Examining Dynamic Interdependencies Among Major Global Financial Markets

Sanjay Sehgal
University of Delhi, India

Sakshi Saini*
Institute of Economic Growth, India

Florent Deisting
Groupe ESC Pau, France

This paper investigates dynamic interdependencies among major global financial markets from January 1999 to April 2017 by examining their risk and return spillovers. Risk and return interactions are also analyzed within the sample markets. Using block-aggregation technique under the Diebold-Yilmaz framework, strong information linkages are observed among the global equity markets that intensify during the crisis period. Results establish the dominance of the US in the global financial system based on information linkages. Further, systematic factors are found to be more prevalent in spillovers among return and volatility as compared to idiosyncratic factors. With regards to interaction between risk and return, results reveal return spillovers of high magnitude onto risk and almost negligible risk spillovers onto return. These findings have important implications for international investors and policymakers. (JEL: C13, F21, F36, G01, G15)

Keywords: financial markets; Diebold and Yilmaz; spillovers; conditional volatility

---

* Corresponding author: Sakshi Saini, Assistant Professor, Institute of Economic Growth, University Enclave, University of Delhi (North Campus), Delhi 110 007, India, E-mail: s.sakshi1408@gmail.com, s.sakshi@iegindia.org, Contact: +91-11-27666364 (Ext.203). The paper has benefitted from the comments and suggestions of the participants of 13th Annual Conference on Economic Growth and Development, Indian Statistical Institute, Delhi, India and 6th IIFT Conference on Empirical Issues in International Trade and Finance, Indian Institute of Foreign Trade, Delhi, India where an earlier version of this paper was presented. The authors thank the journal Editor-in-Chief, Panayiotis Theodossiou, and the two anonymous reviewers for their valuable inputs and suggestions that helped in improving the paper.

(*Multinational Finance Journal*, 2019, vol. 23, no. 1/2, pp. 103–139)

Article history: Received: 30 December 2018, Received in final revised form: 31 July 2019, Accepted: 6 September 2019, Available online: 10 October 2019

I. Introduction

With the advance of globalization, financial markets across the globe have experienced increased linkages over the past few decades. Several factors like the arrival of information and communication technologies, development of electronic trading systems and databases, access to information in continuous time and sophisticated marketing tools have contributed to this greater interaction among the markets (Jawadi, Louhichi and Cheffou, 2015). Financial markets are, thus, no more isolated and information originating in one market quickly propagates to another via transmission channels. The Global Financial Crisis and the European Sovereign Debt Crisis have led to a rapid intensification of the spillovers across the global markets and have underscored the importance of ensuring financial stability through policy actions. Assessing the dynamics of financial linkages between the global markets can help in formulating and implementing appropriate policies during the turbulent times. It is also important from the perspective of international investors as they strive to manage their portfolio and risk exposure through diversification.

Extant research has been conducted on examining linkages among international equity markets by analyzing risk and return spillovers. These studies typically focus on investigating risk spillovers across markets by using volatility as a measure of risk. Early contributions to this literature include Koutmos and Booth (1995) and Theodossiou et al. (1997). Koutmos and Booth (1995) examine price and volatility spillovers across New York, Tokyo and London stock markets and find that volatility spillovers are much more pronounced when the news arriving from the last market to trade is bad. Theodossiou et al. (1997) investigate volatility reversion in stock markets of the US, Japan and the UK. They find the existence of mean and volatility spillovers from the US and Japan to the UK, but the magnitude of the spillovers is generally low. Recent studies that analyze volatility spillovers across the markets include Bhar and Nikolova (2009); Singh, Kumar and Pandey (2010); Sugimoto, Matsuki and Yoshida (2014); Zhang and Wang (2014); Ding, Huang and Pu (2014); Alotaibi and Mishra (2015); Celements, Hurn and

Volkov (2015); Liow (2015); Rejeb and Arfaoui (2016); Kundu and Sarkar (2016); Fowowe and Shuaibu (2016); Allen et al. (2017); Liu et al. (2017); Rahahleh and Bhatti (2017); Shahzad et al. (2017); Huo and Ahmed (2017); among others. The risk-return relationship is crucial in financial decision making as investors manage their portfolio based on risk-return profiles of assets. Portfolio balancing by global investors alters the risk-return profiles of assets and generates feedback effects leading to a complex array of interactions between risk and return (see Greenwood-Nimmo, Nguyen and Rafferty, 2016). Standard asset pricing models postulate that return is linearly related to market-wide volatility risk. In the empirical literature, the relationship between return and volatility as a proxy for risk has been extensively studied (for recent literature, see Cotter, O'Sullivan and Rossi, 2015; Badshah et al., 2016; Chang, 2016; Frazier and Liu. 2016; Kundu and Sarkar, 2016; Jin, 2017; Liu, 2017).

In this light, this paper investigates dynamic interdependencies among major global financial markets by examining their risk and return spillovers. In particular, the study aims to address the following research questions: (a) What is the magnitude of spillovers across the global financial markets among return and risk? (b) What is the overall information transmission across markets that channelizes through both risk and return? (c) Which is the dominant market in the global financial system based on information linkages? (d) What is the magnitude of spillovers across risk and return and how much of the spillovers can be attributed to within-market (idiosyncratic) and cross-market (systematic) effects? (e) What is the time-varying nature of the spillovers across the markets?

The analysis is based on volatility as a risk factor. Since equity market returns are generally characterized by asymmetric volatility dynamics as has been evidenced by overwhelming literature, the Exponential GARCH (EGARCH) Model introduced by Nelson (1991) is employed to compute conditional volatility. Block-aggregation technique under the Diebold-Yilmaz framework proposed by Greenwood-Nimmo, Nguyen and Shin (2015) is used to examine risk and return spillovers within and across the major global financial markets. Extant literature employs several other time series models including multivariate GARCH models (like CCC GARCH, DCC GARCH, ADCC GARCH), copula functions, etc. to estimate linkages among international equity markets. These models yield the estimates of conditional correlations but do not allow quantification of cross-market directional spillovers. Diebold and Yilmaz (2012) spillover index methodology is a contemporary and widely used model that allows assessment of linkages by quantifying pairwise directional spillovers across the markets. However, this spillover index approach can be used to measure spillovers among individual variables or to summarize aggregate spillover activity among all variables, but cannot be used to measure spillovers among a group of variables (Greenwood-Nimmo, Nguyen and Rafferty, 2016). The advantage of using the block-aggregation technique under the Diebold-Yilmaz framework over other time series models is that it allows us to examine spillovers by grouping a set of variables, thus providing a comprehensive account of spillovers across groups of variables. In this study, block-aggregation routine is used to examine cross-market spillovers in a combined manner that encompasses return as well as conditional volatility. Other time series models allow us to capture linkages across mean and volatility separately, but the block-aggregation methodology allows us to examine spillovers in a unified manner. Block-aggregation is, therefore, a novel approach that augments the flexibility of the Diebold-Yilmaz framework by integrating a set of individual variables to examine spillovers among a group of variables. In this manner, it provides a richer analysis of risk and return spillovers within and between the global financial markets as compared to other time series models.

The analysis is carried out on 13 major global financial markets selected from the ranking based on the Global Financial Centers Index (GFCI 21).[1] The selection of major global financial markets for analyzing the risk and return spillovers within and across markets entails two benefits. First, these markets being the hub of investment activities encapsulate the bulk of trading transactions of the investor's community. Analysis of these markets, thus, provides a concise account of risk and return spillovers in the global financial system. Additionally, the existing rating system for the financial centers can be evaluated in light of information transmission across the markets. One would naturally assume that the greater competitiveness of financial market based on GFCI would consequently imply its stronger linkages with the global markets, thereby creating a global financial network. The investigation of financial interdependencies among the markets shall,

1. Global Financial Centres Index (GFCI) 21 report is available from the following web link: https://www.longfinance.net/media/documents/GFCI21_05_04_17.pdf

therefore, elucidate the dominance or strength of a financial market and provide useful insights regarding the global financial market rating system.

The study makes important contributions to the literature. Information transmission across the global financial markets is assessed by analyzing risk and return spillovers. The analysis of information transmission encompasses return and the accompanying risk that investors face, which is captured by conditional volatility. The underlying strength or dominance of financial markets is assessed and insights into the financial market rating system are provided. Spillovers across the two moments (mean and volatility) are also examined and levels of within and cross-market effects are discerned. The study, therefore, undertakes a comprehensive investigation of linkages among the markets. The empirical findings provide rich insights into the dynamic linkages among the major global financial markets, based on which implications are drawn for international investors who are interested in portfolio management and risk assessment, as well as for policymakers for policy formulation.

Results suggest that financial linkages among the sample equity markets are high, but regional integration is relatively strong as compared to global integration. International equity markets have limited exposure to the idiosyncratic effects as they are largely driven by common global economic factors. The systematic effects in these markets intensify during the turmoil period, pointing to financial contagion. The US equity market is found to be the most dominant market in the global financial system based on information linkages. Germany emerges as the dominant market in Europe; meanwhile, Singapore takes lead in the Asian region. Further, results highlight that systematic factors are more prevalent in spillovers among return and volatility as compared to idiosyncratic factors. With regards to interaction between risk and return in global financial markets, results reveal return spillovers of high magnitude onto volatility and almost negligible volatility spillover onto returns. Spillovers across risk and return dampen during the crisis period, directing to weakening of the risk-return relationship during uncertainty. These findings are relevant for portfolio management, risk assessment and policy formulation. These results also have implications for asset pricing theories and global financial market rating system.

The remainder of the paper is structured as follows: Section II describes data along with the estimation of the conditional volatility.

Section III outlines the methodological framework adopted in the paper. Section IV presents empirical results and robustness checks. Section V concludes.

II. Data and Conditional Moments

A. Data

The dataset for the study comprises of daily equity index closing prices of 13 major global financial markets viz. Australia, Canada, China, Germany, Hong Kong, India, Japan, Luxembourg, Singapore, South Korea, Switzerland, the United Kingdom (UK) and the United States (US) over the period January 13, 1999 to April 26, 2017. The starting date chosen for our sample data is motivated by the introduction of the Euro and is also subject to the availability of data for the sample markets. Daily closing prices of the Luxembourg LuxX index and MSCI indices for the rest of the markets have been retrieved from Thomson Reuters Eikon. The ranking of global financial centers based on the Global Financial Centers Index (GFCI 21) is taken as a reference to select the sample markets for our study. The GFCI is a widely known and accepted index measuring the competitiveness of financial centers worldwide based on five key parameters viz. business environment, financial sector development, infrastructure, human capital and reputation.[2] First, the top 25 financial centers are considered and the financial market in which these centers are based is specified. A condensed list of 13 major global financial markets is formed as the overlapping markets are dropped from the list.[3] UAE, however, is dropped from the analysis because of the unavailability of data since the start of our sample period. Instead, India is considered among the list of major global financial markets for analysis as it is one of the fastest growing emerging markets and has significantly improved its GFCI

2. GFCI is compiled and published twice a year by Z/Yen Group. The assessment of the competitiveness of a financial center is based on instrumental factors obtained from external sources and survey of financial services professionals through an online questionnaire.

3. For example, New York, San Francisco and Chicago are the three financial centers located in the United States and rank 2nd, 6th and 7th according to GFCI 21 rating. Hence, the US as a financial market is considered and rank 2 is assigned to it. Similarly, Japan has two financial centers viz. Tokyo and Osaka ranked 5th and 15th. Thus Japan as a financial market is considered for the analysis and rank 5 is placed on it.

rating over the past years.

As shown in appendix, the international equity markets chosen for the study have heterogeneous trading hours as they operate in different time zones. The stock markets of Canada and the US have overlapping trading hours. Similarly, European (Germany, Luxembourg, Switzerland and the UK) and Asian (China, Hong Kong, India, Japan, Singapore and South Korea) stock markets have overlapping trading hours. Asian stock exchanges overlap somewhat with Australian and European equity markets, whereas the equity markets of America overlap somewhat with that of Europe. However, trading hours of American equity markets are completely non-synchronous with Asian and Australian markets. Considering this, there is a need to address the problem of non-overlapping trading hours of the stock markets. Weekly or monthly data have been used in the empirical literature to deal with non-synchronous trading bias (see, for example, Okimoto, 2014; Fowowe and Shuaibu, 2016; Al Nasser and Hajilee, 2016). However, important news flows much more frequently than weekly or monthly across information-driven stock markets (Sugimoto, Matsuki and Yoshida, 2014) and using such data may lead to significant loss of information. Following Forbes and Rigobon (2002) and Wang et al. (2017), two-day rolling average returns are used to counter the problem of non-synchronous trading bias as the analysis is based on the geographically distant markets. Daily returns are calculated as the first difference of log-transformed price index series. Sensitivity analysis of employing two-day rolling average returns is also conducted by re-estimating our results using daily returns. The results are found to be qualitatively similar in both cases.[4]

B. Preliminary analysis of sample equity returns series

Summary statistics of the sample index return series are presented in table 1. The average return is positive and low, while the standard deviation is high for all sample countries. Mean return is highest in India and lowest in the UK. South Korea, India and China are found to be highly volatile markets, while the US equity market is more stable. All the sample markets are characterized by negative skewness, implying frequent small gains and extreme large losses. Further, all markets exhibit excess kurtosis indicating the presence of fat-tailed

4. Results are not presented due to space constraint but are available on request.

TABLE 1. Summary Statistics of Sample Equity Return Series

Market	Mean	Std. Dev.	Max	Min	Skew	Kurt	JB	LB	ARCH LM	Obsv
AUS	0.0002	0.0108	0.0815	–0.0836	–0.42	9.00	7051.41** [0.00]	1230.20** [0.00]	1188.13** [0.00]	4602
CAN	0.0002	0.0104	0.0813	–0.0967	–0.56	11.16	13004.60** [0.00]	1177.40** [0.00]	468.16** [0.00]	4602
CHI	0.0002	0.0134	0.0804	–0.1065	–0.18	7.08	3218.22** [0.00]	1290.10** [0.00]	881.57** [0.00]	4602
GER	0.0001	0.0116	0.0711	–0.0665	–0.30	6.35	2216.35** [0.00]	1148.90** [0.00]	740.15** [0.00]	4602
HKG	0.0002	0.0098	0.0656	–0.0894	–0.22	7.55	3999.88** [0.00]	1252.70** [0.00]	644.20** [0.00]	4602
IND	0.0004	0.0127	0.1128	–0.0954	–0.29	8.85	6619.50** [0.00]	1399.90** [0.00]	1000.60** [0.00]	4602
JAP	0.0001	0.0097	0.0634	–0.0795	–0.18	6.55	2439.14** [0.00]	928.26** [0.00]	620.95** [0.00]	4602
LUX	0.0001	0.0095	0.0581	–0.0819	–0.62	10.27	10443.24** [0.00]	1391.60** [0.00]	1172.10** [0.00]	4602
SGP	0.0002	0.0097	0.0523	–0.0751	–0.22	7.18	3384.91** [0.00]	1287.90** [0.00]	1721.02** [0.00]	4602
SKOR	0.0003	0.0149	0.1257	–0.1275	–0.30	9.66	8573.23** [0.00]	1257.90** [0.00]	1272.77** [0.00]	4602
SWZ	0.0001	0.0089	0.1014	–0.1120	–0.38	15.96	32295.19** [0.00]	1036.20** [0.00]	84.02** [0.00]	4602
UK	0.0000	0.0104	0.1552	–0.1730	–0.61	36.14	210900.90** [0.00]	976.02** [0.00]	22.27** [0.00]	4602
US	0.0001	0.0084	0.0622	–0.0671	–0.38	8.67	6284.85** [0.00]	955.84** [0.00]	952.89** [0.00]	4602

Note: (a) Std. Dev., Max, Min, Skew and Kurt denote Standard Deviation, Maximum, Minimum, Skewness and Kurtosis of the return series. (b) JB denotes Jarque-Bera test for the null hypothesis of normal distribution. (c) LB denotes Ljung-Box Q-statistic reported at 12th lag and ARCH LM denotes ARCH Lagrange Multiplier test of conditional heteroscedasticity. (d) Obsv denotes number of observations in the return series. (e) Value in [ ] includes p-value. (f) **/* indicates significance at 0.01/0.05 level.

return distribution. The Jarque-Bera test confirms departure of return distributions from normality as the test statistic is found to be significant in all cases. Further, all sample return series are serially correlated and exhibit conditional heteroscedasticity as indicated by Ljung-Box Q-statistic and ARCH Lagrange Multiplier test, respectively. We also perform Augmented Dickey-Fuller (Dickey and Fuller, 1979), KPSS (Kwiatkowski et al., 1992) and Phillips–Perron (Phillips and Perron, 1988) tests as a pre-cursor to time-series analysis.[5] Results reveal that sample equity market indices are non-stationary in level and stationary in the first-differenced form. This means that all stock price series are $I(1)$ and all sample return series exhibit stationarity.

C. Modeling Conditional Volatility

For the analysis, conditional volatility is used as a measure to capture risk that investors face while making investment decisions. The mean equation for equity returns of the sample markets is specified as an autoregressive process of order 1:

$$r_{i,t} = \mu + \varphi r_{i,t-1} + \varepsilon_{i,t} \tag{1}$$

where, $\varepsilon_{i,t}$ is the disturbance term. GARCH modeling is suitable to compute volatility as all return series are characterized by conditional heteroscedasticity, revealed by the ARCH-LM test. Therefore, time-varying conditional volatility is computed by specifying a univariate GARCH process. Exponential GARCH model of Nelson (1991) is used for the specification of conditional volatility to avoid using non-negativity restrictions on GARCH parameters and to capture the asymmetric response to return innovations. EGARCH(1,1) model is given as:[6]

$$\ln\left(h_{i,t}^{2}\right) = \omega + \beta \ln\left(h_{i,t-1}^{2}\right) + \alpha \left|\frac{\varepsilon_{i,t-1}}{h_{i,t-1}}\right| + \gamma \frac{\varepsilon_{i,t-1}}{h_{i,t-1}} \tag{2}$$

The results of AR(1)-EGARCH (1,1) modeling are displayed in table 2.

---

5. Results of ADF, KPSS and Phillips-Perron tests are not reported due to brevity of space but are available on request.

6. EGARCH(1,1) is chosen as the preferred model in the interest of parsimony of parameters (see Kim and Wang, 2006).

TABLE 2. Specification of Conditional Volatility

	see equation (1)		see equation (2)			
Country	μ	φ	ω	Υ	α	β
AUS	0.0002 (0.00)	0.5138** (0.01)	–0.1725** (0.05)	–0.0921** (0.02)	0.1449 (0.14)	0.9824** (0.01)
CAN	0.0002 (0.00)	0.5307** (0.01)	–0.1422** (0.00)	–0.0867** (0.01)	0.1698** (0.02)	0.9857** (0.00)
CHI	0.0003 (0.00)	0.5310** (0.01)	–0.1518** (0.00)	–0.0563** (0.01)	0.1893** (0.02)	0.9837** (0.00)
GER	0.0002 (0.00)	0.5003** (0.01)	–0.1875** (0.01)	–0.0910** (0.01)	0.1761** (0.02)	0.9805** (0.00)
HKG	0.0003* (0.00)	0.5266** (0.01)	–0.1268** (0.00)	–0.0565** (0.01)	0.1515** (0.02)	0.9872** (0.00)
IND	0.0005** (0.00)	0.5446** (0.01)	–0.3416** (0.07)	–0.0868** (0.02)	0.2629** (0.03)	0.9639** (0.01)
JAP	–0.0001** (0.00)	0.4555** (0.02)	–0.3775** (0.02)	–0.0949** (0.01)	0.2034** (0.03)	0.9621** (0.00)
LUX	0.0003* (0.00)	0.5196** (0.02)	–0.2807** (0.02)	–0.0437** (0.01)	0.2555** (0.03)	0.9719** (0.00)
SGP	0.0001 (0.00)	0.5220** (0.01)	–0.1381** (0.02)	–0.0612** (0.01)	0.1906** (0.00)	0.9861** (0.00)
SKOR	0.0003 (0.00)	0.5194** (0.01)	–0.1250** (0.00)	–0.0808** (0.01)	0.1692** (0.02)	0.9864** (0.00)
SWZ	0.0001 (0.00)	0.4925** (0.01)	–0.2849** (0.01)	–0.0889** (0.01)	0.2196** (0.03)	0.9718** (0.00)
UK	–0.0001 (0.00)	0.4797** (0.01)	–0.2897** (0.01)	–0.1089** (0.01)	0.2012** (0.02)	0.9710** (0.00)
US	0.0001 (0.00)	0.4672** (0.01)	–0.2090** (0.01)	–0.1725** (0.01)	0.1410** (0.01)	0.9799** (0.00)

Note: (a) The table presents parameter estimates of the specification of conditional volatility. (b) Value in ( ) includes standard error. (c) **/* indicates significance at 0.01/0.05 level.

The autoregressive parameter, denoted by φ, is significant for all countries.[7] Estimation results show the presence of long-run volatility persistence as is indicated by the significant value of the β coefficient. Both α and Υ measuring size and leverage effect, respectively, are also found to be significant for all sample markets. The negative and significant value of Υ coefficient indicates an asymmetric effect of the news on the volatility factor which increases more after a negative shock than a positive shock, thereby justifying the use of the EGARCH model.

III. Methodology

The spillover index methodology proposed by Diebold and Yilmaz (2009, 2012) which is based on vector autoregressive (VAR) framework allows us to examine spillovers across variables. It quantifies the contribution of shocks to and from each variable in terms of each variable's forecast error variance through variance decomposition analysis and therefore, provides the magnitude and direction of spillovers. Diebold and Yilmaz (2012) use the generalized VAR framework of Koop, Pesaran and Potter (1996) and Pesaran and Shin (1998) which yields forecast-error variance decompositions that are invariant to the ordering of the variables.

The N variable VAR of p^{th} order can be written as:

$$y_t = \sum_{i=1}^{p} \varphi_i y_{t-i} + \varepsilon_t \tag{3}$$

where, $y_t = (y_{1t}, \ldots, y_{Nt})$ is a vector of N endogenous variables, φ_i is $N \times N$ parameter matrix and $\varepsilon_t \sim (0, \Sigma)$ is a vector of innovations. Its moving average representation can be written as: $y_t = \sum_{i=1}^{\infty} A_i \varepsilon_{t-i}$, where $A_i = \sum \varphi_j A_{i-j}$ and $j = 1, \ldots, p$.

The H-step ahead forecast error variance decomposition of i^{th} variable which can be attributed to shocks for j^{th} variable is given as:

$$\theta_{i \leftarrow j}^{g}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \sum A_h' e_j\right)}, \text{ for } i, j = 1, \ldots, N \tag{4}$$

7. Statistical significance of φ coefficient can be attributed to the specification of return series as two-day rolling average. Hence, the result should be interpreted with caution.

where, $\sum$ is the estimated variance matrix for the error term of VAR, σ_{ij} is the standard deviation of the error term for the i^{th} equation and e_i is the selection vector with one for the i^{th} element and zero otherwise. Each forecast error variance decomposition is normalized by the row sum as:

$$\theta^{g}_{i\leftarrow j}(H) = \frac{\theta^{g}_{i\leftarrow j}(H)}{\sum_{j=1}^{N}\theta^{g}_{i\leftarrow j}(H)} \tag{5}$$

The $N\times N$ connectedness matrix can thus be constructed using the forecast error variance decompositions as follows:

$$C(H) = \begin{bmatrix} \theta^{g}_{1\leftarrow 1}(H) & \theta^{g}_{1\leftarrow 2}(H) & \cdots & \theta^{g}_{1\leftarrow N}(H) \\ \theta^{g}_{2\leftarrow 1}(H) & \theta^{g}_{2\leftarrow 2}(H) & \cdots & \theta^{g}_{2\leftarrow N}(H) \\ \vdots & \vdots & \ddots & \vdots \\ \theta^{g}_{N\leftarrow 1}(H) & \theta^{g}_{N\leftarrow 2}(H) & \cdots & \theta^{g}_{N\leftarrow N}(H) \end{bmatrix} \tag{6}$$

where, $\theta^{g}_{i\leftarrow j}(H)$ measures the pairwise spillover from variable j to variable i.

While the Diebold-Yilmaz framework provides the measure of pairwise directional spillovers among individual markets, it does not quantify the spillovers among a group of variables. Greenwood-Nimmo, Nguyen and Shin (2015) extend the Diebold-Yilmaz framework by exploiting block-aggregation of the connectedness matrix which applies an aggregation routine to group a set of individual variables.

Therefore, the same methodology is adopted to examine linkages among the global financial markets. The linkages among N=13 markets are examined wherein each market encompasses two variables- return and conditional volatility. The variables are arranged in the order y_t = $(r_{1t}, v_{1t}, r_{2t}, v_{2t}, \ldots, r_{Nt}, v_{Nt})$.

Generalized VAR framework adopted in Diebold and Yilmaz (2012) ensures that forecast-error decomposition is not sensitive to the variable re-ordering and hence, supports any desired block structure. Therefore, the connectedness matrix is arranged in the following form:

$$C(H) = \begin{bmatrix} B^{g}_{1\leftarrow 1}(H) & B^{g}_{1\leftarrow 2}(H) & \cdots & B^{g}_{1\leftarrow N}(H) \\ B^{g}_{2\leftarrow 1}(H) & B^{g}_{2\leftarrow 2}(H) & \cdots & B^{g}_{2\leftarrow N}(H) \\ \vdots & \vdots & \ddots & \vdots \\ B^{g}_{N\leftarrow 1}(H) & B^{g}_{N\leftarrow 2}(H) & \cdots & B^{g}_{N\leftarrow N}(H) \end{bmatrix}$$

where,

$$B^g_{i\leftarrow j}(H)=\begin{bmatrix}\theta^g_{r_i\leftarrow r_j}(H) & \theta^g_{r_i\leftarrow v_j}(H)\\ \theta^g_{v_i\leftarrow r_j}(H) & \theta^g_{v\leftarrow v_j}(H)\end{bmatrix},\ \text{for } i,j=1,2,\ldots,N \quad (7)$$

The total within-market forecast error variance contribution for the market i is given as:

$$W^g_{i\leftarrow i}(H)=\frac{1}{m}\cdot e'_m\cdot B^g_{i\leftarrow i}(H)\cdot e_m \quad (8)$$

and the total Pairwise directional spillover from market j to market i ($i \neq j$) at horizon H is given as:

$$P^g_{i\leftarrow j}(H)=\frac{1}{m}\cdot e'_m\cdot B^g_{i\leftarrow j}(H)\cdot e_m, \quad (9)$$

where, m is the number of variables that each group is composed of (in this case, m=2) and e_m is $m\times 1$ vector of ones.

Hence, the aggregated connectedness matrix following Greenwood-Nimmo, Nguyen and Shin (2015) can be written as:

$$C(H)=\begin{bmatrix}W^g_{1\leftarrow 1}(H) & P^g_{1\leftarrow 2}(H) & \ldots & P^g_{1\leftarrow N}(H)\\ P^g_{2\leftarrow 1}(H) & W^g_{2\leftarrow 2}(H) & \ldots & P^g_{2\leftarrow N}(H)\\ \vdots & \vdots & \ddots & \vdots\\ P^g_{N\leftarrow 1}(H) & P^g_{N\leftarrow 2}(H) & \ldots & W^g_{N\leftarrow N}(H)\end{bmatrix} \quad (10)$$

Now, total within-market contribution, $W^g_{i\leftarrow i}(H)$, can be decomposed into common-variable forecast error variance contribution within-market i, $O^g_{i\leftarrow i}(H)$, and cross-variable effects, $C^g_{i\leftarrow i}(H)$, which are given as follows:

$$O^g_{i\leftarrow i}(H)=\frac{1}{m}trace\left(B^g_{i\leftarrow i}(H)\right)$$

and (11)

$$C^g_{i\leftarrow i}(H)=W^g_{i\leftarrow i}(H)-O^g_{i\leftarrow i}(H)$$

It should be emphasized here that $O^{g}_{i\leftarrow i}(H)$ is the proportion of forecast error variance of $y_{i,t}$ that is not attributable to spillovers among moments within market *i* nor to the spillovers from other markets to market *i*. On the other hand, $C^{g}_{i\leftarrow i}(H)$ is the proportion of forecast error variance of $y_{i,t}$ that is ascribed to spillovers among moments within-market *i*.

Total pairwise directional spillovers can be decomposed into common-variable, $O^{g}_{i\leftarrow j}(H)$, and cross-variable effects, $C^{g}_{i\leftarrow j}(H)$, expressed as:

$$O^{g}_{i\leftarrow j}(H) = \frac{1}{m} trace\left(B^{g}_{i\leftarrow j}(H)\right)$$

and (12)

$$C^{g}_{i\leftarrow j}(H) = W^{g}_{i\leftarrow j}(H) - O^{g}_{i\leftarrow j}(H), \text{ where } i \neq j$$

Here, $O^{g}_{i\leftarrow j}(H)$ measures the proportion of common-variable forecast error variance of $y_{i,t}$ that is attributable to spillovers from other markets to market *i*, while $C^{g}_{i\leftarrow j}(H)$ captures the proportion of forecast error variance of $y_{i,t}$ that is ascribed to spillovers among moments from other markets to market *i*.

The total directional spillover of market *i* to/from all other markets in the model can also be estimated from the connectedness matrix. Total directional spillovers transmitted by market *i* from and to all other markets, in other words, the aggregate from and to connectedness of market *i* are expressed as:

$$F^{g}_{i\leftarrow\bullet}(H) = \sum\nolimits_{j=1}^{N} P^{g}_{i\leftarrow j}(H)$$

and (13)

$$T^{g}_{i\leftarrow\bullet}(H) = \sum\nolimits_{j=1}^{N} P^{g}_{j\leftarrow i}(H), \text{ respectively.}$$

Gross and Net directional spillover of market *i* can be obtained as follows:

$$G^{g}_{i}(H) = T^{g}_{i\leftarrow\bullet}(H) + F^{g}_{i\leftarrow\bullet}(H)$$

and (14)

$$N^{g}_{i}(H) = T^{g}_{i\leftarrow\bullet}(H) - F^{g}_{i\leftarrow\bullet}(H), \text{ respectively.}$$

The block-aggregation technique under the Diebold-Yilmaz framework described above is in the context of analyzing linkages among markets by aggregating moments. In the same vein, linkages among moments can be examined by aggregating markets. The variables are reordered in the form $y_t = (r_{1t}, r_{2t}, \dots, r_{Nt}, v_{1t}, v_{2t}, \dots, v_{Nt})$ such that returns for all markets and conditional volatility of all markets are placed in succession. Block structure can be expressed with N=2 groups, composed of m=13 variables or markets. Correspondingly, the aggregation routine can be applied to examine spillovers among moments.

IV. Empirical Results

A. Full-sample analysis

Application of Diebold and Yilmaz (2012) spillover index methodology to the dataset which comprises of return and conditional volatility of 13 sample markets yields a 26 × 26 connectedness matrix representing the linkages across the two moments of each market. To begin with, full-sample analysis is undertaken by estimating the connectedness matrix under the Diebold-Yilmaz framework, wherein the optimal lag length is determined by minimizing Schwarz Information Criterion (SIC) and the forecast horizon is set to H=10 days. The connectedness matrix depicting pairwise spillovers across return and volatility of all 13 markets is presented in table 3. The diagonal elements of the matrix represent within-variable spillovers and off-diagonal elements represent cross-variable spillovers. The sensitivity of the results to the choice of forecast horizon is also tested by experimenting with 5 and 15 days ahead forecast (similar to that in Greenwood-Nimmo, Nguyen and Rafferty 2016). The connectedness matrices obtained from the different length specification of forecast horizon (i.e. H=5,10,15 days) remain almost similar, thus, confirming the robustness of our results.[8]

First considering return spillovers across the markets, cross-market variance in returns is strong for all countries as compared to own-market variance. Pairwise spillovers across China-Hong Kong, Canada-US,

8. The connectedness matrices obtained from Diebold and Yilmaz (2012) spillover index methodology with forecast horizon of 5 and 15 days are not presented due to brevity of space but are available upon request.

Germany-Switzerland-UK are found to be particularly high, ranging from 12 to 17 percent of return forecast error variance across the market pairs. This indicates that geographically proximate markets have significant bidirectional spillovers and exert substantial influence on each other. The US equity market is found to be the largest transmitter of return spillovers to other markets, indicating that it strongly influences other markets of the global financial system. Asian countries, in general, are found to be insulated from global financial markets as return spillovers received from American or European markets and transmitted to these markets are relatively low. Cross-market spillovers among returns in Asian countries are comparatively strong, suggesting that Asian markets are more integrated among themselves than with the global markets. Similar to Asian markets, there is a case for regional integration in European markets as the cross-market returns spillovers among them are also strong, However, the magnitude of return spillovers across mature European markets are high in comparison to the Asian region in which most of the markets are emerging.

With regard to the volatility spillovers, the level of own-market variance is low relative to the cross-market variance. The US equity market exercises highest influence on the sample global markets as its volatility transmission to other markets is strong. Consistent with the return spillovers, Asian markets are found to be relatively resilient from the global volatility spillovers and also do not exert much influence on them. Also, regional spillovers among volatility are prominent as compared to global spillovers, highlighting greater interactions within the regional markets.

Considering spillovers across moments, the magnitude of cross-interaction between return and volatility is found to be low as much of the interactions are within-return and within-risk. Nevertheless, spillovers onto risk from return are substantially higher as compared to spillovers onto return from risk, both within and between markets. This is contrary to the premise that returns are explained by risk, which is the cornerstone of the asset pricing theories, including Capital Asset Pricing Theory (CAPM) of Sharpe (1964) and Lintner (1965), thereby, questioning the validity of these models.

The analysis presented above focused upon examining connectedness among the variables included in our data set. Greenwood-Nimmo, Nguyen and Shin (2015) bring forth a novel method in which block-aggregation approach is used under the Diebold-Yilmaz framework to integrate a set of individual variables to

TABLE 3. Spillovers Across the Variables

		AUS		CAN		CHI		GER		HKG		IND		JAP		LUX		SGP		SKOR		SWISS		UK		US	
		r	*v*	*r*	*v*	*r*	*v*	*r*	*v*	*r*	*v*	*r*	*v*	*r*	*v*	*r*	*v*	*r*	*v*	*r*	*v*	*r*	*v*	*r*	*v*	*r*	*v*
AUS	*r*	20.0	0.1	11.4	0.2	3.7	0.3	9.4	0.1	4.0	0.5	3.4	0.0	1.9	0.0	5.4	0.0	6.8	0.2	3.4	0.2	7.7	0.0	9.4	0.1	11.6	0.1
	v	8.9	16.0	6.7	2.2	1.9	2.2	5.6	3.6	1.9	1.5	2.1	2.2	0.6	0.7	3.8	2.0	3.6	5.6	1.9	1.5	4.0	3.3	6.9	0.1	6.9	4.7
CAN	*r*	5.8	0.0	28.9	0.7	2.1	0.1	10.9	0.2	2.3	0.5	2.1	0.1	0.5	0.1	4.9	0.2	3.8	0.2	1.5	0.2	7.8	0.1	10.1	0.2	16.6	0.1
	v	2.2	2.0	12.3	27.8	0.8	0.8	4.3	4.6	0.7	0.8	0.7	0.4	0.1	0.3	1.8	1.7	1.1	1.2	1.0	0.7	3.2	5.8	4.9	0.2	7.9	12.9
CHI	*r*	5.1	0.0	6.3	0.2	25.7	0.1	5.7	0.1	13.5	0.5	4.8	0.1	1.9	0.0	4.0	0.0	9.5	0.1	5.8	0.1	3.8	0.1	5.4	0.1	7.1	0.2
	v	1.0	5.1	1.2	1.0	4.2	35.5	1.2	1.6	3.0	13.9	1.7	4.4	0.3	2.1	1.6	1.5	1.9	9.1	1.0	2.7	0.5	1.8	1.3	0.0	1.7	0.9
GER	*r*	4.7	0.0	10.1	0.2	2.0	0.1	24.5	0.1	2.3	0.4	2.4	0.1	0.6	0.0	5.7	0.0	4.2	0.2	2.0	0.0	13.7	0.1	13.9	0.0	12.8	0.1
	v	2.2	1.8	5.6	1.9	0.8	0.4	11.1	22.9	0.9	0.4	1.1	0.8	0.1	0.3	3.8	3.2	1.7	1.2	0.7	0.2	7.1	11.8	7.8	0.1	7.2	4.9
HKG	*r*	5.1	0.1	6.9	0.2	11.8	0.1	6.6	0.1	23.3	0.3	4.1	0.0	1.7	0.0	4.4	0.0	9.9	0.2	5.5	0.0	4.2	0.1	6.3	0.1	8.9	0.2
	v	1.8	5.0	1.7	0.5	2.5	13.3	1.7	1.6	5.2	30.4	1.6	3.9	0.5	1.6	1.8	0.9	3.0	11.8	1.1	3.2	0.8	1.3	2.1	0.0	2.4	0.8
IND	*r*	4.4	0.1	6.0	0.2	5.3	0.0	6.4	0.2	5.4	0.2	37.9	0.1	0.7	0.0	4.9	0.1	7.5	0.1	3.8	0.1	4.2	0.1	5.4	0.1	6.8	0.1
	v	2.5	2.9	2.5	0.5	2.1	2.9	2.1	1.3	2.6	1.8	9.0	47.6	0.6	0.4	1.3	0.8	2.7	6.4	0.9	1.7	1.1	1.4	1.7	0.0	2.9	0.6
JAP	*r*	5.3	0.1	7.5	0.2	4.1	0.1	7.5	0.1	4.5	0.1	2.4	0.1	30.1	0.3	4.1	0.0	6.3	0.2	5.0	0.1	5.9	0.1	6.3	0.0	9.7	0.1
	v	2.5	1.9	2.8	0.7	1.6	2.6	3.0	2.0	2.3	2.4	1.2	1.0	9.4	39.2	2.8	2.2	2.8	1.9	1.8	1.6	2.0	3.0	2.9	0.0	4.0	2.5
LUX	*r*	3.9	0.0	9.2	0.3	2.6	0.1	10.9	0.2	2.9	0.3	3.3	0.0	0.3	0.0	30.8	0.1	4.2	0.2	1.9	0.1	6.6	0.1	9.7	0.0	12.3	0.1
	v	0.3	2.4	0.7	1.5	0.3	2.2	1.8	8.1	0.4	1.4	0.3	3.0	0.1	1.0	3.9	45.8	0.5	3.1	0.4	1.3	1.2	8.7	2.2	0.0	2.7	6.9
SGP	*r*	6.7	0.0	7.5	0.1	6.6	0.1	7.3	0.1	8.2	0.3	4.8	0.1	2.0	0.0	4.3	0.0	24.8	0.3	5.5	0.1	5.3	0.1	6.6	0.1	8.8	0.2
	v	2.5	7.1	2.2	1.8	1.2	5.9	2.6	2.7	2.4	7.6	1.8	3.9	0.5	0.9	1.7	1.9	4.2	32.7	1.1	3.9	1.5	2.5	2.4	0.0	3.3	1.8
SKOR	*r*	5.2	0.1	6.7	0.1	5.8	0.1	7.5	0.1	6.7	0.5	4.0	0.1	2.9	0.0	4.3	0.0	8.4	0.1	27.7	0.2	4.7	0.1	5.9	0.0	8.8	0.2
	v	2.2	3.0	2.3	3.2	2.1	3.6	2.7	3.0	2.8	3.4	1.8	2.0	0.7	2.3	2.5	3.9	2.9	6.2	9.0	26.1	1.3	2.8	2.5	0.0	3.5	4.1
SWISS	*r*	5.2	0.0	9.0	0.5	1.6	0.2	16.4	0.2	1.9	0.4	1.9	0.1	0.8	0.0	4.4	0.1	4.0	0.1	1.5	0.0	27.7	0.1	10.9	1.4	11.6	0.2
	v	1.2	0.9	3.4	1.8	0.3	0.3	4.4	8.1	0.2	0.4	0.6	0.4	0.0	0.3	2.1	2.5	0.5	0.5	0.2	0.1	5.0	25.6	6.4	26.4	4.8	3.6
UK	*r*	5.5	0.0	10.7	0.3	2.2	0.1	15.1	0.1	2.8	0.3	2.3	0.0	0.5	0.0	5.7	0.0	4.3	0.1	1.9	0.0	9.6	0.2	24.4	0.8	12.6	0.1
	v	0.2	0.1	0.5	0.0	0.2	0.2	0.6	0.1	0.1	0.6	0.2	0.0	0.0	0.0	0.3	0.1	0.1	0.0	0.1	0.0	3.3	6.0	11.1	75.3	0.8	0.1
US	*r*	3.1	0.1	15.2	0.6	1.6	0.2	12.7	0.2	2.0	0.6	1.7	0.1	0.3	0.0	5.0	0.0	3.1	0.2	1.7	0.2	8.1	0.2	9.8	0.1	32.8	0.4
	v	2.4	0.4	11.6	3.6	0.9	0.3	8.5	2.7	1.0	0.4	1.0	0.4	0.1	0.0	4.0	1.7	1.5	0.6	1.3	0.5	5.7	2.4	7.5	0.0	23.6	17.9

Note: (a) The 26×26 matrix in the table represent the spillovers across the variables under Diebold-Yilmaz framework forecast horizon of 10 days. (b) The diagonal elements of the matrix represent within-variable spillovers and off-diagonal elements represent cross-variable spillovers.

examine linkages among a group of variables. The block-aggregation technique is employed to capture the spillover effects that channel through return and volatility across the sample markets. Hence the two moments are aggregated by applying block-aggregation routine to the 26 × 26 connectedness matrix representing pairwise directional spillover indices. This allows us to examine linkages among global financial markets channelizing through return and volatility in a unifying framework and thus, provides a comprehensive picture to elucidate their interactions.

Table 4 presents 13 × 13 market connectedness matrix depicting the spillovers among the sample markets aggregated over return and conditional volatility. The diagonal elements of the matrix represent within-market spillovers and off-diagonal elements represent cross-market spillovers. The last column of the table labeled 'contribution from others' sums the directional spillovers to market *i* from rest of the sample markets and the last row labeled 'contribution to others' represents the directional spillover from market *i* to other markets in the model. The total spillover index (bottom right corner of the table) is approximately 65 percent, indicating that the interdependencies among the financial markets are high. A substantial magnitude of cross-market spillovers is also indicated by the low level of within market spillovers. Pairwise spillovers between China-Hong Kong, Canada-US, Germany-UK, Germany-Switzerland and Switzerland-UK are especially high, reflecting strong interdependencies among geographically proximate markets. The strong influence of the US equity market is apparent from the results as it is the largest transmitter of spillovers to other financial markets. Asian countries are found to be segmented from other financial markets as they are relatively immune to the shocks from the global markets and also do not exert much influence on them. Particularly, India and Japan are less influential in transmitting information to the major global financial markets and are also least responsive to the information originating in them. Singapore stands out as the most influential market in the Asian region as the magnitude of its transmission/reception of spillovers to/from other markets of the region as well as the world is relatively high as compared to other markets of Asia. Thus, it can be inferred that the Asian markets are relatively more integrated among themselves than with the global markets. Among the international financial markets, the US equity market exercises the highest influence on the Asian markets by transmitting a considerable amount of spillovers to them. This is in conjunction with the empirical finding of Shen (2018) who documents the strong influence of the US on the Asian stock markets. A strong case for regional integration is also found in the European markets. However, the magnitude of spillovers across the European markets is high as compared to the Asian markets. Further, European equity markets are more responsive to shocks from the US in comparison to that of Asia. A similar inference has been drawn by Marfatia (2017) who finds evidence of stronger financial linkages of the European stock markets with the US than with the Asian markets.

The dominance of a financial market can be inferred based on the combined effect of directional spillovers ‘to’ and ‘from' other markets. The dominance of a financial market will be established if it is influential in transmitting information to other markets, but is relatively less influenced by them. Hence, analyzing net spillovers of the financial markets, calculated as the difference between ‘contribution to others’ and ‘contribution from others’, is important to gauge their position on a global financial system. Nevertheless, it is pertinent to exercise prudence while drawing inferences based solely on the net spillover index of the markets as it may give spurious picture regarding the dominance of a market if the extent of spillovers ‘to’ and ‘from’ others is low. Therefore, it is of particular interest to decipher the net spillover results in light of the gross spillover of the market (calculated as the total of ‘contribution to others’ and ‘contribution from others’). From the results based on full-sample analysis, the US emerges as the dominant market in the global financial system based on information linkages as it is the lead net transmitter of information to other financial markets and also exhibits highest gross spillover activity (refer table 3). In the European region, Germany is observed to be a dominant market. Meanwhile, Singapore takes the lead position in the Asian region by transmitting a considerable amount of spillovers to other markets of the region.

Asian markets are in general the least influential in the global financial system as they are the net recipients of information from the sample markets. Japan is specifically the least dominant of all sample markets as it is the major net receiver of spillovers from other markets of the system besides having the lowest gross spillover activity. Despite being a mature market, it is found to be relatively decoupled with the global markets. Weak interdependencies of Japan with other major markets have also been well-documented in the literature (see Beirne and Gieck, 2014; Allen et al., 2017; Belke and Dubova, 2018). This can

TABLE 4. Spillovers Among Major Global Financial Markets

	AUS	CAN	CHI	GER	HKG	IND	JAP	LUX	SGP	SKOR	SWZ	UK	US	Contri. from
AUS	22.54	10.26	4.01	9.35	3.89	3.88	1.57	5.58	8.12	3.50	7.48	8.21	11.65	77.47
CAN	5.04	34.87	1.92	9.94	2.12	1.61	0.51	4.31	3.15	1.65	8.44	7.72	18.73	65.12
CHI	5.63	4.30	32.73	4.27	15.46	5.43	2.13	7.07	10.30	4.79	3.06	3.44	4.94	70.80
GER	4.38	8.88	1.64	29.23	2.01	2.14	0.47	6.39	3.60	1.48	16.39	10.91	12.51	70.77
HKG	5.94	4.63	13.83	5.00	29.59	4.81	1.89	3.56	12.41	4.87	3.23	4.21	6.06	70.42
IND	4.95	4.54	5.14	5.02	5.03	47.27	0.85	3.48	8.29	3.24	3.43	3.55	5.25	52.75
JAP	4.84	5.61	4.15	6.32	4.63	2.35	39.49	4.55	5.60	4.27	5.49	4.60	8.14	60.52
LUX	3.33	5.80	2.57	10.51	2.48	3.28	0.71	40.30	3.95	1.84	8.27	5.99	11.00	59.70
SGP	8.16	5.80	6.87	6.37	9.23	5.26	1.73	3.99	31.05	5.31	4.69	4.50	7.06	68.94
SKOR	5.20	6.09	5.84	6.66	6.65	3.93	2.97	5.37	8.82	31.48	4.46	4.22	8.32	68.52
SWZ	3.63	7.31	1.20	14.58	1.49	1.48	0.54	4.53	2.59	0.92	29.18	22.55	10.04	70.82
UK	2.93	5.78	1.32	7.97	1.87	1.28	0.31	3.10	2.28	1.03	9.56	55.82	6.79	44.19
US	3.02	15.48	1.50	12.04	2.04	1.64	0.19	5.32	2.73	1.80	8.18	8.75	37.32	62.67
Contri. to	57.01	84.47	49.98	97.99	56.87	37.08	13.83	57.24	71.81	34.68	82.66	88.63	110.46	64.82

Note: (a) The 13×13 matrix in the table presents spillovers among the global financial markets obtained by applying block-aggregation technique of Greenwood-Nimmo et al. (2015) under Diebold-Yilmaz framework. (b) The diagonal elements of the matrix represent within market spillovers and off-diagonal elements represent cross-market spillovers. (c) The last column of the table, ‘contri from’, represents directional spillovers from other markets to market *i*. (d) The last row of the table, ‘contri to’, represents directional spillovers to other markets from market *i*. (e) The bottom right corner of the table is the total spillover index. (f) All values are measured in percentage units.

plausibly be explained by its market structure which is characterized by concentrated ownership, lack of liquidity and relatively low minatory governance (Bekiros et al., 2017). Another notable observation is that the Chinese economy, which is the second largest as well as the fastest growing in the world, has not emerged as a leader in the global or even regional financial system. China's lack of integration with the global financial markets, despite being a vibrant economy, can be accounted to its strict capital controls and restrictive currency convertibility.

Comparative analysis of the GFCI ranking of the competitiveness of financial centers and the ranking obtained from our empirical results of financial linkages among equity markets based on net spillovers indicates significant variations. This is reflected in weak and insignificant rank correlation (Spearman's rho) of 0.21 between GFCI ranking and ranking based on net spillovers among markets. This clearly establishes that the parameters of GFCI ranking, viz. business environment, human capital, infrastructure, financial sector development and reputation may not necessarily imply financial interdependencies with other markets. Indeed GFCI ranking is derived from several vital parameters, it overlooks financial linkages with other markets as an attribute, based on which underlying strength or dominance of a market can be discerned. It is not argued that the ranking criterion should be based exclusively on financial linkages with the markets, but it should be incorporated in creating the index as it constitutes an integral component in determining the competitiveness of a financial system. Hence, the GFCI ranking should be reviewed in light of the interdependencies among the global financial centers.

Using similar block-aggregation routine, linkages among returns and conditional volatility are also assessed by aggregating the markets. This permits us to investigate the risk-return relationship in the global financial markets, which has important implications for optimal portfolio selection and risk management. As mentioned earlier, the choice of major international financial markets allows us to capture a bulk of the trading transactions of the investor's community as these markets are the hub of investment activities. Hence, we can rationalize risk and return spillovers in the global financial system. 2×2 connectedness matrix presenting the connectedness among the group of returns and volatility, aggregated over all 13 markets is reported in table 5. The prime diagonal represents within-moment spillovers and off-diagonal elements represent cross-moment spillovers. The last column of the matrix labeled 'contribution from others' sums the

TABLE 5. Spillovers Among Moments

	r	*v*	Contri. from
r	98.12	1.88	1.88
v	35.15	64.85	35.15
Contri. to	35.15	1.88	18.51

Note: (a) *r* and *v* denotes return and conditional volatility. (b)The 2×2 matrix in the table presents spillovers among return and volatility obtained by applying block-aggregation technique of Greenwood-Nimmo et al. (2015) under Diebold-Yilmaz framework. (c) The diagonal elements of the matrix represent within moment spillovers and off-diagonal elements represent cross-moment spillovers. (d) The last column of the table, 'contri from', represents spillovers from other moments to moment *i*. (e) The last row of the table, 'contri to', represents spillovers to other moments from moment *i*. (f) The bottom right corner of the table is the total spillover index. (g) All values are measured in percentage units.

directional spillovers to the moment *i* from other two moments and the last row labeled 'contribution to others' represents the directional spillover from the moment *i* to other two moments in the model. The total spillover index (shown at the bottom right of the matrix) is around 18.5 percent indicating that information transmission across moments is quite limited. Results demonstrate return spillovers of high magnitude onto risk (volatility), while almost negligible risk spillover onto returns. This indicates that the risk does not impact returns, rather, is strongly impacted by returns. This is in contrast to the asset pricing theories which hinge on the premise that returns are explained by risk and thus challenges their validity. In this regards, autoregressive or univariate models are superior in modeling the return-generating process compared to the traditional asset pricing models, including CAPM. On the other hand, augmented GARCH specifications will be more relevant for volatility prediction.

Pairwise directional spillovers across return and volatility are decomposed into within-market effect and cross-market effect to examine the relative importance of idiosyncratic and systematic effects in the moments. This has been presented in table 6. It is apparent from the table that cross-market spillovers among return and volatility are more prominent as compared to own-market effect, outlining the role of systematic effects in driving return and volatility spillovers across markets. The cross-market effect in return spillovers is approximately 72 percent of the overall effect (70.53/98.12), while it is 47.5 percent (30.80/64.85) in volatility spillovers. This indicates that investors adjust

TABLE 6. Within and Cross Market Spillovers Among Moments

	r		*v*	
	within-market	cross-market	within-market	cross-market
r	27.58 (28.11)	70.53 (71.89)	0.27 (14.50)	1.61 (85.50)
v	8.99 (25.58)	26.15 (74.42)	34.05 (52.50)	30.80 (47.50)

Note: (a) The table presents pairwise spillovers among moments decomposed into within-market and cross-market effects. (b) Figure in parentheses represents the proportion of within/cross market effect relative to overall spillover across the moments, expressed in percentage form.

their portfolios more often on the basis of returns and are relatively less driven by risk diversification motives. Spillovers across risk and return are predominantly manifested in cross-market effects. This clearly reflects the portfolio diversification and risk management by investors, leading to strong interactions of risk and return across the markets.

B. Rolling-sample analysis

We supplement the static spillover results with rolling window analysis (using 250 days rolling window) to capture the time-varying characteristics of the spillover indices. To test the robustness of our results, we undertake rolling estimations with a window of 200 and 300 days. The results are found to be consistent with the baseline specification of the rolling window (i.e. 250 days). This has been discussed in Section IV, Part *C*.

Figure 1 depicts the dynamic total spillover index across the global financial markets based on block-aggregation under the Diebold-Yilmaz framework with a rolling sample of 250 days. Substantial time-variation is apparent from the figure as there is an increase in the spillover effect since the start of 2001, coinciding with the burst of the dot-com bubble and the US recession which prompted the Federal Reserve to cut down the interest rates. Another marked increase in spillovers has been observed since the onset of the subprime mortgage crisis in the third quarter of 2007 and subsequent Lehman Brothers bankruptcy in September 2008 that triggered the worldwide spread of the Global Financial Crisis. The spillover effect remains pronounced until the end of the Eurozone Debt Crisis in 2012 and starts falling thereafter with the unwinding of stress period and the beginning of global economic recovery. Spurt in the spillovers at the start of 2015 corresponds to the

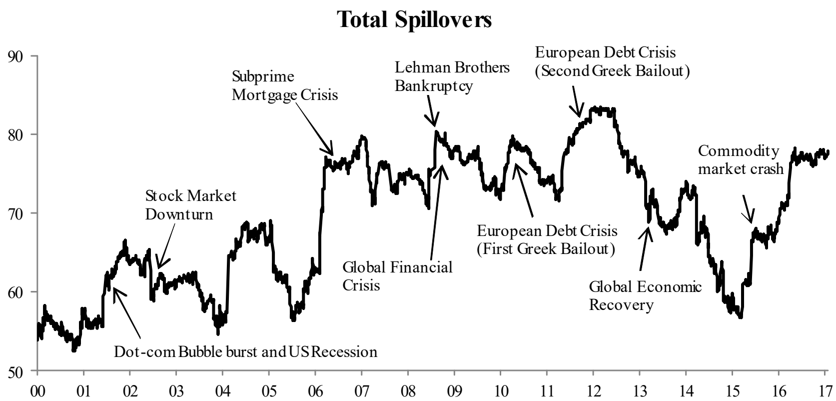


FIGURE 1.— Total Spillovers

Note: (a) The figure illustrates evolution of total spillovers computed from block-aggregation technique under Diebold-Yilmaz framework. (b) Total spillover index is estimated with the forecast horizon of 10 days and rolling window of 250 days.

commodity market collapse that ensued from the economic slowdown in China and other emerging countries, leading to a crash in commodity prices.[9] This pattern of the spillover effects clearly suggests that interdependencies among the markets increase notably during the turbulent times.

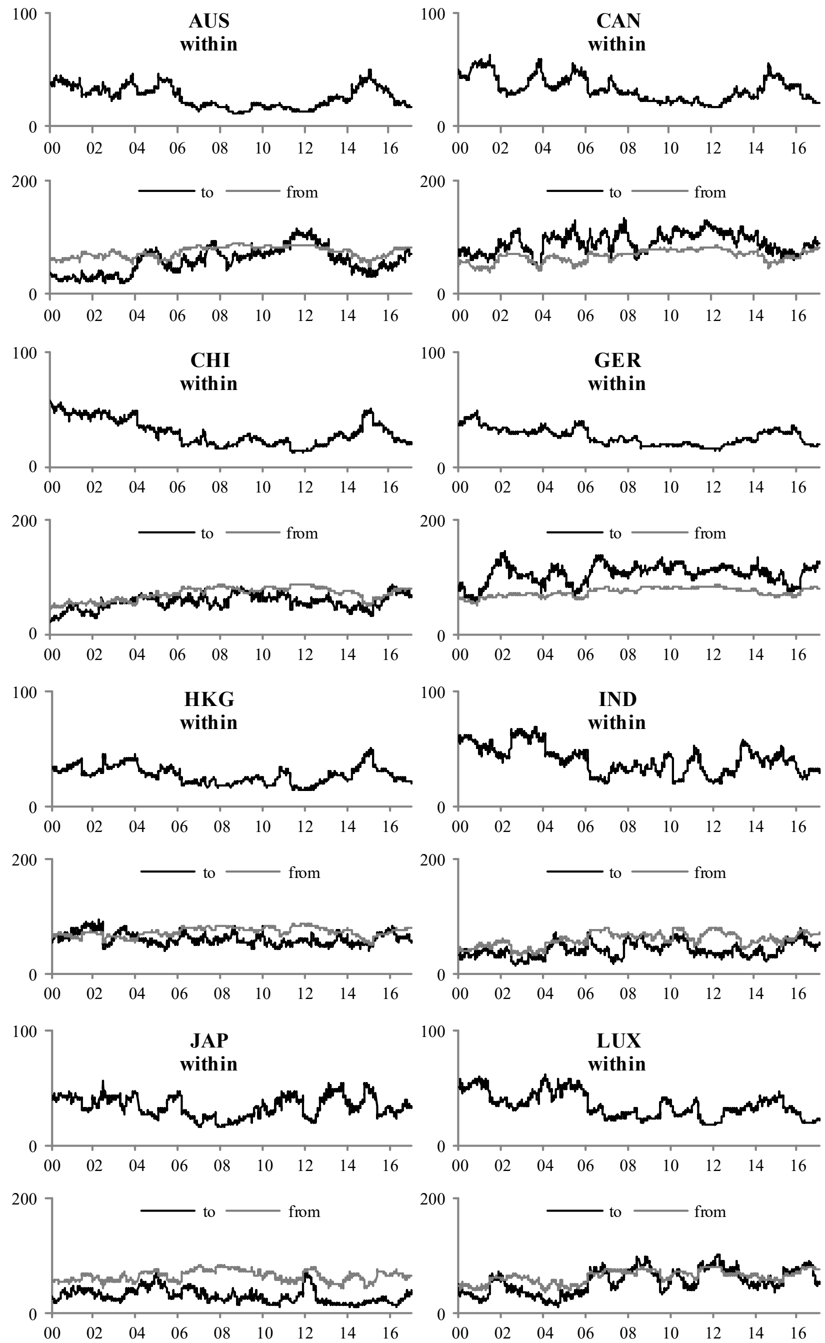
The time evolution of within and directional spillovers of all sample markets is presented in figure 2. For each sample market, the upper plot displays within-market spillovers and the lower plot shows directional spillover 'to' and 'from' other markets in the sample. Within-market spillovers for all sample markets are low, indicating relatively limited exposure to idiosyncratic effect as compared to the systematic effect in these markets. This also suggests that there are substantial linkages among the global financial markets as they are driven by common global economic factors, implying lack of diversification opportunities. Time variation reveals plunge in idiosyncratic effects for all markets following the outbreak of the global financial crisis and gradually increase as the effect of the Eurozone Debt crisis subsides in 2012,

9. See for more details: https://www.weforum.org/agenda/2015/12/why-have-commodities-crashed/ (accessed on 30th December 2017)

demonstrating that systematic effects become more pronounced during the turmoil period. Directional spillovers of each market 'to' and 'from' other markets exhibit significant fluctuations in behavior over the sample period. We find that the spillovers from the US to other sample markets amplify considerably during the crisis period, confirming the role of the US equity market in triggering contagion. The US also experiences an increase in the spillovers from other markets during this time which can be attributed to the feedback effect.

Figure 3 displays the net directional spillover indices computed through rolling analysis. The equity market of the US is consistently the net transmitter of information over the entire sample period, strengthening its case for being the most influential market among others. Shocks transmitted by the equity market of the US intensify markedly since the start of the Global Financial Crisis which ensued from the US subprime mortgage crisis, indicating that it is highly influential in triggering contagion. This is in line with the empirical evidence of Mollah, Quoreshi and Zafirov (2016) that the US is a source of contagion during the crisis. Canada, Germany and the UK are the other markets that remain net transmitter of shocks to other markets over the majority of the sample period. All Asian countries (except Singapore) display consistent behavior in terms of their net spillover dynamics as they remain the net recipients of spillovers for most of the sample period, with spillovers received intensifying during the times of crisis. The sensitivity of these markets to shocks arising in international markets is therefore high, particularly during the turmoil period. Singapore, however, turns out to be an exception in the Asian region as it transitions to being the net transmitter from the net recipient of spillovers in the crisis period.

Figure 4 presents the evolution of directional spillovers across moments. Panel A and B of figure 4 display the spillovers onto return and volatility, respectively, with the upper plot in each panel representing the within-markets effect and the lower plot representing between-markets effect. First considering the spillovers onto returns, the level of within market effect is found to be substantially lower as compared to the cross-market effect (refer Panel A of figure 4). This indicates that systematic effect driven by common factors is more prevalent in spillovers onto returns as compared to the idiosyncratic effect. A surge in the cross-market effect among returns in the wake of the Global Financial Crisis and the Eurozone Debt Crisis is evident from the results, signifying return spillovers across markets intensify


AUS within
to from
CAN within
to from
CHI within
to from
GER within
to from
HKG within
to from
IND within
to from
JAP within
to from
LUX within
to from

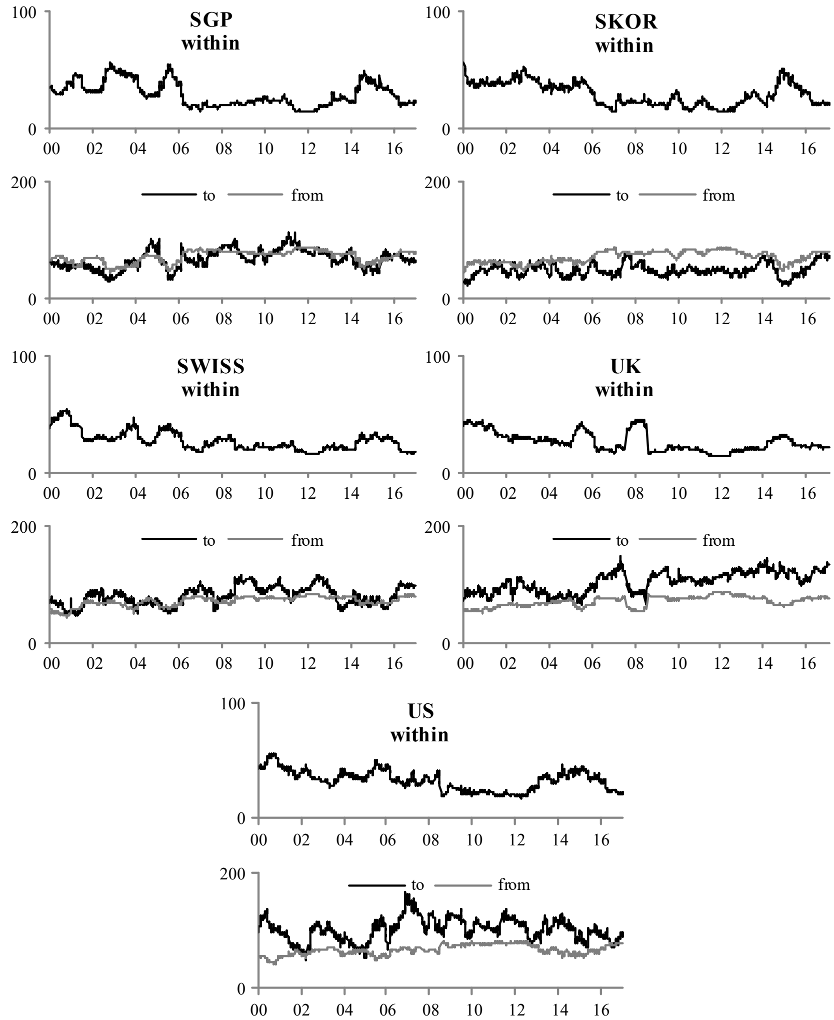


FIGURE 2.— Directional Spillovers Among Major Global Financial Markets

Note: (a) The figure illustrates time evolution of within and directional spillovers of all sample markets computed from block-aggregation technique under Diebold-Yilmaz framework. (b) The upper plot of each sample market displays within-market spillovers and the lower plot shows directional spillover 'to' and 'from' other markets in the sample. (c) Dynamic spillover index is obtained with the forecast horizon of 10 days and rolling window of 250 days.

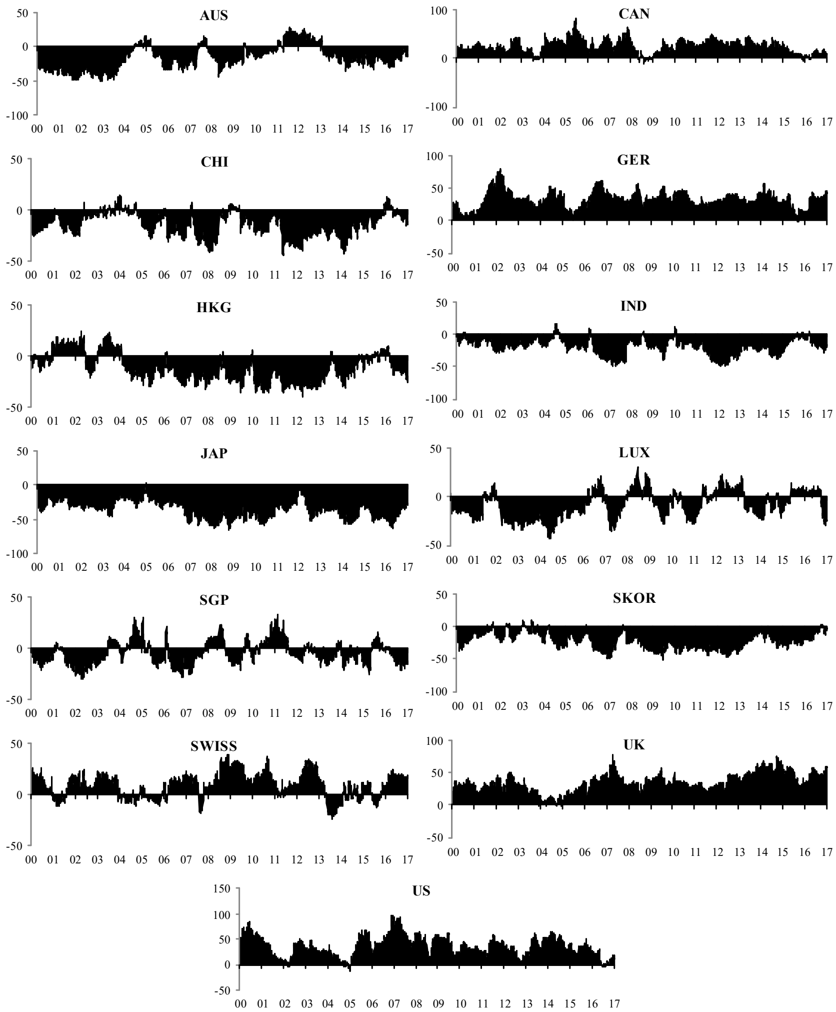


FIGURE 3.— Net Directional Spillovers

Note: (a) The figure presents time evolution of net directional spillovers of all sample markets computed from block-aggregation technique under Diebold-Yilmaz framework. (b) Dynamic spillover index is obtained using forecast horizon of 10 days and rolling window of 250 days.

during the turbulent period. On the other hand, risk spillovers captured by volatility onto returns drop slightly during the crisis period, pointing to the tendency of the risk-return relationship in linear paradigms to become disproportionate during the times of high uncertainty. This

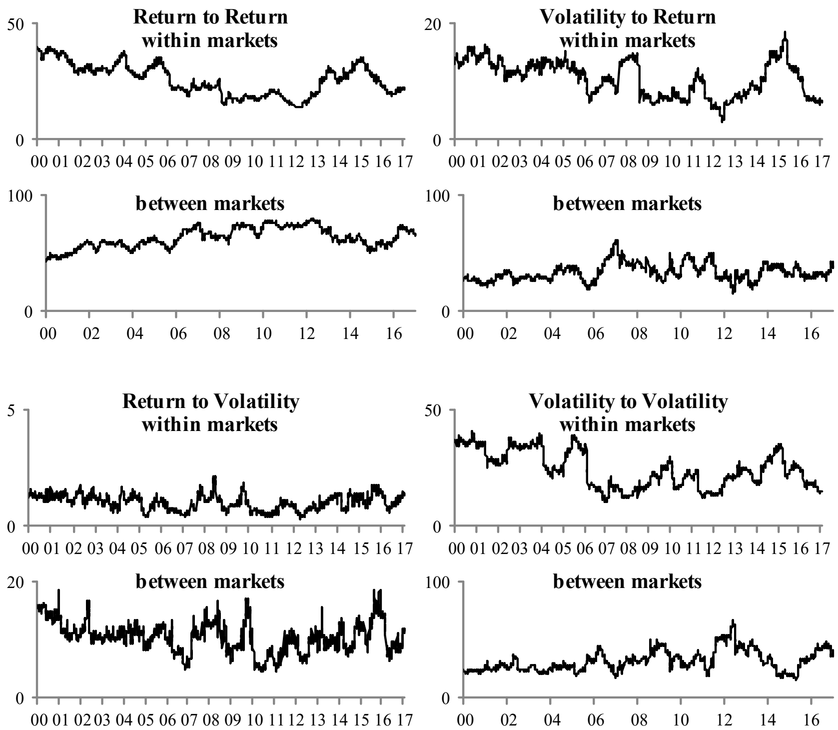


FIGURE 4.— Directional Spillovers Across Moments

Note: (a) The figure illustrates time evolution of directional spillovers among moments computed from block-aggregation technique under Diebold-Yilmaz framework. (b) Panel A (top row) and Panel B (bottom row) display spillovers onto returns and conditional volatility, respectively. (c) The upper plot in each panel depicts within-market effect and the lower plot cross-market effect. (d) Dynamic spillover index is obtained using fixed rolling window of 250 days.

occurrence can be explicated by the fact that investors become more concerned about volatility minimization and are least bothered by return, leading to increased sensitivity to risk when markets stumble. Spillovers to volatility exhibit similar time variations as return spillovers onto volatility across markets plunge during the turmoil period (refer Panel B of figure 4). A clear demarcation in spillovers to volatility within and across the market is visible as the idiosyncratic effect remains weak. Further, the own-variable cross-market effect in volatility soars during the crisis period, highlighting that systematic risk intensifies in the times of stress disrupting all markets simultaneously.

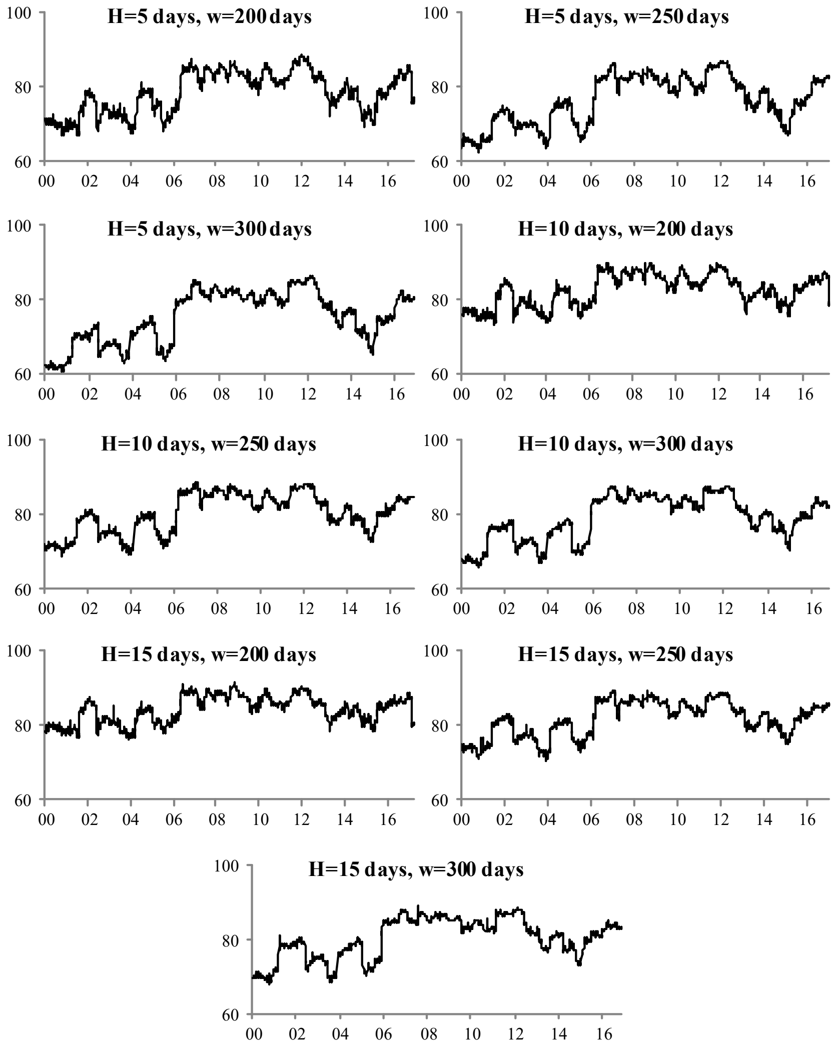


FIGURE 5.— Sensitivity to Forecast Horizon and Window Length

Note: (a) The figure illustrates sensitivity of total spillovers to forecast horizon and window length. (b) Varying specifications of forecast horizon (5, 10 and 15 days) and rolling window (200, 250 and 300 days) are considered. (c) The graph of total spillovers computed by considering 10 days ahead forecast and 250 days rolling window is the baseline model.

C. Sensitivity Analysis

The sensitivity of the results is evaluated by re-estimating the model with several VAR specifications. First, the model is re-estimated with 5 and 15 days ahead forecast. The results are found to be consistent with the baseline specification of 10 days ahead forecast as the connectedness matrices obtained with varying specifications of forecast horizon (i.e. 5, 10 and 15 days) are almost alike.[10] This implies that the results are not sensitive to the choice of the forecast horizon. The robustness of the results is further investigated based on rolling regressions with the window length of 200 and 300 days and varying forecast horizon of 5, 10 and 15 days. Figure 5 illustrates the time evolution of the total spillover index obtained with several specifications of the forecast horizon and rolling window. Visual inspection of total spillover indices reveals that there is a notable similarity in their time-varying pattern, thereby verifying the robustness of the results to the choice of alternative forecast horizons as well as the size of the rolling windows.

V. Summary and Conclusion

This paper investigates dynamic interdependencies among major global financial markets (Australia, Canada, China, Germany, Hong Kong, India, Japan, Luxembourg, Singapore, South Korea, Switzerland, the UK and the US) over the period January 1999 to April 2017 by examining their risk and return spillovers. Block-aggregation technique under the Diebold-Yilmaz framework proposed by Greenwood-Nimmo, Nguyen and Shin (2015) is employed to examine information transmission across the financial markets that channel through return as well as risk captured by conditional volatility. The interlinkages among the two moments are also ascertained to gain insights into the risk-return relationship in the global financial markets. Results demonstrate that financial linkages among the sample equity markets are high, but regional integration is relatively strong as compared to global integration. Asian countries, in general, are found to be insulated from

---

10. The three connectedness matrices obtained from Diebold and Yilmaz (2012) methodology with 5, 10 and 15 days ahead forecast are not presented due to brevity of space, but are available upon request.

other global financial markets as they are relatively less vulnerable to the shocks originating in American or European markets and also do not exert much influence on these markets. International equity markets have limited exposure to idiosyncratic effects as they are largely driven by common global economic factors. The systematic effects in these markets intensify during the turmoil period, pointing to financial contagion. The equity market of the US is found to be the most dominant market in the global financial system based on information linkages. Germany emerges as the dominant market in Europe; meanwhile, Singapore takes lead in the Asian region. Further, results highlight that systematic factors are more prevalent in own-variable spillovers among returns and volatility as compared to idiosyncratic factors as is indicated by the high level of cross-market effect relative to the within-market effect. With regards to interaction between risk and return, results reveal return spillovers of high magnitude onto volatility, while there is negligible volatility spillover onto returns, indicating that return has a greater role to play in volatility prediction than vice-a-versa. Spillovers across return and volatility dampen during the crisis period, directing to the weakening of the risk-return relationship during uncertainty.

These empirical findings have important implications for international investors who seek to manage their portfolio and risk exposure through diversification. High linkages among global financial markets limit diversification opportunities for international investors. The equity markets of India, Japan and South Korea provide considerable diversification opportunities to international investors. While these markets confer substantial gains during the tranquil period, their exposure to systematic effects intensifies during the crisis period, suggesting that investors should invest in alternative asset classes during turbulent times. The study also has relevance for policymakers as it suggests that coordinated response is required in times of uncertainty through policy synchronization to insulate the economy from external headwinds and ensure financial stability. The results have important implications for asset pricing theories. Findings demonstrate that return spillover onto risk is quite high while risk spillover onto returns is almost negligible. This suggests that returns have a substantial role in volatility prediction than vice-a-versa, thus challenging the validity of asset pricing theories which are based on the premise that returns are explained by risk. Considering this, autoregressive or univariate models may be superior in modeling a return-generating process as compared to the traditional asset pricing model, while GARCH models are more suited for volatility prediction. With regards to the global financial market rating system, results suggest that the financial interlinkages among the markets may not necessarily reflect in the parameters on which GFCI ranking is based as there is a weak and insignificant correlation between the GFCI ranking and ranking based on information linkages. Indeed GFCI ranking is derived from several vital parameters, it overlooks information linkages with other markets as an attribute, based on which underlying strength or dominance of a market can be discerned. Hence, the existing system of GFCI ranking should be reviewed in light of the interdependencies among the global financial centers as it constitutes a critical component for determining the competitiveness of a financial system. The study makes an important contribution to the literature on financial market linkages by undertaking a comprehensive assessment of spillovers among risk and return.

Accepted by: *Prof. P. Theodossiou, PhD, Editor-in-Chief* , *September* 2019

Appendix. Trading Hours of Various Stock Exchanges

			Greenwich Mean Time		Local Time	
Country	Stock Exchange	Time Zone	Open	Close	Open	Close
AUS	Sydney	GMT + 10:00	00:00	06:00	10:00	16:00
CAN	Toronto	GMT – 04:00	13:30	20:00	09:30	16:00
CHI	Shanghai	GMT + 08:00	01:30	07:00	09:30	15:00
GER	Frankfurt	GMT + 02:00	06:00	18:00	08:00	20:00
HKG	Hong Kong	GMT + 08:00	01:30	08:00	09:30	16:00
IND	Mumbai	GMT + 05:30	03:45	10:00	09:15	15:30
JAP	Tokyo	GMT + 09:00	00:00	06:00	09:00	15:00
LUX	Luxembourg	GMT + 02:00	07:00	15:30	09:00	17:30
SGP	Singapore	GMT + 08:00	01:00	09:00	09:00	17:00
SKOR	Seoul	GMT + 09:00	00:00	06:30	09:00	15:30
SWZ	Zurich	GMT + 02:00	06:30	15:30	08:30	17:30
UK	London	GMT + 01:00	07:15	15:30	08:15	16:30
US	New York	GMT – 04:00	13:30	20:00	09:30	16:00

Note: Stock exchanges of China, Hong Kong, Japan and Singapore close for lunch from 11:30-13:00, 12:00-13:00, 11:30-12:30 and 12:00-13:00 (in local time), respectively.

References

Al Nasser, O. M., and Hajilee, M. 2016. Integration of emerging stock markets with global stock markets. *Research in International Business and Finance* 36: 1-12.

Allen, D. E.; McAleer, M.; Powell, R. J.; and Singh, A. K. 2017. Volatility spillovers from Australia's major trading partners across the GFC. *International Review of Economics & Finance* 47: 159-175.

Alotaibi, A. R., and Mishra, A. V. 2015. Global and regional volatility spillovers to GCC stock markets. *Economic Modelling* 45: 38-49.

Badshah, I.; Frijns, B.; Knif, J.; and Tourani-Rad, A. 2016. Asymmetries of the intraday return-volatility relation. *International Review of Financial Analysis* 48: 182-192.

Beirne, J., and Gieck, J. 2014. Interdependence and contagion in global asset markets. *Review of International Economics* 22(4): 639-659.

Bekiros, S.; Jlassi, M.; Naoui, K.; and Uddin, G. S. 2017. The asymmetric relationship between returns and implied volatility: Evidence from global stock markets. *Journal of Financial Stability* 30: 156-174.

Belke, A., and Dubova, I. 2018. International spillovers in global asset markets. *Economic Systems* 42(1): 3-17.

Bhar, R., and Nikolova, B. 2009. Return, volatility spillovers and dynamic correlation in the BRIC equity markets: An analysis using a bivariate

EGARCH framework. *Global Finance Journal* 19(3): 203-218.

Clements, A. E.; Hurn, A. S.; and Volkov, V. V. 2015. Volatility transmission in global financial markets. *Journal of Empirical Finance* 32: 3-18.

Chang, K. L. 2016. Does the return-state-varying relationship between risk and return matter in modeling the time series process of stock return? *International Review of Economics & Finance* 42: 72-87.

Cotter, J.; O'Sullivan, N.; and Rossi, F. 2015. The Conditional Pricing of Systematic and Idiosyncratic Risk in the UK Equity Market. *International Review of Financial Analysis* 37: 184-193.

Dickey, D. A., and Fuller, W. A. 1979. Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association* 74(366a): 427-431.

Diebold, F. X., and Yilmaz, K. 2009. Measuring financial asset return and volatility spillovers, with application to global equity markets. *The Economic Journal* 119(534): 158-171.

Diebold, F. X., and Yilmaz, K. 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28(1): 57-66.

Ding, L.; Huang, Y.; and Pu, X. 2014. Volatility linkage across global equity markets. *Global Finance Journal* 25(2): 71-89.

Forbes, K. J.; and Rigobon, R. 2002. No contagion, only interdependence: Measuring stock market comovements. *The Journal of Finance* 57(5): 2223-2261.

Fowowe, B., and Shuaibu, M. 2016. Dynamic spillovers between Nigerian, South African and international equity markets. *International Economics* 148: 59-80.

Frazier, D. T., and Liu, X. 2016. A new approach to risk-return trade-off dynamics via decomposition. *Journal of Economic Dynamics and Control* 62: 43-55.

Greenwood-Nimmo, M.; Nguyen, V. H.; and Shin, Y. 2015. Measuring the connectedness of the global economy. Melbourne Institute Working Paper Series, Working Paper No. 7/15. Available at SSRN: https://ssrn.com/abstract=2586861.

Greenwood-Nimmo, M.; Nguyen, V. H.; and Rafferty, B. 2016. Risk and return spillovers among the G10 currencies. *Journal of Financial Markets* 31: 43-62.

Huo, R., and Ahmed, A. D. 2017. Return and volatility spillovers effects: Evaluating the impact of Shanghai-Hong Kong Stock Connect. *Economic Modelling* 61: 260-272.

Jawadi, F.; Louhichi, W.; and Cheffou, A. I. 2015. Testing and modeling jump contagion across international stock markets: A nonparametric intraday approach. *Journal of Financial Markets* 26: 64-84.

Jin, X. 2017. Time-varying return-volatility relation in international stock markets. *International Review of Economics & Finance* 51: 157-173.

Kim, M. S., and Wang, S. 2006. On the applicability of stochastic volatility models. *Computational Statistics & Data Analysis* 51(4): 2210-2217.

Koop, G.; Pesaran, M. H.; and Potter, S. M. 1996. Impulse response analysis in nonlinear multivariate models. *Journal of econometrics* 74(1): 119-147.

Koutmos, G., and Booth, G. G. 1995. Asymmetric volatility transmission in international stock markets. *Journal of international Money and Finance* 14(6): 747-762.

Kundu, S., and Sarkar, N. 2016. Return and volatility interdependences in up and down markets across developed and emerging countries. *Research in International Business and Finance* 36: 297-311.

Kwiatkowski, D.; Phillips, P. C.; Schmidt, P.; and Shin, Y. 1992. Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of Econometrics* 54(1-3): 159-178.

Lintner, J. 1965. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The Review of Economics and Statistics*: 13-37.

Liow, K. H. 2015. Volatility spillover dynamics and relationship across G7 financial markets. *The North American Journal of Economics and Finance* 33: 328-365.

Liu, X. 2017. Unfolded risk-return trade-offs and links to Macroeconomic Dynamics. *Journal of Banking & Finance* 82: 1-19.

Liu, X.; An, H.; Li, H.; Chen, Z.; Feng, S.; and Wen, S. 2017. Features of spillover networks in international financial markets: Evidence from the G20 countries. *Physica A: Statistical Mechanics and its Applications* 479: 265-278.

Marfatia, H. A. 2017. A fresh look at integration of risks in the international stock markets: A wavelet approach. *Review of Financial Economics* 34: 33-49.

Mollah, S.; Quoreshi, A. S.; and Zafirov, G. 2016. Equity market contagion during global financial and Eurozone crises: Evidence from a dynamic correlation analysis. *Journal of International Financial Markets, Institutions and Money* 41: 151-167.

Nelson, D. B. 1991. Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica* 59: 347-370.

Okimoto, T. 2014. Asymmetric increasing trends in dependence in international equity markets. *Journal of Banking & Finance* 46: 219-232.

Pesaran, H. H., and Shin, Y. 1998. Generalized impulse response analysis in linear multivariate models. *Economics letters* 58(1): 17-29.

Phillips, P. C., and Perron, P. 1988. Testing for a unit root in time series regression. *Biometrika* 75(2): 335-346.

Rahahleh, N., and Bhatti, M. I. 2017. Co-movement measure of information transmission on international equity markets. *Physica A: Statistical Mechanics and its Applications* 470: 119-131.

Rejeb, A. B., and Arfaoui, M. 2016. Financial market interdependencies: A quantile regression analysis of volatility spillover. *Research in International Business and Finance* 36: 140-157.

Shahzad, S. J. H.; Ferrer, R.; Ballester, L.; and Umar, Z. 2017. Risk transmission between Islamic and conventional stock markets: A return and volatility spillover analysis. *International Review of Financial Analysis* 52: 9-26.

Sharpe, W. F. 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance* 19(3): 425-442.

Shen, Y. 2018. International risk transmission of stock market movements. *Economic Modelling* 69: 220-236.

Singh, P.; Kumar, B.; and Pandey, A. 2010. Price and volatility spillovers across North American, European and Asian stock markets. *International Review of Financial Analysis* 19(1): 55-64.

Sugimoto, K.; Matsuki, T.; and Yoshida, Y. 2014. The global financial crisis: An analysis of the spillover effects on African stock markets. *Emerging Markets Review* 21: 201-233.

Theodossiou, P.; Kahya, E.; Koutmos, G.; and Christofi, A. 1997. Volatility reversion and correlation structure of returns in major international stock markets. *Financial Review* 32(2): 205-224.

Wang, G. J.; Xie, C.; Lin, M.; and Stanley, H. E. 2017. Stock market contagion during the global financial crisis: A multiscale approach. *Finance Research Letters* 22: 163-168.

Zhang, B., and Wang, P. 2014. Return and volatility spillovers between china and world oil markets. *Economic Modelling* 42: 413-42.