Estimating financial networks by realized interdependencies: A restricted autoregressive approach

Massimiliano Caporin[a] Deniz Erdemlioglu[b] Stefano Nasini[b]

[a]University of Padova

[b]IESEG School of Management and CNRS

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massimiliano.caporin@unipd.it

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Motivational background

- Consider a trading network involving many financial assets, such as stocks (e.g. $n > 1000$)
- Can we quantify the interdependencies among these assets by exploiting information from HF trading data (returns, volatility, volume, etc)?
- Can we use these realized interdependencies to estimate financial networks?
  - → Matters for practitioners, policy-makers, regulators: return/volatility spillovers, asset allocation, systemic risk assessment, financial stability/stress tests, ...
- Econometric challenges:
  - → Dimension-related problems (many assets, multiple indicators, time)
  - → Convergence / identification / overfitting issues
  - → Computational burden and need for tractability

What we do in this paper

1. We develop a network-based vector autoregressive (VAR) model.
   - → The model uncovers the interactions among financial assets by integrating multiple realized measures.
   - → Under a restricted parameter structure, we can characterize cross-sectional and time dependencies within a large trading network.
   - → We propose a block coordinate descent (BCD) procedure for the least square estimation and investigate its theoretical properties.
2. For the empirical application, we use HF data on realized returns, realized volatility and realized volume of 1095 individual U.S. stocks over fifteen years.
   - → We show the model (Realized VAR) identifies a considerably large array of realized interdependencies with a limited computational effort.
   - → Relying on the model estimates, we construct realized rankings for the systemically important financial institutions (realized SIFIs).
   - → We generate the realized impulse-response functions (realized IRFs) to assess the effects of adverse shocks on the financial system.

Model and Notation

We introduce the three dimensions of our data set as follows:

$\mathcal{S}$	:	a set of assets (with $\lvert\mathcal{S}\rvert = n$);
$\mathcal{I}$	:	a set of indicators for each stock (with $\lvert\mathcal{I}\rvert = m$);
$\mathcal{T}$	:	a set of time periods (with $\lvert\mathcal{T}\rvert = T$);

The endogenous variables are $y_{s,i,t}$, encoding the state of assets $s \in \mathcal{S}$ with respect to indicator $i \in \mathcal{I}$ at time t. We define the VAR(τ) model as follows:

$$\mathbf{y}_t = \Phi_0 + \sum_{\ell=1}^{\tau} \Phi_\ell \mathbf{y}_{t-\ell} + \varepsilon_t, \tag{1}$$

where ε_t is a random noise with zero mean and covariance equal to Σ, Φ_0 is a $mn-$dimensional vector of intercepts, with $\Phi_{0,i}$ being a n-dimensional vector, for $i \in \mathcal{I}$; Φ_ℓ are $mn \times mn$ matrices of coefficients, for $\ell = 1, \ldots, \tau$.

Dependencies and Dynamics

We put forward a restricted specification of Φ_ℓ:

- On the one side, preserving the possible serial dependence characterising each of the endogenous variables $y_{s,i,t}$
- On the other side, allowing for interdependence across the n stocks:

$$\Phi_\ell = \begin{bmatrix} \boldsymbol{\Theta}_{1,l}\boldsymbol{\Gamma} & 0 & \dots & 0 \\ 0 & \boldsymbol{\Theta}_{2,l}\boldsymbol{\Gamma} & 0\dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \boldsymbol{\Theta}_{m,l}\boldsymbol{\Gamma} \end{bmatrix}, \tag{2}$$

which implies a dimensionality reduction from $(\tau n^2 m^2 + nm)$ to $n(n-1) + nm\tau$.

In what follows we demean the data, that is, we work with

$$\tilde{y}_{s,i,t} = y_{s,i,t} - (T - \tau)^{-1} \sum_{t=\tau+1}^{T} y_{s,i,t},$$

thereby suppressing Φ_0. We will now define $\tilde{\mathbf{z}}_t = [\tilde{\mathbf{y}}'_{t-1} \quad \tilde{\mathbf{y}}'_{t-2} \dots \tilde{\mathbf{y}}'_{t-\tau}]^\top$ (a vector of size τmn) and the following $mn \times (\tau mn)$ matrix

$$\tilde{\Phi}(\boldsymbol{\Theta}, \boldsymbol{\Gamma}) = \left[\begin{array}{ccc|ccc|c|ccc} \boldsymbol{\Theta}_{1,1}\boldsymbol{\Gamma} & & & \boldsymbol{\Theta}_{1,2}\boldsymbol{\Gamma} & & & \dots & \boldsymbol{\Theta}_{1,\tau}\boldsymbol{\Gamma} & & \\ & \ddots & & & \ddots & & \dots & & \ddots & \\ & & \boldsymbol{\Theta}_{m,1}\boldsymbol{\Gamma} & & & \boldsymbol{\Theta}_{2,\tau}\boldsymbol{\Gamma} & \dots & & & \boldsymbol{\Theta}_{m,\tau}\boldsymbol{\Gamma} \end{array}\right].$$

We can write the Realized-VAR model as

$$\tilde{\mathbf{Y}} = \tilde{\Phi}(\mathbf{\Theta}, \mathbf{\Gamma})\tilde{\mathbf{Z}} + \mathbf{U},$$

where $\tilde{\mathbf{Y}} = [\tilde{\mathbf{y}}_1 \dots \tilde{\mathbf{y}}_T]$, $\tilde{\mathbf{Z}} = [\tilde{\mathbf{z}}_1 \dots \tilde{\mathbf{z}}_T]$ and $\mathbf{U} = [\mathbf{u}_1 \dots \mathbf{u}_T]$ are matrices of size $mn \times T$ and $\mathbf{\Theta}$ is the list of matrices $\mathbf{\Theta}_{i,\ell}$, for $i \in \mathcal{M}$ and $\ell = 1 \dots \tau$.

Thus, by defining $\tilde{\phi}(\mathbf{\Theta}, \mathbf{\Gamma}) = vec\left(\tilde{\Phi}(\mathbf{\Theta}, \mathbf{\Gamma})^\top\right)$, the error function quantifying the mismatch between the realization and expectation can then be obtained in the usual way as

$$\mathcal{E}(\mathbf{\Theta}, \mathbf{\Gamma}, \tilde{\mathbf{y}}) = \left[\tilde{\mathbf{y}} - \left(I_{mn} \otimes \tilde{\mathbf{Z}}^\top\right) \tilde{\phi}(\mathbf{\Theta}, \mathbf{\Gamma})\right]^\top \left[\tilde{\mathbf{y}} - \left(I_{mn} \otimes \tilde{\mathbf{Z}}^\top\right) \tilde{\phi}(\mathbf{\Theta}, \mathbf{\Gamma})\right]. \quad (3)$$

- It is, however, worth mentioning that the minimization of $\mathcal{E}(\mathbf{\Theta}, \mathbf{\Gamma}, \tilde{\mathbf{y}})$ with respect to $\mathbf{\Theta}$ and $\mathbf{\Gamma}$ is a difficult computational task.
- We hence introduce a set of constraints on the model parameters.

The Least Square Estimator

Proposition (Necessary identifiability condition)

The n constraints $\gamma_{1,1} = \gamma_{2,2} = \ldots = \gamma_{n,n} = \varepsilon$ (for any fixed constant ε) is a necessary identifiability condition.

- Consequently, we assume hereafter n constraints of the form $\gamma_{1,1} = \gamma_{2,2} = \ldots = \gamma_{n,n} = 1$.
- Therefore, the Realized-VAR has $n(n-1) + nm\tau$ free parameters, against the $\tau n^2 m^2 + nm$ ones of a traditional VAR(τ). We have

Proposition (Global bilinear system)

Let $\nabla(\mathbf{\Theta}, \mathbf{\Gamma})$ be the Jacobian matrix of $\tilde{\phi}(\mathbf{\Theta}, \mathbf{\Gamma})$. If $D = \left(I_{nm} \otimes \mathbf{Z}^\top\right)$ is full rank, a least square estimator of $\mathbf{\Theta}$ and $\mathbf{\Gamma}$ can be obtained as the solution of the following system involving linear and bilinear terms:

$$\tilde{\phi}(\mathbf{\Theta}, \mathbf{\Gamma})^\top \nabla(\mathbf{\Theta}, \mathbf{\Gamma}) = \left((D^\top D)^{-1} D^\top \tilde{\mathbf{y}}\right)^\top \nabla(\mathbf{\Theta}, \mathbf{\Gamma}). \tag{4}$$

The Least Square Estimator

- It is important to note that when $\mathbf{\Gamma}$ is fixed, our Realized-VAR reduces to a special case of a STAR model.
- Therefore, the following corollary sets necessary conditions for the consistency of the OLS estimator of $\mathbf{\Theta}$, for a fixed $\mathbf{\Gamma}$.

Corollary (From Theorem 2 of Borovkova et al., 2008)

For a fixed $\mathbf{\Gamma}$, the OLS estimator of $\mathbf{\Theta}$ converges to the true parameter with probability one, under four sufficient conditions:

(i) *The characteristic roots of the matrix $\mathbf{\Phi}_\ell$ are less than one in absolute value.*

(ii) *The sequence $\{\varepsilon_t\}$ forms a vector-valued martingale difference array, with $\mathbb{E}[\varepsilon_t] = 0$.*

(iii) *The variance-covariance matrix $\mathbb{E}[(\varepsilon_t)(\varepsilon_t)^\top]$ is such that $S^{-1}\sum_{t=1}^{S}\mathbb{E}[(\varepsilon_t)(\varepsilon_t)^\top]$ converges to a constant matrix with probability one.*

(iv) *There exists a constant $g \in [1,2]$ for which $\sum_{t=1}^{S} t^{-g}\mathbb{E}[((\varepsilon_t)^\top(\varepsilon_t))^g] < \infty$.*

The minimization of (3) can be seen as a multi-block problem (with two blocks of variables).

To formulate a BCD method for the minimization of (3), we consider the conditional parameterization associated with

$$\tilde{y}_{s,i,t} = \sum_{l=1}^{\tau} \theta_{i,l,s} \underbrace{\left(\sum_{j=1}^{n} \gamma_{s,j} \tilde{y}_{j,i,t-l} \right)}_{\mathbf{w}_{s,i,t-l}(\boldsymbol{\Gamma})} + \varepsilon_{s,i,t} \tag{5}$$

and

$$\tilde{y}_{s,i,t} = \sum_{j=1}^{n} \gamma_{s,j} \underbrace{\left(\sum_{l=1}^{\tau} \theta_{i,l,s} \tilde{y}_{j,i,t-l} \right)}_{\mathbf{r}_{s,j,i,t}(\boldsymbol{\Theta})} + \varepsilon_{s,i,t}, \tag{6}$$

which, respectively, correspond to the two following parameterized minimizers:

$$\boldsymbol{\Theta}^*(\boldsymbol{\Gamma}) \in \underset{\boldsymbol{\Theta}}{argmin}\, \mathcal{E}(\boldsymbol{\Theta}, \boldsymbol{\Gamma}, \tilde{\mathbf{y}}) \quad \text{and} \quad \boldsymbol{\Gamma}^*(\boldsymbol{\Theta}) \in \underset{\boldsymbol{\Gamma}}{argmin}\, \mathcal{E}(\boldsymbol{\Theta}, \boldsymbol{\Gamma}, \tilde{\mathbf{y}}). \tag{7}$$

The next propositions provide fundamental properties of the two conditional OLS estimators.

Proposition (Conditional identifiability)

Let us consider the full OLS estimators,

$$(\boldsymbol{\Theta}^*, \boldsymbol{\Gamma}^*) \in \underset{\boldsymbol{\Theta}, \boldsymbol{\Gamma}}{argmin}\ \mathcal{E}(\boldsymbol{\Theta}, \boldsymbol{\Gamma}, \tilde{\mathbf{y}}), \tag{8}$$

and let $\mathcal{E}_{it}(\boldsymbol{\Theta}, \boldsymbol{\Gamma}, \tilde{\mathbf{y}}_{it})$ be the error from the n terms corresponding to item $i \in \mathcal{I}$ at time $t \in \mathcal{T}$. For any $i \in \mathcal{I}$ and $t \in \mathcal{T}$, the Realized-VAR model satisfies the following identifiability properties:

First

For any fixed $\mathbf{\Theta}$, if $\mathcal{E}_{it}(\mathbf{\Theta}, \mathbf{\Gamma}, \mathbf{q}) = \mathcal{E}_{it}(\mathbf{\Theta}, \mathbf{\Gamma}', \mathbf{q})$ for all $\mathbf{q} \in \mathbb{R}^n$, then $\mathbf{\Gamma} = \mathbf{\Gamma}'$.
Furthermore, if $Tm + 1 > n$ the conditional OLS estimator is uniquely characterized as

$$vec(\mathbf{\Gamma}^*) = \left(R(\mathbf{\Theta}^*)^\top R(\mathbf{\Theta}^*)\right)^{-1} R(\mathbf{\Theta}^*)^\top \tilde{\mathbf{y}}, \tag{9}$$

where $R(\mathbf{\Theta})$ is the $nmT \times n(n-1)$ block-diagonal matrix, constructed in lexicographic order on (s, i, t), using the elements $[\mathbf{r}_{1,1,i,t}(\mathbf{\Theta}^*) \dots \mathbf{r}_{n,n,i,t}(\mathbf{\Theta}^*)]$ from (5) and (6).

Second

For any fixed $\mathbf{\Gamma}$, if $\mathcal{E}_{it}(\mathbf{\Theta}, \mathbf{\Gamma}, \mathbf{q}) = \mathcal{E}_{it}(\mathbf{\Theta}', \mathbf{\Gamma}, \mathbf{q})$ for all $\mathbf{q} \in \mathbb{R}^n$, then $\mathbf{\Theta} = \mathbf{\Theta}'$.
Furthermore, if $T > \tau$ the conditional OLS estimator is uniquely characterized as

$$vec(\mathbf{\Theta}^*) = \left(W(\mathbf{\Gamma}^*)^\top W(\mathbf{\Gamma}^*)\right)^{-1} W(\mathbf{\Gamma}^*)^\top \tilde{\mathbf{y}}, \tag{10}$$

where $W(\mathbf{\Gamma})$ is the $nmT \times nm\tau$ block-diagonal matrix, constructed in lexicographic order on (s, i, t), using the elements $[\mathbf{w}_{1,1,t-1}(\mathbf{\Gamma}^*) \dots \mathbf{w}_{n,m,t-\tau}(\mathbf{\Gamma}^*)]$ from (5) and (6).

We can now obtain a feasible solution of the non-linear system (4) by using a BCD method that decomposes the dependency structure of each equation.

We have the following iterative procedure:

(0) Initialization: $\mathbf{\Gamma} = I_n$, $\mathbf{w}_{s,i,t-l}(\mathbf{\Gamma}) = \gamma_{s,.}\tilde{\mathbf{y}}_{.,i,t-l}$ and build $W(\mathbf{\Gamma})$.

(1) Compute (10), set $\mathbf{r}_{s,,j,i,t}(\mathbf{\Theta}) = \sum_{l=1}^{\tau} \theta_{i,l,s}\tilde{y}_{j,i,t-l}$ and build $R(\mathbf{\Theta})$.

(2) Compute (9), set $\mathbf{w}_{s,i,t-l}(\mathbf{\Gamma}) = \gamma_{s,.}\tilde{\mathbf{y}}_{.,i,t-l}$ and build $W(\mathbf{\Gamma})$.

(3) If converged, stop. Else go to 1.

We call this BCD procedure Realized-VAR-BCD method. We can show

Corollary (From Theorem 1 of Hajinezhad and Shi, 2018)

The sequence generated the Realized-VAR-BCD method converges monotonically to a solution of (4).

High-Frequency Data

- Our data include discretely sampled 1-minute observations of prices and trading volumes of 1095 U.S. stocks listed in the Russell 3000 index.
- We include actual constituents as well as dead companies, from January 2003 to June 2018 (for best quotes, data start in October 2009).

Sector	N	Sector	N
Basic Materials	49	Consumer Goods	117
Consumer Services	136	Financial	231
Healthcare	98	Industrials	229
Oil and Gas	56	Technology	128
Telecommunications	6	Utilities	45

Table: Sectors and number of stocks. The table presents the number of stocks that we consider in our empirical analysis for different sectors.

Realized Measures

We consider the following realized measures based on high-frequency data:

i Realized Returns: $R_t = (1/n)\sum_{i=1}^{n} r_{it}$

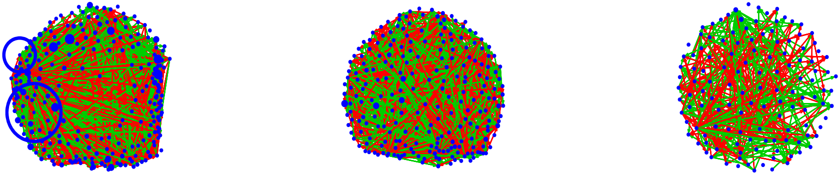
ii "Good" Realized Volatility: $RS^+ = \sum_{j=1}^{n} r_j^2 I(r_j > 0)$;

iii "Bad" Realized Volatility: $RS^- = \sum_{j=1}^{n} r_j^2 I(r_j < 0)$;

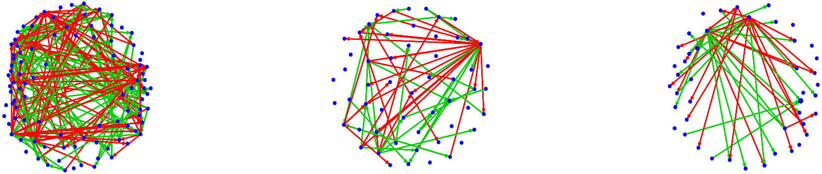
iv Traded Volume: number of traced shared within a one day period

Good and bad volatility meaures capture upside and downside risk, respectively.

Estimated Networks: all sectors (full)



(a) Financials (b) Industrials (c) Technology



(a) Healthcare (b) Energy (c) Utilities

Centrality Distribution: full system

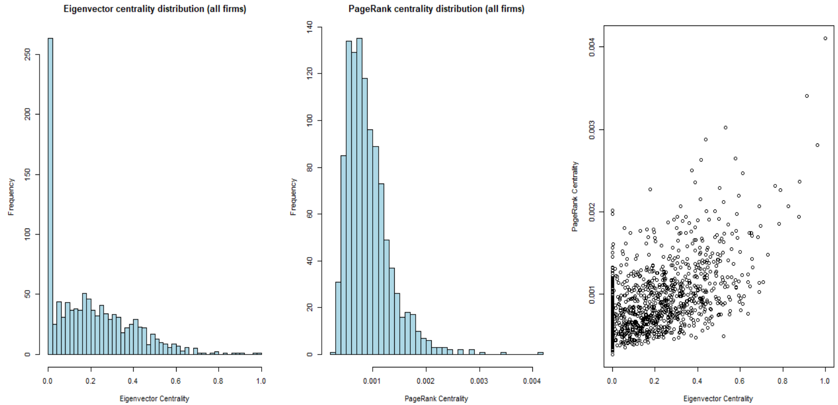


Figure: The distribution of centrality scores of 1095 U.S. firms, when all realized variables are aggregated (i.e., $m = 4$). From left to right: histogram of the eigenvector centrality, the one of the PageRank centrality and a scatter plot between both centrality measures.

Table: Likelihood-ratio test

Network	LogLik (null)	LogLik (full)	LR-stat	df_{null}	df_{fitted}	$df_{fitted-null}$	prob.
Full system	-8503115	-8457230	91771.49	96360	1295385	1199025	0.000

Table: Most influential firms (all sectors combined)

Rank	Node	Ticker	Score	Company name	Industry	Rank	Node	Ticker	Score	Company name	Industry
1	V463	HMN	1.000	HORACE MANN CORP	Insurance	1	V993	UDR	0.004	UNITED DOM REALTY TRUST, INC.	REIT
2	V46	ALL	0.826	ALLSTATE CORP	Insurance	2	V579	LNC	0.003	LINCOLN NATIONAL CORP	Insurance
3	V793	PRU	0.817	PRUDENTIAL FINANCIAL INC	Insurance	3	V925	STT	0.003	STATE STREET CORP	Bank holding
4	V890	SLG	0.749	SL GREEN REALTY CORP	REIT	4	V435	GS	0.003	GOLDMAN SACHS GROUP INC	Inv banking
5	V707	NUE	0.714	NUCOR CORPORATION	Industrial	5	V463	HMN	0.003	HORACE MANN CORP	Insurance
6	V411	GE	0.710	GENERAL ELECTRIC COMPANY	Tech/fin	6	V793	PRU	0.003	PRUDENTIAL FINANCIAL INC	Insurance
7	V116	BEN	0.695	FRANKLIN RESOURCES, INC.	Inv Management	7	V587	LPT	0.003	LIBERTY PROPERTY TRUST	REIT
8	V102	BAC	0.638	BANK OF AMERICA CORP	Inv Banking	8	V46	ALL	0.002	ALLSTATE CORP	Insurance
9	V435	GS	0.588	GOLDMAN SACHS GROUP INC	Inv Banking	9	V77	ASB	0.002	ASSOCIATED BANC CORP	Bank holding
10	V485	IBOC	0.581	INT BANCSHARES CORP	Bank holding	10	V391	FMBI	0.002	FIRST MIDWEST BANCORP INC	Retail banking
11	V472	HRS	0.549	L3HARRIS TECHNOLOGIES INC	Technology	11	V976	TROW	0.002	T. ROWE PRICE GROUP INC	Inv management
12	V534	JPM	0.546	JPMORGAN CHASE & CO.	Inv Banking	12	V892	SLM	0.002	SALLIE MAE	Consumer banking
13	V726	OII	0.539	OCEANEERING INT INC	Technology	13	V745	OXY	0.002	OCCIDENTAL PETROLEUM CORP	Energy
14	V868	SCHW	0.517	CHARLES SCHWAB CORP	Banking	14	V124	BK	0.002	BANK OF NEW YORK M. CORP	Financial services
15	V401	FRT	0.513	FEDERAL REALTY INV TRUST	REIT	15	V60	AMZN	0.002	AMAZON.COM, INC.	Technology
16	V789	PRAA	0.513	PRA GROUP INC	Debt collector	16	V542	KEY	0.002	KEYCORP	Bank holding
17	V760	PEP	0.502	PEPSICO, INC.	Food	17	V219	COF	0.002	CAPITAL ONE FINANCIAL CORP	Bank holding
18	V657	MTB	0.499	M&T BANK CORPORATION	Bank holding	18	V397	FR	0.002	FIRST IND REALTY TRUST, INC	REIT
19	V460	HIW	0.495	HIGHWOODS PROP INC	REIT	19	V411	GE	0.002	GENERAL ELECTRIC COMPANY	Tech/fin
20	V925	STT	0.482	STATE STREET CORP	Bank holding	20	V37	AIV	0.002	APARTMENT INV AND MAN CO	REIT

Centrality Distribution: financial sector

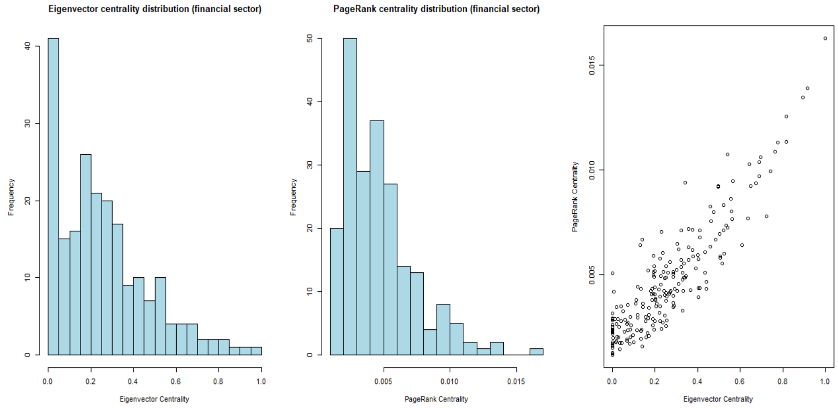


Figure: The distribution of centrality scores of 231 U.S. financial institutions, when all realized variables are aggregated (i.e., $m = 4$). From left to right: the histogram of the eigenvector centrality, the one of the PageRank centrality and a scatter plot between both centrality measures.

Centrality Rankings: financial sector

Table: Likelihood-ratio test

Network	LogLik (null)	LogLik (full)	LR-stat	df_{null}	df_{fitted}	$df_{fitted-null}$	prob.
Financials	-1793642	-1784478	18327.91	20328	73689	53361	0.000

Table: Most influential firms (only financial sector)

Rank	Node	Ticker	Score	Company name	Industry	Rank	Node	Ticker	Score	Company name	Industry
1	V203	TRMK	1	TRUSTMARK CORP	Bank holding	1	V98	GS	0.023	GOLDMAN SACHS GROUP INC	Inv banking
2	V212	USB	0.919	U.S. BANCORP	Bank holding	2	V197	STT	0.021	STATE STREET CORP	Bank holding
3	V126	LPT	0.852	LIBERTY PROPERTY TRUST	REIT	3	V126	LPT	0.014	LIBERTY PROPERTY TRUST	REIT
4	V98	GS	0.815	GOLDMAN SACHS GROUP INC	Inv banking	4	V207	UDR	0.014	UNITED DOM REALTY TRUST, INC	REIT
5	V51	CINF	0.743	CINCINNATI FINANCIAL CORP	Insurance	5	V165	PRU	0.014	PRUDENTIAL FINANCIAL INC	Insurance
6	V140	MTB	0.656	M&T BANK CORPORATION	Bank holding	6	V125	LNC	0.013	LINCOLN NATIONAL CORP	Insurance
7	V8	AIV	0.589	APARTMENT INV CORP	REIT	7	V51	CINF	0.012	CINCINNATI FINANCIAL CORP	Insurance
8	V187	SLG	0.583	SL GREEN REALTY CORP	REIT	8	V221	WFC	0.011	WELLS FARGO & CO	Fin services
9	V7	AIG	0.576	AMERICAN INT GROUP INC	Insurance	9	V203	TRMK	0.011	TRUSTMARK CORP	Bank holding
10	V197	STT	0.566	STATE STREET CORP	Bank holding	10	V231	XL	0.011	AXA XL (XL GROUP)	Insurance
11	V74	ESS	0.513	ESSEX PROPERTY TRUST INC	REIT	11	V26	BK	0.010	BANK OF NEW YORK MELLON CORP	Fin services
12	V67	DDR	0.496	SITE CENTERS	REIT	12	V102	HBAN	0.010	HUNTINGTON BANCSHARES INC	Bank holding
13	V168	RBCAA	0.494	REPUBLIC BANCORP, INC.	Bank holding	13	V58	COF	0.010	CAPITAL ONE FINANCIAL CORP	Bank holding
14	V19	AXP	0.478	AMERICAN EXPRESS COMPANY	Fin Services	14	V214	VNO	0.010	VORNADO REALTY TRUST	REIT
15	V201	TMK	0.473	TORCHMARK CORP	Life insurance	15	V40	CB	0.009	CHUBB LTD	Insurance
16	V2	ACGL	0.443	ARCH CAPITAL GROUP LTD.	Insurance	16	V188	SLM	0.009	SALLIE MAE	Con banking
17	V22	BBT	0.436	TRUIST FINANCIAL CORP	Bank holding	17	V67	DDR	0.009	SITE CENTERS	REIT
18	V31	BPFH	0.428	BOSTON PRIVATE FIN HLDG INC	Bank holding	18	V223	WRE	0.009	WASHINGTON R E INV TRUST	REIT
19	V24	BEN	0.422	FRANKLIN RESOURCES, INC.	Inv Man	19	V106	HMN	0.009	HORACE MANN CORP	Insurance
20	V94	FULT	0.404	FULTON FINANCIAL CORP	Fin services	20	V91	FR	0.008	FIRST IND REALTY TRUST, INC	REIT

Impulse Response Analysis

- We study the impulse response functions (IRFs) generated based on sector-specific (financials) estimation results over the full sample.
- We proceed as follows:
  - → Utilize the rankings based on eigenvector centrality in order to select the financial institution (within top 20 most influential financial institutions)
  - → Orthogonalize the model residuals using spectral decomposition
  - → Consider that each central institution receives a negative shock
- We examine the following three systemically important institutions (among others that are ranked top in the list):
  - (i) Bank of America (BAC)
  - (ii) Goldman Sachs (GS)
  - (iii) JP Morgan (JPM)

Impulse Response Functions for BAC

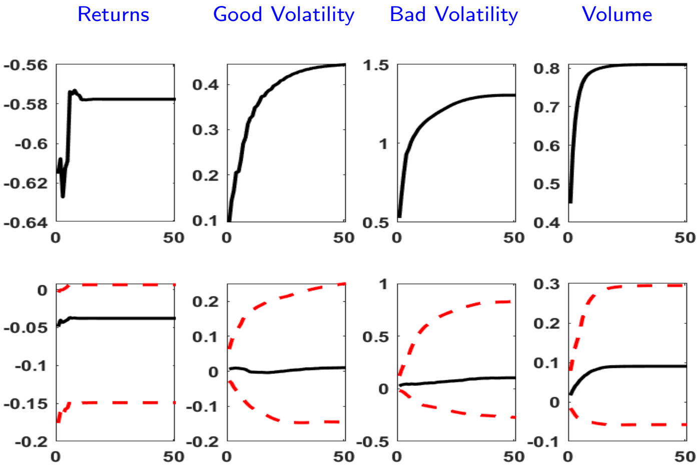


Figure: The upper panel demonstrates the asset-specific quantiles of the IRFs while IRFs in the lower panel are for all other assets (cross-sectional quantiles) when we exclude the target asset (BAC) that received the shock. All IRFs are cumulated.

Impulse Response Functions for GS

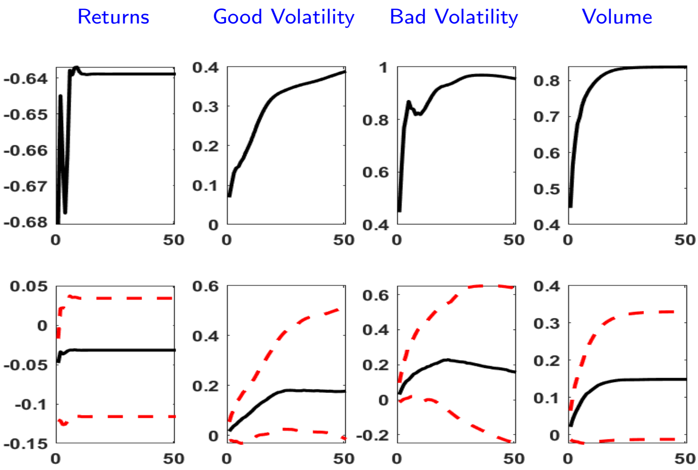


Figure: The upper panel demonstrates the asset-specific quantiles of the IRFs while IRFs in the lower panel are for all other assets (cross-sectional quantiles) when we exclude the target asset (GS) that received the shock. All IRFs are cumulated.

Impulse Response Functions for JPM

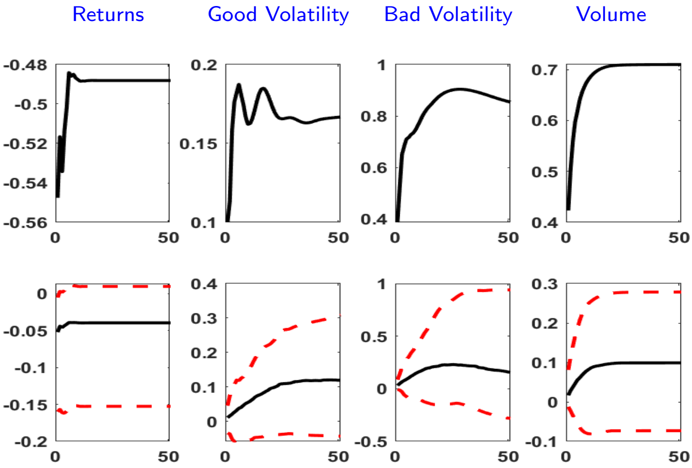


Figure: The upper panel demonstrates the asset-specific quantiles of the IRFs while IRFs in the lower panel are for all other assets (cross-sectional quantiles) when we exclude the target asset (JPM) that received the shock. All IRFs are cumulated.

Concluding Remarks

- We develop a network-based VAR model to characterize interdependencies in a large panel of financial assets.
- The model exploits the intraday (high-frequency) trading information embedded in realized variables containing returns, volumes and volatilities.
- We propose using a block coordinate descent (BCD) procedure to estimate this new realized VAR class (Realized-VAR).
- For our empirical analysis, we use high-frequency returns, signed realized volatilities (good versus bad) and trading volume for each individual stock in a panel of 1095 stocks.
- The results help identify the "systemically important financial institutions" (SIFIs) which reveal significant impulse-responses in the financial system.