Cognitive Biases, Ambiguity Aversion and Asset Pricing in Financial Markets

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ABSTRACT

We test to what extent financial markets trigger comparative ignorance (Fox and Tversky (1995)) when interpreting news, and hence, to what extent such markets instill ambiguity aversion in participants who do not know how to correctly update. Our experiments build on variations of the Monty Hall problem, which, when tested on individuals separately, are well known to generate obstinacy: subjects often refuse to acknowledge that they are wrong. Under comparative ignorance, however, subjects who are not able to correctly solve Month-Hall-like problems should become ambiguity averse. In a financial markets context, we posit that such feeling of comparative ignorance emerges when traders, who do not have the correct solution, face prices that contradict their beliefs. Previous experiments with financial markets have shown that ambiguity aversion makes subjects hold portfolios that are insensitive to prices; subjects instead prefer to hold balanced portfolios, and hence, are not exposed to ambiguity. And because subjects are price-insensitive, they do not contribute to price setting. This led us to hypothesize that, when faced with Monty-Hall-like problems, (i) there would be subjects whose portfolio decisions are insensitive to prices, (ii) price quality would be inversely related to the proportion of price-insensitive subjects, (iii) price-insensitive subjects tend to choose more balanced portfolios (correcting for mispricing), and (iv) price-insensitive subjects trade less. Our experiments confirm these hypotheses. We do discover, however, the presence of a minority of price-sensitive subjects who simply tend to buy more as prices increase. We interpret the behavior of such subjects as herding, a hitherto unsuspected reaction to comparative ignorance. Altogether, our experiments suggest that cognitive biases may be expressed differently in a financial markets setting than in traditional single-subject experiments.

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I. Introduction

Traditional asset pricing models assume that investors are fully rational. Behavioral theories relax this rationality assumption in an effort to explain observed pricing anomalies. In a standard behavioral model of asset pricing, a representative investor deviates from the rational decision due to cognitive limitations and as a result, the cognitive biases of the representative agent directly affect prices. While it provides an appealing explanation for the empirical "irregularities" in the data, the acceptance of the behavioral view is far from being a foregone conclusion (see Brav and Heaton (2002), Barberis and Thaler (2003)). In this paper, we revisit the question about the relevance of cognitive biases to asset pricing.

Cognitive biases are mental errors that agents commit when they evaluate options: agents do not Bayesian update correctly, they overweight their own information and recent information, etc. The existence of cognitive biases has been confirmed in experiments where subjects have no other option but to reveal their biases, if they have any. Subjects have to answer questions or play a game, exposing their cognitive limitations. To refuse to answer or to opt out of the game (and therefore hide the cognitive bias) is usually not part of the experimental protocol. In an experiment in which subjects have an option to refuse to play a dictator game, Lazear, Malmendier and Weber (2006) find less evidence against the Nash equilibrium, because those who deviate from the Nash prediction by sharing if they are forced to play the game are those who choose not to play it when they are given the option to opt out.

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Participants in financial markets need not expose their cognitive biases. The mechanics are not as simple as in the experiments in Lazear, Malmendier and Weber, however, as agents cannot simply opt out of participation. Financial markets exist primarily to share risk. Opting out means forgoing risk sharing opportunities, and assuming risk can be worse than exposing one's cognitive bias. The particular bias on which we focus is improper Bayesian updating. We argue that some agents Bayesian update improperly, and this cognitive bias causes them to perceive ambiguity in the market.

Ambiguity (or Knightean uncertainty, see Knight (1939)) refers to uncertain outcomes with unknown probabilities, as opposed to risk, which refers to uncertain outcomes with known probabilities. According to **?**, agents who face ambiguity assign subjective probabilities to each outcome and then stick to those, treating ambiguity as if it was risk. However, Ellsberg (1961) shows that many agents react differently and they prefer risk over ambiguity. Fox and Tversky (1995) find that people perceive ambiguity when they are confronted with the existence of experts. Agents' confidence in their own predictions and the subjective probabilities attached to them is undermined when they contrast their little knowledge over an event with the superior knowledge of other individuals, and once they call into doubt their subjective probabilities, agents become ambiguity averse and prefer to pay a premium to insure themselves against the uncertainty, choosing outcomes with a sure payoff in every ambiguous state. Fox and Tversky (1995) refer to the phenomenon as *comparative ignorance.*

In the context of financial markets, we argue that comparative ignorance emerges when traders who do have the correct Bayesian update solution, are confronted with prices that contradict their beliefs. An agent who observes a market price that contradicts the price that she expected given her (incorrect) subjective probabilities can lead the agent to infer that there must be other traders who know better, and that her own subjective probabilities are flawed. Such an agent faces ambiguity, and aversion to ambiguity leads her to hedge against it–creating unorthodox portfolio demands.

In the absence of short selling constraints, expected utility agents always adjust their portfolios in reaction to changes in price, so they always contribute to price setting. Agents without cognitive biases know the true probabilities over outcomes, and as such they are expected utility maximizers. We argue that agents who suffer from cognitive biases experience comparative ignorance and therefore no longer trust their subjective probabilities. This causes them to face ambiguity. Ambiguity aversion, in turn, induces the following behavior. For an open range of prices, ambiguity averse agents prefer an ambiguity-neutral portfolio (one that pays the same across all ambiguous states). In consequence, within this range of prices, ambiguity averse agents do not contribute to set asset prices, which is in line with the findings of **?**.

Thus, if agents indeed perceive ambiguity when it is hard for them to solve difficult inference problems, their cognitive biases (that caused them to perceive ambiguity in the first place) *will not* be reflected in prices. Instead, prices will be determined by those who do not perceive ambiguity because they *can* compute the probabilities.[1]

We test the idea in the framework of an experimental financial market. The setting we use provides subjects with difficult updating problems. Namely, the liquidation values of the two Arrow-Debreu securities in the experimental markets are determined through simple card games inspired by the Monty Hall problem. The latter is a notorious example where partial revelation of information is often mis-interpreted as irrelevant. The choice of this exact Bayesian inference problem provides a strong testbed for our hypothesis–the Monty Hall problem has led to numerous heated debates and the fervor with which incorrect solutions are defended may lead one to believe that the inability to find the correct solution does not translate into perception of ambiguity; on the contrary, people obstinately stick to the wrong probabilities.

We design the experiments in such a way that there is no aggregate risk (although this was not known to the subjects). As a result, risk-neutral pricing should obtain in equilibrium. That is, prices are to be expectations of final payoffs, conditional on the information provided. The issue is, of course, whether these prices reflect expectations with respect to true probabilities, or with respect to some other set of (biased) probabilities.[2]

[1] Of course, prices will depend on the risk aversion characteristics of the population of agents who price the assets, and there is a possibility that those are correlated with the cognitive abilities of the agents.

[2] The presence of ambiguity aversion does not alter this conclusion, because ambiguity averse subjects are able to trade to risk-free positions (thereby avoiding exposure to probabilities they cannot compute) without generating aggregate risk to the remainder of the market. That is, their demands do not create an imbalance in

Our experimental data suggest that relatively few of subjects can solve the updating problems correctly (indeed, in some sessions, it appears that no one solved the problems correctly) but that many of the subjects who did not solve the problem correctly treated the situation as ambiguous, rather than assigning wrong probabilities. We find that pricing deteriorates significantly as the number of subjects who cannot make the correct Bayesian inferences increases.

The theory predicts that the subjects who cannot solve the problems will hold more ambiguity-neutral portfolios (which in our setup of two Arrow-Debreu securities corresponds to more balanced portfolios) and also trade less than the subjects who can solve the updating problems (as the latter trade both for rebalancing and speculative reasons). Both predictions are born out in the data.

Our findings shed light on recent experimental findings of Kluger and Wyatt (2004) concerning financial markets with assets whose prices depend on the outcome of a Monty Hall-like problem. In those markets, if at least two subjects solve the problem correctly, prices are right. The authors explain the finding as the effect of Bertrand competition among those who can compute the probabilities correctly. The suggested explanation begs the question, however, for subjects who compute the wrong probabilities surely must Bertrand compete as well.[3] Why do not they set the prices? We provide an alternative explanation: those who cannot compute the right probabilities perceive ambiguity, and, as a result, become infra-marginal.

Our findings also suggest expanded role of financial markets, beyond risk sharing and information aggregation, to facilitating social cognition. That markets may facilitate social cognition was first suggested in Maciejovsky and Budescu (2005) and Bossaerts, Copic, and Meloso (2006).

Others have studied the impact of cognitive biases on financial markets. Coval and Shumway (2005) document that loss aversion has an impact on intra-day price fluctuations on the Chicago Board of Trade, but only over very short horizons. Our study uses controlled experiments. We

the risk available to agents that do not perceive ambiguity, and hence, theoretical equilibrium prices continue to be expectations of final payoffs. The absence of aggregate risk also ensures that equilibrium (with strictly positive prices) exists even if *all* subjects are extremely ambiguity averse. In that case, prices will not be expectations of final payoffs. It can be shown that any price level would be an equilibrium, and that prices would be insensitive to the information provided.

[3] Those agents will be bankrupt in the long run but not in the short life of the laboratory experiment.

focus on pricing relative to theoretical levels. By virtue of experimental control, we know what the theoretical price levels are, unlike in field research such as Coval and Shumway (2005).

Our results also shed light on the relevance of experiments for finance. While our experiments do provide a "micro-cosmos" of field markets, in that they are also populated with subjects who exhibit cognitive biases, they may not be exact replica, because our mix of subjects is unlike the "natural mix" found in field markets. In fact, we find strong *cohort effects* in our experiments: the number of infra-marginal subjects, and hence, the quality of pricing, changes substantially depending on the student pool from which our subjects are drawn.

As a result, our financial markets experiments provide little information about how mispriced field markets are. The experiments are relevant for finance, though, to the extent that they confirm the correctness of a theoretical link between cognitive biases and equilibrium asset pricing – through perception of ambiguity.

The remainder of this paper is organized as follows. Section II presents the theory and the empirical implications. Section IIIdescribes our experiments in detail. Section IV presents the empirical results. Finally, Section V concludes.

II. Theory and Empirical Implications

In what follows, we present a simple two-date model that serves as a theoretical baseline for our experimental results. Let there be a finite number of agents, two assets R and B, or Red and Black, and two states of the world, r and b. At date 0 the realization of the state is not known to the agents. At date 1 agents learn the realization of the state, securities pay off, and consumption takes place. The two assets are Arrow securities: In state $j \in \{r, b\}$, asset $J \in \{R, B\}$ pays one unit of wealth, and the other asset pays no wealth.

At date 0 each agent i is endowed with a number of units of R and B. We assume that the aggregate endowment in the economy of assets R and B is the same (no aggregate risk). Let w_i be the wealth of agent i at date 1, after the state of the world is revealed. Let $u(w_i)$ be the utility that an agent derives from wealth, and assume that this function is strictly increasing and strictly concave.

Let π_R be the probability that state r occurs, and $\pi_B = 1 - \pi_R$ the probability that state b occurs. This probability is not common knowledge, but it can be computed. Agents, however, may have cognitive biases that lead them to computational errors. Let π_j^i be the subjective probability that state j occurs, as calculated by agent i. Note that π_j, the true probability, is equal to the expected value of asset J.

Agents can trade their assets and cash at date 0. Let p_B, p_R be the market prices of assets B and R at date 0. Because there is no aggregate risk, agents can trade to risk-free portfolios. Let (B_i, R_i) be date 2 portfolio of assets for agent i.

Consider an agent i who maximizes expected utility according to her own subjective probabilities π_j^i. The first order conditions for optimality are that

$\frac{\pi_B^i u'(B_i)}{p_B} = \frac{\pi_R^i u'(R_i)}{p_R}$ or $\frac{p_R}{p_B} = \frac{\pi_R^i}{\pi_B^i}\frac{u'(R_i)}{u'(B_i)}$.

Hence for any given price vector, the relative demand of agent i for asset R (as a fraction of the total demand for assets R and B) is increasing in the subjective probability π_R^i. The vector of all subjective probabilities by all agents determines the equilibrium prices.

If all agents correctly compute the true probabilities that state j occurs, then the equilibrium prices are $\frac{p_R}{p_B} = \frac{\pi_R}{\pi_B}$. In this case, all agents trade so as to attain a balanced portfolio.

If an agent i observes that prices do not correspond to $\frac{\pi_R^i}{\pi_B^i}$, agent i must infer that either the market is out of the equilibrium, or else, that some agents, not necessarily i, have computed wrong probabilities. When confronted with this divergence between the market price, and the equilibrium price predicted by the agent, some agents experience comparative ignorance. In lay terms, some agents no longer trust their own computations when confronted with this divergence. As argued by Fox and Tversky (1995), comparative ignorance triggers ambiguity aversion. We assume that agents who no longer trust their subjective probabilities are unsure about the true probabilities. They no longer experience risk. They experience ambiguity, where their payoff depends on the state of the world, and the state of the world depends on probabilities that are unknown to the agent.

Ghirardato, Maccheroni, and Marinacci (2004) develop a general theory on the behavior of agents who face ambiguity. Bossaerts, Ghirardato, Guarnaschelli, and Zame (2008) apply this theory to the case of asset markets with both risky and ambiguous assets in the presence of scarcity of some assets, so that there is aggregate risk in the economy. We adapt the environment of Bossaerts, Ghirardato, Guarneschelli and Zame to a case in which there is no aggregate risk, and where attitudes toward ambiguity emerge endogenously.

Agents who no longer trust their subjective probabilities and face ambiguity have $\alpha - \max\min$ preferences, so that they maximize the following expression:

$$U_i(R_i, B_i) = \alpha \min\{u(R_i), u(B_i)\} + (1-\alpha) \max\{u(R_i), u(B_i)\}$$

The coefficient α measures the degree of ambiguity aversion, where $\alpha = 1/2$ corresponds to ambiguity neutrality, and $\alpha = 1$ is the extreme degree of ambiguity aversion. An agent with $\alpha - \max\min$ preferences acts as if with probability α, the worst possible state will occurs, and with probability $1-\alpha$, the best possible state occurs, where which state is best or worst depends on the portfolio chosen by the agent.

If $R_i > B_i$, then $U_i(R_i, B_i) = \alpha u(B_i) + (1-\alpha)u(R_i)$, so the first order condition for optimality is

$$\alpha \frac{u'(B_i)}{p_B} = (1-\alpha)\frac{u'(R_i)}{p_R} \implies \frac{p_R}{p_B} = \frac{1-\alpha}{\alpha}\frac{u'(R_i)}{u'(B_i)}$$

which, if $\alpha > 1/2$, together with the decreasing marginal utility of wealth, implies $\frac{p_R}{p_B} < \frac{1-\alpha}{\alpha}$.

Similarly, if $R_i < B_i$, then $\frac{p_R}{p_B} > \frac{\alpha}{1-\alpha}$.

Finally, if $\frac{p_R}{p_B} \in [\frac{1-\alpha}{\alpha}, \frac{\alpha}{1-\alpha}]$, then $R_i = B_i$. Ambiguity averse agents, then, balance their portfolio for any price vector in the interval $[\frac{1-\alpha}{\alpha}, \frac{\alpha}{1-\alpha}]$. In other words, for a range of prices, ambiguity averse agents become price insensitive: They do not adjust their portfolios in response to changes in prices, seeking a balanced portfolio regardless of price fluctuations. Hence, within this range, ambiguity averse agents do not affect prices, and prices are set by those agents who stick to their subjective probabilities and do not adopt $\alpha - \max\min$ preferences.

We make the following key assumption.

Assumption 1: Agents who compute the correct probabilities do not feel comparative ignorance and do not adopt $\alpha - \max\min$ preferences when confronted with prices that do not correspond to the predicted equilibrium value. Agents who compute wrong probabilities feel comparative ignorance and adopt $\alpha - \max\min$ preferences with some degree of ambiguity aversion when confronted with market prices that do not correspond to their subjective probabilities.

Informally, this assumption means that people who are right are certain and are not swayed in their certainty when prices diverge from the theoretical prediction, whereas people who cannot compute probabilities are not as certain of their calculations and they lose their confidence as soon as market prices do not correspond to the prices that should occur in equilibrium given the calculated probabilities.

Under Assumption 1, if the market price is initially at the predicted level, all agents who are wrong cease to be expected utility maximizers according to their subjective probabilities, and they become instead ambiguity averse $\alpha - \max\min$ agents who seek a balanced portfolio at any price within some range of prices. Since there is no aggregate risk, these ambiguity averse agents can achieve their desired balanced portfolio without affecting the net availability of assets for the rest of the economy. Since the price is at the theoretical prediction, expected utility maximizers with the correct subjective probabilities can also trade to a balanced portfolio, at the theoretical price.

If, instead, the initial price is off from the theoretical equilibrium, say too high, agents with wrong subjective probabilities that do not correspond to the observed price seek balanced portfolios. Trade occurs between those with the correct subjective probabilities, who seek to sell since the price is too high, and those with the wrong calculation that was initially supported by the market price, who want to achieve a balanced portfolio, since they believe the price is at the expected value of the asset. Trade between agents who want to sell, and agents who want to either sell or buy as needed to balance their portfolio will drive prices down. As the price goes down, those with the wrong calculation will update, realizing that after all their calculation was wrong, hence they will continue to seek to balance their portfolio, and will not buy more as prices go down, while those with the correct probabilities continue to sell, until the price lowers to the theoretical equilibrium price. At this point, those with the correct probabilities will seek to undo their unbalanced positions and seek a balanced portfolio as well, and the price stabilizes.

This is the pure version of the theory. Suppose instead that we relax Assumption 1, substituting it for the weaker Assumption 2:

Assumption 2: A fraction ρ of agents never experience comparative ignorance, regardless of whether they compute correct or incorrect subjective probabilities, and regardless of the market price. These agents are always expected utility maximizers according to their subjective probabilities. A fraction $1-\rho$ of agents, if they compute incorrect subjective probabilities and they are confronted with prices that do not correspond to the theoretical price according to those probabilities experience comparative ignorance and adopt ambiguity averse $\alpha - \max\min$ preferences.

Under this assumption, some agents may be wrong and at the same time sure that are right and hence unswayed by the information conveyed by the market price. If so, the argument outlined above does not function perfectly. If the price is initially off from the theoretical prediction, a fraction of those who are wrong trade in such a manner as to resist the move toward the theoretical prediction. If there are not many agents with the correct probabilities, full convergence does not occur. Ambiguity averse agents, who become price insensitive, achieve a balanced portfolio. Expected utility maximizers, with either right or wrong probabilities, maintain an unbalanced portfolio. Prices are closer to the equilibrium prediction if the number of agents who compute the right probabilities is higher. If we observe a higher number of expected utility maximizers (price sensitive) the extra number above fraction ρ must be agents who compute the right probabilities. Hence, a higher number of observed price sensitive agents should lead to market prices that are closer to the expected value of the asset. Furthermore, as long as prices do not fully converge to this expected value, price sensitive agents (right or wrong) maintain unbalanced portfolios, while price insensitive agents reach a balanced portfolio. Thus, our theory has three testable empirical predictions:

1. The deviation of the market price from the expected value of the asset (mispricing) is negatively related to the number of price sensitive subjects.

2. Given some mispricing, price insensitive subjects hold more balanced portfolios than price insensitive subjects.

3. Price insensitive subjects trade less than price sensitive subjects.

III. Experiments

The experimental sessions were organized as a sequence of *independent* replications of four different situations, with each situation being repeated exactly twice. Each replication was referred to as a *period*. Thus, each experimental session had exactly eight periods.

Twenty subjects participated in each session. This is sufficient for markets to be liquid enough that the bid-ask spread is at most two or three ticks (the tick size was set at 1 U.S. cent). All accounting in the experiments was done in US dollars. The average earnings from participating in the experimental sessions was $49 per subject.

There were nine experimental sessions. The experiments were ran at the following universities: (i) Caltech (one session), (ii) UCLA (four sessions), (iii) University of Utah (two sessions), (iv) simultaneously at Caltech and University of Utah with equal participation from both subject pools (two sessions).

There were three securities on the laboratory markets, two of them were risky and one was risk free. Trade took place through a web-based, electronic continuous open-book system called *jMarkets*.[4] A snap shot of the trading screen is provided in Figure 1.

[4]This open-source trading platform was developed at Caltech and is freely available under the GNU license. See http://jmarkets.ssel.caltech.edu/. The trading interface is simple and intuitive. It avoids jargon such as "book," "bid," "ask," etc. To eliminate as much as possible mistakes, the entire trading process is point-and-

The (two) risky securities were referred to as *Red Stock* and *Black Stock*. The liquidation value of Red Stock and Black Stock was either \$0.50 or \$0 (all accounting and trading is done in U.S. dollars). Red and Black Stock were complementary securities: when Red Stock paid \$0.50, Black Stock paid nothing, and *vice versa*. Red Stock paid \$0.50 when the "last card" (to be specified below) in a simple card game was red (hearts or diamonds); Black Stock paid \$0.50 when this "last card" was black (spades or clubs).

Subjects were allowed to trade Red Stock, but *not* Black Stock. Since subjects were initially given an unequal supply of both securities (which differed across subjects), and subjects are known to display small but significant risk aversion for the amount of risk we induce in the experiments (see Holt and Laury (2002)), there was a reason to trade.

Subjects could also trade a risk free security called *Note*. This security always paid \$0.50. Given cash, it was a redundant security. However, subjects were allowed to short-sell the Note if they wished. Short sales of Notes correspond to borrowing. Subjects could exploit such short sales to acquire Red Stock if they thought Red Stock was underpriced.

Subjects were also allowed to short sell Red Stock, for in case they thought Red Stock was overpriced. To avoid bankruptcy (and in accordance with classical general equilibrium theory), our trading software constantly checks subjects' budget constraints. In particular, subjects could not submit an order such that, if it and the subject's other standing orders were to go through, the subject would generate net negative earnings in at least one state. Only new and standing orders that were within 20% of the best standing bid or ask in the marketplace were taken into account for the bankruptcy checks. Since markets were invariably thick, orders outside this 20% band were effectively non-executable, and hence, deemed irrelevant. No-one ever generated negative earnings in our experiments. (Subjects at times hardly made any money at all, however, so that the possibility of losing one's time without compensation made them sufficiently risk averse.)

Table I provides details of the experimental design. Note the \$5 sign-up reward, compulsory at the experimental laboratories where we ran our experiments (Caltech's SSEL, UCLA's

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click. That is, subjects do not enter numbers (quantities, prices); instead, they merely point and click to submit orders, to trade, or to cancel orders.

CASSEL and the University of Utah's UULEEF). It was for subjects to keep no matter what happened in the experiment. Hence, it constituted the minimum payoff (for an experiment that generally lasted 2 hours in total).[5]

The liquidation values of Red and Black Stock were determined through simple card games played by a computer and communicated to the subjects orally and through the News web page. The card games were inspired by the Monty Hall problem.

One game (out of the four that we used) is as follows. The computer starts a new period with four cards (one spades, one clubs, one diamonds, and one hearts), randomly shuffled, and face down. The computer discards one card, so there are three remaining cards. (The color of the "last card" determines the payoffs of the two risky securities.) Trade starts. Halfway through the period, trading is halted temporarily. The computer picks one card at random from the three remaining cards. *If this card is hearts, the computer places the card back without showing it and picks up another card at random.* This card is then revealed to the subjects, both orally and through the News web page. Trade starts again. At the end of the period, after markets close, the computer picks one of the two remaining cards at random. This *last card* is then revealed and determines which stock pays. If the last card is red (diamonds, hearts) then Red Stock pays $0.50. If the last card is black, then Black Stock pays $0.50.

Four variations on this game (each replicated twice), referred to as *treatments*, were played, whereby we changed the number of cards initially discarded, the number of cards revealed mid-period, and the restriction on which cards could be revealed. This provided a rich set of equilibrium prices and changes of prices (or absence thereof) after mid-period revelation. Table II provides details of the four treatments. Treatment 2 is the one we explained above; it is the closest to the original Monty Hall problem.

The actual trading within the eight periods lasted about one hour. It was preceded by a long (approximately one hour) instructional period and a trading practice session, followed by a short break (15 minutes). The purpose of the long instructional period and the trading practice session was to familiarize subjects with the setting and the trading platform. We

[5]More information about the experimental design, including instructions and a typical news page can be obtained at http://leef.business.utah.edu/market_mh/frames_mh.html

wanted to make sure subjects were not confused about, e.g., the card game (for instance, we absolutely made sure all subjects understood that the computer sometimes had to put back certain cards when picking a card for revelation halfway during a period). To determine to what extent subjects understood the instructions, we asked questions such as, in the game where the computer never reveals halfway a red card, "will you be surprised to see a black card?" Or, if the computer initially discards one card, and then showed one black card when it could also have shown diamonds, "does the chance that the last card is black decrease as a result?" We never gave them information about the correct probability levels, however.

IV. Empirical Analysis

With our hypothesis about the impact of cognitive biases on ambiguity perception in mind, we reiterate the main goals of the experimental study below.

1. To determine whether there are infra-marginal (price-insensitive) subjects.
2. To determine whether the number of marginal (price-sensitive) subjects has an impact on price quality; price quality is measured as the distance between average trade prices and expected final payoff (computed with correct probabilities).
3. To determine whether price-insensitive subjects hold more balanced portfolios.
4. To determine whether price-sensitive subjects trade less.

The third and fourth goal require elaboration. As far as the third goal is concerned, we need to control for mispricing, because, once prices are correct, everyone should hold balanced portfolios. Indeed, there is no aggregate risk in our experiments, and hence correct prices are risk-neutral prices with respect to correct probabilities. When prices are risk-neutral, even price-sensitive subjects should hold balanced portfolios, provided they are risk averse. (Price-insensitive subjects reveal that they are ambiguity averse, and ambiguity averse agents prefer to hold balanced portfolios irrespective of prices.)

The fourth goal is really a consequence of this reasoning. As long as prices are incorrect, price-sensitive subjects should trade to imbalanced holdings, but once their actions have generated correct (risk-neutral) prices, price-sensitive subjects should trade to balanced portfolios. In contrast, price-insensitive subjects, because of their revealed ambiguity aversion, should directly trade to balanced portfolios. Hence, they tend to trade less than price-sensitive subjects.

Figures 2 and 3 display the evolution of transaction prices for Red Stock in two experiments. Time is on the horizontal axis (in seconds). Solid vertical lines delineate periods; dashed vertical lines indicate half-period pauses when the computer revealed one or two cards. Horizontal line segments indicate predicted price levels assuming prices equal expected payoffs computed with correct probabilities. Each star is a trade. (Over 1,100 trades take place typically, or one transaction per 2.5 seconds.)

The figures display trading prices in experiments that represent two extremes. Indeed, price quality is *very bad* in the University of Utah-1 experiment (Figure 1). However, when Caltech students are brought in (Figure 2, where 1/2 of the subjects are from Caltech, and 1/2 from the University of Utah), prices are close to expected payoffs - price quality overall is *good*. The figures illustrate that there are strong cohort effects. As we shall see, there are also strong treatment effects.

In the University of Utah experiment (Figure 1), prices seem to be insensitive to the treatments. There were also a large number of price-insensitive (infra-marginal) subjects (to be discussed later). This suggests that the pricing we observe in that experiment may reflect an equilibrium with only ambiguity averse subjects. As mentioned in the Introduction, when there are only ambiguity averse subjects, equilibrium prices will not react to the treatments. In fact, any price level is an equilibrium. Notice that prices in the University of Utah experiment indeed started out around the relatively arbitrary level of \$0.45 and stayed there during the entire experiment (except on the one occasion when it was sure that Red Stock would pay, namely, the second half of period 1).

For completeness, we should mention that prices in experiments UCLA-1 and UCLA-2 (not shown) also tended to be above expected payoffs. An unfortunate mis-allocation of securities may have contributed: *in total, 17% more Black stock was distributed than Red stock* (see

Table I). As a result, Red Stock was in shorter supply, so that its theoretical equilibrium price is actually *above* the expected value of its final payoff.[6]

Table III reports price quality in each treatment of all the experiments. Price quality is measured in terms of mean absolute mispricing (in U.S. cents).[7] There is a wide variability in mispricing, both across experiments (Utah producing the worst mispricing and Utah-Caltech producing the best pricing) and across treatments (treatment 2 producing larger mispricing).[8] In the sequel, we will focus on mispricing across treatments.

Can we explain the variability in mispricing in terms of the number of price-sensitive subjects, as we conjectured? Table III also reports the number of price-sensitive subjects. Price sensitivity is obtained from OLS projections of the one-minute changes in a subject's holdings of Red Stock onto the difference between (i) the mean traded price of Red Stock (during the one-minute interval), and (ii) the expected payoff of Red Stock, computed using the correct probabilities. As we argue in the Appendix, however, the necessity for the total changes in holdings to balance causes a simultaneous-equation effect which biases the slope coefficients upward. Hence we used a generous cut-off level of the t-statistic to determine whether someone tends to reduce holdings to higher prices (-1.65) while we used a conservative t-statistic to determine whether a subject increases holdings for higher prices (1.9).[9]

Table III demonstrates that the number of price-sensitive subjects was often very low. The flip side of this is that often many subjects were price-insensitive: their actions did not depend on prices. At some instances only *a single* or even *no* subject was found to react systematically to price changes. That is, almost all subjects perceived ambiguity – suggesting that they did not know how to compute the probabilities. It is surprising, however, to discover that a small

[6]To put it in terms of CAPM language: because less of it was available, Red Stock was a "negative beta" security, which means that its theoretical equilibrium price was in fact above its expected value.

[7]We did not attempt to correct for the unbalanced supply of Red and Black Stock in the UCLA experiment. That is, we continues to compute mispricing as the mean absolute difference between traded prices and expected payoffs at correct probabilities. This will have only a marginal effect on the results and does not alter the conclusions qualitatively.

[8]The median mispricing in treatment 2 is significantly higher than that of treatment 1 (p-value of 0.047 on the Wilcoxon signed-rank test comparing the paired absolute mean mispricing across the two treatments), treatment 2 (p-value of 0.016), and treatment 4 (p-value of 0.016). Treatment 2 is closest to the original Monty Hall problem.

[9]We also tried R^2 as a measure of price sensitivity, with no effect on the final conclusions.

minority of subjects were price-sensitive in a perverse way: they tended to *increase* their holdings even for higher prices. We think that their actions reflect *herding*: they interpret higher prices as signaling proportionally higher higher expected payoffs.

Table III also indicates that pricing improves significantly (mean absolute mispricing is lower) when there are more price-sensitive subjects who reduce their holdings to increases in the price relative to the correct value. That is, pricing quality and number of marginal subjects are significantly negatively correlated (the correlation is equal to -0.43), a finding consistent with our comparative ignorance conjecture.

One alternative explanation for the above finding is that those who do not react to price changes are simply noise traders (not necessarily ambiguity averse). The more noise traders in the market, the worse the price quality. To test our hypothesis against this simple alternative, we investigate two relationships. The first is the difference in individual imbalances (equal to the absolute difference between the units of Red and Black Stock in each subject's portfolio) between price-sensitive and price-insensitive subjects. If indeed the latter were noise traders, we should not expect to see any difference between the imbalances of those two groups. If, on the other hand, price-insensitivity indicates perception of ambiguity, those subjects should aim at achieving balanced positions, resulting in the price-insensitive subjects displaying lower imbalance than the price-sensitive ones. Second, if the price-insensitive subjects were noise traders, they would be expected to trade more than the price-sensitive ones (a conclusion opposite to the one we reached with the ambiguity-aversion conjecture).

We compute individual imbalances at mid-period and at the end of the period. Table 4 confirms our conjecture that price-sensitive subjects (who react negatively to prices) tend to hold more imbalanced positions at the end of the period (corrected for mispricing). Similarly, Table 5 shows that this relation holds also at mid-period (both the t-statistics and and the R^2 of the OLS projections are higher at mid-period).[10] The imbalance-price-sensitivity relationship provides evidence against the noise traders hypothesis. The price-insensitive subjects seem to behave in an ambiguity-averse manner.

[10]The task of computing the expected value of the Red Stock is harder in the first half of each period before the additional one or two cards are revealed. So, the relationship between price-sensitivity and imbalance can be expected to be stronger at mid-period.

Next, Table 6 confirms our conjecture that price-sensitive subjects (who react negatively to prices) tend to trade more (interaction with mispricing is marginal). This evidence points again in favor of the price-insensitive subjects displaying ambiguity aversion (and against the noise traders hypothesis).

In short, we find that in our laboratory markets the majority of the subjects are infra-marginal (price-insensitive). The number of infra-marginal subjects in each of the sessions and the four different situations within a session significantly impacts the price quality in the market. The price quality is better, i.e. prices are closer to their theoretical levels, when there are more marginal subjects in the market (or equivalently less infra-marginal ones). The number of marginal subjects likely affects the speed of conversion to equilibrium through its positive relation to price pressure. The higher the number of price-sensitive subjects, the higher the demand (supply) of Red Stock when prices are too low (high) and consequently the faster the price movement in the direction of equilibrium prices. With only a few of the marginal subjects present, market prices remain closer to their starting point than to their equilibrium levels due the the slow price adjustment process.

In summary, we confirm that price-insensitive subjects hold more balanced portfolios and that they also trade less. Both findings are consistent with our conjecture that agents perceive ambiguity when it is hard for them to solve difficult inference problems. We do discover, however, the presence of price-sensitive subjects who increase their holdings of Red Stock as its price increases. This is a unsuspected reaction to comparative ignorance which we interpret as herding.

V. Conclusions

Our experimental results demonstrate that only a minority of subjects often are price-sensitive, and hence, marginal. The fact that the price quality increases in the number of price sensitive subjects suggests that these subjects tend to be able to compute the right probabilities. So, the ones who cannot correctly compute the probabilities must primarily be among the price-insensitive subjects. Since lack of price sensitivity characterizes ambiguity aversion, inability to determine probabilities evidently translates into ambiguity aversion.

It has been suggested before that inability to perform difficult computations may translate into ambiguity aversion, but only in the presence of clear evidence that others may be better [see Fox and Tversky (1995)]. It is particularly striking that financial markets exude the very authority that is necessary to convince subjects who cannot do the computations correctly that they really cannot, and hence, to perceive ambiguity. As such, the role of financial markets includes not only risk sharing and information aggregation, but extends to social cognition. This adds to the results reported in Maciejovsky and Budescu (2005) and Bossaerts, Copic, and Meloso (2006).

Our findings raise an important issue: what cognitive biases translate into ambiguity perception when played out in the context of financial markets? The issue is important, because, as theory predicts and our experiments confirm, ambiguity may keep prices from being affected by the cognitive biases that generated it, because demands affected by ambiguity may be infra-marginal, and hence, price-insensitive. Even if a large majority of investors displays a cognitive bias, prices may still be right.

We discovered the presence of a minority of subjects who tend to *increase* their exposure when prices increase. These subjects seem to interpret higher prices as revealing (proportionally) higher value. Note that their behavior is not consistent with rational expectations: one can demonstrate that in a traditional rational expectations equilibrium, uninformed will not increase their exposure when prices increase; they will merely decrease their exposure at a reduced rate compared to a situation where prices do not reveal any information. Consequently, we interpret the actions of these price-chasing subjects as *herding*. Future research should indicate whether the presence of herders slows down convergence to equilibrium, or is even destabilizing, or whether their presence instead improves convergence.

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Appendix

To determine whether there is any simultaneous-equation bias on the estimated slope coefficients induced by overall balance in the changes in positions, we translate our setting into a more familiar framework, namely, that of a simple demand-supply setting. In particular, we are going to interpret (minus) the changes in endowments of the price-insensitive subjects as the supply in a demand-supply system with exogenous, price-insensitive supply, while the changes in endowments of the price-sensitive subjects correspond to the (price-sensitive) demands in a demand-supply system. The requirement that changes in holdings balance then corresponds to the usual restriction that demand equals supply.

We will consider only the case where price-sensitive subjects reduce their holdings when prices increase; translated into the usual demand-supply setting, this means that we assume that the slope of the demand equation is negative.

Assume there are only two subjects. One is price-sensitive, the other is price-insensitive. The former's changes in holdings corresponds to the demand D in the tradional demand-supply system; the latter's changes corresponds to the (exogenous) supply S. The usual assumptions are as follows:

$$D = A + BP + \epsilon,$$

with $B < 0$, and

$$S = \eta,$$

where ϵ is mean zero, and is independent of η. P denotes price.

We want to know the properties of the OLS estimate of B. Assume that P is determined by equating demand and supply (equivalent to balance between changes in holdings), i.e., from

$$D = S.$$

Then:

$$\mathrm{cov}(P, \epsilon) = -\frac{1}{B}\mathrm{var}(\epsilon) > 0.$$

Because of this, standard arguments show that the OLS estimate of B is inconsistent, with an upward bias. As such, the nominal size of the usual t-test under-estimates the true size, and one should apply a generous cut-off in order to determine whether B is significantly negative.

In our case, however, we also need to identify who is price-sensitive (i.e., whose holdings changes correspond to D in the demand-supply setting?) and who is not (whose holdings changes correspond to S?). For this, we just run an OLS projection of changes in endowments on prices. The subjects with significantly negative slope coefficients are price-sensitive and hence, map into the demand D of the traditional demand-supply system. The argument above, however, indicated that this test is biased. Therefore, a generous cut-off should be chosen; we chose a cut-off equal to 1.6.

While we did not need this for our study, one can obtain an improved estimate of the price sensitivity once subjects are categorized as either price-sensitive or price-insensitive. Indeed, the changes in the holdings of the price-insensitive subjects can be used as instrument to re-estimate the price-sensitivity of the price-sensitive subjects. This is equivalent to using S as an instrument to estimate B. Indeed, S $(= \eta)$ and ϵ are uncorrelated, while S and P are correlated ($\text{cov}(S, P) = \text{var}(S)/B$), so S is a valid instrument to estimate B in standard instrumental-variables analysis.

Instructions

I.THE EXPERIMENT

1. Situation

The experiment consists of a sequence of trading sessions, referred to as *periods*. At the beginning of *even-numbered* periods, you will be given a fresh supply of *securities* and *cash*; in *odd-numbered periods*, you carry over securities and cash from the previous period. Markets open and you are free to trade some of your securities. You buy securities with cash and you get cash if you sell securities.

At the end of *odd-numbered* periods, the securities expire, after paying *dividends* that will be specified below. These dividends, together with your cash balance, constitute your *period earnings*. Securities do not pay dividends at the end of even-numbered periods and cash is carried over to the subsequent period, so your period earnings in even-numbered periods will be zero.

Period earnings are *cumulative* across periods. At the end of the experiment, the cumulative earnings are yours to keep, in addition to a standard sign-up reward.

During the experiment, accounting is done in real dollars.

2. The Securities

You will be given two types of securities, *stocks* and *bonds*. Bonds pay a fixed dividend at the end of a period, namely, $0.50. Stocks pay a random dividend. There are two types of stocks, referred to as Red and Black. Their payoff depends on the drawing from a deck of 4 cards, as explained later. The payoff is either $0.50 or nothing. When Red stock pays $0.50, Black stock pays nothing; when Red stock pays nothing, Black stock pays $0.50.

You will be able to trade Red stock as well as bonds, but not Black stock.

You won't be able to buy Red stock or bonds unless you have the cash. You will be able to sell Red stock and bonds (and get cash) even if you do not own any. This is called short selling. If you sell, say, one Red stock, then you get to keep the sales price, but \$0.50 will be subtracted from your period earnings after the market closes and if the payoff on Red stock is \$0.50. If at the end of a period you are holding, say, -1 bonds, \$0.50 will be subtracted from your period earnings.

The trading system checks your orders against bankruptcy: you will not be able to submit orders which, if executed, are likely to generate negative period earnings.

3. How Payoffs Are Determined

Each period, we start with a deck of 4 cards: one hearts (♡), one diamonds (♢), one clubs (♣) and one spades (♠). The cards are shuffled and put in a row, face down.

Our computer takes randomly one or two cards and it discards them.

From the remaining cards, our computer randomly picks one or two cards. If one of these cards is hearts (♡), then the computer puts it back and picks another one. Sometimes, the computer will even put back diamonds (♢) and pick another one. The computer then reveals the card(s) it picked and we will announce this in the News Page at the end of the period (after that, another period starts with the same securities in which you can trade again). *Note that the revealed card(s) will never be hearts, and sometimes may not even be diamonds.*

Before each period, the News Page will provide all the information that you need to make the right inferences: (i) whether one or two cards are going to be discarded initially, (ii) whether one or two cards are going to be picked from the remaining cards and whether diamonds will ever be shown.

After we show the revealed cards, one or two cards remain in the deck. Our computer randomly picks a card and *this last card determines the payoff on the securities.*

Red stock pays \$0.50 when the last card is either hearts (♡) or diamonds (♢). In those cases, the Black stock pays nothing. This is shown in the following Payoff Table.

	Red Stock	Black Stock
If last card is $\heartsuit$ or $\diamondsuit$	\$0.50	0
If last card is $\clubsuit$ or $\spadesuit$	0	\$0.50

Here is an example. Initially there are 4 cards in the deck, randomly shuffled. They are put in a row, face down, like this:

$$\square \quad \square \quad \square \quad \square$$

Our computer randomly discards one card (the third one in this case):

$$\square \quad \square \qquad\quad \square$$

Our computer then randomly picks one card (the fourth one in this case), and reveals it, provided it is not hearts or diamonds (in this case; if it is hearts or diamonds, it replaces it with another card from the deck that is neither):

$$\square \quad \square \qquad\quad \spadesuit$$

From the remaining two cards, our computer picks one at random that determines the payoffs on the stocks.

$$\diamondsuit \quad \square \qquad\quad \spadesuit$$

In this case, the last card picked is diamonds. As a result, you would be paid \$0.50 for each unit of Red stock you're holding, and nothing for the Black stock you're holding.

Here is another example. Initially there are 4 cards in the deck, randomly shuffled. They are put in a row, face down:

$$\square \quad \square \quad \square \quad \square$$

Our computer randomly discards two cards (the second and third ones in this case):

$$\square \qquad\qquad \square$$

Our computer then randomly picks one card and reveals it, provided it is not hearts (if it is hearts, it replaces it with another card from the deck):

$$\diamondsuit \qquad \square$$

Our computer then picks the remaining card, which determines the payoffs on the stocks.

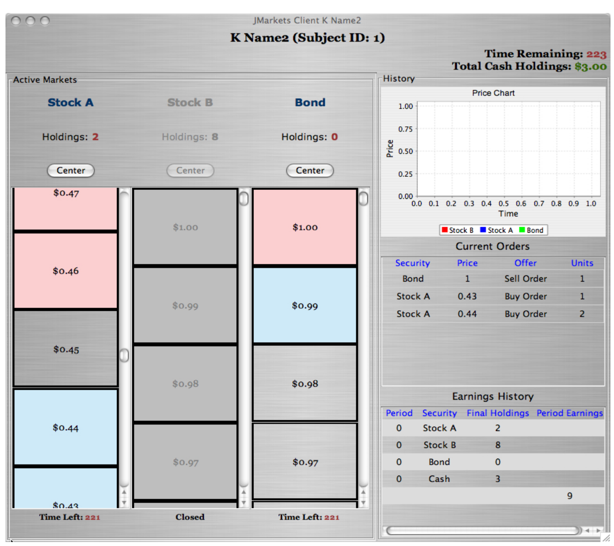
$$\diamondsuit \qquad \heartsuit$$

In this case, the last card picked is hearts. As a result, you would be paid $0.50 for each unit of Red stock you're holding, and nothing for the Black stock you're holding.

Again, the announcements of the number of cards that will be discarded initially and revealed at the end of the period can be found in the News page. This page will also display the card(s) that are turned over at the end of the period, and, at the end of the subsequent period, the final card that determines the payoff on the Stocks.

II. THE MARKETS INTERFACE, jMARKETS

Once you click on the Participate link to the left, you will be asked to log into the markets, and you will be connected to the jMarkets server. After everybody has logged in and the experiment is launched, a markets interface like the one below will appear



1. Active Markets

The Active Markets panel is renewed each period. In it, you'll see several scroll-down columns. Each column corresponds to a market in one of the securities. The security name is indicated on top. At the bottom, you can see whether the market is open, and if so, how long it will remain open. The time left in a period is indicated on the right hand side above the Active Markets panel.

At the top of a column, you can also find your current holdings of the corresponding security. Your current cash holdings are given on the right hand side above the Active Markets panel.

Each column consists of a number of price levels at which you and others enter offers to trade. Current offers to sell are indicated in red; offers to buy are indicated in blue. When pressing the Center button on top of a column, you will be positioned halfway between the best offer to buy (i.e., the highest price at which somebody offers to buy) and the best offer to sell (i.e., the lowest price that anybody offers to sell at).

When you move your cursor to a particular price level box, you get specifics about the available offers. On top, at the left hand side, you'll see the number of units requested for purchase. Each time you click on it, you send an order to buy one unit yourself. On top, at the right hand side, the number of units offered for sale is given. You send an order to sell one unit each time you yourself click on it. At the bottom, you'll see how many units you offered. (Your offers are also listed under Current Orders to the right of the Active Markets panel.) Each time you hit cancel, you reduce your offer by one unit.

If you click on the price level, a small window appears that allows you to offer multiple units to buy or to sell, or to cancel offers for multiple units at once.

2. History

The History panel shows a chart of past transaction prices for each of the securities. Like the Active Markets panel, it refreshes every period. jMarkets randomly assigns colors to each of the securities. E.g., it may be that the price of the Red Stock is shown in blue. Make sure that this does not confuse you.

3. Current Orders

The Current Orders panel lists your offers. If you click on one of them, the corresponding price level box in the Active Markets panel is highlighted so that you can easily modify the offer.

4. Earnings History

The Earnings History table shows, for each period, your final holdings for each of the securities (and cash), as well as the resulting period earnings.

5. How Trade Takes Place

Whenever you enter an offer to sell at a price below or equal to that of the best available buy order, a sale takes place. You receive the price of the buy order in cash. Whenever you enter an offer to buy at a price above or equal to that of the best available sell order, a purchase takes place. You will be charged the price of the sell order.

The system imposes strict price-time priority: buy orders at high prices will be executed first; if there are several buy orders at the same price level, the oldest orders will be executed first. Analogously, sell orders at low prices will be executed first, and if there are several sell orders at a given price level, the oldest ones will be executed first.

6. Restrictions On Offers

Before you send in an offer, jMarkets will check two things: the cash constraint, and the bankruptcy constraint.

The cash constraint concerns whether you have enough cash to buy securities. If you send in an offer to buy, you need to have enough cash. To allow you to trade fast, jMarkets has an automatic cancelation feature. When you submit a buy order that violates the cash constraint, the system will automatically attempt to cancel buy orders you may have at lower prices, until the cash constraint is satisfied and your new order can be placed.

The bankruptcy constraint concerns your ability to deliver on promises that you implicitly make by trading securities. We may not allow you to trade to holdings that generate losses in some state(s). A message appears if that is the case and your order will not go through.

Tables and Figures

Table I
Parameters in the Experimental Design

Experiment[a]	Subject Category (Number)	Signup Reward (Dollar)	Initial Allocations[b] Red Stock (Units)	Black Stock (Units)	Notes (Units)	Cash (Dollar)
Caltech	10	5	0	9	0	4
	10	5	12	3	0	1
UCLA-1	11	5	0	9	0	4
	9	5	12	3	0	1
UCLA-2	11	5	0	9	0	4
	9	5	12	3	0	1
Utah-1	10	5	0	9	0	4
	10	5	12	3	0	1
Utah-Caltech-1	10	5	0	9	0	4
	10	5	12	3	0	1
UCLA-3	10	5	0	9	0	4
	10	5	12	3	0	1
UCLA-4	11	5	0	9	0	4
	9	5	12	3	0	1
Utah-2	10	5	0	9	0	4
	10	5	12	3	0	1
Utah-Caltech-2	10	5	0	9	0	4
	10	5	12	3	0	1

[a]Indicates affiliation of subjects. “Utah” refers to the University of Utah; “Utah-Caltech” refers to: 50% of subjects were Caltech-affiliated; the remainder were students from the University of Utah. Experiments are listed in chronological order of occurrence.

[b]Renewed each period.

Table II
Treatments

Treatment	Periods	Number of Cards Discarded Initially	Number of Cards Revealed Half-time	Cards Never Revealed Half-time
1	1, 5	1	2	hearts
2	2, 7	1	1	hearts
3	3, 6	2	1	hearts
4	4, 8	1	1	hearts, diamonds

Table III
Price Sensitivity

Experiment	Treatment	Mean Absolute Mispricing, M [a]	Number of ($t < -1.65$) Subjects, $N_{(t<-1.65)}$ [b]	Number of ($t > 1.9$) Subjects, $N_{(t>1.9)}$
Caltech	1	3.13	7	2
	2	5.54	3	2
	3	3.40	2	2
	4	1.25	4	6
UCLA-1	1	2.02	0	1
	2	10.91	0	1
	3	4.87	4	1
	4	3.64	0	1
UCLA-2	1	3.91	3	2
	2	12.30	1	0
	3	8.79	5	4
	4	6.60	2	2
Utah	1	3.50	4	1
	2	11.79	1	2
	3	11.28	0	1
	4	7.24	1	0
Utah-Caltech	1	3.35	5	1
	2	4.75	2	0
	3	1.62	2	0
	4	1.89	5	3
UCLA-3	1	4.86	2	1
	2	5.07	3	0
	3	2.53	3	3
	4	2.90	3	0
UCLA-4	1	6.43	2	0
	2	6.06	3	2
	3	2.66	3	2
	4	3.30	1	0
Utah	1	2.54	0	1
	2	7.95	5	2
	3	5.88	4	2
	4	4.19	4	2
Utah-Caltech-2	1	8.06	1	2
	2	2.58	3	1
	3	2.77	7	3
	4	3.38	8	1

$Corr(M, N_{(t<-1.65)}) = -0.38$, UCLA 1-2-4 excluded.
(St. Error = 0.175)

$Corr(M, N_{(t<-1.65)}) = -0.30$, All sessions included.
(St. Error = 0.151)

[a] In U.S. cents.

[b] t is the t-statistic of the slope coefficient estimate in projections of one-minute changes in individual holdings of Red Stock onto difference between (i) last traded price, and (ii) expected payoff using correct probabilities.

Table IV
Price Sensitivity and Imbalance Relation

Panel A of the table presents the slope coefficients from the projections of individual imbalances I onto individual price-sensitivity parameters t (t is the t-statistic of the slope coefficient estimate in projections of one-minute changes in individual holdings of Red Stock onto difference between (i) last traded price, and (ii) expected payoff using correct probabilities).

$$I = a + b_1 t + \epsilon$$

First column is with all subjects included while the second is with subjects ($t > 1.9$) excluded. Panel B presents the slope coefficients from

$$I = a + b_2 t M + \epsilon,$$

where M is the mean absolute mispricing. Standard errors in all projections are corrected for heteroscedasticity and subject clustering.

Treatment	Panel A		Panel B	
	b_1 all t included	b_1 ($t > 1.9$) excluded	b_2 all t included	b_2 ($t > 1.9$) excluded
1	0.190	-0.334	0.057	-0.032
	(0.662)	(0.763)	(0.159)	(0.172)
2	-1.108	-2.140	-0.141	-0.274
	(0.854)	(0.869)	(0.099)	(0.117)
3	-0.260	-0.169	-0.070	-0.035
	(0.579)	(0.683)	(0.094)	(0.125)
4	-0.728	-0.587	-0.027	0.088
	(1.310)	(1.982)	(0.188)	(0.228)
all	-0.457	-0.784	-0.075	-0.123
	(0.504)	(0.617)	(0.062)	(0.074)

Table V
Price Sensitivity and Imbalance Relation: Mid-period

Panel A of the table presents the slope coefficients from the projections of individual mid-period imbalances I onto individual price-sensitivity parameters t (t is the t-statistic of the slope coefficient estimate in projections of one-minute changes in individual holdings of Red Stock onto difference between (i) last traded price, and (ii) expected payoff using correct probabilities).

$$I = a + b_1 t + \epsilon$$

First column is with all subjects included while the second is with subjects ($t > 1.9$) excluded. Panel B presents the slope coefficients from

$$I = a + b_2 t M + \epsilon,$$

where M is the mean absolute (mid-period) mispricing. Standard errors in all projections are corrected for heteroscedasticity and subject clustering.

Treatment	Panel A		Panel B	
	b_1 all t included	b_1 ($t > 1.9$) excluded	b_2 all t included	b_2 ($t > 1.9$) excluded
1	0.726	0.483	0.186	0.135
	(0.590)	(0.692)	(0.127)	(0.132)
2	-1.571	-2.446	-0.165	-0.268
	(0.754)	(0.806)	(0.082)	(0.100)
3	-0.616	-0.496	-0.184	-0.156
	(0.511)	(0.576)	(0.075)	(0.099)
4	-1.087	-1.036	-0.163	-0.085
	(1.118)	(1.713)	(0.167)	(0.208)
all	-0.616	-0.814	-0.104	-0.133
	(0.420)	(0.525)	(0.050)	(0.061)

Table VI
Price Sensitivity and Number of Trades Relation

Panel A of the table presents the slope coefficients from the projections of number of trades NT onto individual price-sensitivity parameters t (t is the t-statistic of the slope coefficient estimate in projections of one-minute changes in individual holdings of Red Stock onto difference between (i) last traded price, and (ii) expected payoff using correct probabilities).

$$NT = a + b_1 t + \epsilon$$

First column is with all subjects included while the second is with subjects ($t > 1.9$) excluded. Panel B presents the slope coefficients from

$$NT = a + b_2 tM + \epsilon,$$

where M is the mean absolute mispricing. Standard errors in all projections are corrected for heteroscedasticity and subject clustering.

Treatment	Panel A		Panel B	
	b_1 all t included	b_1 ($t > 1.9$) excluded	b_2 all t included	b_2 ($t > 1.9$) excluded
1	1.231	-0.428	0.102	0.027
	(1.410)	(1.109)	(0.101)	(0.280)
2	-2.452	-2.730	-0.349	-0.417
	(1.046)	(1.262)	(0.146)	(0.190)
3	0.200	-0.465	0.139	0.103
	(1.062)	(1.187)	(0.174)	(0.205))
4	-0.845	-0.464	-0.059	0.146
	(1.561)	(2.463)	(0.291)	(0.367)
all	-0.367	-0.967	-0.063	-0.125
	(0.707)	(0.873)	(0.104)	(0.140)

Table VII
Price Sensitivity and Number of Trades Relation, UCLA 1 and 2 excluded

Panel A of the table presents the slope coefficients from the projections of number of trades NT onto individual price-sensitivity parameters t (t is the t-statistic of the slope coefficient estimate in projections of one-minute changes in individual holdings of Red Stock onto difference between (i) last traded price, and (ii) expected payoff using correct probabilities).

$$NT = a + b_1 t + \epsilon$$

First column is with all subjects included while the second is with subjects ($t > 1.9$) excluded. Panel B presents the slope coefficients from

$$NT = a + b_2 tM + \epsilon,$$

where M is the mean absolute mispricing. Standard errors in all projections are corrected for heteroscedasticity and subject clustering.

Treatment	Panel A		Panel B	
	b_1 all t included	b_1 ($t > 1.9$) excluded	b_2 all t included	b_2 ($t > 1.9$) excluded
1	0.665	-0.085	0.186	0.075
	(0.697)	(0.697)	(0.135)	(0.142)
2	-1.291	-1.293	-0.159	-0.172
	(0.776)	(0.936)	(0.081)	(0.102)
3	0.264	-0.261	0.056	0.048
	(0.713)	(0.829)	(0.109)	(0.145)
4	-0.645	-0.838	-0.002	0.125
	(1.392)	(2.146)	(0.218)	(0.268)
all	-0.201	-0.601	-0.022	-0.032
	(0.539)	(0.693)	(0.061)	(0.079)

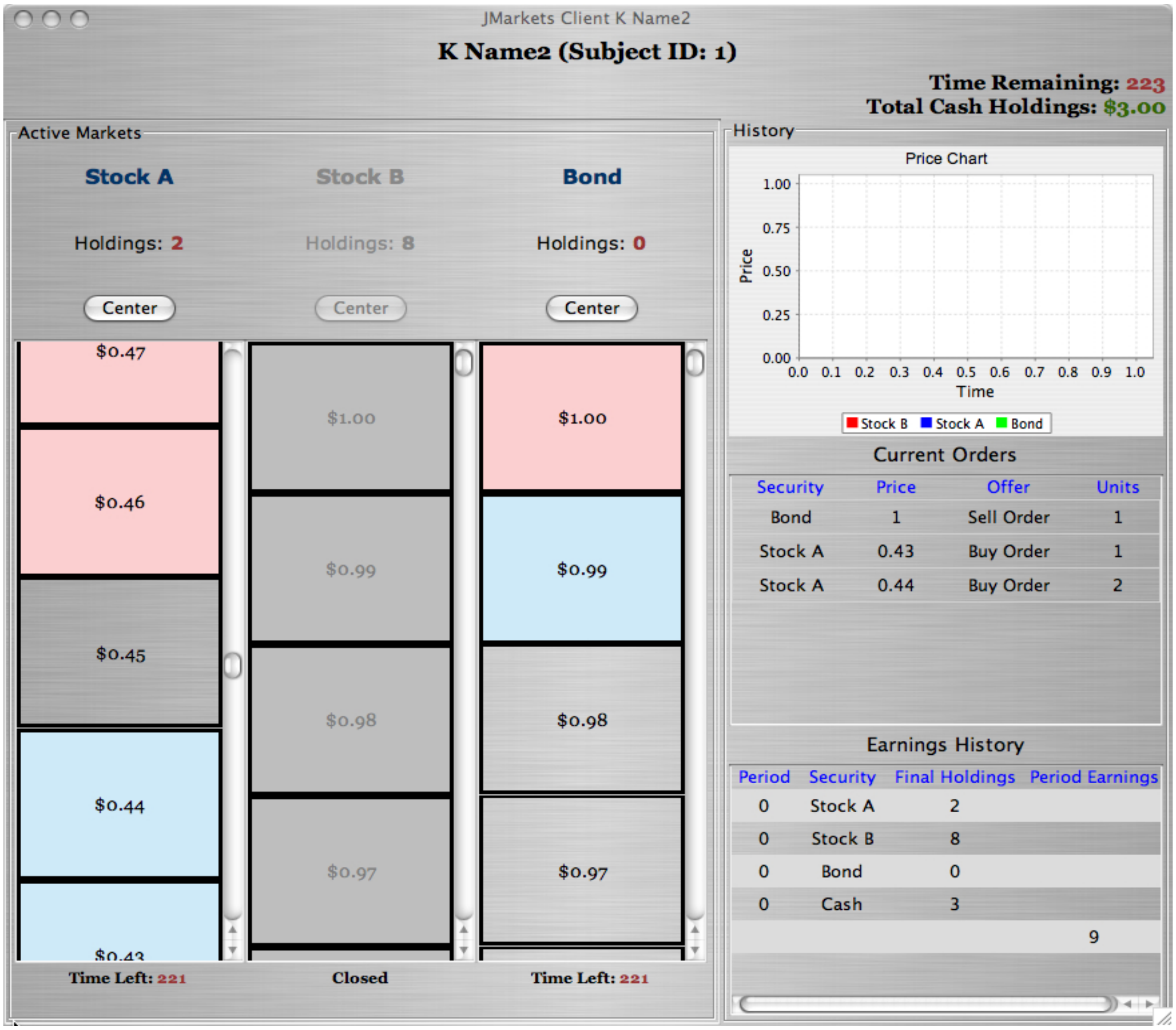


Figure 1. jMarkets Trading Screen

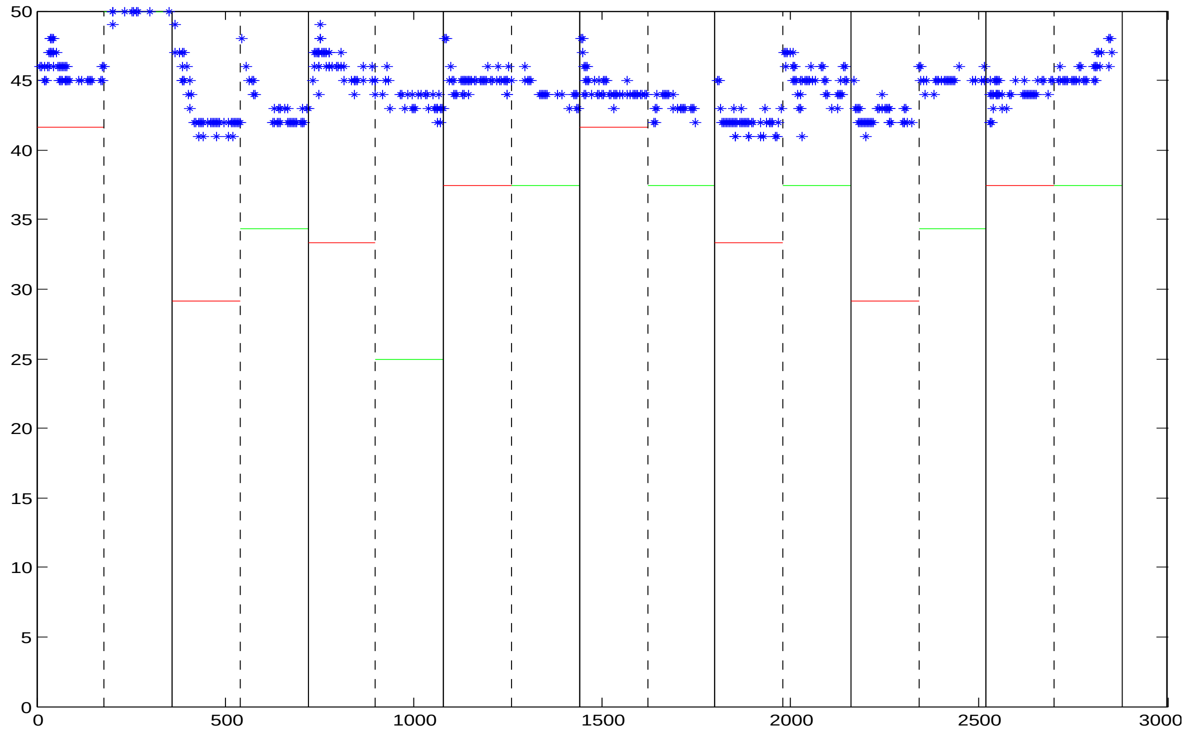


Figure 2. Transaction prices: Utah

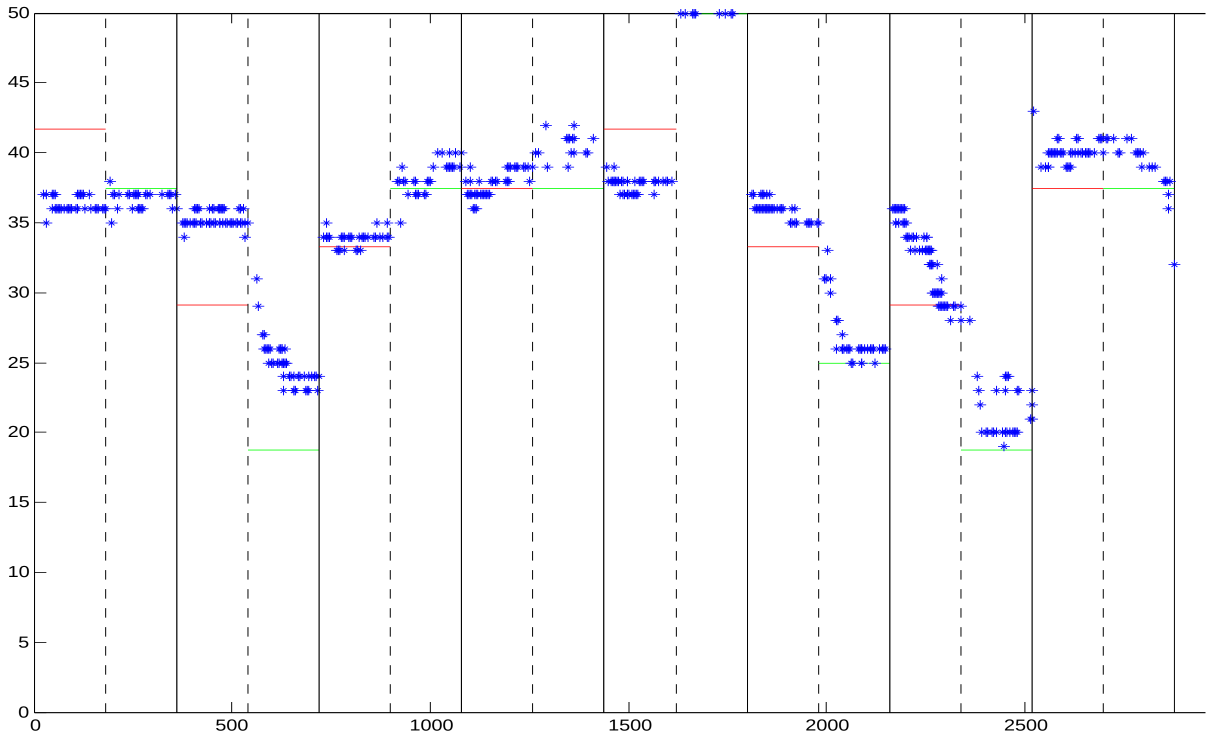


Figure 3. Transaction prices: Caltech-Utah