Why Cognitive Biases May Not Always Affect Asset Prices

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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 really 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 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.

Why Cognitive Biases May Not Always Be Relevant For Asset Pricing[†]

I Introduction

In psychology, many cognitive biases have been discovered in experiments where subjects generally have *no choice* but to reveal their biases – if they have any. Subjects are asked questions, but to refuse to answer the questions is usually not part of the experimental protocol. Recent game-theoretic experiments demonstrate that this may be relevant. (Lazear, e.a. (2006)) document that, if subjects are given the option to not play a dictator game, less evidence against Nash equilibrium emerges because those who tend to share opt out of the game.

This raises the issue whether or when cognitive biases are relevant for asset pricing. In financial markets, agents do not need to expose their cognitive biases. The mechanics are not as simple as in the experiments in (Lazear, e.a. (2006)), however. They cannot just stay away, because that may expose them unduly to risk. Financial markets exists primarily to share risk. To stay away means that one foregoes risk sharing, which may be worse than exposing one's cognitive bias.

We will be concerned here with cognitive biases concerning Bayesian inference. It is well known that many people make mistakes against Bayes' law, thereby drawing the wrong inference

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from the data at hand. One notorious example is the Monty Hall problem, where partial revelation of information is often mis-interpreted as irrelevant.

In the context of Bayesian inference, the argument why cognitive biases may not affect asset pricing runs as follows. If agents have difficulty making the right inference, they will not know the correct probabilities. To not know probabilities is referred to in economics as *ambiguity* [or Knightean uncertainty - see (Knight (1939))]. According to expected utility theory (Savage), agents are then merely to assign probabilities and stick to those, effectively ignoring the ambiguity. (Ellsberg (1961)) documented, however, that many people react very differently. They do perceive the ambiguity and typically end up assigning probabilities depending on the payoffs offered, thereby changing beliefs as payoffs change.

In a financial markets context, aversion to ambiguity generates unorthodox portfolio demands. In the absence of shortsale constraints, expected utility agents are always marginal, and hence, always contribute to price setting. In contrast, ambiguity averse agents choose not to change their positions for a range of prices. In particular, they actively seek positions that pay the same across all ambiguous states, no matter what the prices are (within certain bounds). As such, ambiguity averse agents are *infra-marginal* and their actions do not directly contribute to price setting. The experiments in (Bossaerts, e.a. (2005)) confirm this.

Consequently, *if* agents perceive ambiguity when it is hard for them to solve difficult inference problems, they may opt not to be exposed to the risks involved irrespetive of prices, and hence, they become infra-marginal. As such, they do not directly influence prices. In particular, the 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.

Our explanation sheds light on recent experimental findings that, if at least two subjects appear to solve the Monty Hall problem correctly, prices in financial markets are right. See

(Kluger and Wyatt (2004)), who 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. Why don't 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. Because the markets in (Kluger and Wyatt (2004)) are too thin to distinguish between marginal and infra-marginal subjects, we set out to run new experiments.

Our explanation rests on the hypothesis that those whose inference is biased realize that they do not know the correct probabilities, and hence, perceive ambiguity. It is not sure *a priori* whether our hypothesis is born out in the data, and that is why experiments are needed.

The inference problems that subjects are solving as part of our financial markets experiments are variations on the Monty Hall problem. The Monty Hall problem has led to numerous heated debates. The fervor with which incorrect solutions are defended may make one believe that our hypothesis must be wrong: the inability to find the correct solution does not translate into perception of ambiguity; on the contrary, people obstinately stick to the wrong probabilities.

But one cannot dismiss our hypothesis off hand. It is well known that people perceive ambiguity when confronted with conflicting expert opinion. See (Fox and Tversky (1995)), who refer to the phenomenon as *comparative ignorance*. It is an empirical question whether market prices provide enough authority for this effect to be present. If confirmed, it would expand the 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, e.a. (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 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 experiments consist of a sequence of independent one-period situations, whereby subjects are initially allocated securities, part of which they can trade temporarily through a web-based, continuous electronic open book system, and after which the securities are liquidated. The liquidation values are determined through simple card games inspired by the Monty Hall problem.

We designed the experiments in such a way that there was no aggregate risk (although this was not known to the subjects). As a result, risk-neutral pricing should obtain. 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.

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 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.

We analyze the experimental data in a novel way: we determine the number of infra-marginal subjects and correlate this number with the average deviation of traded prices from correct conditional expectation of final payoffs. Subjects are deemed infra-marginal if they do not change their holdings significantly in reaction to price changes. We find that many subjects are infra-marginal, and that pricing deteriorates significantly as the number of infra-marginal subjects increases.

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 replicae, because our mix of subjects is unlike the "natural mix" found in field markets. In fact, we find very 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 describes our experiments in detail. Section III presents the empirical results. Section IV concludes.

II 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 a two or three ticks (the tick size was set at 1 U.S. cent).

The experiments were ran at the following universities: (i) Caltech, (ii) UCLA, (iii) University of Utah, (iv) simultaneously at Caltech (50% of the subjects) and University of Utah.

There were three securities on the laboratory markets, two of them were risky and one was riskfree. Trade took place through a web-based, electronic continuous open-book system called *jMarkets*.[1]

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. dollar). 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. That is, our experiments were designed for subjects to take advantage of the trading opportunities they were given. We did not invite them to use our trading platform in a situation where theory predicts that they would not want to trade, unlike in some "bubble" experiments.[2]

Subjects could also trade a riskfree security called *Note*. This security always paid $0.50.

[1]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-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.

[2]In (Smith, e.a. (1988)), for instance, there is only initially a reason to trade, to share risk; in the remainder of the experiments, subjects need not re-trade, yet markets remain open.

Given cash, it was a redundant security. However, subjects were allowed to short-sell the Note if they wished. Shortsales of Notes correspond to borrowing. Subjects could exploit such shortsales to acquire Red Stock if they thought Red Stock was underpriced.

Subjects were also allowed to shortsell 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 were taken into account that were within 20% of the best standing bid or ask in the marketplace. 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 1 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 CASSEL and the University of Utah's ULEEF). 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 1 1/2 hours in total).[3]

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

[3]More information about the experimental design, including instructions and a typical news page can be obtained at http://clef.caltech.edu/exp/market-mh/start.htm.

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 2 provides details of the four treatments. Treatment 2 is the one we explained above; it is closest to the original Monty Hall problem.

The actual trading within the eight periods lasted about one hour. It was preceded by a long (more than 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 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 shows 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.

Subjects made on average $49.

III Empirical Results

With our hypothesis of the impact of cognitive biases on ambiguity perception in mind, the main goals of the experiment were as follows.

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.[4]

Figures 1 and 2 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

[4]To see this in more detail, let the price of the Red Stock start too low. There are four types of traders in the market–price-sensitive whose initial portfolio is tilted heavily towards Red Stock, price-sensitive with Black Stock, and price-insensitive with Red and Black Stock endowments correspondingly. The price-insensitive subjects aim at achieving a balanced position. In principle, there is no problem with that: approximately half of them need to buy, the other half needs to sell. As such, their actions have no immediate effect on the price. However, as we shall see, some of them may need to trade earlier due to the buying pressure created by the price-sensitive subjects. Indeed, because the price is too low, price-sensitive subjects prefer to trade to imbalanced position with more Red than Black Stock. Those subjects whose endowment is mostly Red Stock need to sell only a bit of it (not as much as to get an equal amount of Red and Black). The rest of the price-sensitive subjects has mostly Black Stock, which cannot be traded. To trade to a position of more Red Stock than Black Stock, they need to buy plenty of Red. Overall, price-sensitive subjects want to buy more than sell. This is only possible at low prices if price-insensitive sellers trade before price-insensitive buyers; otherwise prices would increase immediately, and reach equilibrium levels, something our experimental results clearly contradict. Eventually, the buying pressure causes prices to go up, to reach the correct level. By the time the price is at the correct level, the price-sensitive *sellers* (who started with Red Stock endowment) will just have traded to a balanced position, and as such they will have traded *as much as* the price-insensitive sellers. The price-sensitive *buyers*, however, who have acquired more Red than Black, now need to *undo their imbalanced position*, to go back to a balanced position. As a result, they need to sell Red. So, these subjects "overshoot," and consequently will *trade more than anyone else*. Again, for price adjustment to be slow, price-insensitive sellers should trade before price-insensitive buyers. But price-insensitive subjects are happy to trade at any price, so there is no particular reason why they would prefer to trade sooner or later – some of them can be enticed to trade early; others can go later.

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 experiment (Figure 1). However, when Caltechers 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 1). 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.[5]

[5] 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.

Table 3 reports price quality in each treatment of all the experiments. Price quality is measured in terms of mean absolute mispricing (in U.S. cents).[6] 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).[7] 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 3 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).[8]

Table 3 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 five instances, only *a single* subject was found to react systematically to price

[6] 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.

[7] 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.

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

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 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 3 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, 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).[9] The imbalance-price-sensitivity relationship provides evidence against the noise traders hypothesis. The price-insensitive subjects seem to behave in an ambiguity-averse manner.

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,

[9] 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.

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.

IV Conclusion

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, e.a. (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 inframarginal, 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:

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

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.

Tables and Figures

Table 1: 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	10	5	0	9	0	4
	10	5	12	3	0	1
Utah-Caltech	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

[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 2: 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 3: 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

$$Corr(M, N_{(t<-1.65)}) = -0.415$$
$$\text{(St. Error} = 0.156)$$

[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 4: 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

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

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	0.116	-0.513	0.022	-0.142
	(0.715)	(0.846)	(0.223)	(0.258)
2	-1.291	-2.894	-0.161	-0.351
	(1.058)	(1.022)	(0.114)	(0.130)
3	-0.909	-0.584	-0.188	-0.121
	(0.726)	(0.884)	(0.112)	(0.166)
4	-1.628	-2.310	-0.223	-0.214
	(1.550)	(2.250)	(0.225)	(0.261)
all	-0.908	-1.519	-0.150	-0.250
	(0.616)	(0.747)	(0.072)	(0.086)
R^2	0.01	0.02	0.007	0.016

Table 5: 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

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

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	0.698	0.441	0.215	0.151
	(0.632)	(0.770)	(0.161)	(0.177)
2	-1.683	-2.947	-0.173	-0.307
	(0.955)	(0.984)	(0.097)	(0.115)
3	-1.401	-1.036	-0.260	-0.210
	(0.588)	(0.723)	(0.079)	(0.113)
4	-1.641	-2.190	-0.274	-0.281
	(1.329)	(1.980)	(0.201)	(0.237)
all	-0.979	-1.356	-0.144	-0.200
	(0.500)	(0.630)	(0.056)	(0.068)
R^2	0.015	0.021	0.012	0.018

Table 6: 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	0.844	-1.520	0.251	-0.324
	(1.552)	(1.032)	(0.401)	(0.289)
2	-2.749	-3.352	-0.378	-0.486
	(1.158)	(1.359)	(0.165)	(0.208)
3	-1.586	-1.685	-0.147	-0.130
	(0.943)	(1.261)	(0.175)	(0.252)
4	-1.023	-1.045	-0.067	0.079
	(1.909)	(3.001)	(0.356)	(0.425)
all	-0.987	-1.804	-0.184	-0.291
	(0.768)	(1.018)	(0.110)	(0.165)
R^2	0.006	0.014	0.006	0.011

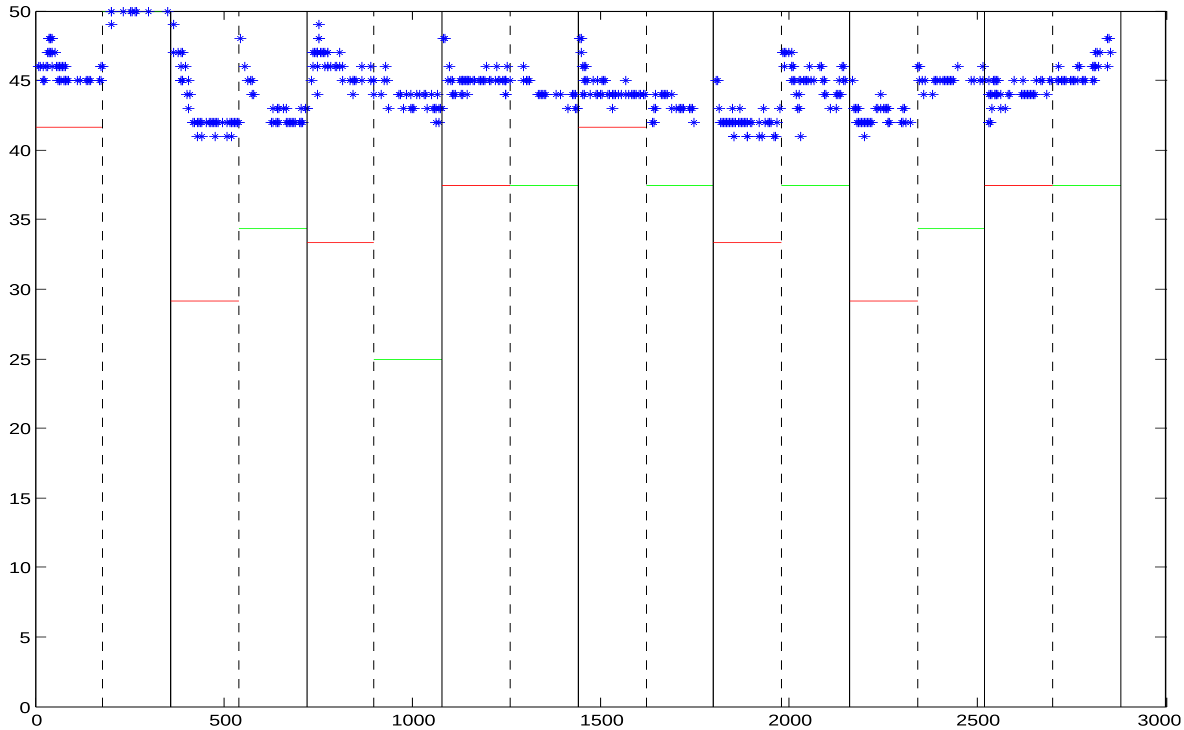

Figure 1: Transaction prices: Utah

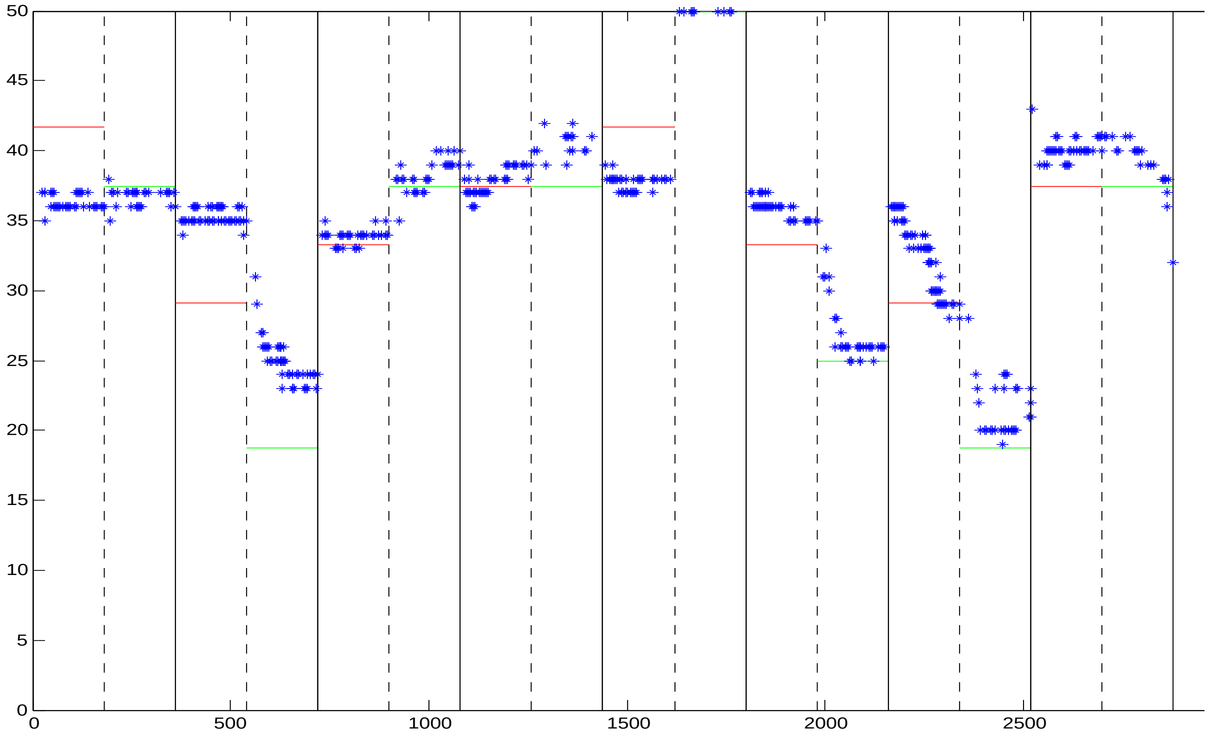

Figure 2: Transaction prices: Caltech-Utah