Monetary Policy, Stock Market and Sectoral Comovement

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What we do

- The stock market is a key element in the transmission mechanism of monetary policy to the real economy
- The degree of comovement between sector-specific asset returns may vary significantly over time
- **What is the role that sectoral comovement plays in the propagation of monetary policy shocks on the stock market?**
- We study the effect of monetary policy shocks on stock returns in periods:
  - (i) when industries tend to move together.
  - (ii) when industries follow more idiosyncratic dynamics.
- Important implications: this information would allow policy makers to identify circumstances in which MP decisions are the most potent on financial markets.

Outline

1. High Frequency Analysis (Two steps)
    - Connectedness Index
    - Event study
2. Low Frequency Analysis (One step)
    - Nonlinear FAVAR
    - Impulse response analysis
3. Conclusions

30-industry Fama-French portfolio data

Abbreviation	*Industry definition*	*Abbreviation*	*Industry definition*
Food	Food Products	**Autos**	Automobiles and Trucks
Beer	Beer and Liquor	**Carry**	Aircraft, ships, and railroad equipment
Smoke	Tobacco Products	**Mines**	Precious Metals, Non-Metallic, Industrial Metal Mining
Games	Recreation	**Coal**	Coal
Books	Printing and Publishing	**Oil**	Petroleum and Natural Gas
Hshld	Consumer Goods	**Util**	Utilities
Clths	Apparels	**Telcm**	Communication
Hlth	Health care, Medical Equipment, Pharmaceutical Products	**Servs**	Personal and Business Services
Chems	Chemicals	**BusEq**	Business Equipment
Txtls	Textiles	**Paper**	Business Supplies and Shipping Containers
Cnstr	Construction and Construction Materials	**Trans**	Transportation
Steel	Steel Works Etc	**Whlsl**	Wholesale
FabPr	Fabricated Products and Machinery	**Rtail**	Retail
ElcEq	Electrical Equipment	**Meals**	Restaurants, Hotels, Motels
Fin	Banking, Insurance, Real Estate, Trading	**Other**	Everything Else

Stock Market Connectedness

- Industry stock returns are subject to complex interactions over time
- We estimate an index of "connectedness" by relying on a VAR at a daily frequency using the returns of the 30 industries portfolio from Fama-French:
  - We follow the line of Korobilis and Yilmaz (2016) where time-variation in the parameters of the VAR is approximated by forgetting factors
- The TVP-VAR can be represented as

$$y_t = \beta_t x_t + \epsilon_t,$$

$$\beta_t = \beta_{t-1} + \eta_t,$$

where $\epsilon_t \sim N(0, \Omega_t)$.

Link

Daily Connectedness Index

- Stock market connectedness experiences significant changes over time
- It tends to pick up during stock market turmoils (October 1987, October 2008)

Event study - regressions

- Monetary policy surprises can be calculated using the 30 days Federal Funds Futures (Bernanke and Kuttner (2005))

$$\Delta i^u = \frac{D}{D-d}(f^0_{m,d} - f^0_{m,d-1}).$$

- The expected component of the rate change is

$$\Delta i^e = \Delta i - \Delta i^u.$$

- The effects of monetary policy on industry-specific stock returns (sp^i_t) are obtained from

$$sp^i_t = \alpha + \beta^e \Delta i^e_t + \beta^u \Delta i^u_t + \epsilon_t.$$

Event study – What role for connectedness?

- Are strongly interconnected systems more prone to the propagation of monetary policy shocks?

- We include information about connectedness in the regression:

$$sp_t^i = \alpha + \beta^e \Delta i_t^e + \beta^u \Delta i_t^u + \beta^C \Delta C_t + \beta^{Cu} \Delta C_t \Delta i_t^u + \epsilon_t$$

- The term ΔC_t denotes the daily change in total connectedness on days of U.S. monetary policy announcements.

- The interaction term $\Delta C_t \Delta i_t^u$ captures the extent to which the effects of monetary policy surprises vary with different degrees of stock market connectedness.

Monetary policy surprises, the stock market, and connectedness

	β^u	β^{Cu}	F-test	Differential in stock returns
AUTOS	-1.873	-12.576***	13.454	-2.365
	(1.163)	(1.407)		
BUSEQ	-2.335	-26.082***	35.541	-4.905
	(2.208)	(2.890)		
FABPR	-2.972***	-12.936***	20.338	-2.433
	(0.929)	(1.262)		
FIN	-2.114*	-8.161***	5.897	-1.535
	(1.126)	(1.639)		
SP500	-3.495***	-9.720***	21.710	-1.828
	(0.804)	(2.031)		

Notes: Standard errors are in parenthesis. The F-test is a joint test for no effect of the monetary policy surprise (i.e., $(\beta^u, \beta^{Cu}) = (0, 0)$). The 5 percent critical value for an F distribution with 2 and 121 degrees of freedom is given by 3.07. The differential in stock returns column measures how much more a given industry reacts to monetary policy surprises when the change in total connectedness is in the 75th percentile compared with a situation where connectedness is in the 25th percentile (i.e. less connectedness).

Summary High Frequency Analysis

- The interaction term is negative for nearly all industries, suggesting that an increase in connectedness is associated with more negative responses of industry level stock returns to monetary policy surprises.
- The differential in stock returns column between high and low connectedness indicates that stronger connectedness leads to a more negative response of stock returns.

The Model (Non-linear FAVAR)

- It assesses shocks propagation, accounting for comovement:

$$\begin{bmatrix} Y_t \\ X_t \end{bmatrix} = \begin{bmatrix} I & 0 \\ \Lambda^Y & \Lambda^F_{S_t} \end{bmatrix} \begin{bmatrix} Y_t \\ F_t \end{bmatrix} + \begin{bmatrix} 0 \\ e^F_t \end{bmatrix}, \quad \begin{bmatrix} 0 \\ e^F_t \end{bmatrix} \sim N(0, \Omega)$$

$$\begin{bmatrix} Y_t \\ F_t \end{bmatrix} = \Phi_{S^*_t}(L) \begin{bmatrix} Y_{t-1} \\ F_{t-1} \end{bmatrix} + \begin{bmatrix} u^Y_t \\ u^F_t \end{bmatrix}, \quad \begin{bmatrix} u^Y_t \\ u^F_t \end{bmatrix} \sim N(0, \Sigma_{S^*_t})$$

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- The dynamics of the factor loadings are given by

$$\Lambda^F_{S_t} = (\lambda^F_{1,S_{1,t}}, \lambda^F_{2,S_{2,t}}, \ldots, \lambda^F_{N,S_{N,t}}), \quad \lambda_{i,S_{i,t}} = \lambda^F_{i,0} + \lambda^F_{i,1} S_{i,t}$$

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- The dynamics of the VAR equation are given by

$$\Phi_{S^*_t} = \Phi_0(1 - S^*_t) + \Phi_1 S^*_t, \quad \Sigma_{S^*_t} = \Sigma_0(1 - S^*_t) + \Sigma_1 S^*_t$$

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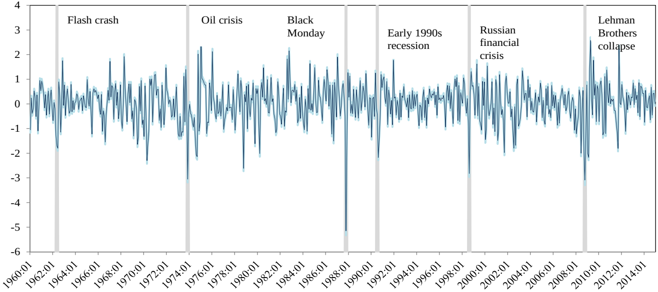
- Each state variable $S_{i,t}$ follows the dynamics of a two-state Markov chain with constant transition probability, and

$$S^*_t = \mathbb{I}\left(\frac{1}{N}\sum_{i=1}^{N} S_{i,t} > c\right) I$$

Data

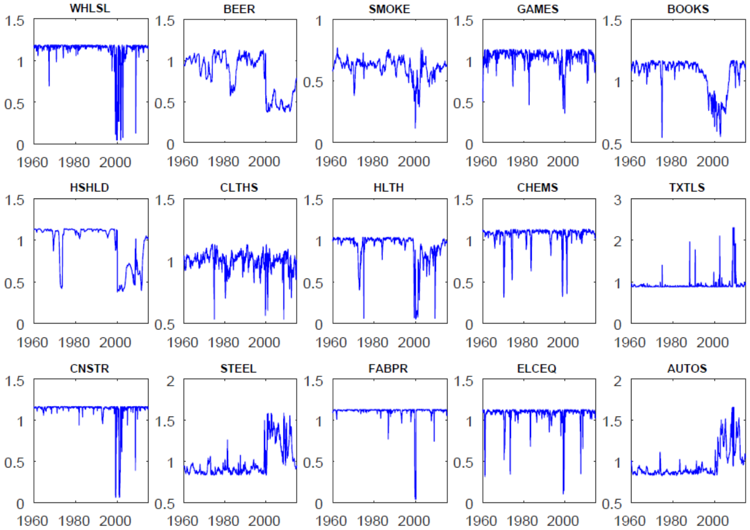
- The sample size extends from January 1960 to December 2014
- The vector Y_t includes: Industrial Production, CPI inflation, Commodity price index, Dividends, Effective feds funds rate (we use the Wu and Xia (2015) shadow interest rate from January 2009 onwards)
- The vector X_t collects the 30 industry-specific equity returns from the Fama-French database (we extract one factor for ease of interpretation)
- We use a recursive identification scheme (same ordering as in Gali and Gambetti (2015))

Factor extracted from the 30 industry portfolio

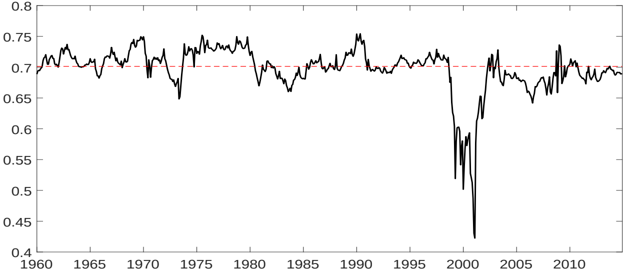


- The estimated factor exhibits a correlation of 0.7 with the returns form the S&P500
- Hence, it can be interpreted as an indicator of the overall performance of the US stock market

Time-varying factor loadings for selected industries



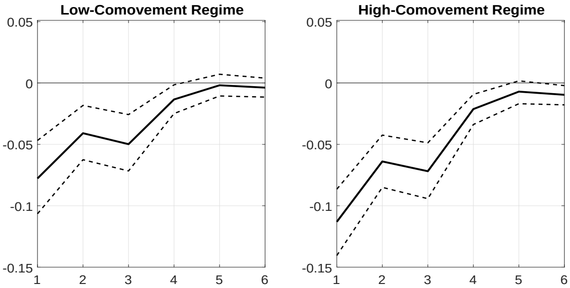
Changes in comovement across industry stock returns



- The figure plots the latent variable that measure the overall degree of comovement across industries, S_t^*.
- Most of industries experienced a declined in comovement around the early 2000s.

Impulse Responses

- Effect of monetary policy shocks on stock returns during:



- In the high-comovement regime, responses of stock returns are amplified compared with responses in the low-comovement regime

- This finding lines up well with the results from the event study

Network of industry-specific stock returns

- The model allows to characterize the interactions among industries:

$$q_{i,j}^{(l)} = 1 - \frac{1}{T} \sum_{t=1}^{T} \left(S_{i,t}^{(l)} - S_{j,t}^{(l)} \right)^2 \tag{1}$$

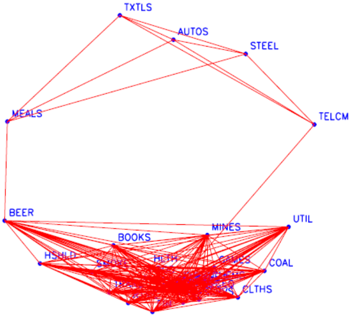
- If industries i and j are highly interconnected, they should experience similar degrees of comovement with the factor: $q_{i,j} \simeq 1$

- All relationships are collected in an adjacency matrix (network)

$$Q = \begin{pmatrix} 0 & q_{1,2} & q_{1,3} & \cdots & q_{1,m} \\ q_{2,1} & 0 & q_{2,3} & \cdots & q_{2,m} \\ q_{3,1} & q_{3,2} & 0 & \cdots & q_{3,m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ q_{m,1} & q_{m,2} & q_{m,3} & \cdots & 0 \end{pmatrix} \tag{2}$$

Network of industry-specific stock returns

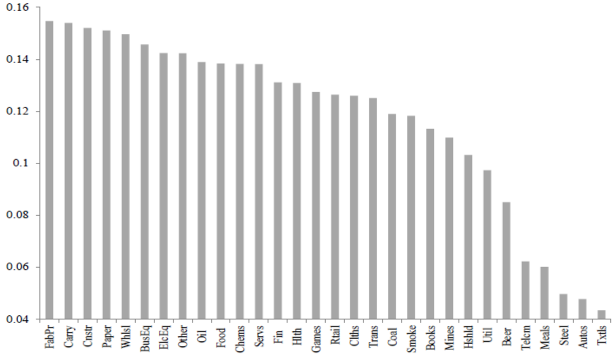
- The network has a core-periphery structure, with a dense core and a sparse periphery



Bilateral relations with $q_{i,j} > 0.5$

Centrality of network of industry-specific stock returns

- We quantify the interconnection of a given industry by computing its corresponding closeness centrality

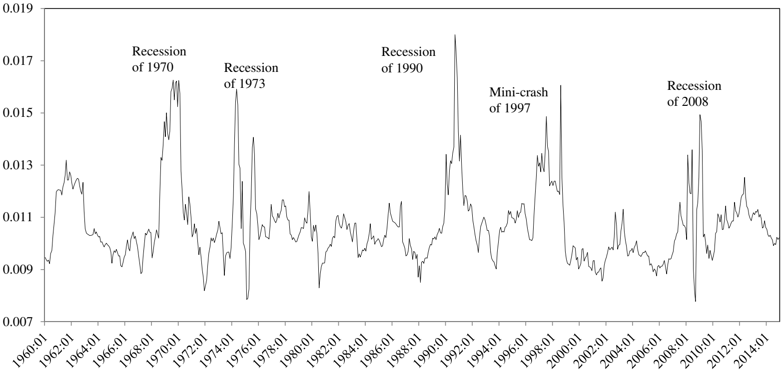


Conclusions

- The effect of monetary policy shocks on the stock market is amplified (about twice) when industries exhibit a higher degree of comovement
- There is a set of key industries acting as main conduits in the propagation of monetary policy shocks throughout the stock market
- We propose an econometric framework that allows us to:
    1. Identify periods in which monetary policy decisions could be the most potent on the stock market
    2. Provide a detailed characterization of the connectedness of industry-specific stock markets

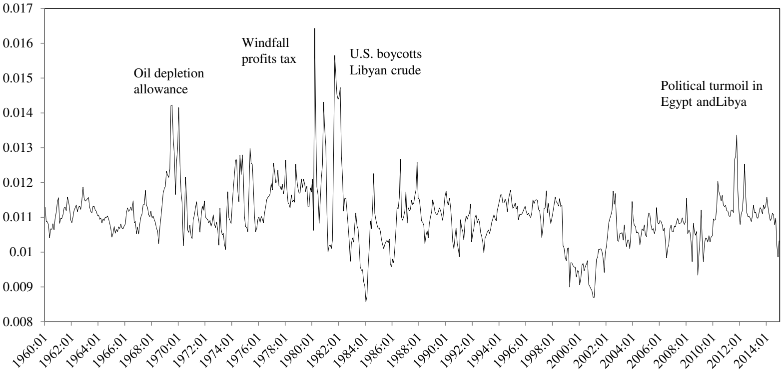
Time-varying Centrality of Industries

- **Financial Industry**



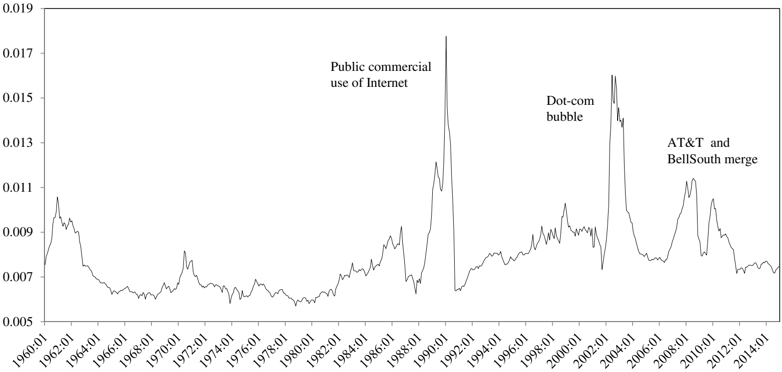
Time-varying Centrality of Industries

- **Oil Industry**



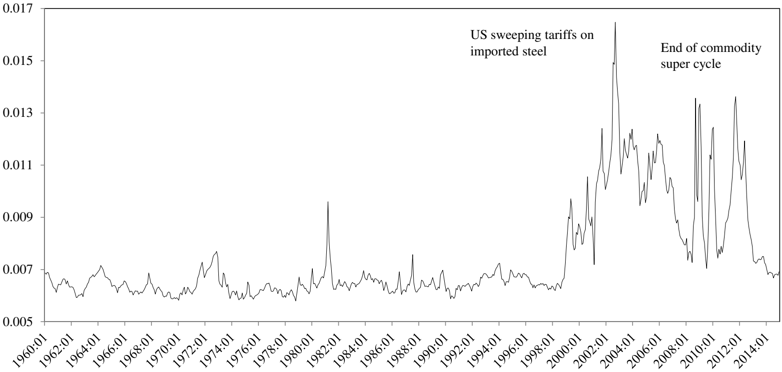
Time-varying Centrality of Industries

- **Telecommunications Industry**



Time-varying Centrality of Industries

- **Steel Industry**



Details on the large TVP-VAR

- The TVP-VAR can be represented as

$$y_t = \beta_t x_t + \epsilon_t,$$

$$\beta_t = \beta_{t-1} + \epsilon_t,$$

where $\eta_t \sim N(0, \Omega_t)$.

- Initial conditions for the model are given by $\beta_0 \sim N(m_0, C_0)$, $\Sigma_0 \sim iW(S_0, n_0)$
- Time t priors are given by

$$\beta_t | D_{t-1} \sim N(m_{t|t-1}, C_{t|t-1})$$

$$\Sigma_t | D_{t-1} \sim iW(S_{t|t-1}, n_{t|t-1}$$

where $m_{t|t-1} = m_{t-1}$, $C_{t|t-1} = \frac{1}{\lambda} C_{t-1}$, $S_{t|t-1} = S_{t-1}$, and $n_{t|t-1} = \delta n_{t-1}$

- Variance discounting/forgetting factors (approximations), λ, $\delta \in (0, 1]$

Link

From variance decompositions to Connectedness index

Variance Decomposition / Connectedness Table

	x_1	x_2	...	x_N	From others
x_1	d_{11}^H	d_{12}^H	...	d_{1N}^H	$\sum_{j\neq 1} d_{1j}^H$
x_2	d_{21}^H	d_{22}^H	...	d_{2N}^H	$\sum_{j\neq 2} d_{2j}^H$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
x_N	d_{N1}^H	d_{N2}^H	...	d_{NN}^H	$\sum_{j\neq N} d_{Nj}^H$
To others	$\sum_{i\neq 1} d_{i1}^H$	$\sum_{i\neq 2} d_{i2}^H$	...	$\sum_{i\neq N} d_{iN}^H$	$1/N \sum_{i\neq j} d_{ij}^H$

- "From" connectedness: $\sum_{j=1,j\neq i}^{N} d_{ij}^H$
- "To" connectedness: $\sum_{i=1,j\neq i}^{N} d_{ij}^H$
- "Net" connectedness: "To" connectedness - "From" connectedness
- "Total" connectedness: $\frac{1}{N} \sum_{i,j=1,i\neq j}^{N} d_{ij}^H$

From variance decompositions to Connectedness index

Variance Decomposition / Connectedness Table

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x_N	d_{N1}^H	d_{N2}^H	$\ldots$	d_{NN}^H	$\sum_{j\neq N} d_{Nj}^H$
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Multi-State Markov-Switching FAVAR (MS2-FAVAR)

The MS2-FAVAR can be represented in a state-space form:

$$\begin{aligned} Z_t &= H_{\mathbf{S}_t} W_t + v_t, \quad v_t \sim N(0, \Theta) \\ W_t &= G_0 + G W_{t-1} + u_t, \quad u_t \sim N(0, \Sigma), \end{aligned}$$

The measurement equation can be alternatively expressed as

$$Z_t = (H_0 \odot (\mathbf{1} - \iota' \otimes S_t^*) + H_1 \odot (\iota' \otimes S_t^*)) \odot W_t + v_t,$$

where $Z_t = (Y_t, X_t)'$, $W_t = (Y_t, F_t)'$, $v_t = (0, e_t^F)'$, $S_t^* = (\mathbf{0}, \mathbf{S}_t)'$

$$H_0 = \begin{bmatrix} & [I_n] & & 0 \\ & & & \vdots \\ & & & 0 \\ \lambda_{1,1}^Y & \cdots & \lambda_{1,n}^Y & \lambda_{1,0}^F \\ \lambda_{2,1}^Y & \cdots & \lambda_{2,n}^Y & \lambda_{2,0}^F \\ \vdots & \ddots & \vdots & \vdots \\ \lambda_{m,1}^Y & \cdots & \lambda_{m,n}^Y & \lambda_{m,0}^F \end{bmatrix} \quad H_1 = \begin{bmatrix} & [I_n] & & 0 \\ & & & \vdots \\ & & & 0 \\ \lambda_{1,1}^Y & \cdots & \lambda_{1,n}^Y & (\lambda_{1,0}^F + \lambda_{1,1}^F) \\ \lambda_{2,1}^Y & \cdots & \lambda_{2,n}^Y & (\lambda_{2,0}^F + \lambda_{2,1}^F) \\ \vdots & \ddots & \vdots & \vdots \\ \lambda_{m,1}^Y & \cdots & \lambda_{m,n}^Y & (\lambda_{m,0}^F + \lambda_{m,1}^F) \end{bmatrix}$$