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Uncertainty about Informed Trading in Dealer Markets - An Experiment*

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Abstract:

We use an economic experiment to examine the impact of an uncertain level of asymmetric information on the behavior of security dealers. Specifically, we distinguish three types of uncertainty with respect to informed trading – risk, compound risk, and ambiguity – for both a monopoly and a duopoly market setting. We find no difference in dealers' bidding behavior between compound risk and ambiguity. At the same time, we find that bidding behavior is more aggressive under risk than under compound risk or ambiguity. In addition, we find that stochastic models of choice does well in explaining the observed differences in market outcomes for both individual (monopoly) and strategic (duopoly) settings.

Keywords: Experiments, Uncertainty, Dealer Markets, Stochastic Choice,

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1 Introduction

In most major financial markets, such as the NYSE and the NASDAQ, dealers play a central role in making markets. Whether —and to what extent— dealers choose to make markets by posting quotes for securities determines the liquidity and performance of the market. One of the most dramatic and famous examples of a market breakdown is the "flash crash" of May 6, 2010, when liquidity vanished in an instant. A detailed study by Easley, Lopez de Prado, and O'Hara (2011) suggests that the key reason for the crash was the exit of liquidity providers due to uncertainty about order toxicity (probability of informed trading). While the purpose of this study is not to try to explain the flash crash itself, we do believe that by getting a clearer sense of how various types of uncertainty may influence dealer behavior, we gain a more precise understanding of dealer markets in environments with severe asymmetric information. In contrast to the use of indirect measures of informed trading based on transaction data, such as the probability of information-based trading (PIN) in Easley, Kiefer, O'Hara, and Paperman (1996) our study seeks to analyze the probability of informed trading directly, by explicitly manipulating this central factor through the use of experimental markets.

Asymmetric information is, by its nature, hard if not impossible to detect in field data. In this scenario, controlled laboratory experiments provide a useful way to generate consistent data because severe asymmetric information can be clearly specified and controlled. Our research is designed to shed light on the effect of uncertainty about the level of asymmetric information on the market liquidity and transaction costs that traders face. We model uncertainty with respect to informed trading as risk, compound risk, or ambiguity, using urns whose composition is either known or unknown to the participants. Thus, in risky and compound situations, the probability distribution is objectively known, while in ambiguous situations, it is not.

Our main goal is to answer the question: Are there any differences in market liquidity within environments in which the level of informed trading is viewed as risky, compound, or ambiguous? Specifically, we focus on two dimensions of liquidity: (i) resiliency, measured as the fraction of time a market is open and (ii) price. We compare the three uncertainty scenarios across the two dimensions of market liquidity.[1] Prior theoretic research (Glosten, 1989) on environments with risky informed trading leads us to predict that a concentrated dealer market, such as a monopoly, will have higher trading costs but be more resilient in environments in which asymmetric information is high, while a dispersed dealer market, such as a duopoly, will break down more often but offer lower trading costs. Whether this fundamental trade-off between resiliency and trading costs actually exists under ambiguity and compound risk is an empirical question that we intend to explore.

Experimental studies related to ours have been conducted by Cason (2000), Krahnen and Weber (2001), Schnitzlein (2002), and Sheh and Wilcox (2009), who consider dealer markets in an asymmetric information environment. Cason (2000) finds that markets organized by dealer intermediaries are sufficiently competitive to generate high informational efficiency, even when informed

[1]In general, liquidity may have many more dimensions and interpretations (e.g., "market liquidity is a slippery and elusive concept, in part because it encompasses a number of transactional properties of markets" (Kyle, 1985)).

traders could not post limit orders. Schnitzlein (2002) examines market liquidity in a continuous dealer market experiment with uncertainty about the presence and number of informed traders.[2] Their main focus is on the strategic timing of actions by informed traders (insiders), who aim to influence dealers to falsely infer the presence or absence of insiders. They find that market outcomes are similar to the case when the number of insiders is known. Krahnen and Weber (2001) find that competition among market makers (four dealers vs. one dealer) in an asymmetric information environment significantly reduces the bid-ask spread, and increases the transaction volume. However, because dealers do not have an option to exit the market, competitive undercutting leads to a net trading loss for market markers, on average.

When allowing dealers to exit the market at their discretion, Sheh and Wilcox (2009) find that, in an asymmetric information setting, a duopoly market structure is more resilient than a monopoly market structure in terms of liquidity provision. But dealers in these experiments were told the exact level of informed trading in the market and did not have to worry about this source of uncertainty. This clearly does not reflect what occurs in actual financial markets, where dealers have to constantly assess the presence of informed traders based on limited information. We believe that this is a crucial factor that needs to be examined closely to facilitate a deeper understanding of the uncertain environments in which market breakdowns occur. Thus, the main difference between our paper and most of the above studies is that we investigate a dealer market with an uncertain level of informed trading; in particular, we distinguish among risk, compound risk, and ambiguity in order to address scenarios in which knowledge of underlying probabilities about informed trading is imprecise at best.

We also contribute to the broader literature on decision making under ambiguity, which has recently gained considerable attention from both the individual (Halevy, 2007; Eliaz and Ortoleva, 2015; Abdellaoui, Klibanoff, and Placido, 2015; Eichberger, Oechssler, and Schnedler, 2014; Moreno and Rosokha, 2016) and the market (Bossaerts, Ghirardato, Guarnaschelli, and Zame, 2010; Corgnet, Kujal, and Porter, 2013; Kocher and Trautmann, 2013; Huber, Kirchler, and Stefan, 2014; Füllbrunn, Rau, and Weitzel, 2014) perspectives. Experimental studies on ambiguity in markets have, typically, assumed that the source of ambiguity is the value of the asset. For example, Bossaerts, Ghirardato, Guarnaschelli, and Zame (2010) study the impact of heterogeneity of ambiguity attitudes and ambiguity aversion on equilibrium asset prices in competitive financial markets, implemented as a continuous double auction. They find that by refusing to hold an ambiguous portfolio, ambiguity-averse investors have a significant effect on prices. Corgnet, Kujal, and Porter (2013) investigate trader reaction to ambiguity when dividend information is revealed sequentially. They find no significant differences between risky and ambiguous assets regarding prices, price volatility, and trading volume. Kocher and Trautmann (2013) experimentally study subjects' self-selection into a first-price, sealed-bid auction for both a risky and an ambiguous prospect. They find that most subjects choose to submit bids to the risky rather than to the ambiguous prospect,

[2]The dimension of liquidity examined in Schnitzlein (2002) is measured in terms of price change per unit order flow on price continuations.

which leads to thinner markets for the ambiguous one. Huber, Kirchler, and Stefan (2014) investigate influence of skewness in asset fundamentals on asset price in a double-auction market setting under risk, ambiguity, and under a scenario in which fundamental value distribution can be learned. They find that ambiguity aversion (as evident from underpricing of assets relative to the risk scenario) is present when asset fundamentals are negatively skewed. Füllbrunn, Rau, and Weitzel (2014) find two key conditions for ambiguity effects to survive in asset markets: that ambiguity aversion is sufficiently strong and that the feedback of other market participants is limited. In contrast to the aforementioned literature on ambiguity in markets and auctions, in which the source of ambiguity is the value of the asset, our key contribution to this literature is to change the focus of ambiguity to the level of informed trading (which is similar in nature to Schnitzlein (2002)). In addition, we aim to compare markets in which informed trading is viewed as compound risk or ambiguity, which has not been explored in the market setting.

Finally, we investigate the implications of the stochastic nature of the decision maker's actions for market outcomes under risk, compound risk, and ambiguity; this turns out to be the key factor that allows us to disentangle an otherwise perplexing set of results. The importance of the stochastic nature of subjects' decisions cannot be overstated, and, as Wilcox (2011) succinctly stated: "I regard stochastic choice as the oldest and most robust fact of choice under risk, and believe that serious interpretive errors can occur when the implications of stochastic choice models are ignored." (pp. 99-100) We show that, even without payoff feedback, subjects refine their decision-making process from early rounds to the late rounds. This reduces strategic uncertainty and results in a significantly different equilibrium distribution of prices. By accounting for the "precision" of decision making,[3] we are able to find a difference in dealer behavior between risky and uncertain (ambiguous and compound) trading environments. Specifically, our design allows us to estimate the attitudes towards risk, compound risk, and ambiguity, as well as to estimate the precision in decision making. We then use these parameters as an input to the Quantal Response Equilibrium model of McKelvey and Palfrey (1995) to provide a theoretical benchmark that corroborates the outcome of the experimental markets for both individual (monopoly) and strategic (duopoly) settings.

The rest of the paper is organized as follows. In Section 2, we introduce the environment. In Section 3, we describe the experimental design and present an overview of the data. In Section 4, we present our results. Finally, in Section 5, we conclude.

2 Environment

In this section, we describe the environment and provide the theoretical prediction on how the subjective beliefs about an uncertain process influence the market outcome.

[3]In the context of the stochastic choice model, as precision increases, the error in the valuation of the difference between two options decreases. In the context of the Quantal Response Equilibrium, the precision parameter is often referred to as the rationality parameter.

2.1 Asset

The underlying risky asset has a payoff $V \in \{H, L\}$ at the end of the period. Specifically, the asset pays H with probability q and L with probability $(1-q)$.

2.2 Agents

The agents that interact in a market setting are *dealers* and *traders*: dealers are part of the market structure itself, while traders can be thought of as general population interested in selling/purchasing the asset. A dealer is a market specialist who provides a Bid and/or Ask quote on the asset prior to the revelation of the true value. The dealer can earn a profit through market operations (quotes), but also has an outside option that pays \$$S$ at the end of the period. While, in reality, dealers could place place a Bid and an Ask quote, in our experiment we focus on the Bid quote.

Traders buy an asset for their personal motives. As is common in the market microstructure literature (O'Hara, 1995), we distinguish between informed traders (insiders), who know the true V, and uninformed traders (outsiders), who do not know the true V but have private reasons to trade the asset. We assume that each trader can trade, at most, one unit of asset. The informed trader knows something that neither the uniformed trader nor the dealer knows – the true V for the trading period. He optimally exploits this privileged "insider" knowledge to maximize his own trading profits by selling the asset at the bid quote if V is lower than the bid price. The uninformed trader, on the other hand, will sell the asset to the dealer at the best bid quote. Thus, a dealer is facing an *adverse selection* problem, and his decision depends on his *belief* about the likelihood that the trader is informed, which we will denote by p.

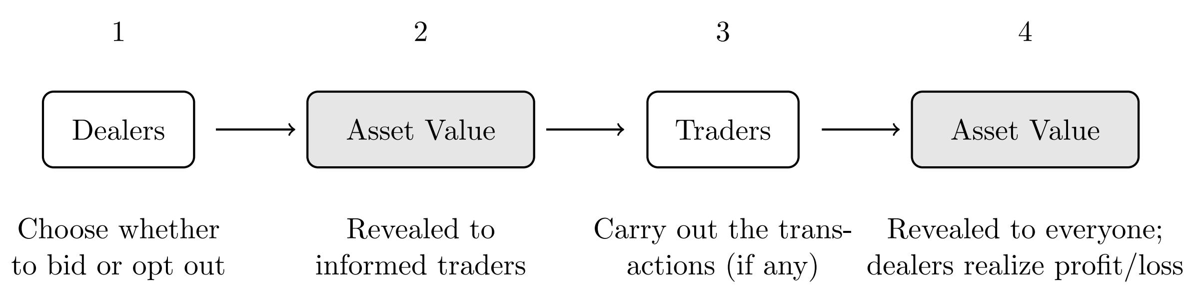


Figure 1: Timeline.

Figure 1 presents the timeline of the four stages within each period. First, dealers decide to either place a bid b, or to opt out. Second, asset value, V, is revealed to the informed trader. Third, traders decide whether to enter the contract (sell the asset) at the posted price. Finally, V is revealed to everyone, and profits and losses are realized for the period. Thus, if the asset is acquired, the dealer earns $(V - b)$.

2.3 Markets

In this study, we consider three market structures that differ with respect to decision complexity and strategic uncertainty. Specifically, we consider the *binary choice* market, the *monopoly* market and the *duopoly* market. In the binary choice market, the dealer decides whether or not to accept an exogenously specified selling price or to opt out and receive his outside option. This format is equivalent to *perfect competition*, whereby the dealers are price takers. In the monopoly market, the dealers are price makers. As such, dealers select among a set of prices and, therefore, the monopolist's decision is that of a multinomial choice. Lastly, in the duopoly market, two dealers compete for the right to buy the asset. Thus, the duopoly market is the most interesting from strategic perspective, as now there is strategic uncertainty about other dealers' price.

The difference between the different markets is one of the fundamental topics in the market microstructure literature. In this paper, we will focus primarily on the difference between the monopoly and the duopoly markets and use the binary choice market to elicit subjects' risk preferences and subjective beliefs in the context of our experiment. We then will incorporate the obtained estimates into the stochastic model of choice to gain an insight into the outcomes of both monopoly and duopoly markets. In what follows, we describe the three market structures in order, from the simplest (binary choice) to the most complex (duopoly).

2.3.1 Binary Choice

The binary choice market structure is the simplest environment presented to the subject: it lacks the strategic element and the complexity of multinomial choice. It also allows us to use the existing canon of work on binary choice to estimate dealer's preferences in the context of our experiment. Figure 2 presents the dealer's decision in the binary choice market structure.

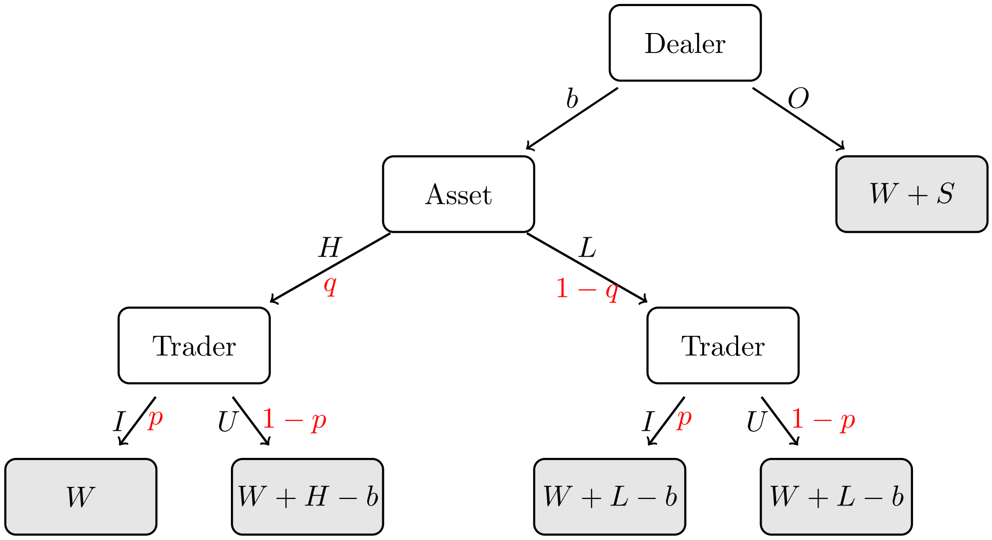


Figure 2: Binary Choice. *Notes*: Dealer chooses between placing a bid, b, and taking an outside option, O. Asset value is H with probability q, and L with probability $1-q$. Trader is informed with probability p and uninformed with probability $(1-p)$. Source of p will vary by uncertainty treatment, while q will be known and constant for all treatments.

In the binary choice market, dealers decide whether or not to accept an exogenously specified selling price, b, or to opt out (O) and receive his outside option, denoted by S. The expected utility of a bid, b, and outside option, O, is given by equations (1) and (2), respectively:

$$EU_B(b) = q \times (1-p) \times u(W+H-b) + q \times p \times u(W) + (1-q) \times u(W+L-b) \tag{1}$$

$$EU_O = u(W+S), \tag{2}$$

where W is the dealer's endowment in the period; $\{H, L\}$ are asset value realizations; S is the payoff of the outside option; and $u(.)$ is the utility function. Thus, the dealer chooses the option with the highest expected value given her current beliefs p and q. Note that the uncertainty about the trader type, which may influence p, will vary between treatments (Section 3.1).

2.3.2 Monopoly

The key difference between the binary choice and monopoly markets is that in the former, the bid amount is fixed, while in the latter, the bid amount is determined by the dealer. Let $b_i = 0$ denote the dealer choosing the opt-out option, O. Then, for the monopolist dealer, the expected utility of a bid, b_i, is given by

$$EU_M(b_i) = \begin{cases} EU_B(b_i), & \text{if } b_i > 0 \\ EU_O, & \text{if } b_i = 0, \end{cases} \tag{3}$$

where EU_B and EU_O are given by equations (1) and (2). Then, the dealer chooses the option with the highest expected utility given her current beliefs p and q. Notice that the monopolist's optimal bid will take on two values:

$$b^* = \begin{cases} b_{min}, & \text{if } EU_B(b_{min}) > EU_O. \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

The optimal decision is either to provide the minimum bid possible or to opt out. However, under the stochastic choice framework, we should expect there to be deviation from the b^*. In particular, we should expect to observe some $b_i > b_{min}$.

2.3.3 Duopoly

The key difference between the monopoly and duopoly markets is in the number of dealers present in the market. Specifically, we consider a structure with two dealers competing for the right to buy one unit of an indivisible asset from a seller. The winning dealer gets the asset and pays an amount equal to her bid, while the losing dealer goes away with no change in her initial wealth. In the case of a tie, each of the two dealers is equally likely to make the purchase. Thus, the duopoly setting is different from the monopoly setting in that the expected utility of the first dealer is a function not only of her own bid, b_1, but also of the second dealer's bid, b_2.

$$EU_D(b_1|b_2) = \begin{cases} EU_M(b_1), & \text{if } b_1 > b_2 \text{ or } b_1 = 0 \\ .5 \times EU_M(b_1) + .5 \times u(W), & \text{if } b_1 = b_2 \text{ and } b_1 > 0 \\ u(W), & \text{if } 0 < b_1 < b_2, \end{cases} \tag{5}$$

where $EU_M(.)$ is the expected utility of the monopolist from equation (4). Thus, dealer 1 (dealer 2) chooses b_1 (b_2) to maximize her expected utility, given by equation (5).

The symmetric mixed-strategy Nash Equilibrium (NE) of this game is presented in Figure 3. Specifically, the figure presents theoretical predictions for the risk-neutral agents for two cases of subjective beliefs: the first case corresponding to $p = 0.50$, and the second case corresponding $p = 0.33$.[4]

[4] The parameters chosen are the same as will be used in the experiment: $V \in \{\$5.00, \$0.00\}$, $q = .5$, $b \in \{0, .1, .2, ..., 4.9\}$. The initial wealth, W, is assumed to be \$5.00 because i) participants are explicitly told that they will earn at least \$5.00; and ii) participants do not learn any payoff outcomes until after all decisions have been made.

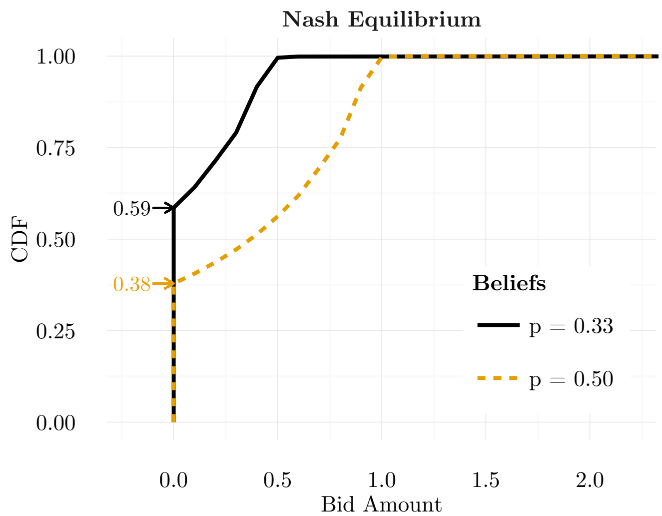


Figure 3: Symmetric Mixed-strategy Nash Equilibrium. *Notes*: The agents are assumed to be risk-neutral. A bid amount of zero means that the dealer is choosing to take an outside option. Arrows mark the fraction of time that an agent would choose the outside option.

Figure 3 shows that when the subjective belief about informed trading is $p = 0.33$, the agent will choose to opt out more frequently and bid lower amounts, as compared to the case when the subjective belief about informed trading is $p = 0.50$. In other words, the theoretical prediction is that there should be a difference in the fraction of time that the dealer chooses to provide a bid and the a difference in bid amounts if the subjective beliefs about the informed trading is substantially different.

3 Experimental Design

The purpose of this paper is to investigate whether behavioral factors, such as compound risk aversion and ambiguity aversion, could lead to a systematic difference in dealers' behavior. Therefore, we use human participants in the role of dealers. The role of traders, on the other hand, is predetermined for both uninformed and informed types. Specifically, the rules for transactions are "the uninformed trader will always sell the asset," and "the informed trader will only sell the asset only if its value is less than dealer's bid," respectively. In this way, the informed trader exploits his private knowledge for his own profit. In our experiment, the trader type is determined by the color of the marble drawn from a physical urn as follows: a black marble denotes informed trader, and a white marble denotes uninformed trader.

3.1 Uncertainty about Informed Trading

We implement the uncertainty about informed trading as risk, compound risk, or ambiguity using physical urns containing black and white marbles. We assume that if a black marble is drawn, the trader is informed, and if a white marble is drawn, the trader is uninformed. Thus, urns differ based on the information regarding their composition. Specifically, the three types of urns are: *risky* urns, whose exact composition is known to the participants; *compound* urns, whose composition "process" is known; and *ambiguous* urns, whose composition process is unknown. Figure 4 presents the risky urn, the compound, and the ambiguous urn used in the experiment.

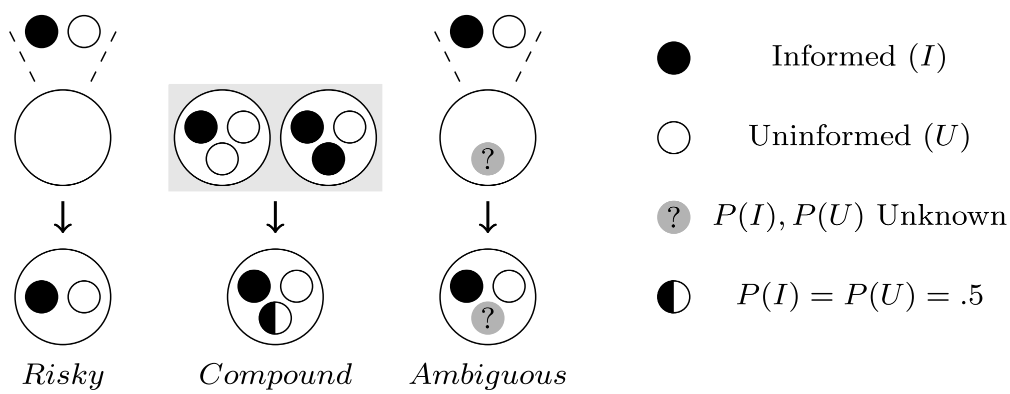


Figure 4: Urns. *Notes*: The *risky* urn is constructed in front of the participant by placing one black and one white marble into an empty urn. The *compound* urn is constructed as follows: two urns are constructed in front of the participants using the same procedure as for the risky urn, but with different numbers of black and white marbles; then, these two urns are placed in a box, and the participant draws one randomly. The *ambiguous* urn is constructed as follows: subjects verify that there is one marble in the urn; they know that it could be either black or white, but they are not informed about the color or the process by which the marbles were selected; then, one black and one white marble are added to the urn.

All urns are constructed in front of the participants. Specifically, for the risky urn, one black marble and one white marble are added to an empty urn. For the compound urn, the construction process is as follows: the participant chooses randomly between two bags, the first containing two black marbles and one white marble, and the second containing one black marble and two white marbles, one is picked at random by a participant. Lastly, for the ambiguous urn, one marble (either black or white) is placed in the urn before participants come into the lab, then one black marble and one white marble are added to the urn in front of the participants. An example of the instructions is provided in Appendix A.

3.2 Treatments

Main treatments of the experiment differ with respect to the type of the market and the type of uncertainty. Specifically, we consider a duopoly, a monopoly, and a binary choice for each of the uncertainty scenarios presented in Section 3.1. Table 1 summarizes the nine possible combinations.

		Uncertainty		
		Risk	*Compound Risk*	*Ambiguity*
Market	*Duopoly*	DR	DC	DA
	Monopoly	MR	MC	MA
	Binary Choice	BR	BC	BA

Table 1: Treatments.

Each participant is faced with five decision tasks for each of the treatments of Table 1. In each decision task, the participant needs to decide on whether to place a bid (b_i) or to opt out (O). For the monopoly and the duopoly treatments, the entered bid amounts are allowed to be between \$0.10 and \$4.90, in increments of \$0.10. Duopoly pairs are randomly re-matched in each round. The feedback provided after each decision is limited to the bid amount(s); this way, we focus on subjects' reaction to uncertainty while minimizing income effects across the sessions.

Table 2 presents a summary of the decision task parameters used in our experimental design. Note that the probability distribution of the asset value is known in all treatments.

Parameter	Variable	Treatment	Value	Comment
Probability of Informed Trading	p	R	$\frac{1}{2}$	Implemented as a draw from an urn
		C	$\frac{1}{3}$ or $\frac{2}{3}$ with **known** probability	
		A	$\frac{1}{3}$ or $\frac{2}{3}$ with **unknown** probability	
Asset Value	V	All	$H = \$5.00$ or $L = \$0.00$	Implemented as a flip of a coin
Probability the Asset Value is H	q	All	$\frac{1}{2}$	
Bid Amount	b	D	$b \in \{.1, .2, ..., 4.8, 4.9\}$	Picked by subject
		M	$b \in \{.1, .2, ..., 4.8, 4.9\}$	Picked by subject
		B	$b \in \{.25, .5, .75, 1.00, 1.25\}$	Exogenous

Table 2: Summary of Decision Task Parameters.

The 3x3 design for the main treatments creates many possible order combinations to consider. We narrow them down as follows. First, we group together decisions pertaining to a specific market and uncertainty treatment. This minimizes any confusion that subjects might experience about the three market structures and uncertainties. Second, the markets of most interest, in terms of complexity of the decision, are the duopoly markets. Therefore, we keep the duopoly market first, which limits the impact of learning from the other markets. Third, we balance the order in which different types of uncertainty are presented.

Table 3 gives a final breakdown of decision rounds that was used in each of the ten sessions of the experiment. Each round, denoted by $R1$ through $R9$, consists of a sequence of five decisions. While all urn compositions are carried out prior to the first decision, participants are reminded of the urn and the urn composition process before making each decision.

Session	R1	R2	R3	R4	R5	R6	R7	R8	R9	Sub.	Dec.	Av.P.	Min.P.	Max.P.
1	DA	DC	DR	BA	BC	BR	–	–	–	10	30	\$18.4	\$6.4	\$31.3
2	DA	DC	DR	BA	BC	BR	–	–	–	10	30	\$25.1	\$14.5	\$44.2
3	DA	DC	DR	MA	MC	MR	BA	BC	BR	8	45	\$35.1	\$19.0	\$50.6
4	DA	DC	DR	MA	MC	MR	BA	BC	BR	10	45	\$19.4	\$13.0	\$25.5
5	DR	DC	DA	BR	BC	BA	–	–	–	10	30	\$30.1	\$17.6	\$38.6
6	DR	DC	DA	BR	BC	BA	–	–	–	12	30	\$14.3	\$7.4	\$28.0
7	DR	DC	DA	MR	MC	MA	BR	BC	BA	10	45	\$23.4	\$10.3	\$38.2
8	DR	DC	DA	MR	MC	MA	BR	BC	BA	8	45	\$30.0	\$22.5	\$43.6
9	DR	DA	DC	MR	MA	MC	BR	BA	BC	10	45	\$24.4	\$5.0	\$36.7
10	DA	DR	DC	MA	MR	MC	BA	BR	BC	10	45	\$35.5	\$18.3	\$42.4
Overall	–	–	–	–	–	–	–	–	–	98	–	\$25.1	\$5.0	\$50.6

Table 3: Sessions Summary. *Notes*: $R1$ through $R9$ denote rounds of the experiment. Each round corresponds to a sequence of five decisions. *Sub.* - number of participants per session; *Dec.* - number of decisions made. $Av./Min/MaxP.$ - average, minimum, and maximum payoffs, respectively.

3.3 Administration and Data

Ninety-eight undergraduate students were recruited for the experiment using ORSEE software (Greiner, 2004) on the Purdue University campus. We administered ten sessions of the experiment between November 2013 and June 2014, with the number of participants varying between eight and twelve. We programmed and conducted the experiment using the software z-Tree (Fischbacher, 2007). All randomization was executed by physical devices (coins and urns). The payment data are summarized by session and presented in Table 3.

Each participant made either six or nine sets of five decisions. Each set of five decisions, denoted by round, corresponds to one of the cells in Table 1. Thus, in total, each participant made either 30 or 45 decisions. The randomization and payoffs were determined at the end of the experiment. Specifically, at the end of the experiment, a coin was flipped 30 (45) times, one for each of the periods, and draws were made from an appropriate bag. The duration of the experiment was about 60 minutes, with payoffs that ranged from \$5.0 to \$50.6, with an average payoff of \$25.1.

4 Results

This section is organized as follows: First, in Section 4.1, we present raw data obtained in our experiment. Second, in Section 4.2, we present the results on market liquidity by uncertainty type and by market structure. Third, in Section 4.3, we consider the effect of order of presentation. Finally, in Section 4.4, we obtain behavioral estimates for risk and uncertainty preferences. We then use these behavioral estimates to calculate the multinomial logit model and the Quantal

Response Equilibrium model of McKelvey and Palfrey (1995), which allows us to bridge the gap on results from order of presentation and difference in liquidity by treatments. Specifically, we note an increased precision in decision making, which has a significant effect on the market outcome.[5]

4.1 Raw Data

Figure 5 presents raw data on dealers' bidding behavior for monopoly and duopoly market structures for each of the three uncertainty scenarios: risk, compound risk, and ambiguity.

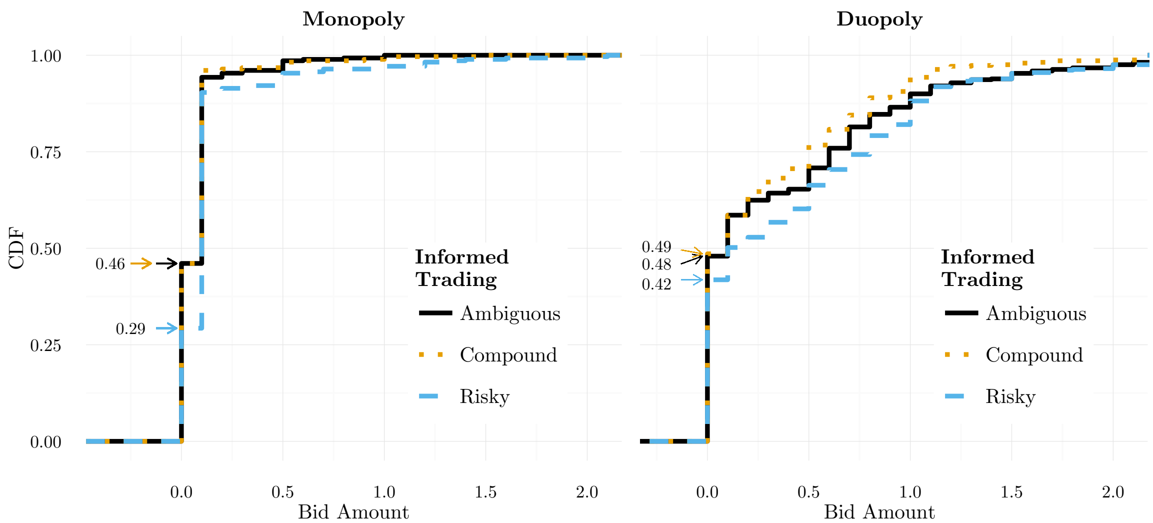


Figure 5: Aggregate Data. *Notes*: **Left Panel** – empirical CDF of dealer bids in the monopoly market. **Right Panel** - empirical CDF of dealer bids in the duopoly market. Bid amount of zero means that dealer is choosing to take an outside option. Arrows denote fraction of the time that dealers choose to take the outside option for each of the three uncertainty scenarios.

We observe that distributions of bid quotes seem to differ both by uncertainty type and by market structure. For example, we find that human dealers in the monopoly market choose to take the outside option less frequently when the uncertainty about the level of informed trading is presented as pure risk (participants opt out 29% of the time) than when the level of informed trading is presented as compound risk or ambiguity (participants opt out 46% of the time). Additionally, the distribution of bids in the ambiguous setting (black solid line) and the compound-risk setting (orange dotted line) are to the left of the distribution of bids under risk (blue dashed line). Finally, there is a stark difference between dealer behavior within the monopoly environment (Figure 5, Left Panel) and the duopoly environment (Figure 5, Right Panel). In what follows, we elaborate on these results and formally test their significance.

[5]Note that, although we could estimate the QRE, we chose not to do so, but, rather, we use parameters obtained from the binary choice part of the experiment to construct a theoretical benchmark to help in our understanding of dealer behavior in the monopoly and duopoly markets.

4.2 Uncertainty about Informed Trading

The main question of interest in this paper is whether there are any differences in market liquidity within environments in which informed trading is viewed as risky, compound, or ambiguous. To answer this question, we focus on dealer participation (providing a bid) and the distribution of bid amount, while accounting for order of presentation and market structure.

Result 1 *Dealer participation is higher under risk than under compound risk or ambiguity; while there is no difference in dealer participation between compound risk and ambiguity.*

Our first result concerns dealer participation and the resulting market resiliency. We run a subject fixed effects logistic regression with the uncertainty type (**A***mbiguous*, **C***ompound*, or **R***isky*), the order of presentation (1st, 2nd, or 3rd), and the market structure (**M***onopoly* or **D***uopoly*) as independent dummy variables and the probability of choosing to provide a bid (Bid or Opt Out) as the dependent variable. The fixed effect approach helps us deal with the fact that each individual is making multiple decisions within our experimental design, and, thus, the unobservable individual characteristics could influence bid behavior for all her decisions. Regression results are presented in Panel A of Table 4.

With a p-value of 0.000, we reject the hypothesis that the proportion of the time that dealers provide a quote is the same for the risky and ambiguous environments. At the same time, with a p-value of 0.701 we find no evidence of a difference between the proportions of the time that subjects choose to provide a bid in the compound versus the ambiguous environment. The latter result is consistent with Halevy (2007), Abdellaoui, Klibanoff, and Placido (2015), and Moreno and Rosokha (2016), who find compound risk aversion beyond the simple risk aversion.

	A: Dealer Participation			B: Dealer Price		
	Dependent Variable: Bid (Yes/No)			Dependent Variable: Bid Amount ($)		
		Coefficient Estimate	p-val.		Coefficient Estimate	p-val.
Uncertainty	A	–	–	A	–	–
	C	-0.059 (0.154)	0.701	C	-0.026 (0.033)	0.429
	R	0.597 (0.125)	0.000	R	0.055 (0.026)	0.036
Market	D	–	–	D	–	–
	M	0.461 (0.118)	0.000	M	-0.510 (0.026)	0.000
Order	1^{st}	–	–	1^{st}	–	–
	2^{nd}	-0.030 (0.163)	0.853	2^{nd}	-0.161 (0.033)	0.000
	3^{rd}	-0.197 (0.130)	0.131	3^{rd}	-0.206 (0.027)	0.000
	Const.	0.131 (0.210)	0.564			
	Observations		2,310	Observations		1,292
	Log Likelihood		-1,280	R^2		0.616
	Akaike Inf. Crit.		2,574	Adjusted R^2		0.584

Table 4: Subject Fixed Effects Regressions. *Notes:* **Panel A** – Dealer participation is a binary variable. **Panel B** – Bid amount is conditional on the dealer providing a bid. The coefficients are relative to "A," "D," and "1st."

Next, we consider whether dealer bid quotes for the three uncertainty environments differ from each other. We do this by looking only at all instances when a dealer chooses to bid. In other words, we consider the question: conditional on providing a bid, are there any differences between dealer bid behavior that is due to the uncertainty being risk, compound risk, or ambiguity?

Result 2 *Dealer bid amounts are higher under risk than under compound risk or ambiguity; while there no difference in bid amounts between compound risk and ambiguity.*

The regression results on bids are presented in Panel B of Table 4. What we find is that the coefficient on R is positive and significant (p-value 0.036). That is, dealers bid more aggressively when uncertainty about informed trading is generated using a risky urn than when generated using an ambiguous urn. The coefficient on C is again indistinguishable from zero (p-value 0.429). Thus, we find no difference between compound risk and ambiguity.

Result 3 *Dealer participation in the monopoly market structure is higher than in the duopoly market structure; while dealer bid amounts are higher in the duopoly market structure than in the monopoly market structure.*

Both panels of Table 4 also shed some light on the difference between dealer behavior in the monopoly and the duopoly market structures. Specifically, at the individual level, the probability of providing a bid in the monopoly market is significantly higher than in the duopoly market, and, at the same time, the amount of the bid is significantly lower. These results corroborate previous findings of lower trading costs in competitive markets by Krahnen and Weber (2001) and Sheh and Wilcox (2009) and a theoretical trade-off emphasized by Glosten (1989). At the market level, however, the fraction of time that a market is open - that is, the fraction of time when at least one dealer is providing a bid - is actually higher for the duopoly market than for the monopoly market.

To summarize our main results on dealer bidding behavior, we find evidence that the type of uncertainty with respect to informed trading matters for dealer bid provision, which, in turn, yields differences in market liquidity in the monopoly and duopoly markets. Specifically, we find that resiliency and prices are significantly higher for the risky treatment than for the compound or the ambiguous treatments. However, we do not find any difference between the compound and ambiguous treatments.

4.3 Order

When we consider the aggregate results in Figure 5, we find that bids are greater for the risky treatment than for the compound or ambiguous treatment. However, this is not the case for all sessions.[6] In particular, the early bid amounts seem to be greater than the later ones. We devote this section to understanding the differences that arise due to the order of presentation and how to reconcile them with our main result. Figure 6 presents the results by order of presentation.

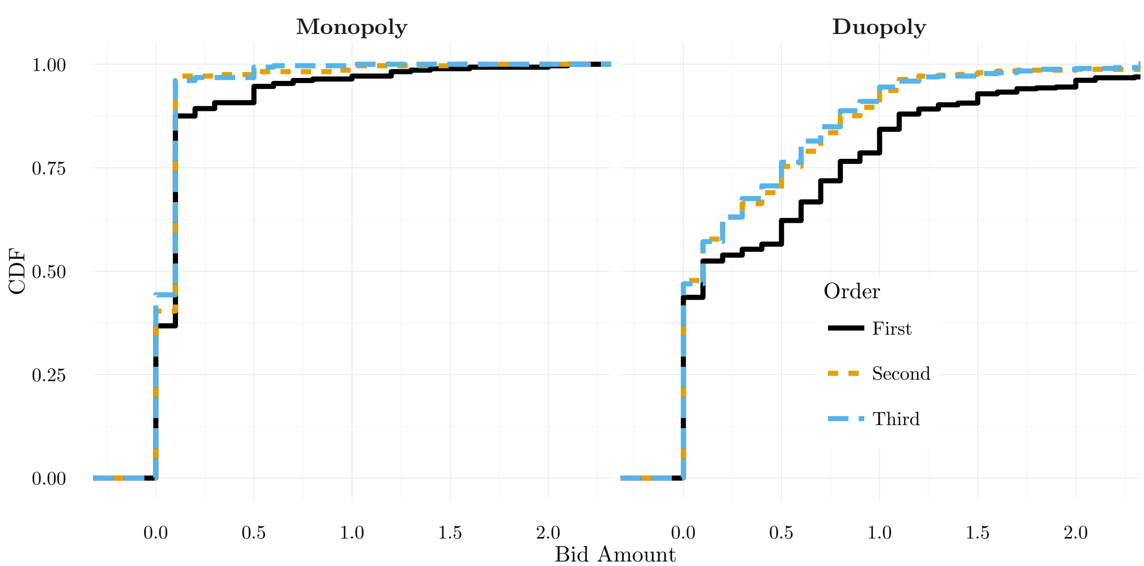


Figure 6: Data by Order of Presentation. *Notes*: **Left Panel** – monopoly treatment. **Right Panel** – duopoly treatment. *First*, *Second*, and *Third* - order in which a set of five decisions is presented within each market type. For example, the ambiguous setting is presented first in Sessions 1-4 and 10, second in Session 9, and third in Sessions 5-8. Similarly, the risky setting is presented first in Sessions 5-9, second in Session 10, and third in Sessions 1-4. Thus, the data is combined across all three types of uncertainty. As before, a bid amount of zero means that the dealer is choosing to take an outside option.

[6]Figures C1, C2 and C3 in Appendix C present market outcomes of each session.

Allowing the order of presentation to vary within each graph, we notice that dealers bid more aggressively in the first set of five rounds than in the second or third set of five rounds.[7] What might be the reason behind this difference? We argue that this is evidence of increased precision in decision making; specifically, subjects are refining their decision-making process, which, in turn, results in fewer "errors" and lower strategic uncertainty. We further build on this idea in Section 4.4, where we estimate the preference parameters in the binary choice setting under the same sequence of presentation and find that precision early on is lower than later on; that is, participants become more "precise" with repetition.

Result 4 *Dealer participation and bid amounts are higher in the early rounds than in later rounds.*

We test this hypothesis formally as part of the regression results in Table 4. While with p-values of 0.853 and 0.131, we find no evidence that dealer participation in the 2nd or 3rd rounds is different than in the 1st round, with p-values of .000 and .000, we find strong evidence that dealer bid amounts are different across the three rounds. These results are in line with Harrison, McKee, and Rutstrom (1989), who document a positive effect of experience on the profitability of the monopolist price in a posted-offer market; and with McKelvey and Palfrey (1995), who estimate the logistic version of the Quantal Response Equilibrium for several experiments on two-person normal-form games and show that precision is lower in early rounds than in later rounds. In other words, the conclusion common to both of the above papers and our work is that the amount of error decreases with experience. Note that in our experiment, participants receive no payoff feedback on the effectiveness of their strategy, and so learning through experience is limited. In Section 4.4, we explicitly test for increased precision in the binary choice treatment of our experiment.

4.4 Stochastic Choice

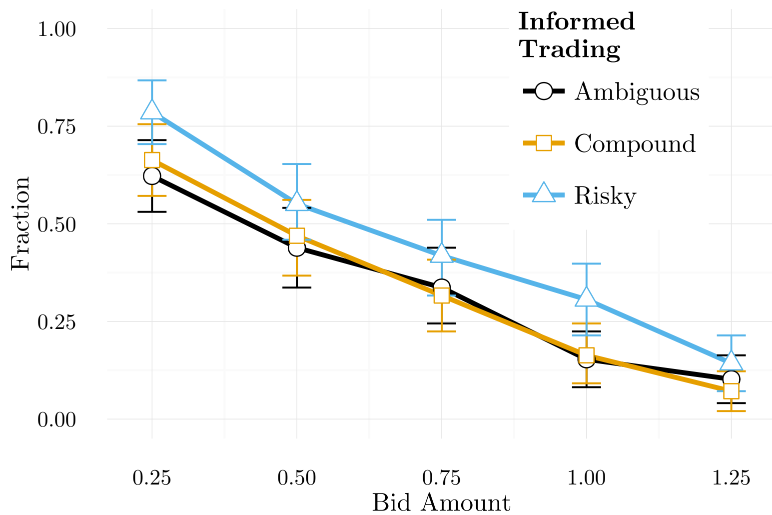
During the last part of the experiment, each participant makes decisions in the binary choice market structure, where dealers are choosing between bidding and opting out for a given bid amount. The aggregate results in Figure 7 present the fraction of participants who choose to bid rather than opt out for five different values of the bid amount. The graph clearly shows that as the bid amount increases, fewer and fewer participants choose to bid and, instead, opt out for the safe option. Another observation is that the fraction of subjects who choose to place a bid in the risky environment is higher than the fraction of subjects who choose to bid in the compound and ambiguous environments.

Using these data, we estimate aggregate attitudes towards risk, as well as subjective beliefs about compound and ambiguous environments.[8] Following Wilcox (2011), we estimate the contextual

[7] These results are consistent with those of the pilot version of this experiment (Appendix E) conducted at the University of Texas at Austin.

[8] Risk aversion is estimated under the assumption that subjects correctly perceive the risky urn to generate $p = .5$. Subjective beliefs can be estimated only once the risk aversion is "pinned down." In essence, we estimate attitudes towards compound risk and ambiguity relative to attitudes towards risk. Thus, an estimate of subjective belief of p=.419 in the ambiguous environment is indicative of more uncertainty aversion than is captured through the

utility specification, which was shown to perform as well as or better than other stochastic models. Results of the estimation are presented in Figure 7.[9] The behavioral estimates are 1) γ – risk aversion parameter; 2) p_C – subjective belief about the probability that an uninformed trader is drawn from the compound urn; and 3) p_A – subjective belief about the probability that an uninformed trader is drawn from the ambiguous urn.[10] In addition to the above parameters, we are interested in capturing any change to the precision in decision making. Therefore, we estimate the precision parameter, λ, for each of the three uncertainty environments, with higher λ implying higher precision in the decision-making process. The right panel of Figure 7 presents the estimation results.



Parameter	Estimate
γ	.858 (.100)
p_C	.429 (.020)
p_A	.419 (.022)
λ_R	15.9 (1.8)
λ_C	18.5 (2.0)
λ_A	16.3 (1.9)

Figure 7: Binary Choice Market. *Notes*: **Left Panel** – aggregate fraction of time that subjects chose to provide a bid rather than opt out for each of the three uncertainty scenarios. Bounds represent the 95% confidence interval around the mean. Bounds are obtained using nonparametric bootstrap. **Right Panel** – structural estimates: γ - risk-aversion parameter; p_C - subjective belief about the probability that an uninformed trader is drawn in the compound urn; p_A - subjective belief about the probability that an uninformed trader is drawn in the ambiguous urn; λ_i - precision parameter of the stochastic choice model for environment $i \in \{R, C, A\}$ (higher values denote higher precision in decision making).

We test whether subjects are compound-risk and ambiguity averse using a likelihood ratio test relative to estimates in Figure 7. Specifically, we test the restricted model ($p_R = p_C = p_A = .5$) against the unrestricted model presented in Figure 7. With a p-value of .000, we reject the restriction. Thus, there is significant evidence that uncertainty type matters. At the same time, using a likelihood ratio test, we find a p-value of .528 when testing a restriction that the subjective

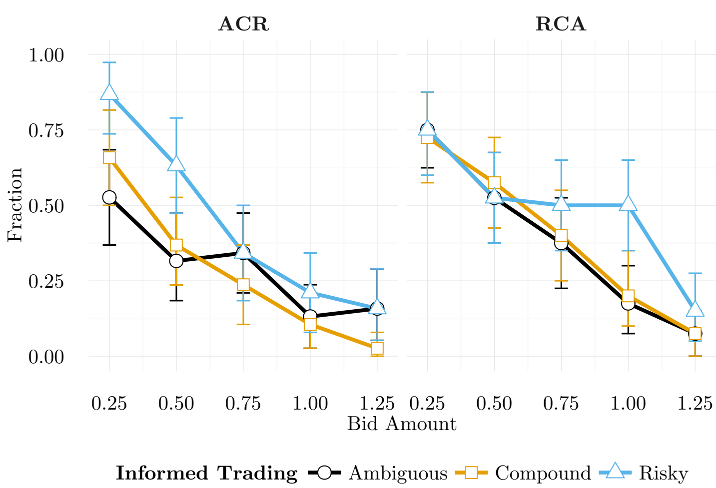
risk-aversion parameter, which is consistent with pessimism or ambiguity aversion. Note, however, that for our environment, we care only about one "side" of uncertainty, which can be captured with the worst-case scenario.

[9] We use the CRRA utility specification normalized by the best and the worst case outcomes on each context. See Appendix B for the estimation procedure.

[10] $p_C < .5$ is consistent with the failure to reduce compound lotteries documented in prior studies (Halevy, 2007; Abdellaoui, Klibanoff, and Placido, 2015) and is indicative of relative pessimism; $p_A < .5$ is consistent with pessimism and ambiguity aversion.

beliefs about the compound and ambiguous environments are the same.[11] Thus our results for the binary choice part of the experiment are consistent with the results for the monopoly and duopoly parts presented in Section 4.2, in which we found a difference in market outcomes for the risky versus the compound or ambiguous environments, but no difference between compound and ambiguous environments by themselves.

Next, we investigate whether there is any order effect in the binary choice setting similar to the one observed in the monopoly and duopoly settings. For presentation purposes, we consider two order sequences for which we ran the most sessions: ACR (Sessions 1-4) and RCA (Sessions 5-8). Figure 8 presents the raw data and estimates for these two order sequences.



Parameter	ACR Estimate	RCA Estimate	Test $\theta_{ACR} = \theta_{RCA}$
γ	.817 (.129)	.660 (.186)	.491
p_C	.398 (.026)	.444 (.033)	.269
p_A	.342 (.049)	.436 (.032)	.071
λ_R	20.7 (3.3)	12.3 (2.7)	.044
λ_C	23.3 (3.8)	20.1 (3.3)	.547
λ_A	12.1 (2.9)	21.2 (3.4)	.039

Figure 8: Binary Choice Decisions by Order. *Notes*: **Left Panel** – Fraction of time that subjects chose to provide a bid rather than opt out for the two order treatments. Bounds represent the 95% confidence interval around the mean. Bounds are obtained using nonparametric bootstrap. **Right Panel** – Structural estimates: γ - risk-aversion parameter; p_C - subjective belief about the probability that an uninformed trader is drawn in the compound environment; p_A - subjective belief about the probability that an uninformed trader is drawn in the ambiguous environment; λ_i - precision parameter of the stochastic choice model for environment $i \in \{R, C, A\}$ (higher values denote higher precision in decision making). In the test of the hypothesis column, θ refers to the the parameter being tested.

Result 5 *Precision in decision making increases across rounds.*

For the decision round that was presented first —the ambiguous in ACR order and in the risky in RCA order— we see a jagged choice pattern, which suggests that the dealers are choosing in a rather imprecise way. But as they gain experience, the pattern is smooth and more vertical when they are presented third, which can be seen in both the ambiguous treatment in RCA order and the risky treatment in ACR order. This observation suggests that the precision of their bids has

[11]For robustness, we use the Wilcoxon signed-rank test, to test whether the frequency distributions in the left panel of Figure 7 are the same and obtain a similar result. Note that the Wilcoxon signed-rank test requires only independent observations to be used; therefore, we considered the distribution of averages of individual subjects.

improved. The estimated preferences and precision parameters for the two order treatments are presented in the right panel of Figure 8. We also provide p-values for a test of equality between the two estimates from the ACR and the RCA treatments.[12]

Notice that, at the 5% level, only the difference in precision parameters is significant. Specifically, using a likelihood ratio test, we obtain a p-value of .039 and .044 and, thus, find significant evidence at the 5% level that λ_R and λ_A vary by order presentation. This is important evidence of increased precision in later rounds of the experiment.

We use the behavioral estimates from Figure 8 as an input into two stochastic models of choice: for the monopoly, we use standard multinomial logit, and for the duopoly, we use the logistic version of Quantal Response Equilibrium (QRE) of McKelvey and Palfrey (1995). Model predictions and the observed data are presented Figure 9.

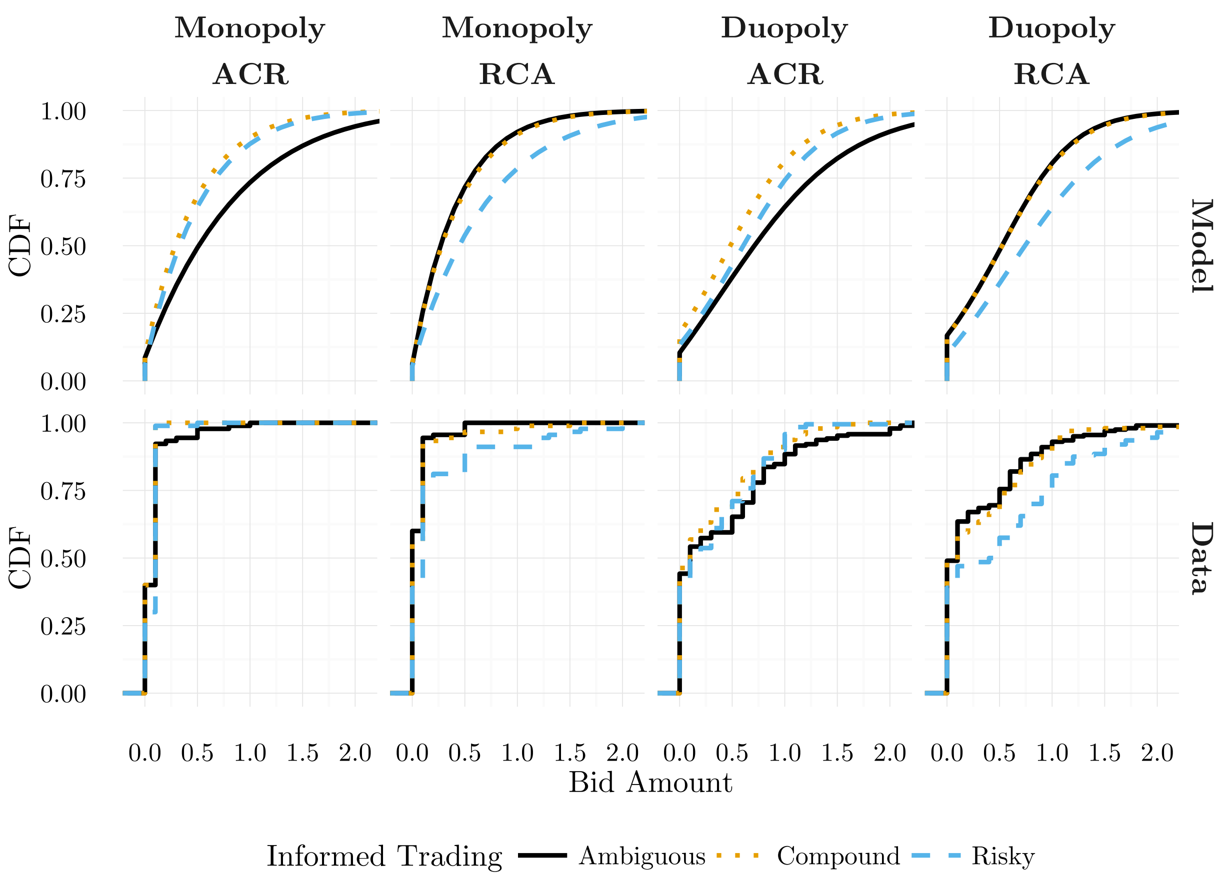


Figure 9: Stochastic Choice Models vs Data. *Notes*: **Top Panel**: model predictions using structural estimates of preference and precision parameters from the Binary Choice Decisions. **Bottom Panel**: aggregate data obtained from Monopoly and Duopoly markets.

We find that models capture the respective order difference between the ACR and the RCA

[12] Likelihood ratio test between unrestricted model (12 parameters) and the restricted model (11 parameters) with the restriction being placed on the equality of the specific parameter. For example, when testing whether risk aversion is the same between the two order treatments, we restrict γ to be the same, obtain the log-likelihood and carry out the likelihood ratio test relative to the unrestricted model. P-values are presented.

orders observed in the data. In particular, for the duopoly market structure in the RCA order treatment, the Risky CDF is clearly to the right of the Ambiguous and Compound CDFs. On the other hand, in the ACR order type, Ambiguous CDF is slightly to the right of the Risky CDF. This similarity between the QRE model predictions and the experimental results is striking because we did not estimate QRE on the data. Our results provide clear evidence of that the precision of decisions is a first-order factor.

In summary, we have shown that precision in decision making has a significant impact on market outcomes. In fact, it has the potential to override any differences that are due to preference parameters such as ambiguity or compound-risk aversion. This finding is important in light of mixed conclusions in the prior literature on ambiguity in experimental markets, such as Bossaerts, Ghirardato, Guarnaschelli, and Zame (2010) and Kocher and Trautmann (2013), who find that ambiguity aversion has a significant impact on the market outcome; Schnitzlein (2002) and Corgnet, Kujal, and Porter (2013), who do not; Huber, Kirchler, and Stefan (2014), who find mixed evidence; and recent work by Füllbrunn, Rau, and Weitzel (2014), who look specifically for conditions under which ambiguity aversion survives in the market.

5 Conclusion

We used market experiments with human subjects in a controlled environment to clarify the impact of uncertainty with respect to the extent of informed trading on market liquidity and trader welfare in monopoly and duopoly dealer markets. Specifically, traders were either informed or uninformed, and the uncertainty with respect to informed trading was generated using three types of urns: (i) a risky urn; (ii) a compound urn; and (iii) an ambiguous urn. We focused our attention on two key criteria of market liquidity - market resiliency (fraction of the time markets were open) and price (dealer bid distributions).

The main result of the paper is that, after accounting for the order of presentation, we find differences in dealer bidding behavior depending on whether the uncertainty about informed trading is presented as risk or compound risk and ambiguity. Specifically, when informed trading is viewed as risky, the bids are the largest; when informed trading is viewed as ambiguous or compound the bids are significantly smaller. Furthermore, we do not find a significant difference between compound risk and ambiguity. We also find evidence of an order effect: early decisions result in higher prices as compared to later decisions, even without any profit feedback. We explain this phenomenon through a refinement of the participant's decision-making process, which results in a more "precise" decision from a stochastic choice point of view.

We hope that the insights gained through this study will contribute to the discussion of how institutions themselves may interact with learning and the precision of decision making. By examining the effects of compound risk and ambiguity within the context of informed trading, we also hope to have shown that there are other important sources of uncertainty beyond asset values that merit attention and study.

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Appendix A: Experimental Instructions

Numbered bags hang on top of the whiteboard at all times during the experiment. Practice bag has 1 unknown ball in it. Bags #1-5 have 1 unknown ball in them. Bags#6 are empty (2 of them). Bag # 7 is empty.

E1: Hello and welcome to the experimental economics laboratory. My name is [Name E1], I am [Position E1]conducting this experiment about decisions under uncertainty. In front of you is an informed consent form. It briefly summarizes the experiment. Please read it.[...wait for students to read the form...] Your participation in this study is voluntary and you may decide not to participate in this study. If you agree to participate in this study, please direct your attention to the computer screen and read the instructions.

Experimental Instructions

Today's experiment will last about 1 hour (up to 1.5 hours). Everyone will earn at least $5. If you follow the instructions carefully, you might earn even more money. This money will be paid at the end of the experiment in private and in cash. *Show Cash.*

It is important that during the experiment, you remain SILENT. If you have any questions, or need assistance of any kind, RAISE YOUR HAND but DO NOT SPEAK. One of the experiment administrators will come to you and you may whisper your question to us. If you talk, laugh, or exclaim out loud, you will be asked to leave and will not be paid.

Each decision task will be a choice between two options. We will start with 3 practice rounds and go over all elements of the screen in detail. Also, we will go over the compensation procedure at the end of the three practice rounds.

In the first part of the experiment (Rounds 1-15) you will be a buyer of an imaginary asset.

Practice Round 1. Let's take a look at the options.

Option A, You can place a bid to purchase an asset from a seller. The asset pays $5.00 (Heads) or $0.00 (Tails) with 50-50% probability. Your purchase will depend on the type of the seller drawn from a practice bag. The seller is not a person in this room; rather, the seller will act according to a simple rule based on whether he is informed or uninformed. The difference between an informed and an uninformed seller is that, the uninformed seller will always sell the asset, while the informed seller will sell the asset only if asset value is $0.00.

After your bids have been placed, a random draw from a bag will determine whether the seller is informed (black ball) or uninformed (white ball). For practice rounds, the draw will be made from the "practice bag." *Show the bag.*

E1: Please direct your attention to E2, who will explain composition of the practice bag

E2: Composition of the practice bag There is one ball of unknown color (either black or white) in this bag. *Show the bag... let a participant verify that there is one ball there by touching it.* We add one black ball to the bag and one white ball. Black ball means the seller is informed. White ball means the seller is uninformed. To better understand this difference let us look at what happens when you select a bid. Please use the scroll bar to select bid=$1.00. The outcome table below option A describes four possible cases. The first two columns correspond to the seller being Informed. The last two columns correspond to the seller being Uninformed.

Use the scrollbar to select your bid. **Bid = $1.00.**

0.10 4.90

The following table summarized possible earnings for this round for Option A.

Outcome Table	Inf & AV = 5 (B & H)	Inf & AV=0 (B & T)	Uninf & AV = 5 (W & H)	Uninf & AV=0 (W & T)
Earnings ($) for this round:	0.00	-1.00	4.00	-1.00

Figure A1: Option A. Summary of Possible Earnings.

Column 1) If the asset value is $5.00 (Heads) and Informed trader (black ball) is drawn. Your earnings for the round will be $0.00. Remember that informed seller will not sell the asset if its value is $5.00 and so the sale did not go through.

Column 2) If the asset value is $0.00 (tails) and Informed trader (black ball) is drawn. Suppose that you place a bid = $1.00 then your earnings for the round will be $-1.00 (what you pay to the seller) + 0.00 (your earning from the asset) = $-1.00

Column 3) If the asset value is $5.00 (Heads) and Uninformed trader (white ball) is drawn. Remember, the uninformed seller will always sell the asset. Suppose that you place a bid = $1.00 then your earnings for the round will be $-1.00 (what you pay to the seller) +5.00 (your earning from the asset) = $4.00

Column 4) If the asset value is $0.00 (tails) and Uninformed trader (white ball) is drawn. Remember, the uninformed seller will always sell the asset. Suppose that you place a bid = $1.00 then your earnings for the round will be $-1.00 (what you pay to the seller) +0.00 (your earning from the asset) = $-1.00

You may change the value of your bid in which case the outcome table automatically recalculates possible earnings.

Now let's look option B. Option B, If you choose options B You receive $0.50 for the round regardless of the asset value and seller type.

This is summarized in outcome table presented below option B. You can see that you receive $0.50 regardless of the asset or seller type.

The following table summarized possible earnings for this round for Option B.

Outcome Table	B & H	B & T	W & H	W & T
Earnings ($) for this round:	0.50	0.50	0.50	0.50

Figure A2: Option B. Summary of Possible Earnings.

At this time please select Bid = 1.00 and click Option A. Followed by 'Submit Choice'.

Okay. Now let's take a look at the Practice Round Summary. It displays your last choice as well as the history of your prior choices together with the outcomes in a table. The outcome will be determined at the end of the experiment (practice rounds) by flipping a coin and drawing from an appropriate bag.

Please click Continue.

In practice round two please select option B and click "Submit choice".

Now you can see the summary for the round and notice how your decision and the outcome table is recorded and displayed in the history table.

History Table

Round	My Choice	My Bid	Other Choice	Other Bid	BH	BT	WH	WT
Practice	A	1.00			0.00	-1.00	4.00	-1.00
Practice	B				0.50	0.50	0.50	0.50

Figure A3: History Table.

Please click Continue. In the first part of the experiment you will be paired with another participant in this room. Pairs will be randomly chosen each round. Both of you will make a choice on whether to choose Option A and place a bid or to choose Option B and receive $0.50 for certain. However, the seller can only sell one asset hence he will sell to the person with the highest bid. This means that if your bid is greater than your partner's bid the outcome will be summarized by the table below option A. But if your bid is lower than your partner's bid, the seller will not sell the asset to you so your earnings for the round will be $0.00 regardless of the type of seller and the asset value.

Please choose between Option A and select a Bid or Option B. After you make your choice please click 'Submit Choice'.

Okay. Now you can see how your decision and your partners decision will be displayed to you during round summary and placed in the history table that you will have access too for the entire session. Note that if you and your partner place exactly the same bid one will be picked randomly and a red asterisk will denote which one was picked.

Each round 1-15 you will be re-matched with a random participant in this room. Let us take a look at the compensation procedure. In total you will make 15 decisions in the first part of the experiment, each corresponding to one of the bags. At the end of the experiment we will flip a coin 15 times (one for each of the rounds 1-15) and make a draw from an appropriate bag. Let's do this for the practice rounds.

Flip a coin 3 times if heads A=5 if tails A=0. Make a draw from the practice bag 3 times. Record everything

Okay. So the earnings for the first part of the experiment will be the sum of 15 round earnings (in this case 3 rounds of practice).

In the second part of the experiment (Rounds 16-30) you will have to make a choice between two options labeled A and B that will be displayed on your screen. Each decision will pertain to one of the bags 1-7, which will be clearly stated on your screen. The earning for the second part of the experiment will be the sum of earnings in rounds 16-30.

Thus the earning for the whole experiment will be the sum of your earnings for rounds 1-30. Notice that the earnings will be determined at the end of the experiment (after all decisions have been made). In case your total earnings are less that $5 you will receive $5.

BAG COMPOSITION

Each round will correspond to a draw from one of these bags. Let's go through the composition.

- Bags 1-5: One Unknown / One Informed / One Uninformed Seller
- Bag 6: 50% chance of 2 Informed Seller (black) & 1 Uninformed Seller (white) and 50% chance of 1 Informed Seller (black) & 2 Uninformed Seller (white)
- Bag 7: One Informed Seller / One Uninformed Seller

Now the tasks for which you will be compensated for will begin. Any information about current round will be displayed on your screen. In total, you will make 30 decisions that will affect your potential earnings. At the end of the experiment, the sum of your earnings for the 30 rounds will be your actual money earnings.

Please click "CONTINUE" when you are ready to begin. You will have 1 minute for each round. And the time will be on top of the screen.

At the beginning of each round let participants know which bag the decision corresponds to and the composition of each bag as follows:

- "Please make your decision for period 1.
- "decision in period 1 corresponds to bag #1". Bag # 1 was composed as follows: "One Unknown / One Informed / One Uninformed Seller."

Summary

- Right now you can see all 30 of your decisions. At this time we will make draws to determine which seller you faced in each round. And flip a coin to determine the asset value. *Flip the coins and write asset value on a board*
- Also, at this time we ask that you fill out the questionnaire that is being distributed.
- At this time we will call out participant ID#. Raise your hand when your number is called and we will bring and envelope containing your total earnings for the session.
- After you have completed your questionnaire and collected your earnings, you may leave.

Thank you for your participation in this experiment.

Appendix B: Estimation

When estimating the risk attitudes and subjective beliefs in Section 4.4, we consider the aggregate behavior, which can be summarized by a representative agent whose utility function is parameterized using a normalized version of the CRRA utility representation of the form:

$$u(x) = \frac{x^{1-\gamma} - 1}{1-\gamma}, \tag{B1}$$

where x is the outcome and γ is the risk-aversion parameter to be estimated. Thus, $\gamma = 0$ corresponds to a risk-neutral agent, and $> (<)0$ corresponds to a risk-averse (-loving) agent. Using the contextual utility approach of Wilcox (2011), we assume that the agents perceive choices relative to the range of outcomes found in the pair of options. That is,

$$U(b) = \frac{u(b) - u(o)}{u(b_{best}) + u(b_{worst})}, \tag{B2}$$

where b is the chosen bid; b_{best} is the available bid that generates the best possible utility; b_{worst} is the available bid that generates the worst possible utility; and o is the payoff of the outside option. Then, the representative agent chooses the option with the highest expected value given her current belief, subject to an error, which is assumed to be distributed according to a logistic distribution centered at zero. Using maximum likelihood, we estimate a latent structural model of choice of the form:

$$Pb = \frac{1}{1 + e^{-\lambda[EU(b) - EU(O)]}}. \tag{B3}$$

We pool the choices made by all participants and estimate a single set of parameters for each model, where P_{bA} is the probability that the subject chooses to bid given that she is presented with a choice: option a) bid b or b) opt-out (O). So, for a given subjective belief p_0, we can obtain an expected utility value for the two alternatives presented. Using the Logit specification in the equation above, we obtain maximum likelihood estimates of γ and p.

Appendix C: Data

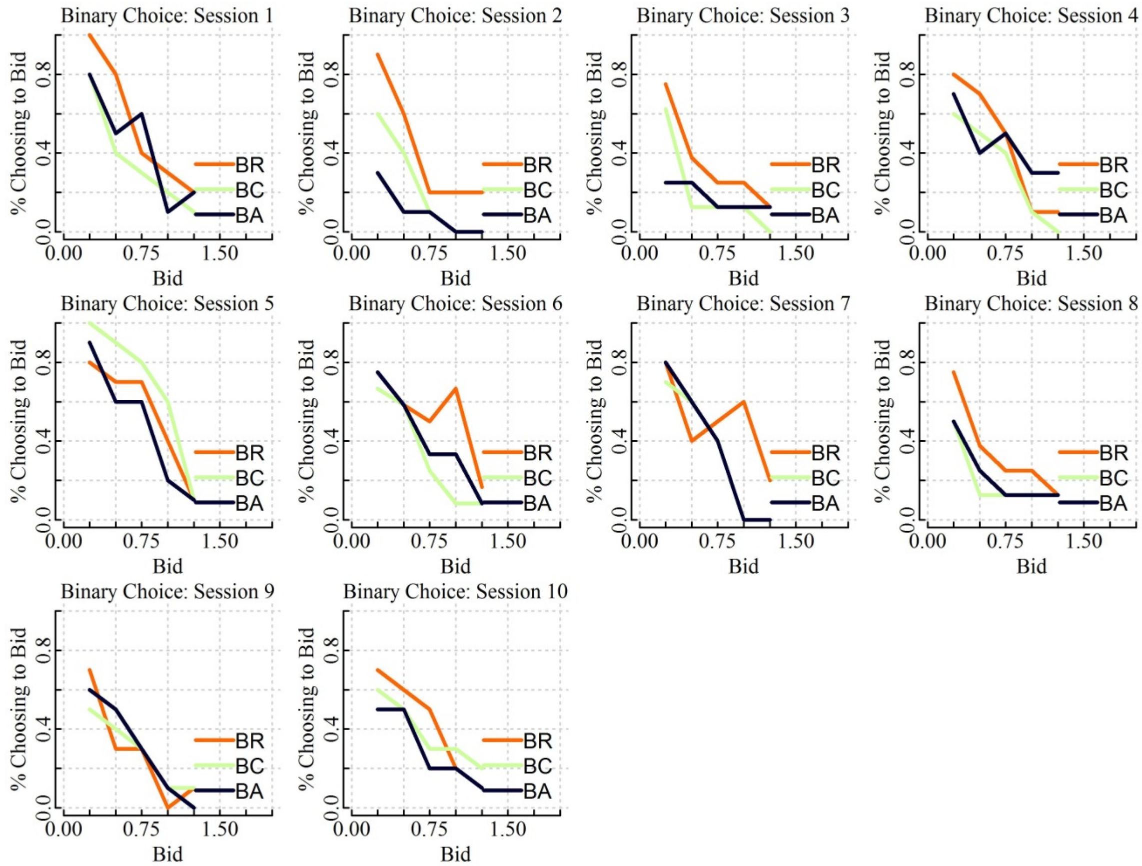

Figure C1: Binary Choice Decisions by Session.

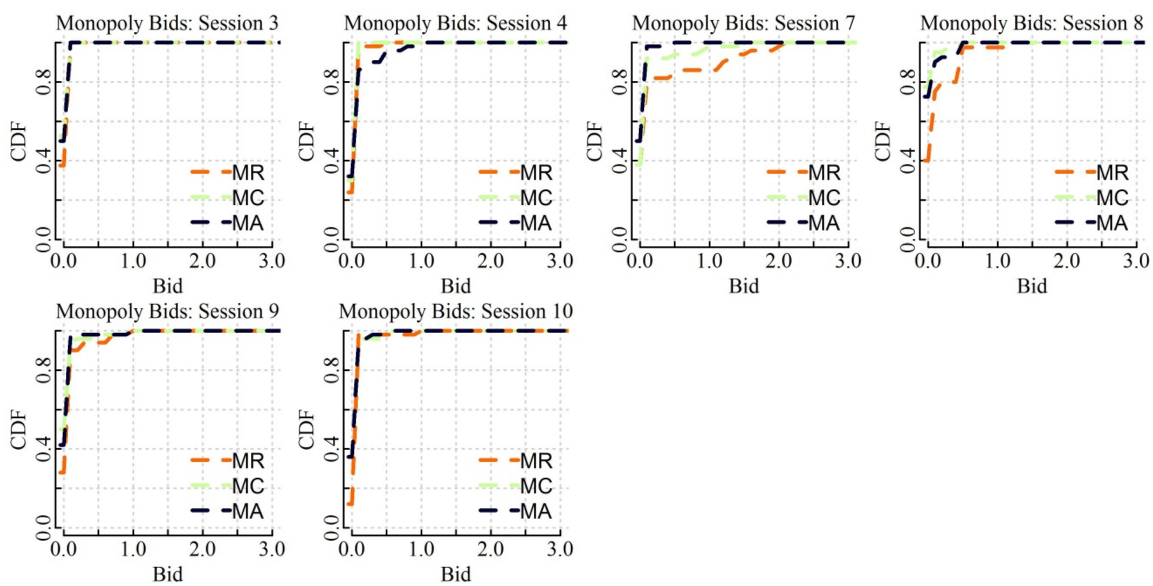

Figure C2: Monopoly Bid Distributions by Session by Session.

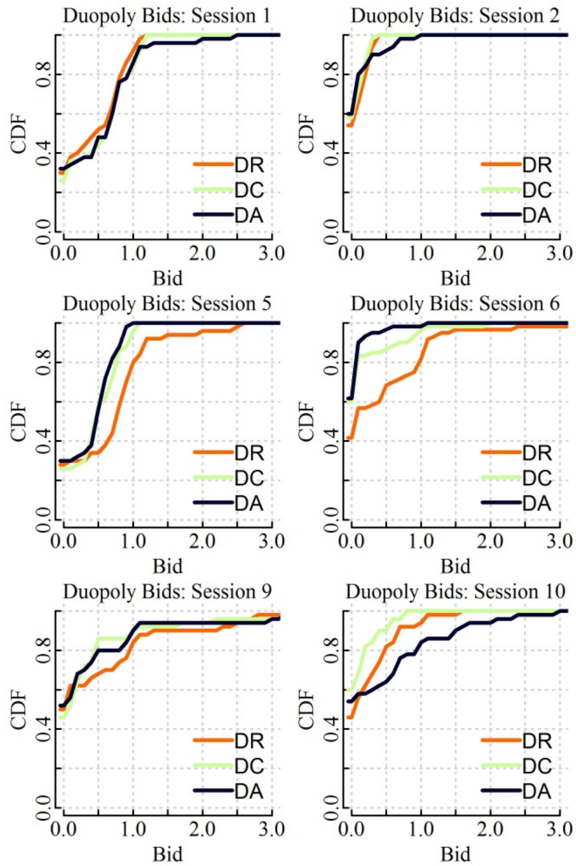

Figure C3: Duopoly Bid Distributions by Session by Session.

Appendix D: Pilot Experiment

Session	Subjects	Decisions	Order R1	R2	R3	R4	R5	R6
1	10	15	DR	DC	DA	–	–	–
2	12	15	DR	DC	DA	–	–	–
3	8	30	DR	DC	DA	MR	MC	MA
4	10	30	DR	DC	DA	MR	MC	MA

Table D1: Treatments Summary. *Notes*: Av. P. - average payoff; Min. P. - minimum payoff; Max. P. - maximum payoff; ** If participants' cumulative earnings are negative, they are subtracted from the show-up fee. If the outcome is still negative, the participant earns $0.00.

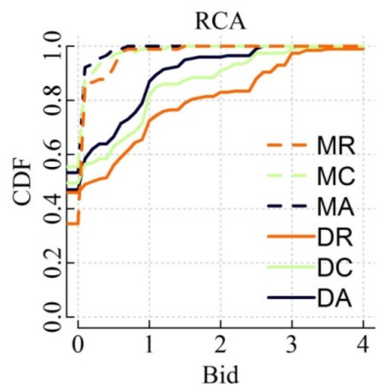

Figure D1: Bid Distribution by Market Type.

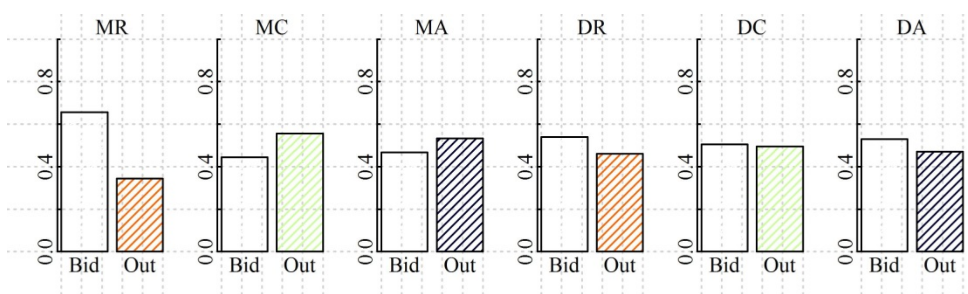

Figure D2: Individual Dealer Participation.