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Application of network vector autoregression model in volatility spillover analysis

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Abstract: Measuring the network connectedness of the financial system is of great importance in systemic risk analysis, and has drawn great attention in recent years. In this paper, we apply the transfer entropy method to analyze the volatility spillover network connectedness of the U. S. stock market. Based on the network structure, we apply the network vector autoregression model (NVAM) and are interested in identifying the influential firms in volatility spillover network of the financial system. In addition, by using rolling windows, the dynamics of total volatility spillover network connectedness indices are obtained, which shows a sharp rise at the beginning of the financial crisis, while it only fluctuates within a controllable range in the steady economic period. The results show that transfer entropy has great potential for understanding the correlation and information flow of financial markets.
Keywords: network connectedness; transfer entropy; network autoregression; systemic risk
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1 Introduction

Connectedness between two financial institutions and the connectedness of network has attracted lots of interests in recent years. Studying connectedness is crucial to understanding market risk, credit risk, macroeconomic risk and system risk. Recently, the multi-discipline mathematical tools have reinforced the research on financial networks, showing its power and potential to analyze the microstructure of networks. At the same time, network analysis theory has drawn great attention in recent years, such as Refs. [1−4]. Related empirical work, which sometimes includes banking contexts, see for example, Refs. [5−9]. Once the connectedness network structure is obtained, different firms in the network may have different influence on other firms in the network. How to identify the influence of an institution becomes an important problem in network analysis theory.

There are three main methods to measure the network connectedness: Granger causality, VAR model and transfer entropy. For the approach of Granger causality network, Billio et al.[5] applied it to the monthly returns of four kinds of financial institutions. Gong et al.[10] constructed the causal complex network of financial institution based on the Granger causality and studied the contribution of individual financial firm to the systemic risk. Mazzarisi et al.[11] used the tail Grange causality test to construct a directed tail risk network. In terms of the VAR approach, Diebold et al.[7] established a unified framework for measuring time-varying connectedness of major US financial institutions stock return volatilities during the financial crisis of 2007 − 2008, based on the variance decomposition. Since that, the variance decomposition based methods have been widely used in financial and industry contexts, as in Refs. [12, 13]. Demirer et al.[14] introduced the LASSO method into the high-dimensional network of publicly-traded subset of the world's top 150 banks, overcoming the drawback of VAR model that it is limited to low-dimensional network. Chen et al.[15] applied the VAR process with a two-step LASSO estimation approach to study the connectedness of Chinese financial firms. Adrian et al.[9] proposed the method CoVaR to measure system risk according to institutions leverage, size, and maturity mismatch. As for the transfer entropy method, the definition was firstly proposed by Schreiber[16], and used in many fields, such as computer science, social science. Kim et al.[17] used transfer entropy in financial field on five monthly macroeconomic variables, showing the inter-relations of the five variables inside each country and the correlation between variables of different countries. Gong et al.[18] also made an

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analysis of stock market network connectedness by using transfer entropy method.

In this paper, a simple and productive method transfer entropy (TE) are used to measure the connectedness of a volatility spillover network consisting of some companies listed on a U. S. stock exchange. In addition, a network vector autoregression model (NVAM) is used to identify the influential firms in terms of communication risk spillovers in the system. To the best of our knowledge, there is no research about the spillover of the company in financial network under transfer entropy connectedness framework. We first apply the transfer entropy method to build the network connectedness of financial listed companies in the U. S. stock market, and then use the NVAR model to identify the influential companies in the network under transfer entropy connectedness framework.

The rest paper is organized as follows: In Section 2, some basic concepts of transfer entropy are introduced, and the network connectedness using transfer entropy is developed. In Section 3, NVAR model and settings are introduced. Section 4 depicts the data and our empirical results. Finally, some implications of this paper are concluded in Section 5.

2 Network connectedness

2.1 Basic concepts about transfer entropy

Transfer entropy (TE) was firstly proposed by Schreiber[16] to quantify the information exchange of two systems in the information theory. It can describe the information transfer between the nodes in a network. Here, we apply the TE to measure the volatility spillover connectedness between the financial firms which is similar to Ref. [18].

We recall some basic concepts in the information theory firstly. Suppose that X is a random variable with probability distribution $p(x)$. Shannon[19] proposed Shannon entropy to measure the average uncertainty of the variable:

$$H_I = -\sum_{x \in \Omega_x} p(x) \log p(x) \tag{1}$$

where Ω_x is the value space of X, and $-\log p(x)$ represents the information. Shannon entropy is then used to measure how much information is needed to identify random samples from a given discrete distribution. The larger the Shannon entropy is, the less information is needed.

In order to facilitate the understanding of transfer entropy which is mentioned below, the Kullback entropy also need to be introduced. Kullback entropy or relative entropy, could be a measure of the difference between these two probability distributions. It is defined as

$$K_I = \sum_{x \in \Omega_x} p(x) \log \frac{p(x)}{q(x)} \tag{2}$$

where $p(x)$ and $q(x)$ are distribution functions of two random variables with same domain of definition. When $p(x)$ and $q(x)$ are the same, the relative entropy equals to 0, which indicates there is no difference between these two distributions.

To measure the network connectedness, we should transfer our view on the situation of two variables. Suppose now that there are two random variables X and Y, with the joint density function $p(x,y)$ and the marginal density functions $p(x)$ and $p(y)$, the joint entropy is defined as

$$H_{XY} = -\sum_{x \in \Omega_x, y \in \Omega_y} p(x,y) \log p(x,y) \tag{3}$$

In the field of finance, we usually consider the risk of an individual firm under certain influence of some events about the other firm or the whole financial system, which leads us to consider conditioal entropy. Conditional entropy is the average uncertainty of the variable X when the information about the other variable Y is already known. It is given by

$$H_{X|Y} = -\sum_{y \in \Omega_y} p(y) \sum_{x \in \Omega_x} p(x \mid y) \log p(x \mid y) = -\sum_{x \in \Omega_x, y \in \Omega_y} p(x,y) \log p(x \mid y) \tag{4}$$

In the same way, Kullback entropy for conditional probability is defined as follows:

$$K_{X|Y} = \sum_{y \in \Omega_y} p(y) \sum_{x \in \Omega_x} p(x \mid y) \log \frac{p(x \mid y)}{q(x \mid y)} = \sum_{x \in \Omega_x, y \in \Omega_y} p(x,y) \log \frac{p(x \mid y)}{q(x \mid y)} \tag{5}$$

where $q(x,y)$ is a benchmark of the joint density of (X,Y).

The mutual information (MI) of two variables X and Y is the information commonly shared by them, and the well known formula is

$$\mathrm{MI}_{XY} = \sum_{x \in \Omega_x, y \in \Omega_y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \tag{6}$$

which could be written as the difference between the entropy of X and the conditional entropy of X given Y.

$$\mathrm{MI}_{XY} = H_X - H_{X|Y} = H_Y - H_{Y|X} \tag{7}$$

This shows that MI is symmetric under the exchange of X and Y, $H_{X|Y}$ could be interpreted as the additional information that contained in the variable X when the information about Y is already known, hence the MI means the information owned by both X and Y. From another perspective, the original definition of MI is in connection with the Kullback entropy. The MI could be seen as the Kullback entropy between the joint distribution $p(x,y)$ and the product of the $p(x)$ and $p(y)$ (i. e. the joint distribution when X and Y are independent). If variable X is independent of Y, $p(x,y)=p(x)p(y)$ and the MI equals to 0. So MI is a measure to quantify the deviation from independence of two variables.

Mutual information quantifies the overlap of the information of two variables and the statistical independence between X and Y, but it contains neither dynamical nor directional information. Schreiber[16] considered the information flows through the system in a directional way over time and derived an alternative information theoretic measure, called transfer entropy. Suppose that there are two series of random variables $\{X_t \mid t=0,1,2,\cdots\}$ and $\{Y_t \mid t=0,1,2,\cdots\}$, X_t, the observation of variable X at time t, is related to the past value of variables $\{X_k \mid k<t\}$ and variables $\{Y_l \mid l<t\}$, in order to quantify the influence or the information transfer from the past Y to current X, transfer entropy from Y to X is defined as

$$T_{X\leftarrow Y} = \sum_{x_t, x_{t-1}^{(k)}, y_{t-1}^{(l)}} p(x_t, x_{t-1}^{(k)}, y_{t-1}^{(l)}) \log \frac{p(x_t \mid x_{t-1}^{(k)}, y_{t-1}^{(l)})}{p(x_t \mid x_{t-1}^{(k)})} \tag{8}$$

where x_t and y_t denote the observations of variables X and Y at time t, $x_{t-1}^{(k)}=(x_{t-1},\cdots,x_{t-k})$ and $y_{t-1}^{(l)}=(y_{t-1},\cdots,y_{t-l})$ mean the past values of X and Y, respectively. Actually, transfer entropy also gets inspiration from Kullback entropy and MI. Probability $p(x_t \mid x_{t-1}^{(k)}, y_{t-1}^{(l)})$ has extra condition $y_{t-1}^{(l)}$ over $p(x_t \mid x_{t-1}^{(k)})$. In the absence of information transferring from the past Y to the current X, the state of Y has no influence on X, that is to say, $p(x_t \mid x_{t-1}^{(k)}, y_{t-1}^{(l)}) = p(x_t \mid x_{t-1}^{(k)})$. On the contrary, the information flow from the past Y to the current X can be quantified by transfer entropy. More over, the transfer entropy takes the direction of information flow into account due to its asymmetry property $T_{X\leftarrow Y} \neq T_{Y\leftarrow X}$. In our next study related to the dynamic propagation of risks to the system, it is important to measure not only the degree of connectedness between financial institutions, but also the directionality of such relationships.

2.2 Network connectedness based on transfer entropy

Since transfer entropy quantifies the information transfer from a variable to another, it is also a measure of the connectedness between two variables. The connectedness from Y to X could be depicted by the transfer entropy from Y to X, which is defined as follows:

$$C_{X\leftarrow Y} = T_{X\leftarrow Y}.$$

Now consider a network consisting of N nodes, which are indexed by $i=1,\cdots,N$. Similarly, the connectedness structure of the network can be described by a connectedness matrix $\{A_{ij}\}_{N\times N}$, with

$$A_{ij} = C_{i\leftarrow j},$$

where i and j denote the nodes of the network. When refer to the connectedness matrix, there are a few points to note here. Since the directional connectedness has orientation, C_{ij} and C_{ji} represent the connectedness of the opposite directions separately, and $C_{ij} \neq C_{ji}$. In addition, if $i=j$, $C_{ii}=0$. Because the nature of transfer entropy is the information difference, which is the subtraction between the information about future observation X gained from past joint observations X_{t-1} and Y_{t-1} and information about future observation X gained from past observation X_{t-1} only. Thus, it is natural that X will not provide extra information to itself.

2.3 Total network connectedness

Inspired by the definition of directional connectedness, the total network connectedness can be obtained by the connectedness matrix $\{A_{ij}\}_{N\times N}$. Intuitively, total network connectedness can be achieved by summing over all systems and is given by

$$C = \frac{\sum_{i\neq j}^{N} A_{ij}}{N} \tag{9}$$

In this equation, all terms in the matrix are added together, and the summation is divided by N, which can be used to measure the volatility spillover connectedness of the whole financial system.

3 Network vector autoregression model

When the financial crisis occurs, companies in the market are generally affected because they have mutually beneficial business relationships. Illiquidity, volatility, insolvency, and losses can quickly propagate and risk is passed from one firm to the others. Although most of the companies in the market are involved in the risk transmission process, different types of companies have different positions in the risk transmission process. Financial institutions such as banks, insurance companies are likely to provide liquidity directly to the market which may have greater influence on the market. Therefore, we adopt a network vector autoregression model (NVAM) to quantitatively analyze the influence of different types of companies in the risk transmission process of the market, and use a parameter to describe the influence of the companies. Employing the transfer entropy, we obtain the weighted and directed connectedness matrix $A=\{A_{ij}\} \in \mathbb{R}^{N\times N}$, where $A_{ij}=C_{i\leftarrow j}$ and $A_{ii}=0$. In addition, define $\Omega=\{\omega_{ij}\} \in \mathbb{R}^{N\times N}$ to be the row-normalized connectedness matrix, where $\omega_{ij}=n_i^{-1}A_{ij}$ and $n_i=\sum_j A_{ij}$, namely the out-degree of node i. Now consider N individual firms in the financial system, and denote Y_{it}, $i=1,\cdots,N$, the daily log-return of firm i at time t and let $Y_t=(Y_{1t},\cdots,Y_{Nt})^{\mathrm{T}}$. In addition, assume for each node, a p-dimensional covariate is obtained as $Z_{it}=(Z_{i1t},\cdots,Z_{ipt})^{\mathrm{T}}$. Then, we consider the following NVAM,

$$Y_{it} = \sum_{j=1}^{N} d_j \omega_{ij} Y_{jt-1} + Z_{it-1}^{\mathrm{T}} \gamma + \epsilon_{it} \tag{10}$$

where $\gamma = (\gamma_1, \cdots, \gamma_p)^{\mathrm{T}} \in \mathbb{R}^p$ is the nodal coefficient, and ϵ_{it} is the noise term. Note the parameter d_j associated with firm j reflects the average multiple of risk spillovers transferrring from firm j to other firms. Therefore, the parameter $d = (d_1, d_2, \cdots, d_N)^{\mathrm{T}}$ can be interpreted as spillover influential powers of the firms.

Let $D = \mathrm{diag}(d_1, \cdots, d_N) \in \mathbb{R}^{N \times N}$ and $Z_t = (Z_{1t}, \cdots, Z_{Nt})^{\mathrm{T}} \in \mathbb{R}^{N \times p}$. One could rewrite the model (10) as

$$Y_t = \Omega D Y_{t-1} + Z_{t-1}^{\mathrm{T}} \gamma + \epsilon_t \tag{11}$$

where $\epsilon_t = (\epsilon_{1t}, \cdots, \epsilon_{Nt})^{\mathrm{T}} \in \mathbb{R}^N$ is the noise vector. The model is motivated from the network autoregression model (NAM) of Zhu et al.[20], where they applied the model to study the social network and considered the contemporaneous covariates, and we consider the lagged values as covariates to study the financial risk connectedness network. The model (11) is also similar to the spatio-temporal model dicussed by Dou et al.[21], which is defined as

$$Y_t = D_1 \Omega Y_{t-1} + D_2 \Omega Y_{t-2} + \epsilon_t \tag{12}$$

where $D_k = \mathrm{diag}(d_{k1}, \cdots, d_{kN}) \in \mathbb{R}^{N \times N}$ $(k = 1, 2)$ are diagonal matrices. However, the parameter d_{ki} is interpreted as how much the node i is influenced by other nodes, which could not directly quantify the spillover influential powers of each firm. Our model, on the other side, can help to identify the system influential firms that have a significant impact on risk transmission.

4 Empirical study

4.1 Data description

The U. S. stock market is the most developed and the largest stock market in the world. It has the characteristics of large scale, mature market, standardized operation and stable stock price. Because of these advantages, our main analysis focuses on publicly traded U. S. financial institutions listed on the U. S. exchanges. The selected companies are listed in Table 1, which include 6 banks, 4 insurance companies, 4 broker-dealers and 4 others. All of them have a large market capitalization and play a leading role in their respective industries. The sample covers the period from January 2005 to December 2014. This period involves the 2007－2009 global financial crisis which has caused huge losses and injuries to the global market, many big companies failed and millions of people have lost their jobs.

We use volatility rather than stock price index to depict the connectedness, because volatility represents risk, it can indicate the risk connectedness between different financial institutions. We use daily range-based realized volatility. That is, following Garman and Klass's work[22], we estimate the daily volatility as

Table 1. The selected financial institutions in U. S. stock markets.

Banks	Bank of America Corp (BAC)
	JP Morgan Chase & Co (JPM)
	M&T Bank Crop (MTB)
	Suntrust Banks Inc (STI)
	PNC Financial Services Group (PNC)
	Commercial Inc (CMA)
Insurance companies	American International Group (AIG)
	AFLAC Inc (AFL)
	Allstate Corp (ALL)
	AON Corp (AON)
Broker-dealers	E Trade Financial Crop (ETFC)
	Goldman Sachs Group Ins (GS)
	Morgan Stanley Dean Witter & Co (MS)
	T Rowe Price Group Inc (TROW)
Others	Schlumberger Ltd (SLB)
	Coca-Cola Co (KO)
	3M Co (MMM)
	International Business Machines Crop (IBM)

$$\sigma_{it}^2 = 0.511(H_{it} - L_{it})^2 - 0.019[(C_{it} - O_{it})(H_{it} + L_{it} - 2O_{it})] - 2(H_{it} - O_{it})(L_{it} - O_{it})] - 0.383(C_{it} - O_{it})^2 \tag{13}$$

where H_{it}, L_{it}, O_{it} and C_{it} are the logs of daily high, low, opening and closing prices for stock i on day t, respectively. Range-based realized volatility is nearly as efficient as realized volatility based on high-frequency intra-day sampling, yet it requires only four readily available inputs per day, and it is robust to certain forms of microstructure noise[23]. Table 2 summarized the descriptive statistics of the daily range-based realized volatility of each firm.

Then, the model of measuring connectedness is given by

$$C_{ij} = \sum_{\sigma_{it}, \sigma_{i,t-1}^{(k)}, \sigma_{j,t-1}^{(l)}} p(\sigma_{i,t}, \sigma_{i,t-1}^{(k)}, \sigma_{j,t-1}^{(l)}) \cdot \log \frac{p(\sigma_{i,t} \mid \sigma_{i,t-1}^{(k)}, \sigma_{j,t-1}^{(l)})}{p(\sigma_{i,t} \mid \sigma_{i,t-1}^{(k)})} \tag{14}$$

The selection of parameters k and l is of great importance to the accuracy of the estimation of transfer entropy and connectedness. If the historical length of the target variable k is too short, the transfer entropy may be overestimated, because the influence of the past

Table 2. Descriptive statistics of daily volatility series σ_{it} of U. S. stock market.

	BAC	JPM	MTB	STI	PNC	CMA
min	0.275	0.303	0.244	0.258	0.221	0.245
max	34.12	17.75	19.84	27.58	37.57	22.48
SD	2.353	1.681	1.609	2.432	1.951	1.984
	AIG	AFL	ALL	AON	ETFC	GS
min	0.225	0.296	0.231	0.274	0.378	0.295
max	99.62	29.33	21.037	19.29	34.47	23.36
SD	3.908	1.838	1.483	1.027	2.718	1.647
	MS	TROW	SLB	KO	MMM	IBM
min	0.341	0.341	0.383	0.183	0.236	0.206
max	53.15	27.41	13.61	7.916	19.32	7.974
SD	2.662	1.635	1.234	0.665	0.836	0.760

[Note] The AIG has the largest standard deviation during the sample period, while the KO has the smallest standard deviation during the sample period.

of the target on itself may not be totally conditioned out. If the historical length of the target variable is too long, the transfer entropy may also be overestimated due to insufficient multi-dimensional sampling. On the contrary, for the source variable, selecting a short history may underestimate the transfer entropy, because we may not fully consider the influence of the source variable's past on the target variable. In this paper, we set k and l to 1 based on the efficient market hypothesis and random walk behavior of stock prices.

4.2 Dynamic total volatility spillover connectedness

We use a rolling window method to construct a dynamic total volatility spillover connectedness index. Thoughout the paper, the width of rolling window is set to 1 year. Since the rolling window becomes wider, the time interval of dynamic changes of total volatility spillover connectedness becomes shorter and the scope of dynamic changes becomes smaller. Therefore, the rolling time window should not be too wide and 1 year is reasonable.

The result of the dynamic index is presented in Figure 1, where we can divide the graph into four economic periods. The first period starts at the begin of 2005 and ends in the middle of 2007. Although the connectedness of the financial system is low at the begin of 2006, it rose sharply following the Fed's unexpected decision to tighten monetary policy in May and June 2006. Then, following the collapse of several mortgage originators in the USA, connectedness continued to rise rapidly, and during the liquidity crisis of August 2007 it reached a peek. During this period risks and shocks

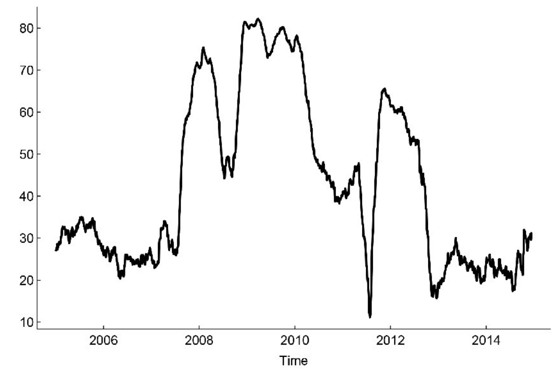

Figure 1. The dynamic total volatility connectedness index of U. S. market based on transfer entropy. Note: We obtain the dynamic index using rolling window. The width of rolling window is set to be one year.

continue to gather and eventually trigger the financial crisis. The second period starts at the end of 2007 and ends in late 2010. This period contained the 2007−2009 financial crisis, from Figure 1, although the total volatility spillover connectedness index declined when the U. S. government used the USD 700 billion Troubled Asset Relief Program (TARP) to inject capital into the major U. S. banks in the months after the Lehman bankruptcy on September 15, 2008. However, we can see that this index stay at a high level most of the time during this period. It means that the linkages between the corporations have a significantly increasing during the financial crisis, and long-term high total connectedness index means the financial crisis of 2007−2009 was long-lasting. The third period starts at the early 2011 and ends in the late 2012, with the Italian and Spanish sovereign debt crisis in 2011. The dynamic total volatility spillover connectedness increase sharply again. The fourth period is the rest of the sample period. With the government's intervention and the introduction of economic policies and various measures to save the market, the entire financial system has gradually stabilized. The dynamic total volatility spillover connectedness indices declined.

4.3 Spillover influential powers based on NVAM

Based on the connectedness matrix obtained by transfer entropy, and the network vector autoregression model, we obtain the estimation of the dynamic spillover influencial powers (SIFP) of each firm. The results are shown in Figure 2. From this graph, we can see that banks except MTB usually have large SIFP during the 2008−2009 financial crisis, while insurance firms have relatively large SIFP to other firms in most of the sample period. AS for the broker-dealers, they usually have low SIFP during the crisis period, but have relatively high SIFP during the steady economic period. The potential reason maybe that people are willing to invest part of their assets in securities companies in the period

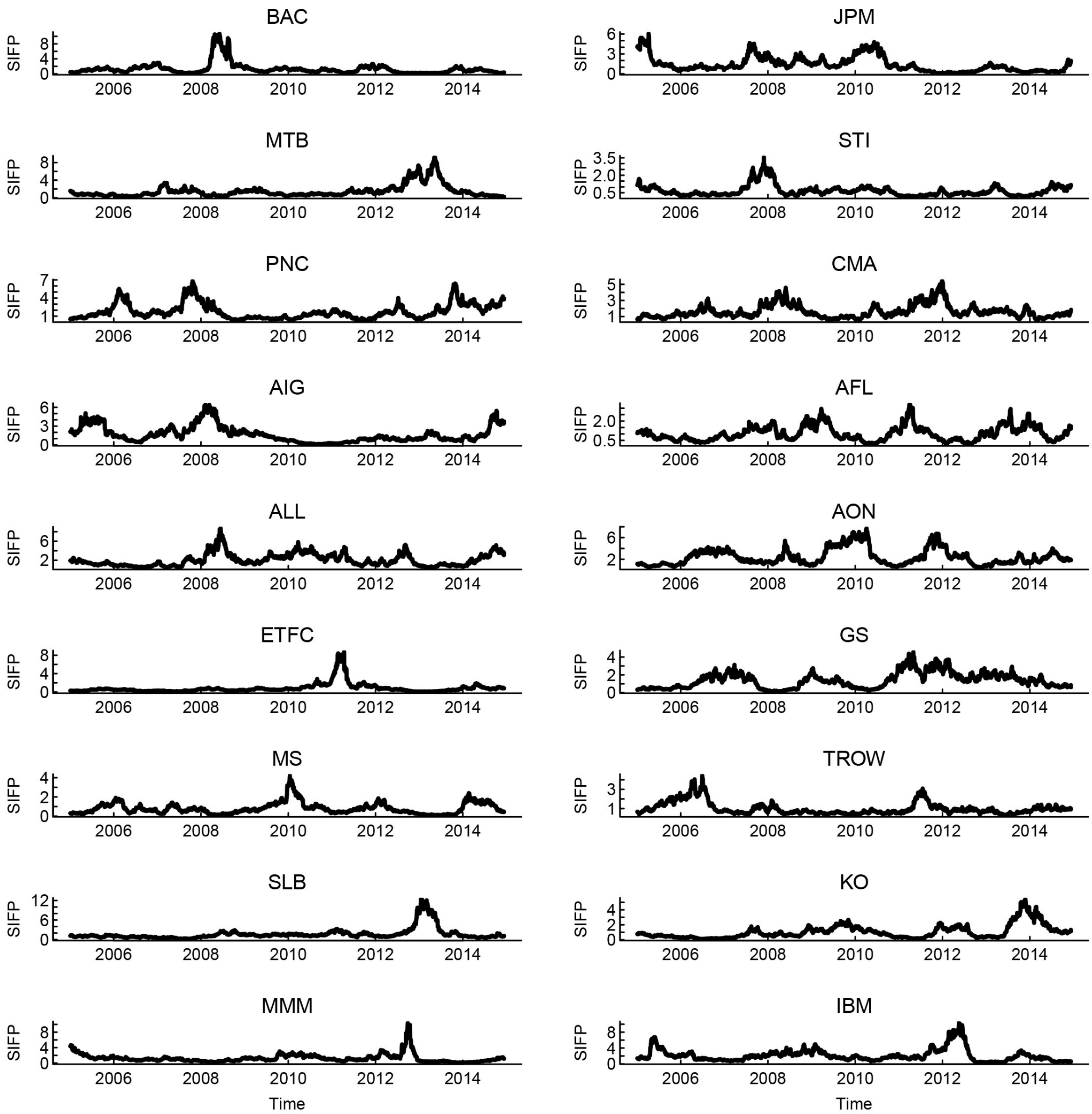

Figure 2. The dynamic spillover influential powers of each firms based on NVAM. Note: We obtain the dynamic index using rolling window. The width of rolling window is set to be one year.

of stable economy, but they will redeem a lot of these assets in the period of crisis, which leads to the low SIFP of broker-dealers during the crisis period. The other firms usually have low SIFP during most of the sample period.

5 Conclusions

This paper applies transfer entropy on the analysis of volatility transfer between different firms in the U. S. stock market. In addition, a network vector autoregression model is employed to identify the influential firms that transfer volatility spillovers in the system. For the total network connectedness, it is evident that the connectedness shows a sharp increase when subject to financial crisis, while it only fluctuates within a controllable range in absence of crisis. As for the influential firms, it suggests that the banks usually have large SIFP during the crisis period. Thus, the government's assistance to financial markets, such as injecting capital into major banks or providing loans, would be helpful to reduce total volatility spillover connectedness and prevent or remit the systemic financial crisis.

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Conflict of interest

The authors declare no conflict of interest.

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网络向量自回归模型在波动性溢出分析中的应用

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摘要:如何度量金融系统的网络连通性是系统风险分析的重要内容,在近年受到广泛的关注. 本文采用传递熵方法分析了美国股票市场的波动性溢出网络连通性. 基于构建的网络结构,我们应用了网络向量自回归模型(NVAM)并且感兴趣的是识别在金融系统构成的波动溢出网络中具有影响力的公司. 此外,本文采用滑动窗口方法得到了总波动性溢出网络连通性的动态变化规律,该指标在金融危机初期急剧上升,而在经济稳定时期仅在可控范围内波动. 结果表明,传递熵在帮助理解金融市场的相关性和信息传递性上具有较大的潜力.

关键词:网络连通性;传递熵;网络自回归;系统风险