JOURNAL OF FINANCIAL AND QUANTITATIVE ANALYSIS Vol. 53, No. 3, June 2018, pp. 1371–1390
COPYRIGHT 2018, MICHAEL G. FOSTER SCHOOL OF BUSINESS, UNIVERSITY OF WASHINGTON, SEATTLE, WA 98195
doi:10.1017/S0022109018000108

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

# Measuring Interconnectedness between Financial Institutions with Bayesian Time-Varying Vector Autoregressions

Marco Valerio Geraci and Jean-Yves Gnabo*

## Abstract

We propose a market-based framework that exploits time-varying parameter vector autoregressions to estimate the dynamic network of financial spillover effects. We apply it to financials in the Standard & Poor's 500 index and estimate interconnectedness at the sectoral and institutional levels. At the sectoral level, we uncover two main events in terms of interconnectedness: the Long-Term Capital Management crisis and the 2008 financial crisis. After these crisis events, we find a gradual decrease in interconnectedness, not observable using the classical rolling-window approach. At the institutional level, our framework delivers more stable interconnectedness rankings than other comparable market-based measures.

## I. Introduction

In this paper, we develop a market-based statistical framework that uses Bayesian estimation of time-varying parameter vector autoregressions (TVP-VAR) to model the dynamic nature of connections between financial institutions. The framework allows connections to evolve gradually through time as opposed to the classical approach, which favors sudden, often unjustified, changes in interconnectedness. Paired with graph theory, our framework allows us to reconstruct a continuously evolving network of directed spillover effects. We use our

*Geraci (corresponding author), mvg23@cam.ac.uk, University of Cambridge INET Institute and Université Libre de Bruxelles ECARES; Gnabo, jean-yves.gnabo@unamur.be, University of Namur CeReFiM and University of Paris Nanterre EconomiX-CNRS. We thank Tobias Adrian (the referee), Matteo Barigozzi, Christiane Baumeister, Sophie Béreau, Oscar Bernal, Monica Billio, Christian Brownlees, Alain de Combrugghe, Frank Diebold, Michele Lenza, Matteo Luciani, Paul Malatesta (the editor), David Veredas, and Kamil Yılmaz and conference and seminar participants at the 2016 French Finance Association Conference, the 2016 Conference on Financial Risk and Network Theory, the 2016 European Economic Association Meeting, Fordham University, Université Libre de Bruxelles, University of Mannheim, and Université de Namur for valuable comments. We also gratefully acknowledge financial support from the Communauté Française de Belgique. We are responsible for all remaining errors and omissions.

framework to study the evolution of the interconnectedness of the U.S. financial sector over the past two decades.

Market-based measures of interconnectedness apply statistical measures of association (e.g., correlation, Granger causality, tail dependence) to asset prices to map and analyze the network of spillover effects between financial institutions (e.g., Diebold and Yılmaz (2009), (2014), Hautsch, Schaumburg, and Schienle (2014), (2015)). These standard statistical measures presuppose that the inferred relationships are time invariant over the sample used for the estimation. To retrieve a dynamic measure of interconnectedness, the usual approach has been to divide the original sample period into multiple subsamples and calculate these statistical measures over rolling windows of data.

We argue that this is unsuitable if the system studied is time varying. By relying on short subsamples, rolling windows lower the power of inference and induce dimensionality problems. Moreover, the rolling-window approach is known to be susceptible to outliers because in small subsamples, these have a larger impact on estimates (Zivot and Wang (2006)). Conversely, choosing longer windows will lead to estimates that are less reactive to change, biasing results toward time-invariant connections (Clark and McCracken (2009)). The rolling-window approach will always involve a trade-off between the precision and reactivity of estimates of interconnectedness.

Our framework builds on the literature that uses *temporal* dependencies for measuring interconnectedness (Billio, Getmansky, Lo, and Pelizzon (2012), Barigozzi and Brownlees (2017), and Barigozzi and Hallin (2017)). We construct a TVP-VAR model with features that allow for heteroscedasticity, skewness, and excess kurtosis of stock returns. The time-varying cross-autoregressive coefficients of the TVP-VAR capture, in every time period, the strength of directed connections between financial institutions. We determine connections by evaluating the posterior distribution of the parameters using the Bayes factor. The framework is based on the whole sample of observed data and does not require setting any window size.

Although we focus on temporal dependencies, our framework can also be used to study interconnectedness based on *contemporaneous* dependencies (e.g., Acharya, Engle, and Richardson (2012), Acharya, Pedersen, Philippon, and Richardson (2017), Adrian and Brunnermeier (2016), and Dungey, Luciani, and Veredas (2018)). This is possible thanks to the time-varying covariance matrix included in our model, which effectively captures the contemporaneous (undirected) connections between returns.

We also contribute to the literature of Bayesian measures of interconnectedness. In this literature, Bernardi, Gayraud, and Petrella (2015) develop a Bayesian approach for measuring conditional value at risk (CoVaR). They focus on quantile effects, whereas we focus on conditional mean effects. Our framework could be extended with different distributional assumptions (see, e.g., Yu and Moyeed (2001)) to model quantile effects, as in the vector autoregression (VAR) for the value-at-risk (VaR) framework of White, Kim, and Manganelli (2015). Ciccarelli and Rebucci (2007) also adopt Bayesian TVP-VARs to measure contagion in the South American foreign exchange (FX) market. They assume asset returns follow a multivariate $t$-distribution with a constant scale matrix. Our approach is more

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

flexible because we use a multivariate $t$-distribution with a time-varying scale, which allows for both heteroscedasticity and time-varying contemporaneous correlations between asset returns. Moreover, we allow for asset returns to exhibit skewness by including so-called leverage effects between the asset returns and their volatilities.

Another related study by Adams, Füss, and Gropp (2014) examines the interconnectedness between four U.S. financial sectors (commercial banks, investment banks, hedge funds, and insurance companies) by proposing a state-dependent sensitivity value-at-risk (SDSVaR) model. The SDSVaR model is comparable to our proposed framework because it allows for three states of connections between sectors, according to whether financial markets are in a volatile, normal, or tranquil condition. However, our TVP-VAR is more flexible because it does not restrict the number of states and allows connections to vary freely through time.

We apply our framework to analyze the U.S. network of financial spillovers. To do this, we use monthly stock price data for all financial institutions listed from 1990 to 2014 on the Standard & Poor's (S&P) 500 index, including firms that have since gone defunct. We proceed in two steps. First, we estimate the time-varying network of spillovers at the sectoral level between the four sectors comprising our data: banks, broker-dealers, insurance companies, and real estate companies. Second, we estimate the network at an individual level between the 20 systemically important financial institutions. Our analysis yields four main results.

First, at the sectoral level, our framework identifies two main events in terms of interconnectedness: the 1998 Long-Term Capital Management (LTCM) crisis and the 2008 financial crisis. After these crisis events, we observe a gradual decrease in interconnectedness, concurring with the credit freeze that occurred. Conversely, the rolling-window approach yields a volatile measure of interconnectedness that anomalously rises after the crisis events. This result evidences the reliability of the TVP-VAR framework for measuring interconnectedness.

Second, we examine interconnectedness between the four financial sectors included in our study and find that banks and broker-dealers are the largest contributors to financial spillovers. The real estate sector, composed primarily of real estate investment trusts (REITs), is the most influenced by these spillovers. This may be due to real estate investment trusts being less leveraged than banks and less exposed to nonagency mortgage-backed securities.

Third, at the individual institution level, American International Group, Goldman Sachs, and Merrill Lynch are found to be among the largest propagators of financial spillovers, highlighting their potential widespread influence. By contrast, Bear Stearns did not play a major role in the propagation of spillovers but rather was very receptive of incoming spillovers. These results were confirmed in an out-of-sample exercise using only data up to the end of 2007.

Fourth, we show that interconnectedness rankings, computed using the rolling-window approach, are extremely volatile and unlikely to be useful for policy decisions. Conversely, the TVP-VAR framework produces more stable rankings appropriate for monitoring purposes. We also find that our framework yields more stable rankings than other market-based measures (e.g., the marginal expected shortfall of Acharya et al. (2012) and Brownlees and Engle (2017)) while

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

having more reactive rankings than measures based on low-frequency book-value data (e.g., leverage).

The article is structured as follows: In Section II and Section III, we go through, respectively, our proposed framework for modeling interconnectedness and the estimation technique. In Section IV, we briefly describe the market data used to estimate the interconnectedness of the U.S. financial system. In Section V, we measure interconnectedness at the sectoral level, whereas in Section VI, we measure interconnectedness at the financial institution level. We draw our conclusions in Section VII.

## II. The Model

According to the classical approach for measuring interconnectedness by temporal dependencies, financial institution $i$ has a directed spillover to financial institution $j$ if the stock return of $i$ Granger causes the stock return of $j$. Effectively, the classical approach relies on an in-sample test of the cross-coefficients of a time-invariant VAR. If the direction of causality were to change during the sample period, estimation of the VAR and test inference could be affected.

We allow for time-varying spillover effects with the following TVP-VAR:

$$R_t = c_t + B_t R_{t-1} + u_t \equiv X_t' \theta_t + u_t, \tag{1}$$

where $R_t \equiv [r_{1t}, \ldots, r_{Nt}]'$ is the vector of $N$ stock returns. We stack the time-varying intercepts $c_t$ and matrix of time-varying coefficients $B_t$ in $\theta_t$ so that equation (1) can be interpreted as the measurement equation of a state space model.[1]

Paralleling the classical approach, we define a time-varying spillover at period $t$ from $i$ to $j$, denoted $i \rightarrow_t j$, if the $ji$ element of $B_t$, denoted $B_t^{(ji)}$, is different from 0. In particular, the (absolute) value of $B_t^{(ji)}$ represents the strength of the spillover from $i$ to $j$ at period $t$.

We let the vector of disturbances $u_t$ have the following form: $u_t = \sqrt{\lambda_t}\Sigma_t^{1/2}\varepsilon_t$, where $\nu/\lambda_t \overset{\text{iid}}{\sim} \chi_\nu^2$ and $\varepsilon_t$ is a vector of standard normal errors. This means that $u_t$ is $t$-distributed with scale matrix $\Sigma_t$ and degrees of freedom $\nu$.

The $t$-distributed errors allow for the returns in our TVP-VAR to exhibit fat tails. Moreover, the time-varying scale matrix $\Sigma_t$ can capture heteroscedastic volatility and time-varying correlations between errors, which can be interpreted as the contemporaneous spillovers occurring between the financial institutions in the network. For the present study, we concentrate on $B_t$, which represents temporal spillovers and has the advantage of being interpretable as a directed network. Nonetheless, the framework is highly flexible and lends itself to the study of both temporal and contemporaneous spillovers.

As is done in the macroeconomic literature (e.g., Cogley and Sargent (2005), Primiceri (2005)), we let parameters evolve according to a driftless random walk. The state equation of the model is thus as follows:

$$\theta_{t+1} = \theta_t + v_{t+1}, \qquad v_t \sim \mathcal{N}(0, Q_t), \tag{2}$$

where we assume that $\varepsilon_t$ and $v_s$ are independent at all $t$ and $s$.[2]

[1] The framework can be extended to account for higher-order lags.

[2] This assumption is taken solely for reasons of convenience and could be relaxed.

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

We allow the time-varying parameters to have heteroscedastic variance $Q_t$. This allows for additional flexibility for $B_t$ and effectively means that the unconditional distribution of $B_t$ is fat-tailed. We assume that $Q_t$ is a diagonal matrix, with diagonal elements collected in $q_t$ and evolving as a geometric random walk, $\ln q_{t+1} = \ln q_t + \omega_{t+1}$.

Regarding the time-varying scale matrix of the measurement equation $\Sigma_t$, we assume it takes the usual triangular form, $\Sigma_t = A_t^{-1} H_t (A_t^{-1})'$, where $H_t$ is a diagonal matrix containing the stochastic volatilities, and $A_t$ is a lower triangular matrix with 1s across its diagonal and the contemporaneous interactions as lower diagonal elements.

Let $h_t$ denote the vector of diagonal elements of $H_t$, and let $\alpha_t$ denote the lower diagonal elements of $A_t$ stacked by rows. Then, we assume the following laws of motion for the time-varying parameters $h_t$ and $\alpha_t$:

$$\begin{aligned} \ln h_t &= \ln h_{t-1} + \eta_t, \\ \alpha_t &= \alpha_{t-1} + \tau_t. \end{aligned}$$

The vector of errors of the model $[\varepsilon_t, \eta_t, \omega_t, \tau_t]'$ is jointly normal with mean 0 and variance–covariance matrix $V$, defined as

$$V = \begin{bmatrix} I & \Omega & 0 & 0 \\ \Omega & Z_\eta & 0 & 0 \\ 0 & 0 & Z_\omega & 0 \\ 0 & 0 & 0 & S \end{bmatrix},$$

where

$$\Omega = \begin{bmatrix} \rho_1\sigma_1 & 0 & \cdots & 0 \\ 0 & \rho_2\sigma_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \rho_n\sigma_N \end{bmatrix}, \quad Z_\eta = \begin{bmatrix} \sigma_1^2 & 0 & \cdots & 0 \\ 0 & \sigma_2^2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_N^2 \end{bmatrix},$$

$$\text{and} \quad Z_\omega = \begin{bmatrix} \sigma_{\omega,1}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{\omega,2}^2 & \ddots & 0 \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{\omega,N\times(1+N)}^2 \end{bmatrix}.$$

The variance–covariance matrix $V$ and its submatrix $\Omega$ allow the error terms of the measurement and volatility equations, namely, $\varepsilon_t$ and $\eta_t$, to be contemporaneously correlated row by row. In the case of stock returns, this correlation is often negative and is known as the leverage effect (see Nakajima and Omori (2012)). This assumption offers increased flexibility because it allows for the possibility of having skewness in the errors of our VAR in equation (1). Finally, following Primiceri (2005) and Baumeister and Benati (2013), we adopt a block-diagonal structure for $S$, which implies that the non-zero and non-unity elements of $A_t$ belonging to different rows evolve independently.

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

## III. Estimation and Inference

We estimate the model by standard Bayesian methods as described by Kim and Nelson (1999). An overview of the prior specification and the sampling algorithm are given, respectively, in Sections A and B of the Internet Appendix (available at www.jfqa.org).

In order to determine the dynamic network of spillover effects, we evaluate, for every pair of institutions $ij$, $i \neq j$, the time-varying null hypothesis, $\mathcal{H}_{0t}^{ij} : B_t^{(ji)} = 0$, using the Bayes factor. The Bayes factor gives the odds in favor of the null hypothesis, $\mathcal{H}_{0t}^{ij}$, against the alternative hypothesis, $\mathcal{H}_{1t}^{ij} : B_t^{(ji)} \neq 0$. Unlike classical frequentist testing, the Bayes factor weighs evidence in favor of the null and alternative hypotheses equally. We follow Koop, Leon-Gonzalez, and Strachan (2010) to estimate the Bayes factor from the conditional posterior distribution of the parameters. An overview of the procedure is given in Section C of the Internet Appendix.

In order to determine the existence of a connection, we impose a hard threshold of 4 on the estimated Bayes factor. That is, if the estimated Bayes factor is below the threshold, we draw a directed connection between $i$ and $j$ in period $t$; otherwise, we draw no connection. Furthermore, if we draw a connection, we weigh it according to the absolute value of the estimated cross coefficient $B_t^{(ji)}$ in order to capture the strength of that connection. Effectively, the threshold is a filtering mechanism, and a higher threshold leads to a denser network with more links.[3]

We compare the proposed Bayesian TVP-VAR framework against the classical approach of Granger causality over rolling windows in a series of simulation exercises given in Section D of the Internet Appendix. We find that our proposed framework performs well, both in terms of mean-squared error of the estimated parameters and in terms of the precision and recall of the inferred connections.

## IV. Data

We select financial institutions with Standard Industrial Classification (SIC) codes from 6000 to 6799 that are components of the S&P 500 from Jan. 1993 to Dec. 2014. For these companies, we collect the monthly cum-dividend stock price from Thomson Reuters Eikon for the same time period. The monthly frequency makes it possible to reduce the amount of noise in the data. Data at the intra-daily or even daily frequency reveal a higher number of linkages because stocks are more susceptible to market shocks that lead to a higher degree of comovement.

Initially the sample contains 182 firms but is reduced to 154 after constraining our analysis to stocks with at least 36 monthly observations. The final sample of financial institutions is given in the Internet Appendix.

The sample can be subdivided into four sectors based on the SIC code of the companies: banks (SIC codes 6000–6199), broker-dealers (SIC codes 6200–6299), insurers (SIC codes 6300–6499), and real estate companies (SIC codes 6500 and 6799). The final sample included 71 banks, 21 broker-dealers, 40 insurers, and 23 real estate companies.

[3] Similar results are obtained using different thresholds and are available from the authors.

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

We define monthly stock returns for company $i$ at month $t$ as $r_{it} = \ln[(p_{it} + d_{it})/p_{i,t-1}]$, where $p_{it}$ is the stock price of company $i$ at the end of month $t$, and $d_{it}$ are dividends paid that month. Finally, we net the risk-free rate from the stock returns, as is often done in asset pricing. For this, we use the monthly return on the 3-month U.S. Treasury bills.

We proceed by estimating interconnectedness for the U.S. financial system at two levels. In Section V, we estimate interconnectedness at the sectoral level. In Section VI, we estimate interconnectedness at the individual financial institution level, between 20 systemically important financial institutions.

## V. Interconnectedness at the Sectoral Level

Similarly to Adams et al. (2014), we compute sectoral indices from the stock price returns described in Section IV. We then infer the dynamic network of spillover effects between banks, broker-dealers, insurers, and real estate companies using a 4-variable TVP-VAR with 1 lag.

In order to summarize the evolution of interconnectedness between sectors, we compute the network density at every period. The network density is the average strength of a connection in the network at a given time period. It can be computed as

$$\text{DENSITY}_t = \frac{1}{N(N-1)} \sum_{i=1}^{N_t} \sum_{j \neq i} (i \rightarrow_t j) \times |B_t^{(ji)}|, \tag{3}$$

with $i, j \in \{\text{banks, brokers, insurers, real estate}\}$ and $i \neq j$, where $B_t^{(ji)}$ is the cross coefficient connecting $i$ to $j$ in period $t$ in the TVP-VAR and where, in this case, $N = 4$.

The bold solid line in Figure 1 shows the evolution of the sectoral density together with some significant events for the U.S. economy. The sectoral density peaks at two main events for the U.S. financial sectors: the collapse of the LTCM fund in Aug. 1998 and the financial crisis of Sept. 2008. A smaller peak also appears during 2004 when the U.S. Securities and Exchange Commission (SEC) suspended the net capital rule.

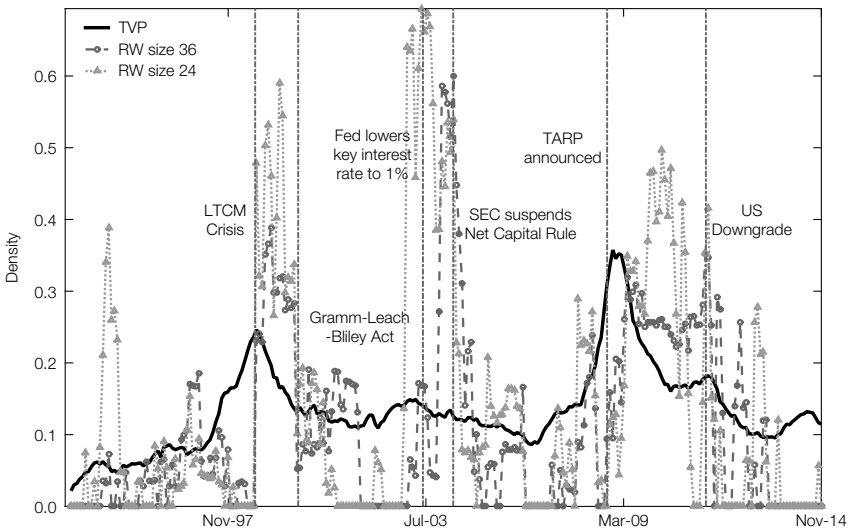
The fall and subsequent bailout of LTCM was a major event in terms of contagion because the fund was highly leveraged and was contractually connected with an extensive number of counterparties (McDonough (1998)). Concerns of spillover effects bringing down financial markets led the Federal Reserve Bank of New York to coordinate a consortium of banks to bail out LTCM.

The 2007–2009 financial crisis represented an even more important event in terms of interconnectedness. The sectoral density measure, based on the TVP-VAR framework, shows that interconnectedness between sectors gradually grew by more than twofold between the beginning of 2005 and Sept. 2008. After the financial crisis, the density gradually decreased to below precrisis levels. This could reflect two phenomena. First, after the default of Lehman Brothers in Oct. 2008, there was an immediate market freeze generated by the high uncertainty among market agents. This caused a drastic decrease in interconnectedness. However, the policies introduced to counter this sentiment, such as the Troubled Asset

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

FIGURE 1
Sectoral Density

Figure 1 shows the sectoral density estimated by the time-varying parameter vector autoregression (TVP-VAR) approach (bold solid line) and by Granger causality testing with rolling windows of 36 months (light dashed line) and 24 months (triangles). Significant events are indicated by the dashed vertical lines.




Relief Program (TARP) and Dodd–Frank Act, could have slowed down the drop. Dungey et al. (2018) found a similar decrease using a realized volatility-based measure of systemic risk.

Figure 1 also depicts the sectoral density found using the classical approach of Granger causality testing (at 10% significance rate) over rolling windows, with windows of 36 months and 24 months, with the light dashed lines. The rolling-window estimates are substantially more volatile than the TVP-VAR estimates, exhibiting sudden, short-lived peaks. The volatility of the sectoral density computed using the TVP-VAR framework was 0.06, whereas it was 0.13 using the rolling-window approach with a window size of 36 months. Using a smaller window size of 24 months leads to a more reactive density measure with an even higher volatility of 0.18.

There are several discrepancies in the two density measures estimated using the rolling-window approach. The density computed using the 24-month rolling window is far noisier because it relies on fewer observations and therefore is more susceptible to extreme events. In particular, after the 2007–2009 financial crisis, the measure appears to jump strongly, whereas the same movement is not observable using 36-month rolling windows. We believe that this peak is generated by the crisis observations, relating to Oct. 2008, exiting the rolling windows and creating an artificial jump in interconnectedness.

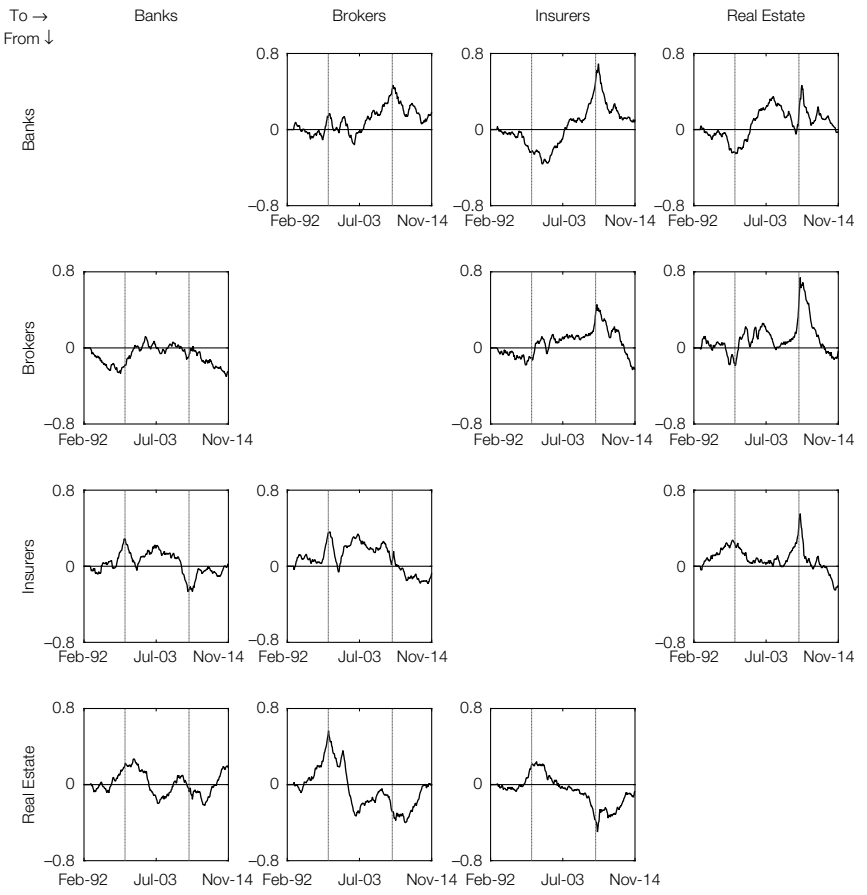
In order to further study the evolution of interconnectedness between sectors, we analyzed the time-varying cross-coefficients of the TVP-VAR model. Figure 2 gives the posterior density mean of the off-diagonal elements of $B_t$ (i.e., the value

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

FIGURE 2

Time-Varying Cross-Autoregressive Coefficients of the TVP-VAR

Figure 2 shows the time-varying cross-autoregressive coefficients of the time-varying parameter vector autoregression (TVP-VAR) with 1 lag at the sectoral level. Each graph displays the cross-autoregressive coefficient representing the temporal spillover effect from a given sector (indicated by the rows of the figure) to another sector (indicated by the columns of the figure). The two dashed vertical lines indicate the day of the Russian default, Aug. 17, 1998, which marked the beginning of the Long-Term Capital Management (LTCM) crisis, and the day of the bankruptcy of Lehman Brothers, Sept. 15, 2008.




of $B_t^{(j\,i)}$ for $i \neq j$). The (absolute) value of the time-varying cross-coefficient represents the strength of the directed spillover effect from a given sector (indicated by the rows of the figure) to another sector (indicated by the columns of the figure). Moreover, the sign of the cross coefficient can help us understand whether the spillover effect was positive or negative. We indicate the 1998 LTCM crisis and the Lehman Brothers default crisis in Figure 2 with two vertical dashed lines.

The coefficients evolved substantially through time, evidencing the usefulness of the TVP-VAR framework. Banks and broker-dealers had the largest increase in outgoing connections prior to the 2008 financial crisis. Both sectors played a crucial role during the crisis in propagating spillover effects. Large banks

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

and broker-dealers were feared to be insolvent, triggering high uncertainty in financial markets. In particular, from Figure 2, it seems that banks and broker-dealers were heavily influencing insurers and real estate companies.

The 2007–2009 financial crisis was very much tied to problems in the housing market, but Figure 2 shows that the real estate sector was receiving spillovers to a greater extent than it was propagating them. We propose two explanations for this result.

First, 21 of the 23 real estate companies in our sample were REITs, which primarily own income-producing real estate and in some cases finance real estate. Only in specific cases do REITs own mortgages, and generally, if they do, these will be through agency mortgage-backed securities (MBSs), which are guaranteed by agencies of the U.S. government. Conversely, banks were directly hit by troubles in the real estate sector because of direct exposure to mortgages and non-agency or private-label MBSs.

Second, banks were heavily leveraged prior to and during the financial crisis, whereas REITs were far less leveraged.[4] Table 1 shows the average leverage ratios for the financial institutions in our sample. During the 2007–2009 financial crisis, the banks in our sample were six times more leveraged than the publicly traded real estate institutions in our sample.

TABLE 1
Leverage Ratio

Table 1 presents the average leverage ratio for the financial institutions in our sample. The data are discussed in Section V.

| Time Period | Banks | Brokers | Insurers | Real Estate |
|---|---|---|---|---|
| 2007–2009 | 32.9 | 12.6 | 8.3 | 4.8 |
| 1993–2014 | 24.0 | 14.6 | 7.5 | 6.9 |

## VI. Interconnectedness at the Financial Institution Level

To measure interconnectedness at the financial institution level, we inferred the dynamic network of spillover effects between 20 systemically important financial institutions. We considered all banks and insurers from the Financial Stability Board (FSB) list of systemically important financial institutions and systemically important insurers. As done by Diebold and Yılmaz (2014), we also considered systemically important financial institutions that were not part of the FSB's list because they were acquired or went bankrupt during the 2007–2009 crisis. Thus, the subsample included the following: American Express, American International Group (AIG), Bank of America, Bank of New York Mellon, Bear Stearns, Citigroup, Fannie Mae, Freddie Mac, Goldman Sachs, JPMorgan Chase, Lehman Brothers, Merrill Lynch, MetLife, Morgan Stanley, PNC Group, Prudential, State Street, U.S. Bancorp, Wachovia, and Wells Fargo.

Because our sample is unbalanced with several stock price time series substantially shorter than the complete sample period, we adopt a *pairwise* approach similar to that of Billio et al. (2012). For each pair of financial institutions,

[4] We thank the referee for this insight regarding REITs.

we estimate a bivariate TVP-VAR (with 1 lag), taking into account the longest common time period of available data between any given pair.

## A. Financial Institution Centrality

In order to assess the importance of each financial institution within the dynamic network, we analyzed each financial institution's degree centrality, which measures the weighted sum of the connections to and from a given financial institution. Because our network is directed, we can measure both the in-degree centrality (IDC) as well as the out-degree centrality (ODC), respectively given by the following:

$$\text{IN_DEGREE}_{i,t} = \frac{1}{(N_t - 1)} \sum_{j \neq i} (j \rightarrow_t i) \times |B_t^{(i\,j)}|, \tag{4}$$

$$\text{OUT_DEGREE}_{i,t} = \frac{1}{(N_t - 1)} \sum_{j \neq i} (i \rightarrow_t j) \times |B_t^{(j\,i)}|, \tag{5}$$

where $i, j \in \{1, \ldots, 20\}$, and $N_t$ is the number of financial institutions present at time $t$. Notice that, as for the density measure in equation (3), we choose to weigh connections by the absolute value of the underlying cross coefficient in the bivariate VAR.

IDC measures the average strength of incoming connections to financial institution $i$. Effectively, it is an indicator of the extent to which other financial institutions influence the stock price of financial institution $i$. Therefore, it is a measure of vulnerability to financial spillover effects.

ODC measures the strength of outgoing links from financial institution $i$. Thus, a financial institution with high ODC is heavily influencing many of its neighbors, making it a propagator of spillovers. As suggested by Hautsch et al. (2014), such financial institutions should be monitored closely because they are highly interconnected.

Figures 3 and 4 depict, respectively, the in- and out-degree centrality for the financial institutions studied. The measures computed using our TVP-VAR framework are shown in bold solid, whereas the light dashed lines depict those computed from the rolling-window approach with a window size of 36 months. By visually inspecting each graph, we can immediately notice that the two methodologies, the TVP-VAR framework and rolling-window approach, produce very different pictures. For example, Figure 3 shows that the in-degree centrality of Fannie Mae peaks at different periods according to the methodology used.

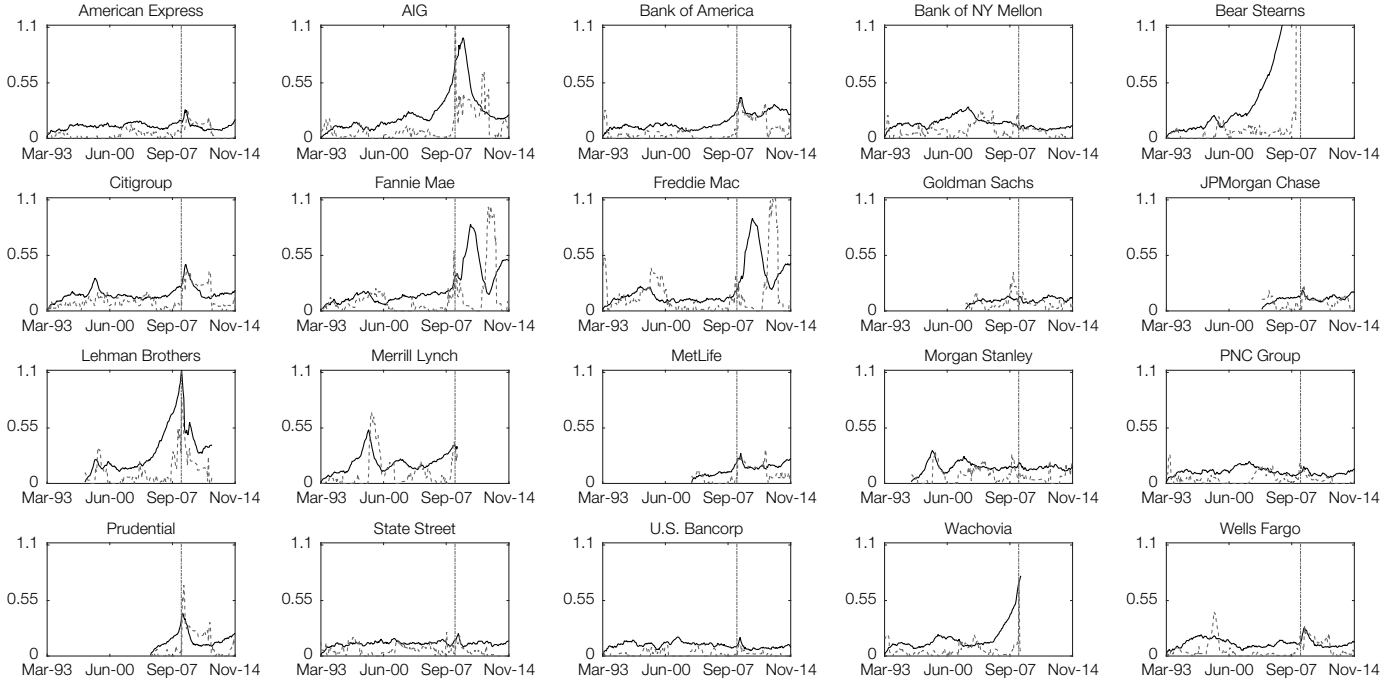
Figure 3 shows that Bear Stearns is the financial institution that attains the highest level of IDC, peaking at a value of 2.4 in Mar. 2008 (the peak is not shown in the figure for visibility reasons). Notice that Bear Stearns' IDC calculated using the classical rolling-window approach jumps suddenly in Mar. 2008, whereas the corresponding measure calculated with our time-varying parameter framework shows an increase that began long before this event. This means that it was receiving stronger spillovers from a growing number of firms, effectively increasing its fragility. Bear Stearns was the first large bank to collapse as a result of the subprime mortgage crisis of 2007. The data involved in calculating its IDC do not contain the financial meltdown of Sept. 2008. This is because the sample

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

FIGURE 3

## In-Degree Centrality for U.S. Systemically Important Financial Institutions

Figure 3 shows the in-degree centrality (IDC) for U.S. banks and insurers identified as systemically important financial institutions. The bold solid lines indicate the IDC estimated using the time-varying parameter vector autoregression (TVP-VAR) framework. The lighter dashed lines indicate the IDC estimated using the classical approach of Granger causality testing over rolling windows of 36 months. The dashed vertical lines indicate the day of Lehman Brothers bankruptcy, Sept. 15, 2008.

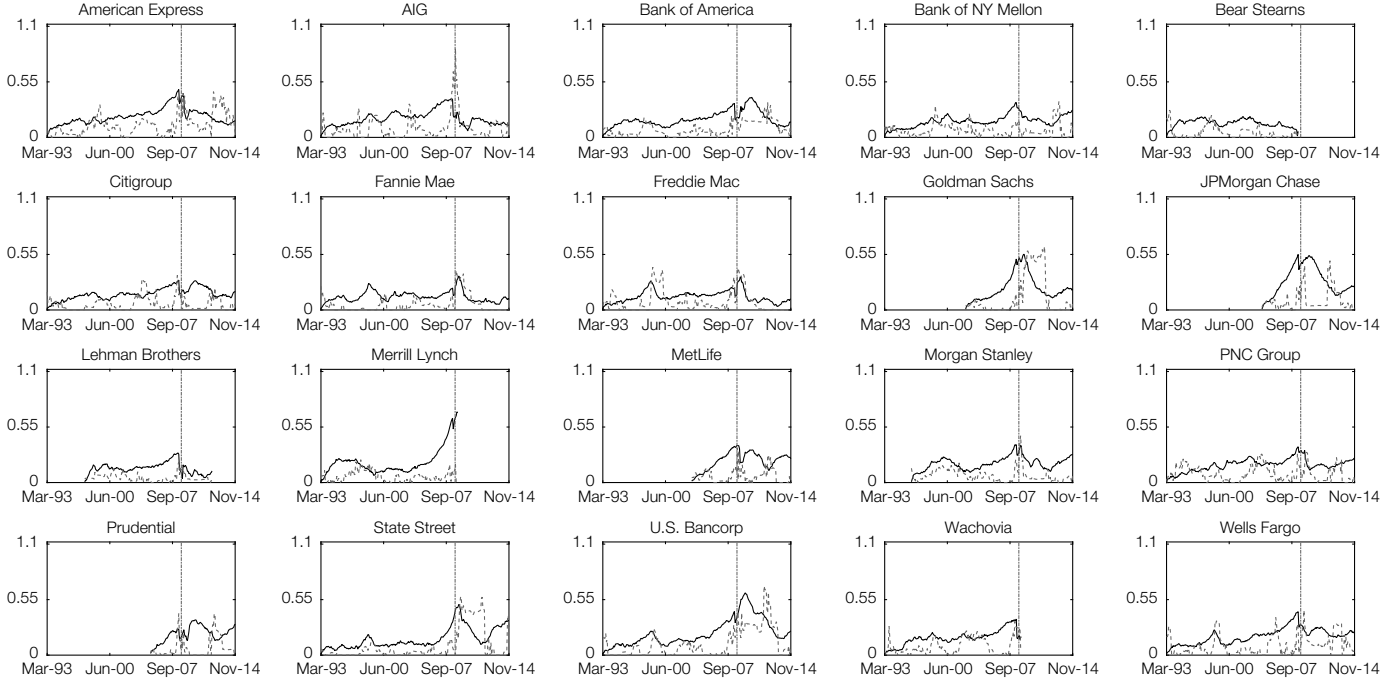



https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

FIGURE 4

## Out-Degree Centrality for U.S. Systemically Important Financial Institutions

Figure 4 shows the out-degree centrality (ODC) for U.S. banks and insurers identified as systemically important financial institutions. The bold solid lines indicate the ODC estimated using the time-varying parameter vector autoregression (TVP-VAR) framework. The lighter dashed lines indicate the ODC estimated using the classical approach of Granger causality testing over rolling windows of 36 months. The dashed vertical lines indicate the day of Lehman Brothers bankruptcy, Sept. 15, 2008.






https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

time series of Bears Stearns' stock price is quoted only until May 2008, when it was acquired by JPMorgan Chase. Therefore, the high IDC of Bear Stearns cannot be attributable to any noise caused by the many events that occurred during Sept.–Oct. 2008.

Figure 4 shows that ODC levels are more homogeneous between financial institutions compared with the IDC levels shown in Figure 3. American International Group, Goldman Sachs, and Merrill Lynch are among the financial institutions with the highest ODC levels. This concurs with the findings of Hautsch et al. (2014) and Dungey et al. (2018), who also identified these banks as very central. For Lehman Brothers, the level of ODC found using our time-varying parameter framework is higher than that found using the rolling-window approach. Nonetheless, it is not among the highest across the financial institutions analyzed. The result is consistent with the policy decision taken by the government and Federal Reserve to not bail out Lehman Brothers during the crisis because it was considered as not systemic (Committee on Oversight and Government Reform (2008)).

According to an asset and liability exposure analysis conducted by Scott (2012), Lehman Brothers's bankruptcy was not particularly destabilizing for its direct counterparties. However, without doubt, Lehman Brothers's bankruptcy triggered a sentiment of fear and uncertainty in markets. Fear was primarily due to the realization that government rescue of large financial institutions was no longer guaranteed, whereas uncertainty surrounded the extent of losses incurred by other institutions due to Lehman Brothers's default. This led to a freeze in the short-term funding market and, effectively, a liquidity crisis that affected financial institutions regardless of their contractual obligations with Lehman Brothers.

Conversely, Lehman Brothers's reliance on short-term rather than long-term funding made it vulnerable to external shocks (Scott (2012)). This is detectable in the growing IDC of Lehman Brothers, which our time-varying framework shows had begun in 2006, as can be seen in Figure 3.

## B. Stability of Centrality Rankings

Using the approach developed by the Basel Committee on Banking Supervision (BCBS), the FSB ranks financial institutions according to their systemic importance and uses this ranking to determine their additional loss-absorbency requirements.[5] In a similar spirit, we ranked the 20 systemically important financial institutions according to their IDC and ODC. These two rankings give only a partial view of systemic risk, one based only on interconnectedness, whereas the rankings drawn by the FSB are also based on other determinants of systemic risk, such as size and leverage. Nonetheless, the rankings can help us identify, at every point in time, the institutions most exposed to spillover effects and the most important propagators of spillover effects.

As discussed by Daníelsson, James, Valenzuela, and Zer (2016) and Dungey et al. (2018), the usefulness of rankings for policymakers is severely limited if these are prone to frequent, drastic changes that lead to unmotivated excessive

[5] Additional loss-absorbency requirements are being phased in, starting in Jan. 2016 and with full implementation by Jan. 2019 (see Financial Stability Board (2011)).

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

alarm. In an attempt to assess and quantify this aspect of interconnectedness rankings, we developed a series of stability indicators.

Let $Z_{it}^{\text{IN}}$ be the ordinal ranking of institution $i$ at time $t$ in terms of IDC. Similarly, let $Z_{it}^{\text{OUT}}$ be the ordinal ranking of institution $i$ at time $t$ in terms of ODC. We compute the *quadratic* ranking stability indicator as

$$\text{SI}_Q^{\text{IN}} = \frac{1}{T-1}\sum_{t=2}^{T}\sqrt{\sum_{i=1}^{N_t}\frac{(Z_{it}^{\text{IN}}-Z_{it-1}^{\text{IN}})^2}{N_t}},$$

$$\text{SI}_Q^{\text{OUT}} = \frac{1}{T-1}\sum_{t=2}^{T}\sqrt{\sum_{i=1}^{N_t}\frac{(Z_{it}^{\text{OUT}}-Z_{it-1}^{\text{OUT}})^2}{N_t}}.$$

Similarly, we construct the *absolute* stability indicator as

$$\text{SI}_A^{\text{IN}} = \sum_{t=2}^{T}\sum_{i=1}^{N_t}\frac{|Z_{it}^{\text{IN}}-Z_{it-1}^{\text{IN}}|}{N_t(T-1)}, \quad \text{SI}_A^{\text{OUT}} = \sum_{t=2}^{T}\sum_{i=1}^{N_t}\frac{|Z_{it}^{\text{OUT}}-Z_{it-1}^{\text{OUT}}|}{N_t(T-1)}.$$

The *quadratic* stability indicators, $\text{SI}_Q^{\text{IN}}$ and $\text{SI}_Q^{\text{OUT}}$, measure the average change in the rankings between adjacent time periods. The quadratic term used in the calculation causes large deviations in the rankings to have a larger impact on the stability indicator compared to smaller deviations. Conversely, for the *absolute* stability indicators, $\text{SI}_A^{\text{IN}}$ and $\text{SI}_A^{\text{OUT}}$, the weight increases only linearly with the distance between ranking positions. As additional indicators of stability, we also compute the average percentage of financial institutions that kept their position in the ranking between adjacent time periods and the average change (in percentage terms) in the top 5 and top 10 rankings between adjacent time periods.

In order to have a reference for comparison, and in a spirit similar to Nucera, Schwaab, Koopman, and Lucas (2016), we compute the stability indicators for four additional rankings based on the following measures of systemic risk: SRisk (Acharya et al. (2012), Brownlees and Engle (2017)), marginal expected shortfall (MES) (Acharya et al. (2017)), leverage ratio (Engle, Jondeau, and Rockinger (2015)), and beta capital asset pricing model (CAPM) (Engle (2016)).[6]

Table 2 shows the stability indicators for rankings based on the IDC and ODC measures found with our time-varying parameter framework and with the rolling-window approach (Panels A and C), as well as for rankings based on the four other systemic risk measures (Panel B).

The first four columns of Table 2 display the *quadratic* and *absolute* stability indicators. Both indicators for both centrality measures (IDC and ODC) show that the rankings based on our time-varying parameter framework are far more stable than the rankings based on the classical rolling-window approach. In fact, according to both stability indicators, the rolling-window approach appears to produce rankings that are more than twice as unstable than those produced by the TVP-VAR framework.

[6]We obtain the monthly time series of systemic risk measures from the V-Lab Web site, http://vlab.stern.nyu.edu. The data cover the 2000–2014 period.

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

TABLE 2
Stability Indicators

Table 2 presents the stability indicators for rankings based on centrality computed with the time-varying parameter vector autoregression (TVP-VAR) framework and with the rolling-window approach (RW-36M), as well as for rankings based on SRisk, marginal expected shortfall (MES), leverage, and beta capital asset pricing model (CAPM). "Stability Indicators" express the extent of monthly changes in the rankings, "% Invariance" measures the percentage of financial institutions that held the same position in the ranking between adjacent time periods, and "ΔTop 5" and "ΔTop 10" measure the average monthly change (in percentage) in the composition of, respectively, the top 5 and top 10 institutions of the rankings.

*Panel A. 2000–2014*

| | Stability Indicators | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Quadratic | | Absolute | | % Invariance | | ΔTop 5 | | ΔTop 10 | |
| | $SI_Q^{IN}$ | $SI_Q^{OUT}$ | $SI_A^{IN}$ | $SI_A^{OUT}$ | IN | OUT | IN | OUT | IN | OUT |
| RW-36M | 2.5 | 2.7 | 1.7 | 1.8 | 36.8 | 36.7 | 18.6 | 22.4 | 11.6 | 13.4 |
| TVP-VAR | 1 | 1.1 | 0.6 | 0.7 | 56.3 | 54.4 | 4.9 | 8.5 | 4.5 | 4.8 |

*Panel B. 2000–2014*

| | $SI_Q$ | $SI_A$ | % Invariance | ΔTop 5 | ΔTop 10 |
|---|---|---|---|---|---|
| SRisk | 1.3 | 0.8 | 57.7 | 17.3 | 10.9 |
| MES | 3.1 | 2.3 | 23.7 | 60 | 33.3 |
| Leverage | 0.8 | 0.5 | 69.2 | 24.2 | 12.8 |
| Beta | 3.1 | 2.3 | 23.5 | 60 | 33.5 |

*Panel C. 1993–2014*

| | $SI_Q^{IN}$ | $SI_Q^{OUT}$ | $SI_A^{IN}$ | $SI_A^{OUT}$ | IN | OUT | IN | OUT | IN | OUT |
|---|---|---|---|---|---|---|---|---|---|---|
| RW-36M | 2.4 | 2.5 | 1.6 | 1.7 | 38.4 | 36.5 | 19 | 20.9 | 11.5 | 12.4 |
| TVP-VAR | 1.2 | 1.2 | 0.8 | 0.8 | 52.1 | 50.8 | 7.3 | 9.2 | 5.5 | 6.3 |

Panel B of Table 2 shows the stability of rankings obtained from other systemic risk measures. Notice that leverage provides the most stable ranking, according to the absolute and quadratic stability indicators. This is because leverage is based on the book value of assets, which is generally observed at low frequencies. Conversely, MES and beta CAPM, which are based on higher-frequency market data, provide the most unstable rankings.

Comparing Panel B to Panel A of Table 2, which shows the stability of the time-varying parameter and rolling-window rankings for comparable periods of our sample, we see that the time-varying parameter framework produces rankings with similar stability to SRisk. SRisk uses a combination of book value and market data, whereas the TVP-VAR framework exclusively uses market data.

The successive two columns headed "% Invariance" denote the average percentage of financial institutions that kept the same position in the ranking between adjacent time periods. Between 2000 and 2014, in the average month, about 55% of financial institutions kept the same position they held in the previous month in the IDC and ODC rankings calculated with the TVP-VAR framework. For rankings computed using the rolling-window approach, only about 37% of financial institutions kept the same position between adjacent months. The same difference is found when using the whole sample from 1993 to 2014 (shown in Panel C of Table 2). This confirms the higher stability of rankings estimated with the TVP-VAR framework. The "% Invariance" of rankings based on other systemic risk measures seem to confirm the previous results, that is, that the TVP-VAR yields more stable rankings than MES and beta CAPM but appears to be similar, in terms of stability, to SRisk and less stable than leverage.

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

The columns in Table 2 headed "ΔTop 5" and "ΔTop 10" show the average changes (in percentage terms) in the composition of, respectively, the top 5 and the top 10 financial institutions in the rankings. For example, for the rankings computed using the rolling-window approach, we can expect, on average, one firm to change in the top 5 (19% for IDC, 20.9% for ODC; see Panel C) every month. Conversely, for the rankings computed using the TVP-VAR framework, only between 7.3% and 9.3% of the top 5 changed on average, so substantially less than one firm per month. Similar magnitudes of results were obtained for the 2000–2014 period (shown in Panel A) and for the stability of the top 10 firms in the rankings.

All measures used to quantify stability indicate that the rolling-window approach, with standard window size, provides less stable rankings compared with the time-varying parameter framework even though both approaches make use of the same data. The reasons for the higher stability offered by the time-varying parameter framework are to be found in the transition law imposed for time-varying connections. By allowing some degree of inertia between successive time periods, large exceptional observations have less influence on the estimated path of connections. Conversely, with the rolling-window approach, these observations have a larger weight in the estimation of connections.

The high instability of the rankings found using the rolling-window approach would make these rankings difficult to use for policy purposes. It would be hard to justify policy decisions based on a ranking that changes, on average, one component in its top 5 most interconnected institutions every month. Conversely, the time-varying parameter framework offers a generally stable ranking while allowing some degree of flexibility that can be useful to motivate policy intervention.

## C. Out-of-Sample Interconnectedness

In order to further illustrate the use of our framework for policy purposes, we conduct an out-of-sample exercise, which consists of estimating interconnectedness using a smaller data sample restricted up to the end of 2007.[7] We then evaluate which institutions are the most interconnected, in terms of IDC and ODC, prior to the crisis at the end of Dec. 2007.

Table 3 shows the top 5 financial institutions, in terms of IDC and ODC, found using our time-varying framework with the restricted data sample. Concurrent with previous results, Bear Stearns is in the top 5 ranking in terms of IDC but is ranked only 18th (not shown) in terms of ODC. Thus, the result that Bear

TABLE 3
Interconnectedness Rankings

Table 3 presents the top 5 financial institutions in terms of in-degree and out-degree centrality on Dec. 31, 2007, using a small sample (1994–2007).

| Ranking | In-Degree | Out-Degree |
|---|---|---|
| 1 | Goldman Sachs Group Inc. | American International Group |
| 2 | State Street Corp. | Bank of America Corp. |
| 3 | Federal Home Loan Mortgage Corp. | Citigroup Inc. |
| 4 | Lehman Brothers Holdings Inc. | Wells Fargo & Co. |
| 5 | Bear Stearns Companies Inc. | Wachovia Corp. |

[7] We thank the referee for suggesting this exercise.

Stearns was not an important propagator of spillover effects, whereas it was susceptible to receiving spillover effects from other institutions, is also detectable in Dec. 2007 using a restricted data sample.

Similarly, the results regarding Lehman Brothers can be confirmed using the restricted data sample. Lehman Brothers is the fourth most interconnected financial institution in terms of IDC in Dec. 2007, whereas it is ranked 12th in terms of ODC for the same period. On the other hand, AIG is ranked first in terms of ODC in Dec. 2007 using the restricted data sample. This highlights the potentially widespread influence its default could have caused and concurs with the decision taken by the Federal Reserve to bail out AIG in Sept. 2008.

Overall, the out-of-sample exercise shows that the TVP-VAR framework can identify highly interconnected financial institutions prior to the crisis using a realistic data sample. Results are consistent with those obtained previously using the full data sample, both in terms of IDC and in terms of ODC.

## VII. Conclusion

We provide a framework for estimating the interconnectedness between financial institutions that accounts for the dynamic nature of connections. We build our framework in a TVP-VAR setting and use Bayesian inference to evaluate, at every moment in time, the posterior probability of a connection existing between any two financial institutions. The framework surpasses several limitations of the classical approach for measuring interconnectedness by sequentially running Granger causality tests over rolling windows of data. Moreover, by modeling both temporal and contemporaneous dependencies, our framework contributes to both strands of the literature on interconnectedness market-based measures. Finally, we contribute to the TVP-VAR literature by proposing a model that accommodates many of the properties of asset returns, namely, heavy tails, heteroscedasticity, and skewness.

We apply the proposed framework to estimate the time-varying network of spillover effects of the U.S. financial system. We show that the TVP-VAR framework delivers measures of sectoral density and financial institution centrality that are less noisy than the same measures delivered by the rolling-window approach. At the sectoral level, we find that interconnectedness evolves gradually over time and peaks around two crucial events: the LTCM crisis in 1998 and the global financial crisis in 2008. At the financial institution level, rankings drawn using our TVP-VAR framework are more stable than rankings drawn using the classical rolling-window approach. The TVP-VAR framework also delivers more stable rankings than other comparable market-based measures of systemic risk, such as the marginal expected shortfall, but delivers more reactive rankings than measures based on book-value data, such as leverage, which only evolve at very low frequencies.

## References

Acharya, V. V.; R. F. Engle; and M. Richardson. "Capital Shortfall: A New Approach to Ranking and Regulating Systemic Risk." *American Economic Review*, 102 (2012), 59–64.

Acharya, V. V.; L. H. Pedersen; T. Philippon; and M. Richardson. "Measuring Systemic Risk." *Review of Financial Studies*, 30 (2017), 2–47.

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

Adams, Z.; R. Füss; and R. Gropp. "Spillover Effects among Financial Institutions: A State-Dependent Sensitivity Value-at-Risk Approach." *Journal of Financial and Quantitative Analysis*, 49 (2014), 575–598.

Adrian, T., and M. K. Brunnermeier. "CoVaR." *American Economic Review*, 106 (2016), 1705–1741.

Barigozzi, M., and C. Brownlees. "NETS: Network Estimation for Time Series." ECARES Working Paper, Université Libre de Bruxelles (2017).

Barigozzi, M., and M. Hallin. "A Network Analysis of the Volatility of High Dimensional Financial Series." *Journal of the Royal Statistical Society, Series C: Applied Statistics*, 66 (2017), 581–605.

Baumeister, C., and L. Benati. "Unconventional Monetary Policy and the Great Recession: Estimating the Macroeconomic Effects of a Spread Compression at the Zero Lower Bound." *International Journal of Central Banking*, 9 (2013), 165–212.

Bernardi, M.; G. Gayraud; and L. Petrella. "Bayesian Tail Risk Interdependence Using Quantile Regression." *Bayesian Analysis*, 10 (2015), 553–603.

Billio, M.; M. Getmansky; A. W. Lo; and L. Pelizzon. "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors." *Journal of Financial Economics*, 104 (2012), 535–559.

Brownlees, A. C., and R. F. Engle. "SRisk: A Conditional Capital Shortfall Measure of Systemic Risk." *Review of Financial Studies*, 30 (2017), 48–79.

Ciccarelli, M., and A. Rebucci. "Measuring Contagion and Interdependence with a Bayesian Time-Varying Coefficient Model: An Application to the Chilean FX Market during the Argentine Crisis." *Journal of Financial Econometrics*, 5 (2007), 285–320.

Clark, T. E., and M. W. McCracken. "Improving Forecast Accuracy by Combining Recursive and Rolling Forecasts." *International Economic Review*, 50 (2009), 363–395.

Cogley, T., and T. Sargent. "Drifts and Volatilities: Monetary Policies and Outcomes in the Post WWII US." *Review of Economic Dynamics*, 8 (2005), 262–302.

Committee on Oversight and Government Reform. "Causes and Effects of the Lehman Brothers Bankruptcy: Hearing before the Committee on Oversight and Government Reform." Available at https://www.gpo.gov/fdsys/pkg/CHRG-110hhrg55766/html/CHRG-110hhrg55766.htm (2008).

Daníelsson, J.; K. James; M. Valenzuela; and I. Zer. "Model Risk of Risk Models." *Journal of Financial Stability*, 23 (2016), 79–91.

Diebold, F. X., and K. Yılmaz. "Measuring Financial Asset Return and Volatility Spillovers, with Application to the Global Equity Markets." *Economic Journal*, 119 (2009), 158–171.

Diebold, F. X., and K. Yılmaz. "On the Network Topology of Variance Decompositions: Measuring the Connectedness of Financial Firms." *Journal of Econometrics*, 182 (2014), 119–134.

Dungey, M.; M. Luciani; and D. Veredas. "Systemic Risk in the US: Interconnectedness as a Circuit Breaker." *Economic Modelling*, 71 (2018), 305–315.

Engle, R. F. "Dynamic Conditional Beta." *Journal of Financial Econometrics*, 14 (2016), 643–667.

Engle, R. F.; E. Jondeau; and M. Rockinger. "Systemic Risk in Europe." *Review of Finance*, 19 (2015), 145–190.

Financial Stability Board. "Policy Measures to Address Systemically Important Financial Institutions." Available at http://www.fsb.org/2011/11/r_111104bb/ (2011).

Hautsch, N.; J. Schaumburg; and M. Schienle. "Forecasting Systemic Impact in Financial Networks." *International Journal of Forecasting*, 30 (2014), 781–794.

Hautsch, N.; J. Schaumburg; and M. Schienle. "Financial Network Systemic Risk Contributions." *Review of Finance*, 19 (2015), 685–738.

Kim, C.-J., and C. R. Nelson. *State-Space Models with Regime Switching: Classical and Gibbs-Sampling Approaches with Applications*. Cambridge, MA: MIT Press (1999).

Koop, G.; R. Leon-Gonzalez; and R. W. Strachan. "Dynamic Probabilities of Restrictions in State Space Models: An Application to the Phillips Curve." *Journal of Business and Economic Statistics*, 28 (2010), 370–379.

McDonough, M. J. "Statement by William J. McDonough, President Federal Reserve Bank of New York before the Committee on Banking and Financial Services U.S. House of Representatives." Available at https://www.newyorkfed.org/newsevents/speeches/1998/mcd981001 (1998).

Nakajima, J., and Y. Omori. "Stochastic Volatility Model with Leverage and Asymmetrically Heavy-Tailed Error Using GH Skew Student's *t*-Distribution." *Computational Statistics and Data Analysis*, 56 (2012), 3690–3704.

Nucera, F.; B. Schwaab; S. J. Koopman; and A. Lucas. "The Information in Systemic Risk Rankings." *Journal of Empirical Finance*, 38 (2016), 461–475.

Primiceri, G. "Time Varying Structural Vector Autoregressions and Monetary Policy." *Review of Economic Studies*, 72 (2005), 821–852.

Scott, H. S. "Interconnectedness and Contagion." Tech. Rep., Committee on Capital Markets Regulation (2012).

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press

White, H.; T.-H. Kim; and S. Manganelli. "VAR for VaR: Measuring Tail Dependence Using Multivariate Regression Quantiles." *Journal of Econometrics*, 187 (2015), 169–188.

Yu, K., and R. A. Moyeed. "Bayesian Quantile Regression." *Statistics and Probability Letters*, 54 (2001), 437–447.

Zivot, E., and J. Wang. "Rolling Analysis of Time Series." Modeling Financial Time Series with S-PLUS, 2nd ed. New York: Springer (2006).

https://doi.org/10.1017/S0022109018000108 Published online by Cambridge University Press