
Management Science

Publication details, including instructions for authors and subscription information:
http://pubsonline.informs.org

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MANAGEMENT SCIENCE
Vol. 61, No. 6, June 2015, pp. 1378–1397
ISSN 0025-1909 (print) | ISSN 1526-5501 (online)

http://dx.doi.org/10.1287/mnsc.2013.1886




# Risk Attitude, Beliefs Updating, and the Information Content of Trades: An Experiment

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We conduct a series of experiments that simulate trading in financial markets. We find that the information content of the order flow varies with the strength of subjects' prior beliefs about fundamentals. The presence of intrinsic uncertainty about the asset's fundamentals reduces informational efficiency. This originates from subjects' risk attitudes and biases in the way some subjects update their beliefs. The behavior of approximately 63% of the subjects is consistent with the expected utility maximization. These subjects are either risk averse (52%) or risk loving (11%). About 22% of the subjects display non-Bayesian updating of beliefs: underconfidence emerges for weak prior beliefs, and confirmation bias occurs for strong prior beliefs. Non-Bayesian belief updating reduces market efficiency when subjects' prior beliefs are weak and increases it when the prior beliefs are strong.

Data, as supplemental material, are available at http://dx.doi.org/10.1287/mnsc.2013.1886.

*Keywords*: behavior under uncertainty; risk attitude; belief updating; financial market efficiency; laboratory experiment

*History*: Received January 14, 2012; accepted November 8, 2013, by Jerome Detemple, finance. Published online in *Articles in Advance* June 6, 2014.

## 1. Introduction

This paper presents the results of a series of experiments that aim to measure how and to what extent private information on asset fundamentals affects investors' trading decisions.

Specifically, we consider an asset whose fundamental value is the sum of two components: an intrinsic uncertainty component and a learnable component. Subjects receive private information only about the learnable component. We find that in the presence of intrinsic uncertainty, subjects tend to ignore their private information. We also find that the strength of common prior beliefs about the learnable component affects the information content of trades. These findings have implications for market informational efficiency: stock prices fail to aggregate the relevant private information dispersed in the economy. This phenomenon is exacerbated for companies whose performance is also affected by uncertain factors for which there is no private information. In addition, the pace at which private information enters a company's stock price depends on the strength of the market's prior belief about the company's fundamentals.

Our experimental protocol allows us to disentangle two factors that explain the limited use that subjects make of their private information: subjects' risk attitude and subjects' belief updating biases. Concerning risk attitudes, our data suggest that there are virtually no risk-neutral subjects. This result has the effect of making the information content of trades a decreasing function of the strength of subjects' prior beliefs. This effect is exacerbated by the presence of intrinsic uncertainty. Regarding subjects' belief updating, we identify two biases: underconfidence, which emerges when prior beliefs are weak and has the effect of further reducing the information content of trades, and confirmation bias, which emerges when subject beliefs are strong and has the effect of increasing the information content of trades.

To better understand the logic behind our result, let us consider the case of a trader who decides on the position (buy, sell, or no trade) to take on a financial asset and who observes a price reflecting a public prior belief about the asset value. Upon receiving private information, such as favorable or unfavorable information about the asset value, the trader updates his prior beliefs to posterior beliefs. To such posterior beliefs correspond a probability distribution of the asset return, which associates each trading decision with a probability distribution for the trader's profit. Thus, once a trader has formed his or her posterior beliefs, choosing the position to take is equivalent to choosing among three different lotteries describing the trader's uncertain profit from buying, selling, or not trading.[1]

Since the seminal paper by Glosten and Milgrom (1985), it is well known that if both privately informed traders and market makers are risk-neutral Bayesian investors and traders' private information on the asset value is either favorable or unfavorable, then the position taken by an informed trader will reflect the sign of his or her private information. Namely, because a risk-neutral trader only cares about the expected profit, the trader will buy after receiving favorable private information and sell if the private information is unfavorable. Because market makers learn from traders' positions, the price will eventually assimilate all of the information dispersed in the economy. However, outside the risk-neutral world, hedging risk matters, and the direction of a trade does not necessarily correspond to the sign of the trader's private information. When market makers and traders differ in their risk aversion, the trades do not necessarily disclose private information, and informational efficiency fails (see, i.e., Décamps and Lovo 2006a, b). This result suggests that the information content of a trade depends on the trader's risk attitude and, more generally, on the decision process underlying the trader's choice.

Since the seminal paper by Anderson and Holt (1997), in most of the informational cascade and market efficiency experimental literature, the analysis of subjects' behavior is based on the assumption that subjects are risk neutral. To the contrary, in this paper, we conduct a series of experiments that allow us to directly relate risk attitude, prior public beliefs, and bias in the interpretation of private information to the information content of trades. This process is possible thanks to four key features in our experimental design.

1. To detect non-Bayesian belief updating, we conducted our experiment in two different formats so that the subjects had to solve equivalent problems that involved various degrees of reasoning. In the format that we denote *market experiment* (ME henceforth), the subjects choose whether to buy, sell, or not trade a risky asset. The asset can be of two types: "high" or "low." The value of the high-type asset is, on average, larger than the value of the low-type asset. When making their trading decisions, the subjects have access to public and private information about the asset type. The public information consists of the ex ante probability that the asset type is "high." We call this information the "market prior belief," and it reflects the asset trading price. The private information consists of a private signal correlated with the true type of the asset. The subjects are asked to declare their preferred position (buy, sell, or no trade) for different levels of the market prior belief. In the format that we label *lottery experiment* (LE henceforth), the subjects are asked to choose from among a series of different lotteries. For each lottery, the probability distribution of payoffs is explicitly stated. More precisely, the subjects choose the preferred lotteries in different menus, and each menu corresponds to one of the levels of market prior belief in ME. Each menu consists of three lotteries reflecting the distribution function of the portfolio payoffs resulting from the three trading choices available in an ME round (i.e., buy, sell, and no trade). In other words, the lotteries in LE are determined so that a Bayesian subject would face the same decision problem in both formats and therefore would make the same choice in ME as in LE. A subject's choices in LE provide a measure of his or her risk attitude. The comparison of a subject's choices in the two formats enables us to detect deviations from the expected-utility or Bayesian-updating paradigms.

2. In both formats, the information content of the order flow is directly observable. More precisely, by using a "strategy method," we observe the subjects' choices in all potential realizations of the private signals and for different levels of prior beliefs. The strategy approach is crucial for identifying situations in which subjects ignore their private information and take the same action irrespective of the sign of their information.[2]

3. In our main treatment, the liquidation value of the asset comprises two components: the type of the asset, which can be learned by aggregating all private information, and an additional intrinsic, non-learnable shock for which subjects have no private information.[3] In a control treatment, the additional non-learnable shock is absent. The comparison of the two treatments allows us to measure the effect of the presence of the non-learnable shock on the market's ability to learn the type of the asset. In addition, these treatments provide a further test for the hypothesis of risk neutrality.

4. In our main treatment, the subjects do not interact; thus, the lack of common knowledge in the participants' rationality cannot explain the deviation from what the theory predicts.

[1] Here, we use the term "lottery" to mean any random payment.

[2] Whereas actual traders make decisions based on the realized private information, the survey of Brandts and Charness (2011) shows that most of the experimental works find no difference between the strategy method or the more standard, direct-response method.

[3] The latter component reflects the fact that real-world investors are aware that future shocks might affect a stock's value even if no private or public information about the sign of these shocks is available at the time of their investment.

Overall, LE was designed so that regardless of the market prior beliefs, a risk-neutral subject would always choose the same two lotteries: the one corresponding to buying upon receiving positive private information and the one corresponding to selling upon receiving negative private information. The experiment results clearly reject the risk-neutrality hypothesis. We find that the behavior of approximately two-thirds of the subjects in LE is compatible with the constant absolute risk aversion (CARA) and/or constant relative risk aversion (CRRA) utility functions, with the subjects' risk attitude ranging from a high degree of risk aversion to a risk-loving attitude. No subject can be classified as close to risk neutral. The absence of risk neutrality is reflected in the way in which the information content of trades varies with the strength of the market prior beliefs: the information impounded in the order flow decreases with the strength of the prior belief.[4]

ME was designed so that a Bayesian subject's behavior in ME equals his or her behavior in LE. We find that subjects' behavior in ME differs from the behavior observed in LE. More precisely, in comparison with LE, for strong prior beliefs, ME presents an increase in strategies that consist of following the private signal when it confirms prior beliefs and of no trading when the private signal and the prior beliefs contradict each other. We also observe that in ME, strong prior beliefs give rise to trades that conform to those beliefs and ignore private information. For weak prior beliefs, regardless of the private signal, we observe an increase in no-trade decisions. After running some control experiments, we find that the different "framing" cannot fully explain the differences between the behaviors in LE and ME. Starting from the utility function implied by the subject's behavior in LE, we can measure the bias in belief updating that is implied by the subject's behavior in ME. We find evidence of confirmation bias for strong public belief and underconfidence bias for weak public belief. That is, in ME, for strong public belief, the subjects tend to overweight (underweight) the information content of a private signal when it confirms (contradicts) prior beliefs. For weak public belief, the subjects tend to systematically underweight their private information.

Whereas subjects do not trade sequentially in our main experiments, we can simulate an arbitrarily large number of sequential trading histories in which the behavior of virtual traders reflects the actual behavior of the pool of subjects in our experiment. These simulations generate sequences of trading prices that we use to more directly measure market informational efficiency. We find that the virtual absence of risk-neutral behavior significantly slows the price convergence to fundamentals. In ME, when public belief is weak, the information content of the order flow is lower than in LE, whereas for stronger public belief, it is higher than in LE. Thus, non-Bayesian updating improves information efficiency when the market is clearly bullish or clearly bearish, but it reduces efficiency when the market has no precise orientation. In a control treatment, we allow subjects to trade sequentially. We find that subjects' behavior is closer to the results from ME rather than LE.

Our paper is related to the experimental literature on information cascades, and particularly to Anderson and Holt (1997), Huck and Oechssler (2000), Kübler and Weizsäcker (2004), Çelen and Kariv (2004), Cipriani and Guarino (2005), Drehmann et al. (2005), Alevy et al. (2007), and Goeree et al. (2007). Similar to our work, these papers studied subjects who had to make an investment decision after receiving some private but partial information about the fundamentals. However, unlike the main treatment in our experiment, their subjects traded sequentially. As a result, their subjects' choices could have been affected by the fact that they interpreted the investment choices previously made by other subjects in a way that did not fully reflect how prices reacted to past trades. In some of these papers, the underlying assumption is that subjects are risk neutral. Thus, deviations from risk-neutral rational behavior are identified with a lack of Bayesian behavior when interpreting private signals and/or with a lack of common knowledge about subjects' rationality when interpreting other subjects' choices. In our main treatments, the subjects do not interact at all, so their beliefs about the other subjects' behavior/rationality play no role. Furthermore, in LE, there is no private signal to be interpreted, so a subject's behavior provides a direct measure of the subject's risk attitude. For two-thirds of the subjects, the trading decisions are consistent with either risk-averse or risk-loving rational behavior. There is no subject whose behavior is consistent with the risk-neutrality premise. The comparison of LE and ME allows us to insulate the effect of the non-Bayesian interpretation of private signals from the effect of risk attitudes. Thus, our paper is related to the literature on the improper Bayesian updating of prior beliefs (see, i.e. Grether 1992, Holt and Smith 2009, among many others). In particular, our experiment identifies situations in which non-Bayesian individuals do not pose informative orders and therefore do not impact market prices. This result relates to Asparouhova et al. (2010), who stress that individuals who suspect that they do not update correctly are induced to hold more balanced portfolios. Our work is also related to experimental papers in decision theory, such as Abdellaoui (2000), Kilka and

[4] This finding is broadly consistent with the theoretical prediction of Décamps and Lovo (2006a, b): when the market is sufficiently convinced about a stock's prospects (positive or negative) and traders are not risk neutral, information dispersed in the economy cannot be integrated into trading prices.

Weber (2001), and Abdellaoui et al. (2005, 2007). Similar to our paper, these experiments allow the elicitation of subjects' utility functions and individual probability weights. However, whereas our data interpretation is primarily based on the expected utility paradigm, these papers take a broader decision theory perspective that encompasses expected utility as a special case. Furthermore, whereas our experiment was designed to allow for a better understanding of subjects' behavior in a Glosten and Milgrom (1985)-style economy, their experiments are explicitly designed to recover subjects' preferences.

The remainder of this paper is organized as follows. Section 2 presents the theoretical setting and its implications for agents' behavior. Section 3 presents the experimental design. Section 4 presents the results of the experiment. Section 5 discusses the implications for the actual financial markets and concludes.

## 2. Theoretical Framework

In this section, we first describe the theoretical setting borrowed from Décamps and Lovo (2006b). Second, we illustrate the main predictions of the model with some numerical examples.

### 2.1. The Model Structure

We consider a discrete time sequential trade model in the manner of Glosten and Milgrom (1985): A single asset is exchanged for money among market makers and traders. We denote the fundamental value of the asset with $\tilde{v} = \tilde{V} + \tilde{\epsilon}$, where $\tilde{V}$ and $\tilde{\epsilon}$ are independently distributed. The random variable $\tilde{V}$ represents a realized shock; market participants are asymmetrically informed of this shock. The random variable $\tilde{\epsilon}$ represents other shocks to fundamentals (e.g., future shocks) whose realization is unknown to everyone. We assume that $\tilde{V} \in \{\underline{V}, \bar{V}\}$, where $\underline{V} < \bar{V}$, and that $\tilde{\epsilon} \in \{-\epsilon, +\epsilon\}$, with $\mathbb{P}[\tilde{\epsilon} = \epsilon] = \mathbb{P}[\tilde{V} = \bar{V}] = \frac{1}{2}$. Each trader observes a conditionally independent and identically distributed private signal $\tilde{s}$ with possible values $l$ and $h$. We assume that $\mathbb{P}[l \mid \underline{V}] = \mathbb{P}[h \mid \bar{V}] = p$, with $p \in (1/2, 1)$, implying that private signals are partially informative regarding $\tilde{V}$ but providing no information regarding $\tilde{\epsilon}$.

At any period $t$, a trader enters the market and faces a unique opportunity to buy or sell one unit of the risky asset at the trading prices posted by the market makers. Let $H_t$ denote the history of trades (past quantities and prices) to date $t-1$. All agents observe $H_t$. We denote the public belief at time $t$ as $\pi_t = \mathbb{P}[\bar{V} \mid H_t]$, whereas $\pi_t^s = \mathbb{P}[\bar{V} \mid H_t, s]$ denotes a trader's belief at time $t$ given a private signal $s \in \{l, h\}$, namely, $\pi_t^h = (\pi_t p)/(\pi_t p + (1-\pi_t)(1-p)) > \pi_t$ and $\pi_t^l = (\pi_t(1-p))/(\pi_t(1-p) + (1-\pi_t)p) < \pi_t$. Because the private signal precision is bounded, the closer the prior $\pi_t$ is to 1 (or to 0), the smaller $|\pi_t^s - \pi_t|$ is; i.e., a smaller change in belief is induced by the private signal. For this reason, we adopt the following labeling. We say that a prior belief $\pi_t$ is *strong* when $|\pi_t - 0.5|$ is large. Furthermore, we call a public belief $\pi_t$ that is larger than 0.5 a *positive prior* and a public belief $\pi_t$ that is lower than 0.5 a *negative prior*.

The demand of a trader with utility function $u$ is as follows:

$$Q^\star(P_t, \pi_t, s) := \underset{Q\in\{-1,0,1\}}{\arg\max}\, \mathbb{E}[u(m + x\tilde{v} + (\tilde{v} - P_t(Q))Q) \mid H_t, s], \qquad (1)$$

where $P_t(\cdot)\colon \{-1, 0, 1\} \to \mathbb{R}$ is the pricing schedule proposed by the market makers. We assume that $u'$ is positive and continuous, but we impose no restriction on $u''$. Thus, our analysis takes risk neutrality, risk aversion, and risk loving into consideration. The variables $m$ and $x$ represent the trader's initial monetary wealth and his or her initial inventory in the risky asset, respectively.

The risk-neutral market makers compete to fill the trader's order without knowing the trader's signal and price the asset efficiently:

$$P_t(Q) := \mathbb{E}[\tilde{v} \mid H_t, Q^\star(P_t, \pi_t, \tilde{s}) = Q]. \qquad (2)$$

All agents are Bayesian. An equilibrium is a situation where Equations (1) and (2) are satisfied at any time $t$. Private information enters prices when market makers can construe it from trading decisions. However, if a trader's private signal does not affect his or her demand, nothing can be inferred from his or her order. Formally, we have the following:

Definition 1. A trader's order is said to be *noninformative* when it is not affected by the trader's private signal, i.e., $Q^\star(P_t, \pi_t, h) = Q^\star(P_t, \pi_t, l)$.

As the percentage of traders submitting noninformative orders increases, the flow of information that can be incorporated into the asset price decreases.

Since Glosten and Milgrom (1985), Easley and O'Hara (1992), and Avery and Zemsky (1998), it is well known that when informed traders are risk neutral, they will systematically buy on receiving positive private information and sell on negative private information. In this instance, the order flow will never stop disclosing the private information dispersed in the market, and the trading price eventually converges to $\tilde{V}$. Décamps and Lovo (2006a, b) show that if market makers and traders differ in their risk attitude, and if the agents' set of actions is discrete,[5] then as soon as the past history of trade provides sufficiently strong, but not complete,

[5] If agents were able to trade a continuum of quantities, risk aversion alone would not be enough to generate market inefficiency. See, for instance, Glosten (1989) and Vives (1995).

information regarding the realization of $\tilde{V}$, in equilibrium, all traders will submit noninformative orders. This result implies that the price will stay bounded away from the realization of $\tilde{V}$.[6] Although we refer to Avery and Zemsky (1998) and Décamps and Lovo (2006a, b) for the formal proof of these statements, in the following section, we illustrate these findings with a numerical example that reflects the setup of our experiment.

### 2.2. An Illustration of the Behavior of a Bayesian Expected Utility Maximizer

Consider the following parameters' values: $\underline{V}=4$, $\bar{V}=12$, $\epsilon=4$, and $p=0.65$. In this instance, the fundamental value of the asset can take three values, i.e., $\tilde{v}\in\{0,8,16\}$. In this illustration and throughout the paper, we will assume that agents can buy and sell at a price set at the expected asset value, conditional upon the available public information at time $t$, i.e., $P(Q)=\mathbb{E}[\tilde{v}\mid H_t]$.[7]

There are two ingredients that can generate noninformative orders: first, the absence of risk neutrality and second, the fact that when prior beliefs are strong, private signals slightly affect posterior beliefs. To better understand this point, consider the following numerical example where the prior belief is $\pi_t=\mathbb{P}(\bar{V}\mid H_t)=0.9930$, corresponding to a trading price of $P_t=\mathbb{E}[\tilde{v}\mid H_t]=11.94$, and consider a Bayesian expected utility maximizer trader endowed with $x=0$ amount of the risky asset and $m=12$ units of money. The problem that this trader faces can be represented as a choice in a menu of lotteries described in Tables 1–3. The entries in the tables report the possible payoffs resulting from the three possible trading decisions and the three possible realizations of the fundamental value $\tilde{v}$, i.e., *traded quantity* $\times$ ($\tilde{v}-$ *trading price*) $+12$. Tables 1–3 differ only in the probabilities of obtaining the payoffs in each column.

Table 1 represents the problem faced by a trader who received no private signal. By definition, a risk-averse trader will prefer the certain payment 12 to the other two lotteries. That is, "no trade" is the strictly preferred action. For a risk-loving trader, either selling or buying is strictly preferred to the other two alternatives, whereas a risk-neutral trader will be perfectly indifferent with regard to the three actions.

**Table 1** **Lotteries When No Private Signal Is Received**

| | $\mathbb{P}[\tilde{v}=0]=$ 0.35% | $\mathbb{P}[\tilde{v}=8]=$ 50.00% | $\mathbb{P}[\tilde{v}=16]=$ 49.65% | Expected value |
|---|---|---|---|---|
| Sell order | 23.94 | 15.94 | 7.94 | 12 |
| No trade | 12.00 | 12.00 | 12.00 | 12 |
| Buy order | 0.06 | 8.06 | 16.06 | 12 |

*Notes.* A trader receiving no private signal must choose between one of the three possible actions reported in this table's rows. Each action corresponds to a lottery with three possible outcomes.

**Table 2** **Lotteries When a Signal *l* Is Received**

| | $\mathbb{P}[\tilde{v}=0]=$ 0.65% | $\mathbb{P}[\tilde{v}=8]=$ 50.00% | $\mathbb{P}[\tilde{v}=16]=$ 49.35% | Expected value |
|---|---|---|---|---|
| Sell order | 23.94 | 15.94 | 7.94 | 12.05 |
| No trade | 12.00 | 12.00 | 12.00 | 12.00 |
| Buy order | 0.06 | 8.06 | 16.06 | 11.95 |

*Notes.* A trader receiving a private signal *l* must choose one of the three possible actions reported in this table's rows. Each action corresponds to a lottery with three possible outcomes.

Now consider the same trader, but suppose that he or she received a private signal $\tilde{s}$ with precision $p=0.65$. Will the private signal affect the trader's order? The probabilities in Tables 2 and 3 are obtained by the Bayesian updating of the public belief $\pi_t=0.9930$ following the private signals $l$ and $h$, respectively. Thus, Tables 2 and 3 represent the choices available to a trader who received the private signals $l$ and $h$, respectively.

It is clear from the expected value column that a risk-neutral trader will prefer to sell when $s=l$ and buy when $s=h$. In contrast, for a sufficiently risk-averse or risk-loving agent, the preferred action will be the same as in the case where he or she has no private information. Hence, a trader who is either sufficiently risk averse or sufficiently risk loving will submit a noninformative order.

The impact of risk attitude and prior belief on trading strategies is further analyzed in Table 4 for the CRRA and CARA utility functions. This table presents the optimal contingent trading strategies for different levels of risk attitude and different levels of public belief $\pi$. For any given level of $\pi$ and risk aversion, we identify

**Table 3** **Lotteries When a Signal *h* Is Received**

| | $\mathbb{P}[\tilde{v}=0]=$ 0.19% | $\mathbb{P}[\tilde{v}=8]=$ 50.00% | $\mathbb{P}[\tilde{v}=16]=$ 49.81% | Expected value |
|---|---|---|---|---|
| Sell order | 23.94 | 15.94 | 7.94 | 11.97 |
| No trade | 12.00 | 12.00 | 12.00 | 12.00 |
| Buy order | 0.06 | 8.06 | 16.06 | 12.03 |

*Notes.* A trader receiving a private signal *h* must choose one of the three possible actions reported in this table's rows. Each action corresponds to a lottery with three possible outcomes.

[6] In other words, the heterogeneity of agents and the fact that $\mathrm{Var}[\tilde{V}\mid H_t]$ remains larger than a positive threshold leads to what Smith and Sørensen (2000) call "confounded learning," i.e., a situation in which history offers no decisive lesson and full social learning is never reached.

[7] This pricing convention is simpler than the one predicted by the theory where buy and sell orders are not necessarily executed at the same price. We adopt this pricing rule in our experiment. By fixing the price at $\mathbb{E}[\tilde{v}\mid H_t]$ for buy and sell orders, we increase the trader's expected profit from trading in the same direction as the private signal. This increased profit reduces the incentive to adopt noninformative orders. In other words, this pricing rule should bias the results of our experiment in favor of market efficiency.

**Table 4** Optimal Strategies for an Investor with CRRA and CARA Utility

| CRRA: $U(x)=x^{(1+\alpha)}/(1+\alpha)$ | $\alpha<-0.85$ | $\alpha=-0.25$ | $-0.034<\alpha<4.7$ | $\alpha=4.83$ | $\alpha=5.91$ |
|---|---|---|---|---|---|
| CARA: $U(x)=-\gamma e^{-\gamma x}$ | $\gamma>0.078$ | $\gamma=0.02$ | $-0.25<\gamma<0.003$ | $\gamma=-0.26$ | $\gamma=-0.32$ |
| $\pi$ | | | | | |
| 0.002 | N, N | N, N | S, B | B, B | B, B |
| 0.013 | N, N | N, N | S, B | B, B | B, B |
| 0.023 | N, N | N, N | S, B | B, B | B, B |
| 0.043 | N, N | N, B | S, B | S, B | B, B |
| 0.078 | N, N | S, B | S, B | S, B | B, B |
| 0.135 | N, N | S, B | S, B | S, B | B, B |
| 0.225 | N, N | S, B | S, B | S, B | S, B |
| 0.350 | N, N | S, B | S, B | S, B | S, B |
| 0.500 | N, N | S, B | S, B | S, B | S, B |
| 0.650 | N, N | S, B | S, B | S, B | S, B |
| 0.765 | N, N | S, B | S, B | S, B | S, B |
| 0.865 | N, N | S, B | S, B | S, B | S, S |
| 0.922 | N, N | S, B | S, B | S, B | S, S |
| 0.957 | N, N | S, N | S, B | S, B | S, S |
| 0.977 | N, N | N, N | S, B | S, S | S, S |
| 0.987 | N, N | N, N | S, B | S, S | S, S |
| 0.998 | N, N | N, N | S, B | S, S | S, S |

*Notes.* To determine the grid of $\pi$, we consider the Bayesian public belief that would emerge in a sequential trading framework should past traders' signals be observable. Namely, any $\pi$ corresponds to a net balance of positive minus negative past private signals.

a contingent trading strategy with two letters indicating the action chosen for signals $l$ and $h$, respectively. Namely, S, N, and B stand for sell order, no trade, and buy order, respectively.[8] The first column of Table 4 shows the different levels that we considered for the public prior belief $\pi$.

Several comments are in order. First, a simple computation shows that the maximization problem faced by an agent with prior belief $\pi$ and private signal $l$ is symmetric to the maximization problem corresponding to prior belief $1-\pi$ and private signal $h$. We call this property the symmetry property with respect to $\pi$.[9] Second, sufficiently risk-averse traders ($\gamma>0.078$ and $\alpha<-0.85$ in Table 4) always choose strategy N-N, whatever the public belief. Third, strategy S-B is optimal for all of the levels of public prior belief only when the trader's risk attitude is sufficiently close to risk neutrality. This strategy is also optimal for traders with intermediate levels of risk aversion (or risk loving), but only when public belief is weak (i.e., $\pi$ around 0.5). However, as soon as public prior belief is sufficiently strong (i.e., $\pi$ close to 1 or close to 0), these traders will submit noninformative orders. More precisely, risk-averse traders will prefer not to trade and will ignore their private signal. Risk-loving traders (i.e., $\gamma<-0.25$ and $\alpha>4.7$ in Table 4) will choose to buy when the prior is strong and negative ($\pi$ close to 0) and to sell when the prior is strong and positive ($\pi$ close to 1), but in both cases, they will ignore their private signal.

These remarks have a number of empirical implications at the individual level as well as at the aggregate level.

Implication 1. *An expected utility maximizer contingent trading strategy is symmetric with respect to $\pi$.*

Implication 2. *By observing an expected utility maximizer's contingent trading strategy for different levels of prior belief $\pi$, one can estimate the trader's risk attitude. In particular, a risk-neutral trader will choose strategy S-B for all levels of $\pi$.*

Implication 3. *In an economy composed of Bayesian traders that are expected utility maximizers but differ in their risk attitude, the stronger the public belief, the higher the frequency of noninformative orders and the lower the information content of the order flow.*

It is interesting to relate the noninformative strategies to what one could classify as conforming or contrarian trading. A trader engages in conforming trading (contrarian trading) if he or she tends to ignore his or her private signals to follow the common wisdom. For instance, a sufficiently positive prior induces him or her to buy (sell) the asset independently of the realization of the private signal. Formally, we have the following:

Definition 2. A subject engages in *conforming trading* if there exist $\pi^*>0.5$ (respectively, $\pi^*<0.5$) such that the subject adopts strategy B-B (respectively, S-S) when $\pi_t\geq\pi^*$ (respectively, $\pi_t\leq\pi^*$).

Definition 3. A subject engages in *contrarian trading* if there exist $\pi^*>0.5$ (respectively, $\pi^*<0.5$) such that the subject adopts strategy S-S (respectively, B-B) for all $\pi_t\geq\pi^*$ (respectively, $\pi_t\leq\pi^*$).

Table 4 suggests that contrarian trading should be related to a risk-loving attitude, whereas conforming trading is not consistent with CARA or CRRA utility functions and Bayesian updating.

Implication 4. *In an economy composed of Bayesian traders that are expected utility maximizers, contrarian trading arises in the presence of risk-loving traders, but conforming trading is not observed.*

Because subjects do not interact and trading is not sequential in our main treatments, conforming and contrarian trading are different concepts from the concepts of herding and contrarian behavior studied in the theoretical and experimental literature related

[8] For example, strategy N-B corresponds to "no trade" when receiving signal $l$ and buy order when receiving signal $h$.

[9] For example, if a trader's contingent strategy is S-N for a given prior $\pi$, then it will be N-B for the prior $1-\pi$.

to rational herding.[10] In those studies, herding and contrarian behaviors relate to the process through which a trader interprets the information content of the previous traders' actions to optimally choose his current trade. Herding (contrarian behavior) results when this optimal choice consists of taking the same (opposite) position as previous traders. Because the other subjects' actions are not observable in our experiment, our findings tell us nothing about the prevalence of rational herding.

### 2.3. Testing Bayesian Updating Rule

In the previous section, we assumed Bayesian updating to illustrate how subjects' contingent trading strategies are affected by their risk attitude. However, subjects need not update their beliefs using Bayes' rule. In this case, a subject's actual behavior for a given risk attitude will differ from that described both above and in Table 4. To separate the effect of risk attitude from the effect of non-Bayesian updating, each subject participated in two formats of the experiment: the *lottery experiment* and the *market experiment*. Both formats reproduce the decision problem of a trader in the economy described in §2.1. However, in LE, the questions are stated in the same form as they are in the menu of lotteries in Tables 2 and 3. By explicitly providing the subjects with the distribution function of payoffs, we ensure that the belief updating rule plays no role in their decision. In ME, the subjects are first informed of the prior $\pi$ and of the accuracy of their private signal and are then asked to declare their preferred trading position contingent on the realization of the private signal. In other words, whereas in LE posterior probability is explicitly provided, in ME, the subjects have all of the elements necessary to derive the posterior probability. The two formats are designed so that a rational Bayesian expected utility maximizer would find them perfectly equivalent.

Implication 5. *The behavior of a Bayesian expected utility maximizer in ME is the same as in LE.*

## 3. Experiment Design

We performed our experiment under two different, but in some ways equivalent, formats: ME and LE. Each subject participated in both formats.[11] Our main treatment matches the theoretical setup described in §2.1, where the random variables $\tilde{V}$ and $\tilde{\epsilon}$ take their value in $\{4, 12\}$ and $\{-4, 4\}$, respectively. We also conducted four control treatments: the *simplified market experiment* (SME henceforth), the *finance framed lottery experiment* (FFLE henceforth), the *no-unlearnable risk treatment* (NUR treatment henceforth), and the *sequential market experiment* (SeME henceforth), which are detailed in §§4.2.1, 4.3, and 4.4. Below is a detailed description of the ME, the LE, the subjects' payoff, and the implementation.

*Market Experiment.* The ME consisted of a series of 17 questions or "rounds." In a given round $\tau$, each subject was asked whether he or she wanted to buy, sell, or not trade a given risky asset, which we denote as asset $\tau$. As described in §2, the fundamental value of asset $\tau$ is a random variable $\tilde{v}_\tau = \tilde{V}_\tau + \tilde{\epsilon}$ with $\tilde{V}_\tau \in \{4, 12\}$ and $\tilde{\epsilon} \in \{-4, 4\}$. The trading price for asset $\tau$ was fixed at $P_\tau = \pi_\tau 12 + (1-\pi_\tau)4$. Both $\pi_\tau$ and $P_\tau$ were made known to the subjects in round $\tau$ (see Figure 1). Moreover, in each round, each subject received a private signal $\tilde{s} \in \{h, l\}$ with precision $p = 0.65$. Before being informed of the private signal realization and after observing $\pi_\tau$ and $P_\tau$, each subject was asked to declare his or her desired trade conditional on receiving private signals $h$ or $l$. The subject was then informed of the realization of his or her private signal and that a transaction took place according to the declared conditional trading strategy. To avoid an effect of past gains or losses on a subject's current trading decision, the subjects received feedback about their actual trading payoffs only at the end of the entire experiment. The only difference among the rounds was provided by the probability $\pi_\tau$ and the corresponding trading price $P_\tau$. For the 17 assets, the variables $\pi_\tau$ were chosen from among the 17 different levels of public beliefs presented in Table 4.[12]

*Lottery Experiment.* The LE was designed so that a rational Bayesian subject would find it perfectly equivalent to ME: the subjects were asked exactly the same questions in exactly the same order but with a different formulation. Instead of asking the subjects the position they would take on a given financial asset, they were asked to choose one item from a menu of lotteries. Three possible outcomes and the corresponding probabilities were specified for each lottery in the menu. Similar to the examples presented in Tables 2 and 3, each lottery in a menu corresponded to the random net gain obtained from selling, no trade,

[10] The literature on rational herding begins with the seminal papers by Bikhchandani et al. (1992), Welch (1992), and Banerjee (1992). Herding with endogenous prices has been recently studied in a series of papers, including Avery and Zemsky (1998), Lee (1998), Chari and Kehoe (2004), and Décamps and Lovo (2006a, b). See, for instance, Hirshleifer and Teoh (2003) for a survey on herd behavior in capital markets and Chamley (2004) for an extensive study on rational herding.

[11] LE preceded or followed ME, depending on the cohort. The order in which the subjects participated in the two formats had no qualitative effect on the behavior observed. Hence, our results refer to the aggregate data across cohorts.

[12] Only from $\pi = 0.013$ to $\pi = 0.987$ for the subjects in cohorts 1 and 2, i.e., 15 assets.

**Figure 1** **Screen Layout in a Market Experiment (Main Treatment)**

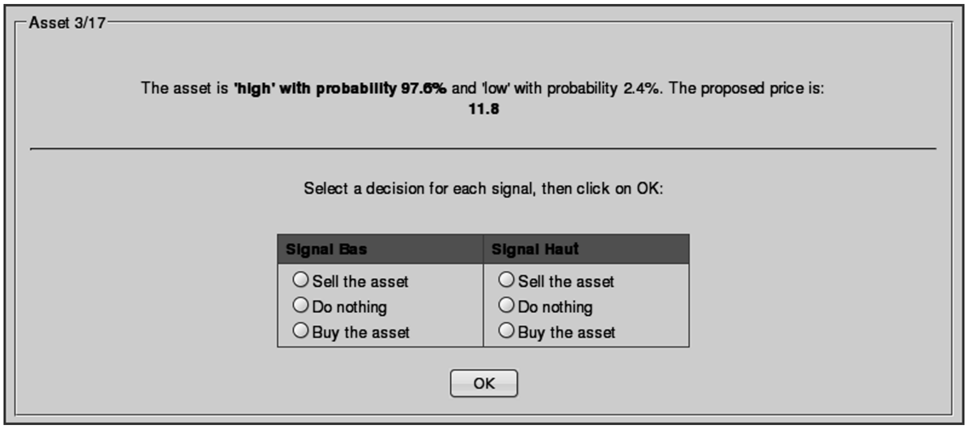
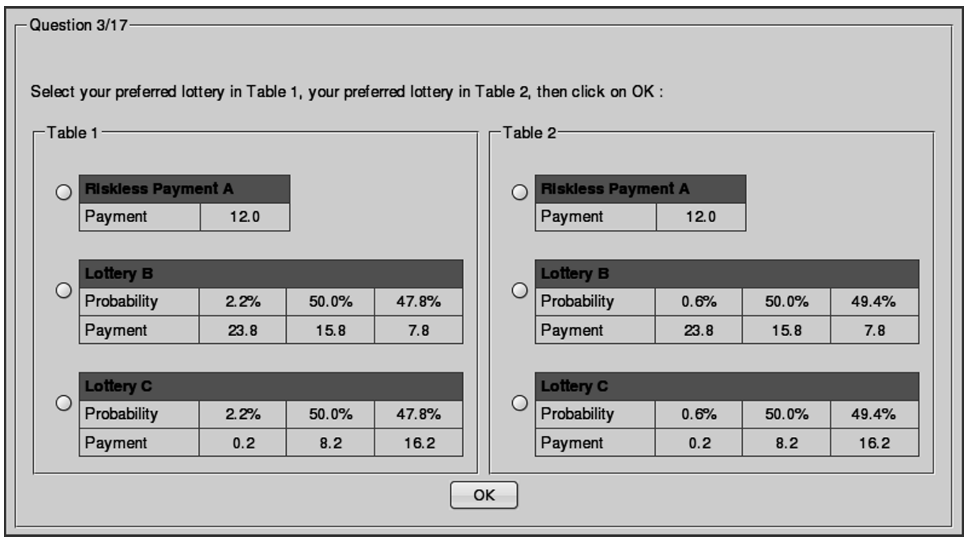



**Figure 2** **Screen Layout in a Lottery Experiment (Main Treatment)**




and buying one unit of asset $\tau$ given the private signal $s$. To match the strategy method implemented in ME, each subject was offered two menus at each stage and asked to choose one lottery in each menu (see Figure 2). The only difference between the two proposed menus in a given round was in the probabilities attached to each payoff. This difference reflected the different impact of the signals $l$ and $h$ on a subject's (Bayesian) posterior probabilities. LE consisted of 17 payoff-relevant rounds, each comprising two menus.[13] Overall, each subject had to choose 34 lotteries in 34 menus. The relationship between the two formats of the experiment was never mentioned to the subjects, nor was the fact that the two experiments were equivalent from the perspective of a Bayesian rational subject.

*Implementation.* The experiment was conducted at HEC Paris and Toulouse University. We recruited 261 subjects from undergraduate finance classes. The subjects had no previous experience in financial market experiments. Between 10 and 43 subjects participated in each session as decision makers. The main treatment involved 134 subjects (five cohorts), and the four control treatments involved 127 subjects (two cohorts for the NUR treatment, three cohorts for SME, and two cohorts for FFLE and SeME). At the beginning of a session, we provided written instructions that were also read aloud by an experiment administrator. Then, two trial subsessions were run, each involving the trade of three assets. Each of the trial sessions reproduced the trading mechanism in the two formats of the experiment. The administrators answered all of the subjects' questions regarding the rules of the game until the distribution of the questionnaire.[14] After this step, the subjects were not allowed to ask additional

[13] Only 15 rounds for cohorts 1 and 2.

[14] After the trial subsessions and before the first payoff-relevant subsession, the subjects answered a questionnaire that tested their level of understanding of the rules of the experiment. Only 5 of the 261 subjects answered more than 3 of the 14 questions incorrectly.

**Table 5 Cohorts and Participants in the Experiment**

| Cohort | Treatment | Order | Nb. of subjects |
|---|---|---|---|
| 1 | Main | LE-ME | 43 |
| 2 | Main | LE-ME | 32 |
| 3 | NUR | LE-ME | 16 |
| 4 | NUR | ME-LE | 26 |
| 5 | Main | ME-LE | 18 |
| 6 | Main | ME-LE | 21 |
| 7 | Main | ME-LE | 20 |
| 8 | SME | — | 10 |
| 9 | SME | — | 21 |
| 10 | SME | — | 20 |
| 11 | FFLE/SeME | FFLE-ME-SeME | 18 |
| 12 | FFLE/SeME | FFLE-ME-SeME | 16 |

*Note.* For each cohort in our experiment, this table reports the treatment that we ran on this cohort, along with the number of subjects.

questions, and the administrators ensured that no form of communication occurred among the subjects. Throughout the experiment, the participants were unable to observe each other's screens. Each experiment lasted approximately an hour and a half. An average of €21.91 was paid to each subject. The subjects were also rewarded with bonus points that would enable them to raise their grades in their core finance course.[15] For each format, LE and ME, the subjects' payoffs were determined based on the gain for one round only. These rounds were randomly selected at the end of the experiment.[16] The final number of observations was 4,256 for 134 subjects in the main treatment, 1,428 for 42 subjects in the NUR treatment, 867 for 51 subjects in the SME treatment, and 1,736 for 34 subjects in the FFLE and SeME treatments. All the treatments are summarized in Table 5.

## 4. Experimental Results

### 4.1. Lottery Experiment

In LE, the probabilities attached to each possible event are explicitly provided. Thus, for this format, an expected utility maximizer's decision depends only on the shape of his or her utility function and not on the way that he or she interprets private information. Also, because the experiment involves no interaction among subjects, the lack of common knowledge regarding the agents' rationality plays no role in the subjects' decision. Consequently, LE provides a simple framework for judging whether the subjects' behavior can be explained by the expected utility assumption and, if so, for measuring the subjects' risk attitude.

We can summarize the main findings of LE as follows:

1. When belief becomes stronger, the information content of trades as well as the volume of trades decrease. This result is in stark contrast to the conventional wisdom that regardless of the level of public belief, a trader will buy upon receiving positive private information and sell if his or her private information is negative.
2. The behavior of approximately two-thirds of the subjects can be explained by subject risk attitude. We can classify approximately 52% of the subjects as risk averse and approximately 11% as risk loving; the rest are not classified. No subject can be classified as risk neutral.
3. Probability weighting does not substantially change the inference about the subjects' risk attitude: the fraction of subjects classified as risk averse increases to 62%, approximately 9% of subjects are classified as risk loving, and approximately 2% of subjects are classified as risk neutral.

In more detail, Table 6 shows the empirical frequency of contingent orders in LE as a function of different regions of the prior belief. Our data show that the subjects' actual contingent strategies are substantially affected by the level of the prior public belief. In particular, we find that the percentage of noninformative orders (i.e., those corresponding to strategies N-N, S-S, and B-B) increases with the strength of the belief (for large and low values of $\pi$). That is, subjects tend to ignore their private information more often when the public information is sufficiently strong. Namely, informative orders represent 51.49% of all trades for neutral prior beliefs ($\pi = 0.5$). This percentage falls to 16.49% and 20.39% for strong negative ($\pi \in [0.002, 0.043]$) and strong positive prior beliefs ($\pi \in [0.957, 0.998]$), respectively.

A closer examination of the noninformative orders for those with strong beliefs shows a large fraction of N-N (62.69% and 51.63% for strong negative and positive prior, respectively). This result is consistent with the presence of risk-averse subjects. Strategy S-S (B-B) is related to contrarian trading when it occurs for strong positive (strong negative) priors. According to Implication 4, contrarian trading can be attributed to the fraction of subjects who are risk loving. We observe both contrarian buying (14.53%) and contrarian selling (19.96%). Strategy S-S (B-B) is related to conforming trading when it is associated with negative (positive) priors. A relatively small fraction of the subjects engaged in conforming buying (8.03%) and conforming selling (6.29%). Conforming trading is not consistent with the theory outlined in §2. This result translates into a negative relationship between

However, these 5 subjects did not behave substantially differently from the others.

[15] This device is standard in the literature (see, i.e., Camerer and Hogarth 1999, Williams 2008, Biais et al. 2005) and allows researchers to incentivize participants in their experiments without distorting their risk attitude.

[16] See the experiment instructions for a precise description of the algorithm determining a subject's payoff.

**Table 6 Conditional Decisions (in %) in the Lottery Experiment (Main Treatment)**

| Public prior belief $\pi$ | B-B | B-N | B-S | N-B | N-N | N-S | S-B | S-N | S-S |
|---|---|---|---|---|---|---|---|---|---|
| $\pi \in [0.002, 0.043]$ | 14.53 | 0.43 | 1.30 | 5.42 | 62.69 | 1.30 | 4.34 | 3.69 | 6.29 |
| $\pi \in [0.078, 0.350]$ | 16.04 | 1.12 | 0.75 | 19.03 | 47.57 | 0.93 | 5.97 | 4.66 | 3.92 |
| $\pi = 0.5$ | 2.24 | 0.00 | 0.00 | 5.22 | 38.81 | 0.00 | 36.57 | 9.70 | 7.46 |
| $\pi \in [0.650, 0.922]$ | 2.80 | 0.37 | 0.56 | 4.29 | 44.78 | 0.56 | 9.14 | 18.28 | 19.22 |
| $\pi \in [0.957, 0.998]$ | 8.03 | 0.22 | 0.65 | 4.77 | 51.63 | 1.52 | 4.77 | 8.46 | 19.96 |

the strength of beliefs and trading volume. Namely, the fraction of contingent orders involving at least one no-trade decision increases from approximately one-half for a neutral prior to at least two-thirds for extreme priors.

Overall, the aggregate distribution of contingent orders in Table 6 appears to be consistent with the hypothesis that although subjects differed in their risk attitude, each subject behaved similarly to the prediction in Table 4 for his or her risk attitude. Along this line of reasoning, because we observed each subject's contingent strategy for the different levels of $\pi$, we attempted to recover the subject's risk attitude in light of Table 4. For this purpose, we compared each subject's actual behavior in LE with the behaviors predicted by the CARA and CRRA utility functions for different levels of risk aversion. Each subject was then assigned the utility function (CARA or CRRA) and the risk-aversion parameter that most accurately matched that subject's observed behavior. Each subject was also assigned a score measuring the match between the assigned utility function and the observed behavior.[17] The closer the matching score was to 1, the better the subject's behavior could be explained by using the appropriate parametrization of a CARA or a CRRA utility function. For 63.43% of the subjects, the matching score was at least 0.75. These subjects could be classified according to their risk attitude, whereas we did not classify the subjects whose matching score was below 0.75. The distribution of risk aversion across subjects is shown in Table 7 for the CARA and CRRA utility functions.

[17] For each subject, the matching score was computed as follows. Let us begin with the CARA function. A given value for the risk parameter of a CARA utility function implies a particular theoretical behavior, i.e., a set of conditional decisions, one for each level of prior belief $\pi_\tau$. For each of these theoretical decisions, we compute a matching score with the observed behavior by counting 0.5 for each side of the conditional decision that matches the observed behavior and dividing this count by the number of different levels of $\pi_\tau$ considered in LE. The score is thus a number between 0 (no matches) and 1 (perfect match). The theoretical behavior with the highest matching score gives us the aversion CARA utility function parameter assigned to the subject. We repeat this procedure for a CRRA utility function and obtain the aversion parameter for this class of function. Finally, the subject's highest overall matching score determines the aversion parameter and the class of function (CARA or CRRA) that best reflects his or her behavior.

**Table 7 Subject's Risk Attitude**

| | CARA $U(x) = -\gamma e^{-\gamma x}$ | CRRA $U(x) = x^{(1+\alpha)}/(1+\alpha)$ | No. of subjects | % | Average matching score |
|---|---|---|---|---|---|
| High risk averse | $\gamma > 0.078$ | $\alpha < -0.85$ | 43 | 32.09 | 0.98 |
| Medium risk averse | $0.005 < \gamma < 0.078$ | $-0.85 < \alpha < -0.065$ | 27 | 20.15 | 0.88 |
| Close to risk neutral | $-0.25 < \gamma < 0.005$ | $-0.065 < \alpha < 4.7$ | 0 | 0.00 | — |
| Risk loving | $\gamma < -0.25$ | $\alpha > 4.7$ | 15 | 11.19 | 0.90 |
| Not classified | | | 49 | 36.57 | 0.62 |
| All | | | 134 | 100.00 | 0.82 |

*Note.* A subject is not classified if no CARA or CRRA utility functions can explain at least 75% of his or her behavior in LE.

The subjects who chose N-N in at least 75% of the situations represent 32.09% of the population and are classified as highly averse to risk. Approximately 11% of the subjects are classified as risk loving, whereas 20.15% of the subjects display intermediate levels of risk aversion. The remaining 36.57% have a matching score below 0.75. Surprisingly, none of the participants in the main treatment come close to behaving in a risk-neutral way. This finding is in sharp contrast to the hypothesis that the subjects are risk neutral.

**4.1.1. Further Tests of Rationality and Robustness.** Implication 1 of the theory states that the decision problem that a subject faces for a given level of public belief $\pi$ is the same as the problem he or she faces when public belief is $1-\pi$.

For each subject, we compute a "symmetry score" by comparing the preferred lottery for a given prior $\pi$ with that chosen for the prior $1-\pi$. The score gives us the proportion of a subject's choices that respects the symmetry rule.[18] Thus, the closer the score is to 1, the more compatible the subject's behavior is with rationality. The median symmetry score is 0.81, with 75% of the subjects scoring higher than 0.57. Overall, these data suggest that the subjects' behavior is consistent with Implication 1 and does not contradict this basic test of rationality. Nevertheless, there is a

[18] To be precise, for each subject, we count 0.5 each time the conditional decision is symmetric for public beliefs $\pi$ and $1-\pi$. The symmetry score of a subject is then obtained by dividing this count by the count corresponding to a fully symmetric strategy profile.

small fraction of subjects (8.21%) who clearly behave inconsistently and display a symmetry score of less than 0.33.

Probability weighting could provide an alternative explanation for the subjects' behavior in LE. In the presence of probability weighting, the subjects have an incorrect appraisal of the probabilities displayed in LE.[19] This incorrect appraisal could explain the difference between the subjects' behavior in LE and the conventional wisdom that subjects should always adopt the S-B strategy. To test for this alternative hypothesis, we compare each subject's actual behavior in LE with the behaviors predicted by the CARA and CRRA utilities when the expected utility is not computed using the true probabilities but using a probability weighting function $w(q)$. The function $w(q)$ maps the true probabilities $q$ onto the appraised probabilities $w(q)$. We focused on the well-known "linear-in-log-odds" specification introduced by Goldstein and Einhorn (1987):

$$w(q) = \delta q^{\theta}/(\delta q^{\theta} + (1-q)^{\theta}),$$

where the probability appraisal is correct for $\delta = \theta = 1$. For each subject, we associated the parameters of the utility function and of the function $w(q)$ that best matches his or her behavior in LE. Table 8 shows the level of risk aversion and the average values of $\delta$ and $\theta$ resulting from this matching. Because $w(q)$ provides an additional matching tool, unsurprisingly, the matching scores increase. However, the introduction of probability weighting does not substantially affect the distribution of risk aversion in the population. Interestingly, for three subjects, probability weighting has the effect of changing their classification from risk loving to medium risk averse.[20] This result is reminiscent of the gamble effect documented by Kumar (2009): subjects who are, in general, risk averse display a propensity to gamble when facing extreme probabilities.

### 4.2. Market Experiment

Implication 5 of the theory suggests that the subjects will choose exactly the same conditional strategies in both LE and ME. This prediction is clearly rejected by our data. Our primary finding in ME can be summarized as follows:

1. The large majority of subjects behave substantially differently in ME and LE.

**Table 8** **Subject's Risk Attitude Considering Probability Weighting**

| | No. of subjects | % | Average $\delta$ | Average $\theta$ | Average matching score |
|---|---|---|---|---|---|
| High risk averse | 42 | 31.34 | 1.00 | 1.00 | 0.98 |
| Medium risk averse | 42 | 31.34 | 1.01 | 0.91 | 0.88 |
| Close to risk neutral | 3 | 2.24 | 1.00 | 1.37 | 0.79 |
| Risk loving | 12 | 8.96 | 1.00 | 1.00 | 0.91 |
| Not classified | 35 | 26.12 | 1.02 | 0.99 | 0.64 |
| All | 134 | 100 | 1.01 | 0.98 | 0.85 |

*Note.* The levels of risk aversion refer to the values of the parameters for the CARA or CRRA utility functions reported in Table 7.

2. In ME, the information content of trades increases with the strength of prior beliefs. The trading volume slightly increases with the strength of prior beliefs. Conforming trading is more frequent in ME than in LE.
3. The comparison of behaviors in LE with those in the control treatments FFLE and SME suggests that the framing has only a marginal impact on the relationship between the strength of the prior belief and the information content of trades.
4. For one-third of the subjects whose behavior in LE is consistent with the expected utility maximization, the difference in behavior in ME and LE can be ascribed to bias in the way that these subjects update their beliefs. These subjects display confirmation bias for strong beliefs and underconfidence for weak beliefs.

Overall, the subjects' answers were identical for LE and ME in only 43.23% of the observations. For only 28.36% of the subjects, the answers in LE and ME were identical in at least 75% of the questions. In most of these cases, the subjects preferred the strategy N-N for all levels of prior belief in both formats. More specifically, for every level of public belief $\pi$, we run a Bhapkar test of marginal homogeneity and reject at the 1% significance level the hypothesis that the format (LE or ME) has no effect on the frequency of conditional decisions.[21] Table 9 summarizes the distribution of the subjects' strategies.

The only common pattern with LE is the symmetry of the subjects' choices. The rest of the observations differ. First, the contrarian trades (B-B for negative priors and S-S for positive priors) tend to disappear in ME. Second, strategies that consist of following the signal whenever it confirms public history and not trading otherwise (i.e., S-N for negative priors and N-B for positive priors) are more frequent in ME than in LE. Third, for strong (neutral) priors, strategy N-N is less frequent (more frequent) in ME than in LE. Fourth, the frequency of strategy S-B increases in ME.[22] Fifth,

[19] We thank an anonymous referee for suggesting this alternative explanation.

[20] The other effects of introducing probability weighting are as follows: one subject classification changes from highly risk averse to medium risk averse, 11 unclassified subjects are classified as medium risk averse, and three unclassified subjects are classified as risk neutral.

[21] For a presentation of the tests of marginal homogeneity, we refer to Davis and Holt (1993) and Agresti (2002).

[22] With the exception of $\pi = 0.5$.

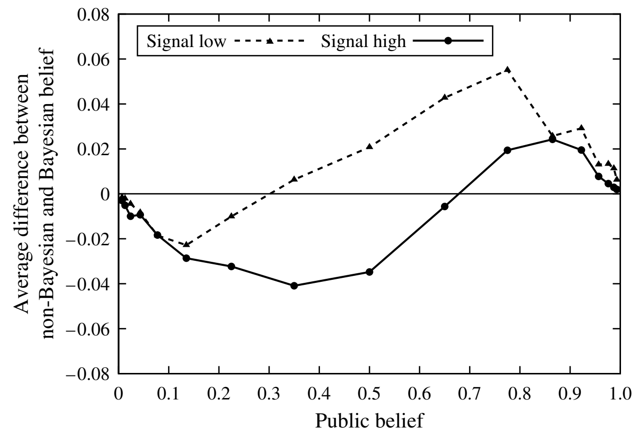
**Table 9 Conditional Decisions (in %) in the Market Experiment (Main Treatment)**

| Public prior belief $\pi$ | B-B | B-N | B-S | N-B | N-N | N-S | S-B | S-N | S-S |
|---|---|---|---|---|---|---|---|---|---|
| $\pi \in [0.002, 0.043]$ | 1.52 | 2.17 | 2.39 | 8.46 | 45.99 | 1.52 | 13.23 | 12.36 | 12.36 |
| $\pi \in [0.078, 0.350]$ | 1.49 | 1.49 | 3.36 | 9.51 | 53.54 | 1.31 | 12.31 | 11.75 | 5.22 |
| $\pi = 0.5$ | 1.49 | 0.00 | 1.49 | 3.73 | 69.40 | 2.99 | 16.42 | 1.49 | 2.99 |
| $\pi \in [0.650, 0.922]$ | 4.10 | 0.75 | 1.31 | 20.71 | 47.20 | 2.43 | 14.55 | 5.97 | 2.99 |
| $\pi \in [0.957, 0.998]$ | 12.58 | 0.65 | 1.30 | 18.22 | 38.61 | 3.90 | 11.71 | 9.11 | 3.90 |

conforming trading increases in ME. As a result, in ME, there is a positive relationship between the information content of trades and the strength of beliefs. For neutral prior beliefs, informative orders represent 26.12% of all orders. This percentage is doubled for extreme prior beliefs. The effect on trading volume is less pronounced. The fraction of orders involving no trade for some signal is approximately 78% for neutral prior beliefs and approximately 71% for strong prior beliefs.

In comparison with LE, the effect of the ME format on the information content of the order flow is ambiguous. We find that informative strategies increase from 27.77% of all choices in LE to 41.59% in ME. For strong prior beliefs, informative strategies are more frequent in ME than in LE, but we observe the opposite for neutral beliefs.

**Figure 3 Bias in Belief Updating Rule**




**4.2.1. Non-Bayesian Updating.** In this section, we investigate whether the difference in the observed behaviors in LE and ME stems from the different level of reasoning that the two formats require to compute posterior beliefs. Namely, in ME, the subjects must interpret public and private information when forming their posterior beliefs and making their decisions. In LE, Bayesian posterior probabilities are explicitly provided. Hence, subjects who do not conform to Bayes' rule would behave differently in ME and LE.

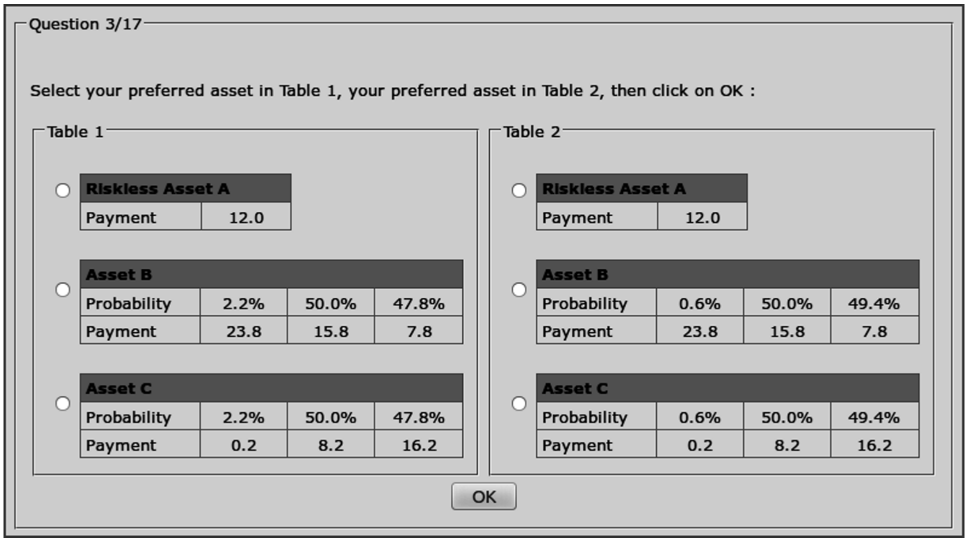
To analyze the hypothesis of non-Bayesian updating, we proceed as follows. We focus on the 85 subjects for whom there exists a CARA or a CRRA utility function that explains at least 75% of their choices in LE of the main treatment. Given subject $i$'s matching utility function, a public belief $\pi$, and a private signal $s$, we look for the set of posterior beliefs that generates the subject's behavior in ME for that $\pi$ and that $s$. Within this set of posterior beliefs, we focus on the belief closest to the Bayesian posterior belief, and we denote it $\hat{\pi}_i(\pi, s)$. Repeating the process for both realizations of the private signals in all levels of $\pi$, we can correlate a subject $i$ with a point-wise function $\hat{\pi}_i(\pi, s)$, mapping prior belief $\pi$ and private signals $s \in \{l, h\}$ into posterior beliefs. We define subject $i$'s "Bayesian score" as the fraction of the 34 posterior beliefs $\hat{\pi}_i(\pi, s)$ that equal the corresponding Bayesian posterior beliefs. We say that a subject is non-Bayesian if his or her Bayesian score is lower than 0.75. According to this definition, 29 of the 85 subjects considered for this analysis are non-Bayesian. Figure 3 represents the average bias in posterior beliefs for the subjects who are non-Bayesian.[23]

For relatively strong public belief ($\pi \geq 0.7$ and $\pi \leq 0.3$), we find that, on average, the non-Bayesian subjects display confirmation bias and tend to interpret private signals in a way that either confirms prior belief or does not challenge it. Namely, Figure 3 shows that when $\pi \geq 0.7$ ($\pi \leq 0.3$), the subjects' behaviors in ME can be explained by posterior beliefs that are higher (lower) than the posteriors derived using Bayes' rule. To illustrate this point, consider a sufficiently positive public belief, i.e., $\pi \geq 0.7$. The impact of a signal *high* is reinforced by the public belief, and subjects are more inclined to buy when they receive a signal of this type. In addition, the impact of a signal *low* is compensated by the positive public belief. It follows that subjects receiving a signal *low* are more inclined not to trade or even to buy. Consequently, contrarian trading disappears, conforming trading appears, and we observe a larger proportion of N-B strategies than in LE. The argument is symmetric for strong negative prior beliefs.

Interestingly, for the public belief $\pi$ between 0.3 and 0.7, the analysis differs. In that case, we find evidence of underconfidence: Subjects underestimate the information content of their private signal. As

[23] For some subjects, the CARA and CRRA utility functions explain behavior in LE equally well. In these cases, the utility function used to determine $\hat{\pi}_i(\pi, s)$ minimizes the average bias of the posterior beliefs.

**Figure 4 Screen Layout in a Financial Framed Lottery Experiment (Main Treatment)**




shown in Figure 3, for a prior belief of approximately 0.5, the behavior of subjects with signal *low* (*high*) in ME can be explained using posterior beliefs that are higher (lower) than the posteriors derived using Bayes' rule. Underweighting the private signal creates a sort of additional uncertainty that leads to a peak in N-N contingent orders.

**4.2.2. Robustness Tests.** We investigate two alternative hypotheses that could explain the difference between LE and ME behavior: a framing effect and a change in risk preferences.

*Framing effect*: The framing within the two formats differs in that although there is no direct reference to financial markets in the presentation of LE, in ME, the subjects are asked to make trading decisions on financial assets. This difference in framing may result in different behaviors when a choice is perceived to be a lottery gamble as opposed to a financial market decision. For example, the financial framing might induce heuristic behaviors in ME that are absent in LE.[24] To test for the effect of framing on behaviors, we conducted two control treatments: the financial framed lottery experiment and the simplified market experiment. For both control treatments, the predicted behavior of a Bayesian expected utility maximizer is identical to the behavior predicted for LE and ME.

The first control treatment, FFLE, is identical to the LE treatment except that the word "lottery" is replaced by the term "financial asset" (see Figure 4 for the screen layout in FFLE).[25] This change allows us to address the question of whether the behavior observed in LE changes substantially when the lottery choice is framed using financial terms.[26] If framing matters, then the subjects' behaviors in FFLE should be closer to ME behavior than to LE behavior.

The second control treatment, SME, is closer to the ME format. The SME treatment takes the frame and format of ME with the difference that the subjects are explicitly provided with posterior beliefs so that they do not have to interpret private and public information. Namely, as in ME, the subjects had the opportunity to trade a financial asset at a given price. However, instead of providing the subjects with a prior belief and private signals, we directly supplied them with the posterior probability that $\tilde{V} = 12$.[27] Figure 5 shows the screen layout presented to the subjects in the SME. In this case, if framing matters, the SME behavior should be closer to the ME behavior than to LE behavior.

The distribution of behavior for the FFLE and the SME control treatments are reported in Tables 10 and 11, respectively. Overall, the subjects' behavior in FFLE and SME is closer to the behavior that we observed in LE than to that observed in ME. In particular, the information content of the order flow decreases as the prior belief becomes stronger, similar to the result that we observe in LE. Furthermore, the strategy S-B (N-N) is more (less) frequent for a neutral prior, as observed in LE. The similarities to LE behavior are stronger for FFLE than for SME. In particular, in one respect, the behavior in SME is closer to that in ME than to that in

[24] Some examples of heuristic behavior are buying (selling) when the prior belief is strong and positive (negative), always trading according to the signal, and buying when the price is low and selling when the price is high.

[25] The change in wording is in both the experiment instructions and the screen layout during the experiment.

[26] We thank an anonymous referee for suggesting this control treatment.

[27] These probabilities were computed as follows. For a given asset $\tau$, we considered the prior belief corresponding to the proposed trading price and used Bayes' rule to update this belief following either a signal $l$ or a signal $h$.

**Figure 5 Screen Layout in a Simplified Market Experiment**

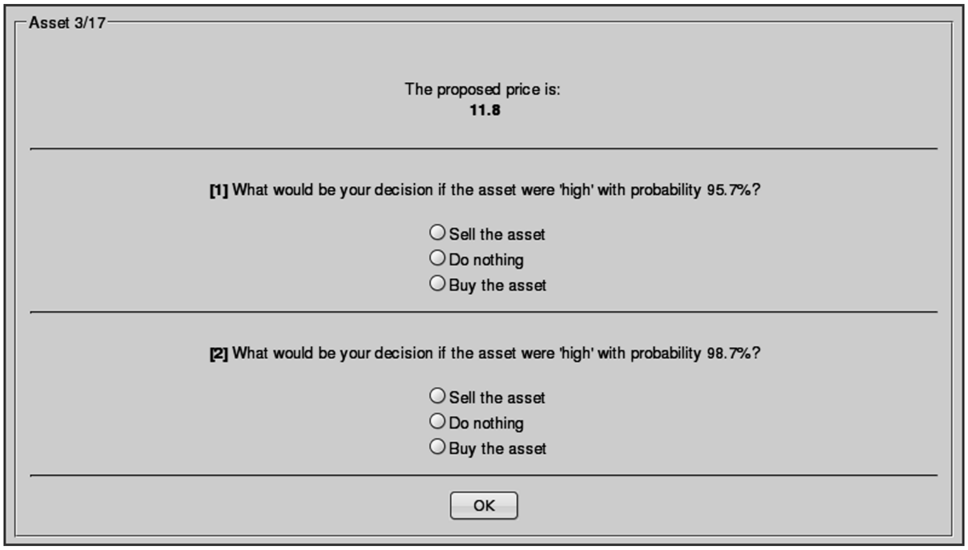



**Table 10 Conditional Decisions (in %) in the Finance Framed Lottery Experiment**

| Public prior belief $\pi$ | B-B | B-N | B-S | N-B | N-N | N-S | S-B | S-N | S-S |
|---|---|---|---|---|---|---|---|---|---|
| $\pi \in [0.002, 0.043]$ | 15.44 | 2.21 | 0.74 | 24.26 | 33.82 | 0.74 | 8.82 | 6.62 | 7.35 |
| $\pi \in [0.078, 0.350]$ | 19.12 | 0.74 | 1.47 | 37.50 | 22.06 | 0.74 | 11.03 | 5.15 | 2.21 |
| $\pi = 0.5$ | 0.00 | 0.00 | 0.00 | 2.94 | 32.35 | 0.00 | 50.00 | 11.76 | 2.94 |
| $\pi \in [0.650, 0.922]$ | 1.47 | 0.00 | 0.00 | 0.74 | 16.91 | 0.00 | 15.44 | 35.29 | 30.15 |
| $\pi \in [0.957, 0.998]$ | 6.62 | 0.74 | 2.94 | 8.82 | 21.32 | 0.74 | 11.76 | 29.41 | 17.65 |

**Table 11 Conditional Decisions (in %) in the Simplified Market Experiment**

| Public prior belief $\pi$ | B-B | B-N | B-S | N-B | N-N | N-S | S-B | S-N | S-S |
|---|---|---|---|---|---|---|---|---|---|
| $\pi \in [0.002, 0.043]$ | 12.75 | 4.41 | 2.45 | 8.82 | 36.76 | 1.47 | 6.86 | 5.88 | 20.59 |
| $\pi \in [0.078, 0.350]$ | 19.61 | 2.45 | 0.98 | 19.61 | 24.02 | 2.94 | 16.18 | 10.29 | 3.92 |
| $\pi = 0.5$ | 3.92 | 5.88 | 1.96 | 19.61 | 23.53 | 1.96 | 31.37 | 5.88 | 5.88 |
| $\pi \in [0.650, 0.922]$ | 6.86 | 0.00 | 1.47 | 20.10 | 22.06 | 2.94 | 21.57 | 18.14 | 6.86 |
| $\pi \in [0.957, 0.998]$ | 21.57 | 1.96 | 4.41 | 22.06 | 25.49 | 1.47 | 12.75 | 5.39 | 4.90 |

LE: conforming trading is more frequent in SME than in LE. Taken as a whole, FFLE and SME suggest that, with the exception of the insurgence of conforming trading for SME, the framing has little impact on the subjects' trading decisions. Thus, it is not mere framing and heuristic behaviors that drive the difference in the subjects' behavior in LE and ME.

*Change in risk preferences*: The second alternative hypothesis to explain the difference in LE and ME behaviors is that whereas the subjects are indeed Bayesian, their risk attitudes substantially change when they participate in LE or ME.[28] To test for this hypothesis, we estimated the subjects' utility functions directly from their behavior in ME, assuming that they are Bayesian.[29] As a result, for each subject, we have a new estimate of the utility function (ME utility) and a matching score (ME matching score) that we can compare with those resulting from the subject's behavior in LE (i.e., the LE utility functions and LE matching scores that are reported in §4.1). If the alternative hypothesis is correct, then we should observe the following empirical features: First, on average, the ME utility functions should explain ME behaviors equally well as the LE utility functions explain LE behaviors. Second, the substantial differences that we observe in LE and ME behaviors should be mirrored in the distributions of the subjects' risk attitudes when comparing the ME and LE utility functions. Third, the ME utility functions should explain the salient differences in ME and LE behaviors. That is, compared to LE, in ME, conforming

[28] See Friedman and Sunder (2011) for a discussion on how utility functions perform to predict behavior out of sample.

[29] We thank an anonymous referee for suggesting this robustness test.

trading emerges, and the order flow becomes more informative with the strength of prior beliefs.

These predictions are not confirmed by the data. First, the average matching score in LE is 0.815, whereas the ME matching score is 0.764. A Wilcoxon signed-rank test shows that the difference in matching scores is significant ($p = 0.0013$), suggesting that the expected utility model performs significantly better for explaining behaviors in LE than in ME. We also find that, whereas in LE the utility function model performs relatively well for all levels of beliefs, in ME, the explanatory power of the utility function model decreases with the strength of the beliefs. Namely, for nonextreme beliefs, i.e., $\pi \in [0.078, 0.922]$, we find that the average ME matching score is 0.784, whereas for extreme $\pi$ outside this interval, the average ME matching score is significantly lower ($p = 0.0234$) at 0.739. In comparison, for LE, we find a matching score close to 0.82 for both extreme and nonextreme beliefs ($p = 0.5005$). Second, Table 12 reports the distribution of the subject's utility functions resulting from ME and LE behavior. For 58 subjects, both the ME and the LE matching scores are above 0.75. These subjects' risk attitudes can be classified based on their behaviors in both LE and ME. Of these 58 subjects, 41 display the same risk attitude in LE and ME. For 15 subjects, the risk aversion that is consistent with their ME behavior is higher by one notch than the risk aversion calibrated using their LE behavior (medium to high risk aversion, or risk loving to risk neutral). For 2 subjects, their risk aversion is either higher or lower by two notches. From this result, we conclude that the distribution of the subjects' risk attitudes measured in ME is not substantially different from that measured in LE. Third, after running a Wilcoxon signed-rank test on these 58 subjects, at the 1% level, we cannot exclude that, on average, the risk aversion measured with ME behavior is higher than the risk aversion measured with LE behavior ($p = 0.0019$). However, an increase in risk aversion in ME cannot account for the salient differences in ME and LE behaviors. First, the positive relationship between the orders' informativeness and the strength of beliefs that we observe in ME cannot result from higher risk aversion.[30] According to the expected utility theory depicted in §2 and illustrated in Table 4, this relationship cannot occur because an increase in the strength of prior beliefs cannot induce an increase in informative orders. In fact, Implication 3 states that informative orders decrease with the strength of beliefs regardless of the subject's risk attitude. Second, the emergence of conforming trading cannot result from an increase in risk aversion because conforming trading is not consistent with the expected utility model, regardless of the subject's risk attitude.

**Table 12** **Distribution of Risk Attitudes in ME and LE**

| | LE-utility | | | | | |
|---|---|---|---|---|---|---|
| ME-utility | High risk averse | Medium risk averse | Close to risk neutral | Risk loving | Not classed | Total |
| High risk averse | 39 | 12 | — | — | 3 | 54 |
| Medium risk averse | — | 2 | — | 1 | 4 | 7 |
| Close to risk neutral | 1 | — | — | 3 | 6 | 10 |
| Risk loving | — | — | — | — | — | 0 |
| Not classed | 3 | 13 | — | 11 | 36 | 63 |
| Total | 43 | 27 | 0 | 15 | 49 | 134 |

Overall, the different pieces of evidence from the FFLE, SME, and ME utility functions suggest that the presence of biases in belief updating is more plausible than changes in risk attitudes for explaining the salient differences between LE and ME.

### 4.3. Effect of Intrinsic Uncertainty

We now describe the results of the NUR treatment, within which the intrinsic risk component $\tilde{\epsilon}$ is absent, i.e., $\underline{V} = 4$, $\bar{V} = 12$, $\epsilon = 0$. By comparing the NUR treatment with our main treatment, we are able to better understand the effect of a nonlearnable risky component $\tilde{\epsilon}$ on the use that subjects make of their private information.

As illustrated in Tables 13 and 14, the subjects' behavior in the NUR treatment shows that the absence of the nonlearnable component $\tilde{\epsilon}$ increases the information content of the order flow at all levels of beliefs and for both the ME and the LE treatment. Namely, for strong negative priors, informative orders in LE (ME) increase from 16.49% (40.13%) of the main treatment to 34.52% (69.64%); for strong positive priors, they increase from 20.39% (44.90%) to 36.31% (68.45%). For neutral priors, the informative orders in LE (ME) increase from 51.49% (25.76%) of the main treatment to 54.76% (35.71%).

However, the qualitative features concerning the distribution of the subjects' strategies obtained in the experiments are the same as in the main treatment, on the whole. Namely, the proportion of noninformative contingent strategies increases with the strength of public beliefs in LE and decreases with the strength of public beliefs in ME.

With respect to conforming trading, in LE, its frequency is more marked in the NUR treatment than in the main treatment. Specifically, conforming selling (S-S for a strong negative prior belief) in the NUR treatment amounts to 13.69%, and conforming buying (B-B for a strong positive prior belief) amounts to 12.50%. In the main treatment, these percentages fall to 6.29% and

[30] We observe these features for the entire population of subjects and for the 58 subjects for whom both an LE utility and an ME utility exist.

**Table 13** **Conditional Decisions (in %) in the Lottery Experiment (NUR Treatment)**

| Public prior belief $\pi$ | B-B | B-N | B-S | N-B | N-N | N-S | S-B | S-N | S-S |
|---|---|---|---|---|---|---|---|---|---|
| $\pi \in [0.002, 0.043]$ | 28.57 | 1.19 | 0.00 | 5.95 | 23.21 | 0.00 | 4.17 | 23.21 | 13.69 |
| $\pi \in [0.078, 0.350]$ | 5.36 | 0.00 | 0.00 | 16.67 | 36.90 | 0.00 | 9.52 | 25.60 | 5.95 |
| $\pi = 0.5$ | 0.00 | 0.00 | 0.00 | 9.52 | 45.24 | 0.00 | 33.33 | 11.90 | 0.00 |
| $\pi \in [0.650, 0.922]$ | 5.95 | 0.00 | 0.00 | 24.40 | 33.33 | 1.79 | 9.52 | 19.64 | 5.36 |
| $\pi \in [0.957, 0.998]$ | 12.50 | 0.60 | 0.00 | 23.81 | 26.19 | 2.38 | 1.19 | 8.33 | 25.00 |

**Table 14** **Conditional Decisions (in %) in the Market Experiment (NUR Treatment)**

| Public prior belief $\pi$ | B-B | B-N | B-S | N-B | N-N | N-S | S-B | S-N | S-S |
|---|---|---|---|---|---|---|---|---|---|
| $\pi \in [0.002, 0.043]$ | 0.60 | 0.00 | 0.00 | 11.90 | 13.69 | 1.79 | 6.55 | 49.40 | 16.07 |
| $\pi \in [0.078, 0.350]$ | 0.00 | 0.00 | 0.00 | 6.55 | 24.40 | 2.38 | 15.48 | 50.00 | 1.19 |
| $\pi = 0.5$ | 0.00 | 0.00 | 0.00 | 4.76 | 64.29 | 0.00 | 30.95 | 0.00 | 0.00 |
| $\pi \in [0.650, 0.922]$ | 3.57 | 0.00 | 0.00 | 52.98 | 19.64 | 0.00 | 17.26 | 6.55 | 0.00 |
| $\pi \in [0.957, 0.998]$ | 13.10 | 0.60 | 0.00 | 50.60 | 18.45 | 0.00 | 5.36 | 11.90 | 0.00 |

8.03%, respectively. Furthermore, in ME for the NUR treatment, traders are more prone to following signals that are consistent with public priors. Specifically, N-B strategies for strong positive priors increase from 18.22% in the main treatment to 50.60% in the NUR treatment. S-N strategies for strong negative priors increase from 12.36% to 49.40%. In light of the analysis in §4.2.1, the NUR treatment suggests that reducing intrinsic uncertainty amplifies the confirmation bias without increasing the propensity of traders to engage in conforming trading.

### 4.4. Sequential Trading

In this section, we explore the effect of introducing interaction across subjects through sequential trading. For this purpose, we run an additional treatment that we call the sequential market experiment.[31] In SeME, the subjects sequentially trade assets at prices that depend on the trading decisions previously made by other subjects. We find that, on average, the subjects' behavior in SeME is closer to their behavior in ME than to their behavior in LE. Also, on average, the difference in behavior when passing from LE to ME is larger than the difference in behavior when passing from ME to SeME. From these observations, we conclude that the subjects' behavior is affected more by the need to deduce posterior probability (i.e., LE versus ME) than by the presence of interaction across subjects (i.e., ME versus SeME).

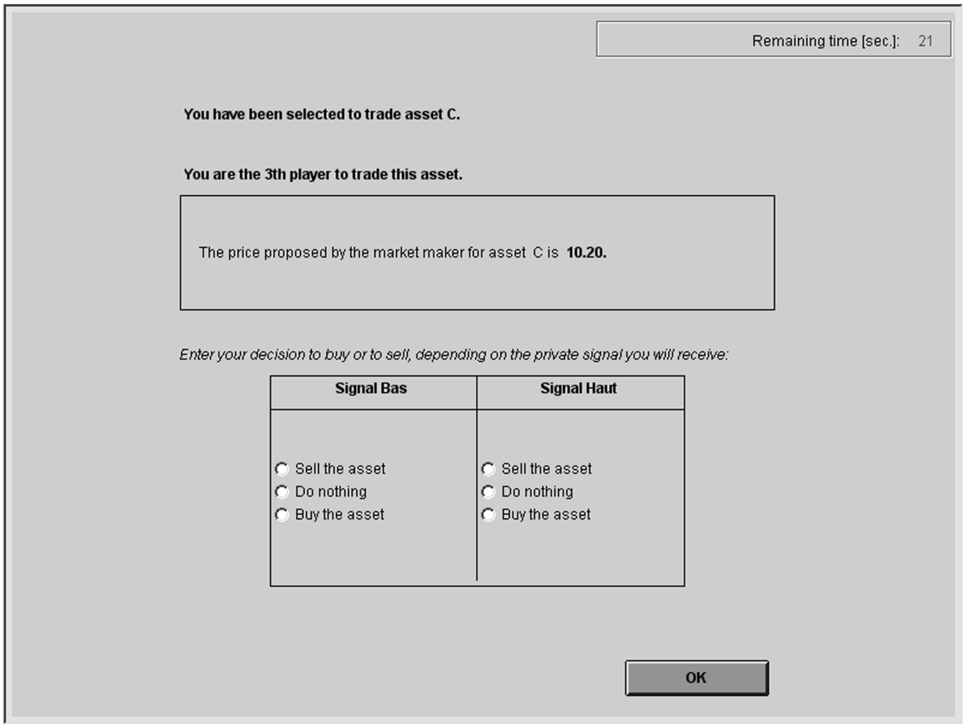
More precisely, SeME takes the frame of ME: Trading prices are proposed to the subjects, who must announce their conditional trading strategies (see Figure 6 for a screenshot of the SeME). The experiment is designed so that each subject has exactly one opportunity to trade each asset, and he or she is the $n$th trader of the $n$th asset that he or she has the opportunity to trade.[32] Unlike in ME, the trading price is not equal to the expected asset value computed using an exogenous and explicit prior belief $\pi$. In SeME, an asset trading price at $t$ is a function of a trading decision previously made by other subjects for the same asset. The theory of sequential trading that we outline in §2 builds on the assumption that at any point in time, an asset price reflects the market's belief and is equal to the expected value of the asset given the information implied by past trades. Therefore, we must engineer a pricing rule for SeME that accounts for the actual information content of past trades. For example, a "straightforward pricing rule" that consists of systematically interpreting a buy decision, a sell decision, and a no-trade decision into signal $h$, signal $l$, and no signal would not do. In fact, the data from LE and ME show that subjects do not systematically adopt the S-B strategy; hence, the straightforward pricing rule would generate prices that do not reflect the asset's expected value given past trades. That is, an objective rational Bayesian subject would find that "straightforward pricing" systematically misprices assets. To choose a pricing rule that minimizes objective mispricing, we proceed as follows.

A few days before participating in SeME, the same subjects participated in FFLE and ME. The SeME pricing rule was then based on the hypothesis that for any given level of market beliefs, the frequency with which each trading strategy is adopted by the group of subjects in the cohort is the same as the frequency

[31] This treatment was programmed and conducted with the software z-Tree (Fischbacher 2007).

[32] For each cohort, the number of assets that subjects can trade is equal to the number of subjects in the cohort. Thus, a cohort of $n$ subjects generates $n$ trading histories; each history corresponds to the sequential trade of one asset by $n$ different subjects during $n$ periods. The subjects do not know the identity of the traders who precede them in the trade; however, because subjects are in the same room, they know the composition of the pool of subjects generating the trades.

**Figure 6 Screen Layout in a Sequential Market Experiment**




observed for that cohort in ME for the corresponding level of public belief.[33] In the instructions for SeME, the subjects were informed that the pricing rule was based on the behavior of the cohort in previous experiments.

Two cohorts of 18 and 16 subjects each participated in SeME. This process produced 18 trading histories of 18 trading rounds and 16 trading histories of 16 rounds, for a total of 580 trading decisions. Each trading history began with an initial price corresponding to a market belief of $\pi = 0.5$. Because the subsequent evolution of prices and market beliefs depended on the realization of the trading histories, the number of decisions made for strong market beliefs is substantially lower than those observed for weak market beliefs.[34] For this reason, it is difficult to compare the aggregate distribution of trading strategies obtained in SeME with those from the other treatments. However, for each subject, it is possible to compare his or her behavior in SeME, FFLE, and ME. For this purpose, we computed three matching scores for each subject: one comparing his or her behaviors in ME and FFLE, one comparing SeME and FFLE, and another comparing SeME and ME.[35]

The average matching score for SeME-ME was 0.6350, whereas the average matching score for SeME-FFLE was 0.4892. Thus, the subjects' behavior when trading sequentially was closer to the behavior in ME than to that in FFLE. Because the FFLE-ME average matching score was 0.5003, on average, the change from ME to SeME affected subject behavior less than the change from FFLE to ME.

One possible explanation for the marginal difference in behaviors between SeME and ME could be the presence of perceived mispricing. That is, whereas in ME the trading price reflected an objective and known probability $\pi$, in SeME, the subject might have perceived that the proposed price was not aligned with his or her beliefs. By basing the pricing rule in SeME on subjects' actual behavior in ME, we minimize objective mispricing. However, non-Bayesian subjects whose posterior beliefs are inconsistent with the price derived using Bayes' rule might have perceived the proposed price as "wrong." Thus, the difference between SeME and ME is probably due to this perceived mispricing. Furthermore, the comparison of LE and ME suggests

[33] The theoretical price obtained using Bayes' rule based on this frequency rule is then approximated to the closest price on the price grid used for the other experiments.

[34] For example, less than 9% of trading decisions were made for extreme levels of a market belief ($\pi \leq 0.043$ or $\pi \geq 0.957$), whereas in LE and ME, 47% of the trading decisions were made for extreme priors by construction.

[35] For example, the SeME-ME matching score was computed as follows. For each conditional decision in SeME, we considered the corresponding conditional decision in ME, that is, the conditional decision by the same subject at the same level of public belief $\pi$. We computed a score for the conditional decision, counting 0.5 for each matching decision conditional on the same private signal. The score for a conditional decision was thus 0, 0.5, or 1. Then, the matching score of the subject was computed as the average of these scores. Thus, a matching score SeME-ME equal to 1 indicates that for every observed level of market belief in SeME, the subject's behavior was identical in ME.

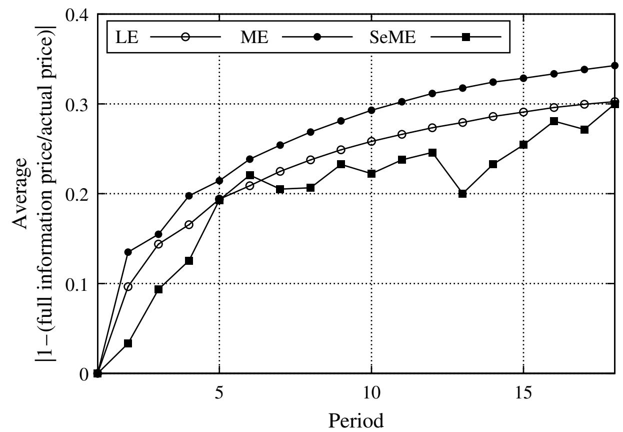
that subjects are not necessarily Bayesian when interpreting their private signal. Hence, it is natural to expect the subjects to not be Bayesian when interpreting the public information provided by the current price.

### 4.5. Market Informational Efficiency and Ex Post Decisions

In the previous sections, we have shown that in LE, the proportion of noninformative orders increases with the strength of public beliefs, whereas the opposite pattern occurs in ME. In this section, we study the actual impact of these findings on price dynamics and on market information efficiency. Within a sequential trade framework, market informational efficiency can be measured by the evolution of the pricing error, defined as the difference between the actual price and the full information price, or the price that would prevail had the market makers directly observed past traders' private information.

We use two approaches to measure market information efficiency. First, we consider the evolution of the average pricing error in the 32 trading histories resulting from SeME. However, because the trading histories in SeME could be affected by objective or subjective mispricing, we also simulate pricing histories that do not suffer from these biases. To create this simulation, we exploit our observations of contingent trading strategies at different levels of public belief and for different formats where the prices faithfully reflect prior beliefs: LE, ME, LE NUR, and ME NUR. To generate virtual trading histories, we assume that the virtual subjects randomly come to the market to trade once and behave as the real subjects did in the corresponding experiment format.[36] As in our experiment, trading prices always reflect prior objective probabilities. Our simulations reflect situations in which there is no subjective or objective mispricing; that is, for any given past history of trades, subjects believe that the asset is correctly priced by the market makers. After each trading round, public belief and price are updated in a way that reflects the assumptions of the theory in §2. Namely, the price updating rule is based on the hypothesis that market makers and traders do not know the identity of past traders, but they do have

**Figure 7** **Evolution of the Pricing Error in the Main Treatment**




a correct estimation of the average behavior of the population of traders. That is, for any given level of public beliefs, the market makers know the frequency with which each trading strategy is adopted by traders. These frequencies are those observed in the experiment and are summarized in Tables 6, 9, 13, and 14.[37] After observing a given action, the public belief and the trading price will change according to the Bayesian probability that the order comes from someone who received a signal $l$ or a signal $h$.[38]

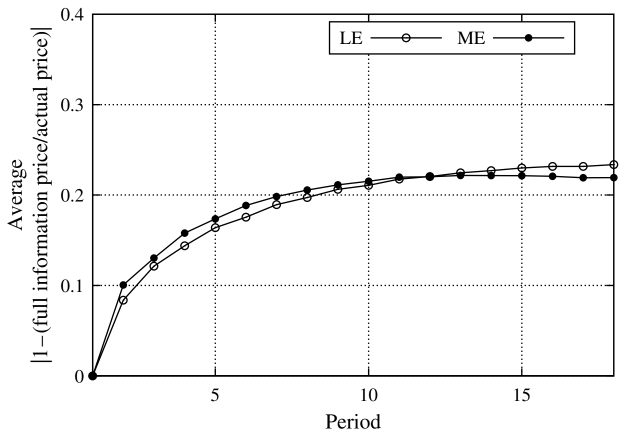
We simulated approximately 10,000 trading histories per treatment (main and NUR) and format (LE and ME), with each trading history covering a maximum of 18 trading rounds. Figure 7 reports the evolution of the average pricing error in the main treatments ME and LE. Additionally, the figure reports the pricing error in SeME, computed over the 34 price series generated by this treatment. The pricing error in ME is consistently higher when compared to that of LE. After 18 trades, the average pricing error is 30.45% in LE, 34.66% in ME, and 29.92% in SeME. This result indicates that in all formats, it is not unusual for the market to fail to aggregate dispersed private information. The average pricing error over the 34 trading histories in SeME is slightly lower but not substantially different when compared to LE and ME. This result suggests that the experimental results regarding market efficiency do not change substantially when introducing a sequential format. Figure 8 reports the evolution of the average pricing error in the NUR treatment. The absence of the additional risk $\tilde{\varepsilon}$ improves the information content of the order flow, leading to an average pricing error at the 18th round of 23.32% and 21.43% in LE and ME, respectively. In comparison with the main

[36] We use the following algorithm to generate a virtual trading history. At the beginning of the trading history, the value of $\tilde{V}$ is randomly determined according to $\mathbb{P}[\tilde{V}=\bar{V}]=\frac{1}{2}$, and the initial public belief is fixed at $\pi_0=0.5$. First, in each trading round, one of the nine possible trading strategies is randomly selected in a way that reflects the empirical frequencies observed in the experiments. These frequencies change with the level of public belief and with the treatment and format used for the simulation. Second, a private signal with precision 0.65 is randomly determined. The virtual trader's order corresponds to the trading strategy and private signal determined in the previous two steps. Finally, the public belief is updated, and a new virtual trading round begins.

[37] It is worth noting that these frequencies account for all of the traders, including the 36.15% of subjects for whom we cannot assign a utility function.

[38] For the simulation, this new belief is approximated to the closest point on the grid of belief used for the experiment.

**Figure 8** Evolution of the Pricing Error in the NUR Treatment




treatment, the average pricing error is lower. Interestingly, although simulations based on the subjects' behavior in LE provide more efficient prices in the short run, ME generates more efficient prices in the long run. Overall, our simulations suggest that market information efficiency is reduced in the presence of additional risk regarding the asset fundamentals, and this phenomenon is amplified by non-Bayesian behavior, at least in the short run.

Our simulations allow us to generate statistics on ex post trades that can be directly compared with the findings in sequential trading experiments such as those by Cipriani and Guarino (2005) (CG) and Drehmann et al. (2005) (DOR). The closest treatments are our ME NUR treatment and the flexible price treatments in CG and DOR. When comparing the distribution of our simulated ex post trades with those reported by CG and DOR, two differences are striking. First, we find that no-trade decisions represent approximately 60% of ex post decisions, whereas in CG and DOR, they range between 22% and 25%. Second, trading opposite to the signal is virtually absent in our simulation, whereas it represents between 13% to 17% of trading decisions in CG and DOR. These differences could be due to the fact that uncertainty about the other subjects' strategies matters in their sequential trading treatments but it does not affect our static treatments. Furthermore, the difference in pricing rules adopted in their experiments and our experiment might play a role. In our ME NUR experiment, prices always reflect objective probability for the asset fundamentals; in CG and DOR, the prices evolve according to "the straightforward pricing rule" and hence tend to overreact to the order flow and induce contrarian trading.

## 5. Conclusion

In this paper, we report the results of a series of experiments that simulate financial market trading. We adopt two formats for our experiment: the lottery experiment and the market experiment. We disentangle the impact on the information content of the order flow from risk preferences, intrinsic uncertainty, and non-Bayesian updating. Intrinsic uncertainty leads the subject to neglect his or her private information and reduces market informational efficiency. Trade information content and trading volume decrease with the strength of prior beliefs in LE but increase with the strength of prior beliefs in ME. None of these behaviors is consistent with the rational/risk-neutral traders hypothesis. However, the behavior we observed in LE is consistent with rationality as long as one allows for heterogeneity in the subject's risk attitude. In contrast, the way that some subjects' behavior is affected when moving from the LE to the ME format is indicative of underconfidence and confirmation biases in the way subjects update their beliefs.

We conclude by discussing the implications of our findings in the ME experiment for real markets. First, the information content of trades and stock price efficiency should be lower for stocks with greater intrinsic uncertainty about the fundamental value. Standard measures of the information content of trades are the price sensitivity to the volume of trade as well as the bid-ask spread. One measure of the informational efficiency is the abnormal stock price return at news.[39] The larger the price reaction, the less private information was previously incorporated into the asset price; hence, the lower the informational efficiency is. Some possible proxies for the presence of intrinsic uncertainty are growth companies versus utility companies, youth of the firm or the firm's sector, product market innovations, R&D investments, business sensitivity to exogenous risks such as weather or other natural risks, and foreign country risk. These proxies for the presence of intrinsic uncertainty should be negatively correlated with proxies for trade information content and market efficiency. Second, the information content of trades should vary with the strength of prior beliefs. A measure for the strength of market prior beliefs on a given stock can result from the number of analysts following the stock and/or the dispersion of analysts' opinions. The greater the number of analysts and the less dispersed their opinions are, the stronger the market beliefs are. According to our observation in ME, the relationship between price sensitivity to the volume of trade and strength of beliefs should be positive. Running such tests would improve our knowledge of the actual linkage between risk preferences, intrinsic uncertainty, and non-Bayesian belief formation.

[39] Note, however, that to better fit the logic of our experiment, the news considered should consider a learnable component of the asset value (e.g., earnings announcements) rather than news resolving a nonlearnable risk.

## Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mnsc.2013.1886.

## Acknowledgments

The authors thank Véronique Bessière, Bruno Biais, Sébastien Pouget, and especially Rosemarie Nagel and Hersh Shefrin for their thoughtful feedback and suggestions. The authors also thank the participants at the AFSE (Association Française de Science Economique) meeting on Experimental Economics, Lyon; the workshop on Individual and Collective Decision Making; the Paris AFFI (Association Française de Finance) international meeting; the International Financial Research Forum of the Europlace Institute of Finance (EIF); and the finance seminars at the Universities of Barcelona, Copenhagen, Louvain, Paris 9, and Toulouse. The authors thank department editor Jerome Detemple, the associate editor, and two anonymous referees for their insightful comments. The authors remain solely responsible for the content of this paper. Financial support from the Agence Nationale de la Recherche [ANR-09-BLAN-0358-01] is gratefully acknowledged. This research also benefited from the support of the Europlace Institute of Finance. Jean-Paul Décamps is an academic fellow at the Europlace Institute of Finance. Christophe Bisière and Jean-Paul Décamps gratefully thank the Chaire "Marché des risques et création de valeurs, fondation du risque/Scor." Stefano Lovo gratefully acknowledges financial support from the HEC Foundation and Investissements d'Avenir [ANR-11-IDEX-0003/Labex Ecodec/ANR-11-LABX-0047].

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