Herding, Contrarianism and Delay
in Financial Market Trading

Andreas Park∗  Daniel Sgroi†
University of Toronto  University of Warwick

January 15, 2009

Abstract

Herding and contrarian behavior are often-cited features of real-world financial markets. Theoretical models of continuous trading that study herding and contrarianism, however, are inherently complex and usually do not allow traders to choose when to trade or to trade more than once. We present a large-scale experiment to explore these features within a tightly controlled laboratory environment. Herding and contrarianism are significantly more pronounced than in comparable studies that do not allow traders to time their decisions. Traders with extreme information tend to trade earliest, followed by those with information conducive to contrarianism, while those with the theoretical potential to herd delay the most.

JEL Classification: C91, D82, G14.

Keywords: Herding, Contrarianism, Endogenous-time trading, Experiments.

*E-mail: andreas.park@utoronto.ca
†E-mail: daniel.sgroi@warwick.ac.uk

Financial support from the ESRC, SSHRC, the Leverhulme Trust and the Cambridge Endowment for Research in Finance is gratefully acknowledged. Special thanks go to Annie Jekova and Malena Digiuni for expert research assistance. We thank seminar participants at the Universities of Cambridge, Toronto, Southampton, Warwick, and Zurich, and the Midwest Economic Theory Meetings 2008. We are also grateful to Gustavo Bobonis, Ernst Fehr, Jordi Mondria, Jim Peck and Xiadong Zhu for extensive discussions.
“Were all these people stupid? It can’t be. We have to consider the possibility that perfectly rational people can get caught up in a bubble. In this connection, it is helpful to refer to an important bit of economic theory about herd behavior.”


Robert Shiller believes that rational herding can and does explain the current housing market difficulties and, by implication, the financial problems faced all over the world. The theory to which he explicitly refers was pioneered by Welch (1992), Bikhchandani, Hirshleifer, and Welch (1992) and Banerjee (1992) who highlight that rationality is no defence against the randomness of herd behavior. Put simply, a few early incorrect decisions, through a process of rational observation and inference, can have serious ramifications for all who follow.

A loose application of herding theory to financial market trading might suggest that early movements by visible traders can induce discontinuous price jumps in one direction or the other, potentially leaving share prices far from their fundamental value. If we could describe cases of wild, short-term movements or dubious run-ups of asset prices using the tools of herding theory, not only would we better understand financial markets, but we would have an intellectual framework to ponder policy suggestions aimed at avoiding financial crises.

Yet, the early work on rational herding was not designed to be directly applied to security market trading. First, this early work on herding does not consider prices that react to actions while in financial markets (efficient) market prices drop after sales and rise after

---

1 The first published paper on the breakdown of informational learning by rational agents is Welch (1992); it is also the first application of herding theory to a financial market setting.

2 Consider a traditional herding setting in which agents receive an informative but noisy signal about which of two states is better. Suppose state A is truly worse than state B. Then it is possible that the first two agents happen to draw incorrect signals, and thereby opt for A. For agent 3, under a natural indifference condition, this means disregarding whatever signal she possesses and following the actions of the first two agents. All later agents find themselves in the same position as the third agent and will follow in the same manner even though they realize that it is only the information conveyed in the first two actions that determines behavior. As the direction of the herd disproportionately depends on the first movers, the ultimate outcome is exposed to a degree of randomness that is not warranted by fundamentals.
buys. Second, economic agents are allowed to act only once, whereas in real financial markets, agents can trade repeatedly. Third, agents must act in a strict, exogenous sequence — they cannot decide when to trade. Arguably, in a market trading environment where learning from others is important, the timing of actions should matter a great deal. In fact, one of the key features of real-world financial frenzies is the clustering of actions in time, a phenomenon that cannot be examined when timing is not considered.

A path-breaking paper by Avery and Zemsky (1998) introduced efficient prices to a sequential herding context. Yet this work showed that in a simple financial market-trading setting with two values herding is not possible because the market price always separates people with good and bad information so that the former always buy and the latter always sell. With multiple states, however, herding can arise when traders receive a particular kind of information; we will employ such a setting in our experimental setup. Moreover, we will also analyze the natural and often cited counterpart situation to herding in which people rationally act against the majority action. Such rational contrarianism has not been studied explicitly in experimental markets before, yet it is often cited as an important phenomenon in real-world markets.

Despite the considerable advances that have been made in the market microstructure literature, there is as yet no theoretical model which allows rational and heterogeneous traders to choose the time of their actions and to trade more than once. The work presented here partly fills this gap in the literature with an experimental analysis that combines a story of informational herding and contrarianism with moving prices, multiple trades and,

---

3See, for example, Park and Sabourian (2008) which gives the conditions on information that must be satisfied to admit herding, contrarianism, or neither of the two.

4For example, see Chordia, Roll, and Subrahmanyam (2002) for a discussion of the importance of contrarianism in financial market trading.
crucially, *endogenous timing*. By explicitly allowing subjects to choose both how and when to trade and, in half of the treatments, to trade twice, we arguably come closer to a true examination of the scope for herding and contrarianism in real-world markets than any other study to date.

When the timing of actions is a choice, the existence and the effect of herding and contrarianism are not immediately obvious. One can argue that eliminating exogenous timing removes an artificial friction, in the absence of which herding and contrarianism might vanish. Alternatively, behavior may well be much more pronounced than with exogenous timing. A casual intuition for the latter is as follows. Traders that are prone to herd are likely to be less confident about the value of an asset. We might then speculate that they delay their trading decision to gain more information by observing others. So once they do trade, their herding behavior may lead to stronger price distortions under endogenous-timing than exogenous-timing. Our results indicate that herd behavior does indeed become much more pronounced when traders can decide when to trade. Thus denying traders the opportunity to time their actions may be underplaying herding and contrarian behavior.

**The Static Decision Problem.** To simplify the exposition, we will distinguish and

---

5Our work is in the tradition of Bloomfield, O’Hara, and Saar (2005) who provide an insightful discussion on the complexity of the trade-timing decision and the justification for tackling this issue using controlled laboratory experiments.

6Experimental work can play an important complementary role to empirical analyses: transaction level data from standard databases such as TAQ does not reveal the party behind a transaction. This makes it difficult to test information based motives for trading. Experiments can bridge the gap between theory and empirics as the experimenter can control the information of each experimental subject and can explicitly observe the behavior of individuals.

7Apart from the relation to the recent financial market turmoil, our model also contributes to some intensely researched aspects of financial market trading. Namely, one persistent finding in financial market microstructure is that the order imbalance (loosely, the difference between buy and sell orders) is serially correlated, i.e. buys tend to follow buys, and sales tend to follow sales (see Chordia, Roll, and Subrahmanyam (2008)). Herding is one of the explanations cited, and our findings of a herding and an information-related timing component indicates a possibly strong intertemporal effect. That being said, if the underlying information structure allows rational contrarianism, then the serial correlation would likely be mitigated.
separate the decision of the trading direction from the timing decision; we will refer to the
former as the static decision problem, and the latter as the dynamic problem. All the while
we emphasize that these two belong together in the full equilibrium problem.

The ‘static’ theoretical model underlying our experiment is a sequential trading setup in
the tradition of Glosten and Milgrom (1985), in which risk-neutral subjects trade single units
of a financial security with a competitive market maker. Past trades and prices are public
information, and the market maker adjusts the price after each transaction to include the
new information revealed by this trade. We differ from Glosten and Milgrom by admitting
endogenous timing, whereas in their model traders act at exogenously determined times.

In our specification, there is a single security with three possible liquidation values (high,
middle, low). There are three possible actions (buy, sell, or no trade). Each subject receives
a private realization of one of three possible signals (high, middle, or low); these signals
are a piece of information about the true liquidation value. Recipients of the low signal
systematically shift probability weight towards low values, recipients of the high signal sys-
tematically shift probability weight towards high values. Recipients of the middle signal
value shift weight either towards the middle value or towards both the high and the low
value. The focus of herding theory is on the trading behavior of the recipients of the middle
signal and we discuss this signal’s structure in detail in the next paragraph. From the static
perspective, rational subjects should buy if their expectation, conditional on their private
signal and all public information, is above the price and sell if it is below. It turns out that,
theoretically, recipients of the “low” signal should always sell and recipients of the “high”
signal should always buy.

A key result of herding theory for financial market trading is that the existence of rational
herding crucially depends upon the shape of the underlying conditional signal distribution
for the middle value. Herders switch from selling to buying as prices rise or from buying to selling as prices fall. To do so, they must update their private expectations upwards faster than the price rises or downwards faster than the price falls. This faster speed of updating is possible if and only if traders have signals that make them shift weight towards both extreme outcomes (see Avery and Zemsky (1998) or Park and Sabourian (2008)), or, in technical terms, if their conditional signal distribution is “U-shaped”. Contrarians switch from selling to buying as prices fall and from buying to selling as prices rise. To do so, they must adjust their private expectations downwards slower than the price falls and vice versa when the price rises. This slower speed of updating is possible if and only if traders receive signals that cause them to shift weight towards the middle outcome, or, in technical terms, if their conditional signal distribution is “hill-shaped”.

As an example of when U-shaped signals might be prevalent, take the situation that markets found themselves in on September 29, 2008, the day when the United States Congress rejected the first version of the “Bailout Bill” (now referred to as TARP). At least three future scenarios were imaginable: the bill might be re-introduced as is, an arguably worse bill could go to the floor, or there will be no bill at all. In this environment it is imaginable that investors were pulled between two opposing possibilities, either thinking that Congress was merely flexing its muscles but with every intention of eventually going with Treasury Secretary Paulson’s recommendations or thinking that Congress would block any attempted bailout. Theory here predicts the potential for herd behavior.

The Dynamic Decision Problem. We employed two different classes of treatments: in the first, people are allowed to trade at most once, in the second they can trade at most twice. The seminal paper which studies this problem with a single irreversible action and without moving prices is Chamley and Gale (1994). A key message of their work is that
decision-makers will move very quickly, since waiting only makes sense when new information arises. Smith (2000) presents a single-trade setup with a single informed trader. He shows that someone who receives a signal that is either good or bad news (which we model with high or low signals) should trade ‘early’, and he also presents an example of a U-shaped signal structure under which people optimally delay. None of these setups is an exact match for the situation that we analyze, but each provides important insights for us to draw upon. Namely, recipients of the high and low signals gain nothing from waiting as their optimal action does not depend on the history — they should thus act soonest. The behavior of the recipients of middle signals, however, is history dependent and there are no unambiguous theoretical predictions. We will thus explore experimentally if they display systematic timing patterns.

Results. In one of the largest laboratory experimental studies of its type (with around 2000 trades spread over 6 treatments) we find scope for rational herding and contrarian behavior, even though prices are efficient. Moreover, comparing our findings with earlier studies, the nature of herding and contrarianism is more pronounced when traders have the opportunity to delay and to trade more than once. Importantly, recipients of the signals that theoretically admit herding and contrarianism systematically delay more than those with high and low signals. Finally, there is significant clustering of decision-making in time.

Overall about 73% of the decisions are in line with the predictions of the static model. This fit compares well with other experimental work that focusses on trading with exogenous timing such as Drehmann et al (2005), Cipriani and Guarino (2005, 2007) and Park and Sgroi (2008). Broken down by signal type, these numbers are 84% and 86% for recipients of the low and high signals respectively. For recipients of signals that admit herding and contrarianism the fit is only 54%. One reason for this lower fit is that the decision with
this signal is more difficult. Recipients of high and low signals act according to the static theory by simply sticking to their initial best action. Recipients of the U-shaped (herding) and hill-shaped (contrarian) signals, on the other hand, have to follow the development of prices very carefully. If they make small mistakes in their computations then their resulting decisions can violate the predictions of the static model.

We thus analyze if the behavior of traders who have U- and hill-shaped signals is in the spirit of the predictions of herding theory. Namely, the implicit hypothesis in the static rational model is that traders who have U- and hill-shaped signals are more prone to engage in herd behavior or contrarianism respectively than recipients of high and low signals. This is what we observe: receiving a U-shaped signal increases the probability of engaging in herding behavior by about 30%. Similarly, receiving the hill-shaped signal increases the probability of engaging in contrarian behavior by 35% while receiving any other signal reduces the chance of acting as a herder or contrarian. The effect of the U-shaped (herding) signal is notably stronger than that in Park and Sgroi (2008) who study a similar setup albeit with exogenous timing. They found that a herding signal increases the chance of acting as a herder by less than 6%. Our much stronger effect highlights the importance of endogenous timing for herding.

We also find evidence that people with the high and low signals trade systematically earlier than people with the U-shaped (herding) or hill-shaped (contrarian) signal. Moreover, recipients of the hill-shaped signal trade earlier than those of the U-shaped signal. Thus contrarians act comparatively earlier than herders.

Our findings on timing complete the picture. As in any herding model, early movers trigger the herd behavior of the later movers. But we identify a systematic difference in who moves early and late: early movers are the ones who receive signals without the theoretically
potential to herd or act as a contrarian, and latest movers are the ones who have the signals for which rational herding is possible. Thus recipients of ‘herding’ signals wait to observe others, and when they have seen sufficient activity they join the majority. Traders who receive other signals act too early to be counted as joining the majority. Taken together, the behavior cause herding to be more pronounced.

We also find evidence of intertemporal clustering of trades in the sense of leader-follower patterns: a significant percentage of all trades (about 50-55%) occur within an interval of 1.5 seconds of their predecessors. Interestingly, private signals play no role in these patterns.

While we believe that our data indicates that people act in the spirit of the static rational model, we also examined several alternative hypotheses, including different assumptions on risk preferences, to see if we could further our understanding. While error adjustment models or probability over- or under-weighting schemes improve the fit of behavior to the data to some degree, they come at the cost of implicitly ruling out some interesting behavior (such as herding).

**RELATED EXPERIMENTS.** The first published paper to consider herding in endogenous-time was Sgroi (2003), a close implementation of the Chamley and Gale (1994) fixed-capital investment framework. This framework was also examined experimentally in Ziegelmeier, My, Vergnaud, and Willinger (2005). We complement this line of work by explicitly allowing moving prices and are thus able to embed the timing decision into a financial market trading environment.

There are several other papers that study herding behavior in a financial market environment: Drehmann, Oechssler, and Roider (2005), Cipriani and Guarino (2005, 2007), Alevy,

---

8For a full explanation and more detail on the alternative models examined see the supplementary appendix. This document also outlines to what extent information theory can explain our results on timing.
Haigh, and List (2007), and Park and Sgroi (2008). The first two provide insights into trading behavior with exogenous timing in a setting where herding is theoretically impossible (as depicted in the underlying theory by Avery and Zemsky (1998)). Both papers confirm that herding does not commonly arise, thus showing that there is no ‘natural tendency’ of people to herd. Cipriani and Guarino (2007) and Park and Sgroi (2008) consider settings that do allow herding theoretically and both show that herding does arise, though not as often as predicted by the theory.

Alevy, Haigh, and List (2007) provide an innovative bridge between theory and empirical work by observing professional Chicago Board of Trade traders (who effectively generate the empirical data that one gathers from databases) in a controlled environment. They observe that the group of professional traders behaves quite differently than student control groups. For instance, professional traders are able to assess public information better than the student group.

This suggests that market data may be less susceptible to being contaminated by misleading herds. Our finding that contrarianism is more pronounced than herding behavior reinforces their findings. As Alevy, Haigh, and List (2007) employ a model without moving prices, it would be interesting to observe the behavior of professional traders in the environment depicted in this paper where prices adjust after each trade.

The major difference of the five studies above to our setup is that they all analyze settings with exogenous timing of trading decisions. We complement these studies by providing insights into the impact of timing on herding and contrarianism.

There are two related experimental papers that do analyze people’s timing behavior in a financial market environment. Bloomfield, O’Hara, and Saar (2005) study a financial market in which people can trade repeatedly throughout a trading day. The focus of their

---

9It is noteworthy, however, that the findings of Cipriani and Guarino (2007), who use professional traders, and Park and Sgroi (2008), who use students, differ only slightly.
study is on the timing behavior of informed traders and on their choice of limit- or market-orders depending on the passage of time. The key feature of their setup is not the kind of information so much as the fact that people do have information, and they do not employ information that could (theoretically) trigger herding or contrarianism.

Ivanov, Levin, and Peck (2008) implement Levin and Peck (2008), which is a model of a fixed capital (green-field), non-financial investments, and they develop important insights into the timing behavior of people’s investment choices. They find that behavior can be classified into three categories: self-contained (ignoring information from observing others), myopic (acting upon the current best decision, ignoring the option to learn from others in the future), and foresighted (the perfectly rational decision). Focussing on non-financial investments, the setting does not consider moving prices.

**Overview.** The remainder of the paper is structured as follows. In the next section we define herding and contrarianism formally. We then examine the theoretical framework in more detail in Section II and also discuss the modifications undertaken to better fit a laboratory experiment. Section III examines the design of the experiment, including a discussion of the nature of the software, the different information structures embodied in the alternative treatments, the information provided to subjects and the hypotheses that are implied by the theory. Section IV presents the results of the experiments and their fit to the rational model. Section V carries out a formal econometric analysis of the static decision. Section VI considers the impact that prices have on decisions. Section VII studies the relation of the first and second trades analyzing the impact of “buy-low, sell-high”-trading. Section VIII analyzes the timing behavior. Section IX summarizes the key findings and concludes. The appendix is provided in a supplementary document, and outlines results from an examination of several alternative behavioral explanations for the observed data and
a discussion of the role of information theory in the timing of decisions, as well as the subject instructions and other supporting materials, including the explicit parameter values.

I. Definition of Herding and Contrarianism

The general movement of prices captures the majority or ‘crowd’ action: rising prices indicate that there are more buyers than sellers, falling prices indicate that there are more sellers than buyers. We define herding and contrarianism against this yardstick. Moreover, the benchmark decision for a herder or contrarian is the action that they would take without observing any of the prices.

We thus say that a trader engages in herding behavior if he switches from selling to buying in the face of rising prices, or if he switches from buying to selling in the face of falling prices. The counterpart situation, contrarianism, arises when a trader switches from selling to buying in the face of falling prices or if he switches from buying to selling in the face of rising prices. Thus, herding represents a history-dependent (social learning induced) switch of opinion in the direction of the crowd, whereas the logical counterpart, contrarianism, describes a history-induced switch of opinion against the direction of the crowd.

For the formal definition we use notation $H_t$ for the trading history at time $t$; this history includes all past actions, their timing, and the transaction prices; $H_1$ is the initial history.

**Definition 1 (Herd- and Contrarian-Behavior)**

(a) A trader engages in herd-buying after a history of trade $H_t$ if and only if

(H1) he would sell at the initial history $H_1$.

---

The definition of herding is in the spirit of Avery and Zemsky (1998) who were the first to provide a formal definition of herding in financial markets. The definition of contrarianism is in the natural counterpart of the definition of herding. A very loose intuition for herding is that herding types have increasing demand functions: they sell when prices are low and buy when they are high.
(H2) he buys at history $H_t$, and
(H3) prices at $H_t$ are higher than at $H_1$.

Sell herding is defined analogously.

(b) A trader engages in buy-contrarianism after a history of trade $H_t$ if and only if
(C1) he would sell at the initial history $H_1$,
(C2) he buys at history $H_t$, and
(C3) prices at $H_t$ are lower than at $H_1$.

Sell-contrarianism is defined analogously.

II. The Underlying Theory

Subjects face a complex decision problem, having to decide both on the timing and
direction of their trade. We split the description here into the trade-direction and the timing
component, while noting that a full equilibrium model requires a simultaneous description
of both.

A. The Static Decision of the Trading Direction

All traders trade a security with an uninformed market maker. The security takes one of
three possible liquidation values, $V_1 < V_2 < V_3$, each equally likely. Traders can be informed,
in which case they receive a conditionally independent signal about the true value of the
security, or they can be noise in which case they trade for reasons outside the model. The
market maker sets a single price at which he is willing to buy or sell one unit of the security.\footnote{This is a simplification of a sequential trading model with three signals and three states in the tradition
of Glosten and Milgrom (1985). In these models, a competitive market maker sets a zero-profit bid and offer
price. In our experiments, we dispense with bid- and ask-prices and focus instead on a single trading price}
Every trader is a noise trader with a fixed probability (25% in our setting) and buys or sells each with 50% probability. Informed traders receive one of three signals: $S_1, S_2$ or $S_3$. Signal $S_1$ is generated with higher probability in state $V_1$ than $V_2$, and likewise in state $V_2$ than state $V_3$. The reverse holds for signal $S_3$. This implies that the recipient of signal $S_1$ shifts probability weight towards the lowest state ($S_1$ is ‘bad news’), whereas the recipient of $S_3$ shifts weight towards the highest state ($S_3$ is ‘good news’).

The signal $S_2$ that we employ here can take several different shapes. If it is hill-shaped or single-polar, then it generated with highest probability in the middle state $V_2$. The recipient of this signal will put most weight on the middle value. If signal $S_2$ is U-shaped or bi-polar, then it generated with high probability in both the good state $V_3$ and the bad state $V_1$. The recipient of this signal puts most weight on both of the extreme outcomes.

Whether we look at buy- or sell-herding and buy- or sell-contrarianism depends on the decision that a trader takes without looking at prices. In the case of hill- or U-shaped signals this decision depends on whether the signal is generated with higher probability in the good or the bad state. In the former, we talk about a positive bias, so that the herder would switch from buying to sell-herding, the contrarian from buying to sell-contrarianism; in the latter case we have a negative bias.

Next, to determine where someone herds or acts as a contrarian, we must determine which decision they would take at the initial history (i.e. before the person see any trading activity by others). This decision depends on the bias of the signal. If at the initial history someone puts more weight on the low state than the high state, then the person would sell. If the person puts more weight on the high state than the low state, the person would buy. We refer to the former case of signals as negatively biased and the latter as positively biased. A to minimize complexity. This is standard practice in the related experimental literature, past experiments with similar frameworks have found that the spread has little to no effect; see Cipriani and Guarino (2005).
negatively biased U-shaped signal distribution is referred to as a negative U-shape, likewise for hill-shape and positive biases.

All past trades and prices are public information. The market maker follows a simple pricing rule by setting the unique trading price as the expectation of the true value of the security, conditional on all publicly available past information; this price does not account for the possible timing decisions of traders but instead is purely backward looking.\footnote{A backward looking market maker should theoretically make losses, but from an experimental perspective we are not concerned if it reduces complexity for subjects.} Once a trader decides to act, he buys if his expectation conditional on his private signal and on the information derived from past trades exceeds the price, and he sells if this expectation is below the price.

The underlying decisions that we categorize are assumed to be static or myopic, i.e. we ignore possible dynamic considerations that may govern a subject’s trading decision. Moreover, we also assume that traders interpret every past decision as taken on the basis of only static considerations. Applied to the experimental design in which bid-ask-spreads are ignored, we assert the following:\footnote{Note that ‘S herds’ is to be read as ‘S herds with positive probability’. For a formal theory backing these assertions see Park and Sabourian (2008).}

(a) Types $S_1$ and $S_3$ never herd.
(b) Type $S_2$ buy-herds if and only if his signal distribution is negative U-shaped.
   
   Type $S_2$ sell-herds if and only if his signal distribution is positive U-shaped.
(c) Type $S_2$ is a buy-contrarian if and only if his signal distribution is negative hill-shaped. Type $S_2$ is a sell-contrarian if and only if his signal distribution is positive hill-shaped.

In this spirit, we can refer to U-shaped signals as \textit{herding signals} and to hill-shaped signals
as contrarian signals. We shall also refer to signal $S_1$ as bad news and to $S_3$ as good news.

To understand the intuition behind the above assertions, observe first, that a buy-herding trader would be selling at the initial history ($H_1/C_1$). Since the prior is uniform, this implies that sellers attach more weight to the lowest than the highest state, i.e. $Pr(S|V_1) > Pr(S|V_3)$. Next, buy-herding also requires that prices have increased ($H_3$); this occurs if and only if the probability of the lowest state is smaller than that of the highest state.

Sufficiency can be best explained by imagining that the probability of the lowest state $V_1$ has dropped to the point where the state can be ignored relative to states $V_2$ and $V_3$. Then a trader who is buying must attach more weight to state $V_3$ than $V_2$, $Pr(S|V_3) > Pr(S|V_2)$. This holds for trader $S_3$ but this type would not be selling at the initial history. Combining the requirements $Pr(S|V_3) > Pr(S|V_2)$ and $Pr(S|V_1) > Pr(S|V_3)$, we observe that a U-shaped signal allows herding.

A similar idea applies to the occurrence of contrarian behavior where the price falls and so that state $V_3$ can be ignored relative to $V_1$ and $V_2$. Now a buyer must put more weight on $V_2$ than $V_1$, $Pr(S|V_2) > Pr(S|V_1)$ which, together with $Pr(S|V_1) > Pr(S|V_3)$ lets us conclude that a hill-shaped signal allows contrarianism.

B. The Dynamic Decision of the Trading Time

Most work on financial market microstructure constructs the trading decision to be either stationary or static. Those that do analyze a dynamic problem usually allow at most one informed insider. Yet the essence of people rationally herding or acting as contrarians is that behavior is non-stationary.

The theoretical paper closest to ours is Smith (2000) which models a single trader who

---

can make a single trade early or late. Smith shows that a trader with a good or bad news signal will trade early. Moreover, Smith also presents an example with a U-shaped signal and shows that within his framework this trader would rationally delay. Applying Smith to our framework, the $S_1$ and $S_3$ types have bad-news and good-news signals respectively and thus they should always act immediately.

Matters are more complex for the $S_2$ types. A U-shaped signal appears to be rather uninformative, giving only an indication that an extreme state has happened. It thus seems reasonable to assert that these types should delay initially to accumulate information. A hill-shaped signal, on the other hand, is a strong indication that the middle state occurred. Consequently, initially there seems to be no rationale for hill-shaped $S_2$ types to trade. If, however, prices move away from the middle state, then it should pay for the hill-shaped $S_2$ types to trade against this general flow because they should expect prices to revert to the middle value. Comparing traders with hill- and U-shaped signals, it seems reasonable that the U-shaped types delay for longer to get a better sense of the direction in which the market is moving whereas for hill-shaped types, it may make sense to act quickly on deviations of the price from the middle value.

This discussion leads to the following assertions

(d) Low ($S_1$) and high ($S_3$) types should trade systematically before middle ($S_2$) types.

(e) Hill shaped type should trade before U-shaped types, who should trade latest.

---

16Smith’s focus is to derive sufficient conditions for early trading, not to provide conditions for delay. So Smith’s work, while insightful in the early trading dimension, cannot answer whether U- or hill-shaped types would generally trade early or late.

17An alternative approach to Smith’s finding is that the expectations that the $S_1$ and $S_3$ types form over the future price are super- and sub-martingales respectively. For instance, an $S_3$ type would always expect that there are more people who have the same signal and thus expects prices to rise. For their own expectation, however, the law of iterated expectations applies.
The statements so far cover the case of a single trade, and there is no theoretical work in the literature that provides guidance as to how people would optimally act when there are multiple heterogeneously informed traders who can trade repeatedly. One reason is the sheer complexity of the issue, having to account for the impact of one’s own decision on others’ actions, how their reaction affects one’s own decision, iterated *ad infinitum*. Despite the lack of a theory to guide our analysis, we can conjecture possible behaviors. With two trades, people can either trade twice in the same direction or they can trade in opposite directions (sell-buy or buy-sell); the latter is referred to as a ‘return’-trade (or ‘round-trip’ transaction). With return trades possible, we must revisit the decision about the trading direction for it is now conceivable that a dynamic trading strategy might involve trading at a static expected loss.

Traders are not infinitesimal. Consequently, as they trade, prices move. As prices move, traders’ information rents are reduced in expectation, at least for the $S_1$ and $S_3$ types (by the same arguments as described in Smith). Thus greater the number of trades, the more intense is the competition for information rents. A very straightforward assertion is thus that trades should occur earlier when people can trade more often.

(f) With two trades trading occurs faster.

Now consider decision of the the bad-news ($S_1$) types. Suppose that they perform a return-trade, for instance, by buying early and selling late. Then after these two transactions, they still hold a share, and on this single share they make an expected loss. While they may gain on the return transaction, it seems most intuitive that the bad news types should sell twice. A similar argument applies to the good news ($S_3$) types: if they sell early and buy late (or vice-versa) they would hold only one share while they could hold three. This leads to the assertion.
(e) Low ($S_1$) types sell twice, and high ($S_3$) types buy twice.

For the $S_2$ types, however, we have no prediction about the dynamic trading direction, nor do we have an intuitive sense for how they should act in equilibrium with two trades. They could trade in the same direction twice, following the crowd or acting against it. Return trades, however, can also be rationalized since even taking a static view the $S_2$ types can change their optimal action after observing different histories of trade. In our analysis we will check if there is persistency in their behavior with respect to (static) herding or contrarianism. Our experiment is thus an exploration of the strategic timing of behavior.

Coming back to the timing of a second trade, we note that a second, same-direction trade may be delayed. Since traders are not infinitesimal, their actions have a discrete price impact. A trader who traded early may thus delay, hoping that the price reverts back against the movement that the trader caused. If delay of the second trade is observed, then it is also no longer clear that we should expect to find a significant difference between the timing of second trades for $S_1$ or $S_3$ types and $S_2$ types.

One conceptual difficulty that arises in the experimental implementation is the manner in which the price is updated. In principle, this should be dictated by a theory that determines who trades when and in what direction. For lack of such a theory we used the reasonable updating rule that would account for the statically optimal actions. For instance, absent herding, a buy would have been assumed to come from either a noise trader or an informed trader with good news ($S_3$). As we argue below, this is ex post justified as the behavior is largely in line with the presumed statically optimal behavior.
III. Experimental Design

Here we discuss the experimental design, focusing on the information provided to the subjects, the differences between treatments, and the predictions made in advance. The supplementary appendix contains further information including a time-line (Appendix C), a full set of instructions and the material given to subjects (Appendices D-F), as well as a thorough description of the purpose-built software used for this experiment (Appendix G).

A. Overview

The design focuses on a financial asset that can take one of three possible liquidation values \( V \in \{75, 100, 125\} \) which correspond to the true value of the asset. The group of traders was made up of 13-25 experimental subjects plus a further 25% of computerized noise traders, with a central computer acting as the market maker. Subjects were informed that they would not interact with each other directly but rather that the actions of all of the traders would effect the current price. They were told that this price is set by the central computer that is operating at the front of the experimental laboratory and that a decision to purchase by a trader raises the price while a decision to sell lowers it.

Prior to each treatment each subject privately received a signal, either \( S_1 \), \( S_2 \) or \( S_3 \). Subjects were also provided with an information sheet detailing the prior probability of each state, and a list of what each possible signal would imply for the probability of each state, and the likelihood of each signal being drawn given the state. In other words, we provided both the signal distribution and the initial posterior distribution, conditional on receiving a signal. The information on the sheet was common knowledge to all subjects. In particular the subjects therefore should have realized that the quality of the signal was \textit{ex post} identical for all subjects. The subjects were not told anything about the implications of U-shaped,
hill-shaped or monotonic information structures or the predictions of the theory.

The nature of the compensation was made clear in advance, in particular that it directly implied that they should attempt to make the highest possible virtual profit in each round, since the final compensation was based on overall performance (in UK currency up to £25 combined with a one-off participation fee of £5, or the equivalent in Canadian funds).

The existence and proportion of noise traders was made known to the experimental subjects in advance, who were also aware that noise traders randomized 50:50 between buying and selling and that they trade at random times.\footnote{Noise traders play an important role in the static theory and add only a mild degree of extra complexity to the experimental design. They also play a useful practical role in the experiment by simulating a degree of uncertainty about the usefulness of any observed actions. Generally, noise traders reduce the informativeness of any observed action and we will see later that this allows us to model errors as an incorrect assessment of the degree of noise trading (see the Supplementary Appendix). Moreover, they also reduce the ability of subjects to accurately predict when other informed traders may have acted. For instance, in a room with 25 subjects, and no noise traders, observing 24 actions immediately tells the final subject that there are no more informative actions to come, and so no further reason to delay.}

The subjects were informed that the sessions would last 3 minutes and that they would receive announcements about the remaining time after 2:30 minutes, and 2:50 minutes. We considered two classes of treatments: in the first people were allowed to trade once, in the second they could trade twice. The software allowed subjects to trade only this specific number of times. The sequence of transactions produced a history of actions and prices, \( H_t \) with \( t \in (0,3) \), that recorded the price, timing (in seconds) and direction of each transaction.

Subjects were shown the history in the form of a continuously updating price chart during each treatment, and they were also given the current price, \( P_t \). This price was calculated by the computer as \( P_t = \mathbb{E}[V|H_t] \) with \( P_1 = 100 \).

Subjects were told that they had three possible actions \( a = \{\text{sell, pass, buy}\} \) one (or two) of which they could undertake during the 3 minutes of trading time. They were instructed that pressing the ‘pass’-button would count as one of the actions that they were allowed. It
was stressed to the subjects that their virtual profits per treatment were generated based on the difference between the price at which they traded, $P_t^*$, and the true value of the share, $V$. It was emphasized that the price at the end of the trading session would not be relevant for their payoffs.

The subjects themselves were recruited from the Universities of Toronto, Cambridge and Warwick. No one was allowed to take part twice. We ran 13 sessions in all: 3 at the University of Cambridge (13 subjects each), 6 at the University of Warwick (18, 19, 22, 22, 22, and 25 subjects) and 4 at the University of Toronto (17, 18, 13, and 13 subjects). We collected demographic data only for the Warwick sessions: of the subjects there, around 49% were female, around 73% were studying (or had already taken) degrees in Economics, Finance, Business, Statistics, Management or Mathematics. 53% claimed to have some prior experience of financial markets, with some 23% owning shares at some point in the past.\footnote{Appendix E details the questions asked in the questionnaire. When asked what motivated their decisions (across different sessions) 44% of subjects mentioned a combination of prices and signals, 31% only price, 18% only signal and the remaining 7% had other motivations. 38% thought that in general the current price was more important than the signal, 36% thought the signal was more important than the current price and the remaining 26% felt they were of similar value. Roughly 24% claimed to have carried out numerical calculations.}

\textbf{B. Treatments}

Following Section II, the rational action for $S_1$ and $S_3$ subject types was to sell or buy respectively, irrespective of $H_t$, while for the $S_2$ types the nature of $H_t$ and the precise information structure determined a unique optimal action. In the first three treatments, subjects were allowed to trade at most once, in the last three treatments subjects were allowed to trade at most twice. The treatments were each designed to enable us to examine behavior under a specific information structure.\footnote{Since in Drehmann, Oechssler, and Roider (2005) the inclusion of transaction costs produced the expected outcomes, we ignored transactions costs and instead focused on the information structure as the key}
Treatment 1: negative U-shaped signal structure making buy herding possible;
Treatment 2: negative hill-shape making buy-contrarianism possible;
Treatment 3: positive U-shaped signal structure making sell-herding possible;
Treatment 4: as Treatment 2 but with two trades;
Treatment 5: as Treatment 3 but with two trades;
Treatment 6: as Treatment 1 but with two trades.

Therefore under each treatment, once we knew the signals and trades, we could exactly calculate the theoretically predicted static (or myopic) action for each subject; in some cases this might be to herd or act in a contrarian way. The underlying parameters are listed in the supplementary appendix together with the instructions given to subjects.

C. Theoretical Predictions

Single-Trade Case. Given the proximity of the design to the theoretical model outlined in Section III, we can reformulate our assertions into hypotheses:

Hypothesis 1 $S_1$ types sell as soon as the treatment starts, and $S_3$ types buy as soon as the treatment starts.

While we generally predict that the $S_1$ and $S_3$ types should trade immediately, we would expect that the distribution of trades for the $S_1$ and $S_3$ types should be strongly tilted towards time 0.

As described in Section III the $S_2$ types’ behavior is a function of both the treatment and history $H_t$. Specifically, from the $S_2$ types, we expect to see possible herding behavior in Treatments 1 and 3 and possible contrarianism in Treatment 2. More formally,
Hypothesis 2. \( S_2 \) types herd and act as contrarians if only if the conditions for herding and contrarianism are met.

Buy-herding is possible in Treatment 1 and sell-herding in Treatment 3. Therefore, since we know the outcome of the random elements (noise trades and the signals for each subject) and conditional on all other subjects behaving optimally, we can calculate which action each subject should have undertaken given \( H_t \) and \( S \), irrespective of the timing.

As stressed before, we have no theoretical prediction concerning the timing of the \( S_2 \) types’ transactions. Following the discussion above, however, we conjecture that

Hypothesis 3. The \( S_2 \) types will act later than the \( S_1 \) and \( S_3 \).

Hypothesis 4. Hill-shaped \( S_2 \)-types will act before U-shaped \( S_2 \) types.

Two-Trade Case. For the cases with two transactions, we have no theoretical predictions, even for the \( S_1 \) and \( S_3 \) types. However, we conjecture that

Hypothesis 5. \( S_1 \) types sell twice and as soon as the treatment starts, and \( S_3 \) types buy twice and as soon as the treatment starts.

The optimal behavior of the \( S_2 \) types is even more difficult to determine. In particular, it is not clear whether the second trade should follow the first one immediately. Following the discussion of the last section, we conjecture that

Hypothesis 6. For the first trade the \( S_2 \) types will act later than the \( S_1 \) and \( S_3 \) types. Likewise, for the first trade hill-shaped \( S_2 \) types will act before U-shaped \( S_2 \) types.
If the $S_1$ and $S_3$ types do not perform their second trade immediately after their first trade, then we do not have any prediction as to whether or not the $S_2$ types should make their second trade before or after the other two types.

Finally, it is worth comparing the treatments with one and two trades. When two trades are allowed, since subjects know that people can trade more frequently, any delay motive that they might possess will be diminished. Consequently, we would expect

**Hypothesis 7** *Trades in the two-unit trade treatments 4-6, should be earlier than in the single trade treatments 1-3.*

**D. Behavioral, non-rational predictions for the static decision**

To complete the analysis, we considered the possible impact of risk aversion and loss aversion on decision making, and various behavioral alternatives to Bayesian updating. First, we considered a model in which subjects do not update their beliefs as prices change but act solely on the basis of their prior expectation. Second, we considered one setting in which subjects update their beliefs on the basis of changing prices at a slower rate than they should and one setting in which people overweigh their own private information. Finally, we developed error correction models in which subjects account for errors made by their peers and react rationally to these errors; these models are in the spirit of level-k beliefs (see Costa-Gomes, Crawford, and Broseta (2001)) and the Quantal Response Equilibrium (see McKelvey and Palfrey (1995) and McKelvey and Palfrey (1998)).

Since none of the alternative specifications provided significant additional insights over and above the standard model of Bayesian rationality and since risk and loss aversion did not provide an improved fit, we relegated the details of the specifications and testing to Section A of the supplementary appendix.
IV. Analysis of the Static Trade-Direction Decision

We will first examine the results by summary statistics and then expand on them with a formal econometric analysis in Section V.

In the numbers to follow we exclude noise trades, and focus only on trades by human subjects. The total number of trades was 1993 spread over all 6 treatments; broken up by trader type we have 623 ($S_1$), 786 ($S_2$) and 584 ($S_3$). For treatments 1 to 3 we had 683 trades ($197 S_1$, $276 S_2$ and $210 S_3$), for treatments 4-6 there were 1310 ($426 S_1$, $510 S_2$ and $374 S_3$) trades.\footnote{We had data on 23 additional trades from one treatment in one session that were excluded from the analysis due to computer error.}

A. The Decision to Pass

Before we discuss the general fit of behavior towards the theoretical model, we need to consider the decision to ‘pass’. Rational traders should buy if their conditional expectation exceeds the price and sell otherwise. Thus passes contradict the theoretical static model.

That being said, the structure of our setup lends some additional meaning to passes. Traders are owners of a share and they have the choice to buy an extra share, or to sell the share that they already own. The third possibility, passing, implies that they hold on to that share, presumably in hope of making a profit on that one share. In this sense, a hold is a positive signal albeit weaker than a buy, so that a pass can be counted as a “weak buy”.

Overall there were 99 passes ($<5\%$ of all trades), 26 from $S_1$ types (4% of $S_1$ trades); 52 from $S_2$ types (7%) and 21 from $S_3$ types (4%). While the theoretical static model predicts that we should see no passes at all, we do see some; one explanation for the presence of passes could be risk aversion, and we will comment on this interpretation at length in the...
supplementary appendix. Yet it should be emphasized that the total number of passes is very small.

**B. Overview of the fit of the data to the static model**

Let us start with a rough overview of decisions that are in line with the static model, as aggregated over all treatments.

The number of trades contradicting the theoretical static model was about 30% when counting passes as categorically incorrect. Now suppose we admit that passes may be ‘weak buys’. Then all passes by $S_1$ types still contradict the static model, whereas all passes by $S_3$ types are admitted. For the $S_2$ types, passes fit the static model whenever the statically optimal action was to ‘buy’.

Examining Hypotheses 1 and 2, let us turn attention to the findings detailed in Table 1. We note that the number of trades that conformed to the theoretical static predictions was 70% treating passes as suboptimal and 73% if passes are admitted as ‘weak buys’. These numbers are similar to those in Cipriani and Guarino (2005) who obtain 73% rationality, or Anderson and Holt (1997) who have 70% rationality, albeit with a fixed-price setting. Park and Sgroi (2008), who employed a similar Glosten-Milgrom trading framework, albeit without endogenous timing, displayed a 70%/75% fit. This similarity to the results in the literature is noteworthy because the setting in our experiment is much more complex. Moreover, the Cipriani and Guarino (2005) experiment effectively considers only types that are equivalent to our $S_1$ and $S_3$ types. Our traders of these types actually performed better than those in Cipriani and Guarino, with rationality in excess of 80%. We might thus reasonably argue that the $S_1$ and $S_3$ types are acting in accordance with the rational static theory.

The $S_2$ types, however, often do not act according to the static theory — almost half of
Table I
Fit of the data to the static model.

The table breaks up the decisions of traders by type and treatment into correct and incorrect. A decision is correct if, given the trading history, a trader buys if his (theoretical static) expectation exceeds the price and if he sells if his expectation is below the price. In the first group of columns (“static model without passes”), all other decisions are counted as incorrect. In the second group of columns (“static model with passes”), the decision to pass is considered as correct if it occurred when the expectation exceeded the price (so it signifies a ‘weak buy’). The table also splits up decisions by treatment types: treatments 1-3 have a single trade, 4-6 have two trades. More details of the underlying treatments are in Section III.

<table>
<thead>
<tr>
<th>Treatment, shape</th>
<th>static model without passes</th>
<th>static model with passes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$S_1$</td>
<td>$S_2$</td>
</tr>
<tr>
<td>Treatment 1, negative U-shape</td>
<td>correct</td>
<td>58</td>
</tr>
<tr>
<td></td>
<td>incorrect</td>
<td>3</td>
</tr>
<tr>
<td></td>
<td>% correct</td>
<td>95%</td>
</tr>
<tr>
<td>Treatment 2, negative hill-shape</td>
<td>47</td>
<td>66</td>
</tr>
<tr>
<td></td>
<td>13</td>
<td>33</td>
</tr>
<tr>
<td></td>
<td>78%</td>
<td>67%</td>
</tr>
<tr>
<td>Treatment 3, positive U-shape</td>
<td>66</td>
<td>44</td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>48</td>
</tr>
<tr>
<td></td>
<td>87%</td>
<td>48%</td>
</tr>
<tr>
<td>Treatment 4, negative hill-shape</td>
<td>127</td>
<td>104</td>
</tr>
<tr>
<td></td>
<td>25</td>
<td>43</td>
</tr>
<tr>
<td></td>
<td>84%</td>
<td>71%</td>
</tr>
<tr>
<td>Treatment 5, positive U-shape</td>
<td>123</td>
<td>106</td>
</tr>
<tr>
<td></td>
<td>30</td>
<td>77</td>
</tr>
<tr>
<td></td>
<td>80%</td>
<td>58%</td>
</tr>
<tr>
<td>Treatment 6, negative U-shape</td>
<td>103</td>
<td>47</td>
</tr>
<tr>
<td></td>
<td>18</td>
<td>133</td>
</tr>
<tr>
<td></td>
<td>85%</td>
<td>26%</td>
</tr>
<tr>
<td>Total</td>
<td>524</td>
<td>389</td>
</tr>
<tr>
<td>Treatments 1-3</td>
<td>171</td>
<td>132</td>
</tr>
<tr>
<td>Treatments 4-6</td>
<td>353</td>
<td>257</td>
</tr>
<tr>
<td>Total%</td>
<td>84%</td>
<td>49%</td>
</tr>
<tr>
<td>Treatments 1-3</td>
<td>87%</td>
<td>48%</td>
</tr>
<tr>
<td>Treatments 4-6</td>
<td>83%</td>
<td>50%</td>
</tr>
<tr>
<td>Overall</td>
<td>70%</td>
<td>73%</td>
</tr>
</tbody>
</table>
their trades were against the static model. In particular in the buy-herding Treatments 1 and 6, the $S_2$ do deviate from the static predictions, even when admitting passes as weak buys. Had they taken each action at random they would have been more likely to trade according to the static theory.

At the same time, the $S_2$ types face a more difficult decision problem than the $S_1$ and $S_3$ types. Theoretically, the decisions of the $S_1$ and $S_3$ types never change, so they can take the correct decision even without following the history carefully. The $S_2$ types on the other hand, have to follow the history of prices carefully and small mis-computations can cause them to be categorized as not fitting the static model.

A further complication that we discuss in Section [VII] is that trades are often clustered. If subjects observe a cluster, they may deduce that many trades in the cluster are by other subjects and not by noise traders. As a consequence, they may suspect that the pricing mechanism is flawed and react to it. Finally, the benchmark against which we measure the decisions assumes that all traders act rationally and it assumes that the subjects themselves trust their peers to act rationally. If subjects suspect that this assumption is not warranted, then they may rationally choose an action that is against the static model.

We explore these possibilities in more detail in the supplementary appendix. More generally, however, we are interested in the decisions that people make in relation to their signals once prices move. Specifically, we are interested whether specific signals are more likely to trigger a change in behavior (contrarianism or herding) than others. In the formal econometric analysis of the next section we will see that such an effect is indeed prevalent in subjects’ behavior as a function of their signals.
C. Herding and Contrarianism

Based on the definitions from Section I of herding and contrarianism we now describe how often such behavior is observed. Specifically, we ask whether the herding candidate $S_2$-types switch from selling to buying if prices rise and whether they switch from buying to selling if prices fall. Of course, while theoretically only $S_2$ types can rationally herd, irrational herding and contrarianism can be observed for all types.

Table II gives the raw numbers for these scenarios. When including passes, herding arises in about 18% of the cases where it is possible, contrarian behavior arises in 33% of the possible cases. Breaking these up by trader types, one can see that $S_2$ types have the highest propensity to herd — 27% including passes as weak buys. While there are relatively more $S_1$ types that act as contrarians than $S_2$ types (47% vs. 44%), the number of possible contrarian trades for the $S_1$ types is also small. Our formal regression analysis will later show that as predicted the hill-shaped signal $S_2$ is the major cause for contrarianism.

Notably, the fraction of $S_2$ type herders is larger than that observed in Drehmann et al (2005) or Cipriani and Guarino (2005), where herding was generally irrational. Our formal econometric analysis in the next section will confirm that the U-shaped signal is the significant cause for herding behavior relative to all other types of signals.

V. Regression Analysis of the Static Decision

The summary statistics from the last section gave a good idea of the determinants of behavior: first, recipients of middle signals are more likely to herd than recipients of the extreme signals. Second, contrarian behavior is observed and occurs more frequently than herding.
The first row in each treatment grouping lists how many herding trades were observed, the second row entries list the number of possible herding trades. An $S_1$ type cannot herd-sell and can herd-buy only if the price has risen. An $S_3$ type cannot buy-herd and can sell-herd only if the price has fallen. Similarly, an $S_1$ type cannot be a sell-contrarian and acts as a buy-contrarian only when buying after prices have fallen; conversely for the $S_3$ types. The description for the herding and contrarian actions for the $S_2$ types are more involved, but they are described in detail in Section III.

We report only the figures for which passes are counted as buys.

<table>
<thead>
<tr>
<th>Treatment</th>
<th>Herd trades</th>
<th>Contrarian trades</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$S_1$</td>
<td>$S_2$</td>
</tr>
<tr>
<td>Treatment 1</td>
<td>occurred</td>
<td>3</td>
</tr>
<tr>
<td>U-negative</td>
<td>possible</td>
<td>60</td>
</tr>
<tr>
<td>% occurred</td>
<td>5%</td>
<td>28%</td>
</tr>
<tr>
<td>Treatment 2</td>
<td>hill-shape</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>83</td>
</tr>
<tr>
<td></td>
<td>13%</td>
<td>27%</td>
</tr>
<tr>
<td>Treatment 3</td>
<td>U-positive</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>70</td>
<td>12</td>
</tr>
<tr>
<td></td>
<td>11%</td>
<td>17%</td>
</tr>
<tr>
<td>Treatment 4</td>
<td>hill-shape</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>128</td>
<td>115</td>
</tr>
<tr>
<td></td>
<td>13%</td>
<td>28%</td>
</tr>
<tr>
<td>Treatment 5</td>
<td>U-positive</td>
<td>25</td>
</tr>
<tr>
<td></td>
<td>139</td>
<td>20</td>
</tr>
<tr>
<td></td>
<td>18%</td>
<td>25%</td>
</tr>
<tr>
<td>Treatment 6</td>
<td>U-negative</td>
<td>17</td>
</tr>
<tr>
<td></td>
<td>116</td>
<td>175</td>
</tr>
<tr>
<td></td>
<td>15%</td>
<td>29%</td>
</tr>
<tr>
<td>Total</td>
<td>Total</td>
<td>75</td>
</tr>
<tr>
<td>Treatment 1-3</td>
<td></td>
<td>16</td>
</tr>
<tr>
<td>Treatment 4-6</td>
<td></td>
<td>59</td>
</tr>
<tr>
<td>Total%</td>
<td>Treatment 1-3</td>
<td>14%</td>
</tr>
<tr>
<td></td>
<td>Treatment 4-6</td>
<td>9%</td>
</tr>
<tr>
<td></td>
<td>Treatment 4-6</td>
<td>15%</td>
</tr>
</tbody>
</table>
We now take a closer look and run several regressions to test the direct impact of herding and contrarian signals relative to incidences of herding and contrarian trades. In particular we ask the following questions:

(1) Given that someone has a herding signal (aka a U-shaped signal), is this person more likely to herd than someone who does not have the herding signal?

(2) Given that someone has a contrarian signal (aka a hill-shaped signal), is this person more likely to act as a contrarian than someone who does not have the contrarian signal?

The random assignment of signals to traders allows us to interpret mean differences in signal-specific effects as the average causal effect of the signal. Formally, we estimate the following equation to test the hypothesis that a type of signal is a significant cause for herding or contrarian behavior respectively:

\[
\text{herd}_{i,t} = \alpha + \beta \text{u-shape}_{i,t} + \text{fixed}_i + \epsilon_{i,t}, \quad \text{contra}_{i,t} = \alpha + \beta \text{hill-shape}_{i,t} + \text{fixed}_i + \epsilon_{i,t} \quad (1)
\]

where the dependent variables \( \text{herd}_{i,t} \) and \( \text{contra}_{i,t} \) are dummies that apply Definition 1 in the sense that they are set equal to 1 if individual \( i \) herds or acts as a contrarian respectively at trade \( t \) and 0 otherwise, \( \alpha \) is a constant, and \( \text{u-shape}_{i,t} \) and \( \text{hill-shape}_{i,t} \) are signal dummies that are set equal to 1 if the individual received a U-shaped (for the herding estimation) or hill-shaped (for the contrarian estimation) signal. Parameter \( \text{fixed}_i \) is an individual fixed effect that controls for specific traders who persistently err.\(^22\) Given the random assignment of signals, we can assume that \( E[\text{u-shape}_{i,t} \cdot \epsilon_{i,t}] = 0 \) and \( E[\text{hill-shape}_{i,t} \cdot \epsilon_{i,t}] = 0 \), the main identifying assumptions.

Overall, we restrict attention to the cases of trades where herding and contrarianism

\(^{22}\)In unreported regressions we also controlled for treatment, session and treatment-session fixed effects. The results remain unaffected.
respectively are at all possible. This is reasonable since, for instance, when prices rise and a trader has signal $S_3$, then such a trader cannot herd because none of his actions would satisfy the definition of herding.

We ran these regressions on a total of 10 different subsets of the data: we ran the regressions for all treatments, for treatments 1-3 (one trade), for treatments 4-6 (two trades), for the first trade in treatments 4-6, and for the second trade in treatments 4-6. For these five subsets we looked at the situation where all types are included and those where only the $S_2$ types were included. In each scenario we estimated the model by logit and linear probability regressions without fixed effects (i.e. $\gamma_i$ is omitted from (1)) and then ran the linear probability regression controlling for trader fixed effects. All regressions included a constant which is significant at all conventional levels but omitted from the results tables. As a general convention we report standard errors in parentheses and a $\ast$ indicates significance at the 5% level, $\ast\ast$ signifies significance at the 1% level.

**Herding.** In this specification, $\beta$ represents the impact of the signal on individuals’ choices of whether or not to herd, and should be positive if, as dictated by the theory, the U-shaped signal increases the probability of herding. If the inclusion of the fixed effects parameter fixed$_i$ alters the coefficients or the significance of estimates, then this indicates that the results are driven by specific individuals.

Tables III and IV summarize the results from our regression. Overall, obtaining a U-shaped signal $S_2$ increases the probability of herding by about 29% relative to any other signal and it is significant with and without controlling for trader fixed effects; moreover, the coefficients from the logit and linear regression are similar. Among the $S_2$ types, this probability remains about the same at 30.5%. This estimate is significantly different from zero at conventional levels for all subsamples with the exception of the treatments 1-3 trades.
Table III
The Effect of U-Shaped Signals on the Probability of Herding.

The table represents regressions of the occurrence of a herding trade on the trader receiving a U-shaped signal as expressed in equation (2). Logit regressions report the marginal effects. Linear probability fixed effects regressions control for trader-fixed effects. The data is restricted to include only trades that could be herding trades. For all tables that follow, standard errors are in parentheses, * indicates significance at the 5% level, ** at the 1% level. We also omit the constants from the reports.

<table>
<thead>
<tr>
<th></th>
<th>all types</th>
<th>treatments 1-3</th>
<th>treatments 4-6</th>
<th>first trades treatments 4-6</th>
<th>second trade treatments 4-6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logit</td>
<td>0.292**</td>
<td>0.114**</td>
<td>0.397**</td>
<td>0.228**</td>
<td>0.446**</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.032)</td>
<td>(0.032)</td>
<td>(0.025)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>Linear</td>
<td>0.378**</td>
<td>0.138**</td>
<td>0.495**</td>
<td>0.293**</td>
<td>0.552**</td>
</tr>
<tr>
<td></td>
<td>(0.025)</td>
<td>(0.039)</td>
<td>(0.031)</td>
<td>(0.03)</td>
<td>(0.043)</td>
</tr>
<tr>
<td>Linear, fixed</td>
<td>0.352**</td>
<td>0.081</td>
<td>0.434**</td>
<td>0.276**</td>
<td>0.545**</td>
</tr>
<tr>
<td>effects</td>
<td>(0.027)</td>
<td>(0.042)</td>
<td>(0.038)</td>
<td>(0.032)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>Observations</td>
<td>1172</td>
<td>391</td>
<td>781</td>
<td>805</td>
<td>367</td>
</tr>
<tr>
<td>$R^2$ Linear</td>
<td>0.16</td>
<td>0.03</td>
<td>0.25</td>
<td>0.11</td>
<td>0.31</td>
</tr>
<tr>
<td>$R^2$ fixed</td>
<td>0.39</td>
<td>0.67</td>
<td>0.52</td>
<td>0.40</td>
<td>0.74</td>
</tr>
</tbody>
</table>

when focusing on $S_2$ types trades only. Including trader-fixed effect decreases the linear coefficients only slightly; this indicates that the estimates are not driven by some specific traders who persistently take no-herding actions.

Overall the regression confirms the hypothesis that recipients of $S_2$ herding-type signals are generally more likely to herd. The effect of the signal is also much stronger than that in related work in the literature, namely in Park and Sgroi (2008) who find a marginal effect of about 6%.

To obtain a complete picture, we also estimated

\[
\text{herd}_{i,t} = \alpha + \beta_2 \text{u-shape}_{i,t} + \beta_1 \text{low signal}_{i,t} + \beta_3 \text{high signal}_{i,t} + \epsilon_{i,t}
\]  

(2)
Table IV
The Effect of U-Shaped Signals on the Probability of Herding, only $S_2$ types.

The table represents regressions of the occurrence of a herding trade on the trader receiving a U-shaped signal as expressed in equation (2). Logit regressions report the marginal effects. Linear probability fixed effects regressions control for trader-fixed effects. The data is restricted to include only trades that could be herding trades and that are made by $S_2$ types. Standard errors and significance levels are denoted as in Table III.

<table>
<thead>
<tr>
<th></th>
<th>only $S_2$</th>
<th>treatments 1-3</th>
<th>treatments 4-6</th>
<th>first trades treatments 4-6</th>
<th>second trade treatments 4-6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logit</td>
<td>0.305**</td>
<td>0.035</td>
<td>0.446**</td>
<td>0.194**</td>
<td>0.565**</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.066)</td>
<td>(0.066)</td>
<td>(0.055)</td>
<td>(0.104)</td>
</tr>
<tr>
<td>linear</td>
<td>0.284**</td>
<td>0.034</td>
<td>0.406**</td>
<td>0.186**</td>
<td>0.493**</td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.066)</td>
<td>(0.054)</td>
<td>(0.052)</td>
<td>(0.075)</td>
</tr>
<tr>
<td>linear, fixed effects</td>
<td>0.315**</td>
<td>0.031</td>
<td>0.409**</td>
<td>0.236**</td>
<td>0.591**</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.069)</td>
<td>(0.081)</td>
<td>(0.071)</td>
<td>(0.123)</td>
</tr>
<tr>
<td>Observations</td>
<td>481</td>
<td>166</td>
<td>315</td>
<td>330</td>
<td>151</td>
</tr>
<tr>
<td>R-squared linear</td>
<td>0.08</td>
<td>0</td>
<td>0.15</td>
<td>0.04</td>
<td>0.22</td>
</tr>
<tr>
<td>R-squared Fixed</td>
<td>0.47</td>
<td>0.91</td>
<td>0.61</td>
<td>0.55</td>
<td>0.89</td>
</tr>
</tbody>
</table>

where variables low signal$_{i,t}$ and high signal$_{i,t}$ are dummies for signals $S_1$ and $S_3$. Estimating the linear model yields coefficients $\hat{\beta}_2 = .278**(.034)$ on herd-signals, $\hat{\beta}_1 = -.110**(.031)$ on the low signal ($S_1$) and $\hat{\beta}_3 = -.163**(.043)$ on the high signal ($S_3$). So obtaining the herding signal strongly increases the chance of acting as a herder, and the probability of herding decreases for the other signals.

Contrarianism. Next, we estimate equation (1) to test the hypothesis that a hill-shaped signal is a significant explanation of contrarian behavior. Our theory predicts that the coefficient $\beta$ is positive so that a hill-shaped signal indeed has a larger impact on the occurrence of contrarianism relative to other kinds of signals.

Tables V and VI summarize the results from our regression. Receiving the hill-shaped $S_2$
Table V
The Effect of Hill-Shaped Signals on the Probability of Acting as a Contrarian.

The table represents regressions of the occurrence of a contrarian trade on the trader receiving a hill-shaped signal, as expressed in equation (3). Logit regressions report the marginal effects. Fixed effects regressions control for trader-fixed effects. The data is restricted to include only trades that could be classified as contrarian. Standard errors and significance levels are denoted as in Table III.

<table>
<thead>
<tr>
<th></th>
<th>all types</th>
<th>treatments 1-3</th>
<th>treatments 4-6</th>
<th>first trades treatments 4-6</th>
<th>second trade treatments 4-6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logit</td>
<td>0.361**</td>
<td>0.304**</td>
<td>0.419**</td>
<td>0.358**</td>
<td>0.371**</td>
</tr>
<tr>
<td></td>
<td>(0.056)</td>
<td>(0.081)</td>
<td>(0.082)</td>
<td>(0.064)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Linear</td>
<td>0.434**</td>
<td>0.353**</td>
<td>0.508**</td>
<td>0.439**</td>
<td>0.429**</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td>(0.085)</td>
<td>(0.079)</td>
<td>(0.066)</td>
<td>(0.114)</td>
</tr>
<tr>
<td>Linear fixed effects</td>
<td>0.406**</td>
<td>0.300*</td>
<td>0.473**</td>
<td>0.405**</td>
<td>0.655**</td>
</tr>
<tr>
<td></td>
<td>(0.063)</td>
<td>(0.117)</td>
<td>(0.108)</td>
<td>(0.076)</td>
<td>(0.177)</td>
</tr>
<tr>
<td>Observations</td>
<td>820</td>
<td>293</td>
<td>527</td>
<td>553</td>
<td>267</td>
</tr>
<tr>
<td>R-squared linear</td>
<td>0.07</td>
<td>0.06</td>
<td>0.07</td>
<td>0.07</td>
<td>0.05</td>
</tr>
<tr>
<td>R-squared Fixed</td>
<td>0.41</td>
<td>0.67</td>
<td>0.52</td>
<td>0.51</td>
<td>0.79</td>
</tr>
</tbody>
</table>

signal increases the chance of acting as a contrarian by about 36.1% relative to any other kind of signal. As with herding, the linear probability model’s coefficient changes only slightly when we include trader fixed effects. All coefficients are significant at the 1% level. When restricting attention to the sample of $S_2$ types the marginal effect decreases slightly to 31%, and linear probability and marginal logit estimates coincide. All coefficients are significant at the 1% level except when we focus on treatments 1-3 and for those treatments run the regression only on the subsample of $S_2$ types. While the coefficient is of similar magnitude, it is only significant at the 5% level which is due to the large standard error. Including fixed effects renders the coefficient insignificant for the second trades, restricted to only $S_2$ types; this is again due to the small number of relevant data points and the large standard error that is involved.
Table VI
The Effect of Hill-Shaped Signals on the Probability of Acting as a Contrarian.

The table represents regressions of the occurrence of a contrarian trade on the trader receiving a hill-shaped signal, as expressed in equation (3). Logit regressions report the marginal effects. Fixed effects regressions control for trader-fixed effects. The data is restricted to include only trades that could be classified as contrarian and that are made by $S_2$ types. Standard errors and significance levels are denoted as in Table III.

<table>
<thead>
<tr>
<th></th>
<th>only $S_2$</th>
<th>treatments 1-3</th>
<th>treatments 4-6</th>
<th>first trades treatments 4-6</th>
<th>second trade 4-6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logit</td>
<td>0.313**</td>
<td>0.213*</td>
<td>0.402**</td>
<td>0.323**</td>
<td>0.300*</td>
</tr>
<tr>
<td></td>
<td>-0.074</td>
<td>-0.108</td>
<td>-0.108</td>
<td>-0.087</td>
<td>-0.145</td>
</tr>
<tr>
<td>linear</td>
<td>0.312**</td>
<td>0.213*</td>
<td>0.394**</td>
<td>0.324**</td>
<td>0.292*</td>
</tr>
<tr>
<td></td>
<td>-0.069</td>
<td>-0.105</td>
<td>-0.094</td>
<td>-0.081</td>
<td>-0.134</td>
</tr>
<tr>
<td>linear, fixed</td>
<td>0.227*</td>
<td>0</td>
<td>0.343</td>
<td>0.224*</td>
<td>0.667</td>
</tr>
<tr>
<td>effects</td>
<td>-0.096</td>
<td>-0.113</td>
<td>-0.19</td>
<td>-0.111</td>
<td>-0.43</td>
</tr>
<tr>
<td>Observations</td>
<td>305</td>
<td>110</td>
<td>195</td>
<td>208</td>
<td>97</td>
</tr>
<tr>
<td>R-squared linear</td>
<td>0.06</td>
<td>0.04</td>
<td>0.08</td>
<td>0.07</td>
<td>0.05</td>
</tr>
<tr>
<td>R-squared Fixed</td>
<td>0.62</td>
<td>0.96</td>
<td>0.61</td>
<td>0.82</td>
<td>0.97</td>
</tr>
</tbody>
</table>

Overall we confirm that the hill-shaped signal is the significant source of contrarianism relative to all other signals. The marginal effect is comparable to that found in the literature, namely in Park and Sgroi (2008), who is estimated it to be about 34%.

As with herding, to obtain a complete picture, we also estimated

$$contra_{i,t} = \alpha + \beta_2 \text{hill-shape}_{i,t} + \beta_1 \text{low signal}_{i,t} + \beta_3 \text{high signal}_{i,t} + \epsilon_{i,t}. \quad (3)$$

Coefficients here are $\hat{\beta}_2 = .312^{**} (.060)$ for the hill-shaped signal dummy, $\hat{\beta}_1 = -.0414 (.065)$ (insignificant at all conventional levels) for the low signal ($S_1$) dummy and $\hat{\beta}_3 = -.191^{**} (.033)$ for the high signal ($S_3$) dummy. So again, the hill-shaped $S_2$ signal is clearly identified as the major cause of contrarianism.
Finally, we also ran the regressions in this section separating subjects by their locations (Cambridge, Toronto, and Warwick). While the estimates vary slightly, we found no substantial differences in the results and thus omit the corresponding tables.

VI. The Impact of the Price

While the general behavior of the $S_1$ and $S_3$ types is in line with the theoretical static model (over 80% of their traders are ‘rational’), we do observe that $S_3$ types engage in selling and that $S_1$ types engage in buying. We now want to assess if this behavior is systematic. Specifically, we test whether an increase in the price changes the probability of a specific trade. Theoretically, the price should have no impact on the decision because $S_1$ types should always sell and $S_3$ types should always buy. We therefore estimate the following regression

$$\text{trade}_{i,t} = \alpha + \beta \Delta \text{price}_{i,t} + \epsilon_t,$$

where $\text{trade}_{i,t}$ is a dummy that is 1 if there is a buy or hold, and 0 when there is a sale, and the independent variable $\Delta \text{price}_{i,t}$ is the percentage change of the price from 100, i.e. the price at the time of the trade divided by 100 and subtracting 1.\footnote{We ran two unreported control regressions: in the first, we dropped all holds, and in the second, we estimated a specification in which buys received value 2, holds 1 and sales 0 (this specification was estimated using a multinomial logit). The direction of the results and the significance of the coefficients remained unaffected.}

Considering the optimal static decision at the time at which people trade we assert that $E[\Delta \text{price}_{i,t} \cdot \epsilon_{i,t}] = 0$.

We estimated the model by logit, linear probability and linear probability including trader fixed effects, each separately for the three signals. The main variable of interest in \(4\) is $\beta$ which measures whether a rising price affects the probability of a trader buying or selling.
The decision to buy as a function of the price.

The table displays the results from the regression of the decision to buy on the price change, equation (4). The price is measured relative to the prior which is 100. Thus $\Delta \text{price} = \Delta p_t = (p_t - 100)/100$. The regressions were run separately for types $S_1$, $S_2$ and $S_3$. For all traders the probability of a buy is decreasing as the price rises. Standard errors and significance levels are denoted as in Table III.

<table>
<thead>
<tr>
<th></th>
<th>logit</th>
<th>linear</th>
<th>linear, fixed</th>
</tr>
</thead>
<tbody>
<tr>
<td>$S_1$</td>
<td>$\Delta \text{price}$</td>
<td>-1.287** (0.193)</td>
<td>-1.317** (0.204)</td>
</tr>
<tr>
<td></td>
<td>Observations</td>
<td>623</td>
<td>623</td>
</tr>
<tr>
<td></td>
<td>R-squared</td>
<td>0.06</td>
<td>0.5</td>
</tr>
<tr>
<td>$S_2$</td>
<td>$\Delta \text{price}$</td>
<td>-3.381** (0.322)</td>
<td>-2.850** (0.23)</td>
</tr>
<tr>
<td></td>
<td>Observations</td>
<td>786</td>
<td>786</td>
</tr>
<tr>
<td></td>
<td>R-squared</td>
<td>0.16</td>
<td>0.5</td>
</tr>
<tr>
<td>$S_3$</td>
<td>$\Delta \text{price}$</td>
<td>-1.299** (0.159)</td>
<td>-1.681** (0.192)</td>
</tr>
<tr>
<td></td>
<td>Observations</td>
<td>583</td>
<td>583</td>
</tr>
<tr>
<td></td>
<td>R-squared</td>
<td>0.12</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Our static theory predicts that the price should have no impact on whether an $S_1$ or $S_3$ type buys or sells. Consequently, parameter $\beta$ should be insignificantly different from zero. In contrast, if it is not zero, then we gain insights about systematic herding or contrarian behavior. For instance, consider type $S_3$. If the sign of $\beta$ is negative, then this type becomes less likely to buy as prices increase. Such behavior tentatively indicates systematic contrarian behavior. Likewise, if $\beta$ were positive for the $S_1$ type, then this implies that the $S_1$ types are more likely to buy when prices rise; this is a tentative herding effect.

For the $S_2$ types, however, there should be an effect, the sign depending on the shape of the signal distribution. Specifically, for a hill-shaped signal distribution, the $S_2$ type should...
Table VIII
The decision to buy as a function of the price for the $S_2$ types.

The table displays the results from a logit regressing the decision to buy on the price change, equation (4), as in Table VII. Results were run by restricting by the type of $S_2$ signal. Standard errors and significance levels are denoted as in Table III.

<table>
<thead>
<tr>
<th>$\Delta price$</th>
<th>U-negative</th>
<th>Hill</th>
<th>U-Positive</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-1.632**</td>
<td>-2.706**</td>
<td>-4.060**</td>
</tr>
<tr>
<td></td>
<td>(0.576)</td>
<td>(0.404)</td>
<td>(0.73)</td>
</tr>
<tr>
<td>Observations</td>
<td>266</td>
<td>245</td>
<td>275</td>
</tr>
</tbody>
</table>

become less likely to buy as the price increases (for prices above 100, the coefficient should be zero), for a negative U-shaped distribution the probability should be increasing in the price, and for a positive U-shaped distribution it should be increasing (for low prices, this type should be sell-herding).

Table VII summarizes the results of our estimation, Table VIII splits up the $S_2$ trades by signal type.

We find that for all types of signals, an increase in the price decreases the chance that the trader buys: all estimates are significantly different from zero at the 1% level. This is contrary to the theory for the $S_1$ and $S_3$ types who should always be selling and buying respectively, irrespective of the price. While the sign of the estimate for the hill-shaped type has the right sign, the sign is wrong for the U-shaped types. This is, of course, not surprising, given that even the $S_3$ types (the high types) act in a contrarian manner, so it is reasonable to expect the same behavior from the $S_2$ types.
Table IX
Return Trades.

The table lists summary statistics for return (or round-trip) transactions. Row 1 lists the total trades by types in treatments 4-6 (where two trades are possible). Row 2 lists the number of trades that were first trades, Row 3 lists the number of second trades. A discrepancy between Row 2 and 3 indicates that some people choose not to trade twice (Row 4). Row 5 lists how many of the second trades were classified as return trades (buy-sell or sell-buy). Row 6 lists the fraction of return transactions of the cases where people traded twice. Row 7 lists how many of the return trades lead to an immediate trading profit, Row 8 has the corresponding percentage. Rows 9 and 10 do the same as Rows 7 and 8 except that they compute the profits based on the static expected payoff at the time that the transaction was made.

<table>
<thead>
<tr>
<th></th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total trades</td>
<td>425</td>
<td>510</td>
<td>373</td>
<td>1308</td>
</tr>
<tr>
<td>First trades</td>
<td>222</td>
<td>262</td>
<td>190</td>
<td>674</td>
</tr>
<tr>
<td>Second trades</td>
<td>203</td>
<td>248</td>
<td>183</td>
<td>634</td>
</tr>
<tr>
<td>Percent foregone</td>
<td>9%</td>
<td>5%</td>
<td>4%</td>
<td>6%</td>
</tr>
<tr>
<td>Return trades</td>
<td>39</td>
<td>82</td>
<td>29</td>
<td>150</td>
</tr>
<tr>
<td>Percent return</td>
<td>19%</td>
<td>33%</td>
<td>16%</td>
<td>24%</td>
</tr>
<tr>
<td>Profitable return</td>
<td>32</td>
<td>64</td>
<td>19</td>
<td>115</td>
</tr>
<tr>
<td>Percent profitable return</td>
<td>82%</td>
<td>78%</td>
<td>66%</td>
<td>77%</td>
</tr>
<tr>
<td>Profitable return including expectations</td>
<td>23</td>
<td>29</td>
<td>21</td>
<td>73</td>
</tr>
<tr>
<td>Percent profitable return including expectations</td>
<td>59%</td>
<td>35%</td>
<td>72%</td>
<td>49%</td>
</tr>
</tbody>
</table>

VII. The relation between the first and second trade

People have the opportunity to make so-called ‘return’ (or ‘round-trip’) trades by selling first and then buying later or vice versa. This way, they can realize a trading profit in the process. At the same time, if they make such a ‘return’ trade then by the end of the treatment they still own one unit of the security.

Table IX provides summary statistics for the second trade with emphasis on the return trades (recall that return trades can arise only in treatments 4-6).
Not all traders act twice — in about 6% of cases they forego the second trading opportunity. About 76% of all second trades go in the same direction of the first. The remaining 24% are return trades, most of which are performed by the $S_2$ types. The $S_2$ also account for the largest fraction of all type-specific trades (33% of all $S_2$ second trades, 19% and 16% for the $S_1$ and $S_3$ types respectively). About 77% of the return trades yield a trading profit which suggests that return-trades were performed on the basis of “buy low, sell high” (or “sell high, buy low”). Now suppose we account also for expected payoffs, i.e. we employ the expected static profit of a share at the time of each trade. With this measure, only 49% of the return trades are profitable and the $S_2$ types do particularly poorly.

This raises the question of whether there are systematic features of the return trades. Return trades are always either buy-sell or sell-buy. So we ask if is there a particular fashion in which the different signal types perform their return trades.

There is a specific interpretation that can be attached to return trades: for the $S_1$ types a buy-sell return trade has a manipulative connotation in that this type may try to drive up the price in order to sell high later; similarly for sell-buy return trades by the $S_3$ types. The reverse order is either contrarian or herding, where the difference between contrarianism and herding is determined by the general movement of prices. However, for the $S_2$ types it is not clear how one would classify manipulative behavior in terms of the order of buys and sells.

\(^{24}\)In some unreported regressions we analyzed whether the payoffs from return trades are smaller when they occur late. For this we regressed factual payoffs from return trades and also expected payoffs from return trades on the trading time. Yet we found no significant relation and thus concluded that time has no impact on the payoff of return trades. Moreover, we also could find no general relationship between return trades and time for the $S_2$ and $S_3$ types. However, for the $S_1$ types we found a relationship that is significant at the 1%-level. This finding is intuitive in the context of a different finding (which we report below) in that the $S_1$ types tend to act as herders when they perform a return trade. This implies that the $S_1$ types first sold, then waited and observed that prices were increasing. They then bought back the share that they sold.
Table X
Trade-Direction of Return Trades.

The table condenses six regressions of the equations in line (5) (by type and then with respect to herding and contrarian behavior separately). For the $S_1$ types there was no simultaneous occurrence of contrarian behavior and return trades; similarly for the $S_3$ types and herding behavior. Hence the empty cells. Constants were omitted from the report. Standard errors and significance levels are denoted as in Table III.

<table>
<thead>
<tr>
<th></th>
<th>$S_1$</th>
<th>$S_2$</th>
<th>$S_3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Herding case</td>
<td>0.085**</td>
<td>-0.129*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.066)</td>
<td></td>
</tr>
<tr>
<td>Contrarian case</td>
<td></td>
<td>0.181**</td>
<td>0.312**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.039)</td>
<td>(0.064)</td>
</tr>
<tr>
<td>Observations</td>
<td>205</td>
<td>248</td>
<td>182</td>
</tr>
</tbody>
</table>

To understand the common direction and the connotation, we ran the following regressions

$$\text{herd}_{i,t} = \alpha + \beta \text{return trade}_{i,t} + \epsilon_{i,t}, \quad \text{contra}_{i,t} = \alpha + \beta \text{return trade}_{i,t} + \epsilon_{i,t},$$  

where the dependent variables $\text{herd}_{i,t}$ and $\text{contra}_{i,t}$ are the herding and contrarian dummies from equations (1), $\alpha$ is a constant, and $\text{return trade}_{i,t}$ is a dummy for the incidence of a return trade.

For each case we estimated the model by logit, restricted by individual signals and incidences of the second trades; we report the marginal effects. Table X summarizes our findings.

Overall we observe that $S_1$ types act as herders and the $S_3$ types act as contrarians. For the $S_2$ types we observe a negative herding coefficient (significant at the 5% level) and a positive contrarian coefficient (significant at the 1% level). Thus the likelihood of a $S_2$ type herding trade is reduced by the incidence of a return trade and instead, the incidence of a return trade increases the probability that the trade is contrarian.
VIII. Analysis of Timing

As outlined in our discussion in Section II, there is little theory to guide our analysis of subjects’ timing decisions; Hypotheses 1 to 7 formulate those assertions that we feel comfortable making.

The strongest interpretation of the theory is that $S_1$ and $S_3$ types should trade immediately when the session starts. Consequently, according to this view we should observe that all these types trade within the first few seconds of the game. And indeed, we do observe a very large number of trades at the very beginning of trading. Overall, the $S_1$ and $S_3$ types account for 1206 transactions. Table XI displays how many trades we observe in the first five seconds of trading.

<table>
<thead>
<tr>
<th>Number of trades</th>
<th>&lt;1 sec.</th>
<th>1 sec.</th>
<th>2 sec.</th>
<th>3 sec.</th>
<th>4 sec.</th>
<th>5 sec.</th>
</tr>
</thead>
<tbody>
<tr>
<td>by $S_1$</td>
<td>28</td>
<td>46</td>
<td>30</td>
<td>37</td>
<td>21</td>
<td>16</td>
</tr>
<tr>
<td>by $S_3$</td>
<td>72</td>
<td>30</td>
<td>30</td>
<td>13</td>
<td>12</td>
<td>20</td>
</tr>
</tbody>
</table>

Overall, 355 out of the 1206 trades made by $S_1$ and $S_3$ types occur within the first five seconds. Yet while this number is substantial, it is less than 30% of the trades, and so we cannot support the hypothesis that all of the $S_1$ and $S_3$ types trade immediately.

We now attempt to identify systematic differences in the timing behavior for the various signal types and treatment settings. Specifically, we will compare the cumulative distributions of the trade-times for different categories of types. The strongest result that one can
hope for in this context is that one cumulative distribution function (henceforth, cdf) of trade-times stochastically dominates another: distribution $F$ first order stochastically dominates distribution $G$ if $G$ is larger than $F$ for all entry times. If we indeed observe that $F$ first order stochastically dominates $G$, then we can say that the entry times under $F$ are systematically later than under $G$.

Figure 1 provides plots of the relevant cdfs. Specifically, we computed the cdfs for the following subsamples:

D1  all treatments, separated by types $S_1$, $S_2$, $S_3$
D2  treatments 1-3 and first trades in treatments 4-6, separated by types $S_1$, $S_2$, $S_3$
D3  treatments 1-3 separated by types $S_1$, $S_2$, $S_3$
D4  treatments 4-6 separated by types $S_1$, $S_2$, $S_3$
D5  treatments 4-6 first trades, separated by types $S_1$, $S_2$, $S_3$
D6  treatments 4-6 second trades, separated by types $S_1$, $S_2$, $S_3$
D7  treatments 1-3 not separated by types
D8  treatments 4-6 not separated by types
D9  treatments 4-6 first trades only, not separated by types
D10  all treatments, only for $S_2$, separated by hill, U-negative and U-positive
D11  treatments 1-3 and first trades in treatments 4-6, only for $S_2$, separated by hill, U-negative, and U-positive

We will now address the systematic timing issues by referring to the above sets of distributions.

Question 1: Which type acts earliest, which latest? To answer this, we compared the timing-cdfs split up by types. All panels in Figure 1 save for the bottom row, right panel are very clear: the $S_1$ and $S_3$ are indistinguishable, and the $S_2$ trade after the $S_1$ and $S_3$ because
Figure 1
Plots for the timing cdfs by signal types and treatments.

The six panels plot distributions of the trading times, split up by signals types and type of treatment. Time is always on the horizontal axis, with 180 seconds signifying the end of trading. Cumulative probabilities are on the vertical axes. All panels contain three curves, one each for signals $S_1$, $S_2$, and $S_3$. The top left panel aggregates times for all treatments, the top right aggregates across all treatments but considers only the first trade for treatments 4-6. The second row left panel aggregates across treatments 1-3, the second row right panel aggregates treatments 4-6. In this last panel, the stochastic dominance relation between the $S_2$ and the $S_1/S_3$ seems, although still prevalent, the weakest. The panels in the bottom row clarify: for the first trades in treatments 4-6 the dominance order is as before ($S_2$ trade latest), but for the second trade, the order is no longer as clear.
the $S_2$ type’s distribution of entry times is below the entry time distribution for the $S_1$ and $S_3$. Specifically, this holds for all treatments $D1$, for all first trades $D2$, for treatments 1-3, 4-6, and for the first trades only in treatments 4-6. Consequently our findings comply with Smith (2000)’s prediction that people with good-news or bad-news-signals trade early, and that people who receive mixed information delay.

Question 2: Is there a timing order for the second trade? The bottom row, right panel in Figure 1 indicates that there is no timing relation between the three types when it comes to the second trade. This non-finding suggests that settings in which people can trade more than once may not yield clear insights with respect to people’s timing behavior.

Question 3: Will people trade faster when they can trade more often? To answer this question we compare $D7$ to $D8$ and $D7$ to $D9$. The left and middle panels in Figure 2 again paint a clear picture. Allowing people to trade more often speeds up their trade-times in particular when looking only at the first trade in treatments 4-6.

Question 4: For the $S_2$ types, which type of signal is associated with trading earliest and which latest? To answer this question we regard the cdfs in $D10$ and $D11$; Figure 3 visualizes these cdfs. Again, the picture here is clear: recipients of the hill-shaped signal act earliest, whereas recipients of the U-positive signal act last.

In Section 11 we argued that one may expect to see the hill-shaped (contrarian) types act before the U-shaped (herding) types since they would generally act against the general movement of prices. However, note that when prices rise such trades are not contrarian trades as they are in line with the original, slightly negative opinion.

In summary, the $S_2$ types act systematically after the $S_1$ and $S_3$ types, and the hill-shaped types act before the U-shaped types.

Clustering. One significant feature observed during the experiment is that trades are
often clustered. We have already explained that many, though not all, trades occur at the very beginning of the treatment. There also appears to be leader-follower trading in the sense that when one trade occurs, others follow in quick succession. This suggests that people wait for someone to make a move with the intention of immediately reacting thereafter.

To get a sense of systematic behavior, we first determined the number of seconds between one trade and its predecessor. We then looked at the frequencies for which trades occur within 1.5 seconds of one another, split up by signal types. Table XII lists the relevant percentages, Figure 4 plots the frequencies for the case of all signal types taken together.

As can be seen, there are a large number of trades that occur within 1.5 seconds of each other; the concentration is strongest at the very beginning of the treatment and changes only very little as the treatment progresses. The concentration at the beginning is no surprise as

Figure 2
Plots for the timing cdfs by number of trades.

The three panels plot distributions of the trading times, split up by treatments with one and two trades. Axes are as in Figure 1. The left panel plots the cumulative probabilities for all trades; trades in treatments 4-6 occur weakly before those in treatments 1-3. The right panel looks only the distribution of the first trades in treatments 4-6 and all the trades in treatments 1-3. Here, clearly, trading occurs much earlier in treatments 4-6.
Table XII
Clustering of Trades.

The table lists the proportion of trades that were made within 1.5 seconds of their predecessor. Columns divide by signal types, rows successively exclude trades made in the first 5, 10, 20 and 30 seconds. As can be seen, there are no substantial differences by signal type.

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>$S_1$</th>
<th>$S_2$</th>
<th>$S_3$</th>
<th>hill</th>
<th>−ve U</th>
<th>+ve U</th>
</tr>
</thead>
<tbody>
<tr>
<td>All times</td>
<td>67%</td>
<td>66%</td>
<td>63%</td>
<td>71%</td>
<td>64%</td>
<td>66%</td>
<td>61%</td>
</tr>
<tr>
<td>total time &gt;5 sec</td>
<td>58%</td>
<td>56%</td>
<td>57%</td>
<td>62%</td>
<td>57%</td>
<td>60%</td>
<td>55%</td>
</tr>
<tr>
<td>total time &gt;10 sec</td>
<td>54%</td>
<td>52%</td>
<td>53%</td>
<td>58%</td>
<td>55%</td>
<td>55%</td>
<td>50%</td>
</tr>
<tr>
<td>total time &gt;20 sec</td>
<td>51%</td>
<td>48%</td>
<td>51%</td>
<td>55%</td>
<td>56%</td>
<td>50%</td>
<td>49%</td>
</tr>
<tr>
<td>total time &gt;30 sec</td>
<td>50%</td>
<td>44%</td>
<td>50%</td>
<td>54%</td>
<td>56%</td>
<td>49%</td>
<td>46%</td>
</tr>
</tbody>
</table>

about 25% of all trades occur within the first 5 seconds (it takes another 25 seconds before a total of 50% of trades are made). The table also illustrates that there is no measurable variation among types; unreported regressions confirm this insight. We thus confirm that there is a general tendency to trade in a clustered manner, though signals have no impact on the clustering.

Note that there is at least one additional reason to believe that clustering is rational in the context of endogenous-timing. Since noise traders trade at random times spread uniformly across the treatment, observing several trades in close temporal proximity suggests that they are being made by a disproportionate number of informed traders. Subjects might reason that the market maker, who updates prices without taking timing into account, will fail to appreciate this subtlety and so subjects might expect the price to be updated too slowly during a cluster. This creates an opportunity for gains if a trade is made soon after a cluster is first observed, and produces a subtle feedback loop which might work to increase the scale of clustering behavior.

The supplementary appendix discusses an alternative analysis, examining the scope for
Figure 3
Plots for the timing cdfs of the $S_2$ by signal shape.

The two panels plot the distributions of the trading times, split up by types of signals for the $S_2$ (hill-shape, U-positive and U-negative). Axes are as in Figure 1. The left panel aggregates trades for same-type treatments with one and two trades, the right panel aggregates only the first trade for treatments 4, 5 and 6 respectively.

Figure 4
Plots for the time-difference pdfs.

The three panels complement Table XII by plotting the frequencies of the time-difference of each trade to its immediate predecessor. The left panel plots the time-difference for all trades, the middle panel from all trades excluding those that happen in the first 10 seconds, and the right panel excludes trades in the first 30 seconds.
pure information theory to explain the timing of decisions. As is common in the literature on information theory we use the entropy of posteriors to measure the informativeness of a signal. We observe, however, that information theory does not seem sufficient to explain the timing of decisions, and that instead contrarianism and herding motives play an important role.

IX. Conclusion

Herding has long been suspected to play a role in financial market booms and busts. Recent theoretical work shows that informational herding (or contrarianism) is possible in a market with efficient asset prices if the conditional signal distribution for traders has a specific shape. To keep this theory tractable one needs strong assumptions such as an exogenous entry order. We address how behavior changes when traders can choose the time of their trade. Giving traders a choice of when to act is not only natural, but there are also important insights that can be gleaned from such an analysis. For instance, if herding-prone types delay their actions systematically, then herd behavior can become more pronounced and significant compared to exogenous timing settings.

We thus examined the results of an experimental test involving almost 2000 trades, exploring people’s behavior when they can not only choose how to trade, but also when to trade. By contrast with almost all existing experiments, we employ a theoretical framework that allows rational herding and contrarianism in a financial market environment with moving prices.

We found that subjects’ decisions were generally in line with the predictions of static informational learning theory when that theory admits rational herding and contrarianism.
Types theoretically prone to herd or be contrarian are indeed the significant and important source of this kind of behavior when it does arise.

Types with extreme information (good or bad) trade systematically earliest, and those with signals conducive to contrarianism trade earlier than those with information conducive to herding. We thus find strong evidence for the impact of the type of information both with respect to the direction and the timing of trades.

REFERENCES


Bikhchandani, Sushil, and Sharma Sunil, 2000, Herd behavior in financial markets: A review, Staff Paper WP/00/48 IMF.


———, 2008, Why has trading volume increased?, working paper UCLA.


———, 2007, Herd behavior in financial markets: A field experiment with financial market professionals, mineo UCL and GWU.


