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Industries Return and Volatility Spillover in Chinese Stock Market: An Early Warning Signal of Systemic Risk

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ABSTRACT This paper studies the intraday return and volatility spillovers of Chinese CSI 300 industry indices with high-frequency data over the period from May 2012 to June 2016. The dynamic correlation among the industries is calculated with VEC-DCC-GARCH model. The result shows that the correlations between the CSI 300 industry indices are high, but they are susceptible to fluctuation of the index. Furthermore, spillover indicators are calculated with the generalized variance decomposition method with intraday return and volatility, respectively. The time window-rolling method is applied to construct the return and volatility spillover index, which was proposed by Diebold and Yilmaz as connectedness, to discover the dynamic characteristics of CSI 300 industrial return and volatility spillover effect. We conclude that the dynamic characteristics of return and volatility spillover have strong early warning effect on systemic risk, especially the spillover dynamics of the finance and real estate industry. Finally, additional tests are performed with different sample frequencies and forecast steps to prove the robustness of our results.

INDEX TERMS CSI 300 industries, spillover effect, systemic risk, early warning signal.

I. INTRODUCTION

After the recent financial crisis, the systemic risk of financial market attracts both academic and financial industry concern. According to the IMF(2009) report, most countries have considered financial systemic risk prevention as the core regulatory objectives. The financial crisis often occurred with the outbreak of systemic risk, and most financial assets price dropped at the same time. Due to the correlation between financial assets, a decline in the price of one financial asset will also affect other financial assets, resulting in spillover effect. Accordingly, understanding and tracking the correlation of financial assets and the corresponding spillover effect plays an important role in systemic risk management in the current complex financial system, in which financial assets are highly correlated. Narayan *et al.* [1] found that spillover index is helpful to predict stock returns and mutual fund flows. The objective of this paper is to generate an early warning signal from the spillover effects between the financial assets to detect the outbreak of potential crisis, and minimize losses by appropriate regulations.

In this aspect, we focus on the risk contagion and financial system frailty due to interconnection among industries in China and the propagation of shock in financial system. If all sectors in China are highly correlated and risk could easily spillover from one sector to another, then we could not diversify risk among sectors in the stock market, which leads to the systemic risk accumulation in the system. The strong spillover effect could trigger the whole financial system collapse due to one important industry's failure, which is appeared as systemic risk.

This paper focuses on the dynamic correlation and the spillover effect of different industries in China's stock market, to study the industry connectedness in the Chinese financial market. We contribute to the literature from several perspectives. Firstly, while most of existing literatures focused on the co-movement between indices in different countries [2]–[6], we explore this phenomenon with industry indices in the Chinese stock market. As financial market co-movement of different countries is important for investment diversification, focusing on the different industries indices of one country will also bring implications on systemic risk of that financial market. It measures the co-movement of assets of different industries in the certain time period. Especially, individual stock performance is affected greatly by the market index in the Chinese stock market. Therefore, studying the industry indices co-movement is crucial for portfolio diversification.

Secondly, we focus on the dynamics of industry indices correlation and spillover effect, which provides the first empirical evidence in the Chinese stock market. Previous studies indicate that the co-movements of national stock market indices changed significantly in bull and bear markets [7], [8], others may argue that diversification in financial networks may increase systemic risk [9]. Meric *et al.* [10] tested this effect with worlds' major sector index. However, their research only showed the differences between different market periods, but did not capture how this characteristic changed during the market environment change. By time rolling window, we are able to capture the dynamics of industry spillover effect, and then capture the characteristics before and after financial crisis, to generate early warning signals of systemic risk.

Thirdly, we employ the connectedness method proposed by Diebold and Yilmaz [11], [12] to measure spillover effect instead of traditional GARCH specifications. This method captured spillover effect through variance decomposition of out-of-sample forecast error. The advantage of this methodology is that it could apply to several series as a whole, to capture the spillover between each two series as well as total spillover. This methodology had been widely used in spillover study with global financial market [13]–[16].

The paper is organized as follows. The section II reviews the relevant literature; section III introduces the data and the basic statistical description; section IV describes the research method and the model; in section V, we performs empirical test with the CSI 300 Industry indices based on the proposed model; finally, we conclude in section VI.

II. LITERATURE REVIEW

There are several perspectives to study the systemic risk issues. The first stream of literatures focuses on the internal fragileness of the financial systems. Institutions are linked with each other through complex liability networks. The complex correlation and internal risk contagion of the financial system can lead to the rapid collapse of the whole system [17]. Therefore, a large number of academic studies had carried out research on the interaction and correlation of the financial institutions as the main research hotspots of systemic risk accumulation [18]. The relationship between the assets and liabilities of the financial market institutions not only provides the mechanism of risk sharing, but also becomes the main channel of risk contagion [19], [20]. The complex network [21], [22] and asset dependency [23]–[25] emerges as the new method to capture systemic risk.

The second stream of literature tends to focus on the correlation and volatility spillovers. The research on the spillover relationship of stock market mainly includes the regional co-movement and spillover effect [26]–[28]; Industry spillover effect [29]; portfolio optimization [30]; the cross-market co-movement and spillover effect [31], [32]; uncertainty spillover [33] the co-movement effect of the stock market [34], [35]. The early research simply uses linear form, such as Kendall t values, Spearman p values. Many statistical techniques had been developed to capture the linear relationship, such as multivariate regression [36], vector autoregressive model and vector error correction model to describe the short-term and long-term correlations between multivariate variables [37]. Due to the heteroscedasticity of the financial series, the ARCH model began to be widely used to model financial time series, and the multivariate GARCH model is widely used in spillover study. Engle [38] proposed DCC-GARCH model to describe the dynamic correlation coefficient between assets. Diebold and Yilmaz [11] proposed a new measure to study return and volatility spillovers based on the forecast error variance decomposition with VAR model, and applied this method to examine the return and volatility spillovers between financial markets in different countries [11]. Further, they improved this method with generalized variance decomposition, which does not rely on the order of the series of VAR model [12]. Moreover, some new method emerged to face the systemic risk challenge by machine learning of big data analysis had been proposed [39], [40].

In recent years, after financial crisis in 2008, the co-movement of different asset in financial market attracts a lot research concern both for policy makers and in academia. A lot of new methods emerged to describe the co-movement of financial series. The most common method to measure systemic risk including expected Shortfall [39], the codependence risk (Co-Risk), the delta conditional value at risk(ΔCoVaR) [41], Co-VaR [42] and the lower tail dependence LTD [43]. MES is proposed by Acharya *et al.* [44], to calculate the expected loss of financial institutions while the stock index dropped beyond certain percentile. Co-Risk employs quantile regression to measure the financial institution connected strength under bad market condition. The advantage of Co-Risk is that it could provide a method to measure single financial institution risk in the market. ΔCo-VaR measures the difference of financial institutions under financial difficulties and without financial difficulties, to measure its contribution to systemic risk; while Co-VaR represents one institution fell into difficulties due to another institution. LTD measures the joint distribution of single institution return distribution and the whole sector, to study the loss probability under extreme event.

Understanding the correlations and co-movement among different financial assets or institutions could be a possible way to measure systemic risk. However, previous research

TABLE 1. CSI 300 industry price data.

	Energy	Materials	Industry	Optional	Consumer	Pharmaceutical	Finance & real estate	Information	Telecommunications	Utilities
Mean	7.64	7.57	7.63	8.26	8.74	8.69	8.36	7.39	7.67	7.36
Median	7.59	7.58	7.50	8.20	8.71	8.65	8.25	7.35	7.60	7.24
Max	8.14	8.20	8.56	9.00	9.24	9.22	8.99	8.25	8.50	8.15
Minimum	7.28	7.24	7.24	7.85	8.49	8.34	8.03	6.86	7.15	7.00
S.D.	0.21	0.20	0.32	0.26	0.15	0.19	0.26	0.29	0.29	0.28
skewness	0.31	0.46	1.00	0.61	0.67	0.44	0.61	0.61	0.83	0.87
kurtosis	1.87	2.98	3.02	2.60	2.79	2.47	1.98	2.97	3.03	2.60
J-B p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ADF t	-1.99	-1.81	-1.02	-1.14	-1.36	-1.84	-1.04	-1.39	-1.17	-1.05

mostly focuses on the portfolio diversification of systemic risk, thus, failed to capture the linkage of financial assets correlation and financial crisis. With connectedness method, we could explore the dynamic structure of financial assets connectedness, and further construct the spillover index to reflect systemic risk. This paper explores the dynamic connectedness relationship of different industries in Chinese stock market as an emerging market, to generate early warning signal from industry indices spillover dynamics.

III. DATA AND DISCRIPTIVE STATISTICS

This paper selects the CSI 300 industry indices, which are calculated by China Security Index Co., Ltd.. All the companies are divided into 10 industries, and then the industry indices are calculated with all stocks in each industry categories. The 10 industry indices, coded from 000908 to 000917 by Shanghai Stock Exchange, representing energy, raw materials, industry, optional consumption, major consumption, medicine, finance and real estate, information technology, telecommunications, public utilities. Figure 1 shows the percentage of the number and value of stocks in each sector. The number of finance & real estate sector stocks are only 19%, which takes 41% of total market value. Overall, industry, finance &real estate, and optional consumption industry have larger market value and the proportion of stocks, while the telecommunications and medicine industries are relatively small.

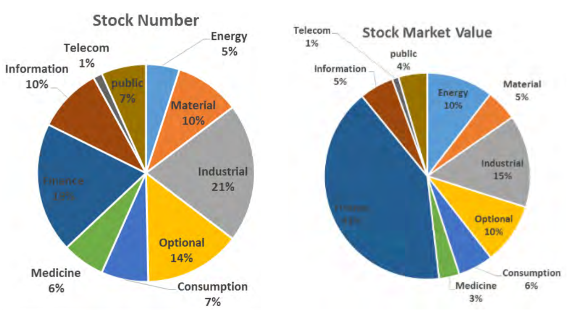


FIGURE 1. CSI 300 industrial structure and market capitalization ratio.

The calculation and correction methods of each industry are the same as the CSI 300 Index, which is based on July 31, 2004 index value, and published in July 2007. The sample data is obtained from the TRTH (Thomson Reuters Tick History) database, and we use 5-minute high frequency data, as it best balance the information and the noise. Our sample starts from May 2012 to June 2016. The log form of the 5-minute price data is taken, the descriptive statistics is presented in Table 1.

In order to eliminate the influence of overnight information, we focus on the intraday industry return and intraday volatility. Intraday return is calculated by taking the natural logarithm of the value of closing price minus the opening price(Table 2):

$$Return_i = \ln(\frac{Close_i}{Open_i}) \tag{1}$$

The intraday volatility is calculated by the realized volatility proposed by Andersen *et al.* [45], which is calculated by the sum of the square of the intraday non-overlapping short period return:

$$RV_{it} = \sum_{j=1}^{M} r_{it,j}^2, \quad t = 1, 2, \ldots T \tag{2}$$

where $r_{it,j}$ is the return of the i-th asset in the time j on day t, and M represents the daily transaction data divided into M equal frequency intervals, in this study $M = 48$, daily transaction time contains 48 5-minute data (Table 3).

IV. METHODOLOGY

Due to the cross-effects among different industries, we consider all industries as a whole system to set up the Vector Error Correction Model:

$$\mathrm{Y}_{i,t} = C_i + \Theta_{i,1} Y_{i,t-1} + \ldots + \Theta_{i,p} Y_{i,t-p} + \varepsilon_{it} \tag{3}$$

where $\mathrm{Y}_{i,t}$ is the return of industry i at time t.

The model is equivalent to:

$$\begin{aligned}\Delta \mathrm{Y}_{i,t} = C_i + e_i Z_{t-1} + \sum_{i=1}^{p} \alpha_{i,1} \Delta Y_{i,t-1} \\ + \ldots + \sum_{i=1}^{p} \alpha_{i,p} \Delta Y_{i,t-p} + \varepsilon_{it}\end{aligned} \tag{4}$$

where $Z_{t-1} = C_0 + Y_{1,\mathrm{t}-1} - \sum_{i=2} \beta_i Y_{i,t-1}$

TABLE 2. CSI 300-industry index of the daily return of the statistical description.

	Energy	Material	Industrial	Optional	Consumpti-on	Medicine	Finance	Information	Telecom	Utilities
Mean	0.0008	0.0009	0.0005	0.0008	0.0010	0.0013	0.0014	0.0014	0.0005	0.0009
Median	0.0007	0.0009	0.0003	0.0012	0.0006	0.0008	-0.0001	0.0019	0.0005	0.0005
Max	0.0929	0.0688	0.0996	0.0777	0.0734	0.0893	0.0722	0.1180	0.1003	0.0689
Min	-0.0764	-0.0853	-0.0846	-0.0895	-0.0739	-0.0725	-0.0763	-0.1243	-0.1087	-0.0775
S.D.	0.0169	0.0178	0.0179	0.0164	0.0152	0.0162	0.0172	0.0209	0.0199	0.0158
skewness	-0.0326	-0.4953	-0.3397	-0.5624	-0.3660	-0.2290	0.2875	-0.4643	-0.2630	-0.3860
kurtosis	6.1622	6.2995	7.1931	6.4519	5.9497	6.2478	6.3464	6.9262	6.7001	7.1970
J-B p	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ADF t	-31.23	-31.68	-30.86	-32.18	-31.21	-24.81	-32.13	-24.94	-32.39	-31.95

TABLE 3. The statistical description of CSI 300 industry index of realized intraday volatility.

	Energy	Material	Industrial	Optional	Consump-tion	Medicine	Finance	Inform-ation	Telecom	Utilities
Mean	0.0003	0.0005	0.0004	0.0004	0.0004	0.0006	0.0008	0.0026	0.0005	0.0005
Median	0.0002	0.0002	0.0001	0.0001	0.0001	0.0001	0.0001	0.0002	0.0002	0.0001
Max	0.0097	0.1994	0.0103	0.1508	0.1690	0.3759	0.4435	2.2130	0.0115	0.2359
Minimum	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
S.D.	0.0007	0.0063	0.0009	0.0048	0.0053	0.0118	0.0139	0.0695	0.0010	0.0074
skewness	6.5653	31.2937	6.2114	31.215	31.2668	31.703	31.690	31.8049	6.4776	31.4950
kurtosis	62.52	990.84	51.74	987.38	989.45	1008.3	1007.8	1012.70	57.21	999.46
J-B p	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ADF t	-6.96	-8.66	-6.52	-8.61	-7.94	-5.09	-9.27	-6.77	-7.55	-8.79

We use the Johansen Co-integration to test whether there exists co-integration relationship between the index series of the CSI 300 indexes. Trace Statistic is applied.

We take the residual sequence from VECM $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{mt})'$, and the variance model is:

$$\varepsilon_t = z_t \odot h_t^{\wedge\frac{1}{2}} = (z_{1t}\sqrt{h}_{11t}, \ldots, z_{it}\sqrt{h}_{iit})' \tag{5}$$

where $\odot$ is the Hadamard product; assuming $z_t = (z_{1t}, \ldots, z_{1t})'$ is independently and identically distributed, with mean 0 and finite variance, then the dynamic correlation coefficient matrix is:

$$R_t = \left[\rho_{ij,t}\right]_{i,j=1,2\ldots m} = \left[\frac{q_{ij,t}}{\sqrt{q}_{ii,t}\cdot\sqrt{q}_{jj,t}}\right]_{i,j=1,2\ldots m} \tag{6}$$

where $Q_t = \left[q_{ij,t}\right]_{i,j=1,2\ldots m} = \left(1-\alpha^{DCC}-\beta^{DCC}\right)\bar{Q} + \alpha^{DCC} z_{t-1}z'_{t-1} + \beta^{DCC} Q_{t-1}$, Q_t is the variance-covariance matrix z_t.

In order to measure the spillover effect, we apply the return and volatility spillover index proposed by Diebold and Yilmaz [11], [12]. This method is based on variance decomposition of forecast errors. The pth-order vector autoregressive model with m covariance stationary variables could be expressed as $x_t = \sum_{i=1}^{p}\phi_i x_{t-i} + \varepsilon_t$, $\varepsilon \sim (0, \Sigma)$. Its moving average expression is $x_t = \sum_{i=0}^{\infty} A_i\varepsilon_{t-i}$, A_i is the (m × m) order matrix and satisfies the recursive variance $A_i = \phi_1 A_{i-1} + \phi_2 A_{i-2} + \ldots + \phi_p A_{i-p}$, where A_0 is the m-order unit matrix, and when $i < 0$, $A_i = 0$. The coefficients of the moving average expression could help us to understand the dynamic characteristics of the system. Based on the variance decomposition method, we could decompose the forecast variance into the contribution of each variable to the system. Using the variance decomposition method, we can decompose the h-step-ahead forecast error variance into the percentage of the impact of each variable to the whole system.

However, the variance decomposition requires orthogonal residuals. The residual sequences from VAR or VEC model are related. In this case, Cholesky decomposition method was applied to achieve orthogonal effects of the sequence during the variance decomposition. Diebold and Yilmaz [11] built the spillover index based on the variance decomposition of Cholesky decomposition. However, Cholesky decomposition result is affected by the order selection of orthogonality variables, and the earlier selected orthogonal variables often have a larger impact on the system. Therefore, Diebold and

Yilmaz [12] improved the method with generalized variance decomposition to avoid the order selection bias to build the return and the volatility spillover index. Compared with previous methods, this method does not require the residuals to be unrelated, which accounts for the impact of the historical correlation of the errors. Thus, since the variables are not orthogonal with each other, the sum of the total contribution to the forecast error is not necessarily to be 1.

Following Diebold and Yilmaz [12], the variance of H-step-ahead forecast error of x_i is decomposed into self-variance contribution ratio and covariance(spillover) contribution ratio. The impact of variable x_i on x_i is the variance contribution ratio, the effect of x_j on x_i is the covariance(spillover) contribution ratio, where i, j = 1, 2, …, m. The forecast error variance decomposition of the H step-ahead is denoted by $\theta_{ij}^{g}(H)$, H = 1, 2, …,

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \Sigma A_h' e_i\right)} \tag{7}$$

where Σ is the variance matrix of the forecast error vector ε, σ_{jj} is the standard deviation of the error term of the jth equation, e_i is a selection vector, equal to 1 at the ith variable, and 0 otherwise. Since the impact of all variables is not always necessarily equal to 1, We standardized the variance matrix

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{8}$$

Therefore, $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H) = 1$, and $\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H) = N$. Based on the generalized variance decomposition, the total spillover index is as follows:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\cdot 100 = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\cdot 100 \tag{9}$$

Since the generalized variance impulse response and variance decomposition do not depend on the sort order of the variable selection, we can examine directional spillover effect, such as all the spillover effect of all other variables to variable i.

$$S_{i\cdot}^{g}(H) = \frac{\sum_{\substack{j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ij}^{g}(H)}\cdot 100 = \frac{\sum_{\substack{j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N}\cdot 100 \tag{10}$$

And the spillover effect of the ith variable on all variables j

$$S_{\cdot i}^{g}(H) = \frac{\sum_{\substack{j=1\\ i\neq j}}^{N}\tilde{\theta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N}\tilde{\theta}_{ji}^{g}(H)}\cdot 100 = \frac{\sum_{\substack{j=1\\ i\neq j}}^{N}\tilde{\theta}_{ji}^{g}(H)}{N}\cdot 100 \tag{11}$$

Thus, we can calculate the net spillover effect of variable i on all the other variables j

$$S^{g}(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H)$$

V. EMPERICAL RESULTS

A. INFORMATION SHARE

From Johansen test, the Trace test statistics showed that there exist one co-integration relation among the CSI 300 industry index of the 5-minute price data(Table 5). Therefore, we applied VEC method to model the whole system. After obtaining the residual sequence from the model, we applied DCC- GARCH to study of the dynamic correlation between industries.

We estimate the parameters of the VEC model, and then calculate the price discovery indicator of each industry with information share (IS). Cholskey decomposition order presented in Table 4 below. From 5-minute data, energy, telecommunications and industrial industry have the larger information share; while at daily frequency, energy, telecommunications and finance and real estate industry have the larger information share. In general, despite that the energy and telecommunications industry are stable in discovery with different sample frequency, the other industries showes quite different pattern in high and low frequency sample, especially the finance and real estate industry. From 5-minute data, the information share is only 2.17%, while the daily data accounted for 25.61 %.

TABLE 4. Co-integration test.

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
Trace	0	1	1	1	1
Max-Eig	1	1	1	1	1

Selected (0.05 level*) Number of Co-integrating Relations by Model ; Critical values based on MacKinnon-Haug-Michelis (1999)

TABLE 5. Industry information share.

Unit (%)	Energy	Material	Industrial	Optional	Consumption	Medicine	Finance	Information	Telecom	Utilities
5 min	16.26	12.94	21.51	1.09	2.36	4.28	2.17	12.97	21.18	5.24
Daily	19.43	0.89	8.81	10.95	0.60	1.45	25.61	1.75	28.53	1.99

B. DYNAMIC CORRELATION

According to the dynamic correlation of VEC-DCC-GARCH model, the correlation coefficients are relatively high among all industries. The correlation between telecommunications industry and the public industry is low, which may due to relatively small number of stocks and market value of the two industries; on the other hand, the enterprises of these two industries are mostly large state-owned enterprises, the nature of these two special industries may also lead to this small correlation with other industries. In general, we could observe

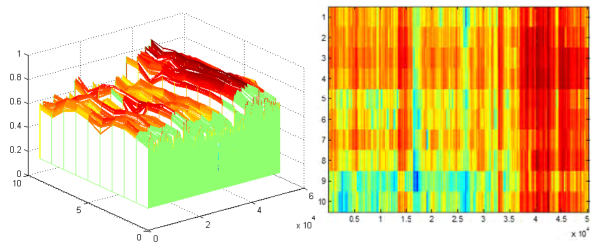


FIGURE 2. **Inter-industry dynamic correlation coefficient (5 minutes). In the left figure, the axis numbers 1-10 represent ten industries, respectively.1. Energy; 2. Raw materials; 3. Industry; 4. Optional consumption; 5. Major consumption; 6. Medical and health; 7. Finance & real estate;8. Information technology; 9. Telecommunications services; 10. Utilities; vertical coordinates indicates dynamic correlation coefficient. In the right figure, the horizontal axis is the time axis and the figure in vertical axis indicates the industry is the same as the left graph. We calculate the dynamic correlation coefficient of one industry with other 9 industries, and then obtained the average value of dynamic correlation coefficient of each industry respectively. The color indicates the value, the larger the value is, the deeper the color is. The horizontal axis starting point is May 1, 2012, and ended on June 30, 2016 with 5 minutes sample frequency.**

from Figure 2, the correlation between the various industries began to increase significantly from the beginning of 2015, the color of the figure deepened since then.

Taking the financial industry as an example, we obtain its dynamic correlation coefficient diagram with the other nine industries, represented in Figure 3 (1) to 3 (9). We could observe that the dynamic correlation between the financial industry and other industries showed a consistent trend, but the degree of the volatility is different. In general, its correlation coefficient with telecommunications and information technology is low. We also tested this with daily data of the finance industry, which showed the same trend.

The daily dynamic correlation coefficient is similar to the result from 5-minute data(Appendix 1). Raw materials, industrial, optional consumption all have higher correlation coefficients than other industries, while medical and health sector has lower correlation coefficient. From January 2015, the correlation coefficients between each industry began to rise significantly, and then decreased slightly around February 2016. This period coincided with the stock market's transition from bull market to bear market in practice. Moreover, CSI 300 industries indices showed high correlations especially in the large volatility period, which indicated diversified investment among different industries could not diversify risk, thus accumulated systemic risk.

C. SPILLOVER

According to the generalized variance decomposition of forecast errors, we calculate intraday return and volatility spillover in the whole sample period, as shown in Table 6 and Table 7 below. From the perspective of return spillovers (Table 6), the effects of return spillovers from the energy, consumption, finance, and information and telecommunications industries are larger. After excluding their own spillover,

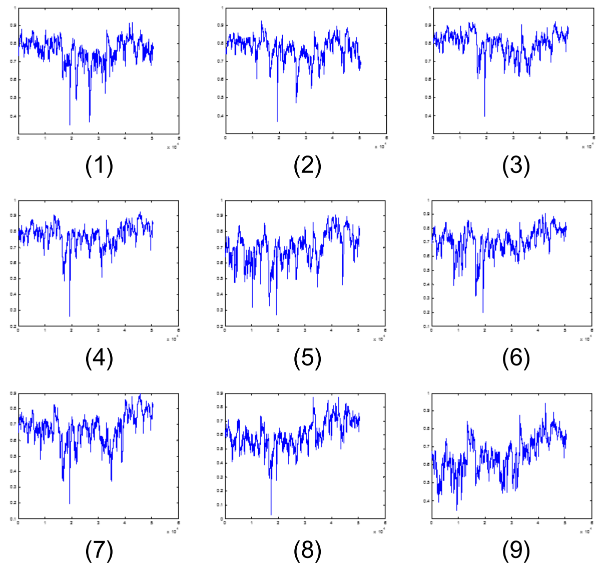


FIGURE 3. **The correlation coefficient between finance & real estate industry and other industries (5 minutes). (1) - (9) represented the dynamic correlation coefficients of the finance & real estate industry with the other industries during 2012.5 to 2016.6. Each sub-figures indicated as follows:(1) Energy; (2) Raw materials; (3) Industry; (4) Optional consumption; (5) Main consumption; (6) Medical and health; (7) Information technology; (8) Telecommunications business; (9) Utilities.**

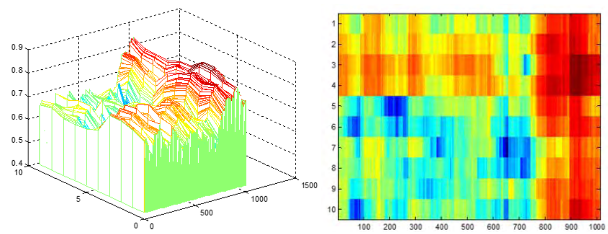


FIGURE 4. **Industry dynamic correlation coefficient (daily data). In the left figure, the axis numbers 1-10 represents ten industries, respectively.1. Energy; 2. Raw materials; 3. Industry; 4. Optional consumption; 5. Major consumption; 6. Medical and health; 7. Finance & real estate;8. Information technology; 9. Telecommunications services; 10. Utilities; vertical coordinates indicates dynamic correlation coefficient. In the right figure, the horizontal axis is the time axis and the figure in vertical axis indicates the industry is the same as the left graph. We calculate the dynamic correlation coefficient of one industry with other 9 industries, and then obtained the average value of dynamic correlation coefficient of each industry respectively. The color indicates the value, the larger the value, the deeper the color. The horizontal axis starting point is May 1, 2012, and ended on June 30, 2016 with 5 minutes sample frequency.**

larger impact industries are finance, information, energy and telecommunications industries, while industry sector spillover to other industries is the smallest. From spillover received from others, the information and telecommunications industries are smaller, while materials, industries and utilities are larger.

According to the result in Table 7, the telecommunications, information, industrial and energy industries have the largest spillover effect. Different with the return spillover, the financial sector's volatility spillover are very low. Moreover, the spillover of material, optional, consumption, medicine, finance, utilities industries received from other industries are significantly higher, even more over 90%, while the telecommunications and information industry own spillover contributed around 50% of total.

To study the dynamic characteristics of return and volatility spillovers, we construct the time rolling window, and estimate the model parameter in each 250 days(approximately 1 trading year) with VAR(5) model, forecast with 5-step-ahead(1 week) and then decomposed the variance of forecast errors. Followed Diebold and Yilmaz [12], we construct the intraday return and volatility spillover index (Fig. 5). Further, we use the 10-step-ahead and 1-step-ahead forecast step for robustness test (Appendix 2 and 3).

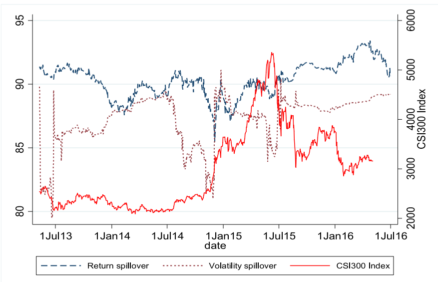


FIGURE 5. Time rolling window of connectedness index.

From figure 5, the return and volatility spillover show the opposite changing trend in most of the time, however, they showed a rapid decline after the rapid upward trend in early 2015 when the index increased rapidly. Around June 2015, with the index fell from the highest point, the return and volatility spillover among industries showed an obvious upward trend and maintained at the highest level. Compared with the return spillover, the fluctuation of the volatility spillovers is larger, and before each period of market turning point, a "V" shape is captured on the graph with the significant change of the volatility spillover. Return spillover are lower in the early uptrend period of the market, and rising with the index increasing.

On the other hand, the larger return spillover indicates that the trend of one or more industries make more impact on other industries. In figure 5, the return spillover is smaller in the early stage during the period of then index rapid rise from 2500 to 5000, which suggests that the bull market is driven by certain sectors. The greater influence during the medium-term suggests the effect of this return spillovers to other sectors; during the index from 4500 to 5000 points period, the return spillover effect began to decrease and the co-movement between the sectors reduced. The intraday volatility spillover which represents the interaction of fluctuations among industries, suggesting that there exists a significant change in volatility spillovers before the market rapid change period.

To further examine the interaction among industries and their different characteristics, we decompose the total spillover index to spillover from others and spillover to others, as shown in the equation (10, 11). Figure 6 and Figure 7 show the estimated results of the time rolling window, with spillover to others and spillover from others respectively.

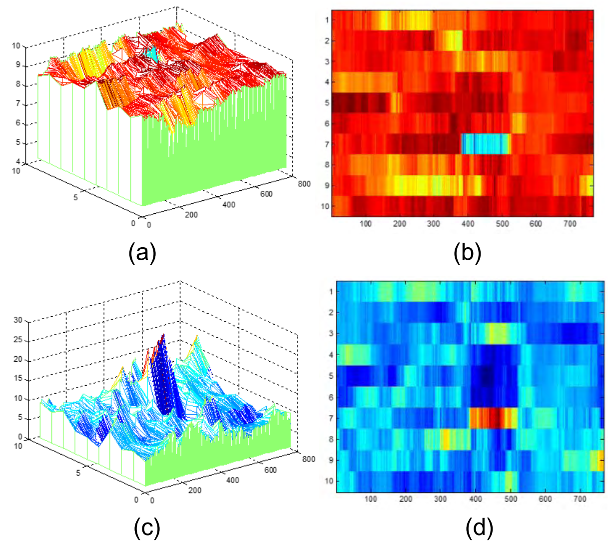


FIGURE 6. Time rolling index of return spillover. Figure 6 shows the time rolling window method with 250 days(about 1 year's trading day) as the estimation window, the VAR (5) model is applied to forecast 5-step-ahead out-of-sample return (one week trading time), to perform the variance decomposition to construct the return spillover index. The time axis starts from May 2013, and ends at June 2016, the horizontal interval is one trading day. In figure 6-a, 6-c, the x-axis numbers 1-10 represent ten industries, respectively, 1. Energy; 2. Raw materials; 3. Industry; 4. Optional consumption; 5. Major consumption; 6. Medical and health; 7. Financial real estate; 8. Information technology; 9. Telecommunications business; 10. Utilities; the y-axis 0-800 are timelines, representing the corresponding date; the z-axis is the level of return spillovers to the others 6-(a) and spillover received from others 6-(c). In 6-(b) and 6-(d), the x-axis is the time axis, while the y-axis indicating industries which were the same as the 6-(a) and 6-(c). We calculate the sum of the return spillover to other industries 6-(b) and the return spillover from other industries 6-(d). The spillover level is represented in color, the darker color indicates larger spillover 6-(b), while the darker color in Figure 6-(d) indicates spillover received from others is smaller.

According to the return spillover to the others industries in Figure 6-(a) and Figure 6-(b), the consumption sector had the highest volatility spillover effect, while the telecom industry spillovers were low. On the time axis, the return spillover to the others industries has a gradually increased trend, especially after the beginning of 2015. In addition, the index of the finance and real estate sector rose sharply in the early stage, the spillover effect to other industries is strong, however, turned to relatively low spillover during the index rapidly rose; at the same time, the spillover to financial real estate industry is high. The spillover effect of each industry in different periods of the market showed the alternation of the rotation characteristics. During the index decline, each industry shows a high spillover effect both to and from other sectors.

In the early of 2015, the volatility spillover from other industry was high while the spillover to other industries was relatively low, which indicated that the volatility of one sector

TABLE 6. Full sample return spillover.

	Energy	Material	Industrial	Optional	Consumption	Medicine	Finance	Information	Telecom	Public	Spillover from others
Energy	10.81	4.02	2.51	7.47	13.30	7.97	27.71	13.81	7.72	4.67	89.19
Material	8.02	3.27	1.26	10.25	8.77	6.92	32.09	13.09	7.84	8.48	96.73
Industrial	18.56	7.25	5.88	7.91	10.96	6.40	22.59	9.82	4.07	6.56	94.12
Optional	11.95	9.32	6.51	9.66	7.77	7.42	7.61	14.86	15.51	9.40	90.34
Consumption	13.39	9.12	5.88	8.06	10.73	6.91	7.40	16.82	13.50	8.20	89.27
Medicine	10.09	9.95	9.67	7.21	6.04	8.19	4.16	13.60	19.26	11.85	91.81
Finance	12.96	8.47	8.11	7.34	9.96	6.29	9.44	10.08	15.66	11.69	90.56
Information	6.28	8.05	9.39	9.42	7.07	9.94	3.28	16.07	17.87	12.63	83.93
Telecom	12.42	6.84	3.70	7.03	16.70	7.26	9.96	12.34	13.48	10.27	86.52
Utilities	16.55	8.61	5.19	7.21	13.07	7.47	19.41	12.26	5.69	4.54	95.46
Spillover to others	110.22	71.64	52.22	71.89	93.64	66.57	134.20	116.67	107.13	83.75	Total Spillover:
Spillover including own	121.03	74.91	58.10	81.55	104.37	74.76	143.64	132.73	120.61	88.29	90.79%

TABLE 7. Full sample volatility spillover.

	Energy	Material	Industrial	Optional	Consumption	Medicine	Finance	Information	Telecom	Public	Spillover from others
Energy	27.33	1.96	26.95	1.53	1.53	0.52	0.65	0.13	38.16	1.25	72.67
Material	26.12	0.25	25.41	0.10	0.09	0.75	1.21	13.16	32.75	0.15	99.75
Industrial	26.47	1.65	28.80	1.18	1.04	0.26	0.20	0.15	39.35	0.89	71.20
Optional	23.16	0.11	24.62	0.05	0.03	0.99	1.84	16.43	32.56	0.20	99.95
Consumption	21.57	0.18	26.82	0.24	0.19	0.77	1.45	14.56	34.05	0.17	99.81
Medicine	8.69	2.48	7.98	1.97	1.69	5.85	8.66	49.67	9.57	3.44	94.15
Finance	10.13	2.93	6.31	2.17	1.63	6.47	6.63	52.19	8.13	3.40	93.37
Information	4.46	6.21	3.96	4.98	4.52	7.82	9.94	43.60	8.26	6.25	56.40
Telecom	24.59	1.34	26.68	0.97	0.69	0.14	0.10	0.67	44.23	0.58	55.77
Public	22.84	0.31	22.27	0.29	0.15	2.02	2.39	23.79	25.59	0.34	99.66
Spillover to others	168.03	17.18	171.01	13.44	11.38	19.75	26.44	170.74	228.43	16.34	Total Spillover:
Spillover including own	195.36	17.43	199.80	13.49	11.56	25.60	33.07	214.33	272.66	16.68	84.27%

was sensitive to the spillovers of other sectors. Before 2015, the volatility spillover from medical and health, and utilities to the other sectors were higher, but gradually decreased during the bull market. After January of 2015, the financial industry volatility spillover to the other sectors had declined sharply, and the volatility spillover from other industries had increased; and the financial industry received large spillover in this period.

From the view of a specific industry, the return spillover of the energy industry is relatively stable, the spillover to other industries decline while the spillover from others increased before the bull market. The return spillover of Raw materials and industrial industries showed complementary relationship, one rose while the other one declined, their volatility in the former half period also showed a similar pattern when the latter half is more consistent, the return and volatility spillover stay in the middle level among all sectors. The return spillover of optional consumption to the other sectors was large during the bull market, while its spillover from other industries was the smallest among all industries. However, its volatility spillover to other industries was stronger than other industries after the bull market, especially in the market downturn period. The return spillover from major consumer industry in the initial period is high with low volatility spillovers. The return spillover effect kept stable when during market rose, until its return and volatility spillover to the other sectors began to decrease when the market began to fall. The medical and health industry received more return spillover and had less spillover to other industries, which might be attributed to the characteristics of the defensive sector nature. The volatility spillover to other industries was relatively high in the early stage when the market was in uptrend period, and decreased

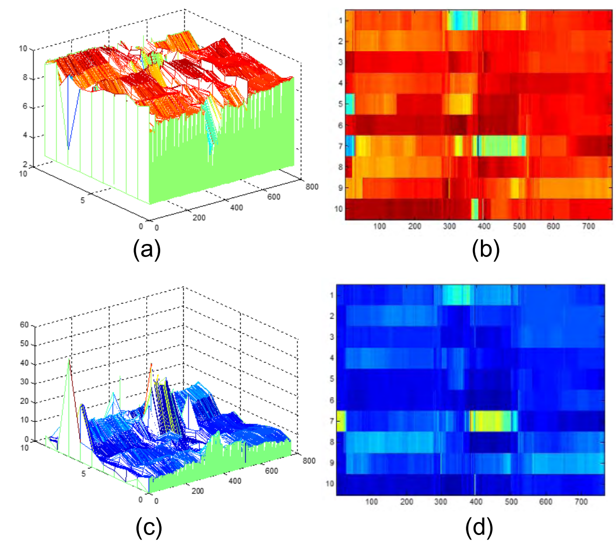


FIGURE 7. Time rolling index of volatility spillover. Figure 7 showed the time rolling window method with 250 days (about 1 year's trading day) as the estimation window, the VAR (5) model is applied to forecast 5-step-ahead out-of-sample volatility (one week trading time), to perform the variance decomposition to construct the volatility spillover index. The time axis starts from May 2013, and ends at June 2016, the horizontal interval is one trading day. In figure 7-(a), 7-(c), the x-axis numbers 1-10 represent ten industries, respectively, 1. Energy; 2. Raw materials; 3. Industry; 4. Optional consumption; 5. Major consumption; 6. Medical and health; 7. Financial real estate; 8. Information technology; 9. Telecommunications business; 10. Utilities; the y-axis 0-800 are timelines, representing the corresponding date; the z-axis is the level of return spillovers to the others 7-(a) and spillover received from others 7-(c). In 7-(b) and 7-(d), the x-axis is the time axis, while the y-axis indicating industries were the same as the 7-(a) and 7-(c). We calculate the sum of the return spillover to other industries 7-(b) and the return spillover from other industries 6-(d). The spillover level is represented in color; the darker color indicates larger spillover 6-(b), while the darker color in Figure 6-(d) indicates spillover received from others is smaller.

in the market decline period. The finance and real estate sector, which had the largest market value proportion, its return spill over to the other sectors gradually increased in the early stages until the bull market started, it dropped rapidly. Its volatility spill over showed a similar pattern, although the spillover was smaller than that of return. The spillover effect of information technology sector was different from finance real estate, which presented the largest spillover during the bull market, showing the leading effect in the market. The telecommunications industry had small return and volatility spillover effect to other industries while received significant spillover from other sectors, due to the small number and market value of component stocks. There was no obvious trend of spillover return from or to public industry sector, while its volatility spillover to the other sectors was stronger during the first half period, and its volatility spillovers from other industries were low.

VI. CONCLUSION

This paper studies the correlation and spillover relationship between 10 industries of CSI 300, to conclude the characteristics of corresponding industries and propose the early warning signals of financial systemic risk.

Firstly, the VECM model is applied to study the information share of each industry, which brings us with different price discovery characteristics with 5-minute and daily data. Under the daily frequency, the information share of telecommunication, finance and energy is the higher. From 5-minute data, the price discovery finance & real estate industry only ranked 9, while telecommunications, industry and energy sector has stronger price discovery ability.

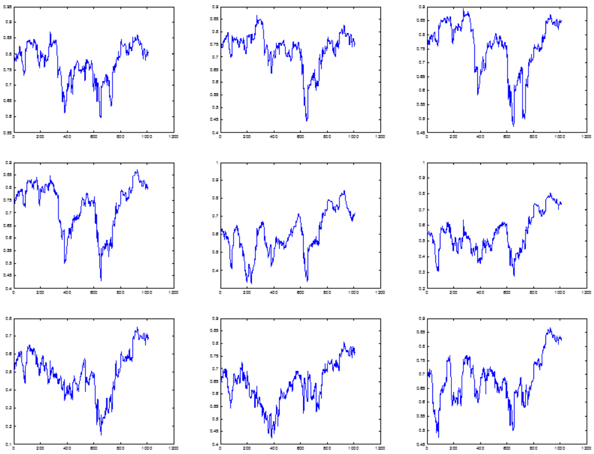
Secondly, from the dynamic correlation perspective, the correlation coefficient between each industry increased rapidly in the market decline period. In general, raw materials, industrial and optional consumer sectors were highly correlated with other sectors. It is noteworthy that in February 2016, the index started a relative stable and slowly increasing stage, but the dynamic correlation between the industries is still at a high position, suggesting a higher potential systemic risk, as risk could not be efficiently diversified among sectors. After that, we applied the out-of-sample forecast variance decomposition to calculate the volatility and return spillover index. Energy, consumption, finance, information and telecommunications industries have the greatest effect on return spillover to other industries, while materials, industries and utilities have the largest return spillovers from other industries; telecommunications, information, industry and energy industries have more spillover to other industries, not like return spillover, the volatility spillover of financial industry is very low. On the other hand, volatility spillover of material, optional, consumption, medical and health, finance, public sector was significantly higher than other industries, which were over 90%.

Finally, in order to find out the dynamic pattern of return and volatility spillovers between industries to generate early warning signals of systemic risk, we applied the rolling time window method to compose the calculated return and the volatility spillovers to a continuous index sequence. The results show that the overall trend of return spillovers is similar to the trend of CSI 300, and the trend is slightly ahead of the CSI 300 Index. Such as the volatility, spillover index fluctuates significantly around 3 months before CSI 300 Index fluctuates significantly. When the financial industry shows significant fluctuations and return spillovers increase, indicating the rising stage of the CSI 300 index, and when its spillover effect decline to the original level, the whole market started decline stage. In addition, when the spillover to and from each industry increases indicates a coming significant volatility of the market.

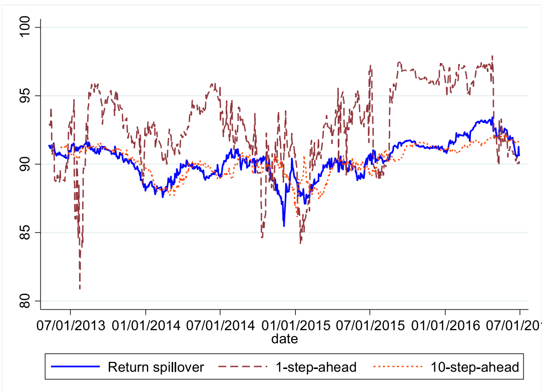
The results show there is a high correlation and strong return and volatility spillover effect between the CSI 300 industries at the end of June 2016, suggesting that we should pay attention to the increase in systemic risk. The supervision should especially pay close attention to the spillover effect changes of the finance and industry sector.

APPENDIX

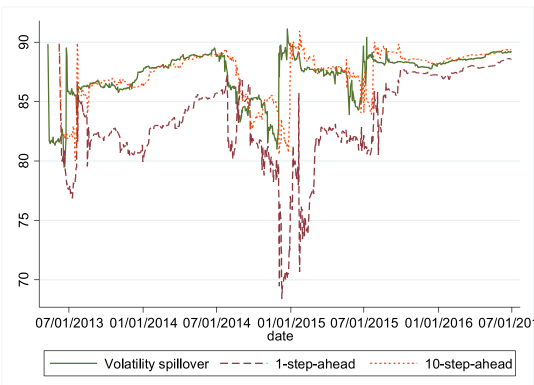
A. APPENDIX 1



B. APPENDIX 2



C. APPENDIX 3



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REFERENCES

[1] P. K. Narayan, S. Narayan, and K. P. Prabheesh, "Stock returns, mutual fund flows and spillover shocks," *Pacific-Basin Finance J.*, vol. 29, pp. 146–162, Sep. 2014.
[2] J. E. Hilliard, "The relationship between equity indices on world exchanges," *J. Finance*, vol. 34, no. 1, pp. 103–114, 1979.
[3] O. M. Joy, D. B. Panton, F. K. Reilly, and S. A. Martin, "Comovements of major international equity markets," *Financial Rev.*, vol. 11, no. 1, pp. 1–20, 1976.
[4] S. G. Makridakis and S. C. Wheelwright, "An analysis of the interrelationships among the major world stock exchanges," *J. Bus. Finance Accounting*, vol. 1, no. 2, pp. 195–215, 1974.
[5] R. Maldonado and A. Saunders, "International Portfolio diversification and the inter-temporal stability of international stock market relationships, 1957-78," *Financial Manage.*, vol. 10, no. 4, pp. 54–63, 1981.
[6] I. Meric, J. H. Kimb, L. Gong, and G. Meric, "Co-movements of and linkages between Asian stock markets," *Bus. Econ. Res. J.*, vol. 3, no. 1, p. 1, 2012.
[7] G. Meric, R. P. C. Leal, M. Ratner, and I. Meric, "Co-movements of U.S. and Latin American equity markets before and after the 1987 crash," *Int. Rev. Financial Anal.*, vol. 10, no. 3, pp. 219–235, 2001.
[8] B. Solnik, C. Boucrelle, and Y. Le Fur, "International market correlation and volatility," *Financial Anal. J.*, vol. 52, no. 5, pp. 17–34, 1996.
[9] J. Garnier, G. Papanicolaou, and T.-W. Yang, "Diversification in financial networks may increase systemic risk," in *Handbook on Systemic Risk*, J.-P. Fouque and J. A. Langsam, Eds. Cambridge, U.K.: Cambridge Univ. Press, 2013, pp. 432–443.
[10] I. Meric, M. Ratner, and G. Meric, "Co-movements of sector index returns in the world's major stock markets in bull and bear markets: Portfolio diversification implications," *Int. Rev. Financial Anal.*, vol. 17, no. 1, pp. 156–177, 2008.
[11] F. X. Diebold and K. Yilmaz, "Measuring financial asset return and volatility spillovers, with application to global equity markets," *Econ. J.*, vol. 119, no. 534, pp. 158–171, 2009.
[12] F. X. Diebold and K. Yilmaz, "Better to give than to receive: Predictive directional measurement of volatility spillovers," *Int. J. Forecasting*, vol. 28, no. 1, pp. 57–66, 2012.
[13] B. Awartani, M. Aktham, and G. Cherif, "The connectedness between crude oil and financial markets: Evidence from implied volatility indices," *J. Commodity Markets*, vol. 4, no. 1, pp. 56–69, 2016.
[14] A. I. Maghyereh, B. Awartani, and E. Bouri, "The directional volatility connectedness between crude oil and equity markets: New evidence from implied volatility indexes," *Energy Econ.*, vol. 57, pp. 78–93, Jun. 2016.
[15] J. A. Batten, C. Ciner, and B. M. Lucey, "The dynamic linkages between crude oil and natural gas markets," *Energy Econ.*, vol. 62, pp. 155–170, Feb. 2017.
[16] F. X. Diebold and K. Yilmaz, "Trans-atlantic equity volatility connectedness: U.S. and European Financial Institutions, 2004–2014," *J. Financial Econometrics*, vol. 14, no. 1, pp. 81–127, 2015.
[17] P. Angelini, G. Maresca, and D. Russo, "Systemic risk in the netting system," *J. Banking Finance*, vol. 20, no. 5, pp. 853–868, 1996.
[18] F. Allen and D. Gale, "Financial contagion," *J. Political Econ.*, vol. 108, no. 1, pp. 1–33, 2000.
[19] H. Asgharian and C. Bengtsson, "Jump spillover in international equity markets," *J. Financial Econometrics*, vol. 4, no. 2, pp. 167–203, 2006.
[20] R. R. Bliss and G. G. Kaufman, "Derivatives and systemic risk: Netting, collateral, and closeout," *J. Financial Stability*, vol. 2, no. 1, pp. 55–70, 2006.
[21] A. Krause and S. Giansante, "Interbank lending and the spread of bank failures: A network model of systemic risk," *J. Econ. Behav. Org.*, vol. 83, no. 3, pp. 583–608, 2012.
[22] S. Markose, S. Giansante, and A. R. Shaghaghi, "'Too interconnected to fail' financial network of US CDS market: Topological fragility and systemic risk," *J. Econ. Behav. Org.*, vol. 83, no. 3, pp. 627–646, 2012.
[23] F. M. Longin, "The asymptotic distribution of extreme stock market returns," *J. Bus.*, vol. 69, no. 3, pp. 383–408, 1996.
[24] A. J. Patton, "Estimation of multivariate models for time series of possibly different lengths," *J. Appl. Econometrics*, vol. 21, no. 2, pp. 147–173, 2006.
[25] A. J. Patton, "Modelling asymmetric exchange rate dependence," *Int. Econ. Rev.*, vol. 47, no. 2, pp. 527–556, 2006.
[26] C. Pirinsky and Q. Wang, "Does corporate headquarters location matter for stock returns?" *J. Finance*, vol. 61, no. 4, pp. 1991–2015, 2006.
[27] E. Dabla-Norris, R. Espinoza, and S. Jahan, "Spillovers to low-income countries: Importance of systemic emerging markets," *Appl. Econ.*, vol. 47, no. 53, pp. 5707–5725, 2015.

[28] J. Hua and B. Sanhaji, "Volatility spillovers across daytime and overnight information between China and world equity markets," *Appl. Econ.*, vol. 47, no. 50, pp. 5407–5431, 2015.
[29] D. R. Lessard, "World, national, and industry factors in equity returns," *J. Finance*, vol. 29, no. 2, pp. 379–391, 1974.
[30] Z. Dai and F. Wen, "A generalized approach to sparse and stable portfolio optimization problem," *J. Ind. Manage. Optim.*, vol. 14, no. 4, pp. 1651–1666, 2018.
[31] N. Benlagha, "Dependence structure between nominal and index-linked bond returns: A bivariate copula and DCC-GARCH approach," *Appl. Econ.*, vol. 46, no. 31, pp. 3849–3860, 2014.
[32] H. Jiang, N. Todorova, E. Roca, and J.-J. Su, "Dynamics of volatility transmission between the U.S. and the Chinese agricultural futures markets," *Appl. Econ.*, vol. 49, no. 34, pp. 3435–3452, 2017.
[33] X. Gong and B. Lin, "Forecasting the good and bad uncertainties of crude oil prices using a HAR framework," *Energy Econ.*, vol. 67, pp. 315–327, Sep. 2017.
[34] F. Han and H. Xiao, "Analysis of comovement between China and US stock markets," (in Chinese), *J. Financial Res.*, vol. 305, no. 11, pp. 117–129, 2005.
[35] H. Zhu, Y. Tang, and P. Guo, "Asymmetric spillover effects between the Shanghai and Hong Kong stock markets: Evidence from quantile lagged regression," *Appl. Econ.*, vol. 49, no. 9, pp. 886–902, 2017.
[36] M. A. King and S. Wadhwani, "Transmission of volatility between stock markets," *Rev. Financial Stud.*, vol. 3, no. 1, pp. 5–33, 1990.
[37] R. F. Engle and C. W. J. Granger, "Co-integration and error correction: Representation, estimation, and testing," *Econometrica*, vol. 55, no. 2, pp. 251–276, 1987.
[38] R. Engle, "Dynamic conditional correlation," *J. Bus. Econ. Statist.*, vol. 20, no. 3, pp. 339–350, 2002.
[39] A. Serguieva, "Systemic risk identification, modelling, analysis, and monitoring: An integrated approach," in *Proc. Comput. Intell. Financial Eng. Econ.*, Mar. 2014, p. 8.
[40] A. L. Jia, R. Rahman, T. T. Vinkó, J. A. Pouwelse, and D. H. J. Epema, "Systemic risk and user-level performance in private P2P communities," *IEEE Trans. Parallel Distrib. Syst.*, vol. 24, no. 12, pp. 2503–2512, Dec. 2013.
[41] T. Adrian and M. K. Brunnermeier, "CoVar: A method for macroprudential regulation," Federal Reserve Bank New York, New York, NY, USA, Tech. Rep. 348, 2009.
[42] T. Adrian and M. K. Brunnermeier, "CoVaR," *Amer. Econ. Rev.*, vol. 106, no. 7, pp. 1705–1741, 2016.
[43] G. N. F. Weiß, S. Neumann, and D. Bostandzic, "Systemic risk and bank consolidation: International evidence," *J. Banking Finance*, vol. 40, no. 1, pp. 165–181, 2014.
[44] V. Acharya, R. Engle, and M. Richardson, "Capital shortfall: A new approach to ranking and regulating systemic risks," *Amer. Econ. Rev.*, vol. 102, no. 3, pp. 59–64, 2012.
[45] T. G. Andersen, T. Bollerslev, and F. X. Diebold, "Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility," *Rev. Econ. Statist.*, vol. 89, no. 4, pp. 701–720, 2007.

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