

Herd Behavior in Financial Markets:
A Field Experiment with Financial Market Professionals
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Herd Behavior in Financial Markets: A Field Experiment with Financial Market Professionals

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Abstract

We study herd behavior in a laboratory financial market with financial market professionals. We compare two treatments: one in which the price adjusts to the order flow in such a way that herding should never occur, and one in which the presence of event uncertainty makes herding possible. In the first treatment, traders herd seldom, in accordance with both the theory and previous experimental evidence on student subjects. A proportion of traders, however, engage in contrarianism, something not accounted for by the theory. In the second treatment, on the one hand, the proportion of herding decisions increases, but not as much as the theory would suggest; on the other hand, contrarianism disappears altogether. In both treatments, in contrast with what theory predicts, subjects sometimes prefer to abstain from trading, which affects the process of price discovery negatively.

JEL classification codes: C93, D82, D83, G14

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1. Introduction

In recent years, there has been much interest, both theoretical and empirical, on the extent by which trading in financial markets is characterized by herd behavior; such an interest stems from the potential effects that herding may have on financial markets' stability and ability to achieve efficient allocative and informational outcomes. The theoretical work (see, e.g., Avery and Zemsky, 1998; Lee, 1998; Cipriani and Guarino, 2001; Dasgupta and Prat, 2005; Sabourian and Park, 2006) has tried to identify the mechanisms that can lead traders to herd.¹ Papers in this literature have emphasized that, in financial market, the fact that prices adjust to the order flow makes herding more difficult to arise than in other setups, studied in the social learning literature, where there is no price mechanism. Nevertheless, it is possible that rational traders herd, because there are different sources of uncertainty in the market, because traders have informational and non informational (e.g., liquidity or hedging) motives to trade or because trading activity is affected by reputation concerns.

To test herding models directly with data from actual financial markets is difficult. In all the models, "herding" means making the same decision independently of the private information that one receives. The problem for the empiricist is that there are no data on the private information available to the traders and, therefore, it is difficult to understand whether traders make similar decisions because they disregard their own information and imitate (as opposed, for instance, to reacting to the same piece of public information).²

To overcome this problem some authors (Cipriani and Guarino, 2005; Drehman et al., 2005) have tested herd behavior in a laboratory financial market.³ The advantage of the laboratory is that one can observe variables

¹For a survey of the recent literature on herding behavior, see Hirshleifer and Teoh (2003), Chamley (2004) and Vives (2007).

²A series of empirical papers have documented the presence of herding in financial markets and have tried to identify its sources (see, e.g., Lakonishok et al., 1992; Grinblatt et al., 1995; Wermers, 1999; Sias, 2004). Almost all the existing empirical literature does not test the theoretical models of herding directly; an exception is a recent paper by Cipriani and Guarino (2006) that estimates a structural model of informational herding.

³These experimental studies build on previous experimental work on non-financial herding, based on the Bickchandani et al. (1992) model (see, among others, Anderson and Holt, 1997; Çelen and Kariv, 2004; Huck and Oechssler, 2000; and Kübler and Weiszsäcker, 2004).

not available for actual markets, in particular, the private information that agents have when making their decisions. This allows the researcher to test models of herding directly. Yet, one may wonder how representative laboratory experiments are of the behavior of professionals operating in actual financial markets. The external validity of experimental studies is, indeed, a well known concern in the literature. In our specific case, one may imagine that professional behavior in the field might differ from students' behavior in the laboratory because of the professionals' different age, level of education and training; moreover, professional expertise, developed in the day-by-day working in financial markets, may lead to the development of trading heuristics, different from those used by non financial professionals.

To address these issues, in this paper, we present a field experiment in which the subjects trading in the laboratory are financial market professionals. We are, therefore, able to observe how financial professionals involved in the daily operation of financial markets behave in a controlled environment. Many papers in the past have compared the way in which the usual experimental subjects (undergraduate students) play strategic games to the way in which professionals (broadly defined) do so. The spirit of this paper is different. Our goal is not to assess whether, in general, professionals (broadly defined) behave differently from students, but how financial professionals behave in a controlled financial market. We believe that studying how financial professionals behave in a controlled experiment can shed light on the way they operate in actually occurring markets. Moreover, the work can help to connect empirical analyses with theoretical and experimental studies.

This is the first study of herd behavior in financial markets that uses financial market professionals in a laboratory setting. Similarly to us, Alevy et al. (2007) also use financial professionals to study herd behavior. In contrast to our study, however, they test a standard cascade game à la Bikhchandani et al. (1992) and not a model of trading in financial markets. Drehman et al. (2005) study herding behavior in financial markets using both a sample of students and a sample of professionals; professionals in their sample, however, are not financial market professionals, and, as a result, the same limitation as in the analysis with students apply.

In our laboratory market, participants receive private information on the value of a security and observe the history of past trades. Given these two pieces of information, they choose sequentially (in a financial market à la Glosten and Milgrom, 1985) if they want to sell, to buy or not to trade one unit of the asset with a market maker. The market maker is an automaton,

that uses a predetermined rule to update the price according to the order flow. We ran two treatments, which differ in the way the price is set. In one treatment (from now on Treatment *I*), the price is set in such a way that, according to the theory, subjects should always use their private information and never herd. In another treatment (from now on Treatment *II*), instead, herding becomes optimal because of event uncertainty (see Avery and Zemsky, 1998). After a series of buys (sells) the price is not high (low) enough to prevent that traders should buy (sell) independently of their private information. Therefore, by observing the way in which financial professionals use their private information and react to the decisions of the previous participants in the two treatments, we can directly detect the occurrence of herding.

The results of the experiment show that, as theory suggests, the proportion of herding decisions is very low in Treatment *I*. Therefore the theoretical prediction by Avery and Zemsky (1998) that price adjustment to the order flow reduces the scope for herding behavior, is confirmed by the experimental data on financial market professionals. Moreover, also in accordance with the theory, herding increases in Treatment *II*, where the price adjustment rule is consistent with the presence of event uncertainty. Nevertheless, some important anomalies do occur in the laboratory. First, in Treatment *I*, some subjects engage in contrarianism, something not accounted for by the theory. These subjects go against the market, selling (for whatever private signal) when the price is high, and buying (for whatever private signal) when it is low. Moreover, in the second treatment, herd behavior is lower than what theory predicts. Finally, in both treatments, subjects have a tendency to abstain from trading, which is not accounted for by the theory. Abstention from trading implies that the market is unable to infer the subjects' private signals, which lowers the informational efficiency of the market.

Compared to the existing experimental literature on herding in financial markets, our paper introduces some other important novelties. First, the economy studied in Treatment *II* (in which rational herding may arise because of event uncertainty) has never been analyzed experimentally (not even with a more standard pool of participants), although event uncertainty is recognized in the theoretical literature as one of the main channels of herding in financial markets. Second, in both Treatment *I* and *II*, we ran the experiment using a strategy method like procedure that allowed to detect herding behavior directly (whereas in previous work it could only be inferred). In particular, whereas in previous work subjects first would receive a private signal and then make a decision, in our experiment they first made

their decisions conditional on both signal realizations and, then, observed the realized value of the signal. Since a subject made a decision for any signal realization, we could observe directly whether and when he chose the same action irrespective of his private information.

The structure of the paper is as follows. Section 2 describes the theoretical model and its predictions. Section 3 presents the experimental design. Section 4 illustrates the main results. Section 5 compares them with the results in the existing experimental literature. Section 6 discusses individual behavior. Section 7 concludes.

2. The Theoretical model

2.1. The model structure

Our experimental analysis is based on the theoretical model of herding in financial markets by Avery and Zemsky (1998), who analyze herd behavior in an economy similar to that of Glosten and Milgrom (1985) and Easley and O'Hara (1987). In contrast to these papers, however, we assume that the market maker can post only one price, i.e., it is not allowed to post different prices at which traders can buy (the ask price) or sell (the bid price). We do so because it simplifies the implementation of the trading game in the laboratory. All the results that we present in this theoretical section hold independently of whether the market maker is allowed to post a bid-ask spread.

In our economy there is one asset traded by a sequence of traders who interact with a market maker. Time is represented by a countable set of trading periods, indexed by $t = 1, 2, 3, \dots$

The asset value

The fundamental value of the asset, V , is a random variable distributed on $\{0, 50, 100\}$. With probability $\frac{p}{2}$ the asset takes value 0 or 100, whereas with probability $(1 - p)$ it takes value 50. This assumption is meant to capture the idea that, in the market, an information event may occur. If an information event happens (which occurs with probability p), the asset value goes up or down with equal probabilities.⁴ In the case of no event, the asset value remains at its unconditional expected value of 50.⁵

⁴The event is called “informational” since—as we shall see—when it occurs, some traders receive private information on it.

⁵Easley and O'Hara (1987) introduced this type of structure. In their framework, the

The market

At each time t , a trader can exchange the asset with a market maker. The trader can buy, sell or decide not to trade. Each trade consists of the exchange of one unit of the asset for cash. The trader's action space is, therefore, $\mathcal{A} = \{buy, sell, no\ trade\}$. We denote the action of the trader at time t by $x_t \in \mathcal{A}$. Moreover, we denote the history of trades and prices until time $t - 1$ by h_t .

The market maker

At any time t , the market maker sets the price at which a trader can buy or sell the asset. The market maker is only allowed to set one price (i.e., we do not allow for a bid-ask spread). He sets the price equal to the expected value conditional on the public information available at time t , i.e.,⁶

$$p_t = E(V|h_t).$$

The traders

There are a countably infinite number of traders. Traders act in an exogenously determined sequential order. Each trader, indexed by t , is chosen to take an action only once, at time t . Traders are of two types, noise traders and informed traders. If the value of the asset is 50 (i.e., there is no information event), there are only noise traders in the market. Noise traders act for "liquidity" or other exogenous reasons, buying, selling or not trading with exogenously given probabilities. If, instead, an information event occurs and the value of the asset is either 0 or 100, there is a proportion μ of informed traders and a proportion $1 - \mu$ of noise traders in the market. Informed traders receive private information on the realization of the asset value. In particular, if at time t an informed trader is chosen to trade, he observes a

value of the asset can change day by day. If during the night there is an informational event, the value of the asset goes up or down with respect to the previous day's value. Otherwise, it remains constant. Here, in order to make the theoretical model implementable in the laboratory, we do not have sequences of days and the informational event is represented by a realization of the asset different from its unconditional expected value. This setup is the same as that analyzed by Avery and Zemsky (1998).

⁶In the original Glosten and Milgrom (1985) model the market maker posts a bid price and an ask price and makes zero expected profits because of unmodeled potential competition. As we mentioned before, we avoid the presence of two prices (the bid and the ask) and assume that the market maker sets only one price equal to the expected value of the asset. By setting one price only, the market maker earns negative expected profits. This is not a problem, since in the experiment the market maker is not a subject, but an automaton.

private signal on the realization of V . The signal is a random variable S_t distributed on $\{0, 100\}$. We denote the conditional probability function of S_t given a realization of V by $q(s_t|v)$, where s_t is a realization of S_t and v is a realization of V .⁷ We assume that the random variables S_t are independently and identically distributed across time. In particular, we assume that

$$q(0|0) = q(100|100) = 0.7.$$

In addition to his signal, an informed trader at time t observes the history of trades and prices and the current price. Therefore, his expected value of the asset is $E(V|h_t, s_t)$. The informed traders' payoff function $U : \{0, 100\} \times \mathcal{A} \times [0, 100] \rightarrow \mathbf{R}^+$ is defined as

$$U(v, x_t, p_t) = \begin{cases} v - p_t & \text{if } x_t = \textit{buy}, \\ 0 & \text{if } x_t = \textit{no trade}, \\ p_t - v & \text{if } x_t = \textit{sell}. \end{cases}$$

Informed traders are risk neutral and choose x_t to maximize $E(U(V, x_t, p_t)|h_t, s_t)$. Therefore, they find it optimal to buy whenever $E(V|h_t, s_t) > p_t$, and sell whenever $E(V|h_t, s_t) < p_t$. They are indifferent among buying, no trading and selling when $E(V|h_t, s_t) = p_t$.

2.2. Theoretical predictions

We now illustrate the predictions of our model, by analyzing two distinct parameterizations, each corresponding to one of the two treatments that we ran in the laboratory. In the first parametrization, we set $p = 1$, i.e., we assume that an event occurs with certainty. This is the case studied in the seminal paper by Glosten and Milgrom (1985). In this case we also assume that $\mu = 1$, i.e., that all traders in the market are informed. In the second parametrization, we set $p = 0.15$ and $\mu = 0.95$, i.e., we assume that an information event occurs with probability strictly smaller than 1, and that, if the event occurs, there is a small proportion of noise traders in the market. Moreover, noise trader abstain from trading with probability 0.33 during an informed day and with probability 0.02 during an uninformed day and, if they trade, they buy and sell with equal probability.⁸ This is the set up

⁷In the entire paper, we will use capital letters for random variables and lower-case letters for their realizations.

⁸This parametrization, with a strictly positive proportion of noise traders and a different probability of no trade by noise traders when there is no information event, makes the implementation of the model in the laboratory more natural. We will explain this in detail

(with “event uncertainty”) introduced by Easley and O’Hara (1987).⁹

To discuss the theoretical predictions of the model, let us first introduce the formal definition of herd behavior. We say that there is herd buying at time t when, following a history with more buys than sells, a trader buys independently of his private signal. Similarly, we say that there is herd selling at time t when, following a history with more sells than buys, a trader sells independently of his private signal. We say that there is herd behavior if there is either herd buy or herd sell. In a period of herding, the trader will neglect his signal and just conform to the established pattern of trade.

Following Avery and Zemsky (1998), it is easy to show that, in the first setup (i.e., when an informational event occurs with probability one), herd behavior cannot arise, whereas in the second setup (with event uncertainty) herd behavior arises with positive probability. We summarize this in the next two results:

Result 1 If an informational event occurs with certainty ($p = 1$), in equilibrium traders always trade according to their private signal and never herd.

To explain the result, let us recall that, in order to decide whether to buy or sell the asset, a trader computes its expected value and compares it to the price. If at time t a trader receives a signal of 100, his expected value will be

$$\begin{aligned} E(V|h_t, s_t = 100) &= 100 \Pr(V = 100|h_t, s_t = 100) = \\ &100 \frac{(.7) \Pr(V = 100|h_t)}{(.7) \Pr(V = 100|h_t) + (.3)(1 - \Pr(V = 100|h_t))} > \\ &100 \Pr(V = 100|h_t) = E(V|h_t). \end{aligned}$$

when we illustrate the experimental procedures.

⁹It should be noted, however, that Easley and O’Hara (1987) restrict the analysis to the case in which the signal is perfectly informative, i.e., $q = 1$. Such a case is unsuitable to study herd behavior, since if informed traders know the realization of the asset value, the history of trades cannot add any additional information. Studies that analyze financial markets with event uncertainty are abundant in the market microstructure literature, see, e.g., Easley and O’Hara (1992) and Easley, Kiefer and O’Hara (1997). See also the surveys by O’Hara (1995) and Hasbrouk (2006).

Therefore, he will buy. Similarly, if he receives a signal of 0, his expected value will be

$E(V|h_t, s_t = 0) < E(V|h_t)$, and he will sell. This shows that an agent will always find it optimal to trade according to his private information and herd behavior cannot arise.

Let us turn now to study the case in which $p = 0.15$, i.e., in which there is uncertainty on whether the value of the asset changed or not from its unconditional expectation. In such a case, it can be optimal for agents to neglect their private information and herd:

Result 2 In the presence of event uncertainty ($p < 1$), in equilibrium herd behavior occurs with positive probability.

Here, we only discuss the intuition for this result and refer the reader to Cipriani and Guarino (2006) for a formal proof.¹⁰ When an informed trader receives a private signal, he learns that an event has occurred. Therefore, when he observes a sequence of trades, he knows that each buy or sell comes from an informed trader with probability 0.95. He will update his belief on the asset value on the basis of this information. The market maker, in contrast, has a prior of 0.86 that the trades just come from noise traders.¹¹ Therefore, when he receives a buy or a sell order, he updates his belief (i.e., the price) by less than the traders. As a result, after a sequence of buys (sells) the expectation of a trader may be higher (lower) than the price even if he receives a bad (good) signal.

In Figure 1, we show the sequence of expectations and prices after a series of buy orders. At time 3, the equilibrium price is lower than both the expectation of a trader receiving a good signal and the expectation of a trader receiving a bad signal. Therefore, the trader at time 3 will buy whatever signal he will receive, i.e., he will herd.

The presence of herding in the market is, of course, important for the informational efficiency of prices. During periods of herd behavior, private information is not efficiently aggregated by the price. In these periods traders do not make use of the private information they have and, as a result, the market cannot learn such information.

¹⁰Avery and Zemsky (1998) prove this result in a similar setup, but with a different (and non conventional) definition of herd behavior.

¹¹The value 0.86 is equal to $(1 - p) + p(1 - \mu)$.

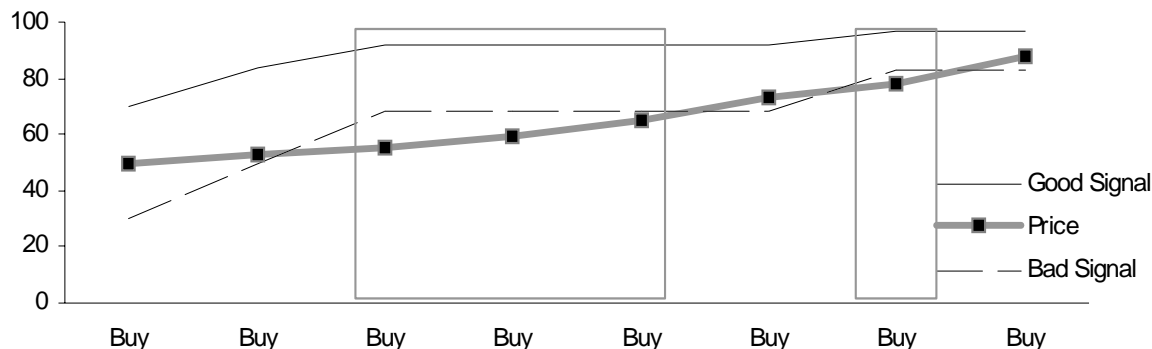


Figure 1: Prices and Traders' Expectations after a History of Buys

Even during a period of herding, although the price does not aggregate private information efficiently, the market maker does learn something on the true asset value.¹² Indeed, even in a period of herding, he updates his belief on whether there has been an informational event. For this reason in Figure 1 the price keeps moving even after time 3, although traders are herding.¹³ The market maker observes more and more traders buying the asset and gives more and more weight to the event that these traders are informed (noise traders would indeed buy or sell with equal probabilities). Because of this price movement, herd behavior will eventually disappear. As shown in Figure 1, during a period of herding the traders' expectations do not move (since the traders already know that an event has occurred, and they also

¹²This means that, although in our model there is herd behavior, there is no *informational cascade*. An informational cascade requires that the action be independent of the asset value. Formally, an informational cascade arises at time t when $\Pr(X_t = x|h_t, s_t) = \Pr(X_t = x|h_t)$ for all $x \in \mathcal{A}$ and for $s_t \in \{0, 100\}$. In a situation of informational cascade, the market maker is unable to infer the traders' private information from their actions and, hence, is unable to update his beliefs on the asset value. This never occurs in our model, since, even when traders do not use their private signals, the traders' actions are informative on whether an information event occurred.

¹³Of course, during periods of herding, the price is updated in a Bayesian way by taking into account that, if the event has occurred and there are informed traders in the market, they make the same trading decision independently of the signal.

know that informed traders are not using their signals but herding). When the price becomes higher than the expectation conditional on a bad signal, agents will no longer find it optimal to herd. On the contrary, they will trade according to their private information. In our figure this occurs at time 7. The model, therefore, explains *temporary* herd behavior. Clearly, Figure 1 is just an example: the occurrence (and then the breaking) of herd behavior depends on the specific sequence of trading.

3. The Experiment and the Experimental Design

3.1. The experiment

We ran the experiment in the Experimental Laboratory of the ELSE Centre at the Department of Economics at UCL between December 2006 and February 2007. The participants were 32 financial professionals working for financial institutions operating in London. We ran 4 sessions, and each subject participated in one session only.¹⁴

The experiment was programmed and conducted with the software z-Tree (Fischbacher 2007). The sessions started with written instructions (available on request) given to all subjects. We explained to participants that they were all receiving the same instructions. Subjects could ask clarifying questions, which we answered privately. The experiment consisted of two treatments. The first treatment started with two “practice” rounds, followed by 7 rounds in which subjects received monetary payments. After completing the first treatment, participants received the instructions for the second one. Then they took part in the second treatment, which consisted again of 7 paid rounds.¹⁵

In both treatments, the participants acted as informed traders and could exchange an asset with a computerized market maker. The two treatments differed for the price updating rule used by the market maker.

Let us now see the procedures for each round of the experiment in detail:

1. At the beginning of each round, the computer program randomly chose the asset value. The value was equal to 0 or 100 with the same probability $\frac{1}{2}$. Each random draw was independent.

¹⁴We also conducted a pilot session with 8 more participants. In that session, we used a different payoff function to pay the traders. For this reason, we do not include the data from the pilot session in the analysis of our results.

¹⁵The 7 rounds of the second treatment were not preceded by practice rounds since the two treatments were very similar.

2. Participants were not told the realization of the asset value. They knew, however, that they would receive information on the asset value, in the form of a symmetric binary signal. If the asset value was equal to 100, a participant would get a “white signal” with probability 0.7 and a “blue signal” with probability 0.3. If the value was equal to 0, the probabilities would be inverted.
3. Each round consisted of 8 trading periods. In the first trading period, all 8 subjects made two trading decisions, conditional on the two possible signal realizations. They had to choose whether they would like to buy or sell one unit of the asset (at the price of 50) or not to trade, both in the event of receiving a white signal and in the event of receiving a blue signal. After all 8 participants made their decisions, the computer program randomly selected one of them (with equal probability) as the actual trader for that period. That subject received a signal (according to the rule indicated under point 2) and his decision conditional on the signal was executed.
4. The other subjects observed on their screens the executed trading decision, as well as the new price for period 2. The identity of the subject whose decision was executed, however, was not revealed.
5. In the second period, there were 7 subjects who had not traded yet. Similarly to the first period, they indicated whether they wanted to buy, sell or no to trade conditional on the good and the bad signal. Similarly to the first period, one of them was randomly chosen to trade.
6. The same procedures were repeated for 8 periods, until all subjects had traded once. Note that all subjects (including those who had already traded) observed the trading decisions in each period and the corresponding price movement. Indeed, the computer program moved from one period to another only after all 8 participants had observed the history of trades and prices, and had clicked on an “OK” button.
7. The round finished when the decisions of all the 8 traders were executed. At this point, the realization of the asset value was revealed and subjects saw their payoff for that round on the screen. The payoffs were computed as follows: in the event of a buy, the subject obtained $v - p_t$ of a fictitious experimental currency called “lira;” in the event of

a sell, he obtained $p_t - v$ lire; finally, if he decided not to trade he earned (and lost) nothing. After participants had observed their payoffs and clicked on an OK button, the software moved to the next round

As should be clear from this description, compared to the existing experiment literature on informational cascades, we introduced the procedural novelty of a strategy-like method. This has the advantage that we could detect cascade behavior directly. A subject engages in cascade behavior when he makes the same decision, independently of his signal realization. Since in our experiment a subject makes a decision for each possible signal realization, we could directly observe whether he chose the same action for both signal realizations.¹⁶ Furthermore, with this method, we collect much more information on the subjects' decision process than with the traditional procedures used in informational cascades experiments (in which a subject is first chosen to trade, then receives a signal and finally makes a decision). Indeed, in each treatment, we observed on average 36 decisions per subject, instead of just 7 (one per round). At the same time, our procedure was easy to implement and was quite natural for financial market professionals, since they are used to the idea of a conditional market order that is not necessarily executed.¹⁷

At the end of the experiment, we summed up the per round payoffs of both treatments and converted them into pounds at the rate of 3 lire per pound. With this exchange rate the incentives were clearly much stronger than in most experiments. In addition, we gave subjects £70 just for participating in the experiment.¹⁸ On average, subjects earned £134 (approximately equal to \$265) for a 2.5 hour experiment. The minimum payment amounted to £38

¹⁶In the existing experimental literature, instead, cascade behavior is typically detected by focusing on the decisions of subjects when they receive a signal against the history of trades. The reason is that, in almost all the existing experiments, subjects first receive the signal and then are asked to make a decision. An important exception is Çelen and Kariv (2004), who employ continuous action and signal spaces to distinguish informational cascades from herd behavior in a non-market experiment.

¹⁷Note that the procedure that we employ is not identical to the strategy method. With a strategy method, we should have asked each participant to make a decision for each possible contingency. Since there is a very large number of histories of trades, this would have been impossible to implement. In contrast, our method allowed us to collect a large dataset while, at the same time, keeping the process of trading simple.

¹⁸The fixed payment was given to make sure that participants did not end up with losses.

while the maximum was £268, with a standard deviation equal to £44.¹⁹

Finally, before leaving, subjects filled in a short questionnaire, in which they reported some personal characteristics (sex, age, education, work position, job tenure) and described their strategy and their beliefs on other subjects' strategy in the experiment. Immediately after filling the questionnaire, subjects were paid (in private) and could leave the laboratory.

3.2. Experimental design: the two treatments

As we mentioned before, the difference between the two treatments is in the price updating rule. In Treatment *I*, we implemented in the laboratory the model without event uncertainty described in Section 2 (i.e., the parametrization with $p = 1$ and $\mu = 0$). In Treatment *II*, instead, we implemented the model with uncertainty on the informational event (i.e., with $p = 0.85$ and $\mu = 0.95$). From the participants' viewpoint, the main difference between the two treatments was how the price was updated for a given order flow.

Let us illustrate how we updated the price. As we explained in the previous section, according to the theory, in Treatment *I* in equilibrium subjects should always follow their signal, i.e., they should buy after seeing a positive signal and sell after seeing a negative one. No one should decide not to trade, as private information allows the traders to make profits by trading with the market maker. Therefore, when a subject decided to buy, the price was updated assuming that he had seen a positive signal. Similarly, when a subject decided to sell, the price was updated assuming that the subject had observed a negative signal. Finally, in the case of a no trade, the price was kept constant. As a result, in this treatment, the price moved through a grid. It would start, at time 1, at the unconditional expected value of 50. After a sequence of buys, it would move, in a Bayesian way, to 70, 84, 93, 97, 99,... After a sequence of sells, it would move to 30, 16, 7, 3, 1,... The price at each time t only depended on the trade imbalance, i.e., on the difference between the number of buys and sells observed until the previous period $t - 1$.

In Treatment *II*, we changed the price updating rule, following the theoretical model with event uncertainty. We ran the experiment conditioning on

¹⁹We could have used the lottery method to pay our subjects in order to try to control for risk preferences. Since previous experimental work by Drehman et al (2005) has found that using the lottery method does not produce significantly different results in this type of experiment, we have preferred to use the more natural and simple way of computing payoffs.

an information event having occurred (i.e., V being equal to 0 or 100); participants played the role of informed traders. We implemented the treatment in the laboratory by explaining to the subjects that, in the second part of the experiment, the market maker would update the price as if, with high probability, he were trading not with informed traders, but with noise traders.²⁰ As in the previous treatment, participants could observe the amount by which the computer updated the price, before they made their decisions. Therefore, they had all the information needed to maximize their payoffs. Figures 1 and 2 show the price movement after a sequence of 8 buys and 8 sells. We have already commented Figure 1 in the previous section. Let us focus on Figure 2 here. After sell orders the price decreases, but less than in Treatment *I*. As a result, subjects should follow the signal in the first two periods but then they should sell independently of the signal (herding on the previous actions) in periods 3 to 6. At time 7 the price is low enough that subjects should now sell only conditional on a blue signal (and buy conditional on a white one). Figure 3 offers another example of the price changes, following a sell at time 1 and a series of buys later on. In this case subjects should herd only starting at time 6, whereas they should follow their signals in the first 5 times. Note, that, as in Treatment *I*, the price is updated assuming that traders chose the optimal action, i.e., they follow their private information when their expectation conditional on a white (blue) signal is above (below)

²⁰ Another difference between the parametrization of the first and the second treatment, is that, in the second treatment, there were 5% of noise traders. We implemented this in the laboratory by having a 3.3% probability in each trading period of a wrongly executing trading order (e.g., with a 3.3% probability a sell or a no trade was executed, although the true order coming from the participant was a buy). This is equivalent to saying that there was a 5% probability that in each period the trade was coming from a “noise trader.” The presence of noise traders in the second treatment was necessary for the following reason. Suppose that at time t a rational subject should always buy (because we are in a herd buy period). If the subject chosen to trade decides to sell, in the absence of noise traders, the market maker would infer that the market is uninformed, i.e., that all traders are noise traders. The market maker would, therefore, set the price equal to 50 for the entire round. Having a proportion of noise traders when there is an information event prevents this from happening. Also recall that, in the parametrization of the second treatment, the probability of a noise traders deciding not to trade differs according to whether an information event has occurred or not (33% and 2% respectively). This is tantamount to imposing that no trades do not convey information on the likelihood of an information event to the market maker and, as a result, the Bayesian updating rule implies no change in the price after a no trade (as it also happens in the first treatment), which is a natural and desirable feature.

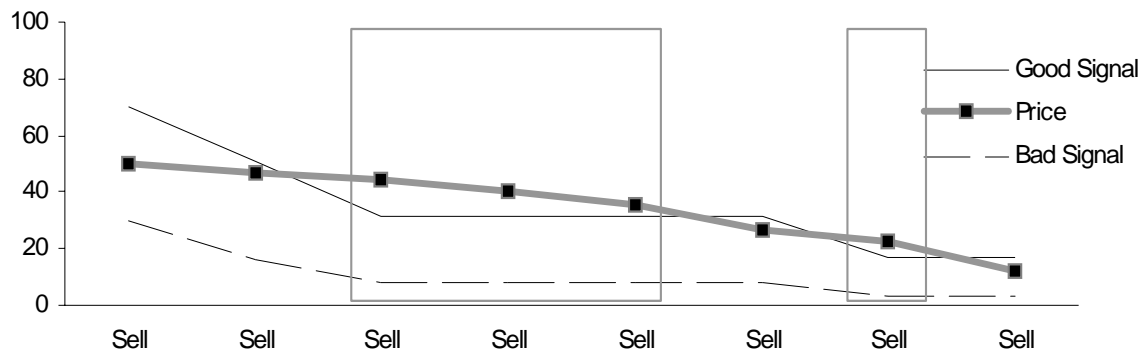


Figure 2: Prices and Traders' Expectations after a History of Sells

the market price, and they buy (sell) irrespective of their signal when we are in a herd buy (herd sell) period.

3.3. The pool of participants

The study was conducted with 32 financial professionals employed in 13 different financial institutions, all operating in London. Out of the 32 participants, 28% were traders, 47% market analysts, 9% sale or investment management persons, 9% investment bankers and 6% managers.²¹ 84% of subjects were male and 16% female. The participants' age ranged between 21 and 40 years, with a mean equal to 28 years and a standard deviation equal to 4.9. The average job tenure was 4 years, with a range between 3 months and 16 years (standard deviation: 4.2). Finally, 8% of participants had a Ph.D., 61% an M.A./M.S. and 31% a B.A./B.S. Most participants (68%) with a B.A./B.S. degree had studied economics/finance/business; the Masters degree were instead almost equally split between economics/finance/business and scientific or technical disciplines such as physics, mathematics or engineering; finally, the Ph.D. degrees were in physics or computer science.

²¹We use "investment banking" in its stricter meaning, as one of financial institutions' core functions. Moreover, "analyst" refers to the function within the institution and not to the rank.

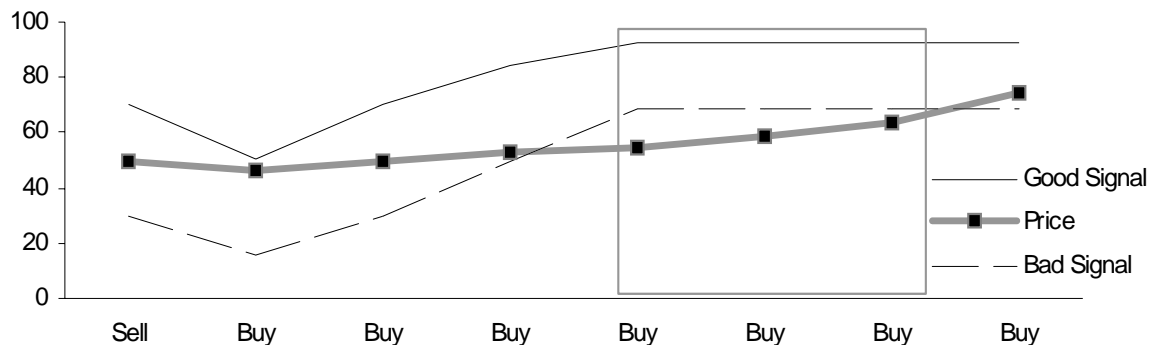


Figure 3: Prices and Traders' Expectations after a Sell Followed by a History of Buys

4. Results: Rationality, Herding and Contrarian Behavior

We now turn to discuss the results of the experiment. For expositional reasons, we find it convenient to present first the results of Treatment *I*, and then (in Section 4.2) to illustrate those of Treatment *II*.

4.1. Treatment *I*

Table 1 breaks down the participants' decisions in Treatment *I* according to how they used their own private information. In 45.7% of the cases, subjects just followed their private signal, buying on a white signal, and selling on a blue one. Recall that this is the rational behavior that theory predicts in equilibrium.²² In 19.6% of the cases, instead, they followed one of the two signals, but preferred to abstain from trading conditional on the other. In 19% of the cases, they decided to disregard private information

²²Following one's private information is rational only if each subject believes that all his predecessors are rational, that all his predecessors believe that their predecessors are rational and so on. Furthermore, after a no trade decision, which is always off the equilibrium path, subjects should not update their beliefs (which is consistent with our price updating rule), believe that their predecessors did not update their beliefs, and so on.

Decision	
Following Private Information	45.7%
Partially Following Private information	19.6%
Cascade Trading	19.0%
Cascade No-Trading	12.3%
Errors	3.4%
Total	100%

Table 1: Average behavior in Treatment I.

and buy or sell conditional on both signals. We refer to the case in which in the experiment an action does not depend on the private signal as “cascade behavior.”²³ In particular, if a subject decided to engage in cascade behavior and buy or sell, we say that he engages in cascade trading behavior. Another case in which subjects engaged in cascade behavior is when they preferred not to trade, again independently of their private information. This occurred in 12.3% of the the total decisions. Finally, there are few cases (3.4%) in which subjects made decisions that are self-contradictory for any possible belief.²⁴

This aggregate behavior clearly shows that whereas the theory captures some of the trading rules that subjects used in the laboratory, there are some departures from the equilibrium predictions that must be explained.²⁵ First, we must understand why subjects sometimes decided to engage in cascade behavior and trade independently of the signal. One possibility is that a subject may neglect private information to “herd” and follow the trend in the

²³In previous work (see, e.g., Anderson and Holt, 1997; Cipriani and Guarino, 2005) cascade behavior is defined as the *rational* decision to neglect the private signal. Here, instead, we define cascade behavior as the decision to choose the same action conditional on receiving both signals, independently of whether such a decision is rational (as may be sometimes the case in Treatment *II*) or not (as is always the case in Treatment *I*).

²⁴For instance, we observed some decisions to sell conditional on a white signal, but not to trade conditional on a blue signal, which can only be interpreted as a mistake since a white signal always conveys more positive information about the asset value than a blue one.

²⁵Note that the results in Table 1 overweigh decisions taken in the first periods (when all subjects take a decision) with respects to those taken at later periods (when fewer subjects do so). This implies that the results overweigh decisions taken when the trade imbalance is 0 with respects to those taken when the trade imbalance is high. In the following analysis, we will control for this, by studying the decisions taken conditional on a given level of the trade imbalance.

Absolute Value of the Trade Imbalance	Cascade Trading	Herd Behavior	Contrarian Behavior
0	5.8%		
1	18.5%	5.7%	12.9%
2	42.7%	16.1%	26.6%
3	54.3%	23.9%	30.4%
≥ 4	62.5%	21.9%	40.6%

Table 2: Cascade trading behavior in Treatment I.

order flow: a subject may buy (conditional on both signals) when the trade imbalance (i.e., the number of buys minus the number of sells) is positive, or sell (conditional on both signals) when it is negative. Theoretically, this should not occur in equilibrium in this treatment. Subjects in the laboratory, however, may give more weight to public information (i.e., the history of trades) than our price updating rule does and believe that conditioning the trade on the private signal is not optimal when the order flow already shows evidence in favor of the value being high or low. A second possibility is that a subject may decide to act as a “contrarian” by going against the market. In this case, the agent would sell for any possible signal when the trade imbalance is positive (and the price is “high”) and buy when it is negative (and the price is “low”). This behavior should not occur in equilibrium, but a subject may use the strategy of going against the market to sell at a high price and buy at a low one.

Table 2 shows how cascade trading behavior evolved according to the absolute value of the trade imbalance. There is a monotonic increase in the proportion of cascade-trading decisions as the trade imbalance increases: when the trade imbalance is 0, cascade trading behavior accounts for less than 6% of decisions; for an absolute value of the trade imbalance of 3 or more, instead, it accounts for more than 50% of decisions.

Note that, when the trade imbalance is 0, we cannot classify the cascade behavior as herding or contrarianism. In such a case the number of buys and sells is identical, and the price is equal to the unconditional expected value of 50. Therefore, the subjects’ decision to opt for buy or sell independently of the signal cannot be explained either in terms of following the crowd or going against it. When the value of trade imbalance is at least 1, instead, we can distinguish cascade behavior depending on whether the subject chose to buy

or to sell independently of the signal. In the first case we label the decision as herd behavior, and in the second as contrarian behavior. Similarly, when the trade imbalance is at most -1 , we classify the decision to sell conditional on both signals as herd behavior and the decision to buy as contrarian behavior.

As Table 2 shows, the evolution of herding and contrarianism with the trade imbalance is quite different. When the absolute value of the trade imbalance increases, so does the evidence in favor of the asset value being 0 or 100. This could have induced subjects to follow more and more the predecessors' decisions. As a matter of fact, herding almost triples when the imbalance goes from 1 to 2, but then it stabilizes at a level close to 20%. Contrarianism, instead, increases monotonically and by a substantial amount with the trade imbalance and accounts for a large percent (40%) of all decisions when the trade imbalance is high (at least 4). Overall, our experiment seems to indicate that, in the presence of a price that fully reacts to the order flow, subjects do not have a strong tendency to herd. In contrast, they do have a strong tendency to behave as contrarians.²⁶

One could wonder whether the observed deviations from the theory can be explained by the fact that subjects deciding in later periods may factor in the possibility of errors by their predecessors. As standard in the experimental literature, we answer this question through an analysis of errors.²⁷ By taking into account the possibility of errors by predecessors, we can indeed explain a proportion of contrarian trades. In particular, when the absolute trade imbalance is equal or higher than 4 all the contrarianism that we find in the data can be considered rational. Contrarianism at lower levels of the absolute trade imbalance, however, remains a non rational behavior even if one takes

²⁶Our result on herding and contrarianism is further confirmed when one looks at the decisions to follow one of the two signals only (and not to trade conditional on the other). The figure reported in Table 1 (19.6%) results from two different types of behavior: the decision to follow the signal that agrees with the trade imbalance (e.g., the white signal after more buys than sells) and not to trade conditional on the signal at odds with it; and the decision to follow the signal that is at odds with the trade imbalance (e.g., the blue signal after more buys than sells) and not to trade conditional on the one that agrees with it. Interestingly, this latter type of behavior is more frequent (11.5%) than the former (6.6%), indicating, again, that subjects had a higher tendency to go against the market than to follow it.

²⁷We do not give a detailed description of the methodology, since the analysis of errors is now quite standard in the literature. In particular, we followed the same procedures as in Cipriani and Guarino (2005). The interested reader can find a complete discussion in that paper (p.1437).

Absolute Value of the Trade Imbalance	Cascade No Trading
0	19.4%
1	5.4%
2	7.3%
3	13.0%
≥ 4	15.6%

Table 3: No trade in Treatment I.

into account previous subjects’ mistakes.²⁸

We will discuss individual behavior in detail in Section V. Here, however, it is worth noting that there was significant heterogeneity in the decision to herd, with the vast majority of subjects never herding. As a matter of fact, 24 out of the overall 39 decisions to herd for an absolute trade imbalance of at least 2 (i.e., 62% of these decisions) are due to two subjects only. If we excluded these two subjects, the percentage of herding would become very low (only 8% of decisions taken for an absolute trade imbalance of at least 2). The results also show significant heterogeneity in the degree of contrarianism, with slightly more than half of the subjects never acting as contrarians. In contrast to herding, however, the overall proportion of contrarian decisions is not affected by the behavior of only few subjects.

Now, let us look at the decision of subjects not to participate in the market, i.e., the decision not to trade independently of the signal (cascade no trading).

Cascade no trading occurred mainly under two circumstances: when the trade imbalance was 0 and when it was high (greater than or equal to 3). A trade imbalance of 0 means that either no one has yet traded in the market or that the order flow has not taken any direction. In such a circumstance, subjects have sometimes used the strategy of not taking a trading position, opting for trading only when the market had already taken a direction. For strictly positive levels of the absolute trade imbalance, the level of no trade is then monotonically increasing. It is worth recalling that a higher level of the trade imbalance is equivalent to a price farther away from the unconditional expected value. Therefore, a higher trade imbalance also meant that

²⁸Similarly, the modest proportion of herding remains not rational even taking into account the errors in the laboratory.

the possible loss (i.e., buying when the fundamental was 0 or selling when it was 100) was higher. The higher this potential loss, the lower was the participation in the market.

4.2. Treatment *II*

Let us now move to the analysis of subjects' decisions in Treatment *II*. Recall that the theoretical predictions for this treatment are different from those of Treatment *I*. In particular, in Treatment *II*, it is no longer the case that subjects should always follow their private information. After a given history of trades, it is possible that the optimal decision for a rational trader is to buy irrespective of the signal (herd buy periods) or to sell irrespective of the signal (herd sell periods). Table 4 breaks down the participants' decisions in Treatment *II* according to how they used their own private information. In 51% of the cases, subjects followed their private signal, buying on a white signal, and selling on a blue one. Whereas in Treatment *I* the proportion of decisions in accordance with private information is also a measure of how the participants' strategies agreed with the theoretical predictions, this is no longer the case now. For this reason, we also computed the percentage of times in which the participants' strategies agreed with the theoretical prediction: such a percentage is 48, almost identical to that of Treatment *I*.²⁹ As for the other figures reported in Table 4, it is worth noting that there is slightly less cascade trading than what reported in Table 1, and slightly more cascade no trading. The strategy of following one of the two signals and not trading on the other was chosen almost the same percentage of time as in Treatment *I*.

The difference between the behavior in the two treatments becomes striking when one contrasts Table 5 with Table 2. In contrast with the previous treatment, contrarianism is now very modest. It does not increase at all with the trade imbalance and remains always at an almost negligible level. On the other hand, herd behavior is steadily increasing with the trade imbalance. For a trade imbalance of at least 4, herd behavior explains all cascade trading behavior; it amounts to 40% of all decisions taken for such levels of the imbalance. The different propensity to herd with respect to Treatment *I* can easily be appreciated by noting that in that treatment, even for the highest

²⁹In other words, this is the percentage of the time in which subjects followed the signals when theory prescribes to follow the signal and herded when the theory prescribes to do so. Of course, the same remark as in footnote 22 applies to this computation.

Decision	
Following Private Information	50.9%
Partially Following Private information	20.1%
Cascade Trading	12.0%
Cascade No-Trading	16.5%
Errors	0.05%
Total	100.0%

Table 4: Average behavior in Treatment II.

Absolute Value of the Trade Imbalance	Cascade Trading	Herd Behavior	Contrarian Behavior
0	2.2%		
1	8.2%	4.4%	3.8%
2	23%	18.4%	4.6%
3	34.3%	30.3%	4.0%
≥ 4	40.4%	40.4%	0.0%

Table 5: Cascade trading behavior in Treatment II

levels of the trade imbalance, herd behavior was around 20%, a relatively low increment from the 5.8% of cascade behavior when the trade imbalance was 0. In the present treatment, instead, cascade behavior is only 2.2% for a trade imbalance of 0 but jumps to 40.4% (all due to herding) for a trade imbalance higher than 3. Therefore, we can conclude that theory correctly predicts the higher level of herding in this treatment with respect to the previous one.³⁰

The level of herding observed in the laboratory, however, is lower than what the theory predicts. We computed the percentage of herd behavior in the periods in which herding is theoretically rational.³¹ The result is

³⁰Another significant difference with respect to Treatment *I*, is that here, when participants followed only one signal and did not trade conditional on the other, they mainly followed the signal that agreed with the trade imbalance. In fact, this behavior accounts for 16.9% of subjects decisions, out of the 19.6% of cases in which subjects followed only one signal (and decided not to trade for the other). This contrasts with what observed in footnote 26 for Treatment *I*, i.e., that, when agents decided to follow only one signal, they mainly did so for the signal that did not agree with the trade imbalance.

³¹The same remark as in footnote 22 applies to this computation too.

that herding occurred only 23% of the cases.³² Since this type of financial market has never been tested previously in the laboratory, we cannot compare our results to those of other studies, not even to experiments conducted with students. The closest study is the “fixed price treatment” presented in Cipriani and Guarino (2005). In that treatment, subjects (undergraduate students) had three options as in the present context, and the price was always set equal to the unconditional expected value of 50. Subjects engaged in herd behavior 50% of the time. The difference may well be due to the fact that here there is a price movement, although less pronounced than in the previous treatment; this may have induced subjects to disregard the previous history of trades even in cases in which doing so was not optimal. Our low level of herding, however, is also reminiscent of the result by Alevy et al. (2007) according to whom, financial professionals put more weight on private information than students do and are less inclined to follow predecessors.

In summary, we can draw two conclusions on herding and contrarianism. First, whereas in Treatment *I* we observe a significant deviation from the theory because of contrarian behavior, this does not happen in Treatment *II*, where, as the theory predicts, contrarianism is not present. Second, the comparison between the experimental results in the two treatments supports the theoretical prediction that informational uncertainty is a source of herding behavior. In particular, in Treatment *II* herd behavior occurs, especially for high values of the trade imbalance, and occurs more often than what we observe in Treatment *I*. The level of herding observed in Treatment *II*, however, is lower than what theory predicts.

Another significant difference between the two treatments emerges when we look at the decisions not to trade. As Table 6 shows, in Treatment *II*, cascade no trading is monotonically and sharply decreasing with the absolute value of the trade imbalance. Subjects decided not to participate in the market mainly for a trade imbalance of 0. To explain such a behavior it is worth recalling that in this treatment, even for a high level of the trade imbalance, the price never reached values close to the extremes (0 or 100) and, as a result, the maximum loss was never very high. A high trade imbalance revealed information on the asset value, without making the maximum loss too high. For a high value of the imbalance, when subjects wanted to use

³²Note, however, that if we take into account previous subjects’ mistakes through an analysis of errors, the proportion of decisions in which traders correctly decided to herd increases to 31%.

Absolute Value of the Trade Imbalance	Cascade No Trading
0	25.3%
1	16.0%
2	8.0%
3	4.0%
≥ 4	2.1%

Table 6: No trade in Treatment II.

the option of not trading, they typically preferred to do so conditional on one signal only (the signal at odds with the trade imbalance) than to do so conditional on both.

5. Comparison with Previous Experimental Results

As we mentioned in the Introduction, Cipriani and Guarino (2005) and Drehman et al. (2005) have run experiments similar to our Treatment *I*, but with subjects who are not financial market professional. It is useful to compare their results to ours.

Cipriani and Guarino (2005) and Drehman et al. (2005) reach similar conclusions: subjects have a modest propensity to herd; at the same time, there are deviations from the equilibrium predictions in terms of abstention from trading and of contrarian behavior. Our first treatment is the most similar to Cipriani and Guarino’s (2005) “Flexible Price Treatment” (CG-FPT from now on), since the parameter values chosen to implement the experiment are the same. This makes the comparison with that study particularly easy. It should be noted, however, that whereas we used a strategy-like method, in Cipriani and Guarino (2005) each subject made only a decision per round, after observing the signal realization. Therefore, comparing the statistics we have reported in the previous section with those reported in CG-FPT would not be correct.³³ In order to compare our experimental results with those

³³Indeed, the differences in procedures imply that even the definitions of rationality, herding and contrarianism are different. For instance, we classified an action as rational when the subject made the correct decision (according to theory) conditional on both signals. In CG-FPT, instead, since subjects made a decision after observing the signal, rationality meant that the decision taken was correct given the observed signal. Clearly, the definition of rationality in this paper is stricter than that in CG-FPT.

of CG-FPT, we computed the same statistics as CG-FPT using our dataset (e.g., we computed the proportion of rational decisions only considering those decisions that were actually executed, which is what we would have observed had we used the same procedures of that study).

In CG-FPT, the proportion of decisions that were rational, i.e., consistent with the theory, was 65%. This is the same percentage that we obtain in our study. The average proportion of no trades was 22% in CG-FPT and 24% in ours. Cipriani and Guarino (2005) studied herd behavior by analyzing the subjects' decisions when they faced a trade imbalance of at least two (in absolute value) and received a signal against the imbalance. In CG-FPT subjects decided to neglect their private information and engage in herd behavior in 12% of cases; in 42% of cases they decided not to trade and in 46% they followed their signal. The corresponding numbers in our study are 5% for herding, 32% for no trade and 63% for following the signal. Finally, contrarianism was studied in Cipriani and Guarino (2005) by analyzing the case in which a subject observed a bad signal and a trade imbalance lower than or equal to -2 or a good signal and a trade imbalance greater than or equal to 2 . Using this criterion, we observed 28% of contrarianism, versus 19% in CG-FPT.

It is clear from these numbers that the behavior of financial market professionals is not very dissimilar from that of undergraduate students used in Cipriani and Guarino (2005). The similarity of results is reassuring for previous experimental findings. Our study confirms the low propensity to herd, and it shows an even more pronounced propensity to go against the market by financial professionals. Interestingly, it also shows that abstention from trading remains an important deviation from the theoretical predictions, even for financial professionals.

6. Individual Behavior

In the previous section we have characterized the aggregate choices of all the participants in the experiment. We now turn to discuss whether there is heterogeneity in individual behavior and its sources. Table 7 classifies individuals depending on the percentage of time in which their decisions agreed with the theoretical ones.

The table clearly shows that in both treatments participants behaved quite differently. For instance, in both treatment, there are almost 10% of subjects that made the theoretically optimal decision more than 80% of the

Percentage of Decisions in Accordance with the Theoretical Predictions	Percentage of Participants Treatment I	Percentage of Participants Treatment II
0 – 20	18.7	25.0
21 – 40	21.9	12.5
41 – 60	31.3	18.8
61 – 80	18.8	34.4
81 – 100	9.4	9.4

Table 7: Percentage of decisions in accordance with the theoretical prediction at individual level.

time; on the other hand, there are almost 25% of subjects that made the theoretically optimal decision less than 20% of the time. It is worth studying whether such an heterogenous behavior can be related to the participants' characteristics.

At the end of the experiment we collected information on the participants' age, gender, education, job tenure and job position. Table 8 shows the results of regressing the proportion of decisions taken in accordance to theory for each participant against the participants' age, education, gender and a dummy for traders.³⁴ Only the participants' age has a statistically significant and positive effect. The subjects' level of education, gender and being an actual trader are not significant determinants of the level of rationality.³⁵

Participants showed heterogeneity also in the specific trading strategies discussed in the previous sections (i.e., propensity to herd and act as contrarians). For instance, as already mentioned before, in Treatment *I* only very few subjects engaged often in herding behavior, whereas many never did.³⁶ Through regression analysis, we have studied whether the participants' propensity to herd or act as a contrarian are affected by their personal characteristics. None of the characteristics that we analyzed had a significant

³⁴The variable education takes value 1 if the participant's highest degree of education is a BA./BSc, 2 for an MA/MSc and 3 for a PhD. The dummy variable for trader takes value 1 if the participant was a trader and 0 otherwise.

³⁵We also used the job tenure as a regressor, instead of age and obtained similar results. Unfortunately, our dataset does not allow to disentangle which of these two (collinear) variables has effect on rationality. If we include both age and job tenure as regressors, both coefficients become not significant.

³⁶For an absolute trade imbalance of at least 2, 66% of participants never herded.

	(1)	(2)	(3)	(4)	(5)
Gender	0.039 (0.704)				0.019 (0.877)
Age		0.014 (0.013)			0.014 (0.028)
Degree			-0.134 (0.201)		-0.139 (0.215)
Trader				-0.114 (0.281)	-0.104 (0.386)
Observations	32	32	32	32	32
R ²	0.00	0.09	0.129	0.053	0.279

Table 8: Regressions of the level of rationality in the experiment on individual characteristics. P-values in parenthesis.

impact, except gender: women made significantly fewer contrarian decisions in the first treatment and more herd decisions in the second treatment.³⁷

Table 9 shows the relationship between a subject’s payoff and his personal characteristics. Traders earned significantly more than the other participants. No other characteristics significantly affected the subjects’ payoffs. The significantly higher payoff of traders was due to higher earnings in Treatment *I*, whereas no significant difference emerged in Treatment *II*.³⁸ It is, however, difficult to gauge from the data how traders achieved higher payoffs. Indeed, as Table 10 shows, being a professional trader did not change the tendency to act as a herder, or a contrarian, or to abstain from trading or to behave rationally. It appears that professional traders had an ability to earn more money than the other participants, even though, with respect to herding, contrarianism and no-trading, their trading strategies do not look different.

7. Conclusions

In this paper we have tested a theoretical model of sequential trading with private information by observing the behavior of financial market professionals in a controlled experiment. We have run two treatments: one in

³⁷In the interest of space, we do not report the regression results, since most of the coefficients are not significant.

³⁸The p-values of the per-treatment regressions (which, in the interest of space, we do not report) are 0.06 and 0.23 respectively.

	(1)	(2)	(3)	(4)	(5)
Gender	-30.302 (0.640)				3.757 (0.962)
Age		3.779 (0.236)			4.142 (0.313)
Degree			-8.944 (0.759)		-10.230 (0.670)
Trader				67.403 (0.050)	69.831 (0.107)
Observations	32	32	32	32	32
R ²	0.00	0.02	0.001	0.054	0.080

Table 9: Regression of subjects' payoff at the end of the experiment on individual characteristics. P-values in parenthesis.

	(1)	(2)	(3)	(4)	(5)
	Herd 1	Herd 2	Contr 1	Contr 2	No Trade
Trader	0.292 (0.204)	0.268 (0.206)	0.131 (0.199)	0.026 (0.744)	0.018 (0.855)
Observations	32	32	32	32	32
R ²	0.147	0.121	0.021	0.007	0.002

Table 10: Regressions of participants' proportion of herding, contrarianism and no trading on the trader's dummy. Herd 1 and Contrarian 1 refer to Treatment I. Herd 2 and Contrarian 2 refer to Treatment II. P-values in parenthesis.

which the price adjusts to the order flow in such a way that subjects should simply follow their own private information; and one in which the price does not fully reflect the information contained in the order flow and, as a result, it is sometimes rational for subjects to neglect the private information and imitate the predecessors.

We find that, as theory suggests, the proportion of herding decisions is very low in Treatment *I*. Therefore the theoretical prediction by Avery and Zemsky (1998) that price adjustment to the order flow reduces the scope for herding behavior, is confirmed by the experimental data on financial market professionals. Moreover, also in accordance with the theory, herding increases in Treatment *II*, where the price adjustment rule is consistent with the presence of event uncertainty.

Important deviations from equilibrium predictions, however, appear in the experimental data. In the first treatment, subjects had a tendency to go against the market that the theory does not account for. In the second, they herded, but less than theory predicts. Moreover, in both treatments, subjects sometimes prefer to abstain from trading although they had an informational advantage over the market maker, a phenomenon already observed in undergraduate students. Abstention from trading, therefore, remains an important deviation from theory (and one that significantly affects the process of price discovery) even with financial market professionals.

Our study combines the advantage of the controlled experiment with that of observing the behavior of professionals, who are engaged in the day-by-day activity of trading, pricing and analyzing financial assets. We believe that the challenge for future research is twofold. On the one hand, the existing experimental results offer suggestions for empirical research, which should study whether the behaviors observed in the laboratory are present in actual financial markets; on the other hand, more theoretical work is needed to capture the behaviors that the present model is unable to predict, such as contrarianism and abstention from trading activity.

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