Herd Behavior in a Laboratory Financial Market

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Abstract

We study herd behavior in a laboratory financial market where a sequence of subjects trades an asset whose value is unknown. In two treatments the price is updated according to a deterministic rule based on the order flow, and in another it is updated by experimental participants. Theory predicts that agents should never herd. Our experimental results are in line with this prediction. Nevertheless, we observe a phenomenon that cannot be accounted for by the theory. In some cases, subjects decide not to use their private information and choose not to trade. In other cases, they ignore their private information to trade against the market (contrarian behavior). (JEL C92, D8, G14)

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1 Introduction

In recent years there has been an increasing interest in herd behavior in financial markets. Especially after the financial crises of the 1990s, many scholars have suggested that herd behavior may be a reason for excess price volatility and financial systems fragility.

The theoretical research on herd behavior starts with the seminal papers by Abhijit Banerjee (1992), Sushil Bikhchandani et al. (1992), and Ivo Welch (1992).[1] These papers do not discuss herd behavior in financial markets, but in an abstract environment, in which agents with private information make their decisions in sequence. They show that, after a finite number of agents have chosen their actions, all following agents will disregard their own private information and herd. This is an important result, because it gives a rationale for the imitating behavior that we observe in consumers' and investors' decisions. In these first models of herding, however, the cost of taking an action (e.g., investing in a new project) is held constant. In other words, these models do not analyze situations in which, when agents make their decisions to buy or sell a good, the price of that good changes. Therefore, they are unsuitable to discuss herd behavior in financial markets, where prices are certainly flexible and react to the order flow.

More recently, Christopher Avery and Peter Zemsky (1998) have studied herd behavior in a financial market where the price is efficiently set by a market maker according to the order flow. They show that the presence of an efficient price mechanism makes an informational cascade (i.e., a situation in which an agent does not use his own information and herds) impossible. Agents always find it optimal to trade on the difference between their own information (the history of trades and the private signal) and the commonly available information (the history of trades only). For this reason, the price aggregates the information contained in the history of past trades correctly.[2]

It is difficult to test these theoretical models of herding empirically. The existing literature (see, e.g., Joseph Lakonishok et al., 1992, Grinblatt et

[1] In this paper we study only informational herding. We do not discuss herd behavior arising because of reputational concerns, as in David Sharfstein and Jeremy Stein (1990), or payoff externalities.

[2] For other theoretical contributions on informational herding in financial markets, see, e.g., In Ho Lee (1998), V.V. Chari and Patrick Kehoe (forthcoming) and Marco Cipriani and Antonio Guarino (2003). For a recent survey of herding in financial markets, see David Hirshleifer and Siew H. Teoh (2003).

al., 1995, Wermers, 1999 and the other papers cited in the survey of Hirshleifer and Teoh, 2003) does not test these models directly, but only analyzes the presence of herding in financial markets through statistical measures of clustering. This literature finds that fund managers tend to cluster their investment decisions. Such clustering, however, may or may not be due to informational herding: for instance, it may be the result of a common reaction to public announcements. The problem for the empirical research on herd behavior is that there are no data on the private information available to the traders and, therefore, it is difficult to understand whether traders decide to disregard their own information and imitate.

This problem can be overcome in an experimental study. In an experiment we can observe variables not available for actual markets, in particular, the private information that agents have when making their decisions. In our laboratory market, subjects 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, if they want to sell, to buy or not to trade one unit of the asset. By observing the way in which they use their private information and react to the decisions of the previous traders, we can directly detect the occurrence of herding.[3] By testing directly the prediction of the theoretical work, we create a bridge between the existing empirical and theoretical literatures.

Our results on herd behavior are in line with the predictions of the theoretical models. We compare two cases, one in which the price is fixed and one in which it is flexible. We implement the flexible price case in two ways: in one the price is updated according to a deterministic rule based on the order flow and in the other it is set by experimental participants. We find that, with either price updating mechanism, when the price is flexible subjects disregard their private information and herd much less frequently than when the price is held constant.

Although the theory is able to predict the effect of a flexible price on herd behavior, it is unable to account for two phenomena that we observe in the laboratory. First, when the price is flexible, subjects sometimes choose not to trade. Second, sometimes (although less frequently) they choose not to follow their private information. A proportion of trading against the private

[3] For previous experimental analyses of herd behavior based on the Banerjee (1992) and Bickchandani et al. (1992) models see Lisa Anderson and Charles Holt (1997), Boğaçan Çelen and Shakar Kariv (forthcoming), Steffen Huck and Jörg Oechssler (2000) and Dorothea Kübler and Georg Weiszsäcker (forthcoming).

signal is “contrarian behavior:” subjects neglect their private information in order to trade against the market. The occurrence of contrarian behavior and of no trade decisions reduces the ability of the price to aggregate private information dispersed across market participants.

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 results of the first three treatments. Section 5 discusses the fourth treatment with endogenous price setting. Section 6 concludes.

2 The Theoretical Model

2.1 The model structure

Our experimental analysis is based on the model by Lawrence Glosten and Paul Milgrom (1985). In our economy there is an asset traded by a sequence of traders who interact with a market maker. Time is represented by a countable set of trading dates indexed by $t = 1, 2, 3....$

The market

The fundamental value of the asset, V, is a random variable distributed on $\{0, 100\}$ with the same probability $\frac{1}{2}$. At each time t, a trader can exchange the asset with a specialist (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 $h_t \in \mathcal{A}$. 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 allowed to set only one price (i.e., we do not allow for a bid-ask spread). We consider two setups, a fixed price setup and a flexible price setup. In the first setup the market maker sets the price equal to the asset's unconditional expected value, i.e.,

$$P_t = E(V) = 50 \quad \text{for all } t.$$

In the second one the market maker sets the price equal to the expected value conditional on the information available at time t, i.e.,[4]

[4]In the original Glosten and Milgrom (1985) model the market maker posts a bid

$$P_t = E(V|H_t).$$

The traders

At each time t, a trader is chosen from a non-atomic continuum of traders. Traders have private information on the asset value.[5] If at time t a trader is chosen to trade, he observes a private signal on the value V. The signal is a random variable x_t distributed on $\{0, 100\}$. We denote the conditional probability function of x_t given V by $q(x_t|V)$. We assume that the random variables x_t are independently and identically distributed across time. Moreover, we assume that

$$q(x_t = x|V = x) = 0.7, \text{ for } x = 0, 100.$$

In addition to his signal, a trader trading at time t observes the history of trades and prices and the current price. Therefore, his expected value of the asset is $E(V|H_t, x_t)$.

Traders are endowed with cash ($K \in \mathsf{R}^+$). Their payoff function U : $\{0, 100\} \times \mathcal{A} \times [0, 100] \times \mathsf{R}^+ \to \mathsf{R}$ is defined as

$$U(V \times \mathcal{A} \times P_t \times \mathsf{R}^+) = \begin{cases} V - P_t + K & \text{if } h_t = buy, \\ K & \text{if } h_t = no\ trade, \\ P_t - V + K & \text{if } h_t = sell. \end{cases}$$

Traders are risk neutral and choose h_t to maximize $E(U(V \times \mathcal{A} \times P_t \times \mathsf{R}^+)|H_t, x_t)$.

Therefore, they find it optimal to buy whenever $E(V|H_t, x_t) > P_t$, and sell whenever $E(V|H_t, x_t) < P_t$. They are indifferent among buying, no trading and selling when $E(V|H_t, x_t) = P_t$.

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price and an ask price and makes zero expected profits because of unmodeled potential competition. 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. The presence of only one price makes our experiment easier to run.

[5]In the original Glosten and Milgrom (1985) model, a proportion of traders are uninformed and trade for exogenous reasons, without regard for their profits. The presence of these noise traders is necessary for the market not to break down. Indeed, a market without gains from trade and where agents are risk neutral would collapse in the absence of noise traders, as proven by the no trade theorem (Milgrom and Nancy Stokey, 1982). In our setup, for simplicity, all traders are informed and we assume that the market maker is willing to trade even if he makes negative profits in expected value.

2.2 Prediction when the price is fixed

In order to study the theoretical predictions of our model, we need to introduce the concepts of trade imbalance and of informational cascade.

For any trading sequence we define the trade imbalance at time t as the number of buy orders minus the number of sell orders until time $t-1$. If a no trade can be the outcome of a rational decision and reveals a trader's private signal, we also take it into account in the computation of the trade imbalance.[6] Moreover, following Anderson and Holt (1997), we define an informational cascade as a situation in which it is optimal for a rational agent to ignore his own private information and conform to the established pattern of trade. During a cascade, agents herd, i.e., they all choose the same action.[7]

When the price is fixed, as in the seminal papers on herd behavior and information cascades, the following result holds:[8]

Result 1 (Banerjee, 1992, and Bikhchandani et al., 1992) When the asset price is fixed at the unconditional expected value $E(V) = 50$, an informational cascade occurs after a trade imbalance higher than or equal to 2, or lower than or equal to -2.

To understand the intuition behind this result, consider the following example. In this setup an agent buys the asset if $E(V|H_t, x_t) > 50$. Suppose that at time 3 there is a trade imbalance of 2, i.e., $H_3 = \{buy, buy\}$. Suppose also that the third trader receives the signal $x_3 = 0$. From the first two buy

[6] When the price is fixed, the decision of no trading can be rational. For instance, it is rational not to trade when there has been a buy order at time 1 and, at time 2, an agent receives a negative signal. From the first buy order the agent can induce that the first agent had a positive signal. Therefore, his expected value of the asset, given one positive and one negative signal, is 50, equal to the asset price.

In the computation of the trade imbalance, a rational no trade is considered as a sell order if it reveals a negative signal, and as a buy order if it reveals a positive one.

[7] In the literature it has been pointed out (see Lones Smith and Peter Sørensen, 2000) that rational herding and informational cascades are not identical concepts. For an experimental analysis of the difference between herd behavior and informational cascades, see Çelen and Kariv (forthcoming). In our setup with discrete signal space, however, an informational cascade implies rational herd and viceversa. In the following pages we will refer to herding to indicate conformity of behavior, which can be rational (as in a cascade) or irrational.

[8] We assume that, if an agent is indifferent, he follows his private information. All our results would hold if we assume that the agent randomizes among the choices.

orders, he can infer that x_1 and x_2 equal 100. Therefore, by Bayes's rule, his expected value of the asset is 70. Given that the price is 50, he will ignore his signal and buy. This starts a cascade.

2.3 Prediction when the price is flexible

Let us discuss now the case in which the price is flexible. The market maker updates the price in a Bayesian way on the basis of the order flow. In this setup, informational cascades cannot arise.

Result 2 (Avery and Zemsky, 1998) When the market maker sets the price P_t equal to $E(V|H_t)$, agents always trade according to the private signal. An informational cascade cannot occur.

To decide whether he wants to buy or sell the asset, an agent computes his expected value and compares it to the price. If at time t a trader receives a signal of 100, his expected value will be

$$E(V|H_t, x_t = 100) = 100 \Pr(V = 100|H_t, x_t = 100) =$$

$$100 \frac{(.7) \Pr(V = 100|H_t)}{(.7) \Pr(V = 100|H_t) + (.3)(1 - \Pr(V = 100|H_t))} >$$

$$100 \Pr(V = 100|H_t) = E(V|H_t).$$

Similarly, if he receives a signal of 0, his expected value will be $E(V|H_t, x_t = 0) < E(V|H_t)$. This shows that an agent will always find it optimal to trade according to his private information and an informational cascade cannot arise.

Note that, when a trader has the opportunity to trade at a certain price, knowing the history of trades does not give him additional information on the asset value than what is already contained in the asset price. Therefore, a rational agent should act according to his private signal, irrespective of whether he is able to observe the history of trades or not.

3 The Experiment and the Experimental Design

3.1 The experiment

This was a paper and pencil experiment. We recruited subjects from undergraduate courses in all disciplines at New York University and University College London. They had no previous experience with this experiment. In total, we recruited 216 students to run 16 sessions (four sessions for each treatment).[9] We now describe the procedure for the first three treatments and postpone the discussion of the fourth to Section 5. For these three treatments, in each session we used 13 participants, one acting as subject administrator and 12 acting as traders. The procedure was the following:

1. At the beginning of the sessions, we gave written instructions (available on request from the authors) to all subjects. We read the instructions aloud in an attempt to make the structure of the game common knowledge to all subjects. Then, we asked for clarifying questions. If a participant had a doubt, one of us went to him to discuss it.

2. Each session consisted of ten rounds. In each round we asked all subjects to trade one after the other.

3. The sequence of traders for each round was chosen randomly. At the beginning of the session each subject picked a card from a deck of 13 numbered cards. The number that a subject picked was assigned to him for the entire session. The card number 0 indicated the subject administrator. In each round, the subject administrator called the subjects in sequence by randomly drawing cards (without replacement) from this same deck.

4. Before each round, an experimenter, outside the room, tossed a coin: if the coin landed tail, the value of the asset for that round was 100, otherwise it was 0. Traders were not told the outcome of the coin flip.

[9] Subjects were recruited by sending an invitation to a large pool of potential participants. For each session of the experiment, we received a large number of requests to participate. We chose the students randomly, so that the subjects in the experiment were unlikely to know each other.

5. During the round, an experimenter acted as market maker, setting the price at which people could trade. The other experimenter was outside the room with two bags, one containing 30 blue and 70 white chips and the other 30 white and 70 blue chips. The two bags were identical. Each subject, before trading, had to go outside the room and draw a chip from one bag. If the coin landed tail we used the first bag, otherwise we used the second. Therefore, the chip color was a signal for the value of the asset. Note that the subject could not tell anyone the chip color. Therefore, neither the market maker nor the other traders knew the realizations of the signal. Finally, after looking at the color, the subject put the chip back into the bag.

6. After observing the chip color, the subject entered the room and declared aloud whether he wanted to buy, to sell or not to trade. The subject administrator recorded all subjects' decisions on the blackboard, where he also recorded the prices at which subjects could trade the asset. Hence, each subject knew not only his own signal, but also the history of trades and prices.[10]

7. At the end of each round, i.e., after all 12 participants had traded once, the realization of the asset value was revealed and subjects were asked to compute their payoffs. All values were in a fictitious currency called lira. Their payoffs were computed as follows. In the event of a buy, the subject obtained $100 + Value - Price$ lire; in the event of a sell, he obtained $100 + Price - Value$ lire; finally, if he decided not to trade he earned 100 lire. This is equivalent to giving each subject 100 lire each round, which he could use to trade. Given that the price was always between 0 and 100 lire, and that they were given 100 lire at the beginning of each round, subjects could never lose money.

8. After the tenth round, we summed up the per round payoffs and converted them into dollars at the rate of $\frac{1}{65}$. In addition, we gave \$7 to subjects just for participating in the experiment. Subjects were paid in private and, on average, earned \$23 for a 1.5 hour experiment.

[10] Subjects were seated far away from each other, all facing the blackboard. No communication was allowed in the room. The entrance was in the back of the classroom. When making his decision, the subject was facing the blackboard, but not the other participants.

3.2 The Experimental Design

Let us now describe the differences between these first three treatments. In the first treatment ("fixed price" treatment), the price was not updated on the basis of the order flow and was fixed at 50. As explained in the previous section, after a trade imbalance of two, an informational cascade should arise, i.e., subjects should buy despite a negative signal or sell despite a positive signal.

In the second treatment ("flexible price" treatment) the price was updated after each trade decision in a Bayesian fashion. Rational 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 money by trading with the market maker. Therefore, in this treatment, 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 the subject had observed a negative signal. Finally, in the case of a no trade, the price was kept constant.

It is worth mentioning that a great advantage of our setting is that the price moved through a grid. Given that the price only depends on the trade imbalance, there were only few values at which the price was set during the entire experiment. In the first three rounds (which we do not consider in our data), subjects had the opportunity to see exactly how the price moved in response to the order flow.

The third treatment ("no history" treatment) was a control treatment: in order to understand the effect of history on the behavior of subjects, we ran an experiment where subjects could not observe the decisions of those who traded before them. When a subject had to make a decision, he could only read the price at which he could trade on a piece of paper, but did not have the history of trades and of prices written on the blackboard. Although we did not want subjects to know the past prices and decisions, we wanted them to know the mechanism of price formation. In order to make sure that students understood this mechanism, not only did we describe it in the instructions, but, in the first three rounds, we also ran the experiment as in the flexible price treatment. In this way, everyone could observe how the market maker updated the price in reaction to the traders' decisions. Starting with the $4th$ round, subjects were not allowed to see the past history of trades and prices.

In the next section we describe the results of these three treatments. The results refer to the last seven rounds of each session only.[11] We do not take into account the first three rounds for two reasons. First, although the experiment was very easy and subjects did not have problems in understanding the instructions, we believe that some rounds were needed to acquaint subjects with the procedures. We wanted to distinguish the decisions that subjects made in the learning stage from the decisions taken afterward. Second, considering only the last seven rounds helps to make the results comparable across the different treatments (as explained above, in the no history design we did not allow the subjects to observe the history of trades and prices starting with the $4th$ round).

4 Results

4.1 Informational Cascades and Contrarian Behavior

We start the presentation of our results by discussing informational cascades. Let us consider, first, the fixed price treatment. In this case, theory predicts that an informational cascade occurs whenever a trade imbalance of at least two (in absolute value) arises. In this treatment there were 58 periods of potential informational cascade, i.e., periods when the trade imbalance was at least 2 or not higher than -2 and, moreover, the subject had received a signal that was against the trade imbalance.[12] In these periods, subjects

[11] In each round, the 12 subjects were asked to trade in sequence. Therefore, the results for each treatment refer to 336 decisions.

[12] An important issue in the computation of the trade imbalance is how to handle the role of deviators. For instance, consider the fixed price treatment and suppose that there have been four buy orders. Suppose that the next subject decides to sell. In this case, his actions is certainly irrational, since, no matter what his signal is, he should buy. One can take into account this sell order in different ways. One could argue that the decision of this person should not be taken into account in the computation of the trade imbalance, as it is irrational and does not reveal anything about his signal. Therefore, after this sell, the trade imbalance should still be counted as four. On the other hand, one can argue (as in Anderson and Holt, 1997) that, although irrational, this person is likely to have received a negative signal, otherwise he would not have had any reason to sell. Therefore, his decision breaks the cascade. The cascade was created by the first two buy orders (the other two buys do not provide any additional information) and now is destroyed by the sell order. The trade imbalance would go from four to one. Now consider the flexible price treatment. In this treatment, informational cascades never happen; therefore the trade imbalance should clearly be computed by taking into account all past actions in the same way. Therefore, the trade imbalance in our example should go from four to three in

engaged in cascade behavior in 52 percent of cases; in 26 percent of cases subjects decided not to trade and in 22 percent of the cases they decided to follow their signal.

What happens when, as in the flexible price treatment, we allow the price to react to the order flow? Do subjects still neglect their signal? Table 1 shows the results of this treatment and contrasts them with those of the fixed price treatment. In the flexible price case there were 66 periods in which the trade imbalance was at least two (or at most -2) and the subject received a signal against it. In these periods, subjects decided to neglect their private information and engage in irrational herd-like behavior only in 12 percent of the cases. In 42 percent of the cases they decided not to trade and in 46 percent they followed their signal even if it was at odds with the history of trades. These results show that subjects rarely decided to follow what other subjects had done. The price movement reduced the incentive to imitate previous decisions. We ran a Mann-Whitney test for the hypothesis that the proportion of herding decisions was the same under the fixed price and flexible price treatments and the null is rejected at the 5 percent significance level.[13]

It is also interesting to note that, in the fixed price treatment, when the trade imbalance was zero (and therefore there was no scope for imitation), only 5 percent of decisions were against private information. This percentage climbed to 52 percent in periods when the absolute value of the trade imbalance was at least 2 and subjects received a signal against it. In contrast, in the flexible price treatment, when the trade imbalance was 0, the percentage of decisions against private information was 10 percent. This number barely increased (to 12 percent), when the absolute level of the trade imbalance was equal to or higher than 2 and subjects received a signal against it.

To understand better the effect of past trades on subjects' decisions, let

this treatment. In this paper we want to understand the role of the price mechanism and compare the fixed price with the flexible price treatment. Therefore, we want to use the same measure of trade imbalance for the two treatments. We have decided to compute the trade imbalance in both treatments considering all past actions, irrespective of whether they could come from a rational decision. Our choice does not affect the results in a significant manner, as in the fixed price treatment we observed very few deviations from a cascade. If we compute the trade imbalance by assuming that a deviator breaks the cascade (as in Anderson and Holt, 1997), in the fixed price treatment cascade behavior arose 54 percent of cases, no trade 24 percent, and following the signal 22 percent.

[13] The test is carried out by taking the proportion of herding decisions in each of the four sessions and using the Mann-Whitney procedure.

us consider the no history treatment, in which subjects could not observe previous decisions. If subjects were significantly affected by previous subjects' decisions, the results of the flexible price treatment and of the no history treatment should be different. In particular, one could expect the percentage of irrational herding to be much higher when subjects do observe previous decisions. This is not what happened (see Table 1). In the no history treatment, out of the 70 periods in which the trade imbalance was at least 2 (or at most -2) and the subject received a signal against it, subjects irrationally traded against the signal in 24 percent of the cases, versus the 12 percent of the flexible price treatment.[14] As in the previous treatment, some decisions (33 percent of cases) were no trades.

So far, we have focused on subjects' behavior when they had private information which was at odds with that conveyed by the history of trades. It is also interesting to see how subjects acted on average during the experiment. Table 2 reports the proportion of decisions that were rational, i.e., consistent with the theory. Rational decisions amounted to 83 percent of the total in the fixed price treatment and to 65 percent in the flexible price treatment. Therefore, although the price mechanism seems able to discourage herding, it also seems to reduce the overall rationality of subjects' behavior. In particular, there are more no trades (22 percent versus 13 percent) and there is a higher proportion of irrational buy and sell orders.[15] In the remainder of this section, we discuss these two phenomena and try to offer possible explanations.

Let us start from the analysis of no trade decisions. In the flexible price treatment, the frequency of no trades increased with the absolute value of the trade imbalance: it is 16 percent for an absolute value of the trade imbalance of 0 or 1, 22 percent for an absolute value of 2 or 3, and 33 percent for

[14]Running a Mann-Whitney test, we cannot reject the hypothesis that the proportion of herds in the flexible and no history treatments are the same (p-value=0.19). In contrast, we can reject the hypothesis that the proportion of herds is the same in the no history and fixed price treatments.

[15]One may wonder whether these results depend on the behavior of some particular subjects or reflect homogeneous behavior. For instance, is the level of irrationality due to some people who behaved irrationally most of the time? Remember that each subject made 10 decisions and we focused on the last 7. For each subject, we computed the number of times in which he acted rationally. In the flexible price treatment, out of 48 participants, only one subject made the rational decision less than 3 times. Regarding no trade decisions, only one subject decided not to trade more than 3 times. Homogeneous behavior across subjects was also observed in the other treatments.

an absolute value higher than 3. In other words, we observed more no trade decisions when the price was closer to 0 or 100. Given the payoffs, it is difficult to reconcile this behavior with plausible levels of risk aversion.[16] A possible alternative explanation is that subjects preferred not to trade mostly when the trade imbalance was high because they faced a high maximum loss[17].

As we commented above, in the flexible price treatment, a percentage of trading decisions was taken against private information. To understand this result we considered the possibility that subjects decided to trade against the signal for reasons other than imitation. We studied another form of irrational behavior (which we call contrarian behavior) in which a subject neglects his signal in order to buy at a low price or sell at a high price . In particular, we say that a subject is a contrarian when he buys, despite a negative signal, at a low price, i.e., at a price lower than 30, and sells, despite a positive signal, at a high price, i.e., a price higher than 70. Equivalently, we can say that a subject acts as a contrarian when he buys with a negative signal and there is a trade imbalance lower than or equal to -2, or sells with a positive signal and the trade imbalance is higher than or equal to 2. The definition of contrarian behavior is meant to capture the behavior of people who use the strategy of "going against the market." Contrarians disregard their positive signal to take advantage of the high price in the market or disregard their negative signal to buy at a low price.

In the flexible price treatment there were 132 periods in which a subject could have acted as a contrarian. Out of these 132 times, subjects behaved as contrarians in 19 percent of the cases, whereas in 18 percent they decided not to trade and in 63 percent they followed their private information. Similar behavior also arose when the history was not observable (see Table 3). In all these cases of contrarianism the market was unable to aggregate private information correctly.[18] Table 3 also reports the percentage of contrarianism

[16] Moreover, in a similar experiment, Mathias Drehmann et al., 2004, obtain a similar proportion of no trades by employing a binary lottery procedure, which should induce risk neutrality.

[17] In our experiment, the maximum loss is computed in the following way. Suppose that a subject faces a price p. If he buys and the value of the asset turns out to be 0 he loses p. If he sells and the value is 100, he loses $100 - p$. Therefore, the maximum loss is $max\{p, 100 - p\}$.

[18] We have also computed the propensity to act as a contrarian for different levels of the trade imbalance. The results are very similar to those presented above. For example, when we consider a trade imbalance of at least 1, we find that 16 percent of the decisions are contrarian, 17 percent are no trade and 67 percent are taken according to the signal.

in the fixed price treatment.[19] With a fixed price, subjects never adopted contrarian behavior and decided not to trade only in 1 percent of cases.

The results reported in Tables 1 and 3 suggest that, while with flexible prices subjects seldom engage in irrational herding (and, therefore, the market is able to learn private information), they also have a lower incentive to use their information when this is consistent with the previous history of trades. This informational inefficiency is not present when the price is not allowed to respond to the history of trades and helps to explain why the percentage of irrational trades is higher in the flexible price treatment than in the fixed price treatment.

When people act as herders or as contrarians, they trade against their own signal and prevent private information from being correctly aggregated by the market price. It is important, however, to remark the different effect of herding and contrarian behavior on social learning. Herd behavior amplifies the importance of early decisions. If these decisions are incorrect, everyone makes the same mistake. In contrast, contrarian behavior goes against the previous history of trades and therefore reduces its importance. In terms of the price path, this means that herding can make the price converge to the wrong value (if, for instance, early traders sell and the value is 100), whereas contrarian behavior makes the price regress towards the mean (given that, for instance, if early traders sell, then contrarians buy).

4.2 Actual and Theoretical Prices

According to theory, the price should converge to the true value of the asset as the number of trading periods goes to infinity. This happens because, in each period, by choosing to buy or to sell, subjects reveal their private information. Therefore, over time, by the law of large numbers, the price reflects the fundamental value of the asset. In our treatment, with only 12 periods of trade, there is, of course, no guarantee that the price should always converge to the fundamental value, as private information may not be able (even if perfectly aggregated) to reveal the fundamental value of the asset. In order to have a clear idea of the price convergence in the laboratory,

When we consider a trade imbalance of at least 3, these figures change only slightly to 21 percent, 19 percent and 60 percent.

[19] In this treatment, given that the price is not updated, the behavior of a subject is defined as contrarian if he sells after a positive trade imbalance of at least 2 or if he buys after a negative trade imbalance of at least -2.

we proceeded in the following way. We studied the price level after all 12 subjects had traded and compared it to the levels that should have been observed theoretically. These theoretical prices were computed assuming that all actions were rational, i.e., that subjects followed their signals.

Figure 1 shows the difference between the theoretical and the actual last prices in the flexible price treatment.[20] Note that, 50 percent of the time, this difference was lower than 5 and 61 percent of the time it was lower than 10. It never occurred that the theoretical and actual prices moved in the opposite direction (i.e., that the distance was greater than 50). However, 14 percent of the time the distance was greater than 30. The average difference (in absolute value) between the last actual and theoretical prices was 12.[21]

This relatively small distance between the last theoretical and actual prices is a direct consequence of the fact that, in the experiment, 65 percent of the time subjects followed their signal (as the theory suggests) and only 13 percent traded against it. Nevertheless, at least in some rounds, irrational decisions no to trade or to trade against the signal created a wedge between the theoretical and the actual prices.

4.3 An Analysis of Errors

As shown by the previous analysis, during the experiment subjects made errors, i.e., they did not behave rationally all the time. In computing their expected payoffs, the subjects who decided in the later periods could factor in the possibility of errors by their predecessors. This, in turn, could change their optimal trading decisions. To explore this issue, we performed an analysis of errors similar to that of Anderson and Holt (1997). We estimated the error rates assuming that expected payoffs are subject to shocks distributed independently as a logistic random variable.[22] At each time t, the probability of an action is a function of the difference between the expected payoff of

[20] Remember that for each treatment we have observations for 28 rounds, i.e., for the last 7 rounds of each of the 4 sessions.

[21] Drehmann et al.(2004) report a higher distance between the last theoretical and actual prices than we do. Their results and ours are not perfectly comparable, since they run different treatments with different parameter values and they report the average difference between theoretical and actual prices across these treatments. Moreover, they also report a lower level of rationality in the experiment than we do which can also explain why last period theoretical and actual prices are farther apart.

[22] See McKelvey and Palfrey, 1995, 1997.

buying or selling the asset (Π_t), i.e.,

$$\Pr(j) = \frac{e^{\gamma_j^t \Pi_t}}{\sum_{k=0}^{2} e^{\gamma_k^t \Pi_t}},$$

where $j = 0, 1, 2$ indicates a no trade, a buy or a sell, respectively.[23]

The model implies that a subject may not choose the action that yields the highest payoff, i.e., that he may make a mistake. For each time t, we estimated the parameters of the model by regressing the trading decision on the difference between the expected payoff of a buy and of a sell . The analysis was recursive, i.e., we used the estimated parameters $\gamma_j^1 .... \gamma_j^{t-1}$ to compute the expected payoffs at time t.

Was herding or contrarian behavior ever rational in the flexible price treatment when one recognizes that subjects make mistakes? In principle, this is a possibility. Theory rules out a decision at time t at odds with private information assuming that the price is set efficiently by the market maker and that all traders before t acted rationally. In our experiment, however, whereas the price is set assuming that subjects do not make mistakes, people can indeed choose the wrong action. Suppose, for instance, that some subjects in the first periods made mistakes and bought the asset although they had a negative signal. The market maker assumes that everyone is rational and, therefore, updates the price after each buy on the basis of this assumption. If the next subject takes into account that previous subjects may have chosen the wrong action, he will realize that the price is too high, given the previous history of trades and, therefore, will decide to sell despite a negative signal. This would explain contrarian behavior. Similarly, think of the case where after some buy orders, some subjects decide not to trade. If the next subject believes that these no trade decisions hide some positive signals, he will consider the price too low and therefore decide to herd buy, neglecting his negative signal. This would explain the (modest) proportion of irrational herding that we found in the flexible price treatment.

Tables 4 reports the results of the analysis of errors for contrarian behavior. The table shows the percentage of time in which acting as a contrarian was "rational," for different levels of the trade imbalance (there is not column for the fixed price treatment since observed no contrarianism in that

[23] The expected payoff of a no trade does not enter the model, since it is constant for all times t.

treatment). While contrarianism cannot be reconciled with theory when it occurred at low levels of the trade imbalance, it can be rationalized when the trade imbalance was higher and, therefore, the price was more extreme.

Tables 5 reports the results of the analysis of errors for herd behavior. The modest proportion of irrational herd-like behavior that we observe in the treatments in which the price is flexible, cannot be justified for any trade imbalance.

Finally, let us move to the fixed price treatment. According to theory, informational cascades can arise as a subject's private information, after some trades, is overwhelmed by the public information contained in the history of trades. If people make mistakes, however, this is not necessarily the case. For instance, if two subjects buy the asset, it is not necessarily true that the third should buy as well if he receives a negative signal. In fact, if the probability of the first two subjects making mistakes is high, it may well be that the expected value of the asset, conditional on the first two buys and on the negative signal, is still lower than the price of 50. Our analysis shows that even taking the possibility of errors into account, ignoring the signal and herding was rational in most of the cases that we classified as of potential informational cascade: in fact, it was the rational decision in 93 percent of these cases (see Table 5).

5 Endogenous Price Setting

In the flexible price treatment, we tested how subjects used their own private information in a market in which the price is set as in Avery and Zemsky (1998). This treatment was meant to test a theoretical result, namely, that with such a price mechanism agents will not imitate each other and will act to reveal their private information.

While the flexible price treatment offers a clear benchmark to evaluate experimental traders' behavior, one may wonder what happens when, as in real financial markets, the price is set by economic agents. To analyze these issues, we ran a treatment in which the price was set by two participants, who acted as market makers.[24] This is important since the Bayesian rule that we applied in the flexible price treatment did not take into account subjects'

[24] We thank Douglas Bernheim (the co-editor) for proposing this treatment. For other experiments with endogenous market making, see, e.g., Robert Bloomfield and Maureen O'Hara (1998, 1999, 2000).

actual behavior. In contrast, if the price is decided by subjects acting as market makers, they can modify the way they set the price, depending on how the other subjects trade. This, in turn, may have an effect on the way subjects themselves decide to trade.

The treatment, which we label "endogenous pricing" treatment, was run according to the following procedures. The two experimental market makers chose the prices at which traders could trade, and updated them on the basis of the order flow. They chose their prices independently without observing each other's decision. The subject administrator recorded the prices on the blackboard, which both market makers and traders could see. Then, he called a subject to trade. After observing the subject's decision, the market makers chose the prices for the following trader. The procedures for the rest of the treatment were identical to those described in Section 3.[25]

When a subject was called to trade, he could trade at the better of the two prices set by the market makers. He could buy at the lower price and sell at the higher price.[26] The traders' payoff was computed as in the other treatments. The market makers' payoff was identical to that of the traders, i.e., it depended on the difference between the realized value of the asset and the price of the transaction.[27] Given that the market makers could not set a bid-ask spread, in expected value they would always lose money by trading with informed traders. Therefore, we compensated them with a fixed amount of 110 lire for each trading period (i.e., 10 more lire than what we gave to the traders).[28] Given this price mechanism and payoff structure, competition guarantees that the market makers should set the

[25] In this treatment the sessions lasted approximately 2.5 hours.

[26] With such a mechanism, a rational agent would find it optimal to buy if his expected value is higher than the average price and to sell otherwise. If a subject buys, his expected profit is $E(V|H_t, x_t) - min(P_t^I, P_t^{II})$, where P_t^I and P_t^{II} are the two posted prices. If he sells, his expected profit is $\max(P_t^I, P_t^{II}) - E(V|H_t, x_t)$. Therefore, he will buy if $E(V|H_t, x_t) \geq \frac{min(P_t^I, P_t^{II}) + \max(P_t^I, P_t^{II})}{2}$ and sell if $E(V|H_t, x_t) \leq \frac{min(P_t^I, P_t^{II}) + \max(P_t^I, P_t^{II})}{2}$. Of course, $\frac{min(P_t^I, P_t^{II}) + \max(P_t^I, P_t^{II})}{2} = \frac{P_t^I + P_t^{II}}{2}$.

[27] Note that, in each trading period, at most one market maker was trading. When the market makers chose the same prices, we randomly decided which market maker actually traded. The other market maker's payoff was equal to a no trade payoff.

[28] At the end of the experiment, we divided the total amount of lire earned by the market makers by 12 and then exchanged it at the same exchange rate used for the traders. We divided the total payoff by 12 since the market makers received the fixed endowment 12 times as often as the traders. This guarantees that market makers and traders could earn a similar amount of money in the experiment.

price equal to the expected value of the asset conditional on the order flow. Given that the market makers' task was harder than that of the traders, they participated in training sessions before the experiment.[29] Only the market makers participated in these sessions. This assures that the behavior of subjects acting as traders is comparable to that observed in the other treatments.

Let us now discuss the results. Prices were set at similar levels to those of the flexible price treatment. On average, the absolute value of the distance between the prices set by the market makers and the theoretical ones used in the flexible price treatment is 5.5 lire. Table 6 shows how the market makers updated the prices after a trading order for different absolute levels of the trade imbalance.[30] The table contrasts these price changes with those that we used in the flexible price treatment, i.e., the theoretical Bayesian updating. When the trade imbalance was 0, after a buy or a sell order market makers updated the price less than we did in the flexible price treatment. In other words, market makers did not give as much weight to the arrival of just one buy or sell order. In contrast, when the trade imbalance increased to 1 or 2 (in absolute value), the market makers updated the price slightly more than in the theoretical model For higher trade imbalances their updating was close to the theoretical one. It is also important to note that after a no trade, market makers barely moved the price.

Given these price levels, following the signal that the subject actually received was the rational decision 87 percent of the time (versus 100 percent of the time in the flexible price treatment). In the remaining 13 percent of the time, traders should have traded against the signal (which was never the optimal action in the flexible price treatment).[31]

Let us now turn to the traders's decisions. As we noted above, traders' rational choice depends on the prices set by the market makers (and does

[29] A training session for market makers is also used in Bloomfield and O'Hara (1998, 1999, 2000). In our training sessions, participants received the same instructions as in the experiment. They were told that they were participating in a training session aimed at making the rules of the experiment clear to them. In the training session, the role of traders was played by a computer software, which simulated a sequence of trading orders. At the end of each round, each market maker was informed of the realized value of the asset and could compute his payoff. The training sessions lasted on average 2.5 hours.

[30] The averages were computed considering the price changes of both market makers in all four sessions.

[31] In this analysis, we are assuming that a subject believes that all the previous decisions were rational.

not necessarily coincide with following one's own signal).[32] The proportion of rational decisions accounts for 58 percent of the total. No trades amounted to 24 percent of decisions. These results are in line with what observed in the flexible price treatment.[33]

The $5th$ column of Table 1 reports the results on herd behavior for the endogenous pricing treatment. There were 58 periods in which the trade imbalance was at least two (or at most -2) and the subject received a signal against it. In these periods, subjects decided to ignore private information and engage in irrational herding in 21 percent of the cases; in 34 percent of cases they decided not to trade and in 45 percent they followed their signal. These results, and in particular the low proportion of herd-like decisions, are similar to those of the flexible price treatment.[34] Note that in this treatment herding could potentially be optimal if market makers updated prices incorrectly. For instance, if market makers updated the price too little, it could be optimal to follow previous decisions. In our experiment, however, this was never the case.

The observed herd like behavior cannot be explained even by an analysis of errors (see Table 5, column 5). The level of prices was such that in the experiment there were no periods in which it would have been rational to neglect the signal in order to herd, even recognizing that predecessors could have made mistakes. This means that experimental market makers were able to set prices at which, given the level of rationality in the experiment, no one should have, indeed, herded.

Let us now discuss contrarian behavior. There were 116 periods in which subjects could have potentially acted as contrarians. They behaved as con-

[32]Note that the time-t optimal decision depends not only on the prices chosen at that time, but on the whole sequence of prices until time t. When computing his expectation, a rational agent takes into account that previous agents may have found it optimal to act against their signal given the posted prices.

[33]The null that the proportion of rational decisions was the same under this and the flexible price treatment (or no history treatment) cannot be rejected at the 5 percent significance level (p-value=0.15) (or p-value=0.56) (Mann-Whitney test). Similarly, we cannot reject the hypothesis that the proportion of no trades was the same under this treatment and the flexible price or no history treatment (p-value=0.89 in both cases).

[34]A Mann-Whitney test for the hypothesis that the proportion of herding decisions was the same under this treatment and the flexible price treatment cannot be rejected at the 5 percent significance level (p-value=0.15). The hypothesis that the proportion of herding decisions was the same under this treatment and the no history treatment cannot be rejected either (p-value=0.67).

trarians in 24 percent of these periods, whereas in 23 percent they decided not to trade and in 53 they followed their private information. The results are similar to those of the previous treatments with flexible prices.[35] Part of this contrarian behavior can be justified by looking at the price levels set by the market makers. Indeed, 46 percent of the cases in which a subject acted as a contrarian, this was the optimal choice considering the prices set by the market makers. Also the analysis of errors helps to explain part of contrarian behavior (see Table 4, column 4): in particular, when the absolute level of the trade imbalance was equal or higher than 4, all contrarian decisions were rational if we assume that traders could correctly estimate previous subjects' level of rationality.

Now, let us study price convergence. Figure 2 shows the difference between the theoretical and the actual last prices. As in the flexible price treatment, 61 percent of the time this difference was lower than 10 and 50 percent of the time it was lower than 5. However, once (in round 20) the actual price moved close to 100, while the theoretical price was close to 0. Moreover, 21 percent of the time the distance was greater than 30. As a result, the average distance between actual and theoretical last prices was 17, slightly higher than what observed in the flexible price treatment.

In all the treatments discussed so far, the market maker (i.e., the experimenter in the previous treatments or a subject in the endogenous pricing treatment) could set only one price and, as a result, there was no bid-ask spread. One may wonder whether the presence of a bid-ask spread would affect our results. To answer this question, we ran a related treatment in which two participants acting as market makers set two prices, a bid and an ask price.[36] For a detailed description of this treatment we refer the reader to an addendum, available on request from the authors. Here we only summarize the main results concerning traders' behavior.

In this treatment we observed 19 percent of herd-like behavior, a percentage very close to what we observed in the other treatments with a flexible price discussed above. Therefore, the presence of a bid-ask spread does not

[35] A Mann-Whitney test for the hypothesis that the proportion of contrarian decisions was the same under this treatment and the flexible price (or no-history) treatment cannot be rejected at the 5 percent significance level (the p-value in both cases is 0.56).

[36] For other experiments with subjects setting a bid-ask spread, see Bloomfield and O'Hara (1998, 1999, 2000). The bid-ask spread has also been studied experimentally in Bloomfield (1996).

change our result on the effect of flexible price on herd behavior.[37] Contrarian behavior arose in 10 percent of the cases. This percentage is identical to that of the no-history treatment, but lower than what observed in the flexible price and in the endogenous pricing treatments.[38] On average, during the entire experiment, subjects behaved rationally 58 percent of the time, the same percentage observed in the endogenous pricing treatment.[39] The proportion of no trades, 35 percent, was higher than in the other treatments. It should be noted, however, that almost half of the no trade decisions were rational, as the market makers set a bid-ask spread so large (i.e., larger than what theory predicts) that trading was not optimal.

In conclusion, the presence of a bid and ask spread did not modify traders' propensity to herd or the overall level of rationality in the experiment. It reduced contrarian behavior and increased the proportion of no trades. Since in actual financial markets the size of the bid-ask spread varies significantly, the results of our treatment suggest that we may find more contrarianism in liquid markets, i.e., markets where the bid-ask spread is lower. In most financial markets, however, the average size of the bid-ask spread is much smaller than in our experiment. Therefore, one should be cautious in evaluating the quantitative importance of the presence of a bid-ask spread in reducing contrarianism and increasing no trading.

6 Conclusions

In this paper we have reported and discussed the results of an experimental study on herd behavior in financial markets. We have shown that, in a frictionless laboratory market in which traders trade only for informational

[37] Mann-Whitney tests for the hypotheses that the proportion of herd-like decisions was the same under this treatment and the flexible price, no-history or endogenous price treatments cannot be rejected at the 5 percent significance level ($p-values$ = 0.66, 0.47, 0.77).

[38] A Mann-Whitney test for the hypothesis that the proportion of contrarianism was the same under this treatment and the no-history treatment cannot be rejected at the 5 percent significance level (p-value=0.88). We can, however, reject the hypothesis that the proportion is the same under this treatment and the flexible price or the endogenous pricing treatments.

[39] Mann-Whitney tests for the hypotheses that the proportion of rational decisions was the same under this treatment and the flexible price, the no history or the endogenous pricing treatments cannot be rejected at the 5 percent significance level (p-values=0.15, 0.39, 0.67, respectively).

reasons, herd behavior seldom occurs. This result is consistent with the theoretical predictions of Avery and Zemsky (1998). The result suggests that in order to understand herd behavior in actual financial markets we must look for other explanations, such as reputation concerns (Sharfstein and Stein, 1990), or non informational motives to trade (Cipriani and Guarino, 2003).

Theory, however, does not completely capture the behavior observed in the laboratory market. Sometimes, subjects decided not to follow their private information. A proportion of these trades against private information was contrarian behavior, i.e., trade against the market. More frequently, subjects preferred to ignore their private information and abstain from trading. This indicates that limited market participation may be an important source of financial markets' informational inefficiency.

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Table 1: Informational cascades and herd-like behavior

	Fixed Price	Flexible Price	No History	Endogenous Pricing
Trading against the signal	52%	12%	24%	21%
No Trading	26%	42%	33%	34%
Trading following the signal	22%	46%	43%	45%
Relevant Periods	58	66	70	58

The relevant periods are those when the trade imbalance was at least 2 (or at most –2) and subjects received a negative (positive) signal.

Table 2: Rational and irrational decisions

Fixed Price			
Rational Decisions	No Trading	2%	83%
	Buying or Selling	81%	
Irrational Decisions	No Trading	11%	17%
	Buying or Selling	6%	
Flexible Price			
Rational Decisions			65%
Irrational Decisions	No Trading	22%	35%
	Buying or Selling	13%	
No History			
Rational Decisions			61%
Irrational Decisions	No Trading	25%	39%
	Buying or Selling	14%	
Endogenous Pricing			
Rational Decisions			58%
Irrational Decisions	No Trading	24%	42%
	Buying or Selling	18%	

Table 3: Contrarian Behavior

	Fixed Price	Flexible Price	No History	Endogenous Pricing
Contrarian Behavior	0%	19%	10%	24%
No Trading	1%	18%	25%	23%
Following Private Information	99%	63%	65%	53%
Relevant Periods	121	132	134	116

The relevant periods are those when the trade imbalance was at least 2 (or at most –2) and subjects received a positive (negative) signal.

Table 4: Analysis of errors for contrarian behavior

Absolute Value of the Trade Imbalance	Flexible Price	No History	Endogenous Pricing
2-3	0%	40%	69%
4-5	57%	100%	100%
>=6	100%	100%	100%

The table shows, for different absolute values of the trade imbalance, the number and percentage of "contrarian trades" that are rational if subjects take into account the possibility that predecessors have made mistakes.

Table 5: Analysis of errors for informational cascades and herd-like behavior

	Fixed Price	Flexible Price	No History	Endogenous Pricing
Rational decisions	93%	0%	0%	0%

The table shows the percentage of informational cascades (fixed price) or herd-like decisions (other treatments) that is rational if subjects take into account the possibility that predecessors have made mistakes.

Table 6: Price updating in the endogenous pricing treatment

Trade Imbalance (Absolute Value)	0	1	2	3	4	5
After Buy	13 (20)	15.67 (14)	11.93 (9)	2.5 (4)	1.63 (2)	1.4 (1)
After Sell	-11 (-20)	-16.68 (-14)	-11.74 (-9)	-3.07 (-4)	-2.21 (-1)	0 (-1)
After NT	0 (0)	-0.76 (0)	0.85 (0)	-0.08 (0)	0.23 (0)	0 (0)

The table shows the average price updating of market makers for different absolute values of the trade imbalance in the endogenous pricing treatment. In parenthesis, the table reports the price updating that we used in the flexible price and no history treatments.

Figure 1: Distance between the theoretical and the actual last prices in the flexible price treatment

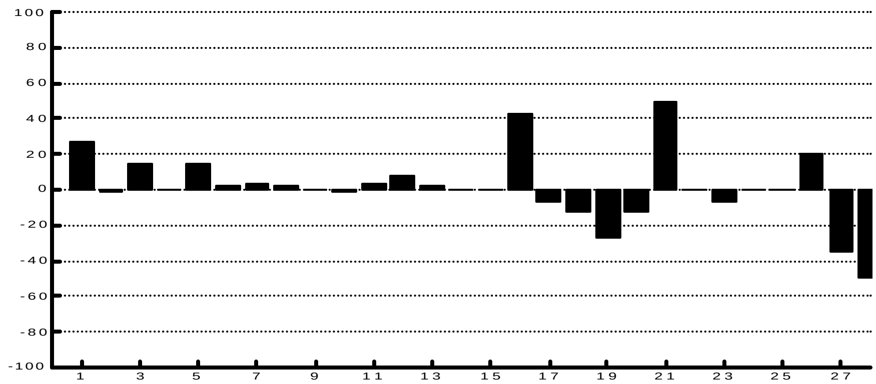

Figure 2: Distance between the theoretical and the actual last prices in the endogenous pricing treatment