Cross-Firm Information Flows

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The Q Group Conference

April 1, 2015

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 $\Rightarrow$ 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 pracititoners

- 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: $\approx 0.14\%$ 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:

$$Ret_t^i = b_0^{ij} + b_1^{ij} Ret_{t-1}^{mkt} + b_2^{ij} Ret_{t-1}^i + b_3^{ij} Ret_{t-1}^j + \epsilon_t^{ij}$$

- 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-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 τ, we aggregate the leader signal across all leaders $j = 1, ..., J_\tau^i$ for stock i:

$$Signal_\tau^i = \sum_{j=1}^{J_\tau^i} w_j \hat{b}_{3\tau}^{ij} Ret_\tau^j$$

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

$$Signal_\tau^i = \sum_{j=1}^{J_\tau^i} w_j \text{sign}(\hat{b}_3) Ret_\tau^j$$

  1. Equal-weight all leaders' returns
  2. Value-weight
  3. Weight by | t-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

Example

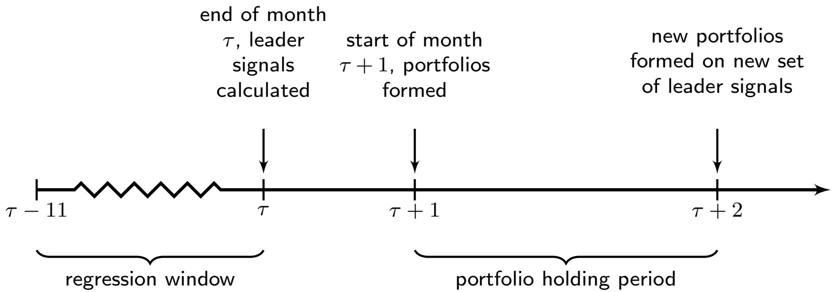
- Leader stocks B and C for follower stock A
- Regression estimated at τ:

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

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: $Ret_\tau^B = 1\%$, $Ret_\tau^C = 3\%$
- Leader signal: $Signal_\tau^A = \frac{1}{2}(1 \cdot 1\% + 1 \cdot 3\%) = 2\%$

Timeline: portfolio formation



Portfolio formation

- Sort all followers by their leader signal in month τ, 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 the last day of previous month
  - are priced at $\geq$ \$5/share, inflation-adjusted

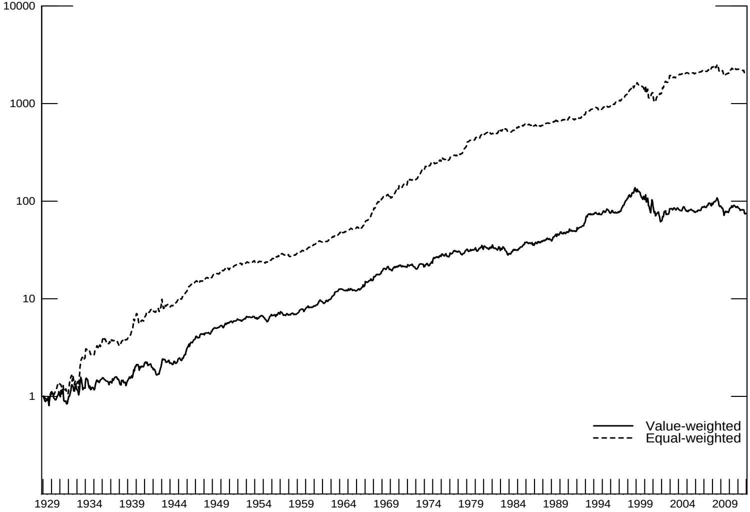
Equal-weighted portfolio returns

Decile	Leader signal	Excess return	Market alpha	3-factor alpha	4-factor alpha
1	-3.58%	0.52%	-0.27%	-0.47%	-0.37%
		(1.93)	(-2.25)	(-5.81)	(-4.61)
2	-1.99%	0.71%	0.00%	-0.16%	-0.10%
		(3.02)	(0.03)	(-2.78)	(-1.62)
3	-1.26%	0.80%	0.10%	-0.08%	0.02%
		(3.44)	(1.13)	(-1.75)	(0.44)
⋮					
9	1.88%	1.21%	0.45%	0.21%	0.29%
		(4.68)	(4.07)	(3.62)	(5.04)
10	3.54%	1.35%	0.52%	0.25%	0.27%
		(4.68)	(3.82)	(3.29)	(3.52)
10-1		**0.83%**	**0.79%**	**0.71%**	**0.64%**
		(7.35)	**(7.03)**	**(6.48)**	**(5.73)**

Value-weighted portfolio returns

Decile	Leader signal	Excess return	Market alpha	3-factor alpha	4-factor alpha
1	-2.85%	0.34%	-0.36%	-0.39%	-0.34%
		(1.46)	(-4.37)	(-4.67)	(-4.07)
2	-1.70%	0.49%	-0.12%	-0.13%	-0.10%
		(2.50)	(-2.02)	(-2.14)	(-1.68)
3	-1.09%	0.53%	-0.04%	-0.05%	-0.02%
		(2.88)	(-0.85)	(-0.88)	(-0.29)
⋮					
9	1.58%	0.77%	0.14%	0.09%	0.10%
		(3.77)	(2.21)	(1.45)	(1.67)
10	2.81%	0.85%	0.16%	0.07%	0.04%
		(3.68)	(1.76)	(0.83)	(0.48)
10-1		**0.52%**	**0.52%**	**0.45%**	**0.38%**
		(4.08)	**(4.09)**	**(3.60)**	**(2.98)**

Cumulative return: monthly portfolios



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

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-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" is 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 predicability 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

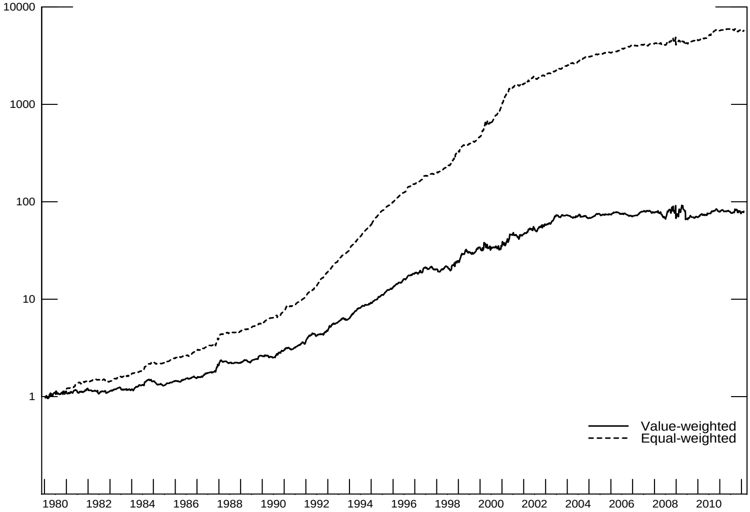
Portfolio	Excess return	Market alpha	3-factor alpha	4-factor alpha
10-1	0.53%	0.54%	0.55%	0.53%
	(12.63)	(12.79)	(12.83)	(12.54)

Value-weighted

Portfolio	Excess return	Market alpha	3-factor alpha	4-factor alpha
10-1	0.28%	0.29%	0.32%	0.29%
	(6.27)	(6.50)	(6.96)	(6.30)

- 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

Conditioning on prior-week return, weekly portfolios

Signal quintile	Prior week's return quintile 1	2	3	4	5	5-1	
Equal-weighted returns							
1	0.41%	-0.04%	-0.19%	-0.35%	**-0.78%**	-1.19%	
	(11.43)	(-1.80)	(-8.43)	(-13.2)	(-18.4)	(-18.74)	
...							
5	**0.91%**	0.37%	0.19%	0.05%	-0.34%	-1.25%	
	(18.52)	(13.22)	(7.56)	(2.08)	(-11.3)	(-19.99)	51-15
5-1	0.50%	0.41%	0.38%	0.39%	0.44%		**1.69%**
	(10.90)	(11.88)	(10.84)	(11.40)	(10.63)		(20.51)
Value-weighted returns							
1	0.25%	0.01%	-0.13%	-0.26%	**-0.53%**	-0.78%	
	(5.74)	(0.26)	(-3.87)	(-8.16)	(-11.18)	(-11.98)	
...							
5	**0.49%**	0.27%	0.11%	-0.01%	-0.27%	-0.77%	
	(10.43)	(7.65)	(3.72)	(-0.25)	(-6.81)	(-12.30)	51-15
5-1	0.24%	0.26%	0.25%	0.26%	0.26%		**1.03%**
	(4.16)	(5.18)	(5.14)	(5.84)	(4.35)		(13.73)

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

	mean	median	5%	95%
All news	92.67	14	0	370
Highly relevant	57.29	12	0	232
Highly relevant corporate	43.02	7	0	179

Explaining the number of followers (1997-2011)

Leaders estimated at monthly frequency

	All highly relevant news			Highly rel. corp. events		
	(1)	(2)	(3)	(4)	(5)	(6)
News ($\times 10^2$)	**0.0075^a**	**0.0056^a**	**0.0112^a**	**0.0100^a**	**0.0074^a**	**0.0123^a**
	(6.30)	**(4.19)**	**(6.15)**	**(6.50)**	**(4.58)**	**(5.40)**
News^2 ($\times 10^4$)			**-0.0002^a**			**-0.0002^b**
			(-3.81)			**(-2.46)**
Inst. Own.		0.0359^a	0.0351^a		0.358^a	0.0351^a
		(6.63)	(6.45)		(6.60)	(6.45)
An. Cov.		0.0020^a	0.0018^a		0.0020^a	0.0019^a
		(6.83)	(5.84)		(6.88)	(6.24)
⋮						

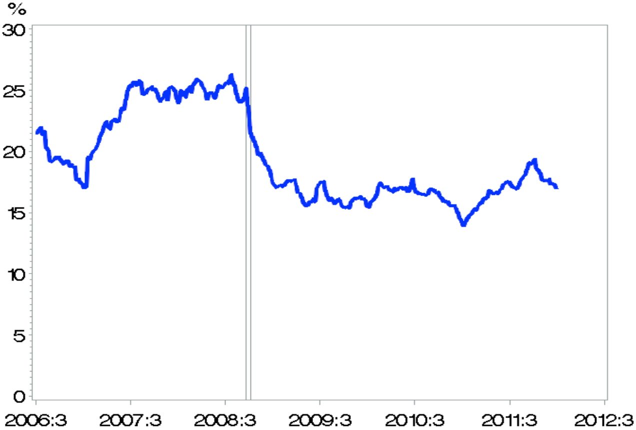
- 5th $\rightarrow$ 95th percentile of news coverage $\Rightarrow$ 4 - 8 additional followers for a median stock

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

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"

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

	(%)
$\hat{b_1}$	0.041**
	(2.11)
$\hat{b_2}$	0.016
	(0.80)

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