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Full Length Article

Asymmetric volatility connectedness among main international stock markets: A high frequency analysis

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Abstract

This paper examines the direction and extent of the asymmetric volatility connectedness among international equity markets using 5-minute interval data from 16 stock markets. We analyze asymmetric volatility connectedness using realized volatility and identify the magnitude of the volatility spillover and of the connectedness through networks. We decompose realized volatility into good and bad, and volatility spillover is time-varying and asymmetric. Bad volatility dominates good volatility in international stock markets. Macroeconomic shocks (negative interest rates in Japan, economic stress in China, a recession in Russia, and double-digit inflation in Brazil) increased volatility asymmetry. Asian markets are responsible for stronger negative spillover, thereby necessitating regulations to reduce the strong negative volatility connectedness with Asian markets.

JEL classification: G14; G15

Keywords: Stock market; Asymmetric spillover; Connectedness; High frequency analysis

1. Introduction

This study uses 5-minute interval data to examine the direction and the extent of the asymmetric volatility connectedness among 16 international equity markets. Moreover, we analyze the volatility connectedness through network diagrams to identify the magnitude of the volatility spillover and the strength of the connectedness. Our empirical analysis contains two stages. First, we estimate the realized variance and determine the total and net directional spillovers index between markets. Second, we decompose realized variances into positive and negative semivariances to account for positive and negative volatility, respectively. Furthermore, we segregate the spillover asymmetry measure (SAM) into two directional spillover asymmetry measures to study the source of the asymmetry among the stock markets. We augment our analysis using robustness tests.

The issue of information spillover is very important for investors, portfolio managers, and policymakers. It is well known that asymmetries in volatility spillovers have several significant practical implications for asset allocation, hedging, market efficiency, and portfolio risk management (Baruník et al., 2017; Fengler & Gisler, 2015; Garcia & Tsafack, 2011; James et al., 2012). The volatility spillovers among financial assets behave differently based on the downside and upside market prices trends (bad news or good unexpected

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news). Currently, market convergence due to sweeping deregulations, evident in increasing cross-border financial flows, is resulting in pure contagious behavior (Masson, 1999). This convergence, driven by financial globalization, the standardization of financial transaction mechanisms, and innovation resulting in complex financial products, has also triggered powerful, common shocks in various markets (Yoon et al., 2019).

As Segal et al. (2015) argued, the behavior of volatility differs depending on the sources and specifically on whether they are good or bad innovations. "Bad" uncertainty or volatility is driven by negative shocks to the macroeconomy, which reduces prices and investment; whereas "good" volatility, exhibited by positive shocks, results in higher asset prices and investment. This motivates us to undertake a thorough analysis of the asymmetric volatility spillover among major international stock markets. In particular, we ask the following questions: *Are asymmetries in volatility present among stock markets? If asymmetry is a common phenomenon, then how do markets transmit this asymmetry? Are there any differences in the way one particular market receives (contributes to) asymmetric volatility spillover from (in) other markets? If so, how do global macroeconomic events or shocks influence asymmetry and what are the extent and the direction of the spillovers?*

The above questions seeking to capture the asymmetry in the volatility spillover and multiscale connectedness in international stock markets have not yet been answered using high frequency data. However, the asymmetry in volatility spillover is a better metric for identifying which shocks trigger higher spillover asymmetry when asymmetry is dominated by negative spillovers.[1]

However, the analysis of asymmetric spillovers provides better "early warning systems" for dormant crises (Diebold and Yilmaz, 2009, 2012; Kang et al., 2017) and helps us to understand the existing crises. Recent studies of Chen et al. (2019) and BenSaïda (2019) focus on the asymmetric volatility connectedness among different sectors within the same market and across different markets, respectively. Their results also indicate the importance of asymmetric volatility spillover to better understand the transmission of shocks. Policymakers and regulators can act optimally by introducing the appropriate regulatory norms if they know which markets transmit higher volatility, especially bad volatility, to their domestic markets. Investors would enjoy more benefits if they know which international markets transmit higher bad volatility or which macro events can cause more spillover of negative volatility as they would be able to actualize their expected returns and rebalance their portfolios better.

[1] For example, if one market transmits higher volatility to another market, this may not necessarily mean that both good and bad news trigger the same magnitude of volatility spillover. It is more important to know whether the high volatility transmission by a particular market is due to good or bad news. It is possible that two markets are connected through volatility spillover; however, their connectedness increases when one market receives any negative shocks.

Our paper extends Prasad et al.'s (2018) study that examines the aggregate (symmetric) spillovers between Europe, Asia-Pacific and American stock markets using the spillover indices of Diebold and Yilmaz (2012, 2014). The results reveal that the stock markets in Australia, New Zealand, Brazil, Indonesia, Hong Kong, Korea, India, Thailand, and Taiwan transmitted more negative spillovers to other markets during 2016 and 2017. It is interesting to observe that most of the Asia-Pacific countries transmitted negative shocks to other markets in 2016. Furthermore, through examining the directional asymmetric volatility spillover, it is observed that the majority of equity markets received negative spillovers in 2016 and 2017, which reflects the overall pessimistic mood in the markets.

This paper contributes to the related literature in three main aspects. First, it examines the magnitude of the realized volatility spillover indices of high-frequency data by using the vector autoregression (VAR) based on the forecast error variance decomposition (FEVD) framework developed by Diebold and Yilmaz (2009, 2012). Unlike the previous studies of Chen et al. (2019) and BenSaïda (2019) that focused on Chinese and G7 markets without intraday data, respectively, our selected sample encompassing the equity markets of 16 major economies with 5-minute interval data provides a unique opportunity to understand the transmission of shocks through volatility spillover and connectedness networks. Our choice of the markets sampled is based on practical considerations: they are the most significant and relevant benchmark indices in their respective countries, are commonly found in investors' portfolios, are highly liquid and have been previously considered in related literature. Therefore, institutional and individual investors can obtain a better understanding of the market dynamics for portfolio diversification and efficient asset allocations.

Second, we decompose realized variances (RVs) into positive and negative semivariances (RSs) and positive and negative volatility to estimate SAM and understand the magnitude of the positive and negative spillovers of the individual markets and the strength of the positive and negative volatility connectedness. Our rolling window-based spillover index differentiates between periods of spillover among markets during periods of crisis or high volatility and periods of relative calmness and stability. Thus, it provides an "early warning system" for an imminent crisis and its intensity.

Third, the further decomposition of SAM into two directional spillover asymmetry measures across markets sheds light on the source of the asymmetry among stock markets. The high transmission (receipt) of negative volatility spillover from (in) a particular market can help investors determine in which market to remain invested for the short or the long term. Moreover, the asymmetric volatility spillover approach also offers investors the opportunity to understand when a market becomes more sensitive and vulnerable to macroeconomic shocks.

The remainder of this paper is organized as follows: Section 2 reviews the literature. Section 3 presents the methodology. Section 4 describes the data and preliminary analysis.

Section 5 reports and discusses the empirical results. Section 6 concludes the paper.

2. Literature review

The relevant literature provides evidence that equity markets are interdependent (Dean et al., 2010) and experience spillover effects (Kang et al., 2017; Zhang & Broadstock, 2020). Volatility spillovers are also found to extend beyond borders, that is, between emerging and world equity markets (Su, 2020; Zhou et al., 2012). Most existing studies focusing on cross-border contagion (Caporale et al., 2005; Dungey et al., 2006; Matei, 2010; Morales & Andreosso-O'Callaghan, 2014; Skintzi & Refenes, 2006; Golosnoy and Gribish Liensenfeld, 2015) or cross-border and cross-asset contagion (Alter & Beyer, 2014; Baur & Lucey, 2009, 2010; Collet & Ielpo, 2018; Hartmann et al., 2004; Liu & Jiang, 2020; Nguyen & Liu, 2017) only examine the interaction among markets where volatility is considered symmetric (Ahmad et al., 2018; Kang et al., 2017; Mensi et al., 2017). However, the literature argues that volatility spillover does not remain the same as financial market returns across markets have asymmetries, that is, when negative returns have higher correlations than positive returns (Longin & Solnik, 2001; Ang & Chen, 2002; Barunik et al., 2015). The negative correlations in returns and volatility tend to react more to adverse shocks, which creates asymmetry in the volatility. Hence, the existence of asymmetric volatility can significantly reduce portfolio diversification (Amonlirdviman & Carvalho, 2010; Barunik et al., 2015, 2017). However, the major challenge of quantifying volatility spillover through a single index remained unanswered until the seminal studies of Diebold and Yilmaz (2009, 2012) (hereafter, DY). They showed that a volatility spillover index, a better way to quantify the spillover effects across market, can be constructed using vector autoregression-based forecast error variance decomposition with and without being sensitive to the ordering of the variables.

Nevertheless, this method did not analyze any of the asymmetric effects of spillover. Barndorff-Nielsen et al. (2010), followed by Barunik et al. (2015), have shown that the volatility concerning realized variances can be decomposed into positive and negative realized semivariances (RSs) using high-frequency data. Semivariances measure the volatility asymmetry due to positive and negative shocks. Recently, Chen et al. (2019) used ten Shanghai Shenzhen CSI 300 sector indices to find that there is an asymmetric volatility spillover and macroeconomic shocks are the main driver behind the asymmetries in transmission of the spillover. Similarly, BenSaïda (2019) also showed that asymmetric volatility spillover exists and a crisis intensifies the asymmetric spillover, especially that of bad volatility. However, Chen et al.'s (2019) study is limited to Chinese markets only. Yang et al. (2018) examine the dependence structure between Chinese stock markets and global factors (gold prices, crude oil prices, the US stock market volatility index (VIX), the US dollar index, and the three-month repurchase rate in China) during bearish and bullish market conditions. Prasad et al. (2018) examine the spillovers across major developed and emerging stock markets using DY's (2012) spillover index methodology. They find that bond yield returns, FX volatility, stock market turnover, and macro news indices explain the spillover indices. Caloia et al. (2018) use the methodology of DY (2012) and the Vector Heterogeneous Autoregressive (VHAR) model to examine the strength and the direction of downside/upside semivolatility spillovers between five European stock markets (France, Germany, Italy, the Netherlands, and Spain). Su (2020) extends the spillovers index of DY (2009) with the quantile regression approach to account for extreme spillovers. The author finds extreme risk spillover predominantly from G7 stock markets to BRICS (Brazil, Russia, India, China, and South Africa) stock markets and that the US, Germany, France and Canada are net contributors of risk spillovers whereas the remaining markets are net receivers of risk spillovers. BenSaïda (2019) did not employ intraday data and employed the GJR-GARCH model to estimate good and bad volatility. The study includes only G7 markets.

3. Econometric modeling framework

3.1. Realized variance and semivariance

We measure the realized volatility spillover as suggested by Barndorff-Nielsen et al. (2010) and Baruník et al. (2015, 2016, 2017) to identify asymmetries due to negative and positive shocks. Based on the literature (Andersen & Bollerslev, 1998), the "realized variances" (RV_t) are defined as the square of the stock index returns estimated at every 5-minute interval. The realized variance can be expressed as:

$$RV_t = \sum\nolimits_{s=1}^{N} r_{t,s}^2, t = 1, 2, \ldots, T \tag{1}$$

where $s = 1, \ldots, N$ is an observation, that is, a 5-minute interval frequency of stock returns. Stock returns are calculated as the first difference of log prices. Barndorff-Nielsen et al. (2010) decompose RV_t into positive and negative components (RS_t^- and RS_t^+, respectively) to measure the volatility asymmetry due to negative or positive movements in specific volatility (i.e., bad and good volatility). The negative RS_t^+ and positive RS_t^- are defined as follows:

$$RS_t^- = \sum\nolimits_{s=1}^{N} r_{t,s}^2 I(r_{t,s} < 0) \tag{2}$$

$$RS_t^+ = \sum_{s=1}^{N} r_{t,s}^2 I(r_{t,s} > 0) \tag{3}$$

Eqs. (2) and (3) provide a complete decomposition of realized variances into positive and negative RS_t. Thus, we can express the realized variance as the sum of two semivariances, that is, $RV_t = RS_t^- + RS_t^+$. The $RS_t^-(RS_t^+)$ term implies negative or bad (positive or good) semivariance/volatility due to negative (positive) shocks. The semivariance approach helps us to capture volatility asymmetry (bad or good volatility).

3.2. Spillover index framework

We employ the DY (2012, 2014) approach to measure the volatility spillover index for total, positive, and negative volatility. We start with the VAR (p) model

$$RV_t = \alpha + \sum_{j=1}^{j} \beta_j RV_{t-j} + \varepsilon_t \tag{4}$$

where $RV_t = (RV_{t,1}, RV_{t,2}, \ldots, RV_{t,N})'$ is an N-dimensional vector representing the realized variances of N stock market indices, and β is the matrix of dynamic coefficients. Similar to Eq. (4), we can estimate VAR (p) models for the semi-variances RS_t^- and RS_t^+.

Using the generalized VAR framework of DY (2012, 2014), we denote the entries of the connectedness by $c_{ij}^g(H)$, an estimate of the contribution of market j to the H-step-ahead generalized forecast error variance of market i, as:

$$c_{ij}^g(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\left(e_t' \Theta_h \Sigma e_j \right)^2 \right)}{\sum_{h=0}^{H-1} \left(e_i' \Theta_h \Sigma \Theta_h' e_i \right)} \tag{5}$$

where the covariance matrix of the error terms in the non-orthogonalized VAR is represented by Σ. σ_{jj} denotes the standard deviation of the errors of the jth equation, and e_i is an $N \times 1$ vector whose ith element is 1 and all other elements are 0. Finally, Θ_h is the coefficient matrix that multiplies the h-lagged error in the infinite moving average representation of the nonorthogonalized vector autoregression (VAR).

As the contributions of the own- and cross-market variance do not sum to 1 under the generalized decomposition, the sum of the rows is used to normalize each element of the variance decomposition matrix:

$$\tilde{c}_{ij}^g(H) = \frac{c_{ij}^g(H)}{\sum_{j=1}^{N} c_{ij}^g(H)'} \tag{6}$$

where $\sum_{j=1}^{N} \tilde{c}_{ij}^g(H) = 1$ and $\sum_{i,j=1}^{N} \tilde{c}_{ij}^g(H) = N$ by construction. The total spillover index is computed as the ratio of the contributions of the spillovers from the volatility shocks across markets in the system to the total forecast error variance:

$$\mathrm{C}(H) = \frac{\sum_{i,j=1,\, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{i,j=1, i \neq j}^{N} \tilde{\theta}_{ij}(H)}{N} \times 100 \tag{7}$$

3.3. Asymmetric spillovers

We further replace RV_t in VAR (p) with semivariances, either with $RS_t^+ = (RS_{t,1}^+, RS_{t,2}^+, \ldots RS_{t,N}^+)'$ or with $RS_t^- = (RS_{t,1}^-, RS_{t,2}^-, \ldots RS_{t,N}^-)'$. We utilize a 180 day rolling window and an $H = 10$ steps ahead FEVD to calculate the dynamic asymmetric behavior of the volatility spillover indices. However, most of the studies used 200 day rolling windows, but this affects the degrees of freedom. We also test the sensitivity of our choice of 180 day rolling windows and an $H = 10$ days ahead forecast horizon in section 5.4.

Following Baruník et al. (2016), we further quantify the extent of the asymmetric volatility spillovers (SAM) defined as follows:

$$SAM = 100 \times \frac{C^+ - C^-}{1/2(C^+ + C^-)} \tag{8}$$

where C^+ and C^- are the volatility spillover indices signifying positive and negative semivariances, respectively. The value of SAM indicates the magnitude of the asymmetry due to the positive and negative semivariances/volatility. SAM is negative (positive) when the bad (good) volatility of RS_t^- (RS_t^+) dominates the good (bad) volatility of RS_t^+ (RS_t^-). A straight line of SAM values at zero suggests equal spillovers from both positive and negative volatility and, thus, no asymmetry.

We further decompose the SAM in Eq. (8) into two directional spillover asymmetry measures $(SAM_{i\leftarrow *}$ and $SAM_{i\rightarrow *})$ and study the source of asymmetry among stock markets. The asymmetry measure for directional spillovers to market i from all other markets can be expressed as:

$$SAM_{i\leftarrow *} = 100 \times \frac{C_{i\leftarrow *}^+ - C_{i\leftarrow *}^-}{1/2\left(C_{i\leftarrow *}^+ + C_{i\leftarrow *}^-\right)} \tag{9}$$

Likewise, we can also estimate the magnitude of the asymmetry in the directional spillovers by market i to all other markets as:

$$SAM_{i\rightarrow *} = 100 \times \frac{C_{i\rightarrow *}^+ - C_{i\rightarrow *}^-}{1/2\left(C_{i\rightarrow *}^+ + C_{i\rightarrow *}^-\right)} \tag{10}$$

Both $SAM_{i\leftarrow *}$ and $SAM_{i\rightarrow *}$ provide information on the direction of the spillover to (from) market i from (to) others. A negative (positive) value of $SAM_{i\leftarrow *}$ suggests that the negative spillover from all other markets to a particular market (market i) is higher than the positive spillover.

4. Data and preliminary analysis

In this study, we employ high-frequency, namely, 5-minute interval, data of 16 stock market indices in international locations. They include Australia (All Ords index), Brazil (BOVESPA index), Canada (TSX index), France (CAC 40 index), Germany (DAX 30 index), Hong Kong (HSI index), India (Sensex index), Indonesia (JKSE index), Japan (Nikkei 225 index), Korea (KOPSI index), New Zealand (NZX 50), Russia (RTS index), Shanghai (SSE index), Thailand (SET index), Taiwan (TAIEX index), and the United States (S&P500 index). The 5-minute interval sample data are used to obtain a daily measure of positive and negative semi-variances. The sample period spans the period from January 22, 2014 to December 31, 2019 and covers several international financial, economic, and political events. The data are extracted from the Thompson Reuter Tick History database (TRTH) maintained by the SIRCA (Security Industry Research Centre of Asia-Pacific). All the stock market indices are highly liquid and they are the benchmark indices of different countries.

Table 1 presents the summary statistics for the realized variances (RV_t) and semivariances (RS_t) of stock market returns. The daily mean value of RV is similar across all markets. We see that the highest RV is in Russia followed by the RV in China. However, the skewness and kurtosis values of all markets are highly divergent from normal distributions. Returning to the summary statistics of the positive (RS_t^+) and negative (RS_t^-) semivariances/volatility, we observe that mean values of both semivariances for the market are very close. However, given the differences in the skewness and kurtosis, this interpretation may be incorrect (Wang & Wu, 2018). For example, the German market has a skewness of 4.62 for positive semivariances and a skewness of 33.59 for negative semivariances. Similarly, the kurtosis for negative semivariances is higher than that for positive semivariances. These findings suggest that the dynamics of positive and negative volatility are dissimilar and negative volatility tends to have heavier tails.

5. Empirical analysis

5.1. Volatility spillover analysis

Table 2 presents the estimates of the total volatility spillover matrix.[2] As shown in this table, the total volatility spillover is 50.1%. The US and Hong Kong equity markets (32.2%), followed by the Indian market (30.8%), exhibit the highest net volatility spillover on the other markets. The stock markets of Canada, France, Korea, and Taiwan are net transmitters whereas the stock markets of Australia, Brazil, China, Germany, Indonesia, Japan, New Zealand, Russia, and Thailand are net receivers of volatility. Furthermore, we find that New Zealand and Russia are the highest net receivers of volatility shocks, at 61.2% and 55.2%, respectively.

We proceed to examine the volatility spillover to the other markets due to the positive and negative shocks in each stock market. Tables 3 and 4 allow us to differentiate between positive/good and negative/bad volatilities from an individual stock market disseminated across the markets, respectively. By comparing results in Tables 3 and 4, we find differences between positive and negative volatility connectedness. For example, the total spillover value (64.10%) for negative semivariances RS_t^- is larger than that (40.10%) for positive semivariances RS_t^+. This finding indicates the markets themselves explain the positive volatility (RS_t^+) better than they explain the negative volatility (RS_t^-) of all equity markets, suggesting that volatility connectedness and volatility spillover are influenced more by bad news than by good news. This

[2] We decompose the total volatility spillover index into two directional spillovers: (i) the receiver of volatility spillovers, termed directionally as "From"; and (ii) the transmitter of volatility spillovers, termed directionally as "To." The dynamic net volatility spillover index is then calculated by subtracting the directional "To" spillovers from the directional "From" spillovers. Positive (negative) values indicate a transmitter (receiver) of returns and volatility to (from) others.

Table 1
Descriptive statistics for 16 international stock market indices' realized volatility and semivariances.

	US	Australia	France	Germany	Japan	Canada	New Zealand	Brazil	Indonesia	Hong Kong	Korea	Russia	India	Thailand	China	Taiwan
Panel A: Daily RV_t																
Mean	0.5404	0.3965	0.9805	1.0823	1.0698	0.4110	0.2586	1.4803	0.5594	0.8636	0.4355	2.5018	0.5874	0.5043	1.7288	0.5638
St.dev.	1.3599	0.5299	1.8023	3.3415	1.9871	1.191	0.6269	2.1204	1.0912	1.3545	0.5111	5.6452	0.9241	1.0996	4.4513	1.409
Minimum	0.0020	0.0274	0.0609	0.0417	0.0031	0.0036	0.0234	0.1610	0.044	0.076	0.0683	0.1886	0.0016	0.0287	0.0706	0.0599
Maximum	43.506	7.0558	42.91	119.6	28.077	40.786	13.763	35.97	14.91	19.149	8.4945	147.7	19.282	22.572	61.43	42.518
Skewness	21.602	5.4033	12.002	29.71	5.7985	26.212	11.226	8.4237	6.4062	7.3208	7.4768	14.018	11.165	10.765	7.2137	18.963
Kurtosis	654.83	47.237	228.15	1036.3	50.761	862.95	188.72	110.85	63.415	77.141	72.657	308.57	183.59	166.19	68.975	524.84
Panel B: Daily RS_t^+																
Mean	0.2638	0.2032	0.5665	0.5964	0.5396	0.1956	0.1300	0.7517	0.2713	0.4356	0.2178	1.221	0.3059	0.2422	0.7475	0.2711
St.dev.	0.4977	0.3315	0.8325	0.7174	1.1514	0.3951	0.3846	1.4719	0.5919	0.7498	0.2496	2.6458	0.4572	0.6587	1.792	0.5683
Minimum	0.0110	0.0162	0.0144	0.0189	0.0153	0.0001	0.0049	0.0555	0.006	0.032	0.0241	0.0981	0.0273	0.0096	0.0361	0.0248
Maximum	9.0006	4.5473	14.444	8.4219	17.523	8.6322	9.5608	33.482	6.9337	11.685	3.9097	44.847	10.775	14.778	27.539	8.1586
Skewness	8.5110	5.6802	7.2223	4.6201	6.7753	10.968	12.645	14.817	5.3805	7.3365	5.1467	8.2578	10.500	13.989	7.4352	6.9720
Kurtosis	117.52	50.295	88.750	34.618	68.559	185.42	256.45	300.97	41.792	81.806	49.630	99.005	197.08	263.22	76.677	72.185
Panel C: Daily RS_t^-																
Mean	0.2763	0.1935	0.4966	0.5769	0.5308	0.2153	0.0795	0.7287	0.1669	0.428	0.2176	1.1278	0.2815	0.1883	0.9901	0.1884
St.dev.	0.9994	0.3408	1.36	3.0609	1.3952	0.9698	0.4189	1.2895	0.6191	0.9737	0.3939	4.3812	0.6278	0.6326	3.1034	0.4951
Minimum	0.0022	0.0092	0.0204	0.0180	0.1598	0.0002	0.0006	0.3395	0.005	0.023	0.0224	0.0616	0.0016	0.0055	0.0204	0.0196
Maximum	34.506	4.6011	37.565	114.06	22.055	35.079	13.962	26.859	14.04	18.20	7.156	114.74	14.788	12.683	56.236	9.2086
Skewness	26.961	6.5141	17.471	33.594	7.8019	30.779	25.695	10.443	13.344	10.698	9.6415	18.576	13.488	11.995	9.6341	9.1459
Kurtosis	898.49	63.252	412.28	1234.3	82.822	1091.7	805.74	164.06	239.42	157.04	136.41	433.29	254.63	183.66	130.15	123.14

Note: This table reports summary statistics for realized variances and positive and negative semivariances.

Table 2
Total spillovers in daily realized variances.

	US	Australia	France	Germany	Japan	Canada	New Zealand	Brazil	Indonesia	Hong Kong	Korea	Russia	India	Thailand	China	Taiwan	From
US	31.8	3.68	7.8	4.22	1.14	24.4	0.24	3.76	2.03	3.8	8.49	0.51	3.22	1.2	1.37	2.39	68.2
Australia	8.41	29.5	9.68	7.35	6.11	6.13	1.09	3.65	1.01	6.52	9.1	0.39	6.29	0.75	2.14	1.87	70.5
France	7.94	7.14	27.9	19.4	6.01	5.52	0.13	3.55	0.41	4.85	7.77	1	4.99	1	1.85	0.56	72.1
Germany	4.7	7.43	23.5	32.0	6.83	2.4	0.07	2.81	0.22	4.41	8.66	1.08	4.14	0.79	0.62	0.31	68
Japan	6.38	8.5	10.2	8.07	34.0	4.86	0.56	3.12	0.37	7.27	9.2	0.88	4.72	0.69	0.62	0.56	66
Canada	28.0	2.62	6.17	2.62	0.92	33.3	0.07	4.55	2.45	3.82	7.98	0.72	2.94	1.04	1.3	1.49	66.7
New Zealand	3.68	3.74	1.44	0.88	0.95	2.14	53.6	0.64	1.22	1	3.5	0.01	6.36	0.7	0.75	19.42	46.4
Brazil	2.15	1.92	2.18	0.46	1.77	2.18	0	83.1	0.27	1.31	1.88	0.46	1.04	0.82	0.23	0.21	16.9
Indonesia	5.67	1.26	1.34	0.65	0.52	5.29	0.7	1.18	68.5	2.84	4.44	0.24	2.21	1.5	0.49	3.18	31.5
Hong Kong	6.8	6.69	7.34	5.01	3.87	5.52	0.17	2.77	1.49	35.1	12.5	0.71	4.5	0.9	5.79	0.84	64.9
Korea	4.27	8.2	9.13	9.34	5.89	2.29	0.43	2.46	0.95	11.4	36.7	0.43	4.66	1.09	1.38	1.46	63.3
Russia	1.76	0.7	3.35	2.67	1.4	1.96	0.08	1.93	0.09	1.52	1.2	80.1	0.68	1.67	0.75	0.11	19.9
India	5.03	7.32	8.61	6.04	2.66	4.07	0.28	2.5	1.05	5.38	6.36	0.38	48.2	0.77	0.71	0.65	51.8
Thailand	3.13	1.1	2.26	1.66	0.91	2.56	0.4	0.78	1.28	1.61	2.63	0.65	1.16	77.6	0.13	2.18	22.4
China	8.19	2.03	5.9	2.01	0.38	10.0	0.14	1.68	0.89	5.63	5.09	0.49	1.87	0.59	54.3	0.82	45.8
Taiwan	4.33	3.05	1.44	0.78	0.65	2.69	1.2	1.18	1.3	2.34	4.33	0.12	1.88	1.43	1	72.3	27.7
To	100.4	65.4	100.3	71.2	40	82	5.5	36.6	15	63.7	93.2	8.1	50.7	14.9	19.1	36.1	802.1
All	132.2	94.9	128.2	103.2	74	115.4	59.1	119.7	83.5	98.7	129.8	88.2	98.8	92.5	73.4	108.3	Total: 50.10%
Net	32.2	−5.1	28.2	−0.9	−28	16	−61.2	−9.8	−1.9	32.2	28.3	−55.2	30.8	−36.9	−3.3	8.4	

Note: The underlying variance decomposition is based on a daily VAR of order 4 (as determined by the Schwarz information criterion), identified using a generalized VAR spillover framework, as suggested by Diebold and Yilmaz (2012). The (i,j)th element of this table shows the estimated contribution to the variance of the 10-day-ahead forecast error of market *i* from innovations to variable *j*.

Table 3
Total volatility spillovers in semivariances RS_t^+.

	US	Australia	France	Germany	Japan	Canada	New Zealand	Brazil	Indonesia	Hong Kong	Korea	Russia	India	Thailand	China	Taiwan	From
US	53.5	0.76	7.2	11.2	0.01	22.8	0.22	0.8	0.02	0.01	0.76	0.3	0.28	0.06	1.49	0.58	46.5
Australia	15.8	40.7	5.58	7.33	6.12	8.77	0.71	0.88	0.3	2.93	6.3	0.45	1.79	0.02	1.31	1.02	59.3
France	11.2	2.06	38.6	28.2	3.55	7.26	0.2	1.01	0.2	1.47	2.21	1.06	1.14	0.1	1.31	0.45	61.4
Germany	15.9	2	24.0	35.1	2.44	9.24	0.11	1.54	0.25	1.71	2.37	1.07	1.38	0.09	2.43	0.45	64.9
Japan	7.81	6.55	6.1	7.12	38.4	6.44	3.17	0.75	0.1	6.83	9.7	1.19	3.18	0.17	0.31	2.14	61.6
Canada	27.7	0.24	6.17	10.5	0.41	46.0	0.43	1.88	0.26	0.84	0.6	2.22	0.31	0.36	1.28	0.8	54
New Zealand	0.88	3.19	0.41	0.38	6.13	0.71	76.2	0.03	0.53	0.69	2.49	0.04	1.63	0.11	0.29	6.28	23.8
Brazil	3.1	0.26	2.27	3.86	0.77	5.01	0.02	82.3	0.03	0.56	0.14	0.89	0.37	0.13	0.17	0.16	17.7
Indonesia	5.99	0.78	0.94	2.06	0.27	3.22	0.54	0.19	79.05	2.17	0.87	0.26	0.84	0.47	0.77	1.58	20.9
Hong Kong	11.4	3.08	3.25	5.09	6.69	8.38	0.46	0.75	1.03	41.9	8.07	1.33	2.02	0.34	4.96	1.25	58.1
Korea	7.02	6.6	4.23	6.31	10.7	4.54	1.27	0.44	0.43	8.86	43.2	0.43	2.06	0.23	0.43	3.28	56.8
Russia	2.5	0.12	2.56	3.24	0.84	5.8	0.18	1.06	0.11	1.66	0.51	78.3	0.53	0.57	1.56	0.51	21.7
India	4.35	2.03	2.84	4.58	2.53	3.38	0.17	0.38	0.67	2.64	2.15	0.77	72.7	0.13	0.27	0.44	27.3
Thailand	1.64	0.03	0.37	0.78	0.32	2.27	0.2	0.12	0.54	0.68	0.41	1.58	0.15	88.9	0.21	1.83	11.1
China	6.2	0.83	1.45	3.24	0.02	6.36	0.13	0.3	0.04	2.68	0.19	0.4	0.06	0.02	78.0	0.11	22
Taiwan	3.91	1.66	1.52	2.63	3.66	2.73	5.11	0.16	1.24	2.34	5.21	0.89	0.92	1.73	0.45	65.8	34.2
To	125.3	30.2	68.9	96.6	44.4	96.9	12.9	10.3	5.8	36.1	42	12.9	16.7	4.5	17.2	20.9	641.5
All	178.8	70.9	107.4	131.7	82.9	142.9	89.1	92.5	84.8	78	85.2	91.1	89.3	93.4	95.2	86.7	Total: 40.10%
Net	78.8	−29.1	7.5	35.2	−20.5	35.3	−41.1	−13.5	−11.9	15.2	−16.1	−43.9	−5	−22.8	6.1	−13.3	

Note: See the notes of Table 2.

Table 4
Total volatility spillovers in semivariances RS_t^-.

	US	Australia	France	Germany	Japan	Canada	New Zealand	Brazil	Indonesia	Hong Kong	Korea	Russia	India	Thailand	China	Taiwan	From
US	24.5	3.03	6.72	4.14	1.61	20.91	0.54	5.22	6.6	4.42	7.76	0.75	5.17	2.02	0.66	5.97	75.5
Australia	5.86	27.8	8.3	5.96	8.52	4.89	0.63	2.84	3.56	7.29	7.56	0.94	7.59	2.04	1.36	4.9	72.2
France	6.86	6.44	23.47	18.2	7.19	4.21	0.29	4.43	1.84	4.85	5.84	1.85	7.9	2.15	1.14	3.31	76.5
Germany	4.99	6.08	23.18	29.5	8.05	1.98	0.18	4.08	0.69	3.46	4.94	2.2	6.68	1.64	0.35	1.96	70.5
Japan	5.21	8.97	9.57	7.92	28.65	3.89	0.66	3.01	2.89	6.84	7.62	1.57	7.09	1.88	0.44	3.78	71.3
Canada	23.2	2.97	4.58	1.99	1.16	26.2	0.63	5.13	8	3.78	7.47	0.61	4.68	2.04	0.86	6.75	73.8
New Zealand	6.97	1.77	2.3	1.42	3.36	7.06	54.21	1.7	5.05	2.44	3.71	0.29	3.55	1.33	0.82	4.03	45.8
Brazil	8.5	3.52	7.39	5.41	3.03	7.45	0.34	40.0	3.52	4.1	4.07	1.62	5.05	1.85	0.3	3.84	60
Indonesia	9.01	2.73	2.58	0.89	2.32	10.1	0.51	3.44	38.6	4.64	6.85	0.88	4.87	3	0.79	8.76	61.4
Hong Kong	5.91	7.16	6.38	3.63	4.57	4.6	0.45	3.4	4.34	28.7	13.7	0.74	5.7	1.87	4.46	4.33	71.3
Korea	3.74	6.78	7.59	5.46	5.81	2.1	0.41	2.35	4.29	13.4	33.2	0.84	6.07	2.05	1.02	4.83	66.8
Russia	1.84	1.95	4.69	4.43	3.25	1.37	0.07	2.79	1.73	1.41	1.86	61.03	1.22	11.2	0.2	1	39
India	6.04	7.5	9.84	6.65	6.86	4.77	1.02	3.45	3.96	5.63	6.67	0.61	29.7	1.8	0.7	4.82	70.3
Thailand	4.3	3.24	4.42	2.79	2.87	4.01	0.7	2.26	4.58	3.19	4.25	3.34	3.1	53.41	0.47	3.07	46.6
China	9.17	2.11	3.6	1.21	0.62	10.3	0.47	1.98	5.16	6.92	5.5	0.55	3.3	1.76	42.99	4.33	57
Taiwan	7.56	6.89	4.66	2.31	3.44	7.5	0.75	3.08	7.71	6.11	7.62	0.6	5.24	1.98	2.76	31.78	68.2
To	109.1	71.1	105.8	72.5	62.7	95.2	7.6	49.2	63.9	78.5	95.5	17.4	77.2	38.6	16.3	65.7	1026.2
All	133.6	98.9	129.3	102	91.3	121.3	61.9	89.2	102.6	107.2	128.7	78.4	106.9	92	59.3	97.4	Total: 64.10%
Net	33.6	−1.1	29.3	−4	−7.8	23.9	−66.2	3.4	3.9	17.1	24.2	−49.4	38.2	−31.7	−30.3	−2.5	

Note: See the notes of Table 2.

result supports the leverage effect hypothesis across stock markets.

5.2. Dynamic total and asymmetric volatility spillover

We estimate the time-varying FEVD of the realized variances (Panel a), semivariances (Panel b), and *SAM* (Panel c). Fig. 1(a) illustrates the total volatility spillover over time and shows a sudden jump in the total spillover after the second half of 2015 until the first half of 2016. The spillover index reaches its maximum level (78%). In addition, we observe a jump in total volatility spillovers in early 2018 followed by a tranquil evolution of total volatility spillovers in 2019. Different shocks occur in the second half of 2015 including the German bond collapse in May and June 2015. In addition, we notice that 2 trillion euro worth of eurozone sovereign bonds trade with negative yields at the end of 2015.[3] The high spillover among international stock markets is also due to the China crisis, the second most important economy in the world, where the stock prices dropped by 45%, leading to capital flight and an important plunge in currency reserves. The high volatility during the period coincided with the Chinese stock market crash and the bubble bursting on June 12, 2015, which continued frequently until June 14, 2016. The crisis led to the loss of one-third of the Shanghai stock exchange's A-share value within one month.[4] Then, there was a fall followed by another rise until the end of 2017. We notice that there are fewer stocks on the stock markets in 2017 and equity investors are optimistic and view any dips as a good investment opportunity. Our results are in line with the findings of Su (2020) where the author finds a decrease in total spillovers among stock markets from 2014 to 2015.

Fig. 1(b) shows the dynamic connectedness of positive volatility and semivariances (RS_t^+) and of negative volatility and semivariances (RS_t^-). The positive volatility spillover is relatively small and confined to the range of 70%; however, negative volatility spillover shows higher jumps and reaches 90% or above during the period from mid-2015−mid-2017, followed by a decrease between 2018 and 2019. We notice that the spillovers decrease at the end of 2014 and in early 2015 due to the crude oil price plunge in October 2014. The results of the dynamic connectedness of positive and negative volatility are consistent with those of Luo and Ji (2018) who also find that positive volatility spillover is relatively small without jumps for some time.

Fig. 1(c) provides more insights into total volatility connectedness, combining both the positive and negative semivariances of volatility. *SAM* is estimated for all 16 equity markets with the realized semivariances as inputs. Consistent with the literature, we further conduct bootstrapping using the volatility spillover indices to ensure that these indices are significantly different from zero. We are able to reject the null hypothesis of no asymmetrical connectedness using the

[3] https://www.investing.com/news/economy/the-10-biggest-events-in-financial-markets-in-2015-377487.

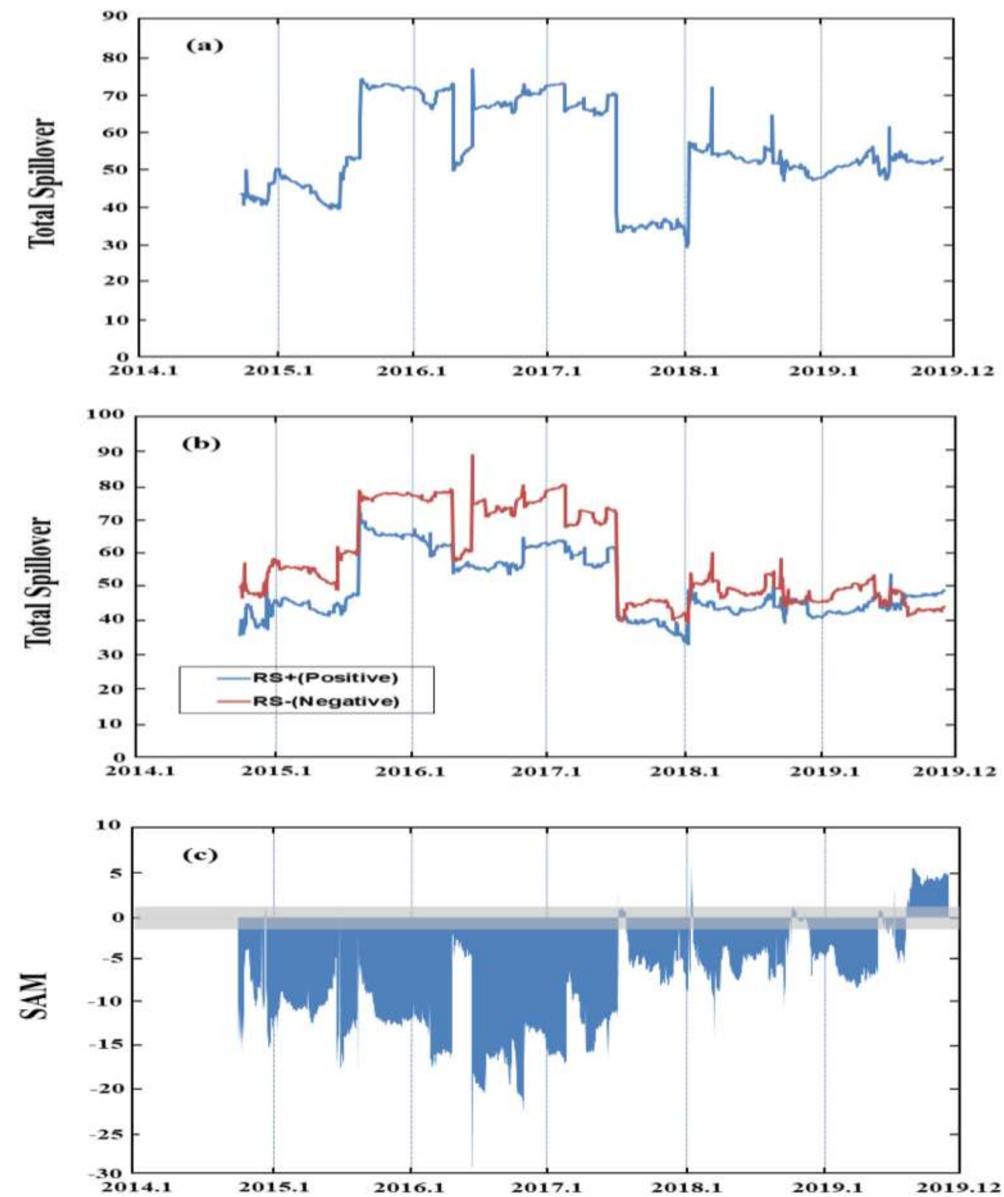

Fig. 1. Total volatility spillover in aggregated stock markets. **Notes:** Panel (a): Spillovers from realized volatility. Panel (b): Spillovers from RS_t^+ (dashed) and RS_t^- (solid), respectively. Panel (c): Spillover asymmetry measure (SAM). The shaded band represents the 95% confidence interval based on bootstrapping.

bootstrapped 95% confidence level. Surprisingly, we find that for the entire period, asymmetries due to negative shocks or volatility are in the negative domain, with the exception of the period from June 2019 to October 2019. The volatility due to negative shocks (RS_t^-) dominates the entire period and has a higher magnitude during the second half of 2016. The highest magnitude of asymmetries in 2016 also reflects the economic stress coupled with the depreciating currency in China. This resulted in the selling of reserves by the central bank to support the currency. Thus, equity investors sought to sell their equity assets. It is worth noting that high asymmetries due to negative shocks reflect the growing debt as a percentage of gross domestic product (GDP) in China, Greece, Japan, Spain, and the US. The total private and public debt as a percentage of GDP in 2015 was 500%, 400%, and 300% in Japan, Spain, and China, respectively. In 2016, the Bank of Japan embraced negative interest rates, which steered many investors away from Japan to the US, the UK, and the eurozone and higher yield debt instruments. This eventually drove drown the interest rates of the developed markets. The falling yields and the bond price rally in 2016 also reflect investors' shift from equity to bond markets. The 2015−2016 period also reflects the results of the Brexit vote, which was contrary to investors' prediction that the UK would remain in the European Union.

Furthermore, OPEC's decision to cut oil production to 33 million barrels a day was soon followed by similar moves in other oil-producing countries such as Russia, driving oil prices upward. This caused a jump in oil prices by 5%. The higher oil prices affected the overall demand and growth of many oil-importing countries. Our *SAM* results suggest that the

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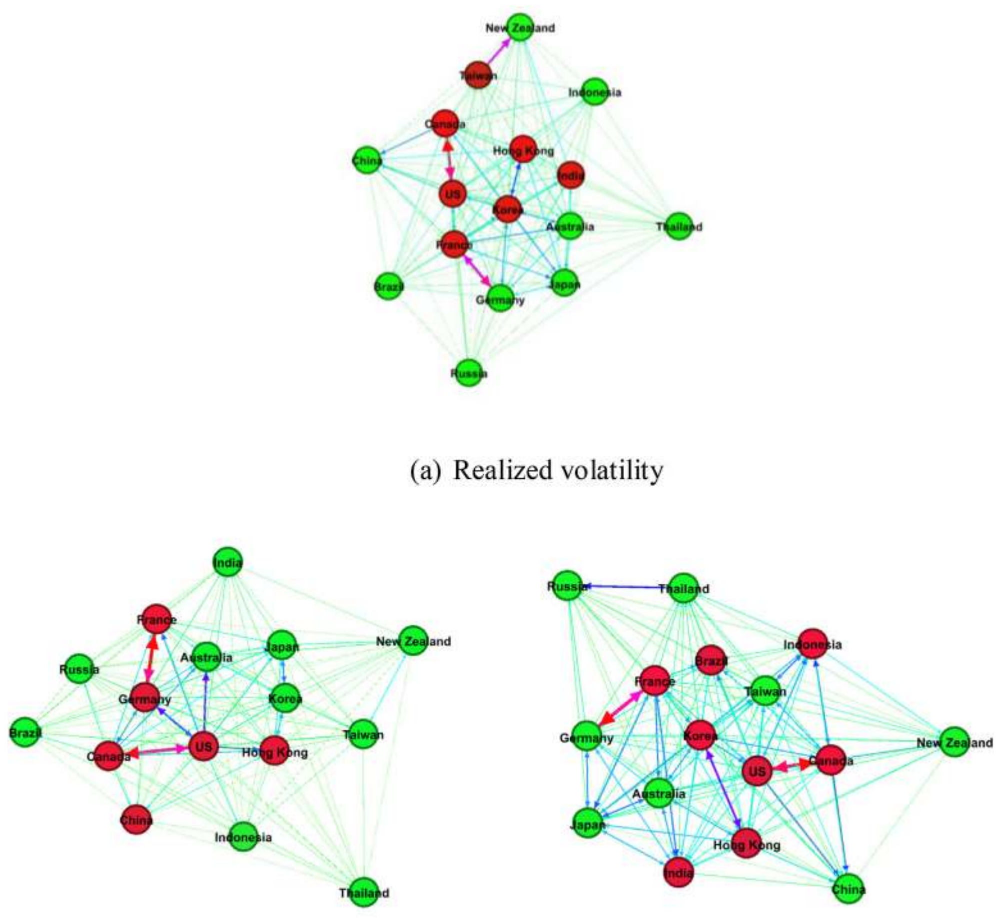
selling activity explains the dominant role of negative volatility during 2016–2017, which was caused by uninformed traders in response to the market turmoil (Avramov et al., 2006). Thus, negative spillover caused by liquidity driven uninformed traders not only dominates the market, but it also transmits larger shocks (BenSaïda, 2019). Wang and Wu (2018) argued that the dynamics of *SAM* reflect the market expectations about the present and near-future movements. The negative *SAM* in the sample period indicates that the majority of equity investors across the emerging and developed markets maintained a pessimistic attitude toward economic activity and financial markets. It is worth noting the good volatility dominates the bad volatility from June 2019 to October 2019. This result may be due to the economy recovery for almost all economies.

5.3. Connectedness network

Fig. 2 illustrates the volatility spillover network of the volatility among all stock markets. The color of each node also indicates the nature of the market. A red (green) node denotes the most significant transmitter (recipient). The size of the node shows the extent of the spillover. As Fig. 2(a) shows, the US, French, Canadian, Korean, Hong Kong, Taiwanese, and Indian stock markets are net transmitters of volatility. Furthermore, we note strong volatility connectedness between the US and Canadian markets, between the French and German markets, and between the Hong Kong and Korean markets. The strong connectedness in each pair is due to strong cross-border regional trade and investment flows. Among all markets, Canada is the largest receiver of shocks from the US stock market. This result may be due to the high linkages between the two economies, especially after forming the North American Free Trade Agreement (NAFTA) agreement to promote trade between the US, Canada, and Mexico by eliminating most tariffs on trade between these economies. The magnitude of the connectedness is different across markets. This result is in line with the findings of Liu and Jiang (2020) where they find evidence of the heterogeneity of the volatility propagation among international stock markets at different scales.

Fig. 2(b) also shows that stock markets such as those in China, the US, France, Canada, Germany, and Hong Kong



(a) Realized volatility

(b) Positive semivariances RS_t^+

(c) Negative semivariances RS_t^-

Fig. 2. Volatility spillover networks: (a) Realized volatility, (b) RS_t^+ , and (c) RS_t^-. Note: The size of a node represents the magnitude of a net transmitter and receiver to/from other markets. A red (green) node indicates the transmitter (receiver) of spillover. The edge size shows the magnitude of the pairwise spillover. The magnitude is also reflected in the color (green (weak), light blue (medium), and blue and red (strong)).

are net transmitters of good volatility. In contrast, Fig. 2(c) shows that India, Indonesia, Brazil, Canada, the US, France, Korea and Hong Kong are transmitters of negative shocks. Similar to the network of Fig. 2(a), we observe that the Canada and US pair and the France and Germany pair are strongly connected, both when the volatility spillover is positive and negative. Additionally, strong negative volatility connectedness is observed between the Hong Kong and Korean markets. The network also corroborates our findings that negative volatility dominates positive volatility and that Asian markets are found to have strong negative volatility spillover effects.

5.4. Net asymmetric volatility spillovers

We further examine the net asymmetric directional spillover as the difference between good and bad volatility spillover (Fig. 3). The magnitude of *SAM* indicates the degree of asymmetry in the spillover due to RS_t^+ and RS_t^-. The net asymmetric volatility spillover can also be a good indicator of whether the good volatility of a specific market spills over to the other markets more than the bad volatility. The net asymmetric volatility spillover dynamics of each market also show how investors in the specific markets respond to good/positive news and bad/negative news. As shown in Fig. 3, the volatility spillover transmitted from one equity market to other equity markets is asymmetric. The graphical evidence shows that the stock markets in Australia, New Zealand, Brazil, Indonesia, Hong Kong, Korea, India, Thailand, and Taiwan transmitted large negative spillovers to other markets from 2016 to 2017 and in 2019.

Overall, Thailand and Taiwan transmitted negative shocks. Taiwan remained dominant as a transmitter of negative shocks from 2016 to 2017. It is interesting to reveal that most Asia-Pacific countries transferred negative shocks to other markets in 2016. The low sentiment of investors in Asian markets is because of the economic stress in China in 2016. China's rising influence has implications for financial markets and capital flows to the Asia-Pacific region (Shu et al., 2014). The economic situation in China, in addition to the deflationary pressure and negative debt yields in Japan and other developed markets, played a role in decreasing the global liquidity conditions and investor sentiment. Markets such as those in France, Germany, Canada, and Shanghai are observed to have optimistic (positive) expectations about the present and near-future movements of the markets. The evidence of asymmetry in volatility spillovers is also confirmed by Yarovaya et al. (2017).

5.5. Directional asymmetric volatility spillovers

We further examine the directional asymmetric volatility spillover to measure the contribution of (receipt by) individual equity markets volatility to (from) other markets. Fig. 4(a—p) plots the directional spillover asymmetry measure. The first column of Fig. 4 depicts the receipt of spillover asymmetry by market i from other markets, denoted by $SAM_{i\leftarrow *}$. The second column illustrates the transmission of volatility asymmetry from market i to other markets, denoted by $SAM_{i\rightarrow *}$. Both the $SAM_{i\leftarrow *}$ and $SAM_{i\rightarrow *}$ measures allow us to identify the extent to which volatility to (from) the ith market spills over from (to) other markets asymmetrically. If the negative spillover from one market in the system is larger than the positive spillover, $SAM_{i\rightarrow *}$ is negative. This information provides the direction of the asymmetry volatility across markets.

We show that the majority of equity markets received negative spillovers in 2016, 2017, 2018 and 2019, which reflects an overall pessimistic mood across markets. Emerging stock markets such as those of the BRIC (Brazil, Russia, India and China) countries and Thailand heavily experience asymmetric spillovers with more negative volatility. This phenomenon is seen because of the price drop of equity assets in a majority of the markets as a result of the global macroeconomic uncertainty. Emerging economies continued to witness decreased growth, driven by lower commodity prices, tighter external financial conditions, rebalancing in China, and economic distress due to geopolitical factors (World Economic Outlook, 2015). The World Bank reported that the growth in emerging markets slowed from 7.6% in 2010 to only 3.7% in 2015. The economic decline is owing to the declining growth in China because of a steady fall in commodity prices, which has hurt the growth of commodity-exporting countries. Persistent weak growth in South Africa and the continued recessions in Russia since 2014 and in Brazil since 2015 have further worsened the situation in equity markets. The volatility transmission to Asian markets is consistent with Lau and Sheng's (2018) results that inter-regional spillover effects from Hong Kong and India to China are asymmetric and the Chinese market is susceptible to the negative shocks from Hong Kong.

We also observe that emerging markets not only received higher negative volatility than positive volatility, but they have also transmitted a larger number of negative shocks to other markets. The high dollar debts of emerging markets are also the reason behind their sensitivity to global events. Companies in emerging markets such as China, India, and Indonesia are among the top dollar debtors, which reflect their vulnerability to inflows and outflows of foreign investments. It is evident in the second column of Fig. 4 that markets such as Australia, Russia, Brazil, Indonesia, Korea, Taiwan, India, and China experienced negative spillover in 2016 and 2017. However, Russia and Brazil also transmitted positive shocks to other markets in 2017. As Russia started to emerge from a prolonged recession in 2017, the Russian economic and financial indicators improved. Moderately tight monetary policy has helped Russia reduce its inflation rate from 15.6% in 2015 to 4% in April 2017. Employment and labor force participation rates reached their maximums and the banking sector presented a sign of stability with precrisis levels of profitability (World Bank, 2017). Similarly, Brazil has also experienced GDP growth of 1% in 2017 compared to a 3.5% contraction in 2015 and 2016. Brazil has also been successful in reducing its double-digit annual

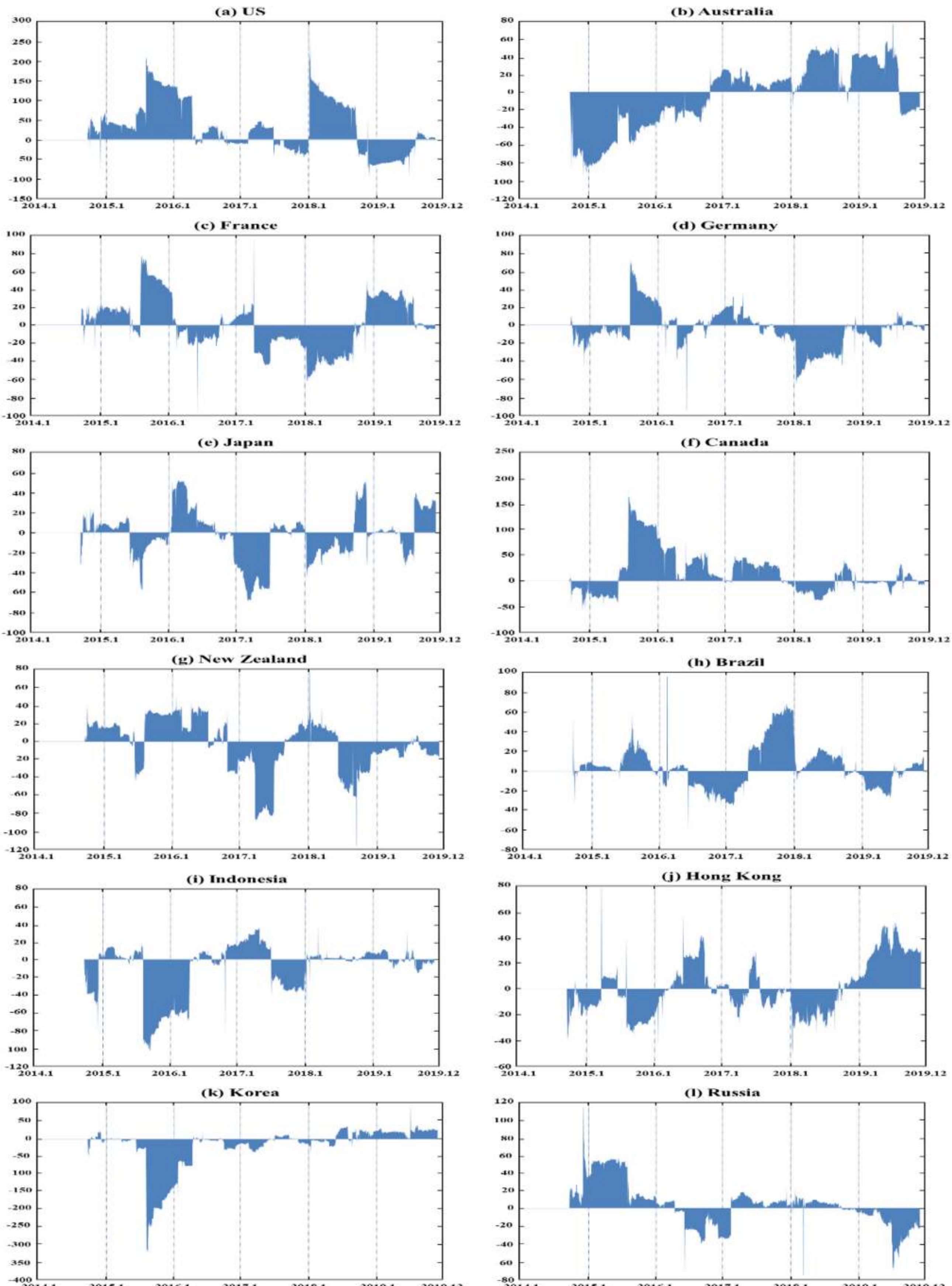


Fig. 3 Spillover asymmetry measures (*SAMs*) in each stock market.

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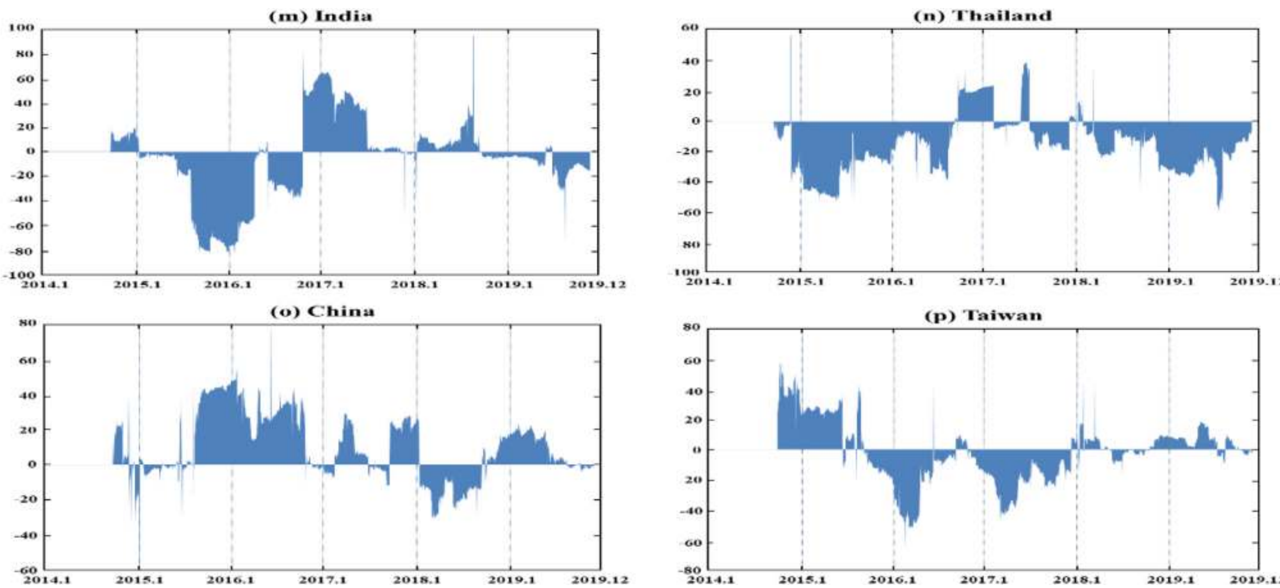

Fig. 3. (*continued*).

inflation rate to 4.5% in 2017. In 2018−2019, the US received shocks from the other markets and transmitted bad volatility to the other markets. In contrast, Australia (France, Germany, Canada, New Zealand, and Indonesia) receives and transmits good (negative) volatility.

At the end of 2016, the countries also showing signs of positive spillover to other markets were the US, Canada, France, Germany, China, and Japan on account of the global recovery and country-specific fiscal and monetary policies. Although spillover asymmetry was high during the turmoil periods, crisis or expansion periods may not be the main drivers of the increased spillover. The sudden increase in spillover asymmetry is more influenced by specific global events than by country-specific macroeconomic conditions (Collet & Ielpo, 2018). Our findings are consistent with the findings of BenSaïda (2019). The author concludes that crises have more impacts that cause asymmetric volatility spillover, especially bad volatility.

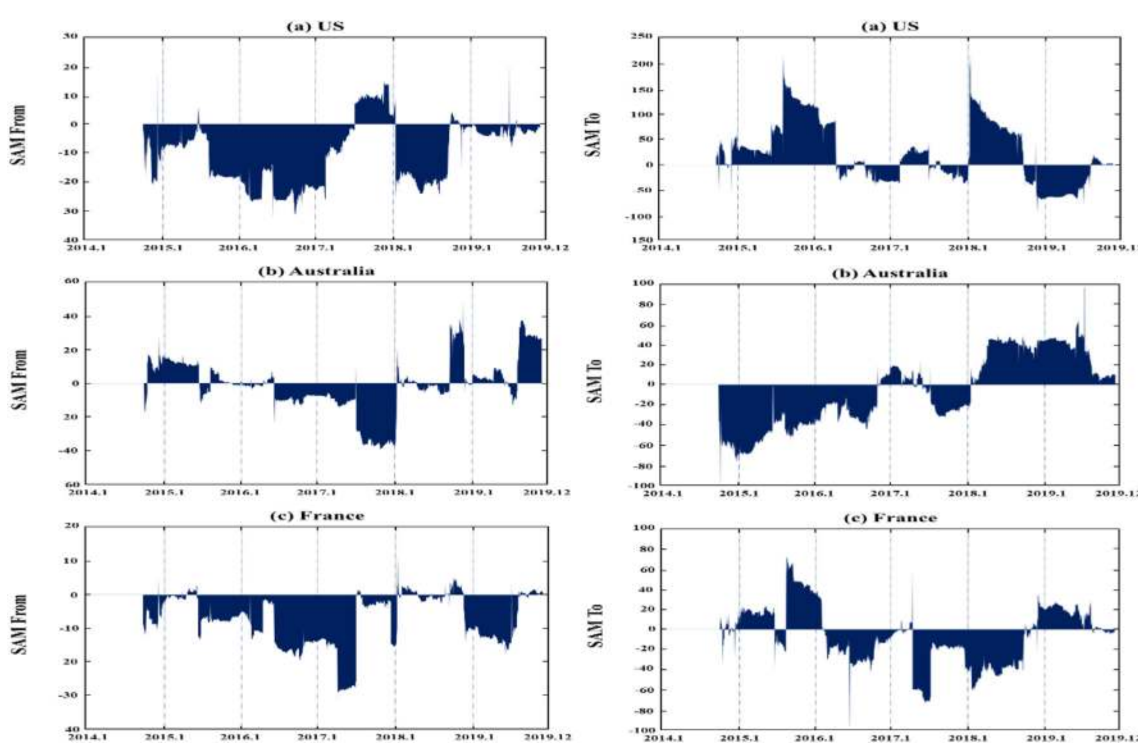

Fig. 4 Directional spillover asymmetry measures "*SAM* From" ($SAM_{i\leftarrow *}$) and "*SAM* To". ($SAM_{i\rightarrow *}$)

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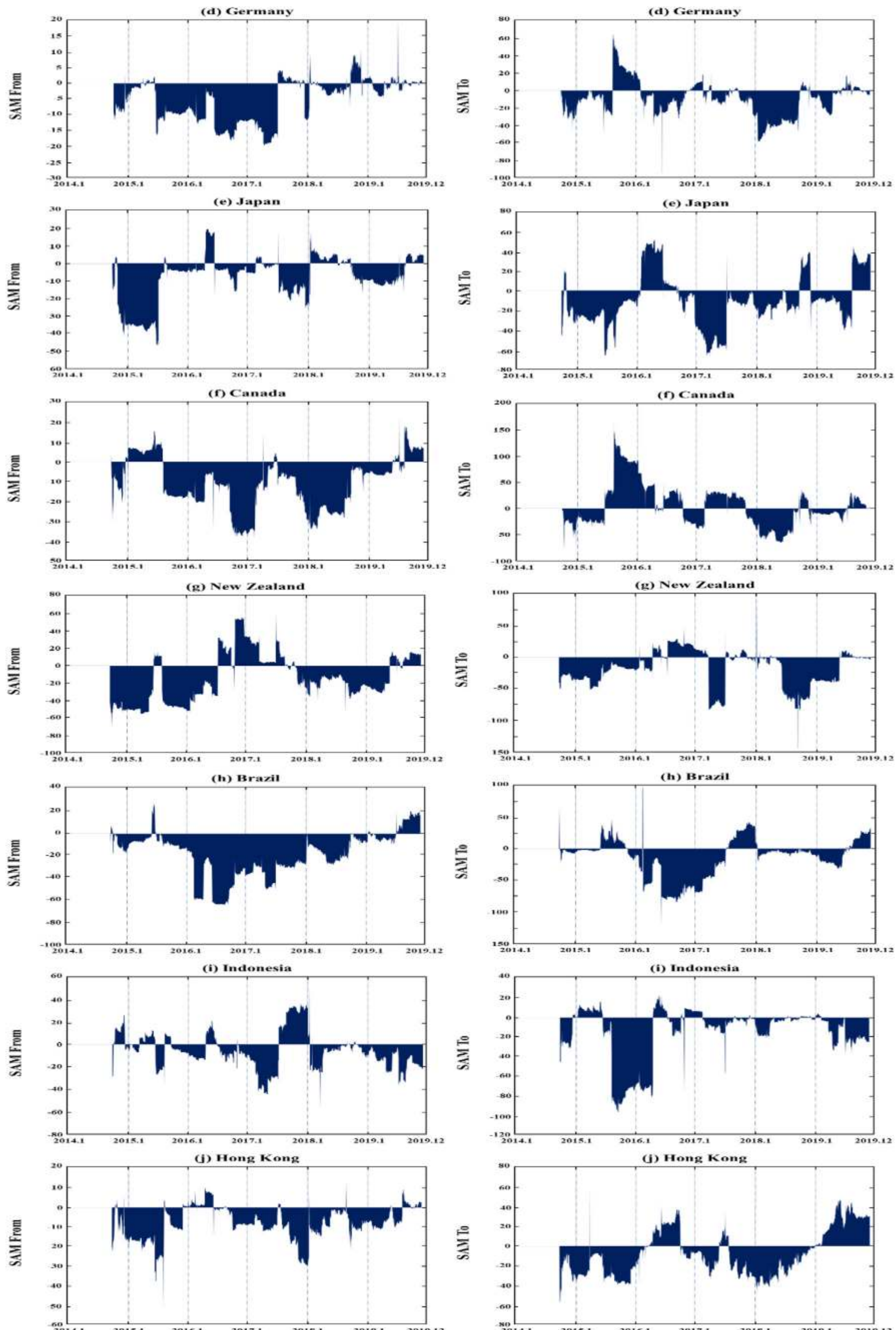

Fig. 4. (*continued*).

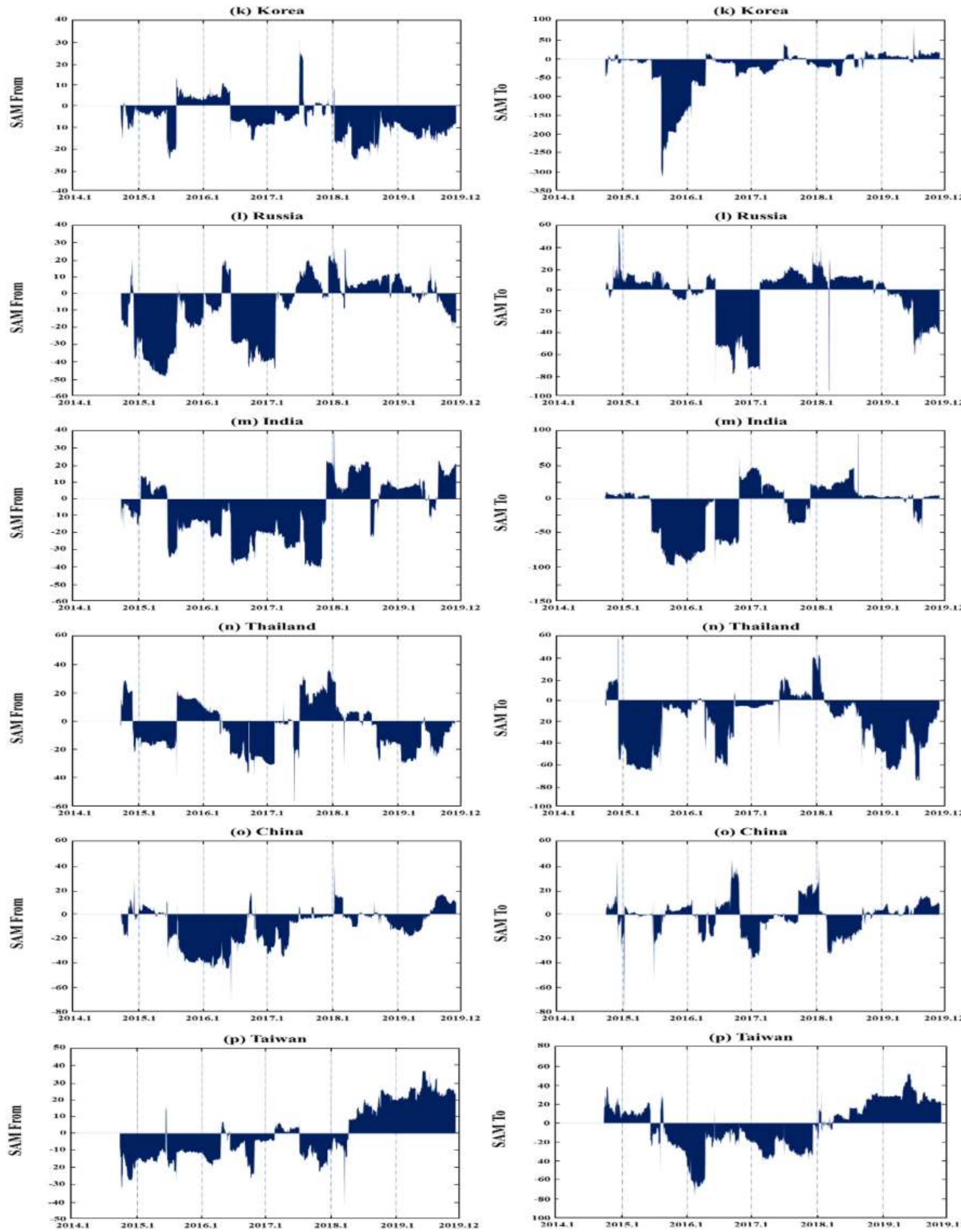

Fig. 4 (*continued*).

6. Conclusions

This study examines the volatility connectedness among equity markets using high-frequency, namely, 5-minute interval, data. We study the static and dynamic volatility spillover of both symmetric (that is, realized) and asymmetric (that is, positive and negative semivariances) volatility by employing spillover indices (DY, 2012). We further analyze the asymmetric volatility connectedness through a network approach.

The overall important findings of volatility spillover and connectedness are summarized below. First, we note that the stock markets of Japan, New Zealand, Brazil, Russia, and Thailand are net receivers whereas those of the United States, France, Canada, Indonesia, Korea, India, and Taiwan are net transmitters. Further, India, the United States, Korea, and

Indonesia are very strong transmitters. Second, we find that the volatility spillover transmitted from one equity market to other equity markets is asymmetric. We note that the stock markets of Australia, New Zealand, Brazil, Indonesia, Hong Kong, Korea, India, Thailand, and Taiwan transmitted large numbers of negative spillovers to other markets during 2016 and 2017. It is interesting to observe that most Asia-Pacific countries transmitted negative shocks to other markets in 2016. Third, Canada and the United States, France and Germany, and Hong Kong and Korea are strongly connected. The network also corroborates our findings that negative shocks dominate positive volatility. Finally, by examining the directional asymmetric volatility spillover, we observe that the majority of equity markets received negative spillovers in 2016 and 2017. Emerging economies such as India, Thailand, China, Taiwan, Brazil, and Russia heavily experienced asymmetric spillover with more negative volatility.

Our findings offer implications for investors and policymakers. The asymmetric volatility spillover and connectedness provide better ways to manage portfolio diversification strategies. Investors can be more informed about the markets, which become connected when there are negative news or positive news. Further, equity investors can precisely judge when and which markets they need to be more concerned about under negative and positive shocks. Policymakers can also identify the markets that are the major sources of negative shock spillover. Accordingly, they can intervene and reduce the negative shock transmission either by controlling capital flows or by announcing definite policy measures to elevate the sentiment of the markets and overall economy. Thus, the volatility asymmetry analysis assists policymakers to know when to intervene to stabilize the markets and reduce the uncertainty.

It will be intriguing in the future to extend this study by analyzing the impact of the global health crisis (COVID-19 pandemic spread) on the spillovers among international stock markets in short, medium and long terms. Such a “black swan” event may act as a catalyst of spillover, generating increases or shifts in spillover behaviors in different investment horizons (Goodell, 2020). Understanding the impact of the COVID-19 crisis on international stock markets can help investors to improve their portfolios’ risk-adjusted returns, adjust their asset allocations to account for the impacts of spillovers and reduce contagion risks in different investment horizons.

Declaration of competing interest

This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. We have read and understood your journal’s policies, and we believe that neither the manuscript nor the study violates any of these. There are no conflicts of interest to declare.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bir.2020.12.003.

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