Rational Herding and Rational Contrarianism in Exogenous and Endogenous Time
A Financial Herding Experiment

Andreas Park & Daniel Sgroi

University of Toronto & University of Warwick

October 31, 2008
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!
What About Prices?

- 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, leaving only private information as a means of profit.
- For instance, with a single price: $p_t = E[V|H_t]$, so profit comes from $E[V|H_t, S_t] - E[V|H_t]$.
- Note that with a spread we need noise traders to allow profits since the market (MM) can take into account the action of the trader.
- We seem to have lost the potential for herding from the restaurant example.
Exogenous Time

- The theory is taken from Park & Sabourian (2006)
- Asset value $V \in \{V_1, V_2, V_3\} = \{75, 100, 125\}$. 
  \(\Pr(V_1) = \Pr(V_2) = \Pr(V_3)\).
- Random exogenous arrival of traders in a sequence of two types:
  1. Informed (subjects, 75%: can buy, sell or hold as they wish);
  2. Noise (computer traders, 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 \(H_t\).
- Optimal rational choice for informed (assuming indifferent agents buy) is buy if 
  \(E[V|H_t, S_t] \geq \text{price}\), 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 $p_t = E[V|H_t]$.
- Subjects know that he will adjust price upwards with a buy and down with a sell.
Definitions

- A trader rationally engages in herd-buying (herd-selling) after a history of trade $H_t$ iff:
  1. he would sell (buy) at the initial history $H_1$;
  2. he buys (sells) at history $H_t$;
  3. prices at $H_t$ are higher (lower) than at $H_1$.

- A trader rationally engages in buy-contrarianism (sell-contrarianism) after a history $H_t$ iff:
  1. he would sell (buy) at the initial history $H_1$;
  2. he buys (sells) at history $H_t$;
  3. prices at $H_t$ are lower (higher) 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 centre of their beliefs - we call this **hill-shaped** information.
Conditional Signal Distributions

\[ \Pr(S_i | V_i) \]

\( S_1, S_2, S_3 \)

hill-shaped \( S_2 \)

\[ \Pr(S'_i | V'_i) \]

\( S_1, S_2, S_3 \)

U-shaped \( S_2 \)
Theorem

- Types $S_1$ and $S_3$ never herd or act in a contrarian manner.
- Type $S_2$ buy(sell)-herd iff his csd is negative(positive) U-shaped.
- Type $S_2$ buy(sell)-contrarian iff his csd is negative(positive) hill-shaped.
Timing

- So far (and in all existing theoretical and experimental studies into financial herding) we require 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.
- This is especially important since timing and herding may be linked, for example herding candidates (bi-polar information) may be those who have least certainty and so may opt to wait.
- For the static decision of how to trade we continue with the exogenous-time theory, for the dynamic decision we have some further observations.
- Of course they are both part of a single decision problem. We separate them 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).
Two Trades

- 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.
Objectives

- Does the informational structure matter?
- Under **exogenous-time**, we have iff relationships so we can setup treatments to check that $S_1$ types should always sell, $S_3$ types should always buy and $S_2$ types will herd iff the conditions are met and be contrarian iff the conditions are met.
- Under **endogenous-time** our examination will be more speculative, but we maintain the same desire to examine the impact of different information structures.
- We also examine various of behavioral alternatives.
- And the impact on prices.
We ran 1 + 12 treatments, 6 of which were in exogenous-time and 6 in endogenous-time.

Exogenous-time treatments were as follows:

1. negative hill-shape ⇒ buy-contrarianism possible;
2. increasing signal structure ⇒ no herding, no contrarianism;
3. negative U-shape ⇒ buy-herding possible;
4. decreasing signal structure ⇒ no herding, no contrarianism;
5. positive U-shape ⇒ sell-herding possible;
6. positive hill-shape ⇒ sell-contrarianism possible.
Endogenous-time treatments were as follows:

1. negative U-shape $\Rightarrow$ buy-herding;
2. negative hill-shape $\Rightarrow$ buy-contrarianism;
3. positive U-shape $\Rightarrow$ sell-herding;
4. negative hill-shape + two trades $\Rightarrow$ buy-contrarianism;
5. positive U-shape + two trades $\Rightarrow$ sell-herding;
6. negative U-shape + two trades $\Rightarrow$ buy-herding.
Time-line

- Initial instructions including hand-outs that could be viewed at any time. The existence and proportion of noise-trades explained, and subjects are 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 $H_1$ and then signals handed out via the computer.
- Exogenous-time: Computer allocates sequential time-slots to each trader (noise and subject) and they can act only in their window (screens flash).
- Endogenous-time: Subjects can act whenever they wish within a 3 minute time period, with regular announcements of time.
The Trading Software

- Traders can always see their signal, current price and the history of prices (actions).

![Graph showing trading client interface with game time, asset holdings, cash balance, signal, and stock price.](image)
We ran 13 sessions in total (3 at UCambridge, 6 at UWarwick, 4 at UToronto).

Group sizes were 13-25.

Exogenous-time: we had 1382 trades minus 28 time-outs = 1354 trades total for the 6 treatments considered today. By type: 394 ($S_1$), 553 ($S_2$), 407 ($S_3$).

Endogenous-time: 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 $S_3$.

In total we had almost 3400 trades making this one of the largest experiments of its type ever run.
Starting with the exogenous-time results the rational model explains about 75% of trades (comparable to other herding studies, even those without prices).

Herding candidates are less well explained by the rational model (61%).

Assuming different levels of risk aversion doesn’t improve fit ⇒ risk neutrality a fair assumption.
Herding vs Contrarianism

- Less rational herding than theory predicts (31%).
- However, theoretical herding types are significantly more prone to herd than others (confirmed by regressions: an $S_2$ herding signal is highly significant as a cause of herding).
- Rational contrarianism more common (66%), though still less than predicted.
- In fact, $S_2$ types did occasionally exhibit contrarian behavior across all treatments if and when prices rose.
- Hence much more contrarianism, fitting received wisdom (eg Chordia, Roll & Subrahmanyam, 2002 JFE).
In treatments where herding possible is the herding U-shaped signal significant?

<table>
<thead>
<tr>
<th></th>
<th>All candidate herding trades</th>
<th></th>
<th>S2 candidate herding trades</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Logit</td>
<td>OLS</td>
<td>Fixed</td>
<td>Logit</td>
</tr>
<tr>
<td>herding signal</td>
<td>0.059* (0.026)</td>
<td>0.069* (0.030)</td>
<td>0.076* (0.033)</td>
<td>0.04 (0.037)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.215** (0.009)</td>
<td>0.100** (0.013)</td>
<td>0.099** (0.012)</td>
<td>-0.233** (0.014)</td>
</tr>
<tr>
<td>Obs</td>
<td>761</td>
<td>761</td>
<td>761</td>
<td>372</td>
</tr>
<tr>
<td>R^2</td>
<td>0.01</td>
<td>0.4</td>
<td>0.0</td>
<td>0.0</td>
</tr>
</tbody>
</table>
In treatments where contrarianism is possible is the contrarian hill-shaped signal significant?

<table>
<thead>
<tr>
<th></th>
<th>All candidate contrarian trades</th>
<th>S2 candidate contrarian trades</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Logit</td>
<td>OLS</td>
</tr>
<tr>
<td>contra signal</td>
<td>0.336**</td>
<td>0.458**</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.239**</td>
<td>0.187**</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Obs</td>
<td>591</td>
<td>591</td>
</tr>
<tr>
<td>R^2</td>
<td>0.06</td>
<td>0.5</td>
</tr>
</tbody>
</table>

*Park & Sgroi A Financial Herding Experiment*
General Price Sensitivity

- $S_1$ should always sell, $S_3$ always sell, irrespective of price. Do they?

<table>
<thead>
<tr>
<th></th>
<th>$S_3$ passes are buys</th>
<th>$S_3$ passes are omitted</th>
<th>$S_1$ passes are buys</th>
<th>$S_1$ passes are omitted</th>
</tr>
</thead>
<tbody>
<tr>
<td>% price change</td>
<td>-0.549** (0.167)</td>
<td>-0.692** (0.176)</td>
<td>-0.231 (0.209)</td>
<td>-0.075 (0.177)</td>
</tr>
<tr>
<td>constant</td>
<td>0.246** (0.016)</td>
<td>0.255** (0.016)</td>
<td>-0.206** (0.016)</td>
<td>-0.195** (0.018)</td>
</tr>
<tr>
<td>obs</td>
<td>407</td>
<td>380</td>
<td>394</td>
<td>363</td>
</tr>
</tbody>
</table>
Behavioral Explanations I
Alternative Hypotheses

- Complexity: (i) $S_2$ types more likely to be irrational than other types; (ii) $S_2$ types more likely to fail if decision is close.
- Prospect theory: subjects follow prospect theory valuation functions.
- Prior action: subjects ignore prices, relying only on their signal.
- Prior expectation: subjects do not update based on other traders’ actions, but do use the price.
- Probability shifting: subjects update beliefs at a slower rate than they should.
Behavioral Explanations II

Alternative Hypotheses

- **Noise**: subjects update their beliefs based on an incorrect estimate of noise trades.
- **Trend chasing**: subjects chase short-run trends.
- In cases where hypotheses are parameterised we considered the full range and used the best performing parameter.
- However generally, all of these do no better than the rational model, many doing much worse.
- When we allow subjects to imagine noise trades account for around 3.5 times the actual rate (which they are told) we start to see a small improvement in fit. A link to QRE perhaps, but only at infeasible levels?
Deviation from the rational model will cause prices to deviate from the rational benchmark.

We can measure this using the formula:

\[
\text{level of inefficiency} = \frac{\text{rational price} - \text{observed price}}{\text{rational price}}
\]

According to this measure:

- 16% of prices coincide with the rational price;
- on average the price is 7% below average;
- the standard deviation is 10%.
The rational (exogenous-time) model explains about 73% of trades (comparable to other herding studies, even those without prices).

Recall that in the exogenous-time treatments this number was 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.

Once again behavioral alternatives don’t greatly improve the fit.
light more complex since time enters the regression, but once again we check whether U-shape/hill-shape significant source for herding/contrarianism:

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

Park & Sgroi  A Financial Herding Experiment
## Herding

<table>
<thead>
<tr>
<th></th>
<th>all types</th>
<th>T1-T3</th>
<th>T4-T6</th>
<th>first trade T4-T6</th>
<th>second trade T4-T6</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Logit</strong></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><strong>OLS</strong></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><strong>OLS fixed effects</strong></td>
<td>0.352**</td>
<td>0.081</td>
<td>0.434**</td>
<td>0.276**</td>
<td>0.545**</td>
</tr>
<tr>
<td></td>
<td>(-0.027)</td>
<td>(-0.042)</td>
<td>(-0.038)</td>
<td>(-0.032)</td>
<td>(-0.057)</td>
</tr>
<tr>
<td><strong>Observations</strong></td>
<td>1172</td>
<td>391</td>
<td>781</td>
<td>805</td>
<td>367</td>
</tr>
</tbody>
</table>

*Park & Sgroi: A Financial Herding Experiment*
## Contrarianism

<table>
<thead>
<tr>
<th>Contra</th>
<th>all types</th>
<th>T1-T3</th>
<th>T4-T6</th>
<th>first trade T4-T6</th>
<th>second trade T4-T6</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>OLS</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>OLS 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>
</tbody>
</table>
Absolute Timing

• 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: if traders have two trades then the first trades typically occur before their first trade when they have only one trade:
CDFs of timing all types, first trades only, T1–T3 vs. T4–T6

- **CDF**
- **Time**

- **T1–T3**
- **T4–T6 first trades**
CDFs by types, all treatments
**Relative Timing**

- 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>
</tr>
</thead>
<tbody>
<tr>
<td><strong>All times</strong></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>
Frequency of Time-differences

- **Park & Sgroi**
- A Financial Herding Experiment
Return Trades I

- Return trades are trades in opposite directions.

Summary Stats

<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>% 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>
</tr>
</tbody>
</table>

- Are there systematic differences between signals types in how they perform their return trades?
Return Trades II

Intuitively: For $S_1$ (the reverse for $S_3$)

- *buy-sell* is manipulative,
- *sell-buy* is herding when prices rose, and
- *sell-buy* is contrarian if prices fell.

So question: when herding (contrarianism) arises, is it likely to be a return trade?

We regressed by type for the two-trade case

\[
\begin{align*}
\text{herd}_{i,t} & = \alpha + \beta \text{return-trade}_{i,t} + \epsilon_{i,t}, \\
\text{contra}_{i,t} & = \alpha + \beta \text{return-trade}_{i,t} + \epsilon_{i,t}.
\end{align*}
\]
Return Trades III

<table>
<thead>
<tr>
<th>S1</th>
<th>S2</th>
<th>S3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Herding case</td>
<td><strong>0.085</strong></td>
<td>-0.129*</td>
</tr>
<tr>
<td></td>
<td>(-0.028)</td>
<td>(-0.066)</td>
</tr>
<tr>
<td>Contrarian case</td>
<td>0.181**</td>
<td>0.312**</td>
</tr>
<tr>
<td></td>
<td>(-0.039)</td>
<td>(-0.064)</td>
</tr>
<tr>
<td>Observations</td>
<td>205</td>
<td>248</td>
</tr>
</tbody>
</table>

- **S_2** type herding is negatively related to the incidence of a return trade; an incidence of a return trade increases the probability that the trade is contrarian.
- In summary, **S_1** return trades tend to be herders, **S_2** and **S_3** as contrarians.
As with exogenous time various alternative behavioral models were tested and did not add much.

We did try a new variation, inspired by level K-belief (Costa-Gomes, Crawford and Broseta, EMA 2001) & quantal response equilibrium (McKelvey and Palfrey GEB 1995). The key is to add a *rational reaction to irrationality*.

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%.
Behavioral Explanations II

- 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 $\delta = 0.22$
  - With 0.22 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 - we are the first to do so.

Rational herding and contrarianism can take place in the lab, though neither occur as often as predicted by theory.

Herding candidates are much more likely to herd than those theory suggests should not.

Rational contrarianism is more common than rational herding. Courtesy of contrarianism, behavior in the lab is more mean-reverting than theory might predict.

The price is typically inefficiently low.

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

- Behavior is largely consistent with static theory for $S_1$ and $S_3$, less for $S_2$.
- 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%)).
- Prices do have an effect: the larger the price, the less likely traders are to buy (end-point effect).
- Once again, behavioral theories don’t greatly improve the fit.
Endogenous-time II

- 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.

- Relative timing: there is evidence of clustering, but does not depend on information.

- Overall, endogenous timing contributes to the importance of herding and contrarianism relative to exogenous timing.