buyer signals. However, since buyers condition their decision on their information, and are more likely to accept when their signal is higher, sellers end up incurring net losses in 4 out of the 6 treatments. As an immediate consequence, and abstracting from endowment considerations, it is preferable in this game to be a buyer under the ave and max value functions and a seller under the min value function.[10] The results for min and max are not surprising. In the min treatment, a rational and cautious seller has at his disposal a simple strategy to induce a boundedly rational buyer to trade and at the same time guarantee no losses, by asking s. In the max treatment, the same is true for the buyer, who can offer b.[11] We call these, the "easy" cases to solve. In fact, given the behavior of buyers and sellers these strategies would actually generate positive profits and, as we will see below, it is employed by some subjects.

To evaluate whether subjects do as well as they can given the behavior of their rival, we look at gains and losses as a function of the realized private information. Figure 1 displays for the price (left column) and auction (right column) treatments, the potential –positive or negative– net gain of sellers (price minus value of the asset) as a function of the seller's signal, where each dot is one observation. It also shows whether the terms of the trade were accepted and thus the net gains realized (dark circle) or not (light triangle). (The analogous information from the buyer's viewpoint is omitted for brevity).

[FIGURE 1 HERE]

The figures clearly illustrate the adverse selection effect. Although the expected gains would be positive if the behavior of buyers were uncorrelated with their information, they are generally negative in the ave and max treatments and around zero in the min treatments once we condition on the buyers' actual decisions, that is, when we look only at the dark circle dots. More interestingly, the biggest losses occur when the signal of sellers are high in the min treatment and low in the max treatment. Indeed, these are the cases where the dispersion of prices is highest and therefore the selective acceptance of buyers has the largest impact on payoffs.

Result 3 *Aggregate behavior differs across asset value treatments: asking prices and bids increase from min to ave and from ave to max.*

[10] Since the seller is, by assumption, endowed with the good, his final payoff is greater than that of the buyer if there is no trade ($v(s, b)$ vs. 0). We define profit in net terms.

[11] By contrast, the only way to ensure no losses for a seller in the max treatment and for a buyer in the min treatment is to ask 100 and offer 0, respectively.

The seller's price and the buyer's bid all increase from min to ave and from ave to max, as expected. It is easy to see that the expected value of the asset conditional on an agent's signal also increases from min to ave and from ave to max. This suggests that players exhibit some level of rationality with respect to the asset value function. Note also that the variance is important, mainly because choices are greatly affected by signals. The average differences between bid and ask prices are significantly higher in the min and max treatments (27.9 and 25.0) than in the ave treatment (13.0). It reflects the greater difficulty for sellers to determine which price to set in the max treatment (where the only equilibrium is 100) and for buyers to determine which bid to make in the min treatment (where the only equilibrium is 0). We call these, the "difficult" cases to solve.

Result 4 *Aggregate behavior is similar across mechanisms.*

The frequency of trade in the auction mechanism is between 3.1% higher (ave treatment) to 3.7% lower (min treatment) than in the price mechanism. The differences in prices set by sellers are small and lower prices do not necessarily translate into greater losses. Moving from the price to the auction mechanism slightly increases the gains of subjects playing the "simple" cases (sellers in the min treatment and buyers in the max treatment) at the expense of subjects playing the "difficult" cases (sellers in the max treatment and buyers in the min treatment).

4.2 Aggregate behavior and payoffs conditional on signals

4.2.1 Strategies of sellers

The picture presented so far is useful, but incomplete since it aggregates across traders' private information. If traders condition their decisions on their private information, then such an analysis has left out an important component of behavior. Formally, a behavioral strategy for a seller, in both mechanisms, is a mapping from their private signal to a probability distribution over prices. We can summarize all the aggregate joint distribution of seller signals and prices graphically and compare them across treatments. Figure 2 displays for each of the 6 treatments (ave-min-max and price-auction variants) the sellers' asking price as a function of their signal. Each dot in the graph is one observation. Figure 2 also identifies cases where the prices resulted in a trade.

[FIGURE 2 HERE]

As a natural benchmark for studying seller behavior, we use the Nash equilibrium price correspondence. That equilibrium differs across value treatments, but is the same for both mechanisms. The equilibrium price correspondences are:

$$\begin{cases} p_e(s) \in \left[\frac{s}{2} + 50, 100\right] & \text{(ave)} \\ p_e(s) \in [s, 100] & \text{(min)} \\ p_e(s) = 100 & \text{(max)} \end{cases}$$

Note that equilibrium is characterized by a range of equilibrium prices for the ave and min cases, and is a fixed constant $p_e = 100$ in the max treatment.

Result 5 *Seller pricing strategies are consistently below the Nash equilibrium.*

Seller pricing behavior coincides with Nash equilibrium play rather infrequently, particularly in view of the wide range of Nash equilibrium prices in the ave and min treatments. In those two cases, prices are in the Nash equilibrium range 17% and 66% of the time, respectively. In the max case, only 12% of the observed prices are at the Nash equilibrium ($p = 100$). All other prices are too low. Pooling across the three value treatments, sellers set prices below Nash equilibrium about 70% of the time. The lower envelope of Nash strategies for the sellers are $p = \frac{s}{2} + 50$, $p = s$, and $p = 100$ in the ave, min, and max treatments, respectively. In equilibrium, these prices should yield no net profit to the seller because they are too high to induce buyers to trade. At the same time, they are high enough to *guarantee* a net profit if a buyer (out of equilibrium) accepts. However, even zero or very low profits would be an improvement over the losses sellers are incurring in the ave and max treatments from the lower prices they set in the experiment.

As a final bit of evidence about aggregate seller strategies, we estimated a regression of seller prices as a function of seller signal as a rough test to look for differences in behavior across mechanisms. Theoretically there should be no difference. Coefficients on the seller's signal are highly positive and highly significant (p $<$ .001), even in the max treatments where it should be zero. (Table omitted for brevity). A one unit increase in s translates into a .24 to .45 increase in price, depending on the treatment. Also, the response is greater with the auction than with the price mechanism (lower intercept and higher slope) except for the ave treatment where the coefficients are not significantly different from each other. As a consequence prices are higher in the auction treatment, especially so for high seller signals.

Result 6 *Seller prices are increasing in their signal; they are also more responsive to signals in the auction than in the price treatment.*

The existence of these systematic differences show that sellers make pricing decisions differently under the auction and price mechanisms, in spite of the fact that equilibrium strategies are identical for the sellers in the two mechanisms. This suggests that sellers have different expectations about how buyers are behaving under the price and auction mechanisms. As we report in the next subsection, this is indeed the case.

4.2.2 Strategies of buyers

We now turn to study the behavior of buyers. A behavioral strategy for a buyer in the auction treatment is analogous to that of the seller. That is, it is a mapping from buyer signal to a probability distribution over bids. In the price treatment however, the strategy is quite different from that of the seller. It is a mapping from the pair (buyer's signal, seller's price) to a probability of accepting the terms of trade. We can graphically display the empirical strategies of buyers and compare them across treatments.

The left column in Figure 3 displays the accept/reject (trade/no trade) decision of buyers as a function of their signal and the seller's asking price, in all three price treatments. The right column displays the buyers' bid as a function of their signal, in all three auction treatments. It also displays whether the bid resulted in trade (dark circle) or not (light triangle). These are obviously two different (and not readily comparable) pieces of information.

[FIGURE 3 HERE]

As with the analysis of seller behavior, we use the Nash equilibrium as the benchmark for studying buyer behavior. Unlike the seller equilibrium strategies, buyer equilibrium strategies differ across the two mechanisms as well as across value treatments. In fact, for the buyers their information sets and action sets are different in the two mechanisms. For the price mechanism, we summarize the equilibrium strategies in terms of *Acceptance Regions*, $A_e(b, p)$, for each value treatment that are consistent with Nash equilibrium. The acceptance region specifies the set of buyer signal - price pairs at which a buyer accepts the price and trade occurs. For the auction treatment, we specify strategies in a similar way to sellers: for each value treatment we specify the range of bids, $B_e(b)$ consistent with Nash equilibrium. The equilibrium price correspondences are:

$$\text{Price} \quad : \quad \begin{array}{ll} A_e(b,p) = \left\{(b,p) \,|\, p \leq \frac{b}{2}\right\} & \text{(ave)} \\ A_e(b,p) = \{(b,p) \,|\, p = 0\} & \text{(min)} \\ A_e(b,p) = \{(b,p) \,|\, p \leq b\} & \text{(max)} \end{array}$$

$$\text{Auction} \quad : \quad \begin{array}{ll} B_e(b) \in \left[0, \frac{b}{2}\right] & \text{(ave)} \\ B_e(b) = 0 & \text{(min)} \\ B_e(b) = [0, b] & \text{(max)} \end{array}$$

Note that equilibrium is characterized by a range of equilibrium bids (or acceptance regions) for the ave and max cases, and is a fixed constant $B_e(b) = 0$ in the min treatment. This contrasts with the seller's equilibrium strategies which were a fixed constant in the max treatment and a range in the min treatment, reflecting the much different strategic problems facing buyers and sellers for the min and max treatments.

To summarize the aggregate behavior of buyers in the price mechanism, we ran a probit regression of buyer acceptance decisions as a function of the seller's price and the buyer's signal. For the auction treatments, we ran an Tobit regression of the buyer's bid as a function of his signal. All six buyer signal coefficients are positive and highly significant (p $<$ .001). This clearly contradicts the equilibrium for the min treatment, where a buyer's equilibrium strategy is independent of the b. All three seller coefficients in the price mechanism are negative and highly significant (p $<$ .001). This clearly contradicts the equilibrium for the max treatment, where a seller's equilibrium strategy is independent of s. (Table omitted for brevity).

Result 7 *In the price mechanism, buyer acceptance decisions are strictly increasing in b and strictly decreasing in p in all value treatments. In the auction mechanism, buyer bids are strictly increasing in b.*

To understand the choices of buyers at a deeper level we perform the following analysis. Consider a model of buyer behavior where there exists a linear *Acceptance Threshold Function (ATF)* $\psi(b)$ such that a buyer with signal b agrees to trade if and only if the asking price is $p < \psi(b)$. For any hypothetical ATF, we use our data to construct a "misclassification score" or **MS** for that function, for each value function and each mechanism. This is done by adding up the number of misclassified observations (trade when $p > \psi(b)$ or no trade when $p < \psi(b)$) weighted by the magnitude of the misclassification (that is, the absolute difference between the actual price and the cutoff price such that the observation would not be misclassified) divided by the total number of observations. Table 3 reports the estimated ATF, $\widehat{\psi}(b)$, that minimizes the misclassification score. We also report the minimized **MS**. This value reflects the average amount by which observations are misclassified, with each correctly classified observation taking value 0. Last, we determine the percentage of observations that are misclassified by $\widehat{\psi}(b)$, which we call **MO**. Graphically, $\widehat{\psi}(b)$ corresponds to the best empirical dividing line between trade and no trade regions.

For the price treatments, this analysis involves using all the available information (buyers observe their signal and the ask price and decide whether to trade or not). In order to construct a comparable measure for the auction treatments, the only information used is whether trade occurred at the asking price or not, rather than incorporating the additional information in the buyer's bid.

Asset Value	Treatment	$\widehat{\psi}(b)$	**MS**	**MO**
ave	price	$22.8 + 0.55\,b$	1.33	16.5%
ave	auction	$37.2 + 0.20\,b$	1.25	16.7%
min	price	$17.4 + 0.33\,b$	2.28	19.2%
min	auction	$21.2 + 0.28\,b$	1.55	16.7%
max	price	$37.3 + 0.56\,b$	1.59	14.2%
max	auction	$39.5 + 0.31\,b$	2.69	20.4%

Table 3. Linear ATF estimation results.

Result 8 $\widehat{\psi}(b)$ *is steeper in the price treatments than in the auction treatments.*

For all three value treatments, the estimated classification line has a higher slope and lower constant term in the price treatment than in the auction treatment. In other words, buyers with high (low) signals act in a more (less) conservative way in the auction than in the price treatments. The result, combined with our previous findings about sellers' behavior, suggests a difference in behavior between mechanisms by *both* buyers and sellers: in the auction mechanism trade is lower when buyers and sellers have high signals and higher when buyers and sellers have low signals than in the price mechanism. Finally, the linear misclassification function $\widehat{\psi}(b)$ performs quite well across all treatments and mechanisms, with a range of 80% to 86% of observations correctly classified.

4.2.3 Trading probabilities

Our next look at the data consists in describing the relation between the buyer-seller signal *combinations* and the likelihood of trade. Figure 4 plots for each treatment and each (s, b) pair whether the outcome of the game is trade (dark circle) or no-trade (light triangle).

[FIGURE 4 HERE]

Due to the deterministic and pure common value nature of the asset, the region where trade should occur consists only of the (0,1) pair. As we already know, this is not what is observed. Generally trade occurs when the seller's signal is sufficiently low and the buyer's signal is sufficiently high. The empirical likelihood of trade depending on whether the buyer's signal exceeds the seller's signal or not is reported in Table 4.

Asset Value	Treatment	% trade given $b < s$	% trade given $b \geqslant s$
ave	price	10.6	57.6
min	price	12.2	32.0
max	price	7.5	40.0
ave	auction	11.7	57.4
min	auction	6.4	36.0
max	auction	9.6	35.7

Table 4. Frequency of trade.

Result 9 *Trade rarely occurs when the seller's signal exceeds the buyer's signal. The probability of trade is increasing in the buyer's signal and decreasing in the seller's signal.*

Individuals engage in trade between 30% and 60% of the time whenever the buyer's signal exceeds the seller's signal (and between 6% and 12% of the time otherwise). This is particularly striking given that the no-trade theoretical prediction does not dependent on the risk tolerance of individuals. In other words, since all that matters for our theory is that utility is increasing in the trader's monetary payoff, risk-aversion, disappointment aversion or kinks in the utility function could not account, even partially, for the observed outcomes.

We then ran a simple probit regression of the likelihood of trade as a function of the seller's and buyer's signal. The results are reported in Table 5.

Asset Value	Mechanism	Constant		Seller signal		Buyer signal		pseudo R^2
ave	price	-1.31***	(.23)	-.013***	(.003)	.029***	(.003)	.26
min	price	-1.39***	(.29)	-.005	(.004)	.016***	(.004)	.10
max	price	-1.73***	(.35)	-.013***	(.004)	.028***	(.004)	.26
ave	auction	0.01	(.28)	-.028***	(.004)	.016***	(.004)	.30
min	auction	-1.03***	(.37)	-.013***	(.004)	.015***	(.004)	.15
max	auction	-1.10***	(.24)	-.009***	(.003)	.015***	(.003)	.10

Table 5. Probability of trade as a function of signals.

All slope coefficients have the expected sign, and eleven out of twelve are significant at the 1% level. Trade depends more on the buyer signal than the seller signal in all but the ave-auction treatment. However, the R^2 are low, which suggests that a probit regression is probably not the most appropriate method for the purpose of our analysis.

To look at the relationship between buyer and seller signals more closely, we conduct a classification analysis similar to section 4.2.2. Consider a linear function $\phi(s)$ with the property that trade occurs if the pair of signals (s, b) is such that $b > \phi(s)$. As in the estimation of ATFs, for any $\phi(s)$ we empirically determine the number of misclassified observations (trade when $b < \phi(s)$ or no trade when $b > \phi(s)$) weighted by the magnitude of the misclassification (that is, the absolute difference between the actual signal of the buyer and the cutoff signal such that the observation would not be misclassified). This value divided by the total number of observations is called the misclassification score or **MS**. For each treatment, we report the estimated function, $\widehat{\phi}(s)$, that minimizes the misclassification score. We also report the percentage of misclassified observations or **MO**. Graphically, $\widehat{\phi}$ corresponds to the best dividing line between the trade and no trade regions in the (b, s) signal space. The results of the estimated functions are presented in Table 6 and included in the graphs of Figure 4.

Asset Value	# obs.	Treatment	$\widehat{\phi}(s)$	**MS**	**MO**
ave	[260]	price	$42.3 + 0.40\,s$	3.82	23.5%
ave	[240]	auction	$23.4 + 0.84\,s$	5.09	25.8%
min	[240]	price	$69.9 + 0.15\,s$	5.34	30.0%
min	[240]	auction	$71.8 + 0.19\,s$	4.57	22.5%
max	[240]	price	$61.8 + 0.29\,s$	2.82	20.0%
max	[240]	auction	$68.9 + 0.14\,s$	4.89	20.8%

Table 6. Estimated trade vs. no-trade divisions.

Result 10 $\widehat{\phi}(s)$ *is an increasing function.*

The slope of the classification function is positive in all six treatments. Sellers with higher signals set higher prices for the asset, thus decreasing the likelihood of a trade. Conversely, buyers with higher signals set higher bids and are also more likely to accept a given trade. Overall, the model correctly classifies about 75% of the trade outcomes, although the slope and accuracy of classification differ substantially across value treatments and mechanisms. The misclassification score is two to four times higher than the ATF estimation of Table 3, suggesting that this optimal division model is less appropriate for the analysis of trade as a function of signals. The differences between the estimated functions in the price and auction treatments reinforce the argument we made previously about the impact that the trading mechanism has on strategies.

4.3 Learning

A natural question to ask is whether individuals adapt their strategies over the course of a session. We designed the experiment so that subjects could gain experience in both roles. This seems especially important when the strategic considerations of the two roles are much different. Understanding the incentives of a seller may lead a buyer to adjust behavior, and vice versa, thereby speeding up learning. Clearly, the behavior is out of equilibrium, and for this reason we wanted subjects to have considerable feedback, in both roles, with a total of twenty repetitions of the game. A player who is initially naive has an opportunity to recognize that his or her losses (as a seller in ave and max and as a buyer in min) are due to the adverse selection problem and adapt their behavior accordingly. A simple first cut to investigate learning consists in breaking the data down into early and late plays. In each session, there were 20 rounds of play. We code the choices in the first 10 rounds as "inexperienced" and the choices in the last 10 rounds as "experienced". Table 7 presents the average choices in all six treatments broken down by experience level.

Treatment	Round	Seller price	Buyer bid	% trade	Seller gain given trade
ave – price	inexp.	62.2 (3.12)	—	33.1	-3.8 (2.28)
	exp.	60.8 (2.92)	—	30.8	-5.4** (2.35)
ave – auction	inexp.	55.2 (2.87)	44.8 (2.55)	39.2	-1.7 (3.27)
	exp.	61.4 (3.67)	45.8 (2.38)	30.8	-3.0 (3.48)
min – price	inexp.	52.2 (3.14)	—	24.2	-1.3 (3.41)
	exp.	51.0 (2.25)	—	20.8	3.8 (4.25)
min – auction	inexp.	57.7 (2.44)	31.5 (3.35)	19.2	4.5 (4.16)
	exp.	55.1 (2.98)	25.5 (3.03)	18.3	6.6 (4.01)
max – price	inexp.	80.4 (2.28)	—	29.2	0.5 (3.19)
	exp.	84.1 (2.42)	—	18.3	-14.2*** (3.63)
max – auction	inexp.	75.9 (2.41)	50.6 (2.51)	20.8	-11.2** (4.71)
	exp.	77.0 (3.06)	52.2 (5.06)	23.3	-7.8 (6.08)

Table 7. Average choices of sellers and buyers by level of experience.

Result 11 *There is no clear evidence of learning by either buyers or sellers.*

There is little evidence of systematic changes in the average behavior of sellers and buyers between early and late rounds. Sellers increase prices in two treatments, and keep them roughly constant in the other four. Trade is constant in the treatments where sellers' price do not change and decreases otherwise. This suggests small changes in buyers' behavior as well. The result is consistent with the findings of Carrillo and Palfrey (2009) in a related two-sided game of incomplete information, and contrasts with the trade game by Angrisani et al. (2009) and the common value auctions literature where subjects learn over time to trade and bid close to equilibrium predictions.

The absence or near absence of learning trends occurs in spite of substantial feedback after each round of play, as well as experience in both roles. For example, the buyer knows the price asked by the seller and, at the end of each round, learns the seller's signal. Therefore, in principle, buyers can partially reconstruct an average price function of sellers. The same applies to sellers, who learn the buyer's bid and signal (in the auction treatments) or the acceptance decision and signal (in the price treatments). It appears, however, that this information does not lead to changes in individual behavior substantial enough to produce trends at the aggregate level.

To explore this issue in more detail, we next ask whether the behavior of buyers and sellers as a function of their own signal is different at the beginning than at the end of the experiment. Again, we divide the sample into early play (first 10 rounds) and late play (last 10 rounds). We then perform a maximum likelihood estimation in each subsample and in the full sample. For all traders in the auction treatment and sellers in the price treatment, we run a linear regression of price (seller) or bid (buyer) on own signal and constant term, for the two experience levels separately, and compare it to the results from the pooled regression. For the case of buyers in the price treatment, we instead perform a probit estimation, and control for the seller's offer price and the buyer's signal. We then conduct a likelihood ratio test to determine whether differences in choices between early and late rounds are statistically significant. The findings are summarized in Table 8.

Player	Treatment		Likelihood estimation			χ^2-test
	Asset value	mechanism	constrained	unconstrained	d.f.	
seller	ave	price	-1280.4	-1281.2	2	1.57
seller	min	price	-1013.1	-1016.4	2	6.63**
seller	max	price	-972.0	-975.9	2	7.81**
seller	ave	auction	-1169.2	-1173.1	2	7.61**
seller	min	auction	-999.8	-1002.7	2	5.90
seller	max	auction	-1015.0	-1015.2	2	0.48
buyer	ave	price	-86.2	-87.5	3	2.61
buyer	min	price	-93.0	-95.4	3	4.71
buyer	max	price	-79.2	-84.5	3	10.63**
buyer	ave	auction	-1154.9	-1165.1	2	20.35***
buyer	min	auction	-1043.8	-1046.4	2	5.26
buyer	max	auction	-1095.0	-1097.6	2	5.20

Table 8. Effect of experience on prices, bids and acceptance rates.

In five out of twelve treatments differences are statistically significant (four at the 5% level and one at the 1% level). Four of them correspond to cases where both buyers and sellers in a given treatment changed their behavior, so only subjects in one of the roles eventually benefit from their modified strategy. Overall, it reinforces the idea that traders do not change behavior significantly over time.

5 Individual behavior

One possible explanation for our finding of non-equilibrium behavior and substantial trade, and possibly also an explanation for the variation of trade frequency across our treatments is that there is a relatively small fraction of subjects in the pool who violate equilibrium behavior, by systematically overbidding (or over-accepting) as buyers and underpricing as sellers. This could present a much different picture of our results than the one seen from a purely aggregate analysis of behavior, where the data is presumed to be generated by a "representative subject". The possibility of these different behavioral types requires a closer look at the individual level data. There are not enough observations at the individual level to obtain good estimates of pricing functions and bidding/acceptance functions (20 rounds of data for each subject on both roles), but there is enough data to identify certain kinds of behavior.

Because the most significant observation from the aggregate analysis is the strong violations of Nash equilibrium behavior that result in substantial trade in all mechanisms and value treatments, the natural starting point for an individual analysis of behavior is to explore variations across subject with respect to the use of equilibrium strategies. We use the following simple classification approach. For each subject and for both subject roles, we simply look at the fraction of their decisions that are consistent with Nash equilibrium. Recall that inconsistencies take the form of overbidding (or over-accepting) by buyers and underpricing by sellers. Thus, for each subject and for each role and signal draw we observe for that subject, we classify whether their decision was consistent or inconsistent with equilibrium behavior.[12]

This results in two "scores" for each subject: the frequency they play Nash (do not overbid) as a buyer and the frequency they play Nash (do not underprice) as a seller. These scores, rounded to the nearest .05, are summarized in Figure 5 which displays the frequency distribution of these individual scores for each of our six treatments.[13]

[12] Recall that for some treatments and roles there are several possible decisions that are consistent with equilibrium. For example, in the min treatment, equilibrium behavior of sellers only requires that the seller post a price at least as high as her signal. Thus, for this treatment, any observation of a price at least as great as the seller's signal is counted as consistent with equilibrium.

[13] Because roles were randomly assigned in each round, most subjects did not have exactly 10 rounds as a seller and 10 rounds as a buyer. Also, each treatment has 24 subjects except ave-price which has 26 subjects.

[FIGURE 5 HERE]

We then classify a subject, separately for each role, as a Nash player if at least 80% of the decisions they made in that role were consistent with Nash equilibrium. A subject is classified as non-Nash if at least 80% of the decisions they made in that role were inconsistent with Nash equilibrium.[14] Table 9 reports the results of that analysis.

Asset Value	Mechanism	N	Seller Role		Buyer Role	
			Nash	non-Nash	Nash	non-Nash
ave	price	26	4	21	7	1
ave	auction	24	1	18	0	19
min	price	24	11	2	13	0
min	auction	24	8	1	0	24
max	price	24	0	22	23	0
max	auction	24	1	19	8	5

Table 9. Number of Nash players by role and treatment.

There are several observations about this classification analysis. First, non-Nash behavior is highly dependent on the trader role. In the price mechanism it was much more prevalent among traders in the seller position than in the buyer position. For buyers in the price treatment, only 1 subject out of 74 systematically exhibits non-Nash behavior. This contrasts sharply with the 45 of the 74 subjects who are non-Nash in the seller's role. (Recall that they are the same 74 subjects, just different roles.) Second, the prevalence of non-equilibrium behavior is highly dependent on the asset valuation. Nearly all sellers are non-Nash in the ave and max treatments and almost none in the min treatment. For buyers in the auction treatment, nearly all are non-Nash in the ave and min treatment, and very few in the max treatment. Third, for sellers, non-Nash behavior did not depend on the mechanism, which makes sense since the seller strategy space is the same in both. For the buyers, non-Nash behavior increases dramatically in the auction mechanism, especially for the ave and min valuation treatments (19/24 and 24/24 subjects classified as non-Nash in the buyer role, respectively). This is partly due to the different strategy space that buyers face

[14] The choice of 80% is somewhat arbitrary, but a similar picture emerges with other thresholds, as one can see from the figures. Indeed, for buyers in the min auction treatment, there was not a single Nash-consistent bid ($B = 0$) for any of the 24 subjects.

in the two mechanisms.[15] Fourth, non-equilibrium behavior and the high frequency of trade does not appear to be caused by irrational behavior of a few confused subjects. In all cases where we observe significant non-Nash behavior, more than 75% traders share that behavior.[16] Thus, while there is some evidence of subject heterogeneity we do not see it as being a major factor in explaining the results.

Fifth, there are a significant number of traders who play Nash equilibrium nearly all the time, and this differs substantially depending on the asset valuation and the mechanism. With the max asset valuation, 31 of 48 subjects are Nash players nearly all the time in the buyer's role, while only 1 of (the identical) 48 subjects is a Nash player in the seller's role. In the other two asset valuation treatments, 40% of subjects are Nash players in the buyer's role in the price mechanism, but 0% are Nash players in the auction mechanism. For sellers, there is much more Nash play in the min treatment (40% are Nash players) than either of the other asset valuation treatments. This suggests that there is a difference across roles and across treatments in terms of the strategic complexity or difficulty of the bargaining games. For example, for the buyers, the max price game seems particularly easy, because the buyer can guarantee himself a profit by taking any price below his signal. Similarly, the seller can guarantee no loss in the min game simply by setting price at any level greater than or equal to her signal. Thus, for these games, equilibrium strategies coincide with secure strategies, and have the side benefit of generating profits if the trading partner is not a Nash player. In contrast, the ave games seem particularly difficult for traders in both roles.

6 A behavioral theory

In this section, we consider a behavioral theory that may account for the choices of our traders. We assume that players have an (incorrect) mutually held belief that the action of an opponent is less correlated with their information than is actually the case. This type of cognitive limitation was first discussed in Holt and Sherman (1994). Two recent theories have generalized the argument: "cursed equilibrium" (Eyster and Rabin, 2005) and "analogy based expectations" (Jehiel and Koessler, 2008). We focus on this behav-

[15] For example, for the min asset valuation buyers should reject any positive price in the price mechanism and set a bid equal to 0 for all b in the auction mechanism.

[16] This includes sellers in the ave and max treatments for both mechanisms, and buyers in the ave-auction and min-auction treatments.

ioral theory for two reasons. First, it is built around the central element of our game, namely belief formation under private information. Second, cursed equilibrium has received support over two other theories, quantal response equilibrium and cognitive hierarchy, in the related "compromise game" (Carrillo and Palfrey, 2009).

For analytical tractability we solve the game only for the price mechanisms and with "fully cursed" players. In this extreme case, subjects have a mutual belief that action and information are completely uncorrelated. Applying this to our model, a fully cursed buyer in the price treatments will trade if and only if the price set by the seller is less than the buyer's expected value of the asset given his own signal, $\mathrm{E}[v(s,b)\,|\,b]$. Simple computations yield:

$$\mathrm{E}[v(s,b)\,|\,b] = \begin{cases} 25 + b/2 & \text{(ave)} \\ b - b^2/200 & \text{(min)} \\ 50 + b^2/200 & \text{(max)} \end{cases} \tag{1}$$

The decision problem for sellers is slightly more complex. A fully cursed seller in the price treatments anticipates correctly how the buyer's probability of acceptance will depend on the offer price, p. However, once a price is accepted, the seller fails to recognize that the value of the asset should reflect that only buyers with certain signals b have accepted the trade. Formally and given a price p, a cursed seller believes that his expected payoff from setting price p, given signal s, is:

$$\Pi(p\,|\,s) = \Pr(\mathrm{E}[v(s,b)\,|\,b] > p) \times p + \Pr(\mathrm{E}[v(s,b)\,|\,b] < p) \times \mathrm{E}[v(s,b)\,|\,s]$$

So for example and given (1), the profit of a cursed seller for the ave asset value treatment can be written as:

$$\begin{aligned} \Pi(p\,|\,s) &= \Pr(25 + b/2 > p) \times p + \Pr(25 + b/2 < p) \times (25 + s/2) \\ &= \frac{150 - 2p}{100} \times p + \frac{2p - 50}{100} \times \frac{50 + s}{2} \quad \forall\, p \in [25, 75] \end{aligned}$$

and analogously for the min and max treatments.

Denote by $p^*(s) = \arg\max_p \Pi(p\,|\,s)$, the optimal price of a fully cursed seller. After some algebra, we get:

$$p^*(s) = \begin{cases} 50 + \frac{s}{4} & \text{(ave)} \\ \frac{100}{3} + \frac{1}{3}s - \frac{1}{600}s^2 & \text{(min)} \\ \frac{1100}{18} + \frac{1}{600}s^2 + \sqrt{\frac{10000+3s^2}{81}} & \text{(max)} \end{cases}$$

Having determined the theoretical choices of cursed individuals in the price treatments, we can now compare them with the data.

For the analysis of buyers, we follow the classification method employed in Table 3 of section 4.2.2. Note that the equations in (1) correspond to nonlinear theoretical ATFs for the cursed equilibrium model. We therefore consider the best quadratic (rather than linear) ATF, to make it comparable to the cursed prediction. The performance of the cursed and empirical quadratic ATFs of buyers are described in Table 10 and graphically represented in the left column of Figure 3, with the misclassification score (**MS**) and the percentage of misclassified observations (**MO**) computed exactly as in Table 3.

Value	Strategy	$\widehat{\psi}(b)$	**MS**	**MO**
ave	cursed	$25 + 0.5\,b$	1.33	16.9%
	empirical	$33.8 + .02\,b + .005\,b^2$	1.29	16.2%
min	cursed	$b - .005\,b^2$	2.12	17.9%
	empirical	$-10.2 + 1.70\,b - .012\,b^2$	1.90	18.3%
max	cursed	$50 + .005\,b^2$	1.46	9.6%
	empirical	$63.1 - .33\,b + .007\,b^2$	1.43	12.1%

Table 10. Classification of buyers' acceptance decision.

Result 12 *The cursed equilibrium model classifies buyer acceptance decisions as well as the best fitting quadratic ATF and better than the best linear ATF.*

Based on misclassification analysis, the dividing line for the cursed model is remarkably accurate in all price treatments. In the ave and max treatments, the cursed and empirical strategies are virtually identical in terms of the misclassification score (for the max treatment fewer observations are misclassified with the cursed function). In the min treatment, the difference in performance is slightly bigger, but this may be due to a limited number of observations. In fact, according to the empirical strategy, the likelihood of acceptance is decreasing in the buyer's signal for all $b > 70.8$. This is the result of a few buyers with high signals of 75 and above who play the Nash equilibrium, and therefore refuse to trade even when the asking price is low (see Figure 3). When comparing with Table 3, it is also remarkable that the cursed quadratic functions perform better than the best linear fits in both the min and max treatments. Also, although the number of misclassified observations is non-negligible (up to 18%), in more than 50% of the cases, the price is within 10 units of the correctly classified value. Finally, **MS** is greatest in the most difficult case for buyers, namely the min treatment where the equilibrium strategy (but not the best response to the empirical behavior of sellers) is never to trade.

The cursed equilibrium strategy of sellers can also be compared to its empirical counterpart. In Table 11, we report a quadratic OLS regression of the seller's price as a function of the signal. Both the theoretical cursed function, $p^*(s)$, and the empirical quadratic estimates reported below are graphically represented in the left column of Figure 2.

Value	Mechanism	Constant	s	s^2	adjusted R^2
ave	price	41.5*** (3.94)	.44** (.214)	-.001 (.002)	.276
min	price	31.3*** (4.79)	.49** (.187)	-.001 (.002)	.281
max	price	76.0*** (4.38)	-.10 (.135)	.003** (.001)	.215

Table 11. Seller's quadratic OLS.

Result 13 *The cursed equilibrium model implies seller pricing functions similar to what is observed in the data.*

The theoretical cursed pricing functions predict that the constant terms should be ordered max > ave > min and the linear coefficients should be ordered min > ave > max. The quadratic coefficient is predicted to be 0 in the ave treatment, small and negative in the min treatment and small and positive in the max treatment. This is the pattern we find in Table 11, with the exception that the quadratic coefficient for the min treatment is not significantly different from 0. In general, the overall shape of the empirical function is quite similar to the cursed prediction for the ave and max treatments and somewhat steeper for the min treatment (Figure 2, left column).

Finally, we can compare the empirical likelihood of trade and seller profits with the predictions of the fully cursed model given our data. The results are presented in Table 12.

	ave		min		max	
	cursed	empirical	cursed	empirical	cursed	empirical
% trade	31.2	31.9	27.9	22.5	20.0	23.8
% trade given $b < s$	0.0	10.6	0.0	12.2	0.0	7.5
% trade given $b \geqslant s$	47.4	57.6	55.5	32.0	41.0	40.0
Average profit (seller)	-0.3	-1.5	2.9	0.2	0.2	-1.2

Table 12. Cursed equilibrium: trade and seller profits in price mechanism.

Result 14 *The cursed equilibrium model implies trade frequencies similar to what is observed in the data. It implies an ordering of seller profits that we find in the data. However, we observe seller losses in the max treatments that are not predicted by the cursed model.*

The theoretical predictions of trade range between 20% and 31% of the time in the price mechanism, depending on the value treatment. This compares with the observed range between 23% and 32%. The biggest departure is a 5% overestimation of trade by the curse model in the min treatment. Furthermore, the model predicts trade only if $b > s$. In the experiment, there was very little trade (10%) when $b < s$.

In the cursed equilibrium model, expected seller profits range between 2.9 in min and -0.3 in ave, whereas the corresponding numbers in our data range between 0.2 in min and -1.5 in ave. The ordering is therefore correct, but the magnitudes are not. The sellers in our price mechanism lose slightly more money on average than the expected losses in a cursed equilibrium. However, the difference is not statistically significant.

7 Conclusion

This study investigated behavior in a common value bilateral bargaining game with two sided private information. We first prove that the theoretical result of no trade can be extended to our setting. The results of an experiment identify systematic ways in which the extent of behavioral violation of no trade in these environments is highly dependent on the trading mechanism and asset valuation structure, and has different economic consequences for buyers and sellers of the asset. Despite the compelling and general logic of no-trade equilibrium, traders trade frequently. When the buyer's signal exceeds the seller's signal, the likelihood of trade is between 32% and 58% depending on the treatment. Buyers generally outperform sellers and the difference persists even when traders have gained experience both in the role of buyers *and* sellers. In fact, for all six treatments there is little evidence of learning by traders in either the buyer or seller role, despite the substantial amount of feedback provided. The results also demonstrate that the type of mechanism (a seller's take-it-or-leave-it price vs. a seller-price double auction) affects the likelihood of trading even though both are strategically equivalent. Furthermore, the asset valuation structure has a significant effect on the violations of Nash equilibrium by buyers and sellers and as a consequence on the extent of trade and its effect on the division of surplus between buyers and sellers. The cursed equilibrium theory explains some general patterns of the data, such as the buyer's acceptance behavior and the aggregate probabilities of trade. However, it has a more difficult time accounting for the variance in the behavior of sellers and the profits of traders in the different roles.

The effect of the trading mechanism on outcomes is particularly surprising and deserves further investigation. We have restricted our attention to two mechanisms, seller price setting and double auction, but there are many other bargaining structures that could be considered and compared. Obtaining behavioral insights on how strategic choice depends on mechanisms that are strategically equivalent could be of interest not only to improve our understanding of bilateral trading games but also to learn how to design efficient allocation mechanisms in more general economic environments.

This approach could also be usefully applied to study bargaining between three or more parties, as in markets and auctions. It is an interesting open question whether the tendency to trade excessively is exacerbated or attenuated in environments with additional buyers and/or sellers.

Finally, on the theoretical side, it is worth exploring alternative models to explain better the main features of the data (substantial trade, advantage of buyers, importance of the order of moves, and absence of learning). Some natural candidates would be partially cursed equilibrium, quantal response equilibrium (McKelvey and Palfrey, 1995), and theories based on levels of strategic sophistication such as cognitive hierarchy (Camerer et al., 2004). Based on our earlier study of the compromise game (Carrillo and Palfrey, 2009), these theories provide only partial explanations even when combined into hybrid models, and there remains much to learn about behavior and outcomes in games with two-sided private information and common values.

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Appendix: Sample Instruction Script (auction – min)

Thank you for agreeing to participate in this research experiment on group decision making. During the experiment we require your complete, undistracted attention. So we ask that you follow these instructions carefully. You may not open other applications on your computer, chat with other students, or engage in other distracting activities, such as using your cell phones or head phones, reading books, etc.

For your participation, you will be paid in cash, at the end of the experiment. Different participants may earn different amounts. What you earn depends partly on your decisions, partly on the decisions of others, and partly on chance. So it is important that you listen carefully, and fully understand the instructions before we begin. You will be asked some review questions after the instructions, which have to be answered correctly before we can begin the paid session.

The entire experiment will take place through computer terminals, and all interaction between you will take place through the computers. It is important that you not talk or in any way try to communicate with other participants during the experiment except according to the rules described in the instructions.

We will start with a brief instruction period, where you will be given a complete description of the experiment. If you have any questions during the instructions, raise your hand and I will answer your question. If any difficulties arise after the experiment has begun, raise your hand, and I will assist you privately.

You will make decisions over a sequence of 20 different decision rounds, called matches. In each match, you will receive a payoff, that depends on your decision in that match and on the decision of one randomly selected participant you are matched with.

At the end of the experiment, you will be paid the sum of what you have earned in all 20 decision rounds, plus the show-up fee of $10.00. Everyone will be paid in private and you are under no obligation to tell others how much you earned. Your earnings during the experiment are denominated in POINTS. Your DOLLAR earnings are determined by multiplying your earnings in POINTS by a conversion rate. In this experiment, the conversion rate is 0.02, meaning that 50 POINTS equals one dollar.

Here is how each decision round, or match, goes in this experiment. First, the computer randomly matches you into pairs. Since there are 10 participants in today's session, there will be divided into 5 matched pairs in each match. You are not told the identity of the participant you are matched with. Your payoff depends only on your decision and the decision of the one participant you are matched with. What happens in the other pairs has no effect on your current or future payoffs, and vice versa. Your decisions are not revealed to the other pairs.

Next, the computer randomly assigns a number to you, which is equally likely to be any integer from 1 to 100. This number is called your "clue." The clue is chosen independently for each participant. Therefore usually you and the person you are matched with will have different clues, although there is a very small (1%) chance the other participant in your pair has the same clue you have. You are told your clue, but will not be told the clue of the person you are matched with until after both of you have made your decisions.

The decision problem each pair faces is one in which there is a single object that must be allocated to one of the two participants in that pair. The object has a real money value which is equal to the minimum of the two clues of the participants. For example, if your clue is 78 and the other's clue is 19, then the value equals 19. Notice that your clue gives you only partial information about this value, since it also depends on the other participant's clue.

For each pair, the computer randomly selects one participant to be "the seller" and the other participant to be "the buyer". This buyer-seller assignment is completely random and does not depend in any way on anyone's clues or past decisions. These assignments will randomly change from round to round.

The seller then submits an offer, stating the lowest price at which they would be willing to sell the object to the buyer. At the same time, the buyer submits a bid, stating the highest price they would be willing to pay the seller for the object. If the seller's offer is less than or equal to the buyer's bid, we say "a trade occurs," the buyer is allocated the object and pays the seller a price equal to the seller's offer. In this case, the seller earnings for that match equals the price and the buyer earnings equal the value minus the price. If the seller's offer is strictly greater than the buyer's bid, then "no-trade occurs," and the seller keeps the object. In this case, the seller earnings simply equal the value and the buyer earnings are zero. We will now proceed through two practice matches to familiarize you with the computer screens.

Notice that it is possible for a trade to occur at a price above the value. In this case, the buyer earns a negative amount in that decision round. If this value-price difference is negative, and trade occurs, it will be subtracted from the buyer's earnings. Remember that earnings accumulate during the experiment, so negative earnings in one match are offset with positive earnings in other matches. When all pairs have finished the match the computer will then show you the results of your match only, displaying the other participant's clue, and summarizing whether there is trade, the price, the payoff, etc. We then proceed to the next match. For the next match, the computer randomly matches participants into new pairs, and randomly reassigns a new clue to each participant. Your new clue does not depend in any way on the past decisions or clues of any participant including yourself. Clues are completely independent across pairs, across participants, and across matches. After learning your new clue, you are randomly assigned to be either a buyer or seller. Decisions and payoffs are determined in a similar manner as in the previous match.

This continues for 20 matches, after which the experiment ends.

We will now begin the Practice session and go through two practice matches. During the practice matches, please do not hit any keys until you are asked to, and when you enter information, please do exactly as asked. Remember, you are not paid for these 2 practice matches. At the end of the second practice match you will have to answer some review questions. Everyone must answer all the questions correctly before the experiment can begin. The screen in front of the room summarizes the main features of the experiment.

[Hand out record sheets and pencils.]

[AUTHENTICATE CLIENTS]

Please double click on the icon on your desktop that says "NT". When the computer prompts you for your name, type your First and Last name. Then click SUBMIT and wait for further instructions.

[START GAME]

[SCREEN 1][SCREEN 2]

You now see the first screen of the experiment on your computer. It should look similar to this screen if you are a buyer, and this screen if you are a seller. [show both screens] Do not do anything right now with the computers, but listen to my instructions and follow them carefully.

[Explain BASIC PARTS of screen pointing as you read.]

At the top left of the screen, you see your subject ID. Please record that on your record sheet now. You have been randomly matched by the computer with exactly one of the other participants. These pairings will change randomly after each match.

The first line states whether you have been randomly assigned as the buyer or the seller for this match. Please record this on your record sheet in the column labeled You (B/S). Write S if you are a seller and B if you are a buyer. The second line states your clue for this match. This is revealed to you on your screen, but is not revealed to anyone else. [point on overhead]. Please record your clue on your record sheet in the column labeled "Your Clue". Of course your clue is probably different from the one on this slide.

The participant you are matched with was also randomly assigned a clue, but that will not be revealed to you until the end of the match. All you know now is that their clue is some number between 1 and 100, with every number being equally likely.

If you are a seller, you are asked to use your keyboard to submit an offer. The offer must be an integer between 1 and 100. DON'T DO THIS YET! When it is time to start, we will tell each seller exactly what offer to type in.

If you are the buyer, you are asked to use your keyboard to submit a bid. The bid must be an integer between 1 and 100. DON'T DO THIS YET! When it is time to start, we will tell each buyer exactly what bid to type in.

Point to Seller Offer Screen [explain it]

Point to Buyer Bid Screen [explain it]

After the seller has submitted an offer and the buyer has submitted a bid, the results are displayed for both the buyer and the seller, including BOTH clues, as well as the value, whether there is trade, the price if there is trade, and the earnings. Remember, the value of the object is equal to the minimum of the two clues.

If the buyer's bid was greater than or equal to the seller's offer, then trade occurs at a price equal to the seller's offer. The buyer payoff is the value minus the price and the seller payoff is the price. If the buyer's bid was less than the seller's offer, then no trade occurs. In that case, the buyer payoff is zero and the seller payoff is the value.

We will now proceed with the first practice match but I will tell you exactly what to type. Your are not paid for the decisions in the practice matches. At this time, regardless of your clue, please type in an offer or bid equal to the last two digits of your SSN + 1. For example, if your SSN ends in 32, you would type in 32+1=33. When everyone has entered these bids and offers, the results of your match are summarized on your screen (point to slide).

[SCREEN 3] [SCREEN 4]

[Go through the seller and buyer results screens of the example.]

The bottom half of your screen contains a table summarizing the results for all matches you have participated in. This is called your history screen. Notice that it only shows the results from your first match, not the results from any of the other pairs. It will be filled out as the experiment proceeds.

[Go over each column of history screen. Go around and verify that all subjects correctly filled out their record sheet]

Record this information on your record sheets in the appropriate columns. We now proceed to the second practice match

[Start next practice match]

You have been be randomly re-matched into new pairs, randomly assigned new roles as sellers or buyers, and randomly assigned new clues. Please take note of your new clue, and also note whether you are the buyer or the seller. [Ask if everyone sees it, and wait for confirmation from them.] Please make your decisions in match 2 following the same instructions as match 1, (bid or offer equals your last two digits of SSN +1) and then wait for further instructions, recording the information, as before.

[wait for them to complete practice match 2]

Practice match 2 is now over. Please pull out the privacy panels on both sides of your workstation. [Make sure they do!]

You now see a screen with the first page of the review quiz. Please complete the first page of review questions. You must answer all the questions correctly to go to page 2 of the review quiz. Raise your hand if you have a question about the quiz. After you have correctly answered all the questions on both pages of the quiz, wait quietly for everyone else to finish. [WAIT for everyone to finish the Quiz]

Are there any questions before we begin with the paid session? We will now begin with the 20 paid matches of the experiment. If there are any problems or questions from this point on, raise your hand and an experimenter will come and assist you.

[START First Paid MATCH; do not auto advance]

[After MATCH 21, read:]

This is the end of the experiment. You should now see a popup window, which displays your total earnings in the experiment. Please record that amount on the bottom row of your record sheet.

We will round this amount up to the nearest quarter, and pay you that plus the show-up fee of $10 in cash. We will pay each of you in private in the next room in the order of your Subject ID numbers. Remember you are under no obligation to reveal your earnings to the other players.

Please put the mouse behind the computer screen and do not use either the mouse or the keyboard at all. Please be patient and remain seated and keep the dividers pulled out until we call you to be paid. Do not talk with the other participants or use your cell phone or laptops while you are in the laboratory. Thank you for your cooperation.

Could the person with ID number 0 please go to the next room to be paid.

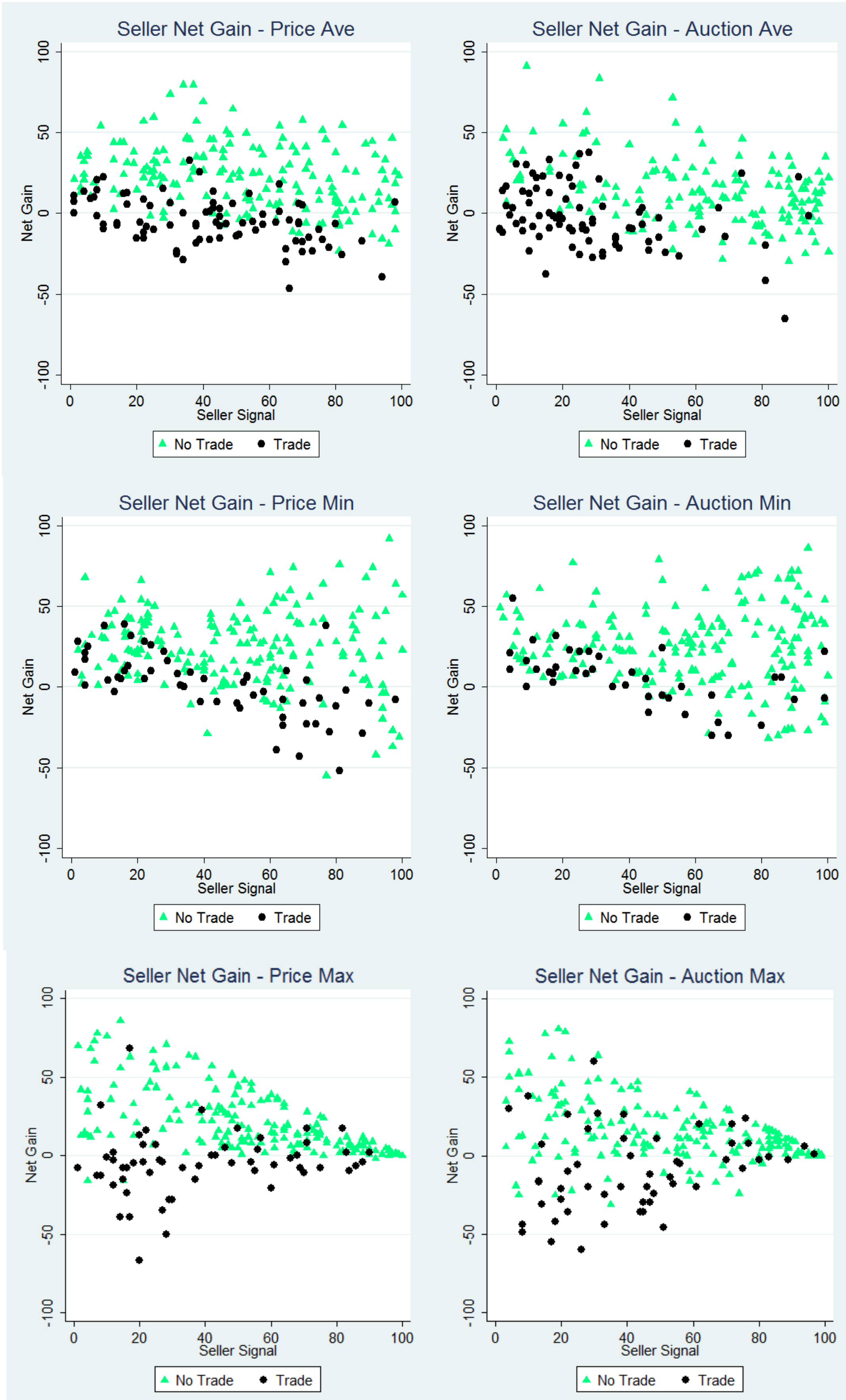

Figure 1. Seller's Net Gains by Treatment

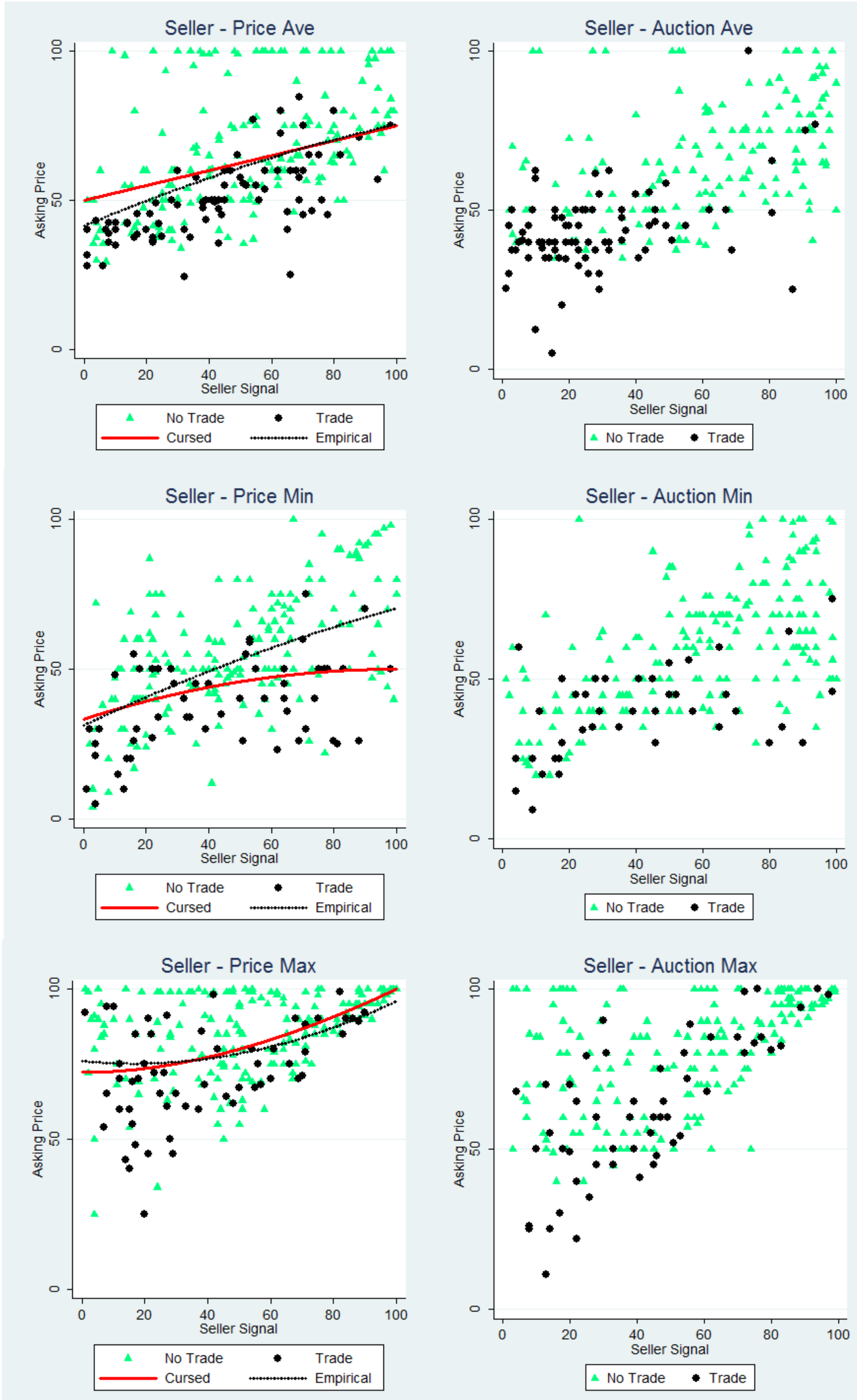

Figure 2. Seller's Asking Price by Treatment

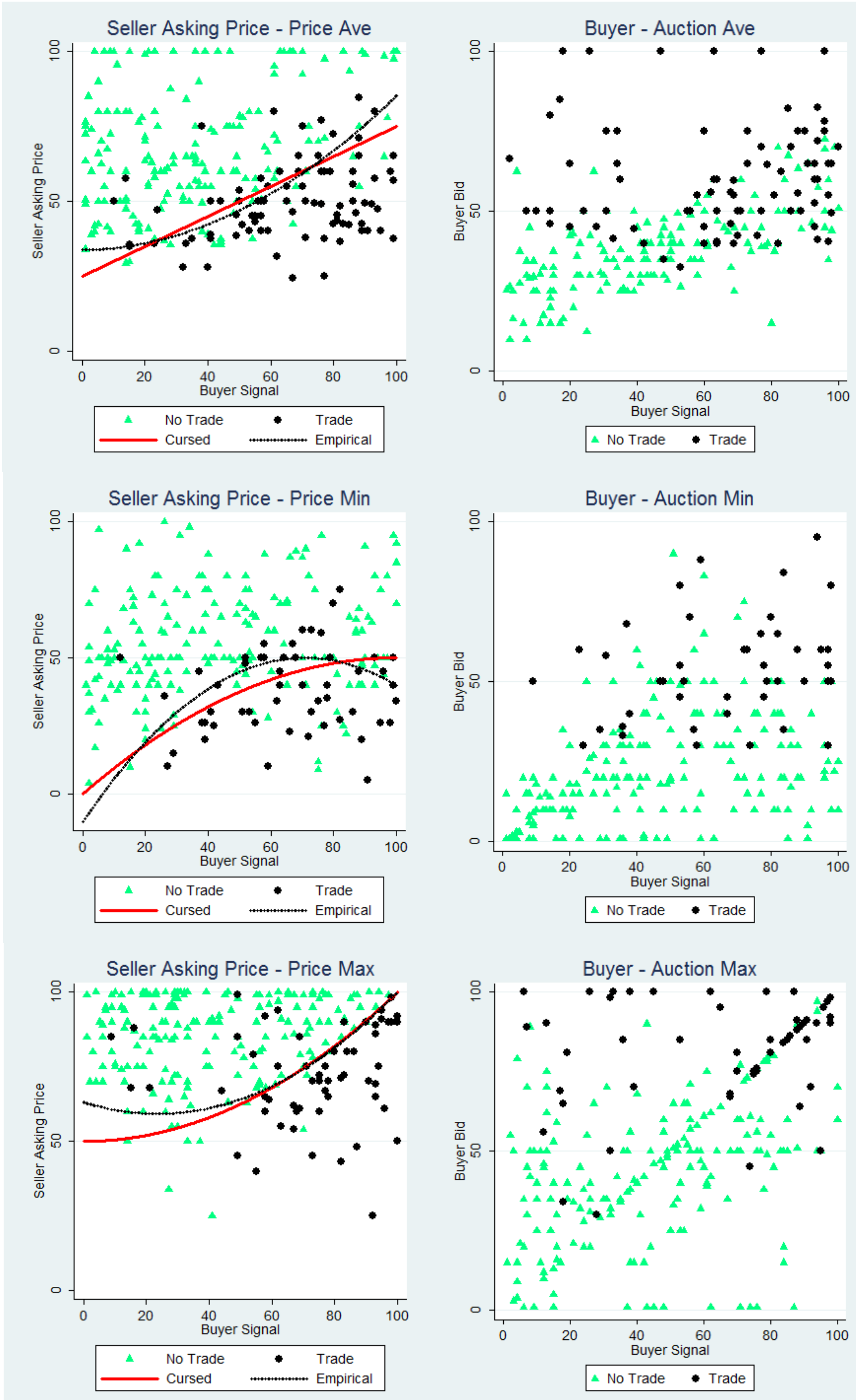

Figure 3. Buyer's Acceptance or Bid by Treatment

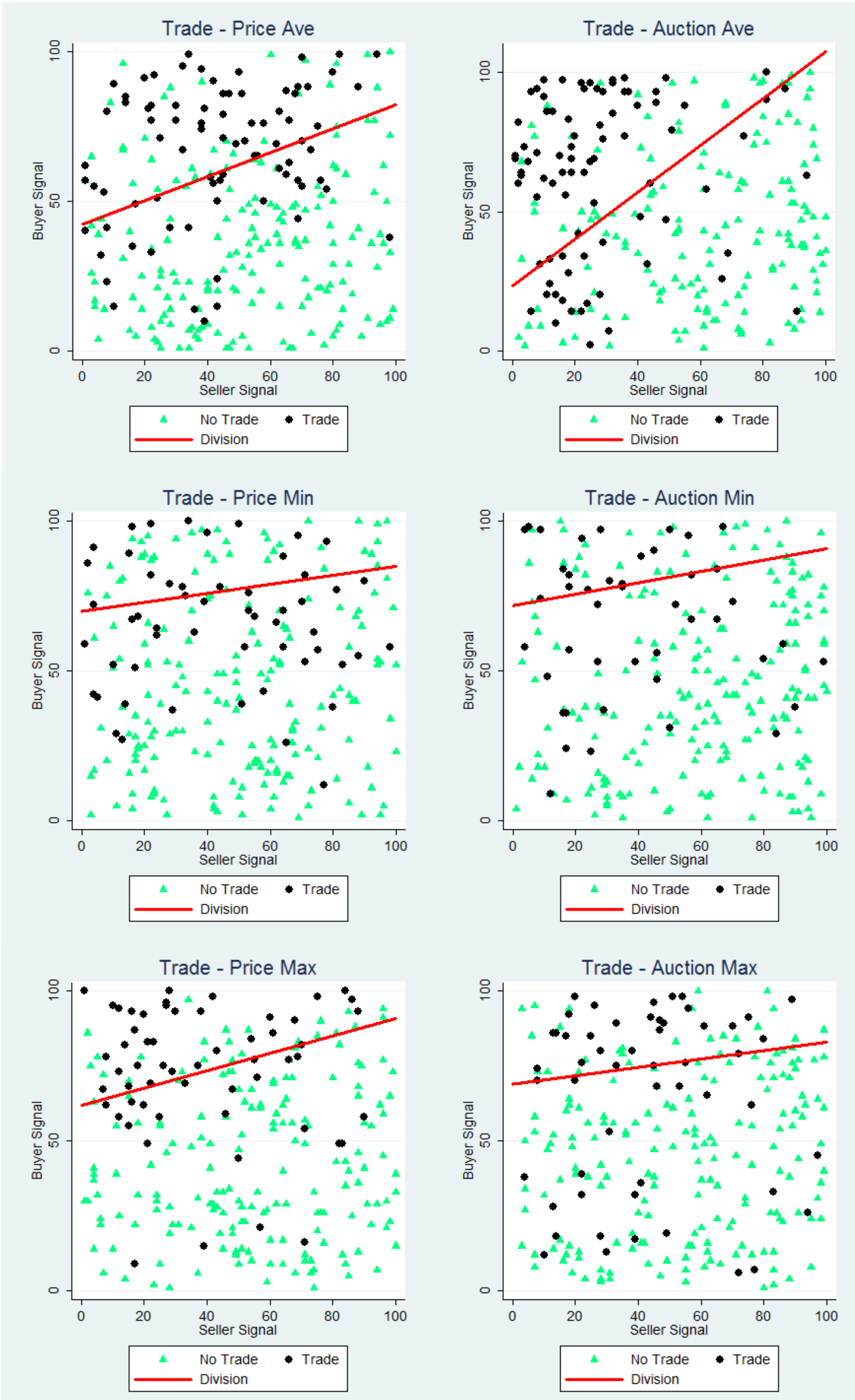

Figure 4. Likelihood of Trade as a Function of Signals

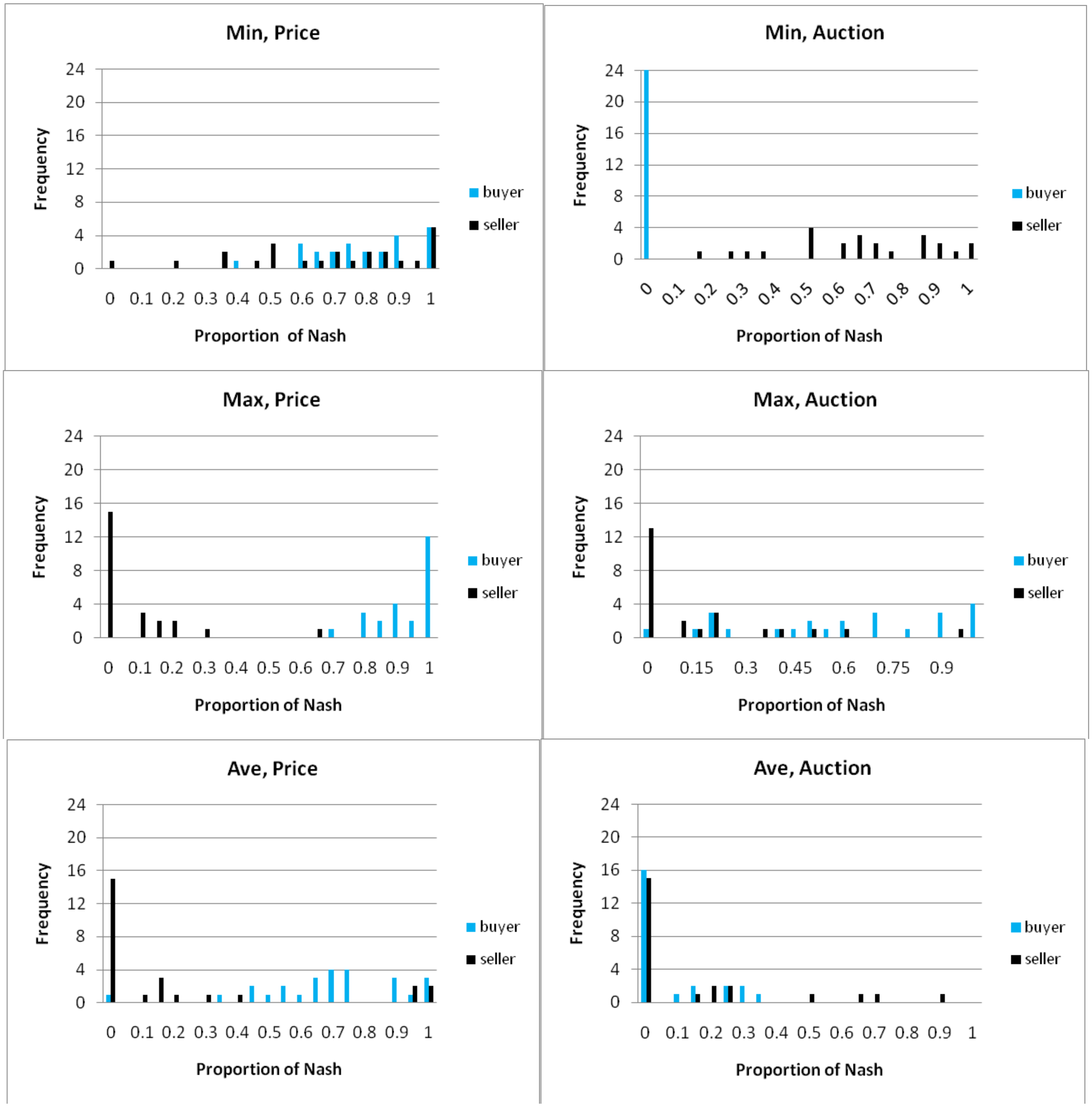

Figure 5. Distribution of Individual Proportions of Nash Play by Role and Treatment.