News and network structures in equity market volatility

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Background

- A lot of focus the link between news flow and volatility of a single asset or market
- Little understanding of how the news flow relating to a specific asset influences its relationships with other assets
- Moving beyond a single asset, there a lot of models for correlation (often MGARCH) capturing the association between assets
- Correlation is a linear and symmetric pairwise measure of association
- Therefore correlation is of limited value in understanding broader linkages between multiple assets

Background

- Network structures offers a framework to analyse the interconnections between a potentially large number of assets
- Network analysis has been used in various areas of science
- It has gained popularity in the finance literature since the GFC
- Diebold and Yilmaz (2014) proposed network models for systemic risk
- They propose a number of summary measures of network structure
- We employ and extend this framework

Previous work: volatility and news

- Well developed literature examining drivers of volatility
- For example, macroeconomic announcements (Ederington and Lee, 1993) political interventions (Christies-David and Chaudry, 1999) or earnings announcements (Hautsch, Hess and Veradas, 2011)
- Individual equities and news announcements (many of these do use the same data as the current study):
  - Kalev, Liu, Pham and Jarnecic (2004) individual company news announcements of daily volatility
  - Ho, Shi and Zhang (2013) examine impact of firm specific and macroeconomic announcements on daily volatility of US firms
  - Groß-Klußmann and Hautsch (2011) look at how news arrivals influence high frequency trading activity in UK individual stocks
  - Riordan, Storkenmaier, Wagener and Zhang (2013) examine impact of newswire messages on intraday price discovery, liquidity, and trading intensity of Canadian stocks

Research ideas

- A network structure is used to examine the links between (the structure in) the volatility of a portfolio of stocks
- Examine how the structure in volatility linkages change over time
- Consider how news arrivals relating to individual firms impact on:
  - Their importance within a larger portfolio
  - Response to the behaviour other assets in a portfolio
  - Characteristics of the portfolio (in terms of linkages within the portfolio) as a whole
- Attempt to directly identify the structure in the linkages due to news flow

Data and volatility

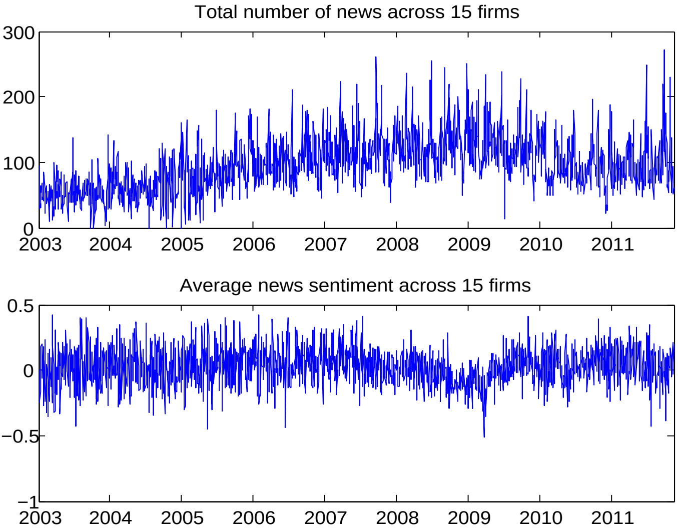
- Data relates to a portfolio of 15 large stocks (are all members of the Dow Jones)
- Sample period is 28 January 2003 to 05 December 2011, representing 2218 trading days
- Prices from TRTH are sampled at a 10-minute frequency to construct estimates of daily volatility
- Simple daily RV estimates are constructed from these 10 minute returns:

$$RV_t^i = \sum_{j=1}^{M} r_{i,t_j}^2$$

News and sentiment

- Pre-processed news data from the Thomson Reuters News Analytics database
- The text of news items broadcast over the Reuters network are analysed using linguistic pattern recognition algorithms
- Wide range of characteristics attached to each news item for each firm: relevance to the specific firm, sentiment and novelty
- Sentiment for each news item is coded +1, 0, -1 for positive, neutral and negative tones
- We take all ARTICLES which are new items with headline and body
- Given all items for each firm, for each day take measures of:
  - The total number of news items for firm j (denoted below as $NF_{j,t}$)
  - The average sentiment of news for firm j (denoted below as $NS_{j,t}$)

News and sentiment across the 15 stocks



Measuring network structure

- Diebold and Yilmaz (2014) propose a method for analysing network structure
- Based on Vector AutoRegression (VAR) and variance decompositions
- Here we are interested in how this structure changes over time
- Employ the time varying VAR approach of Gary and Dimitris (2013) (as opposed to rolling windows):

$$\mathbf{y_t} = \mathbf{Z_t}\beta_\mathbf{t} + \varepsilon_\mathbf{t},$$

and

$$\beta_\mathbf{t+1} = \beta_\mathbf{t} + \mathbf{u_t},$$

- $\mathbf{y_t}$ is vector containing 15 RV.

Measuring network structure

- Examine the share of forecast error variation in one firm's RV due to shocks arising from other firms' RVs: variance decomposition
- d_{ij}^{H} measures the fraction of variable $i's$ H-step forecast error variance due to shocks in variable j:

$$d_{ij,t}^{H} = \frac{\sigma_{jj,t}^{-1} \sum_{h=0}^{H-1} (e_{i,t}' A_{t,H} \Sigma_t e_{j,t})^2}{\sum_{h=0}^{H-1} (e_{i,t}' A_{t,H} \Sigma_t A_{t,H}' e_{i,t})},$$

- $e_{j,t}$ is a selection vector with *jth* element unity and zeros elsewhere at time t
- $A_{t,H}$ is the coefficient matrix of the H-lagged shock vector in the infinite MA representation of the VAR model
- Σ_t is the covariance matrix of the shock vector in the VAR

Measuring network structure

Table: Network Connectedness Matrix

	Y_1	Y_2	$\cdots$	Y_N	From Others
Y_1	d_{11}^H	d_{12}^H	$\cdots$	d_{1N}^H	$\sum_{j=1,j\neq 1}^N d_{1j}^H,$
Y_2	d_{21}^H	d_{22}^H	$\cdots$	d_{2N}^H	$\sum_{j=1,j\neq 2}^N d_{2j}^H,$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
Y_N	d_{1N}^H	d_{2N}^H	$\cdots$	d_{NN}^H	$\sum_{j=1,j\neq N}^N d_{Nj}^H,$
To Others	$\sum_{i=1,i\neq 1}^N d_{i1}^H,$	$\sum_{i=1,i\neq 2}^N d_{i2}^H,$		$\sum_{i=1,i\neq N}^N d_{iN}^H,$	$\frac{1}{N}\sum_{j=1,i\neq j}^N d_{ij}^H,$

Measuring network structure

- Can now define a number of measures of connectedness
- Directional connectedness:

$$C^H_{i \leftarrow j} = d^H_{ij}$$

- In general $C^H_{i \leftarrow j} \neq C^H_{j \leftarrow i}$, $\therefore 15^2 - 15$ separate pairwise directional
- Total directional connectedness from others to i (fragility, $f_{i,t}$)

$$C_{i \leftarrow \bullet} = \sum_{j=1, j \neq i}^{N} d^H_{ij},$$

Measuring network structure

- Total directional connectedness to others from j (centrality, $c_{j,t}$)

$$C_{\bullet \leftarrow j} = \sum_{i=1, i \neq j}^{N} d_{ij}^{H}.$$

- Grand total of the off-diagonal entries in D^H measures total connectedness (TC_t),

$$C^{H} = \frac{1}{N} \sum_{i,j=1, i \neq j}^{N} d_{ij}^{H}.$$

- Summarises the total structure in the system into a single number reflecting the total interdependency in the system

News and network structure

- Impact of news on the whole portfolio:

$$TC_t = \gamma_0 + \gamma_1 RV_{index} + \gamma_2 \sum_{j=1}^{N} NF_{j,t} + \gamma_3 \frac{1}{N} \sum_{j=1}^{N} NS_{j,t} + \varepsilon_{i,t}$$

- Impact of news at the individual firm level:

$$\begin{aligned} f_{i,t} &= \alpha_0 + \alpha_1 RV_{index} + \alpha_2 \sum_{j=1, j\neq i}^{N-1} NF_{j,t} + \alpha_3 \frac{1}{N-1} \sum_{j=1, j\neq i}^{N-1} NS_{j,t} + \varepsilon_{i,t} \\ c_{i,t} &= \beta_0 + \beta_1 RV_{index} + \beta_2 NF_{i,t} + \beta_3 NS_{i,t} + \varepsilon_{i,t} \end{aligned}$$

- These have been estimated using both pooled and panel regressions
- Both raw $NS_{j,t}$ and the difference between $NS_{j,t}$ and mean sentiment of all other firms has been used

Does the impact of news change over time?

- Two measures of market conditions are used:
  - RV_t, the volatility of the Dow Jones Index
  - Aruoba-Diebold-Scotti business conditions index, denoted below as BC_t
- To capture changes in market conditions two indicator variables are defined:
  - $\mathbb{I}(BC_t < 0)$ indicates below average macroeconomic conditions
  - $\mathbb{I}(RV_t > \overline{RV})$ indicates above average volatility.

Does the impact of news change over time?

$$
\begin{aligned}
TC_t &= \gamma_0 + \gamma_1 BC_t + \gamma_2 \sum_{j=1}^{N} NF_{j,t} \\
&+ \gamma_3 \frac{1}{N} \sum_{j=1}^{N} NS_{j,t} + \gamma_5 \sum_{j=1}^{N} NS_{j,t} \times \mathbb{I}(BC_t < 0) + \varepsilon_{i,t}, \\
f_{i,t} &= \alpha_0 + \alpha_1 BC_t + \alpha_2 \sum_{j=1,j\neq i}^{N-1} NF_{j,t} \\
&+ \alpha_3 \frac{1}{N-1} \sum_{j=1,j\neq i}^{N-1} NS_{j,t} + \alpha_4 \sum_{j=1,j\neq i}^{N-1} NS_{j,t} \times + \mathbb{I}(BC_t < 0)\varepsilon_{i,t}, \\
c_{i,t} &= \beta_0 + \beta_1 BC_t + \beta_2 NF_{i,t} + \beta_3 NS_{i,t} + \beta_4 NS_{i,t} \times \mathbb{I}(BC_t < 0) + \varepsilon_{i,t},
\end{aligned}
$$

- These are estimated with BC_t and $\mathbb{I}(BC_t < 0)$ replaced with RV_t and $\mathbb{I}(RV_t > \overline{RV})$

Preliminary full sample results

- Little to discern from individual pairwise connectedness
- Little variation in the centrality of the individual firms
- Implies that no single firm is much more important than the others
- Probably little surprise given that the stocks are all large firms
- Is a lot more variation in the fragility of individual firms

Total market connectedness

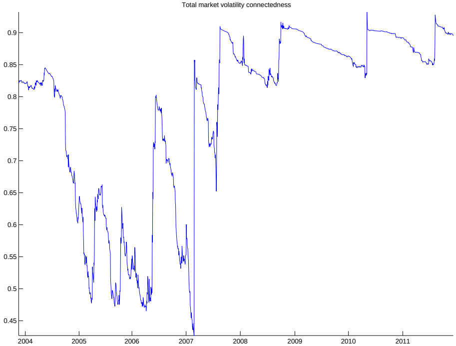


Figure: Time-varying Total Connectedness.

Centrality

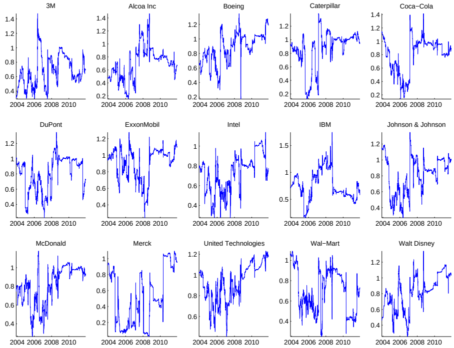


Figure: Time-varying centrality.

Fragility

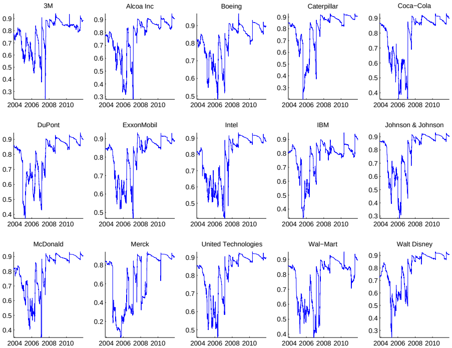


Figure: Time-varying fragility.

The impact of news on connectedness

Table: Regression Results of the Impact of News on Connectedness

	Centrality		Fragility		total market
	pool	panel	pool	panel	
Constant	0.7377	0.7489	0.7362	0.7504	0.7368
	342.9219	**461.8621**	**272.7534**	**687.8158**	**77.4195**
DJ index RV	47.3667	45.0114	41.9731	42.6709	42.3451
	17.6213	**18.1027**	**23.5252**	**24.4637**	**6.8415**
No. of News	0.0005	0.0012	0.0001	0.0001	0.0001
	2.7525	**5.9942**	**3.6542**	**3.2012**	0.9435
News Sentiment	-0.0138	-0.0178	-0.0772	-0.0677	-0.0726
	-4.1592	**-5.6745**	**-10.4886**	**-9.3967**	**-2.7653**

Does the impact of news change?

Table: Regression results based on BC_t and $\mathbb{I}(BC_t < 0)$.

	Centrality		Fragility		total market
	pool	panel	pool	panel	
Constant	0.7396	0.7492	0.7401	0.7529	0.7409
	349.8688	474.9544	272.7143	707.5783	77.3511
BC	-0.0298	-0.0281	-0.0263	-0.0269	-0.0266
	-17.8831	-18.1821	-23.1999	-24.2233	-6.7573
No. of News	0.0005	0.0012	7.26E-05	5.68E-05	5.73E-05
	2.4880	5.7070	2.5800	2.0541	0.61541
News Sentiment	0.0220	-0.0065	-0.0515	-0.0421	-0.0745
	4.1004	-1.2943	-4.4534	-3.7009	-2.2410
$\mathbb{I} \times Sent$	-0.0120	-0.0170	-0.0273	-0.0271	0.02935
	-1.7748	**-2.7209**	**-1.8756**	**-1.9042**	0.56660

Does the impact of news change?

Table: Regression results based on RV_t and $\mathbb{I}(RV_t > \overline{RV})$.

	Centrality		Fragility		total market
	pool	panel	pool	panel	
Constant	0.7377	0.7487	0.7362	0.7503	0.7368
	343.0178	461.7627	272.7602	685.5838	77.4056
DJ index RV	46.7564	44.3181	41.5693	42.2352	41.8761
	17.3713	17.8028	23.0093	23.9143	6.6779
No. of News	0.0005	0.0012	9.84E-05	8.4E-05	8.32E-05
	2.5192	5.7330	3.5337	3.07041	0.9033
News Sentiment	0.01945	-0.0114	-0.0720	-0.0621	-0.0664
	5.4096	-3.3452	-8.7634	-7.7211	-2.2616
$\mathbb{I} \times Sent$	-0.0366	-0.0416	-0.0275	-0.0297	-0.0322
	-4.0421	**-4.9727**	-1.4211	-1.5714	-0.4690

Other analysis

- Also directly measure the degree of volatility connectedness that is driven by news flow
- Include news flow as exogenous variables in the VAR structure
- Variance decomposition of the forecast errors related to the news flow
- Total connectedness driven by news has dropped off again after the GFC
- This is in contrast to connectedness due to total volatility spillovers
- Robustness check: Run weekly models on 5 minute RV using 1 minute returns
- This reveals very similar patterns in terms of the impact of news on connectedness measures

News driven connectedness

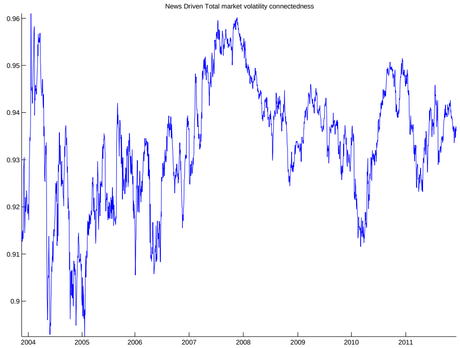


Figure: News-driven total market volatility connectedness.

Concluding comments

- Impact of news on network links between the volatility of stock returns
- Total degree of market connectedness has increased since the GFC
- Total degree of market connectedness increase when negative news flow occurs
- Centrality increases when a firm experiences more (and negative) news and more when market conditions are poor
- Fragility increases as news flow of other firms increases (and is more negative)
- Total connectedness directly due to news flow peaks around the GFC and falls subsequently: stronger connections after GFC are not due to links in news

Current work

- We are currently doing more work along the following lines:
  - Dividend and earnings announcements (and their surprises) these are scheduled
  - Good earnings news reduces centrality and volatility spillovers
  - Bad news increases centrality but only moderately
  - Event study: reactions in centrality around scheduled announcements

Some ideas for the future

- Some ideas we are interested in pursuing further
  - Examining idiosyncratic volatility
  - Forecasting market instability
  - At an index level: Does the sensitivity to news flow change with connectedness
  - What is news: What are the impacts of news vs. large price chnages