Cross-Firm Information Flows

Anna Scherbina (joint with Bernd Schlusche)

The Q Group Conference

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Motivation

• Searching for a collection of “bellwether” stocks for individual stocks

• Relevant information may flow from a firm at the center of an important news development
  • Such leaders will be temporary and not ex-ante identifiable
  • Their news may go unnoticed
  • Reaction especially slow when news originate at small firms
Preview of the results

- Identify a collection of stocks that predict returns of individual firms, using simple Granger-causality methodology
- Leaders are not easily identifiable with stock characteristics
- Some leaders are transitory
- Leader signals often uncorrelated within industries ⇒ within-industry trading strategies possible
- Leadership scope is associated with higher firm-level news intensity, but nonlinearly
- Results consistent with the limited attention explanation
  - information flows slower from smaller leaders
  - small stocks react with a longer delay
- Frequent trading is required
- Sophisticated investors trade on leader signals
Relevance to practitioners

- The Granger-causality methodology allows to identify all sources of cross-predictability in individual stocks returns
  - We know that customers predict suppliers’ returns. This methodology allows to identify return leaders and followers without having to collect data on customer/supplier relationships
  - Many other types of inter-firm linkages may create lead-lag patterns in stock returns. Data on such linkages may be unavailable
Motivation

• It is difficult to process all firm-level news
• $\approx 218$ important firm-level news issued daily, only $\approx 20\%$ financial news (Neuhierl, Scherbina and Schlusche (2012))

• Examples of firm-level news relevant for other firms:
  
  • Texaco Inc. (1994-1996)
    • employee discrimination lawsuit
    • threat of similar lawsuits, boycott by customers and investors
    • NSS: $\approx 1\%$ are legal news of which $\approx 30\%$ are about class action lawsuits
  
  • Novartis patent case (2012)
    • erosion of intellectual property protections in India
    • NSS: $\approx 2\%$ are news about expansion to new markets
  
  • John Wiley & Sons, Inc. (2008-2013)
    • resale in the U.S. of items priced cheaper abroad
    • eBay and Google: prohibiting this practice “threatens the increasingly important e-commerce sector of the economy”
Motivation

• Examples (cont’d)
  • WorldCom earnings manipulation (1999-2002)
    • telecom, cable, and media stocks also affected due to accounting similarities
    • NSS: ≈ 0.14% are news about earnings restatements
  • From my paper “Economic Linkages Inferred from News Stories ...”, journalists possess soft information that helps identify inter-firm connections. In particular, such connections are established in stories about:
    • customer/supplier relationships
    • strategic alliances
    • merger prospects
    • legal issues
    • similar production/labor issues
    • similar exposure to regulation
    • similar regional/geopolitical concerns
Related literature

• Our results indicate that information diffuses slowly across firms, especially when it originates at smaller firms

• Literature on delayed price reaction due to limited attention:
  • Firms with higher levels of investor attention lead in reacting to common shocks (this is not due to non-trading)
    • Attention proxies: size (Lo and MacKinlay (1990)), analyst coverage (Brennan et al. (1993)), institutional ownership (Badrinath et al. (1995)), and turnover (Chordia and Swaminathan (2000))
  • Single-segment firms lead conglomerates in reacting to industry news (Cohen and Lou (2012))
  • Leadership along the supply chain (Cohen and Frazzini (2008), Menzly and Ozbas (2010))

• Such leaders are ex-ante identifiable; signals are likely correlated within an industry
Identifying information leaders for each stock

• Identify a set of leaders for each firm \( i \) by checking which stocks \( j \) Granger-cause its returns:

\[
Ret^i_t = b^i_0 + b^i_1 Ret^{mkt}_{t-1} + b^i_2 Ret^i_{t-1} + b^i_3 Ret^j_{t-1} + \epsilon^i_{jt}
\]

• Run the regression for each pair \( \{i, j\} \), using 12- (36)-month (or 52-week) rolling regression window and monthly (weekly) returns

• Stock \( j \) is a leader for stock \( i \) in the current month if \( t\text{-stat}(b_3) \geq 2.00 \) (\( \geq 2.56 \))
  • positive leader if \( \hat{b}_3 > 0 \)
  • negative leader if \( \hat{b}_3 < 0 \)
Leadership summary

| Average # of leaders       | 286.89 |
| % positive leaders         | 53.03% |
| $\hat{b}_3$ for positive leaders | 0.87  |
| $\hat{b}_3$ for negative leaders | -0.90 |
| % obs. with at least one leader | 90.97% |

- How many leaders are falsely identified as such?
  - 4.55% $p$-value $\times 3,305$ stocks in the cross-section $\approx 150$ stocks

- Is there any useful information?
  - yes, if leaders help predict future returns
  - in the future, discard misidentified or correlated leaders
Aggregating leader signals

- Each month $\tau$, we aggregate the leader signal across all leaders $j = 1, ..., J^i_\tau$ for stock $i$:

$$Signal^i_\tau = \sum_{j=1}^{J^i_\tau} w^i_j \hat{b}^i_{3\tau} Ret^j_\tau$$

- Equal- or value-weight across leaders using market capitalization at time $\tau - 1$
- Or “non-parametrically” by ignoring the magnitude of $\hat{b}_3$:

$$Signal^i_\tau = \sum_{j=1}^{J^i_\tau} w^i_j \text{sign}(\hat{b}_3) Ret^j_\tau$$

1. Equal-weight all leaders’ returns
2. Value-weight
3. Weight by $|t\text{-statistic}(\hat{b}_3)|$
4. Weight by $|\hat{b}_3|$

- In the future, develop a more efficient weighting scheme taking into account the var-covar structure of the signals

A. Scherbina, Cross-Firm Information Flows
Example

- Leader stocks B and C for follower stock A
- Regression estimated at $\tau$:

$$Ret_t^A = b_0^{Aj} + b_1^{Aj} Ret_{t-1}^{mkt} + b_2^{Aj} Ret_{t-1}^A + b_3^{Aj} Ret_{t-1}^j + \epsilon_t^{Aj},$$

with $t \in [\tau - 11, \tau]$ and $j \in \{B, C\}$

- Coefficient estimates: $\hat{b}_3^{AB} = 1$ and $\hat{b}_3^{AC} = 1$
- Leader returns: $Ret_T^B = 1\%$, $Ret_T^C = 3\%$
- Leader signal: $Signal_T^A = \frac{1}{2} (1 \cdot 1\% + 1 \cdot 3\%) = 2\%$
Timeline: portfolio formation

- **End of month**
  - \( \tau \), leader signals calculated
- **Start of month**
  - \( \tau + 1 \), portfolios formed
- **New portfolios**
  - Formed on new set of leader signals

**Regression window**: \( \tau - 11 \) to \( \tau \)

**Portfolio holding period**: \( \tau \) to \( \tau + 2 \)
Portfolio formation

• Sort all followers by their leader signal in month $\tau$, form equal- or value-weighted portfolios in month $\tau + 1$
  • sort within industries or not (36 or 12 industries)

• Baseline specification:
  • monthly returns
  • 12-month rolling window
  • equal-weighted leader signals
  • within-industry sorting (36 industries)

• Include only followers that:
  • had a trade on the last day of previous month
  • are priced at $\geq$ $5$/share, inflation-adjusted
## Equal-weighted portfolio returns

<table>
<thead>
<tr>
<th>Decile</th>
<th>Leader signal</th>
<th>Excess return</th>
<th>Market alpha</th>
<th>3-factor alpha</th>
<th>4-factor alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-3.58%</td>
<td>0.52%</td>
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<tr>
<td></td>
<td>(1.93)</td>
<td>(-2.25)</td>
<td>(-5.81)</td>
<td>(-4.61)</td>
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</tr>
<tr>
<td>2</td>
<td>-1.99%</td>
<td>0.71%</td>
<td>0.00%</td>
<td>-0.16%</td>
<td>-0.10%</td>
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<tr>
<td></td>
<td>(3.02)</td>
<td>(0.03)</td>
<td>(-2.78)</td>
<td>(-1.62)</td>
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</tr>
<tr>
<td>3</td>
<td>-1.26%</td>
<td>0.80%</td>
<td>0.10%</td>
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<tr>
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<td>(1.13)</td>
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<tr>
<td>9</td>
<td>1.88%</td>
<td>1.21%</td>
<td>0.45%</td>
<td>0.21%</td>
<td>0.29%</td>
</tr>
<tr>
<td></td>
<td>(4.68)</td>
<td>(4.07)</td>
<td>(3.62)</td>
<td>(5.04)</td>
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</tr>
<tr>
<td>10</td>
<td>3.54%</td>
<td>1.35%</td>
<td>0.52%</td>
<td>0.25%</td>
<td>0.27%</td>
</tr>
<tr>
<td></td>
<td>(4.68)</td>
<td>(3.82)</td>
<td>(3.29)</td>
<td>(3.52)</td>
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<tr>
<td>10-1</td>
<td>0.83%</td>
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<td>0.71%</td>
<td>0.64%</td>
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<tr>
<td></td>
<td>(7.35)</td>
<td>(7.03)</td>
<td>(6.48)</td>
<td>(5.73)</td>
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</tr>
</tbody>
</table>
## Value-weighted portfolio returns

<table>
<thead>
<tr>
<th>Decile</th>
<th>Leader signal</th>
<th>Excess return</th>
<th>Market alpha</th>
<th>3-factor alpha</th>
<th>4-factor alpha</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-2.85%</td>
<td>0.34%</td>
<td>-0.36%</td>
<td>-0.39%</td>
<td>-0.34%</td>
</tr>
<tr>
<td></td>
<td>(1.46)</td>
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<tr>
<td>2</td>
<td>-1.70%</td>
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<tr>
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<td>-1.09%</td>
<td>0.53%</td>
<td>-0.04%</td>
<td>-0.05%</td>
<td>-0.02%</td>
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<tr>
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<td>(2.88)</td>
<td>(-0.85)</td>
<td>(-0.88)</td>
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<tr>
<td>9</td>
<td>1.58%</td>
<td>0.77%</td>
<td>0.14%</td>
<td>0.09%</td>
<td>0.10%</td>
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<tr>
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<td>(3.77)</td>
<td>(2.21)</td>
<td>(1.45)</td>
<td>(1.67)</td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>2.81%</td>
<td>0.85%</td>
<td>0.16%</td>
<td>0.07%</td>
<td>0.04%</td>
</tr>
<tr>
<td></td>
<td>(3.68)</td>
<td>(1.76)</td>
<td>(0.83)</td>
<td>(0.48)</td>
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</tr>
<tr>
<td>10-1</td>
<td>0.52%</td>
<td>0.52%</td>
<td>0.45%</td>
<td>0.38%</td>
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<tr>
<td></td>
<td>(4.08)</td>
<td>(4.09)</td>
<td>(3.60)</td>
<td>(2.98)</td>
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</tr>
</tbody>
</table>
Cumulative return: monthly portfolios

- End value: $2,010.09 for EW and $75.26 for VW

A. Scherbina, Cross-Firm Information Flows
Alternative specifications

1. Use 36-month trailing period to determine leaders
   - Works substantially better for EW portfolios
2. Value-weight leader signals:
   - Works worse because signals from small leaders are incorporated slower but are being underweighted
3. Sort over entire sample and not within industry
   - Higher return differentials
4. Alternative signal aggregation methods:
   - leader returns are equal-weighted, disregarding $\hat{b}_3$
   - leader returns are weighted by $t\text{-stat}(\hat{b}_3)$
     - both methods produce similar results
Other results

- Waiting one month produces significant returns for EW but no longer for VW portfolios.
- Signals from “positive leaders” work better than from “negative leaders” in forecasting returns.
- Restricting the leader sample to leaders exclusively from other industries and leaders smaller than the follower also works.
- Both transitory and recurring leaders are significant predictors of followers’ returns.
- Predictability independent from quarterly earnings announcements of leaders or followers.
- Predictive ability of leader signals is independent of other known cross-sectional predictors of stock returns.
- Return predictability at monthly frequency declined over time.
Higher frequencies

• Pros
  • can estimate regression coefficients more precisely in shorter windows
  • can identify short-term leader-follower relations
  • would identify shorter delays in price reaction

• Cons
  • more regressions to run
  • trading strategies would work only if stocks are sufficiently liquid
### Weekly-frequency leaders, weekly portfolios (1980-2011)

#### Equal-weighted

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Excess return</th>
<th>Market alpha</th>
<th>3-factor alpha</th>
<th>4-factor alpha</th>
</tr>
</thead>
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<tr>
<td>10-1</td>
<td>0.53%</td>
<td>0.54%</td>
<td>0.55%</td>
<td>0.53%</td>
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<tr>
<td></td>
<td>(12.63)</td>
<td>(12.79)</td>
<td>(12.83)</td>
<td>(12.54)</td>
</tr>
</tbody>
</table>

#### Value-weighted

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Excess return</th>
<th>Market alpha</th>
<th>3-factor alpha</th>
<th>4-factor alpha</th>
</tr>
</thead>
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<tr>
<td>10-1</td>
<td>0.28%</td>
<td>0.29%</td>
<td>0.32%</td>
<td>0.29%</td>
</tr>
<tr>
<td></td>
<td>(6.27)</td>
<td>(6.50)</td>
<td>(6.96)</td>
<td>(6.30)</td>
</tr>
</tbody>
</table>

- Return differentials survive also at a 1-week lag, more so for EW portfolios.
Cumulative return: weekly portfolios

- End value: $5,749.11 for EW and $79.78 for VW

A. Scherbina, Cross-Firm Information Flows
### Conditioning on prior-week return, weekly portfolios

<table>
<thead>
<tr>
<th>Signal quintile</th>
<th>Prior week’s return quintile</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>5-1</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Equal-weighted returns</strong></td>
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<tr>
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<td>-0.19%</td>
<td>-0.35%</td>
<td><strong>-0.78%</strong></td>
<td>-1.19%</td>
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<td>(-8.43)</td>
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<td>(-18.4)</td>
<td>(-18.74)</td>
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<tr>
<td>5</td>
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<td><strong>0.91%</strong></td>
<td>0.37%</td>
<td>0.19%</td>
<td>0.05%</td>
<td>-0.34%</td>
<td>-1.25%</td>
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<td></td>
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<td>(18.52)</td>
<td>(13.22)</td>
<td>(7.56)</td>
<td>(2.08)</td>
<td>(-11.3)</td>
<td>(-19.99)</td>
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<td>(10.90)</td>
<td>(11.88)</td>
<td>(10.84)</td>
<td>(11.40)</td>
<td>(10.63)</td>
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<td><strong>Value-weighted returns</strong></td>
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<tr>
<td>1</td>
<td></td>
<td>0.25%</td>
<td>0.01%</td>
<td>-0.13%</td>
<td>-0.26%</td>
<td><strong>-0.53%</strong></td>
<td>-0.78%</td>
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<td>(5.74)</td>
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<td>(-3.87)</td>
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<td>(-11.18)</td>
<td>(-11.98)</td>
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<td>5</td>
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<td><strong>0.49%</strong></td>
<td>0.27%</td>
<td>0.11%</td>
<td>-0.01%</td>
<td>-0.27%</td>
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<tr>
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<td>(10.43)</td>
<td>(7.65)</td>
<td>(3.72)</td>
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<td>(-6.81)</td>
<td>(-12.30)</td>
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<tr>
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<td>0.25%</td>
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<tr>
<td></td>
<td></td>
<td>(4.16)</td>
<td>(5.18)</td>
<td>(5.14)</td>
<td>(5.84)</td>
<td>(4.35)</td>
<td></td>
</tr>
</tbody>
</table>
Break-even trading costs for the weekly strategy

• High trading costs
  • Portfolio turnover is high
  • Weekly trading frequency

• Break-even trading costs for the simple long-short strategy (portfolio 10-portfolio 1):
  • 0.15% for EW portfolios
  • 0.09% for VW portfolios.

• Break-even trading costs for the simple strategy based on the combination of leader signal and current return (portfolio 51 - portfolio 15):
  • 0.45% for EW portfolios
  • 0.27% for VW portfolios.

• For comparison, 0.25% is the average effective spread for a typical stock and a typical trade (Sadka and Scherbina (2007))

• \(\Rightarrow\) difficult to trade large amounts
### Annual news counts, TRNA dataset, average over 1996-2011

<table>
<thead>
<tr>
<th>Category</th>
<th>mean</th>
<th>median</th>
<th>5%</th>
<th>95%</th>
</tr>
</thead>
<tbody>
<tr>
<td>All news</td>
<td>92.67</td>
<td>14</td>
<td>0</td>
<td>370</td>
</tr>
<tr>
<td>Highly relevant</td>
<td>57.29</td>
<td>12</td>
<td>0</td>
<td>232</td>
</tr>
<tr>
<td>Highly relevant corporate</td>
<td>43.02</td>
<td>7</td>
<td>0</td>
<td>179</td>
</tr>
</tbody>
</table>

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Explaining the number of followers (1997-2011)

Leaders estimated at monthly frequency

<table>
<thead>
<tr>
<th></th>
<th>All highly relevant news</th>
<th>Highly rel. corp. events</th>
</tr>
</thead>
<tbody>
<tr>
<td>News (×10^2)</td>
<td>(1) 0.0075^a 0.0056^a</td>
<td>(1) 0.0100^a 0.0074^a</td>
</tr>
<tr>
<td></td>
<td>(2) 0.0112^a</td>
<td>(2) 0.0123^a</td>
</tr>
<tr>
<td></td>
<td>(3) 0.0056</td>
<td>(3) 0.0074</td>
</tr>
<tr>
<td></td>
<td>(6.30) (4.19)</td>
<td>(6.50) (4.58)</td>
</tr>
<tr>
<td></td>
<td>(6.15)</td>
<td>(5.40)</td>
</tr>
<tr>
<td>News^2 (×10^4)</td>
<td></td>
<td>-0.0002^a -0.0002^b</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(-3.81) (-2.46)</td>
</tr>
<tr>
<td>Inst. Own.</td>
<td>0.0359^a</td>
<td>0.358^a</td>
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<tr>
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<td>(6.63)</td>
<td>(6.60)</td>
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<tr>
<td></td>
<td>0.0351^a</td>
<td>0.0351^a</td>
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<td>(6.45)</td>
<td>(6.45)</td>
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<td>An. Cov.</td>
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<td>0.0020^a</td>
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<td>(6.83)</td>
<td>(6.88)</td>
</tr>
<tr>
<td></td>
<td>0.0018^a</td>
<td>(5.84)</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(6.24)</td>
</tr>
</tbody>
</table>

- 5th → 95th percentile of news coverage ⇒ 4 - 8 additional followers for a median stock

A. Scherbina, Cross-Firm Information Flows
Do sophisticated investors trade on this strategy?

• Data Explorers: data on stock loan trading (new positions, available inventory, number of loans, average loan fee, etc.) covering approximately 85% of the OTC securities lending market
  • Daily frequency: 3 July 2006 to present
  • Weekly frequency: 4 August 2004 to 28 June 2006
  • Monthly frequency: 22 May 2002 to 21 July 2004
Utilisation

- Utilisation = Shares sold short / shares available for lending

- ban on naked short selling of 19 fin. stocks: 21 Jul-12 Aug’08
- permanent ban on naked short selling: form 18 Sep’08
- ban on short selling of about 976 fin. stocks: 18 Sep-8 Oct’08

A. Scherbina, Cross-Firm Information Flows
Do sophisticated investors trade on this strategy?

- Fama-MacBeth weekly regressions, after end of ban on short selling fin. stocks: 8 Oct’08 - 31 Dec’11; remove stocks “on special”

\[
\Delta Utilisation_{it} = b_0 + b_1 \times \mathbb{1}\{\text{entered bottom signal decile}\}_{it} \\
+ b_2 \times \mathbb{1}\{\text{exited bottom signal decile}\}_{it} \\
+ b_3 \times \mathbb{1}\{\text{entered top return decile}\}_{it} \\
+ b_4 \times \mathbb{1}\{\text{exited top return decile}\}_{it} \\
+ b_5 \times \mathbb{1}\{\text{entered top ind. return decile}\}_{it} \\
+ b_6 \times \mathbb{1}\{\text{exited top ind. return decile}\}_{it} + \epsilon_{it}
\]

| \(\hat{b}_1\) | 0.041** |
| (\%) | (2.11) |
| \(\hat{b}_2\) | 0.016 |
| (\%) | (0.80) |

A. Scherbina, Cross-Firm Information Flows
Summary

- Firm-level information leaders identified with Granger causality regressions generate significant return predictability for followers at monthly (weekly) horizons.

- Limited attention/costly information processing are likely explanations:
  - Equal-weighted portfolios produce higher returns.
  - Equal-weighting signals across leaders works best (investors are more likely to overlook signals from smaller leaders).
  - Predictive power lower after quarterly earnings announcements.
  - Returns of the long-short portfolio decline over time.

- The return predictability works within industries.

- Some leaders are transitory, small and not easily identifiable ex-ante.

- Leadership scope is positively related to news developments at the firm level, but nonlinearly.

- Short sellers trade on this strategy.

- The presence of sophisticated traders speeds up information diffusion.
Possible extensions

- Improve the identification of “true” leaders
- More efficient signal aggregation
- Volatility transmission
  - implications for option returns
- Apply to entire sectors or industries
  - Hou, Scherbina, Tang and Wilhelm (2012) identify transitory industry leaders that include small stocks
- Apply to the entire market
- Switch to higher frequencies, include more return lags
  - allows to more reliably identify short-lived leader-follower pairs