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A Comparative Study on Volatility Spillovers in the Stock Markets of Korea, China and Japan

Jin-Soo LEE · Tae-Yeong CHOI†
(Pukyong National University)

한·중·일 주식시장의 변동성 전이효과에 관한 비교연구

이진수 · 최태영†
(부경대학교)

Abstract

The purpose of this research is to conduct a comparative study on the characteristics of daily volatility spillovers across the stock markets of Korea, China, and Japan. We employ generalized spillover definition and measurement developed by Diebold & Yilmaz (2009, 2012). The sample period is January 5, 1993 to September 25, 2015. From a static full-sample analysis, we find that 8.60% of forecast error variance comes from volatility spillovers. From a 250-day rolling-sample analysis, we discover that there exist significant volatility fluctuations in the stock markets of Korea, China and Japan, expecially during the Asian Financial Crisis (1998-1999) and the US Credit Crisis (2008-2009) after the collapse of Lehman Brothers. From the net directional spillovers across three countries, we come upon that there is neither a definite leader nor a significant follower during the sample period.

Key words : Spillover measurement, Rolling-sample analysis, Spillover table, Generalized variance decomposition.

Ⅰ. Introduction

Financial market volatility can have huge impact on the global economy. For example, the Asian Financial Crisis (1998-1999), unprecedented terrorists' attack of the United States on September 11, 2001, the US Credit Crisis (2008-2009), and the ongoing European Debt Crisis (2012-to date) have caused great fluctuations in the global financial markets. Thus, volatility forecasting is an important task in financial markets, accordingly it has received keen interest from academics and practitioners as well.

Given the vital role of volatility forecasting, we aim to conduct a comparative study on the characteristics of daily volatility spillovers across the stock markets of Korea, China, and Japan. (For the analysis of co-movement of stock market across these countries, see Choi & Kang 2014; for a non-technical explanation on this issue, see Yoon, et al. 2015). As used in this paper, comparison across countries or between different groups is one of the popular research methodologies in social science. Examples include Kim (2015), Rhu, et al.

† Corresponding author : 051-629-5729, tychoi@pknu.ac.kr.
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(2015), and Lee, et al. (2015).

We employ generalized spillover definition and measurement developed by Diebold & Yilmaz (2009, 2012). The sample period is January 5, 1993 to September 25, 2015, covering historical episodes such as China's shareholding right reform (株權分置改革, 2005-2007; For details, see Seo 2011), the U.S. Credit Crisis, and the ongoing European Debt Crisis. (Note that there are abundant number of volatility definitions and measurements. For an excellent literature review on this subject, see Poon & Granger 2003).

We use generalized forecast error variance decompositions introduced by Pesaran & Shin (1998). In dynamic analysis of vector autoregressive (VAR) models, the advantage of this relatively new method over the orthogonalized impulse responses proposed by Sims (1980) is its invariant ordering of the variables in the VAR.

The rest of this paper is organized as follows. Section II explains the methodology such as generalized spillover index, variance shares and spillover measurements. Section III provides data source, descriptive statistics, and results of unit root and normality tests. Section Ⅳ presents empirical results. Section Ⅴ contains the conclusions.

Ⅱ. Methodology

We employ the generalized spillover definition and measurement developed by Diebold & Yilmaz (2009, 2012). The spillover index is based on forecast error variance decomposition from vector autoregressive (VAR). The VAR model is a general framework to describe the dynamic interrelationship between stationary variables. (Hill, et al. 2008, p. 347).

The following spillover definitions and spillover measurements are borrowed from equations (1) to (7) in Diebold & Yilmaz (2012, pp. 58-59).

1. Spillover Definitions

We can define own variance shares as the fractions of the s-step ahead error variances in forecasting X_i that are due to shocks to X_i for $i=1,2,\cdots,N$. We can also define cross variance shares, or spillovers, as the fractions of the s-step ahead error variance in forecasting X_i that are due to shocks to X_j for such that $i \neq j$.

Let denote the s-step-ahead forecast error variance decompositions by $\theta^g_{ij,s}$ for $s=1,2,\cdots$,

$$(1)\ \theta^g_{ij,s} = \frac{\sigma_{ii}^{-1}\sum_{h=0}^{s}(e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{s}(e_i' A_h \Sigma A_h' e_i)}, \quad i,j=1,2,\cdots,m$$

where Σ is the variance matrix for the error vector ϵ, σ_{ii} is the standard deviation of the error term for the i^{th}equation, and e_i is the selection vector, with one as the i^{th} element and zeros otherwise. The sum of the elements in each row of the variance decomposition table is not equal to one, ie. $\sum_{j=1}^{m}\theta^g_{ij,s} \neq 1$. (Pesaran & Shin 1998).

We normalize each entry of the variance decomposition matrix by the row sum as

$$(2)\ \tilde{\theta}^g_{ij,s} = \frac{\theta^g_{ij,s}}{\sum_{j=1}^{m}\theta^g_{ij,s}}$$

2. Spillover Measurements

We can construct total volatility spillover index as

(3) $$SP^{total} = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{m} \tilde{\theta}^{g}_{ij,s}}{\sum_{i,j=1}^{m} \tilde{\theta}^{g}_{ij,s}} \times 100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{m} \tilde{\theta}^{g}_{ij,s}}{m} \times 100$$

The total spillover index computes the contribution of return spillover shocks across the four indices to the total forecast error variance.

We can estimate the directional spillovers received by index i from all other indices j as

(4) $$SP_{i}^{inflow} = \sum_{\substack{j=1 \\ j \neq i}}^{m} \tilde{\theta}^{g}_{ij,s} \times 100$$

Similarly, we can compute the directional spillovers transmitted by index i to all other indices j as

(5) $$SP_{i}^{outflow} = \sum_{\substack{j=1 \\ j \neq i}}^{m} \tilde{\theta}^{g}_{ji,s} \times 100$$

We can obtain the net spillovers from index i to all other indices j as

(6) $$SP_{i}^{net} = SP_{i}^{outflow} - SP_{i}^{inflow}$$

The net spillover in equation (6) is simply the difference between the total volatility shocks transmitted to and those received from all other indices. It provides summary information about how much each index contributes to the return in other indices.

Finally, we can compute the net pairwise volatility spillover between index i and index j as

(7) $$SP_{ij}^{net} = SP_{ij}^{outflow} - SP_{ij}^{inflow}$$

$$= \left(\frac{\tilde{\theta}^{g}_{ji,s}}{\sum_{i,k=1}^{m} \tilde{\theta}^{g}_{ik,s}} - \frac{\tilde{\theta}^{g}_{ij,s}}{\sum_{j,k=1}^{m} \tilde{\theta}^{g}_{jk,s}} \right) \times 100$$

The net pairwise spillovers is simply the difference between the total volatility spillovers transmitted from index i to index j and those received from index j to index i. (Diebold & Yilmaz 2012, p. 59).

Ⅲ. Data

We collect daily closing stock price indices for Korea, China and Japan from January 5, 1993 to September 25, 2015. Shanghai Stock Exchange Composite Index (SSEC) and Nikkei Index 225 (Nikkei 225) are obtained from Yahoo Finance while Korea Composite Stock Price Index 200 (KOSPI) is retrieved from Samsung Securities Co. Ltd. (Korea). After eliminating the observations by holiday-matching in the stock markets of three countries, final sample size becomes 5,119.

<Table 1> presents correlation matrix for the raw data. The correlation coefficient between KOSPI and SSEC is 0.688, implying a relatively strong positive association between Korea and China. On the other hand, the correlation coefficients between Nikkei 225 and KOSPI, and Nikkei 225 and SSEC are −0.206 and −0.258, respectively, indicating a weak negative association between Japan and Korea, and Japan and China.

<Table 1> Correlation Matrix for Raw Data

	Korea (KOSPI)	China (SSEC)	Japan (Nikkei 225)
KOSPI	1		
SSEC	0.688	1	
Nikkei 225	-0.206	-0.258	1

From the three index series, we calculate three daily return volatility series defined by

(8) $\tilde{\sigma}_{i,t}^{2} = [\ln(P_{i,t}/P_{i,t-1})]^2$

where $\sigma_{i,t}$ is the natural logarithm of return volatility for country i at time t, and $P_{i,t}$ is the country index for country i at time t. (Garman & Klass 1980).

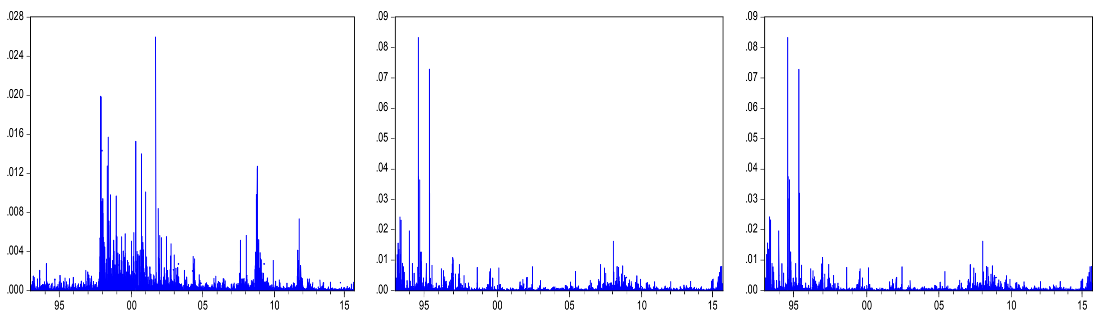
[Fig. 1] provides plots of daily volatility series for KOSPI, SSEC, and Nikkei 225. They clearly illustrate that volatilities vary considerably over time. Large changes in volatilities are followed by large changes while small changes in volatilities are trailed by small changes. The modeling and forecasting of volatility are therefore crucial for financial markets. (The Royal Swedish Academy of Sciences 2003, p. 3).

<Table 2> presents descriptive statistics and unit root tests of the daily return volatility series for KOSPI, SSEC and Nikkei 225. J-B refers to the empirical statistics of the Jarque-Bera test for normality. ADF and PP are the empirical statistics of the augmented Dickey-Fuller (1981) and the Phillips-Perron (1988) unit root tests, respectively. The Jarque-Bera test for normality is based on two measures, skewness and kurtosis. For a normal distribution, the skewness is zero, and the kurtosis is three (Hill, et al. 2008, p. 89).

As shown in Panel A, the volatilities of SSEC reveal the highest mean followed by KOSPI and Kikkei 225. Regarding to risk, the SSEC shows the highest value of standard deviation, trailed by KOSPI and Nikkei 225. Regarding to non-normality features, the excess skewness and kurtosis values for all volatility series indicate the presence of peaked distribution and fat tails. Large values of the skewness and kurtosis lead to a large value of Jarque-Bera statistic with small p-values. Accordingly, we conclude that the sample data are not normally distributed.

In Panel B, the results of two types of unit root tests are provided. Since the ADF and PP test statistics are large and negative, the null hypothesis of a unit root is rejected. Thus, we conclude that all volatility series are stationary processes.

(a) KOSPI (b) SSEC (c) Nikkei 225



[Fig. 1] Daily Return Volatility Plots for KOSPI, SSEC and Nikkei 225

<Table 2> Descriptive Statistics and Unit Root Tests

	KOSPI	SSEC	Nikkei 225
Panel A : descriptive statistics			
Mean	0.000353	0.000493	0.000247
Median	6.97E-05	7.70E-05	6.91E-05
Maximum	0.025971	0.083296	0.017515
Minimum	0.000000	0.000000	0.000000
Standard deviation	0.001068	0.002257	0.000672
Skewness	10.15989	20.87352	11.33805
Kurtosis	159.3150	621.8327	200.7215
J-B	5299716***	82052613***	8448058***
No. of Observations	5119	5119	5119
Panel B : unit root tests			
ADF	-7.936598***	-8.415675***	-9.178908***
P-P	-102.8432***	-88.74832***	-93.68527***

Notes : *** denotes the rejection of the null hypotheses of normality, and no unit root at the 1% significance level.

Ⅳ. Empirical Results

1. Full-sample Analysis

The results of full-sample analysis for volatility spillovers in the stock markets of Korea, China and Japan are provided in <Table 3>. This table presents an approximate "input-output" decomposition of the total volatility spillover index. The ij^{th} entry is the estimated contribution of index i coming from shocks of index j to the forecast error variance. Each entry is computed using SP^{total} in equation (3). The results are based on VAR of lag 4 and generalized variance decompositions of 10-day-ahead forecast errors. We employ the Akaike information criterion (AIC) to select the optimal lag. We choose 10-day-ahead forecast errors following Diebold & Yilmaz (2012).

<Table 3> Total Spillover Table across Korea, China, and Japan

	KOSPI	SSEC	Nikkei 225	From Others
KOSPI	86.6	0	13.3	13.3(c)
SSEC	0.5	99.9	0.1	0.5
Nikkei 225	11.5	0.1	88.5	12
To Others	12(b)	0.1	13	25
Including Own	98.6(a)	100	102	8.60%(d)

Notes : (a) $98.6 = 86.6 + 0.5 + 11.5$; (b) $12 = 0.5 + 11.5$; (c) $13.3 = 0 + 13.3$;
(d) ΣFrom Others / ΣIncluding Own $8.60\% = [(13.3 + 0.5 + 12)/(98.6 + 100 + 102)] \times 100$.

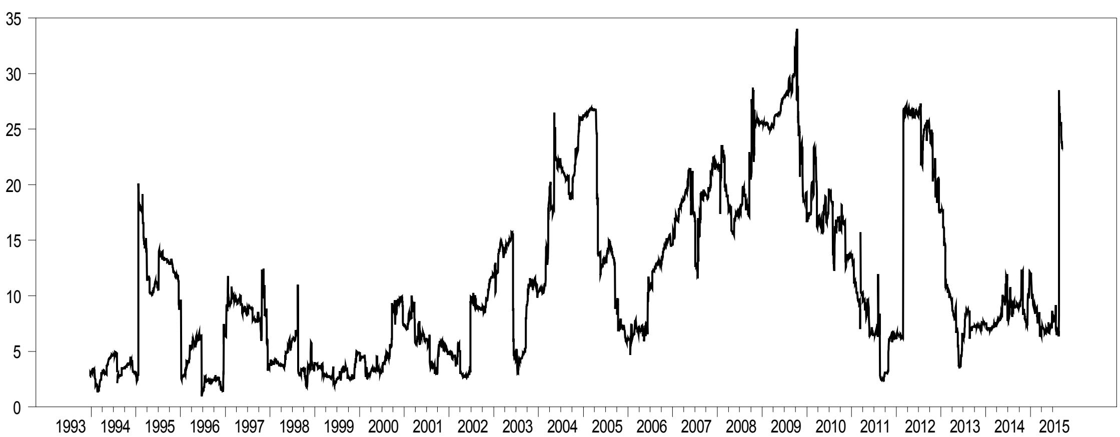
From the “To Others” row, we can observe that total directional volatilities spillovers to others are significantly different across countries, ranging from 0.1 (SSEC) to 13 (Nikkei 225). From the “From Others” column, we can also observe that total directional volatilities spillovers from others are different across countries, ranging from 0.5 (SSEC) to 13.3 (KOSPI). The total volatility spillover index is given in the lower right corner of <Table 3>. It is approximately the grand off-diagonal column sum (or row sum) relative to the grand column sum including diagonals (or low sum including diagonals) expressed as a percentage. This implies that on average 8.60% of volatility forecast error variance comes from spillovers across three countries. (For details, see Yang, et al. 2015).

2. Rolling-sample Analysis

Although the preceding full-sample analysis provides a useful summary of average behavior, it is likely to overlook the notable secular and cyclical trends in spillovers. To overcome this limitation of full-sample analysis, we evaluate the models using a 250-day rolling sample analysis to examine the extent and disposition of time-varying total volatility spillovers. We choose the 250-day rolling sample based on our robustness test.

2.1 Total volatility spillovers

Time-varying volatility spillovers are displayed in [Fig. 2]. The plot starts at 2.5% in the 1st window, and ends at 26% in the last 4,869th window. (Here, total number of windows = total observations − no of days in a window = 5,119 - 250 = 4,869). As in Diebold & Yilmaz (2012, p. 61, range 3%-32%), and Lee & Chang (2013, p. 1626, range 50%-87%), it displays high fluctuations over time (range, 2%-33%). It reveals low volatilities during the Asian Financial Crisis (1998-1999), but it shows a big peak during the U.S. Credit Crisis (2008-2009). In addition, it unveils an upward movement for one year since the outbreak of ongoing European Debt Crisis (2012-present), then it stays relatively low around 9%, but it suddenly rises like a skyrocket in July 2015 due to the crash of Chinese stock market. (For details on the crash, see Economist 2015).



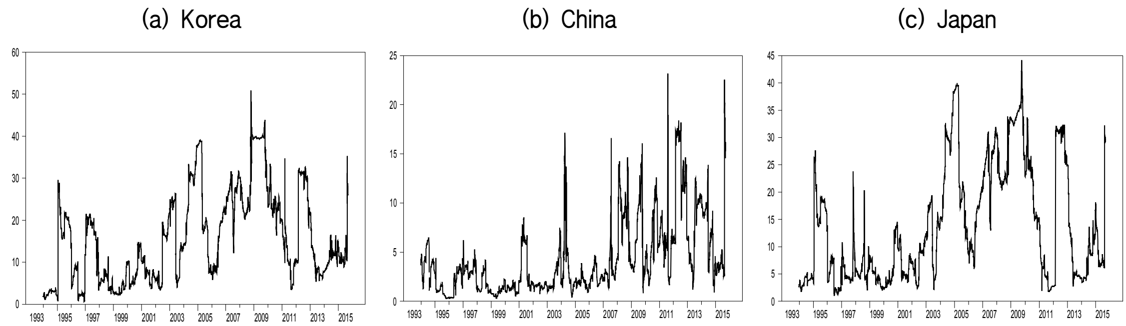
[Fig. 2] Time-varying Total Volatility Spillover

2.2 Directional Volatility Inflow Spillover by Countries

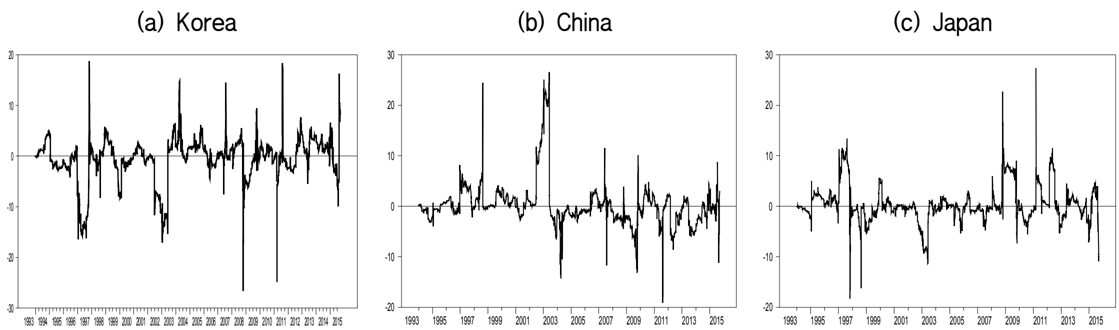
Thus far, we have only examined time-varying total volatility spillovers. This is interesting but which throws away the directional spillovers received by index i from all other indices, or the directional spillovers transmitted by index i to all other indices. That information is corresponding to “From Others” column, or “To Others” row, respectively in <Table 3>. The sum of “From Others” column is computed from SP_i^{inflow} while the sum of “To Others” row is calculated from $SP_i^{outflow}$. Directional volatility inflow spillovers by countries are presented in [Fig. 3]. They show dynamic directional spillovers of each country index transmitted from other country indices. These dynamic estimations are precisely the same as the preceding total volatility spillovers plot in [Fig. 2].

2.3 Net Directional Volatility Spillover by Countries

Net directional volatility spillover plots by countries are presented in [Fig. 4]. It displays time-varying net directional volatility spillovers for three country indices. Each point in this figure is calculated from $SP_i^{net} = SP_i^{outflow} - SP_i^{inflow}$ as defined in eq. (6). It is simply the difference between “From Others” column sum and “To Others” row sum in <Table 3>. When the net directional volatility spillover plot is above the horizontal line of zero, it indicates that the index is leading the other indices. On the other hand, if the net directional volatility spillover plot is below



[Fig. 3] Directional Volatility Inflow Spillover by Countries



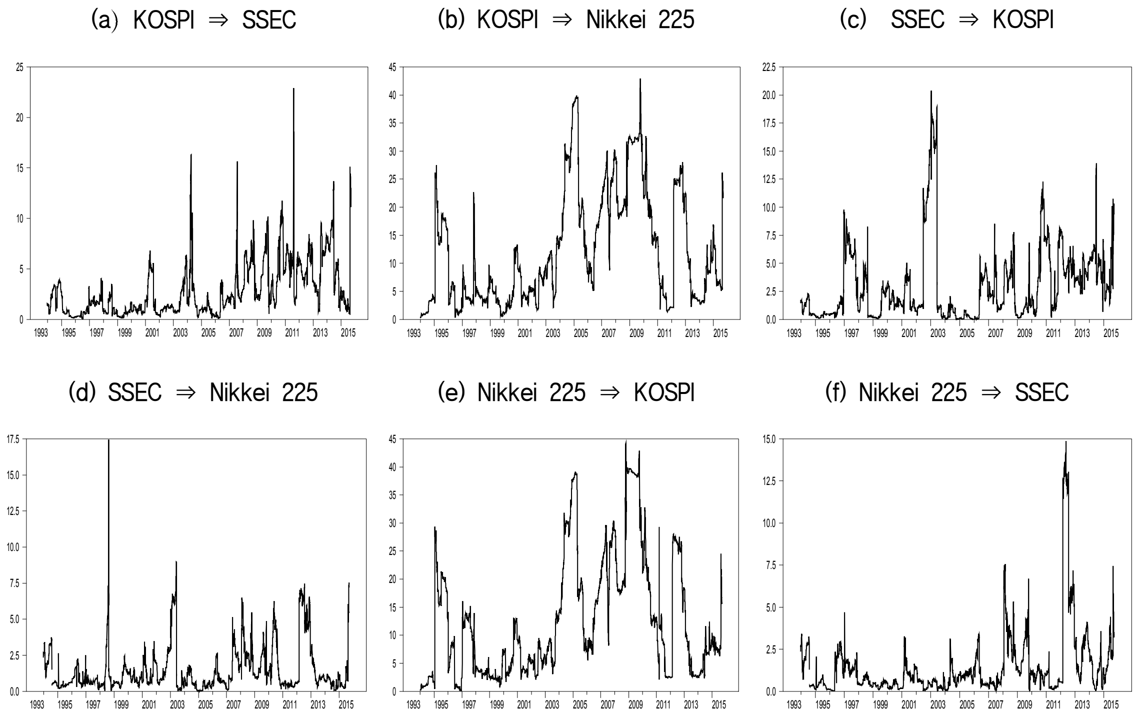
[Fig. 4] Net Directional Volatility Spillover by Countries the horizontal line of zero, it implies that the index is following the other indices. A close look at [Fig. 4] reveals that there is neither a definite leader nor a significant follower during the sample period.

2.4 Net Pairwise Volatility Spillovers by Countries

Finally, we examine the net pairwise volatility spillovers defined as $SP_{ij}^{net} = SP_{ij}^{outflow} - SP_{ij}^{inflow}$ in eq. (7). The net pairwise spillovers is simply the difference between the total volatility spillovers transmitted from index i to index j and those received from index j to index i.

Net pairwise volatility spillovers by countries are presented in [Fig. 5]. During the Asian Financial Crisis (1998-1999), the volatilities from the Korean Stock Market are transmitted both to Chinese and Japanese stock markets, but remarkably to the Japanese Stock Market ([Fig. 5(b)]). Net volatility spillovers from the Japanese Stock Market to the Chinese Stock Market are smaller ([Fig. 5(f)]) than the net spillovers from the Korean Stock Market ([Fig. 5(e)]).

In [Fig. 5], we can observe interesting results that KOSPI volatility influences SSEC more than the others, an “odd” finding since we typically presume that big (core) economies influence small (periphery) ones. This abnormal phenomenon may be explained by the China’s crazy stock market (Economist, 2015).



[Fig. 5] Net Pairwise Volatility Spillovers by Countries

Ⅴ. Conclusions

We aim to conduct a comparative study on the characteristics of daily volatility spillovers across the stock markets of Korea, China, and Japan. Using generalized spillover definition and measurement developed by Diebold & Yilmaz (2009, 2012), we have presented both total and net directional volatility spillover measures. The advantage of this method is its independence on the order of variables employed for volatility forecasting error variance decompositions.

From a static full-sample analysis, we find that 8.60% of forecast error variance comes from volatility spillovers. From a 250-day rolling-sample analysis, we discover that there exist significant volatility fluctuations in the stock markets of Korea, China and Japan, expecially during the Asian Financial Crisis (1998-1999) and the US Credit Crisis (2008-2009) after the collapse of Lehman Brothers. From the net directional spillovers across three countries, we come upon that there is neither a definite leader nor a significant follower during the sample period. These findings might help both individual and institutional investors significantly increase their global diversification benefits.

We need to point out the limitations of this paper: First, we cannot perform a formal test to check if the spillover effects across countries are significantly the same or not. As far as we know, there is no such formal test. Second, in VAR(p) model, we assume that the error terms are independent and identically distributed (i.i.d.), and follow a normal distribution.

In future research, we can further examine the association between Diebold & Yilmaz measure and other measures such as traditional time-varying correlation of Engel (2009), or CoVar of Adrian & Brunnermeier (2008). We can also use T-GARCH to test similar information spillover across countries.

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