Ambiguity about Informed Trading in Dealer Markets
- An Experiment*

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Abstract:
We use an economic experiment to examine the impact of an ambiguous 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 that dealer’s bidding behavior is less aggressive under an ambiguous than under a risky level of informed trading. Additionally, we find that the stochastic nature of choice can hinder our ability to observe a difference in market outcomes among the risky, the compound, and the ambiguous environments.

Keywords: Dealer Markets, Market Experiments, Uncertainty

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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, including whether the market will shut down under duress. 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, leading to a 1000-point (∼9%) plunge in the Dow Jones Industrial Average - losses that were recovered just twenty minutes later. 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) and that the crash would have been avoided had liquidity providers remained in the marketplace. In contrast to the use of indirect measures of informed trading based on actual transaction data, such as the probability of information-based trading (PIN) in Easley, Kiefer, O’Hara, and Paperman (1996) and subsequent empirical proxies, our study seeks to analyze the probability of informed trading in dealer markets 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. Specifically, we construct the risky (R) urns, whose exact composition is known to the participants; the compound (C) urn, whose composition “process” is known; and the ambiguous (A) urn, whose composition process is unknown. Thus, in risky and compound situations, the probability distribution is objectively known, while in an ambiguous situation, it is not.

In this paper we ask: “What is the role of uncertainty about informed trading in dealer market liquidity?” To answer this question, we build a simple version of a financial market in which dealers face uncertainty about the level of informed trading. The value of the asset that they

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1 Easley, de Prado, and O’Hara (2012) develop the volume synchronized probability of informed trading (VPIN) to use as a short-term indicator of order toxicity in high-frequency markets, which, they suggest, was the primary reason for the “flash crash” of 2010. Recently developed alternative measures, such as intra-day probability of informed trading (PROBINF) by Kumar and Popescu (2014), also seek to empirically determine the level of information asymmetry.

2 The C urn was composed as follows: two urns of known composition (one with one black marble and two white marbles and one with two black and one white marbles) are placed in a box and one is randomly chosen by a participant to be the C urn used for the draws. The A urn was composed as follows: one marble is placed in the urn prior to start of the experiment, and the only information provided to the participant is that it could be either black or white. During the experiment, subjects verify that there is one marble in the urn by touching it, and they observe one black and one white marble added to the urn. Thus, the outcome space is the same between the C and the A urns; however, unlike the C urn, no objective probabilities are given for the composition of the A urn - there is ambiguity about the number of black marbles.
trade is drawn from a distribution with known mean and variance. Given the well-known fact in market microstructure literature that liquidity has multiple dimensions (e.g., “Market liquidity is a slippery and elusive concept, in part because it encompasses a number of transactional properties of markets” (Kyle, 1985)), we focus on two of its dimensions: (i) resiliency, measured as the fraction of time a market is open and (ii) price. 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? That is, we compare the three scenarios of uncertainty about the informed trading across the two dimensions of market liquidity.

Prior theoretic research (Glosten, 1989) for environments with risky informed trading leads us to predict that a concentrated dealer market, such as a monopoly specialist, will have higher trading costs but be more resilient in environments where asymmetric information is high, while a dispersed dealer market with multiple dealers will break down more often but offer lower trading costs. Whether this fundamental trade-off in resiliency and trading cost actually exists under ambiguity, though, is an empirical question 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 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. 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 makers, on average. When allowing dealers to exit the market at their discretion, Sheh and Wilcox (2009) find that a duopoly market structure is more resilient than a monopoly market structure in an asymmetric information setting in terms of liquidity provision. But dealers in these experiments were told exactly the level of informed trading in the market and did not have to worry about this source of uncertainty. This is clearly not reflective of what occurs in actual financial markets, where dealers have to constantly assess and react to potential 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

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3 For our experimental design, trading cost is inversely related to the bid amount. That is, the higher the bid quote, the lower the trading cost.
4 The dimension of liquidity examined in Schnitzlein (2002) is measured in terms of price change per unit order flow on price continuations.
order to address scenarios in which knowledge of underlying probabilities about informed trading is imprecise at best.

Our work contributes to the broader literature on decision making under ambiguity, which has recently gained considerable attention from both the individual (Halevy, 2007; Eliaz and Ortoleva, 2012; Abdellaoui, Klibanoff, and Placido, 2013; Eichberger, Oechssler, and Schnedler, 2014) and the market (Bossaerts, Ghirardato, Guarnaschelli, and Zame, 2010; Corgnet, Kujal, and Porter, 2013; Kocher and Trautmann, 2013; Füllbrunn, Rau, and Weitzel, 2014) perspectives. In contrast to the aforementioned literature on ambiguity in asset markets, 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)). We do so by comparing dealer markets where informed trading is presented as pure risk, compound risk, or ambiguity. In particular, 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 choose to submit bids to the risky rather than the ambiguous prospect, which leads to thinner markets for the ambiguous one.\(^5\) 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 summary, while all of the above studies consider an asset’s value ambiguous, we consider the impact of ambiguity with respect to the level of informed trading while the asset’s value in question is known to be risky, not ambiguous.

Additionally, we investigate the implications of the stochastic nature of the decision maker’s actions for market outcomes; 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’ decision 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.” We show that subjects refine their decision-making process from early rounds to the late rounds, even without payoff feedback, which reduces strategic uncertainty and results in a significantly different equilibrium distribution of prices. By accounting for the precision, we are also able to find a difference in dealer behavior between risky and ambiguous informed trading environments. Finally, we use behavioral estimates of precision obtained from binary choice decisions as an input to the Quantal Response Equilibrium

\(^5\) Kocher and Trautmann (2013) state: “The one-shot auction design is applied because of the inherent uniqueness of ambiguous situations and because it avoids possible biases in learning with repeated auctions.” This is the reason that we use a first-price sealed bid auction in our experimental design and eliminate payoff feedback.
model of McKelvey and Palfrey (1995) to provide a theoretical benchmark that corroborates the outcome of the experimental dealer markets.

The rest of the paper is organized as follows. In Section 2, we introduce the environment and potential challenges when incorporating risk aversion and stochastic choice on the part of the dealer. In Section 3, we describe the experimental design and present an overview of the data. In Section 4, we present and discuss theoretical predictions and results. Finally, we present our conclusions in Section 5.

2 Environment

In this section, we describe the environment and demonstrate potential challenges when testing for differences in behavior that could arise from the stochastic nature of choice and subjective beliefs about an uncertain process.

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, or market maker, is a market specialist who provides a Bid and Ask quote on the asset prior to the revelation of the true value. While in reality, dealers place a Bid and an Ask quote, in our experiment we will focus on the bid side. 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.

Traders buy or sell one unit of 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 (liquidity) reasons to trade the 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 market maker 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 \( p \).
Choose whether to bid or opt out. Asset value, $V$, is revealed to the informed trader. 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 $(V - b)$, where $b$ is the bid amount.

2.3 Markets

Three market structures considered in this study differ with respect to decision complexity and strategic complexity. Specifically, we consider the binary choice (B) structure, the monopoly (M) structure and the duopoly (D) structure. Arguably the most interesting (and applicable) of these is the duopoly market structure, where uncertainty about the level of informed trading interacts with the strategic uncertainty about other dealers’ actions, while the monopoly and the binary market structures are used to provide useful theoretical and experimental benchmarks. In particular, the difference between the monopoly and the competitive markets is one of the fundamental questions in the market microstructure literature, while the binary choice structure is used to estimate the subject’s preferences, which, in turn, are used to provide theoretical benchmarks for both monopoly and duopoly markets.

2.3.1 Binary Choice

The binary choice market structure is equivalent to ultimatum bargaining, whereby the dealer decides whether or not to accept an exogenously specified selling price (choose to bid $b$) or to opt out and receive his outside option, denoted by $S$. Figure 2 presents the dealer’s decision in the binary choice market structure.
The expected utility of a bid, $b$, and outside option, $O$, is given by equations (1) and (2), respectively:

$$EU_B(b) = q(1 - p)u(W + H - b) + qpu(W) + (1 - q)u(W + L - b)$$  \hspace{1cm} (1)$$
$$EU_O = u(W + S)$$  \hspace{1cm} (2)$$

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 $q$. The uncertainty about the trader type ($p$) will be the key element of our experimental design and will be described in detail in Section 3.1.

The binary choice market structure is the simplest environment presented to the subject: it lacks the strategic element and the complexity of multinomial choice. However, it allows us to use the existing canon of work on binary choice to estimate risk preference, as well as subjective beliefs in compound and ambiguous environments. Additionally, we estimate the precision with which subjects make their decision, which is also known as the “rationality” parameter. This is useful because we then can feed these estimates into a theoretical model and obtain a meaningful benchmark.

### 2.3.2 Monopoly

The key difference between the binary choice (B) and the monopoly (M) market is that in the former, the bid amount is fixed, while in the latter, the dealer determines the bid amount. Therefore, the monopolists decision is a multinomial discrete choice as opposed to a binary discrete choice.
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

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

(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:

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

(4)

The optimal decision is either to provide the minimum bid possible or to opt out. Under the stochastic choice framework, however, 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 (M) and the duopoly (D) structures 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 and 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 his own bid, $b_1$, but also of the bid by the second dealer, $b_2$.

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

(5)

where $EU_M(\cdot)$ is the expected utility of 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) and Quantal Response Equilibrium (QRE) of this game, presented in the Figure 3, depend on the beliefs about the probability of informed trading ($p$) and the risk preference ($\gamma$) of the dealer. Specifically, we consider theoretical predictions for the risk-neutral and risk-averse agents and two subjective beliefs corresponding to $p = 1/2$ (“neutral beliefs”) and $p = 1/3$ (“pessimistic beliefs”) for comparison.\(^6\)

\(^6\)The parameters chosen are the same as will be used in the experiment: $V \in \{5.00, 0.00\}$, $q = .5$, $b \in 0, .1, .2, .49$. 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 the payoff outcome of their decisions until the after all decisions have been made.
Consider the top left graph of Figure 3. With a sharp distinction between the two cases of subjective beliefs, it would seem that any difference in subjective beliefs would be easily identified within the duopoly set-up. The challenge arises when one considers risk aversion and the stochastic nature of choice. First, once we assume that agents exhibit mild risk aversion, which is commonly documented in the experimental literature, the difference between the two cases is reduced (bottom left). If we incorporate the stochastic nature of choice and consider the Quantal Response Equilibrium (McKelvey and Palfrey, 1995) with the precision parameter of $\lambda = 15$, the difference decreases significantly for the risk-neutral agent (top right), and even more so for the risk-averse agent (bottom right).

Interestingly, the distribution of bids for a combination of low precision ($\lambda = 15$) and the “worst case scenario” subjective belief ($p = 1/3$) is actually to the right of the bid distribution of high precision ($\lambda \to \infty$) and “neutral” subjective belief ($p = 1/2$) - that is, the low precision of decision making could negate the effect of any pessimism associated with an ambiguous environment. Later, we will present evidence that suggests that low dealer precision is a crucial factor that limits our ability to detect ambiguity aversion effects. We consider our study’s emphasis on the precision of dealer decision making a unique and important contribution to our understanding of behavior under uncertainty in dealer markets.

The choice of $\lambda = 15$ is for demonstration purposes and is motivated by the estimates from Section 4.
An important question from an experimental design perspective, is whether we expect to distinguish between the equilibrium behavior for the “neutral” and the “pessimistic” scenarios at all. In other words, given two samples of i.i.d. bids drawn from the “neutral” and “pessimistic” bid distributions (e.g., Figure 3), what is the minimum precision at which we can statistically detect any difference? Alternatively, what sample size is required to distinguish between the two bid distributions for a given precision parameter? To help answer these questions, we conduct a simulation experiment by drawing a sample of \( n = 100 \) from distributions for the “neutral” and “pessimistic” subjective beliefs and a given precision parameter (\( \lambda \)) and find the p-value associated with the Kolmogorov-Smirnov test. We repeat this 100 times and plot the average, as well as 95% confidence bands for different values of \( \lambda \). Results are presented in Figure 4.

![Figure 4: Effect of \( \lambda \) on our ability to distinguish between bid distributions generated from “neutral” and “pessimistic” beliefs. Notes: Bounds represent the 95% confidence interval around the mean. Bounds are obtained using nonparametric bootstrap. Notice that as \( \lambda \to \infty \), QRE \( \to \) NE.](image)

Thus, our ability to reject the difference between the two best response functions with 100 observations is limited when the precision with which agents make their decision is low. The challenge is even greater when we consider risk aversion: the “Risk Averse” line is to the right of the “Risk Neutral” line in Figure 4. In our study, we will estimate the precision with which agents make their bid decisions from the binary choice part of the experiment. We then verify whether the sample size is sufficient for us to expect the difference to be significant.
3 Experimental Design

Since the purpose of this paper is to investigate dealer behavior, we use human participants in the role of dealers, while role of traders is predetermined (for both informed and uninformed). 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. The rule for transactions is that “the uninformed trader will always sell the asset, while the informed trader will only sell the asset only if its value is less than dealer’s bid.” In this way, the informed trader exploits his private knowledge for his own profit.

3.1 Uncertainty about informed trading

The uncertainty about informed trading is implemented as risk, compound risk, or ambiguity. The three scenarios are implemented as 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 (R) urns, whose exact composition is known to the participants; compound (C) urns, whose composition “process” is known; and ambiguous (A) urns, whose composition process is unknown.

![Urn Diagram](image)

Figure 5: Urns. *Notes:* R - risky urn. C - compound urn. A - ambiguous urn. Urn C is constructed as follows: two urns are constructed in front of the participants using the same procedure as for the R urn; then, these two urns are placed in a box, and one is randomly drawn by a participant to be the C urn used in the experiment. Urn A 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 marbles are added to the urn.

Figure 5 shows the R urn, the C urn, and the A urn used in the experiment. The R (risky) urn contains 1 black marble and one white marble. The C (compound) urn is constructed as follows: among 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. And
the A (ambiguous) urn is constructed as follows: 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

Treatments of the experiment differ based on the type of decision made by the participant, the type of uncertainty, and the order of presentation. Specifically, we consider a duopoly (D) and a monopoly (M), as well as a binary choice (B) for each of the uncertainty scenarios presented in Section 3.1. Table 1 summarizes the nine possible combinations.

<table>
<thead>
<tr>
<th>Decision Type</th>
<th>Uncertainty</th>
</tr>
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<tbody>
<tr>
<td>D</td>
<td>DR, DC, DA</td>
</tr>
<tr>
<td>M</td>
<td>MR, MC, MA</td>
</tr>
<tr>
<td>B</td>
<td>BR, BC, BA</td>
</tr>
</tbody>
</table>

Table 1: Treatments. Notes: Decision Type: D - duopoly; M - monopoly; B - binary choice; Uncertainty of Informed Trading: R - risky; C - compound; A - ambiguous.

A participant is faced with five decision tasks for each of the treatments of Table 1. In each decision task, the dealer needs to decide on whether to place a bid ($b_i$) or to opt out ($O$). For the monopoly and the duopoly treatments, the 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 subject’s reaction to uncertainty and minimize learning and income effects.

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, while the probability distribution of informed trading is unknown in the ambiguous case.

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

Table 2: Summary of Decision Task Parameters.
With so many possible order combinations, we have to narrow them down to a reasonable number of order treatments for our design. First, we group together decisions pertaining to a specific market treatment, thus minimizing any confusion that subjects might experience about the three market structures that they are in. Second, we go back to our main goal - to test differences between uncertainty treatments and to ensure comparison validity fix order in which the markets are presented. Finally, the markets of most interest in terms of complexity of the decision and applicability are the duopoly markets; therefore, we keep them first. Table 3 gives a final breakdown of treatments that we used in each of the ten sessions of the experiment.

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<td>–</td>
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<td>BR</td>
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<td>–</td>
<td>–</td>
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<td>MA</td>
<td>MC</td>
<td>MR</td>
<td>BA</td>
<td>BC</td>
<td>BR</td>
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<td>$19.4</td>
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<td>$25.5</td>
</tr>
<tr>
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<td>DR</td>
<td>DC</td>
<td>DA</td>
<td>BR</td>
<td>BC</td>
<td>BA</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>10</td>
<td>30</td>
<td>$30.1</td>
<td>$17.6</td>
<td>$38.6</td>
</tr>
<tr>
<td>6</td>
<td>DR</td>
<td>DC</td>
<td>DA</td>
<td>BR</td>
<td>BC</td>
<td>BA</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>12</td>
<td>30</td>
<td>$14.3</td>
<td>$7.4</td>
<td>$28.0</td>
</tr>
<tr>
<td>7</td>
<td>DR</td>
<td>DC</td>
<td>DA</td>
<td>MR</td>
<td>MC</td>
<td>MA</td>
<td>BR</td>
<td>BC</td>
<td>BA</td>
<td>10</td>
<td>45</td>
<td>$23.4</td>
<td>$10.3</td>
<td>$38.2</td>
</tr>
<tr>
<td>8</td>
<td>DR</td>
<td>DC</td>
<td>DA</td>
<td>MR</td>
<td>MC</td>
<td>MA</td>
<td>BR</td>
<td>BC</td>
<td>BA</td>
<td>8</td>
<td>45</td>
<td>$30.0</td>
<td>$22.5</td>
<td>$43.6</td>
</tr>
<tr>
<td>9</td>
<td>DR</td>
<td>DA</td>
<td>DC</td>
<td>MR</td>
<td>MA</td>
<td>MC</td>
<td>BR</td>
<td>BA</td>
<td>BC</td>
<td>10</td>
<td>45</td>
<td>$24.4</td>
<td>$5.0</td>
<td>$36.7</td>
</tr>
<tr>
<td>10</td>
<td>DA</td>
<td>DR</td>
<td>DC</td>
<td>MA</td>
<td>MR</td>
<td>MC</td>
<td>BA</td>
<td>BR</td>
<td>BC</td>
<td>10</td>
<td>45</td>
<td>$35.5</td>
<td>$18.3</td>
<td>$42.4</td>
</tr>
<tr>
<td>Overall</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>98</td>
<td>–</td>
<td>$25.1</td>
<td>$5.0</td>
<td>$50.6</td>
</tr>
</tbody>
</table>

Table 3: Sessions Summary. Notes: R1-9 - rounds, each corresponding to a sequence of 5 decisions; Sub - number of participants; Dec. - number of decisions made; Av./Min/Max P. - average/minimum/maximum payoff.

### 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 numbers of participants varying between eight and twelve. We programmed and conducted the experiment using the software z-Tree (Fischbacher, 2007). All randomization were 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

Table 4 present aggregate results for individual dealer’s bidding behavior for monopoly (M) and duopoly (D) market structures for each of the three uncertainty scenarios: risk (R), compound risk (C), and ambiguity (A).

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Dealer Bid %</th>
<th>Average Bid $</th>
<th>Min Bid $</th>
<th>25% Bid $</th>
<th>Median Bid $</th>
<th>75% Bid $</th>
<th>Max Bid $</th>
</tr>
</thead>
<tbody>
<tr>
<td>MR</td>
<td>71</td>
<td>0.20</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>2.1</td>
</tr>
<tr>
<td>MC</td>
<td>54</td>
<td>0.14</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>1.5</td>
</tr>
<tr>
<td>MA</td>
<td>54</td>
<td>0.14</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>0.1</td>
<td>1.0</td>
</tr>
<tr>
<td>DR</td>
<td>58</td>
<td>0.77</td>
<td>0.3</td>
<td>0.7</td>
<td>1.0</td>
<td>4.9</td>
<td></td>
</tr>
<tr>
<td>DC</td>
<td>51</td>
<td>0.60</td>
<td>0.2</td>
<td>0.5</td>
<td>0.8</td>
<td>4.9</td>
<td></td>
</tr>
<tr>
<td>DA</td>
<td>52</td>
<td>0.73</td>
<td>0.3</td>
<td>0.6</td>
<td>1.0</td>
<td>4.9</td>
<td></td>
</tr>
</tbody>
</table>

Table 4: Individual Dealer Bids. Notes: Dealer bid % - fraction of the time an individual dealer provides a bid as opposed to choosing a safe outside option; Aver. Bid $ - average bid conditional on providing a bid.

We observe that the distributions seem to differ both by uncertainty type and by market structure. In particular, when the uncertainty about the level of informed trading is presented as pure risk, we find that human dealers choose to bid more frequently and with higher bid amounts than when the level of informed trading is presented as compound risk or ambiguity. Additionally, there is a stark difference between dealer behavior within the monopoly and the duopoly environments. In what follows, we formally test the main hypotheses of this paper.

First, in Section 4.1, we test whether market liquidity varies by uncertainty type and market structure. Second, in Section 4.2, we test whether market liquidity varies by order of presentation. Finally, in Section 4.3, we analyze subject behavior within the binary choice structure; specifically, we obtain behavioral factor 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 construct a meaningful theoretical benchmark and shed light on the nature of the learning and the effect of precision in decision making on the market outcome.8

4.1 Uncertainty Type

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 bid amount distribution while holding order of presentation and market structure fixed. Figure 6 presents the data.

8We do not estimate the QRE, but, rather, use parameters obtained from the binary choice part of the experiment to construct a meaningful benchmark to help in our understanding of dealer behavior.
As Figure 6 demonstrates, subjects choose to provide bids more frequently in the R uncertainty treatment for all six cases. In other words, dealer participation depends on the uncertainty type:

**Hypothesis 1** *Dealer participation varies by uncertainty type.*

Our first research hypothesis deals with dealer participation and the resulting market resiliency. We run a subject fixed effects logistic regression with the uncertainty type (A, C, or R), the order of presentation (1st, 2nd, or 3rd), and the market structure (M or D) 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 Table 5.

The coefficient on R is positive and significant (p-value of 0.000). Therefore, 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, the coefficient on C is indistinguishable from zero (p-value of 0.701), meaning that there is no difference between the proportions of the time that subjects choose to provide a bid in the compound treatment compared to the ambiguous treatment. The latter result is consistent with Halevy (2007) and Abdellaoui, Klibanoff, and Placido (2013),
who find more aversion to the compound risk than the simple risk, and an association between the ability to reduce compound risk and ambiguity attitudes.

<table>
<thead>
<tr>
<th>A: Dealer Participation</th>
<th>B: Dealer Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable: Bid (Yes/No)</td>
<td>Dependent Variable: Bid Amount ($)</td>
</tr>
<tr>
<td>Coefficient Estimate</td>
<td>Coefficient Estimate</td>
</tr>
<tr>
<td>p-val.</td>
<td>p-val.</td>
</tr>
<tr>
<td>H1: Uncertainty</td>
<td></td>
</tr>
<tr>
<td>A</td>
<td>-</td>
</tr>
<tr>
<td>C</td>
<td>-0.059 (0.154)</td>
</tr>
<tr>
<td>R</td>
<td>0.597 (0.125)</td>
</tr>
<tr>
<td>H2: Market</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>-</td>
</tr>
<tr>
<td>M</td>
<td>0.461 (0.118)</td>
</tr>
<tr>
<td>1st</td>
<td>-</td>
</tr>
<tr>
<td>2nd</td>
<td>-0.030 (0.163)</td>
</tr>
<tr>
<td>3rd</td>
<td>-0.197 (0.130)</td>
</tr>
<tr>
<td>H3: Order</td>
<td></td>
</tr>
<tr>
<td>Const.</td>
<td>0.131 (0.210)</td>
</tr>
</tbody>
</table>

Observations | 2,310 |
Log Likelihood | -1,280 |
Akaike Inf. Crit. | 2,574 |
Observations | 1,292 |
R² | 0.616 |
Adjusted R² | 0.584 |

Table 5: Subject Fixed Effects Regressions. Notes: The coefficients are relative to “A”, “D”, and “1st.” A: Dealer participation is a binary variable. B: Bid amount is conditional on the dealer providing a bid.

Next, we consider whether dealer bid quotes for the three uncertainty environments differ from each other. We do this by looking only at 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 pure risk, compound risk, or ambiguous?

**Hypothesis 2** Dealer bid amounts vary by uncertainty type.

We run a subject fixed effects regression with the uncertainty type (A, C, or R), the order of presentation within same market structure (1st, 2nd, or 3rd), and the market structure itself (M or D) as the independent dummy variables and the bid amount as the dependent variable. The regression results are presented in Table 5B. 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).

Table 5 also sheds 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 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 ambiguous treatment.

### 4.2 Order

When we consider the aggregate results in Table 4, it appears that bids are greater for MR (DR) treatment than for MC and MA (DC and DA). However, this is not the case for all sessions. In particular, the early bid amounts seem to be greater than the later ones. A natural question arises: how do early decisions of whether and which quote to provide differ from later decisions of the same kind? We devote this section to understanding differences that arise due to the order of presentation within the monopoly and duopoly markets. Figure 7 presents the results by the market structure and uncertainty type.

![Order Graph](image)

**Figure 7:** Holding Market and Uncertainty Type Fixed. *Notes:* First/Second/Third order in which a set of five decisions corresponding to the same uncertainty setting is presented for a given market. For example, the ambiguous (A) setting is presented first in Sessions 1-4 and 10, second in Session 9, and third in Sessions 5-8. Bid amount of zero means that dealer is choosing to take an outside option.

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9Figures 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 when the risky environment is presented first, as in Sessions 5-9, the dealer is bidding more aggressively than when the risky environment is presented second or third, as in Sessions 1-4 and 10. A similar pattern holds true when the ambiguous environment is presented first, as in Sessions 1-4 and 10, as compared to when the ambiguous environment is presented second or third, as in Sessions 5-9. What might be the reason behind this difference? We argue that this is evidence of learning; specifically, subjects are refining their decision-making process, which, in turn, results in fewer “errors” and lower strategic uncertainty. Next, we test whether the difference between order treatments are significant. We further build on this idea in Section 4.3, where we estimate the preference parameters in the binary choice setting under the same sequence and find that precision early on is lower than later on; that is, participants become more “precise” with repetition.

**Hypothesis 3** Dealer behavior varies by order of presentation.

We test this hypothesis formally as part of the regression results in Table 4. While with p-values of 0.852 and 0.131, we find no evidence that dealer participation in the 2nd or 3rd rounds is different than 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 common conclusion in the literature is that the amount of error decreases with experience. The difference in our experiment is that participants receive almost no feedback on the effectiveness of their strategy and so learning through experience is limited. Our explanation of this order effect with no profit feedback would be through the refinement of the dealer decision-making process, resulting in a higher precision of decision making in later rounds. In Section 4.3, we explicitly test for increased precision in a related binary choice setting.

### 4.3 Stochastic Choice

During the last part of the experiment, each participant made 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 8 present the fraction of participants who chose 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 both the fraction of subjects who choose to bid in both the compound and ambiguous environments.

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10These results are consistent with the pilot version of this experiment (Appendix E).
Using these data, we estimate aggregate attitudes towards risk, as well as subjective beliefs about compound and ambiguous environments. Following Wilcox (2011), we estimate the contextual utility specification, which was shown to perform as well as or better than other stochastic models. Results of the estimation are presented in Figure 8. The behavioral estimates are 1) $\gamma$ - risk aversion parameter; 2) $p_C$ - subjective belief about probability that an uninformed trader is drawn from the C urn; and 3) $p_A$ - the subjective belief about probability that an uninformed trader is drawn from the A urn. In addition to the above parameters, of special interest to us, is the ability to capture the stochastic nature of decision under risk. Therefore, we estimate the precision parameter, $\lambda$, for each of the three uncertainty environments, with higher $\lambda$ implying higher precision of the decision-making process.

![Figure 8: Binary Choice Decisions (Left) and the Resulting Structural Estimates (Right).](image)

**Notes:** Aggregate fraction of time subjects chose to provide a bid rather than opt out for each of the three uncertainty scenarios are presented on the right. Bounds represent the 95% confidence interval around the mean. Bounds are obtained using nonparametric bootstrap. Structural estimates: $\gamma$ - 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; $\lambda_i$ - 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 8. Specifically, we test the restricted model ($p_R = p_C = p_A = .5$).

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11 Risk aversion is estimated under the assumption that subjects correctly perceive the R 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 $p=.405$ in the ambiguous environment is indicative of more uncertainty aversion than is captured through the risk aversion parameter, which is consistent with a pessimism or ambiguity aversion. Note, however, that for our environment, we only care about one “side” of uncertainty, which can be captured with the worst-case scenario.

12 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.

13 $p_C < .5$ is consistent with failure to reduce compound lotteries documented in prior studies (Halevy, 2007; Abdellaoui, Klibanoff, and Placido, 2013), and is indicative of relative pessimism; $p_A < .5$ is consistent with pessimism and ambiguity aversion.
against the unrestricted model presented in Figure 8. With a p-value of .000, we reject the restricted in favor of the unrestricted model. 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 beliefs about the compound and ambiguous environments are the same. Using the Wilcoxon signed-rank test, we test whether the frequency distributions in Figure 8 are the same and obtain a similar result. This findings further corroborates our result in Section 4.1, where we found no difference in market outcomes for the compound and ambiguous environments.

Next, we investigate whether there is any order effect in the binary choice setting. For ease of presentation, we consider two order sequences for which we had run the most sessions: ACR (Sessions 1-4) and RCA (Sessions 5-8). Figure 9 presents the frequency of subjects choosing to provide a bid versus choosing to opt out.

Figure 9: Binary Choice Decisions (Left) and Structural Estimates (Right) by Order. Notes: Fraction of time subjects chose to provide a bid rather than opt out for order treatments ACR and RCA are presented on the right. Bounds represent the 95% confidence interval around the mean. Bounds are obtained using nonparametric bootstrap. Structural estimates:

- $\gamma$ - 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;
- $\lambda_i$ - precision parameter of the stochastic choice model for environment $i \in \{R, C, A\}$ (higher values denote higher precision in decision making).

When presented first, both in the ambiguous treatment (in ACR) and in the risky treatment (in RCA), 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, in both the ambiguous treatment (in RCA) and the risky treatment (in ACR), when they are presented third. This observation, suggests that the precision of their bids has improved.
The estimated aggregate preference and precision parameters for the two order treatments are presented in Figure 9. We also provide p-values for a test of equality between the two estimates from the ACR and the RCA treatments. 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 $\lambda_R$ and $\lambda_A$ vary by order presentation. This is important evidence of increased precision in later decisions of the experiment.

(a) Model

![Graph of Model Predictions](image1)

(b) Data

![Graph of Data](image2)

Figure 10: Stochastic Choice Model vs Data. Notes: (a) Model: predictions using structural estimates of preference and precision parameters from the Binary Choice Decisions. (b) Data: aggregate data obtained from Monopoly and Duopoly markets.

To complete our argument that the order of presentation affects the market liquidity through the precision parameter, we use the behavioral estimates from Table 6 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 10.
Models qualitatively capture the respective order difference between the ACR and the RCA treatments that are 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 to the right of the Risky CDF, but at low bids, it is almost identical. This similarity between the QRE model results and the experimental results provides clear evidence of our conclusion that the precision of decisions is a significant factor in determining dealer market outcomes. One element of the experimental data that remains unexplained by the considered models, though, is the high fraction of the population that chooses to opt out in the monopoly setting.

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 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; and recent work by Füllbrunn, Rau, and Weitzel (2014), who specifically look for conditions under which ambiguity aversion survives in the market.

5 Conclusion

We use 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 to 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, compound risk, or 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. We also find evidence that 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 by our research in this study will contribute to the discussion of how institutions themselves may interact with learning and precision of decision making. By examining the effects of 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 further attention and study.
References


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.
Figure A1: Option A. Summary of Possible Earnings. Notes: ...

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.

Figure A2: Option B. Summary of Possible Earnings. Notes: ...

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.
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:

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

where $x$ is the outcome and $\gamma$ is the risk-aversion parameter to be estimated. Thus, $\gamma = 0$ corresponds to a risk-neutral gent, and $\gamma > 0$ 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,

$$U(b) = \frac{u(b) - u(o)}{u(b_{\text{best}}) + u(b_{\text{worst}})},$$  \hspace{1cm} (B2)

where $b$ is the chosen bid, $b_{\text{best}}$ is the available bid that generates the best possible utility, $b_{\text{worst}}$ 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:

$$P_b = \frac{1}{1 + e^{-\lambda(EU(b) - EU(O))}}$$  \hspace{1cm} (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 $\gamma$ and $p$. 

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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

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</table>

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. In case the outcome is still negative the participant earns $0.00.

![Bid Distribution by Market Type](image1)

Figure D1: Bid Distribution by Market Type.

![Individual Dealer Participation](image2)

Figure D2: Individual Dealer Participation.