Herding and Contrarianism in a Financial Trading Experiment with Endogenous Timing

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Classic Herding Example: Two Restaurants

- People have private information about which of two restaurants (A or B) is better.
- They arrive in sequence and can observe predecessors’ actions.
  1. The first follows his signal (say A).
  2. The second knows the first’s signal, and his own (say A, hence goes for A).
  3. The third can disregard his own and will herd to restaurant A.
     - If he had a B this would cancel with the first signal, leaving agent 3 looking to agent 2, hence opting for A.
     - *A fortiori* if he had an A signal.
- Consequence: from agent 3 onwards herding is possible!
Sticking with the 2 state/2 action world of the restaurant example, let’s consider traders deciding whether to buy or sell a stock.

Informationally efficient prices automatically incorporate public information about actions.

So if traders buy prices will rise to incorporate the information embodied in their purchase decisions, and similarly for a sell.

Hence all that is left for traders to use is their private information.

Problem: We seem to have lost the potential for herding from the restaurant example.
General Existence of Herding and Contrarian Behavior

- Herding arises under intuitive informational assumptions, namely,
  - Herding candidates receive info that causes volatile decision rules.
  - ⇒ Information in question causes herding candidates to distribute weight to the tails of their beliefs.
    *We call this U-shaped or bi-polar information.*
  - ⇒ “Something extreme has happened” → ‘go with the flow’.
- Also: Contrarian behavior arises under intuitive informational assumptions, namely,
  - Contrarians behave in a stabilizing manner and prevent extreme movements.
  - ⇒ Information in question causes herding candidates to distribute weight towards center of their beliefs.
    *We call this hill-shaped or single-polar information.*
  - ⇒ “nothing has happened” → ‘go against the flow’.
Do traders really wait in line?

- Another Problem: Theory mandates that traders wait in line until it is their turn to trade.
- That’s not what happens in reality — they choose both how and when to trade!
- Why is this an issue beyond a theoretical limitation? — It may underestimate the importance of herding:
  - Bi-polar information: herding candidates are less certain on info.
  - Delay to wait and see — and then trade as bulk thus pushing prices strongly either way.
- Theoretical Problem: There is currently no theory that captures endogenous time trading with efficient prices and heterogeneously informed traders.
  - But: this does not prevent obtaining insight from an experiment in a tightly controlled environment.
General Existence of Rational Herding and Contrarianism
The Dow’s Roller Coaster Ride on September 29-30

Endogenous Time Herding Experiment
General Existence of Rational Herding and Contrarianism
The Dow’s Roller Coaster Ride on September 29-30

Volume rises → endogenous time herding?
Basic Static Setup

- Asset value $V \in \{V_1, V_2, V_2\} = \{75, 100, 125\}$.
- $\text{pr}(V_1) = \text{pr}(V_2) = \text{pr}(V_3)$.
- Two kinds of traders:
  1. Informed (subjects, 75%: can buy, sell or hold as they wish);
  2. Noise (computer, 25%: buy or sell with equal probability).

- Informed receive private conditionally iid signal $S \in \{S_1, S_2, S_3\}$ about $V$ wlog ordered $S_1 < S_2 < S_3$ and can observe the prior history of actions $H_t$ and prices $p_t$.
- Optimal static rational choice for informed (assuming indifferent agents buy) is buy if $E[V|H_t, S_t] \geq$ price, otherwise sell.
Market Maker

- Trade is organized by a market maker.
- In theory he posts a bid-price (at which he buys) and an ask-price (at which he sells).
- The bid-ask spread plus noise traders enable him to break even.
- But we don’t need to break even, so to keep it simple in the experiment we have a single price for all trades.
Definition of Herding and Contrarianism

Definition (Herd- and Contrarian-Behavior in Experiments)

1. A trader rationally engages in herd-buying after a history of trade $H_t$ if and only if
   (H1) he would sell at the initial history $H_1$,
   (H2) he buys at history $H_t$ and
   (H3) prices at $H_t$ are higher than at $H_1$.

2. A trader rationally 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 $H_1$. 
If $S_2$ types have decreasing or increasing csds they cannot herd or be contrarian (they become similar to $S_1$ and $S_3$ types respectively).

Herding candidates must receive information that makes their decisions more volatile and so they distribute weight to the tails of their beliefs - we call this U-shaped information.

Contrarian candidates behave in a stabilizing manner, distributing weight towards the center of their beliefs - we call this hill-shaped information.
Signal distribution in table-format

| $\text{pr}(S|V)$ | $V_1$ | $V_2$ | $V_3$ |
|------------------|-------|-------|-------|
| $S_1$            | $\ldots$ | $\ldots$ | $\ldots$ |
| $S_2$            | $\ldots$ | $\ldots$ | $\ldots$ |
| $S_3$            | $\ldots$ | $\ldots$ | $\ldots$ |
| $\Sigma = $      | 1     | 1     | 1     |
Properties of the Signal Distribution

\[ \Pr(S_i|V_i) \quad \text{increasing } S_2 \]

\[ \Pr(S_i|V_i) \quad \text{decreasing } S_2 \]
Properties of the Signal Distribution

\[ \text{Pr}(S_i|V_i) \]

V1  V2  V3

\begin{align*}
S_1 & \quad S_2 & \quad S_3 \\
\text{hill-shaped } S_2 & \\
\end{align*}

\[ \text{Pr}(S_i|V_i) \]

V1  V2  V3

\begin{align*}
S_1 & \quad S_2 & \quad S_3 \\
\text{U-shaped } S_2 & \\
\end{align*}
Dynamic Decision: When to trade?

- **Disclaimer:** the decisions of when and how to trade are part of a single decision problem — we merely separate the two for expositional clarity.
- **Smith (AER 2000):** has a single trader setup and shows that trade immediately if information is either good or bad news (="monotonic" signals in our language); also has example of U-shaped signal which mandates delay.
  - Hypothesis 1: $S_1$ and $S_3$ should trade immediately when markets open, $S_2$ should trade later.
  - Hypothesis 2: (weaker) $S_1$ and $S_3$ should trade before the $S_2$.
  - Hypothesis 3: Hill-shape (= more convinced) trades before U-shape (= less convinced).
- **With two trades there is really no theory. Best guess:**
  - Hypothesis 4: $S_1$ and $S_3$ should trade before the $S_2$.
  - Hypothesis 5: No speculative trading (=buy-sell); decision by $S_2$ is triggered by signals, not short-term trading profit.
Experimental Objectives

1. Question 1: Is trading behavior consistent with static equilibrium predictions? Specifically,
   - $S_1$ types should always sell, $S_3$ types should always buy;
   - $S_2$ types will herd iff the conditions are met and be contrarian iff the conditions are met.

2. Question 2: Do we observe herding and contrarianism and are the herding and contrarian signals the driving forces behind behavior?

3. Question 3: To what extent are decisions generally affected by the level of prices?

4. Question 4: When in absolute time will people trade, depending on their information?

5. Question 5: When will people trade relative to others depending on their information? Is there clustering?

6. We also examine a variety of behavioral alternatives.
Preview of Results

1. Question 1: Behavior is largely consistent with static theory for $S_1$ and $S_3$, less for $S_2$.

2. Question 2: Herding and contrarian signals are the significant source of herding and contrarianism. Having such a signal increases the chance of herding by 30% and 36% respectively (the effect of the Herd signal is much stronger than in exogenous time framework (a mere 6%)).

3. Question 3: Price do have an effect: the larger the price, the less likely traders are to buy (end-point effect).

4. Question 4: Absolute timing
   - $S_1$ and $S_3$ trade systematically before the $S_2$.
   - Hill shape trades before U-shape.
   - With two trades allowed, trading occurs earlier.

5. Question 5: Relative timing: There is evidence of clustering, but does not depend on information.
We ran 1 (example) + 12 treatments, 6 of which were devoted to this paper (remaining 6 were exogenous time).

Two kinds of treatments:
1. Single trade.
2. Two trades (to study, for instance speculation etc).

Treatments were as follows:
1. negative U-shape ⇒ buy-herding;
2. negative hill-shape ⇒ buy-contrarianism;
3. positive U-shape ⇒ sell-herding;
4. negative hill-shape + two trades ⇒ buy-contrarianism;
5. positive U-shape + two trades ⇒ sell-herding;
6. negative U-shape + two trades ⇒ buy-herding.
Laboratory Time Line

- Initial instructions including hand-outs that could be viewed at any time.
  - Existence and proportion of noise-trades explained.
  - Subjects told what $S_1$, $S_2$ and $S_3$ signals mean prior to each treatment (so they ”understand” all the signals not just the ones they receive).
- For each treatment they are given the full signal matrix and the posterior for each signal at $H_1$.
- Signals handed out via the computer.
- Computer noise trades at random times.
- Traders can always see their signal, current price and the history of prices (actions); they can trade at time time when the treatment has started. Computer allows only as single (or two) trade(s).
The Trading Software

Game Time: 12
Asset Holdings: 1
Cash Balance: $10000.000
Signal: S1
Stock Price: $116.462
We ran 13 sessions in total (3 at UCambridge, 6 at UWarwick, 4 at UToronto).

Group sizes were 13-25.

We had 1993 trades.

By type:

- 623 ($S_1$), 786 ($S_2$), 584 ($S_3$);
- Single trade: 683 with 197 $S_1$, 276 $S_2$ and 210 $S_3$.
- Two trades: 1310 with 426 $S_1$, 510 $S_2$ and 374 $S_3$.

We also ran an example session and 6 exogenous-time sessions (for a companion paper), making this one of the largest laboratory experiments of its type ever run.
Overall Fit

- Only time for a summary of the results. For a full set of regressions, tables and diagrams please see the paper (www.sgroi.org.uk).
- The rational model explains about 73% of trades (comparable to other herding studies, even those without prices; exogenous time had 75%).
- Herding candidates are less well explained by the rational model (54%).
- Assuming different levels of risk aversion doesn’t improve fit ⇒ risk neutrality a fair assumption.
**Herding and Contrarianism**

Is U-shape/hill-shape significant source for herding/contrarianism?

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

<table>
<thead>
<tr>
<th>HERDING</th>
<th>all types</th>
<th>T1-T3</th>
<th>T4-T6</th>
<th>first trades T4-T6</th>
<th>second trade T4-T6</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>
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<td>(-0.032)</td>
<td>(-0.032)</td>
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<td>OLS</td>
<td>0.378**</td>
<td>0.138**</td>
<td>0.495**</td>
<td>0.293**</td>
<td>0.552**</td>
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<tr>
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<td>(-0.031)</td>
<td>(-0.03)</td>
<td>(-0.043)</td>
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<tr>
<td>OLS fixed effects</td>
<td>0.352**</td>
<td>0.081</td>
<td>0.434**</td>
<td>0.276**</td>
<td>0.545**</td>
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<tr>
<td></td>
<td>(-0.027)</td>
<td>(-0.042)</td>
<td>(-0.038)</td>
<td>(-0.032)</td>
<td>(-0.057)</td>
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<tr>
<td>Observations</td>
<td>1172</td>
<td>391</td>
<td>781</td>
<td>805</td>
<td>367</td>
</tr>
</tbody>
</table>
### Herding and Contrarianism

Is U-shape/hill-shape significant source for herding/contrarianism?

$$\text{herd}_{i,t} = \alpha + \beta u\text{-shape}_{i,t} + \text{fixed}_i + \epsilon_{i,t},$$

$$\text{contra}_{i,t} = \alpha + \beta \text{hill\text{-}shape}_{i,t} + \text{fixed}_i + \epsilon_{i,t}$$

<table>
<thead>
<tr>
<th>CONTRA</th>
<th>all types</th>
<th>T1-T3</th>
<th>T4-T6</th>
<th>first trades</th>
<th>second trade</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>T4-T6</td>
<td>T4-T6</td>
</tr>
<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>OLS</td>
<td>0.434**</td>
<td>0.353**</td>
<td>0.508**</td>
<td>0.439**</td>
<td>0.429**</td>
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<tr>
<td></td>
<td>(-0.057)</td>
<td>(-0.085)</td>
<td>(-0.079)</td>
<td>(-0.066)</td>
<td>(-0.114)</td>
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<tr>
<td>OLS fixed effects</td>
<td>0.406**</td>
<td>0.300*</td>
<td>0.473**</td>
<td>0.405**</td>
<td>0.655**</td>
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<td>(-0.063)</td>
<td>(-0.117)</td>
<td>(-0.108)</td>
<td>(-0.076)</td>
<td>(-0.177)</td>
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<tr>
<td>Observations</td>
<td>820</td>
<td>293</td>
<td>527</td>
<td>553</td>
<td>267</td>
</tr>
</tbody>
</table>
Type S trading systematically before type S’ can be interpreted that the distribution of trading times for type S is first order stochastically dominated by that of type S’.

Graphically, the cdf of S lies above the cdf of S’.

Stark example: the first trade with two trades (T4-T6) occurs before the only trade (T1-T3):
Absolute Timing: \( S_1, S_2, S_4 \)

CDFs by types, all treatments

Andreas Park & Daniel Sgroi
Endogenous Time Herding Experiment
Absolute Timing: Hill, U-pos, U-neg

CDFs for S2 by treatment type

- Hill
- U-Negative
- U-Positive
Clustering

Frequency of Time–differences

- Time difference vs Frequency
- Graph showing frequency distribution with multiple bars
Clustering

- Relative proximity: The percentage of trades that follow within 1.5 seconds of another.

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>S1</th>
<th>S2</th>
<th>S3</th>
<th>hill</th>
<th>−ve U</th>
<th>+ve U</th>
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</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>
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<tr>
<td>total time &gt;10 sec</td>
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<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>
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<td>44%</td>
<td>50%</td>
<td>54%</td>
<td>56%</td>
<td>49%</td>
<td>46%</td>
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Relation of First and Second Trade: Buy low, sell high?

- Are there systematic differences between signals types in how they perform their return trades?
- Intuitively: For $S_1$ (the reverse for $S_3$)
  - $buy\text{-}sell$ is manipulative,
  - $sell\text{-}buy$ is herding when prices rose, and
  - $sell\text{-}buy$ is contrarian if prices fell.

<table>
<thead>
<tr>
<th>Summary Stats</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>% return</td>
<td>19%</td>
<td>33%</td>
<td>16%</td>
<td>24%</td>
</tr>
<tr>
<td>% profitable return</td>
<td>82%</td>
<td>78%</td>
<td>66%</td>
<td>77%</td>
</tr>
<tr>
<td>% profitable return incl. expectations</td>
<td>59%</td>
<td>35%</td>
<td>72%</td>
<td>49%</td>
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</table>
### Summary Stats

<table>
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<td>49%</td>
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</table>

- So question: when herding (contrarianism) arises, is it likely to be a return trade?
- We regressed by type for the two-trade case

\[
\text{herd}_{i,t} = \alpha + \beta \text{return trade}_{i,t} + \epsilon_{i,t},
\]

\[
\text{contra}_{i,t} = \alpha + \beta \text{return trade}_{i,t} + \epsilon_{i,t}.
\]
## Relation of First and Second Trade: Buy low, sell high?

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<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>herding case</strong></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><strong>contrarian case</strong></td>
<td></td>
<td>0.181**</td>
<td>0.312**</td>
</tr>
<tr>
<td></td>
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<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>

- Results: $S_1$ return trades tend to be herders, $S_2$ and $S_3$ as contrarians.
Behavioral Explanations: Rational Reaction to Irrationality

- Inspired by level K-belief (Costa-Gomes, Crawford and Broseta, EMA 2001) & quantal response equilibrium (McKelvey and Palfrey GEB 1995).
- Step 1: Assume only fraction $\delta$ of other subjects acts rationally. Which $\delta$ maximizes the fit?
  - Answer: $\delta^* = \frac{2}{15}$.
  - Fit increases from 70% (‘pass’=wrong) to 73%.
  - Equivalent to factual noise level of 90%.
- Step 2: Assume that fraction $1 - \delta$ of other subjects acts irrationally and fraction $\delta$ reacts rationally to the irrationality.
  - Best fit for $\delta^* = 0$ (no updating); good fit from T1-T3 for $\delta = .22$
  - With .22 improvement from T1-T3 is from 69.8% to 76.1%.
We specifically test a design that admits herding and contrarianism as rational under certain circumstances, using different treatments to examine each possibility in turn — we are the first to do so.

Also the first experiment that combines efficient prices, informational learning and endogenous timing.

Our results suggest that rational herding and contrarianism can take place in the lab and that endogenous timing contributes to the importance of the phenomenon.

Herding and contrarians candidates are the likely culprits of this type of behavior.

The theory is a good match for the data, and alternative theories can do no better when predicting behavior.