

Research Article

Volatility Similarity and Spillover Effects in G20 Stock Market Comovements: An ICA-Based ARMA-APARCH-M Approach

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Financial internationalization leads to similar fluctuations and spillover effects in financial markets around the world, resulting in cross-border financial risks. This study examines comovements across G20 international stock markets while considering the volatility similarity and spillover effects. We provide a new approach using an ICA- (independent component analysis-) based ARMA-APARCH-M model to shed light on whether there are spillover effects among G20 stock markets with similar dynamics. Specifically, we first identify which G20 stock markets have similar volatility features using a fuzzy C-means time series clustering method and then investigate the dominant source of volatility spillovers using the ICA-based ARMA-APARCH-M model. The evidence has shown that the ICA method can more accurately capture market comovements with nonnormal distributions of the financial time series data by transforming the multivariate time series into statistically independent components (ICs). Our findings indicate that the G20 stock markets are clustered into three categories according to volatility similarity. There are spillover effects in stock market comovements of each group and the dominant source can be identified. This study has important implications for investors in international financial markets and for policymakers in G20 countries.

1. Introduction

Given the rising trend of contagion in global financial market, the G20, which was born after the 2008 financial crisis, has become the most important forum of global cooperation to address the crisis [1]. The spillover effects imply that a huge impact on a financial market will increase the returns and relevance of that market and other markets [2]. A further explanation is that the volatility of the stock markets will move together over time (i.e., comovements). So, how do we measure the comovements of the stock markets? Some existing studies [3–5] show that the comovements can be measured by the similarity among multiple markets because volatility similarity enhances information flows across markets and thus lead to comovements among them. That is, we can find that whenever the price of one market drops, its connected markets will also go

down, and vice versa. Therefore, the volatility similarity measured by clustering analysis is applied to quantify comovements of stock markets in this study.

Motivated by this factor, we model on multivariate financial time series as it has long been a standard for studying volatility spillover and comovements [6]. However, the extant empirical literature has dealt with spillover effects focusing on shocks to volatility by multivariate GARCH models, which have the following disadvantages.

First, GARCH models are limited to solving two-dimensional or three-dimensional problems [7–12]. However, the fact cannot be ignored that there are far more than two or three interconnected financial markets at risk nowadays, which is lack of relevant research in the existing literature. To fill this gap, we intend to address high-dimensional volatility modeling problem in G20 financial markets; therefore, a new approach is necessary to deal with such situations.

Second, the existing literature does not include studies of volatility similarity and spillover effects in G20 stock market comovements. In today's increasing economic globalization economy and financial liberalization, it is generally believed that financial markets tend to fluctuate in a similar trend with each other. The fluctuations from more than two markets that have some underlying factors in common may simultaneously transmit to one market [13–16]. It is necessary to quantify the common volatility spillovers as a composite index of market comovements around the world.

Third, multicollinearity might occur when multiple financial market volatility factors act as explanatory variables to explain the volatility spillovers to the same market. If there is a certain correlation between explanatory variables, the result does not truly explain the spillover effects. Therefore, some statistically independent components that represent the volatilities of original multivariate time series must be decomposed.

To overcome these disadvantages, the idea of dimensionality reduction is needed to reflect the information of all indicators through a few indicators. Methods such as principal component analysis (PCA) or independent component analysis (ICA) can be used to decompose the information into unrelated parts in the low-dimensional space for more meaningful interpretation. Principal component analysis assumes that principal components obey Gaussian distribution; however, the actual data usually do not obey Gaussian distribution, such as the fat-tailed and nonnormal of financial time series data. ICA can solve such problems well. The use of ICA in financial data analysis is an exploratory effort to uncover some of the underlying driving mechanisms. This is the essential difference between ICA and other data processing methods, such as principal component analysis and factor analysis.

Therefore, we introduce ICA for volatility spillover effects modeling in G20 stock market comovements. Although the basic model of ICA was mainly applied to signal processing in the previous literature, it has recently shown more advantages when used in financial time series modeling [17]. The strongest point is that ICA can deal with more large-scale data than other competitive models with extremely low computational costs, thereby avoiding the curse of dimensionality. It also reproduces some higher moment features with the heavy-tailed and higher kurtosis distribution that really exist in the financial market [18–20]. In addition, it does not require joint estimation because each one of the components is independent. Based on the above analysis, it is appropriate to introduce ICA to study the co-movements of G20 stock markets in this paper.

Our study aims to address these essential problems as follows. (i) How can we identify the comovements of stock market in G20 countries, or which stock markets in G20 have similar volatility patterns? (ii) Among the markets with similar volatility, are there spillover effects in market comovements? (iii) If there are spillovers in two or more markets, which is the dominant source of spillovers? To address question (i), an ARMA-APARCH-M model and fuzzy C-means clustering method are adopted to explore the comovements according to volatility similarity. To address

questions (ii) and (iii), we propose an ICA-based ARMA-APARCH-M model for investigating volatility spillovers of G20 stock market comovements.

This study is organized as follows. Section 2 discusses the relevant literature. In Section 3, we introduce the methodology and theoretical considerations. The data and empirical results are presented in Section 4. Conclusions are offered in Section 5.

2. Literature Review

The analysis of volatility spillover effects between cross-national stock markets is of high interest in the empirical financial literature, with increasing attention being paid to this issue [6, 21–26]. The transmission of volatility risk is analyzed by examining the spillover effect of volatility between financial markets. In these literatures, the generalized autoregressive conditional heteroskedasticity (GARCH) model, developed by Bollerslev [27], is widely used. Although this model can capture many characteristics of financial time series, its hypothesis ignores the symbol of new information. The negative shocks from bad news tend to trigger higher volatility than the arrival of good news. This phenomenon suggests that it is unreasonable for a simple GARCH model to set positive and negative shocks as symmetrical and equal impacts.

In view of the asymmetric impact, many extension models have been put forward, e.g., Ding et al.'s [28] APARCH (asymmetric power ARCH) model. Since then, the GARCH model with asymmetric items has been widely used in the following studies of stock markets' volatility [23, 29–31]. Mensi et al. [23] employed the bivariate APARCH model to capture volatility spillover effects between the U.S. and BRICS stock markets. Except for the GARCH models, some other conventional econometric methods are used for volatility spillover effects studies, such as the ARMA model [32], Markov regime-switching model [33, 34], and VAR framework [35–38]. However, a large number of parameters have to be estimated in these models when it comes to more than two or three financial assets. To overcome the curse of dimensionality, some network models have been proposed in recent years [1, 18, 20, 39–44]. Geng et al. [18] construct volatility networks of energy companies using the connectedness network approach and provide a reference for risk management.

No matter which method is used to examine the volatility spillover effects of financial markets, there is a common defect in the existing literature. That is, they have not considered the common volatility spillovers as composite index to measure risk contagion brought by the simultaneous movement. Volatility in a market is transmitted from more than two or three markets, which may have common latent elements and move together. Such a transmission of volatility across markets that are moving together is generally referred to volatility spillover effects of market comovements. This can be captured by a composite index that represents the weighting value of multiple stock return residuals as the comovements of financial variables.

To solve the problems described above, ICA which has been popularized in recent years has been adopted. It aims at extracting the independent components of implicit information from the original data without knowing signal-mixing process. Despite its popularity in signal processing, ICA has been recently applied in financial settings, e.g., stock price forecasting [45], realized volatility analysis [46], conditional covariance forecasting [14], portfolio selection [47], gold price analysis [48], and structural shock identification of VAR models [49]. The ICA method has an advantage that it can extract the underlying information in financial time series and provide more valuable information for financial forecasting [45]. The application of ICA in the study can overcome the curse of dimensionality and capture the volatility spillover effects from multiple financial markets to one market.

As an essential concept, the comovements' recognition across international stock markets has attracted many scholars to research [3, 19, 50–57]. Sheng et al. [57] analyze market comovements across eight major stock markets and verify the existence of volatility spillover. Chen [52] examines the comovements of stock markets using a novel Bayesian factor model. Although these studies recognize the concept of comovements, they do not quantify the comovements of stock markets. Since Aghabozorgi and Teh [3] refer to the fluctuations of stock markets in a homogeneous group as comovements, we employ volatility similarity analysis to quantify the comovements. Volatility similarity is defined as a close distance between volatility influencing factors representing fluctuation features, i.e., market movements are organized into homogeneous groups where the distance of within-group objects is minimized and the distance of cross-group objects is maximized. For distance calculation, the method of grouping time series by clustering analysis has been recently applied to address financial time series issues [58–65]. These scholars agree that clusters generated on account of similarity are very accurate and meaningful. Hence, we use volatility similarity measured by a fuzzy C-means (FCM) clustering analysis to quantify comovements of stock markets.

3. Methodology

To examine the volatility similarity and spillover effects in G20 stock market comovements, an ICA-based ARMA-APARCH-M approach has been proposed. As shown in Figure 1, we adopted three steps to solve the problems mentioned in the introduction. The ARMA-APARCH-M model is employed to acquire the residuals of return series and then use ICA to generate the independent components (ICs). Each calculated independent component is a composite index representing the weighting value of multiple stock return residuals. As potential components that capture volatility are statistically independent, we can fit a univariate ARMA-APARCH-M model to each IC. In this way, the volatility spillover effects from multiple financial markets to one in comovements can be examined.

3.1. Independent Component Analysis (ICA). ICA is a method of statistical and numerical analysis to extract the independent components of unknown signals or random variables. This method was originally developed to deal with blind source separation (BSS), also known as the cocktail party problem. The so-called cocktail party problem is that in a banquet full of various conversations and music, people can still focus on hearing what they want to hear despite the different sounds around them. Without knowing the mixing mechanism, it only looks for statistically independent components that are hidden in the complex phenomenon using a linear or nonlinear decomposition of the observed data.

Suppose that $\mathbf{X} = [\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_m]^T$ denotes a given multivariate matrix of size $m \times n$, and \mathbf{x}_i refers to the observed mixture signal. The basic ICA model [66] is given by

$$\mathbf{X} = \mathbf{AS} = \sum_{i=1}^m a_i s_i, \quad (1)$$

where \mathbf{A} is the unknown mixing matrix and \mathbf{S} is the source matrix that cannot be directly observed. The ICA model explains how to generate observations by mixing components s_i . Independent component (IC) is a latent variable that cannot be directly observed. ICA aims to find a specific $m \times m$ demixing matrix \mathbf{W} such that

$$\mathbf{Y} = [\mathbf{y}_i] = \mathbf{WX}, \quad (2)$$

where \mathbf{y}_i is the i^{th} row of the matrix \mathbf{Y} , $i = 1, 2, \dots, m$. It is used to estimate the independent latent source signals (s_i). The independent components (ICs) \mathbf{y}_i must be statistically independent. When demixing matrix \mathbf{W} is the inverse of mixing matrix \mathbf{A} , i.e., $\mathbf{W} = \mathbf{A}^{-1}$, ICs (\mathbf{y}_i) can be used to estimate the latent source signals s_i . In this study, we adopt the FastICA algorithm proposed by Hyvärinen and Oja [66] to solve the demixing matrix \mathbf{W} , as it has been shown to work well with financial data [14]. It is an algorithm on the basis of a fixed-point iteration process to maximize the non-Gaussianity of $\mathbf{w}^T \mathbf{x}$. The derivative of the nonquadratic function G is denoted by g . It is completed by the following four steps:

- Step 1: choose an initial weight vector \mathbf{W}
- Step 2: let $\mathbf{W}^+ = E\{\mathbf{X}g(\mathbf{W}^T \mathbf{X})\} - E\{g'(\mathbf{W}^T \mathbf{X})\}\mathbf{W}$
- Step 3: let $\mathbf{W}^+ = \mathbf{W}^+ / \|\mathbf{W}^+\|$
- Step 4: if not converged, go back to 2

3.2. ARMA-APARCH-M Model. To explain the asymmetric effects of positive and negative shocks in financial markets, Ding et al. [28] propose an asymmetric power ARCH (APARCH) model in consideration of long memory property, which is

$$r_t = \mu + \varepsilon_t, \quad \varepsilon_t | \psi_{t-1} \sim N(0, \sigma_t^2), \quad (3)$$

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^q \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{j=1}^p \beta_j \sigma_{t-j}^\delta, \quad (4)$$

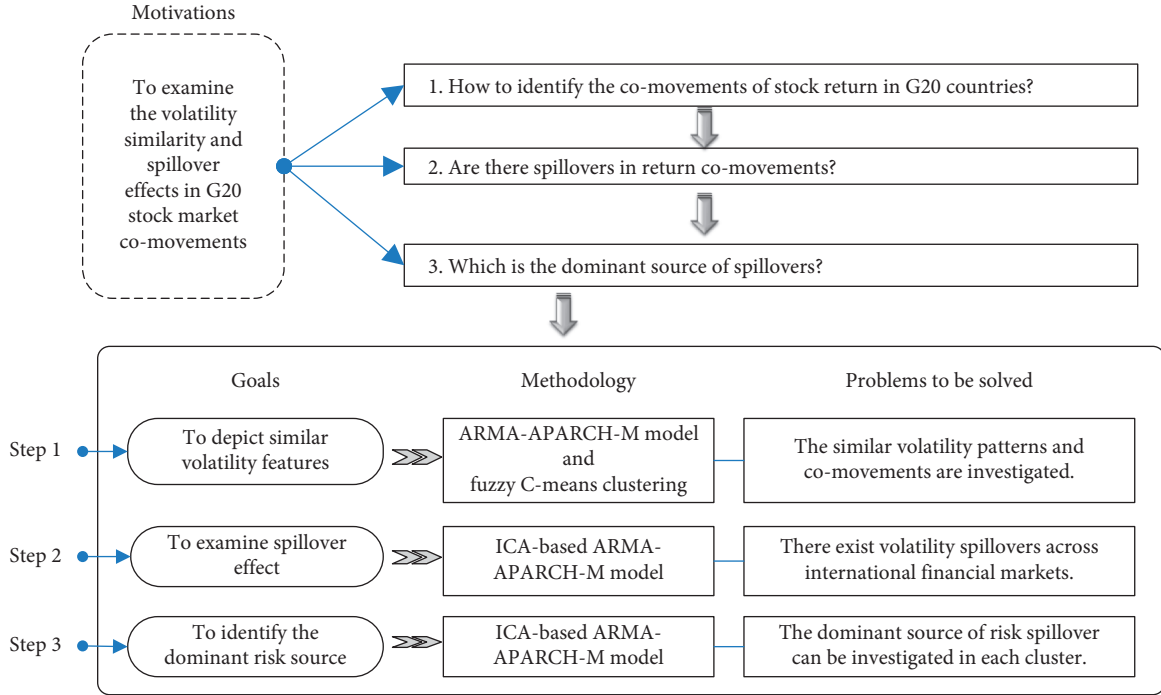


FIGURE 1: The frame diagram of the methodology.

where r_t is the logarithmic returns of stock markets, defined as the sum of a conditional mean μ and a zero-mean disturbance ε_t . The conditional standard deviation σ_t can be estimated by the relevant lagged information over multi-periods. The coefficient γ_i represents the asymmetric effect. The estimated parameter δ is not preset, but estimated from the sample data.

However, in financial investments, the greater the risk, the greater the expected return, a phenomenon called risk reward when risk increases. Therefore, the APARCH model is extended to an APARCH-M model so that the conditional variance can directly influence the mean of returns. In addition, evidence has shown that the financial time series is sequence autocorrelated because it is influenced by its own inertia and lag effect. We incorporate autoregressive moving average (ARMA) in the APARCH-M model, which is named ARMA-APARCH-M.

$$r_t = \mu + \sum_{i=1}^m \varphi_i r_{t-i} + \omega \sigma_t + \varepsilon_t + \sum_{j=1}^n \theta_j \varepsilon_{t-j} \quad (5)$$

$$= \mu + \text{ARMA}(m, n) + \omega \sigma_t + \varepsilon_t,$$

$$\sigma_t^\delta = \alpha_0 + \sum_{i=1}^p \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^\delta + \sum_{j=1}^q \beta_j \sigma_{t-j}^\delta, \quad (6)$$

where $\{\varphi_1, \varphi_2, \dots, \varphi_m, \theta_1, \theta_2, \dots, \theta_n\}$ is the set of AR(m) and MA(n) coefficients and ω is the contribution rates of risk to returns. The definitions of other symbols are same to equations (3) and (4).

3.3. ICA-Based ARMA-APARCH-M Model. Suppose we need to investigate whether there are volatility spillovers

from other z financial markets ($z = 2, \dots, n$) to one financial market x in the comovements process. First, the mean return equations are established for z markets:

$$\begin{aligned} r_{1t} &= \mu_1 + \sum_{i=1}^m \varphi_{1i} r_{1,t-i} + \omega_{1t} \sigma_{1t} + \varepsilon_{1t} + \sum_{j=1}^n \theta_{1j} \varepsilon_{1,t-j} r_{2t} \\ &= \mu_2 + \sum_{i=1}^m \varphi_{2i} r_{2,t-i} + \omega_{2t} \sigma_{2t} + \varepsilon_{2t} + \sum_{j=1}^n \theta_{2j} \varepsilon_{2,t-j} : r_{zt} \quad (7) \\ &= \mu_z + \sum_{i=1}^m \varphi_{zi} r_{z,t-i} + \omega_{zt} \sigma_{zt} + \varepsilon_{zt} + \sum_{j=1}^n \theta_{zj} \varepsilon_{z,t-j}, \end{aligned}$$

where $r_{1t}, r_{2t}, \dots, r_{zt}$ are the logarithmic returns of z financial markets, $\sigma_{1t}, \sigma_{2t}, \dots, \sigma_{zt}$ represent the internal market risks of stock markets, $\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{zt}$ are the return residual sequences, and $\omega_{1t}, \omega_{2t}, \dots, \omega_{zt}$ are contribution rates of the internal market risks to returns. Then, ICA is applied to transform the residual sequences into several statistically independent components that represent comprehensive indices of multiple market fluctuations.

$$\begin{aligned} s_{1t} &= w_{11} \varepsilon_{1t} + w_{12} \varepsilon_{2t} + \dots + w_{1k} \varepsilon_{kt} \\ s_{2t} &= w_{21} \varepsilon_{1t} + w_{22} \varepsilon_{2t} + \dots + w_{2k} \varepsilon_{kt} \\ &\vdots \\ s_{kt} &= w_{k1} \varepsilon_{1t} + w_{k2} \varepsilon_{2t} + \dots + w_{kk} \varepsilon_{kt}, \end{aligned} \quad (8)$$

where $s_{1t}, s_{2t}, \dots, s_{kt}$ are the independent components named as IC_1, IC_2, \dots, IC_k and $\varepsilon_{1t}, \varepsilon_{2t}, \dots, \varepsilon_{kt}$ are the return residual sequences.

Third, a univariate ARMA-APARCH-M model is established to examine spillover effects from other z financial

markets ($z = 2, \dots, n$) to one financial market x in the comovements process. That is, the independent components $s_{1t}, s_{2t}, \dots, s_{kt}$ are substituted into the mean equation of financial market x as explanatory variables to obtain an ICA-based ARMA-APARCH-M model as

$$r_{xt} = \mu_x + \sum_{i=1}^m \varphi_{xi} r_{x,t-i} + \omega_x \sigma_{xt} + \delta_1 s_{1t} + \delta_2 s_{2t} + \dots + \delta_k s_{kt} + \varepsilon_{xt} + \sum_{j=1}^n \theta_{xj} \varepsilon_{x,t-j}, \quad (9)$$

where $\delta_1, \delta_2, \dots, \delta_k$ are contribution rates of the independent components $s_{1t}, s_{2t}, \dots, s_{kt}$ to returns. If δ_i ($i = 1, \dots, k$) is significantly not zero, the new comprehensive index s_i ($i = 1, \dots, k$) has volatility spillover effects on market x .

4. Data and Empirical Results

4.1. Data. To empirically investigate volatility similarity and spillover effects of stock market comovements, we use daily closing prices of G20 stock markets from January 02, 2006, to June 18, 2018. Notably, the G20 is a global organization dealing with financial risks, and it includes nineteen countries plus the European Union as a whole. They are S&P 500 (US), Nikkei 225 (Japan), DAX (Germany), CAC 40 (France), FTSE 100 (UK), MIB (Italy), TSX (Canada), RTS (Russia), SSE Composite (China), Merval (Argentina), All Ordinaries (Australia), Bovespa (Brazil), BSE Sensex (India), Jakarta Composite (Indonesia), IPC (Mexico), TASI (Saudi Arabia), INVSAF 40 (South Africa), ISE 100 (Turkey), and KOSPI (South Korea). The long-term trends of G20 stock prices time series denoted as p_t are shown in Figure 2.

They are inherently nonstationary which means that the distribution of time series changes over time. This universal feature of financial time series makes volatility modeling a challenging task that attracts a large number of scholars to discuss [35, 36, 67]. To settle this issue, the returns r_t are calculated as $r_t = \ln(p_t/p_{t-1}) = \ln(p_t) - \ln(p_{t-1})$, which is the difference in logarithmic price. Some volatility characteristics of return series for G20 stock markets are shown in Figure 3.

First, the fluctuation trend appears to be clustered together in bunches. This phenomenon indicates that there may be conditional heteroskedasticity, which needs to be tested further. Second, there exists significant asymmetric response to positive and negative shocks, which is also called leverage effect. To further explain, the fact is that stock markets tend to be more violent on bad news and less violent on good news. During the 2008 financial crisis, the price fell like a cliff, while the stock volatility jumped dramatically. Therefore, asymmetric terms cannot be ignored when modeling on volatility of financial time series. Third, the volatility features of some stock return series are similar to others in their comovements. For example, the stock markets of the US and UK have similar volatility trends as they are impacted by common factors, such as economic development, international trade, and investment. It indicates that volatility similarity may exist in G20 stock market comovements, which must be examined further. Therefore, we intend to initially identify the comovements

and accurately determine which G20 stock markets have similar volatility features.

Before modeling volatility, we briefly analyze the descriptive statistics of G20 stock markets. The mean, standard deviation (S.D.), skewness, kurtosis, Jarque-Bera statistic, ADF test for unit root, and ARCH effect test for heteroskedasticity are presented in Table 1. The skewness of each return series is nonzero, which indicates that the series distribution is biased relative to the normal distribution. The kurtosis of each return series is greater than 3, that is, the convexity of the distribution is greater than the normal distribution. The Jarque-Bera statistics are relatively large and their associated probability p values are all close to zero.

To sum up, we can reject the null hypothesis and therefore draw a conclusion that the return series do not obey the normal distribution. In this context, some conventional models of normal hypothesis are not applicable. To overcome this drawback, ICA is used for modeling as it can reproduce high kurtosis in return series [17]. The ADF test results of the return series show that it is a stationary series, confirming the necessity of the logarithmic difference transformation on price series. The F -statistic and $T \times R^2$ testing results clearly reject the null hypothesis of no ARCH effect. The evidence shows that GARCH models should also be designed to measure heteroskedasticity. In conclusion, we provide a new approach using an ICA-based ARMA-APARCH-M model to address the cross-markets volatility spillover effects of market comovements.

4.2. Empirical Results

4.2.1. Results of Comovements Identification. One approach of detecting comovements is clustering analysis [3]. The time series clustering methods are summarized into three types: original data, feature extraction, and model parameters [68]. Among these methods, we choose model-based fuzzy C-means clustering. After establishing the ARMA-APARCH-M model to extract volatility features of high-dimensional stock return time series, a fuzzy C-means (FCM) method is used for clustering the model parameters that describe the volatility characteristics. The coefficient results estimated by the ARMA-APARCH-M model are presented in Table 2. All the parameters are significantly nonzero; thus, the actual data satisfy the hypothesis conditions of the model. The asymmetry coefficient γ in the test is statistically significant, which means that this asymmetric behavior does exist, that is, the negative impact on the fluctuation is more severe than the positive impact of the same magnitude.

This result is consistent with the conclusions of Ning et al. [69] and Bekaert et al. [67]. The asymmetry in volatility clusters of stock markets is found to be more obvious than in other financial markets [69]. Compared with a positive impact of the same size, the increase in negative impact and conditional variance is greater [67]. The risk return coefficient ω is nonzero, which denotes that the risk factor has a significant impact on returns. Thus, the risk factor should be considered in the model. The power parameter of conditional heteroskedasticity comes through $\delta > 0$, which is

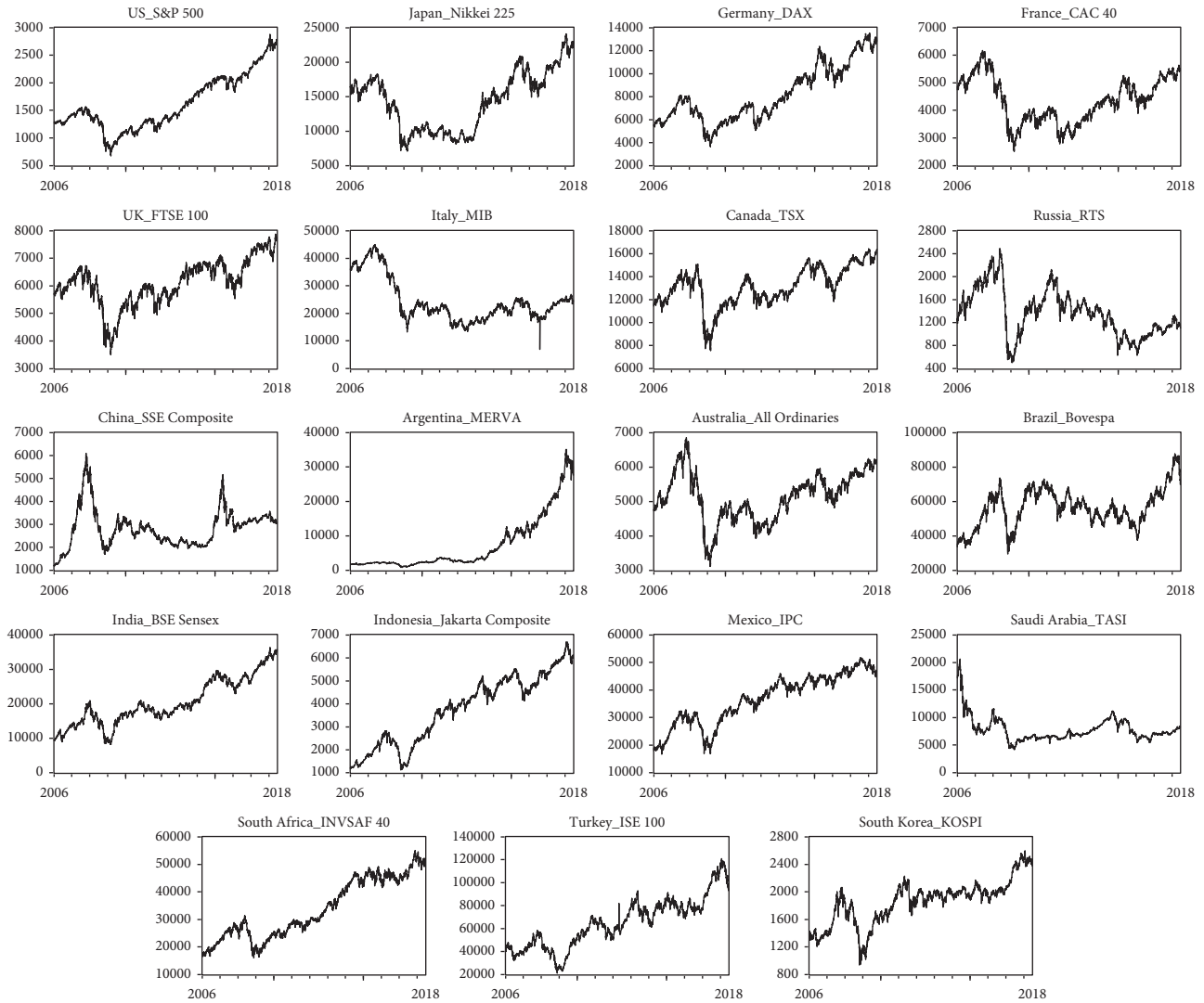


FIGURE 2: The volatility characteristics of G20 stock prices. (a) US_S&P 500, (b) Japan_Nikkei 225, (c) Germany_DAX, (d) France_CAC 40, (e) UK_FTSE 100, (f) Italy_MIB, (g) Canada_TSX, (h) Russia_RTS, (i) China_SSE Composite, (j) Argentina_MERVA, (k) Australia_All Ordinaries, (l) Brazil_Bovespa, (m) India_BSE Sensex, (n) Indonesia_Jakarta Composite, (o) Mexico_IPC, (p) Saudi Arabia_TASI, (q) South Africa_INVSAF 40, (r) Turkey_ISE 100, and (s) South Korea_KOSPI.

neither one in the Taylor/Schwert's model setting nor two in the Bollerslev's model setting, which verifies the rationality of the APARCH model. It is not a specific value setting but rather a parameter estimation. Thus, it can more accurately evaluate the impact of conditional variance. After extracting volatility features by the ARMA-APARCH-M model, we use the fuzzy C-means (FCM) method to cluster G20 stock markets into three categories, as shown in Figure 4. The proposed model identifies clusters of return series with similar volatility patterns and handles simultaneous comovements across international stock markets.

The figure indicates that there exists apparent difference between three groups obtained by clustering the G20 stock markets. Different clusters correspond to different dynamic patterns corresponding to volatility coefficients.

Cluster 1: S&P 500 (US), DAX (Germany), CAC 40 (France), FTSE 100 (UK), MIB (Italy), TSX (Canada), and All Ordinaries (Australia).

Cluster 2: Nikkei 225 (Japan), SSE Composite (China), Merval (Argentina), BSE Sensex (India), Jakarta Composite (Indonesia), TASI (Saudi Arabia), and ISE 100 (Turkey).

Cluster 3: RTS (Russia), Bovespa (Brazil), IPC (Mexico), INVSAF 40 (South Africa), and KOSPI (South Korea).

In cluster 1, the members are mainly well-developed stock markets in Europe and America. The closer economic ties and trade links between these countries have made the volatility features of financial markets more similar to each other.

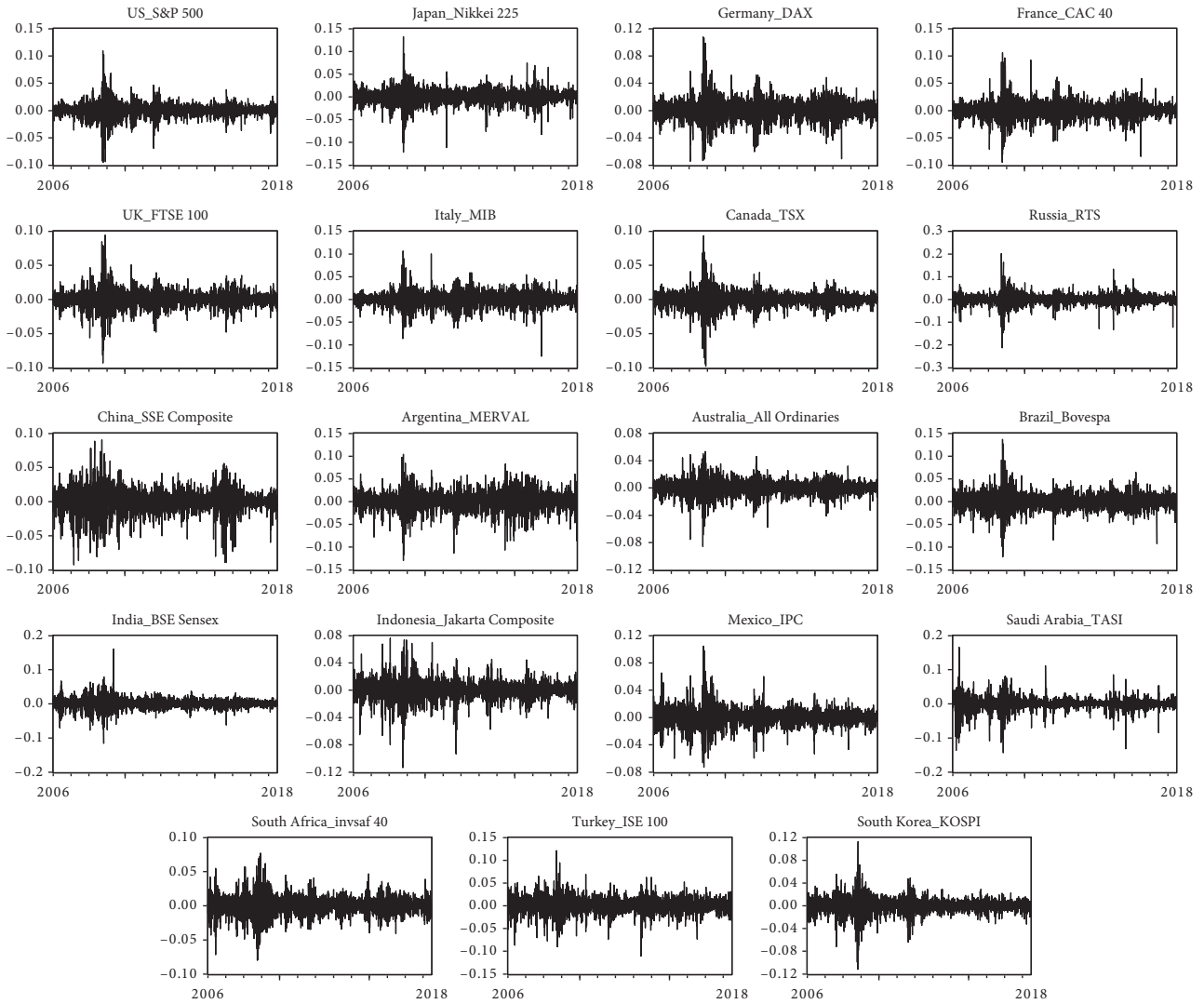


FIGURE 3: The volatility characteristics of G20 stock returns. (a) US_S&P 500, (b) Japan_Nikkei 225, (c) Germany_DAX, (d) France_CAC 40, (e) UK_FTSE 100, (f) Italy_MIB, (g) Canada_TSX, (h) Russia_RTS, (i) China_SSE Composite, (j) Argentina_MERVAL, (k) Australia_All Ordinaries, (l) Brazil_Bovespa, (m) India_BSE Sensex, (n) Indonesia_Jakarta Composite, (o) Mexico_IPC, (p) Saudi Arabia_TASI, (q) South Africa_INVSAF 40, (r) Turkey_ISE 100, and (s) South Korea_KOSPI.

It is special that almost all cluster 1 markets experienced peak volatility in October 2008 when Lehman Brothers closed down. This may be due to the sharp fluctuations of the US market during the financial turmoil, which was immediately transmitted to other member markets in cluster 1. In addition, the comovements with drastic volatile characteristics across multiple markets in cluster 1 exist significantly in the period of the European sovereign debt crisis from late 2009 to the end of 2012 and the Brexit vote on June 23, 2016. Although the volatility of each market is caused by the crisis to inconsistent extent, some similarities are shown obviously in volatility patterns and therefore volatility spillover effects may exist in cluster 1. To further confirm the existence of this effect, more accurate quantification is necessary in the following subsection. In line with our finding, Morales-Zumaquero and Sosvilla-Rivero [70] show that the US stock market is closely related to the other six stock markets, i.e., those of the UK, EU, Australia, Switzerland, Canada, and Japan.

In cluster 2, the members are mainly less well-developed stock markets in Asia, such as Japan, China, India, Indonesia, and Saudi Arabia. As shown by Zhou et al. [71]; the volatility of the Chinese market is more pronounced by the spillover effect of Japan rather than the United States and the United Kingdom. Moreover, the Indian market also has an impact on the Chinese market. Meanwhile, they also specifically point out that these volatility spillover effects exist in both directions. The large fluctuations in the Chinese market in February 2007 have been transferred to the Asian market. These facts may be attributed to the growing trend of financial integration in Asia. Thus, these Asian stock markets are clustered into one group based on volatility similarity.

In cluster 3, the members are mainly emerging stock markets that are less mature and open to foreign investors than the other markets in cluster 1. Three of these countries are the BRICS members, e.g., Russia, Brazil, and South Africa. Due to the weak openness of their domestic financial

TABLE 1: Summary descriptive statistics of G20 stock returns.

Stock indices	Mean	S. D.	Skewness	Kurtosis	Jarque-Bera	ADF test:	ARCH LM test:	
							F-statistic	$T \times R^2$
US_S&P 500	0.0002	0.0120	-0.3770	14.9110	19246.8700	-44.9070	128.3470	123.5320
Japan_Nikkei 225	0.0001	0.0152	-0.5150	11.2390	9314.9420	-59.3620	127.2750	122.5390
Germany_DAX	0.0003	0.0137	-0.0420	9.2260	5238.1310	-57.4980	102.3060	99.2350
France_CAC 40	0.0000	0.0141	-0.0050	9.5690	5831.4690	-59.6110	129.2030	124.3240
UK_FTSE 100	0.0001	0.0117	-0.1440	11.1940	9084.7360	-43.2410	206.3210	194.0850
Italy_MIB	-0.0001	0.0152	-0.2310	8.2470	3748.7100	-58.4250	121.9480	117.5950
Canada_TSX	0.0001	0.0110	-0.7060	14.8520	19249.2100	-25.9650	426.8940	377.4150
Russia_RTS	0.0000	0.0215	-0.4130	14.6270	18359.0100	-51.3530	184.1580	174.3580
China_SSE Composite	0.0003	0.0168	-0.6120	7.3980	2815.7120	-57.0240	111.4290	107.7900
Argentina_MERVAL	0.0009	0.0197	-0.4830	7.0170	2306.2880	-54.7720	191.8890	181.2690
Australia_All Ordinaries	0.0000	0.0106	-0.5830	8.6680	4524.2370	-58.5830	340.7710	308.5220
Brazil_Bovespa	0.0000	0.0170	-0.0390	9.1410	5096.1870	-58.9570	103.6580	100.5060
India_BSE Sensex	0.0000	0.0141	0.1040	13.0620	13687.0800	-54.2680	61.4310	60.3250
Indonesia_Jakarta	0.0001	0.0132	-0.6660	11.5470	10109.4500	-52.3560	118.3860	114.2820
Mexico_IPC	0.0000	0.0123	0.1030	10.1870	6984.7720	-34.9620	65.1940	63.9470
Saudi Arabia_TASI	0.0000	0.0171	-0.9680	16.6220	25581.3500	-39.3160	197.4790	186.2460
South Africa_INVSAF 40	0.0000	0.0132	-0.1170	6.9040	2066.9090	-57.3320	157.3460	150.1490
Turkey_ISE 100	0.0000	0.0164	-0.2950	7.1410	2364.6120	-56.5210	40.7560	40.2750
South Korea_KOSPI	0.0000	0.0123	-0.5950	12.9000	13434.3900	-56.9490	167.4950	159.3580

Note: S. D. is the standard deviation of G20 stock return time series. The Jarque-Bera is the normality test statistic. The critical values of the ADF test are -3.432180 at 1% level, -2.862234 at 5% level, and -2.567183 at 10% level.

TABLE 2: The coefficient results estimated by the ARMA-APARCH-M model.

Stock indices	μ	φ	ω	θ	α_0	α	γ	β	δ
US_S&P 500	0.0008	-0.3444	-0.0655	0.1482	-0.1697	0.9753	-0.0655	0.0008	-0.3444
Japan_Nikkei 225	-0.0008	-0.5427	0.0755	0.1949	-0.1120	0.9543	0.0755	-0.0008	-0.5427
Germany_DAX	0.0002	-0.3315	0.0002	0.1254	-0.1260	0.9735	0.0002	0.0002	-0.3315
France_CAC 40	-0.0003	-0.3307	0.0276	0.1126	-0.1651	0.9726	0.0276	-0.0003	-0.3307
UK_FTSE 100	-0.0009	-0.3532	0.1028	0.1329	-0.1266	0.9732	0.1028	-0.0009	-0.3532
Italy_MIB	-0.0002	-0.3033	0.0101	0.1342	-0.1117	0.9770	0.0101	-0.0002	-0.3033
Canada_TSX	0.0001	-0.2143	-0.0022	0.1196	-0.0976	0.9872	-0.0022	0.0001	-0.2143
Russia_RTS	0.0003	-0.2347	-0.0236	0.1237	-0.0754	0.9823	-0.0236	0.0003	-0.2347
China_SSE Composite	-0.0001	-0.1577	0.0414	0.1407	-0.0013	0.9936	0.0414	-0.0001	-0.1577
Argentina_MERVAL	-0.0003	-0.5958	0.0879	0.2202	-0.0503	0.9460	0.0879	-0.0003	-0.5958
Australia_All Ordinaries	-0.0003	-0.3938	0.0536	0.1503	-0.1124	0.9706	0.0536	-0.0003	-0.3938
Brazil_Bovespa	-0.0012	-0.2782	0.0861	0.1144	-0.0681	0.9771	0.0861	-0.0012	-0.2782
India_BSE Sensex	0.0002	-0.2702	0.0267	0.1745	-0.0703	0.9844	0.0267	0.0002	-0.2702
Indonesia_Jakarta Composite	-0.0005	-0.3691	0.1101	0.2050	-0.0638	0.9759	0.1101	-0.0005	-0.3691
Mexico_IPC	-0.0007	-0.2580	0.0836	0.1386	-0.0903	0.9833	0.0836	-0.0007	-0.2580
Saudi Arabia_TASI	0.0012	-0.3862	-0.0848	0.2432	-0.0741	0.9744	-0.0848	0.0012	-0.3862
South Africa_INVSAF40	-0.0006	-0.3108	0.0870	0.1349	-0.1104	0.9772	0.0870	-0.0006	-0.3108
Turkey_ISE 100	0.0011	-0.4093	-0.0432	0.1610	-0.0746	0.9658	-0.0432	0.0011	-0.4093
South Korea_KOSPI	-0.0006	-0.2821	0.0795	0.1408	-0.0774	0.9808	0.0795	-0.0006	-0.2821

Note: μ , φ , ω and θ denote the coefficients of the mean equation, while α_0 , α , γ , β , and δ denote the coefficients of the conditional variance equation. φ and θ are the coefficients of ARMA process indicating autoregressive and moving average. ω is the risk return which exhibits the impact from the conditional variance to return. γ is the asymmetry coefficient. δ is the power parameter of conditional heteroskedasticity.

markets, they were less impacted by the global financial crisis.

The most important implication of comovements identification is risk management in the stock markets. We can uncover volatility similarities by the method that reveals comovements of stock markets across the world. The motivation of this process is to inspire the investors' interest for higher returns in stock markets by using relevant information of the comoving markets in the same cluster as prior

knowledge. Our results demonstrate the benefits of our study, wherein the empirical discussion allows better understanding of the comovements across multiple markets. Therefore, the risk measured by volatility can be detected in one stock market that is similar to other comoving markets.

4.2.2. Volatility Spillover Effects in Cluster 1. Using an ICA-based ARMA-APARCH-M model, we seek to answer

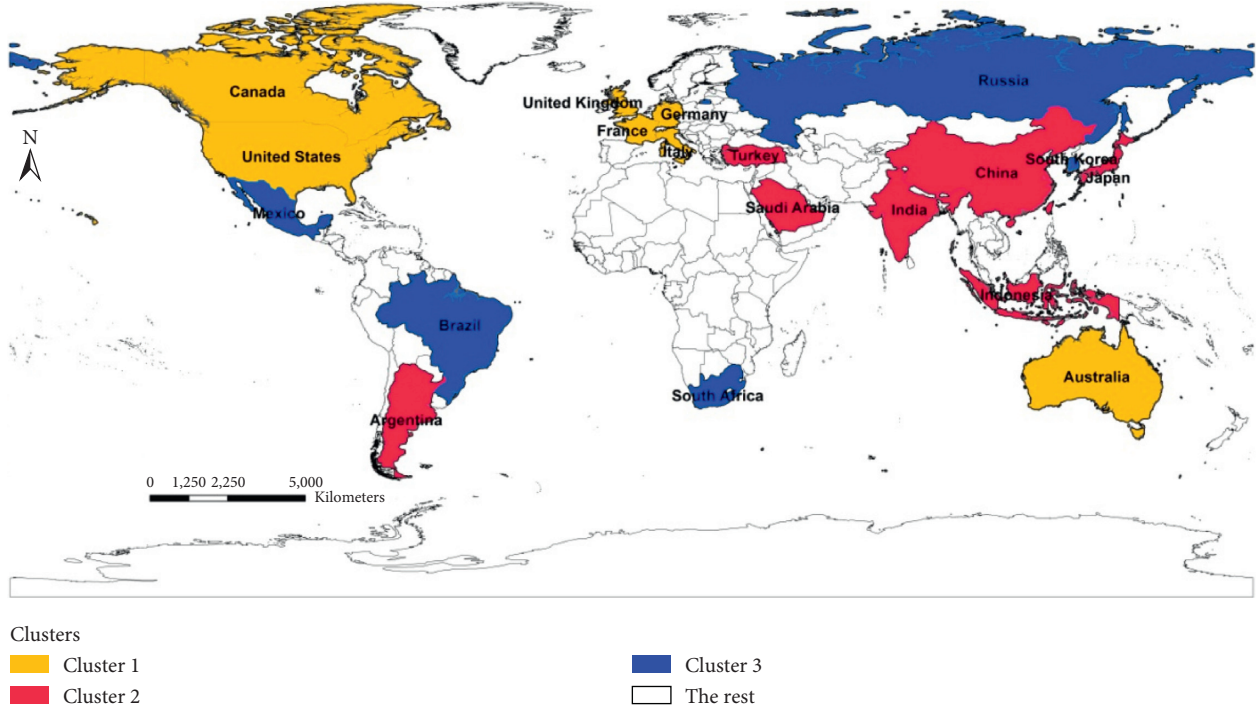


FIGURE 4: The clustering results of G20 stock markets.

questions (ii) and (iii) mentioned in the introduction. That is, among markets with similar volatility, are there spillover effects in market comovements? If there are spillover effects in two or more markets, which is the dominant source of spillovers? To address these questions, we use the FastICA algorithm [66] in each cluster to examine the spillover effects from multiple markets to one market. Take cluster 1 for example. We choose the S&P 500 (US) as the objective or the explained variable to investigate whether the other six stock markets (DAX, CAC 40, FTSE 100, MIB, TSX, and All Ordinaries) with similar volatility patterns in cluster 1 have volatility spillover effects to the S&P 500 and which is the dominant source. The residual series of six

stock returns drawn by the ARMA-APARCH-M model are shown in Figure 5.

First, we employ ICA to the residual series $\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}, \varepsilon_{4t}, \varepsilon_{5t}$, and ε_{6t} of DAX (Germany), CAC 40 (France), FTSE 100 (UK), MIB (Italy), TSX (Canada), and All Ordinaries (Australia). The demixing matrix W_1 is given by equation (10). The numbers in matrix W_1 are the weights of each independent component (IC), which is a composite index obtained by the linear combination of residual series. The weight of each stock market in each independent component is clear.

$$W_1 = \begin{pmatrix} 23.6145 & 109.2491 & -4.9218 & -143.9797 & -2.5157 & -2.1065 \\ 64.4442 & 76.0391 & -187.6554 & 3.0148 & -3.1082 & 7.5524 \\ -58.7561 & -34.8238 & 8.2896 & 26.5095 & -20.7591 & 16.6815 \\ 17.2218 & 11.9073 & 45.4227 & -0.2849 & -106.0729 & 27.1261 \\ 0.7523 & -0.5108 & -1.5688 & -5.5844 & 29.5780 & 88.8336 \\ -165.2102 & 205.4445 & -39.5022 & -8.1738 & 0.0620 & -1.1539 \end{pmatrix}. \quad (10)$$

Then, we further discover something valuable from the weights of each independent component, $IC_1, IC_2, IC_3, IC_4, IC_5$, or IC_6 . In IC_1 , ε_{4t} has the maximum absolute value of the weight (-143.9797) in the first row of the matrix W_1 , which is significantly higher than that of other sequences $\varepsilon_{1t}, \varepsilon_{2t}, \varepsilon_{3t}, \varepsilon_{5t}$, and ε_{6t} . Therefore, it is believed that IC_1 mainly represents the residual series ε_{4t} , i.e., MIB (Italy).

Respectively, IC_2 mainly represents the residual series ε_{3t} , i.e., FTSE 100 (UK); IC_3 mainly represents the residual series ε_{1t} , i.e., DAX (Germany); IC_4 mainly represents the residual series ε_{5t} , i.e., TSX (Canada); IC_5 mainly represents the residual series ε_{6t} , i.e., All Ordinaries (Australia); and IC_6 mainly represents the residual series ε_{2t} , i.e., CAC 40 (France). The ICs shown in Figure 6 are statistically

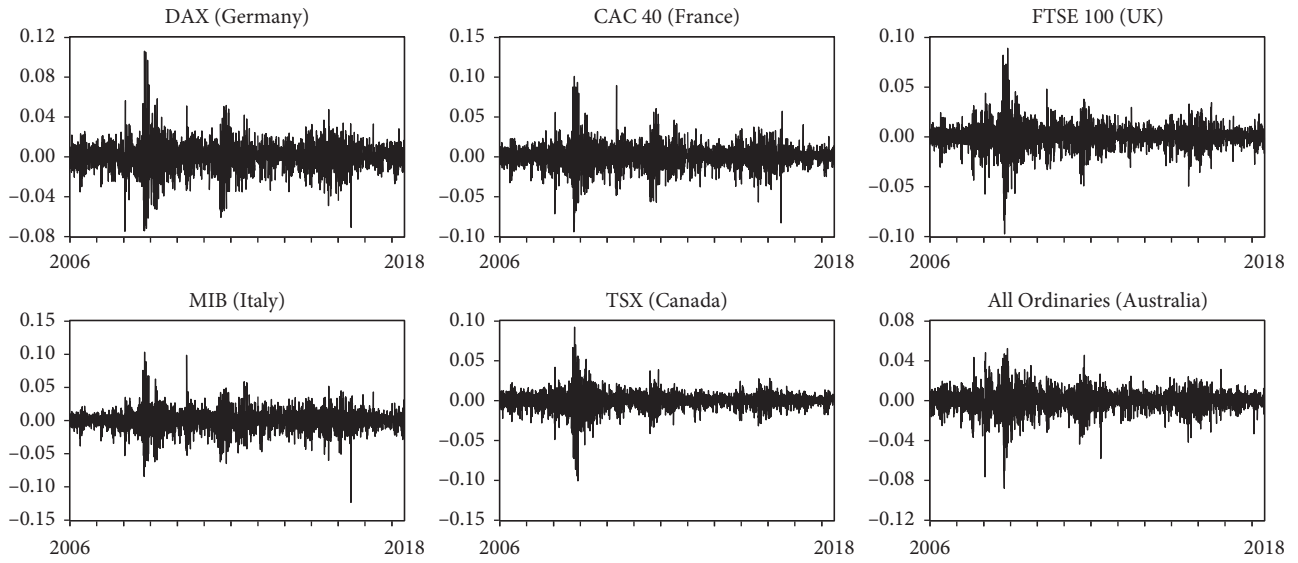


FIGURE 5: The residual series given by the ARMA-APARCH-M model. (a) DAX (Germany), (b) CAC 40 (France), (c) FTSE 100 (UK), (d) MIB (Italy), (e) TSX (Canada), and (f) All Ordinaries (Australia).

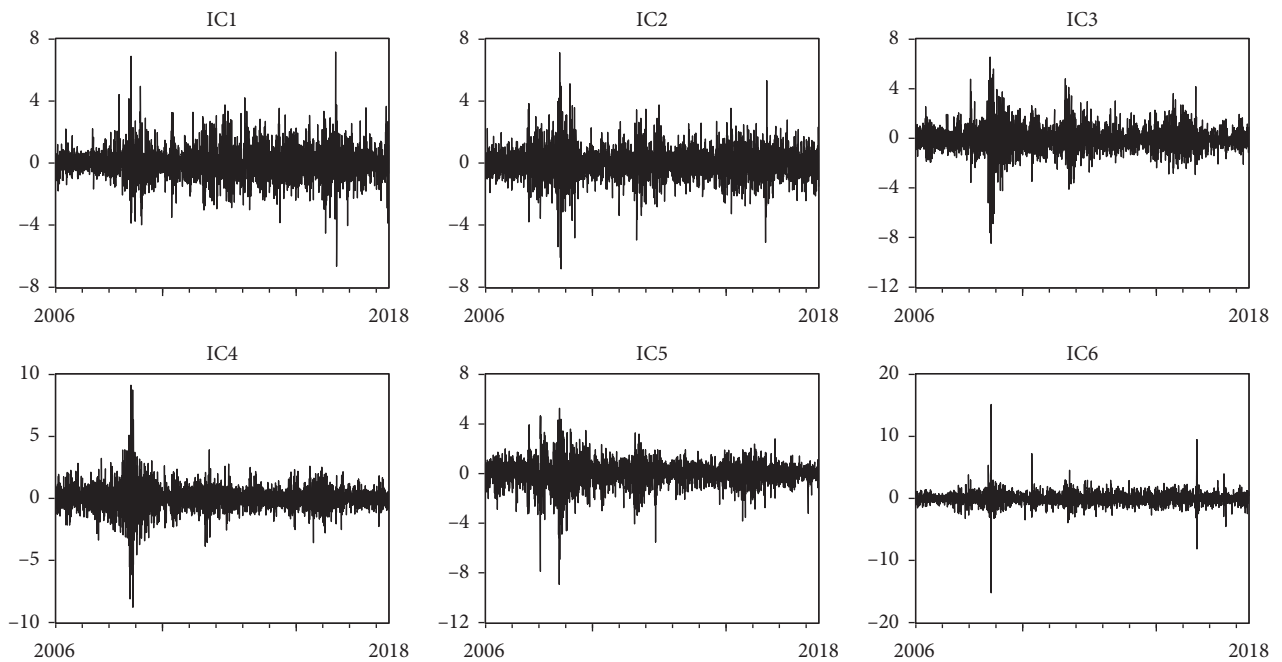


FIGURE 6: The time series of $IC_1, IC_2, IC_3, IC_4, IC_5,$ and IC_6 for cluster 1. (a) IC_1 , (b) IC_2 , (c) IC_3 , (d) IC_4 , (e) IC_5 , and (f) IC_6 .

independent; thus, multicollinearity is avoided in the following model.

After estimating the ICs, we fit a univariate ARMA-APARCH-M model to each of them. That is, $IC_1, IC_2, IC_3, IC_4, IC_5,$ and IC_6 are incorporated as explanatory variables to equation (9). The coefficient results estimated by the ICA-based ARMA-APARCH-M model for cluster 1 are listed in Table 3. The mean equation and the conditional variance equation are given by equations (11) and (12), respectively. The contribution of each IC is listed, which denotes the volatility

spillover effects from each IC to S&P 500 (US) in equation (11). The results show that there are volatility spillovers from independent components (ICs) to S&P 500 (US). According to the coefficients in Table 3, the ICs can be ordered as follows: $IC_3, IC_4, IC_5, IC_1, IC_2,$ and IC_6 . Therefore, the dominant source of volatility spillovers is IC_3 representing DAX (Germany), followed by IC_4 representing TSX (Canada), IC_5 representing All Ordinaries (Australia), IC_1 representing MIB (Italy), IC_2 representing FTSE 100 (UK), and IC_6 representing CAC 40 (France), as shown in Figure 7.

TABLE 3: The results estimated by the ICA-based ARMA-APARCH-M model for cluster 1.

Variable	Coefficient	Std. error	z-statistic	Prob.
IC ₁	-0.0016	0.0001	-17.5293	$p \leq 0.001$
IC ₂	-0.0015	0.0001	-17.1906	$p \leq 0.001$
IC ₃	-0.0073	0.0001	-84.0053	$p \leq 0.001$
IC ₄	-0.0026	0.0001	-24.7667	$p \leq 0.001$
IC ₅	0.0021	0.0001	23.7606	$p \leq 0.001$
IC ₆	0.0007	0.0001	7.2746	$p \leq 0.001$

Note: The coefficient denotes the contribution of each IC which indicates the impact from each IC to S&P 500 (US) in mean equation of return.

$$\begin{aligned}
r_{xt} = & 0.0001 + 0.1174^* r_{x,t-1} + 0.0434^* \sigma_{xt} + \varepsilon_{xt} \\
& - 0.3212^* \varepsilon_{x,t-1} - 0.0016^* \text{IC}_1 - 0.0015^* \text{IC}_2 \\
& - 0.0073^* \text{IC}_3 - 0.0026^* \text{IC}_4 + 0.0021^* \text{IC}_5 \\
& + 0.0007^* \text{IC}_6,
\end{aligned} \quad (11)$$

$$\begin{aligned}
\sigma_{xt}^{1.4777} = & 0.1261^* \left(|\varepsilon_{x,t-1}| - 0.2791^* \varepsilon_{x,t-1} \right)^{1.4777} \\
& + 0.8591^* \sigma_{x,t-1}^{1.4777}.
\end{aligned} \quad (12)$$

This may make sense for the fact that the return series of the G20 stock markets tend to move together over the same periods. It is widely believed that there exist volatility spillover effects across international financial markets, and the comovements among them become more apparent during the global financial crisis [72]. Consistent with that, Shahzad et al. [73] indicated that the US stock market is a major recipient of spillover effects from European markets.

Similarly, BenSaïda et al. [35] revealed that the German market largely contributes to the risk of other markets (US, UK, France, Netherlands, Switzerland, Hong Kong, and Japan), with 94.8% of risk spillovers, followed by UK with 85.3%.

4.2.3. Volatility Spillover Effects in Cluster 2. Repeat the abovementioned procedures for cluster 2. We choose Nikkei 225 (Japan) as the objective or the explained variable to investigate whether the other six stock markets (SSE Composite, Merval, BSE Sensex, Jakarta Composite, TASI, and ISE 100) with similar volatility patterns in cluster 2 have volatility spillovers to Nikkei 225 and which is dominant. The demixing matrix \mathbf{W}_2 is given by the following equation:

$$\mathbf{W}_2 = \begin{pmatrix} -2.3828 & -7.1177 & -15.0659 & -15.6862 & -1.1394 & 68.2009 \\ 5.1260 & 4.1618 & -80.8038 & 22.3446 & 2.8544 & 3.7693 \\ 61.0537 & -0.9735 & -3.2500 & -11.3021 & -0.1312 & 1.7050 \\ 2.8788 & 0.8582 & -0.9470 & 5.1762 & -59.2972 & 2.5249 \\ 2.6402 & 1.0968 & 11.9850 & -82.7679 & 5.5286 & 0.4012 \\ -3.2147 & 53.6616 & -5.3618 & -6.9119 & -1.8459 & -6.4739 \end{pmatrix}. \quad (13)$$

From the weights of each independent component, IC₁, IC₂, IC₃, IC₄, IC₅, or IC₆, we can see that IC₁ mainly represents ISE 100 (Turkey), IC₂ represents BSE Sensex (India), IC₃ represents SSE Composite (China), IC₄ represents TASI (Saudi Arabia), IC₅ represents Jakarta Composite (Indonesia), and IC₆ represents Merval (Argentina), as shown in Figure 8.

The ICs are statistically independent; therefore, multicollinearity is avoided in the following model. The coefficient results estimated by the ICA-based ARMA-APARCH-M model for cluster 2 are shown in Table 4. The mean equation of return and the conditional variance equation are given by equations (14) and (15), respectively. The contribution of each IC is listed, which denotes the impact from each IC to Nikkei 225 (Japan) in equation (14).

$$\begin{aligned}
r_t = & -0.0003 - 0.0451^* r_{t-1} + 0.0469^* \sigma_t + \varepsilon_t \\
& - 0.0599^* \varepsilon_{t-1} + 0.0010^* \text{IC}_1 - 0.0029^* \text{IC}_2 \\
& + 0.0021^* \text{IC}_3 - 0.0015^* \text{IC}_4 - 0.0044^* \text{IC}_5 \\
& + 0.0006^* \text{IC}_6,
\end{aligned} \quad (14)$$

$$\begin{aligned}
\sigma_t^{1.1540} = & 0.0002 + 0.1183^* \left(|\varepsilon_{t-1}| - 0.3823^* \varepsilon_{t-1} \right)^{1.1540} \\
& + 0.8720^* \sigma_{t-1}^{1.1540}.
\end{aligned} \quad (15)$$

The results show that there exist volatility spillover effects from independent components to Nikkei 225 (Japan). According to the coefficients in Table 4, the six ICs can be ordered as follows: IC₅, IC₂, IC₃, IC₄, IC₁, and

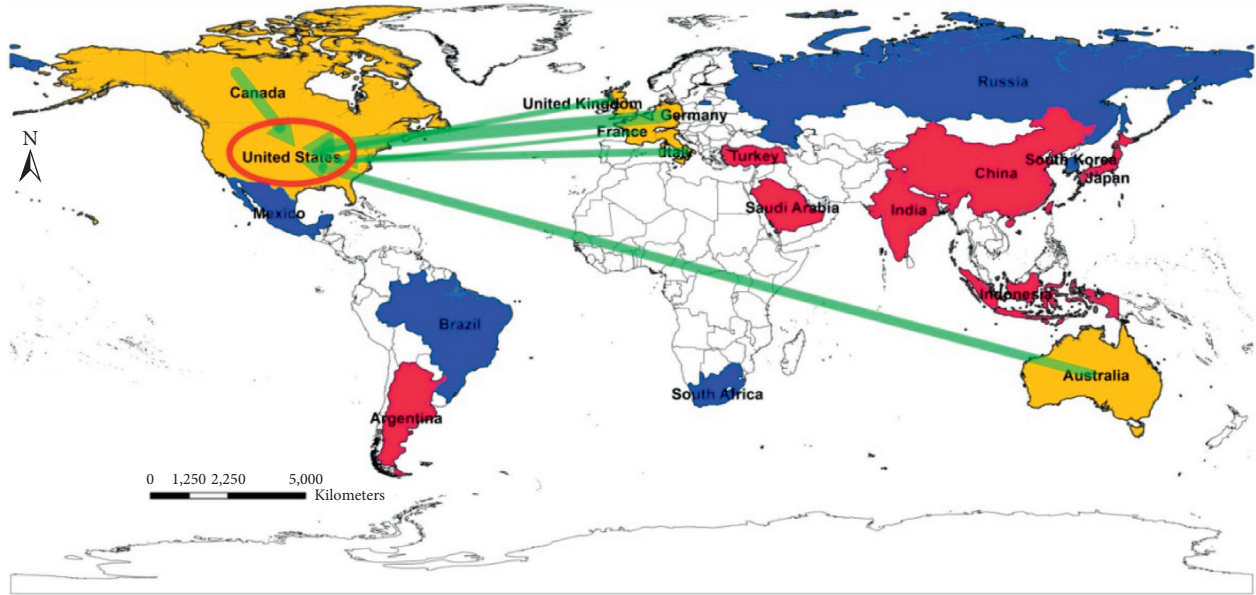


FIGURE 7: The volatility spillovers from DAX (Germany), CAC 40 (France), FTSE 100 (UK), MIB (Italy), TSX (Canada), and All Ordinaries (Australia) to S&P 500 (US).

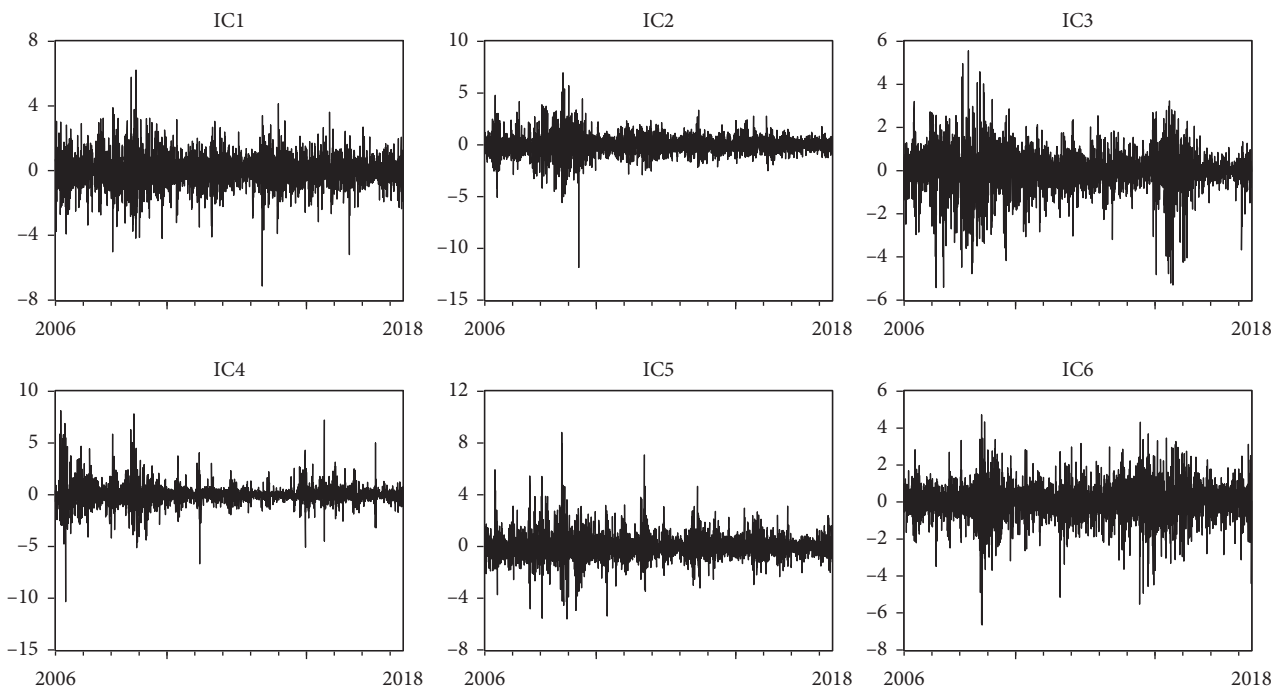


FIGURE 8: The time series of $IC_1, IC_2, IC_3, IC_4, IC_5,$ and IC_6 for cluster 2. (a) IC_1 , (b) IC_2 , (c) IC_3 , (d) IC_4 , (e) IC_5 , and (f) IC_6 .

IC_6 . The dominant source of volatility spillovers is Jakarta Composite (Indonesia), followed by BSE Sensex (India), SSE Composite (China), TASI (Saudi Arabia), ISE 100 (Turkey), and Merval (Argentina), as shown in Figure 9. Different from this result, Zhou et al. [71] concluded that the Japanese stock market is more impacted by the US

market, which is in accordance with the finding of Lien et al. [74]. However, there is another finding in Zhou et al.'s [71] study that volatility spillover effects of equity markets from China to Japan gradually increased from late 2006 and became more pronounced between February and July in 2007. This may be supportive to explain our

TABLE 4: The results estimated by the ICA-based ARMA-APARCH-M model for cluster 2.

Variable	Coefficient	Std. error	z-statistic	Prob.
IC ₁	0.0010	0.0002	5.5578	$p \leq 0.001$
IC ₂	-0.0029	0.0002	-16.9653	$p \leq 0.001$
IC ₃	0.0021	0.0002	11.3034	$p \leq 0.001$
IC ₄	-0.0015	0.0002	-9.1943	$p \leq 0.001$
IC ₅	-0.0044	0.0002	-25.2339	$p \leq 0.001$
IC ₆	0.0006	0.0002	3.2686	$p \leq 0.001$

Note: the coefficient denotes the contribution of each IC which indicates the impact from each IC to Nikkei 225 (Japan) in mean equation of return.

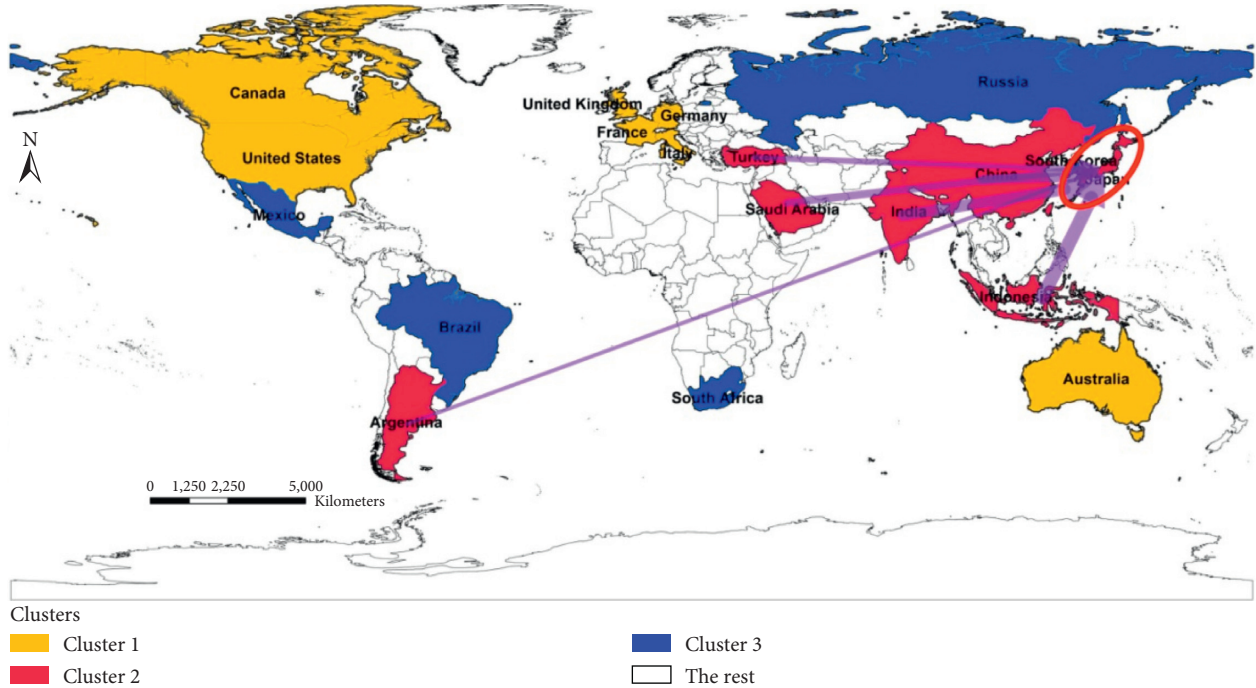


FIGURE 9: The volatility spillovers from SSE Composite (China), Merval (Argentina), BSE Sensex (India), Jakarta Composite (Indonesia), TASI (Saudi Arabia), and ISE 100 (Turkey) to Nikkei 225 (Japan).

result that there exist relatively significant volatility spillover effects between stock markets in China and Japan, since the relationship between these two markets had been experiencing the climax period from the end of 2006 to July 2007.

$$W_3 = \begin{pmatrix} -6.1012 & -12.3333 & 89.1063 & -36.2422 \\ 5.9370 & 82.6484 & -16.2380 & -1.3493 \\ 79.5860 & -71.0763 & -10.1331 & -4.9205 \\ 2.6659 & 14.2862 & -6.2117 & -81.6311 \end{pmatrix} \quad (16)$$

4.2.4. *Volatility Spillover Effects in Cluster 3.* Repeat the abovementioned procedures for cluster 3. We choose RTS (Russia) as the objective or the explained variable to investigate whether the four stock markets (Bovespa, IPC, INVSaf 40, and KOSPI) with similar volatility patterns in cluster 3 have volatility spillovers to RTS and which is dominant. The demixing matrix W_3 is given by the following equation:

From the weights of each independent component, IC₁, IC₂, IC₃, or IC₄, we can see that IC₁ mainly represents INVSaf 40 (South Africa), IC₂ represents IPC (Mexico), IC₃ represents Bovespa (Brazil), and IC₄ represents KOSPI (South Korea), as shown in Figure 10.

The ICs are statistically independent; thus, multicollinearity is avoided in the following model. The coefficient results estimated by the ICA-based ARMA-APARCH-M model for cluster 3 are shown in Table 5. The mean equation

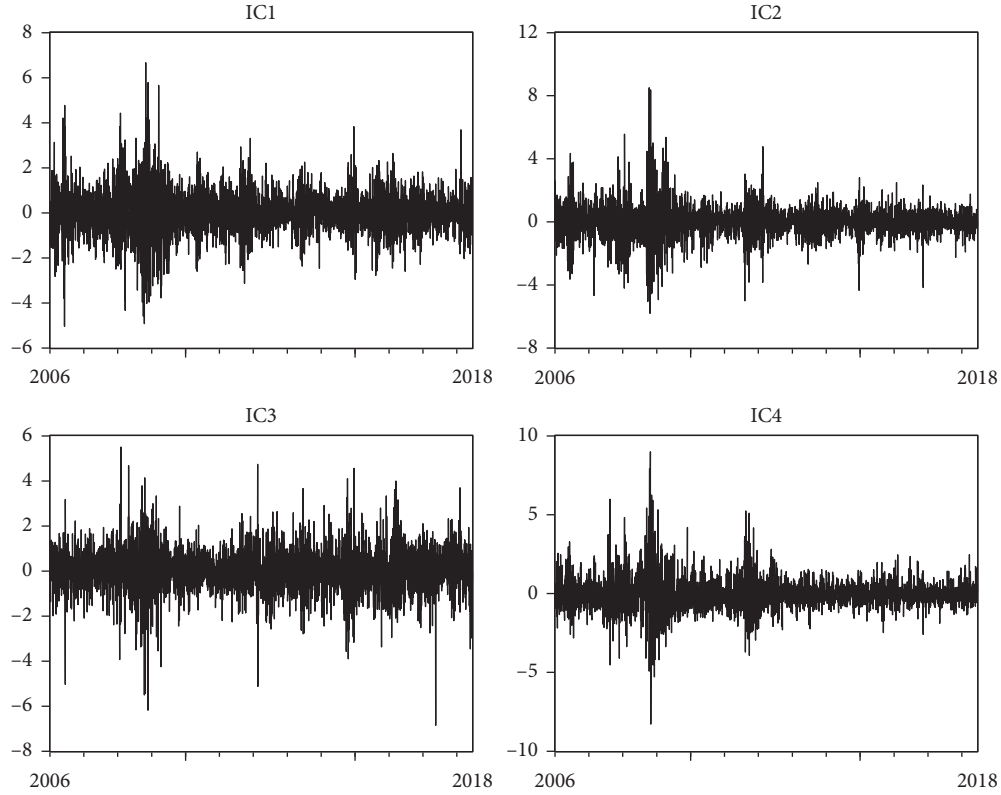


FIGURE 10: The time series of $IC_1, IC_2, IC_3,$ and IC_4 for cluster 3. (a) IC_1 , (b) IC_2 , (c) IC_3 , and (d) IC_4 .

TABLE 5: The results estimated by the ICA-based ARMA-APARCH-M model for cluster 3.

Variable	Coefficient	Std. error	z-statistic	Prob.
IC_1	0.0071	0.0002	29.3460	$p \leq 0.001$
IC_2	0.0057	0.0002	25.0421	$p \leq 0.001$
IC_3	0.0025	0.0002	10.6856	$p \leq 0.001$
IC_4	-0.0062	0.0002	-26.0124	$p \leq 0.001$

Note: the coefficient denotes the contribution of each IC which indicates the impact from each IC to RTS (Russia) in mean equation of return.

of return and the conditional variance equation are given by equations (17) and (18), respectively. The contribution of each IC is listed, which denotes the impact from each IC to RTS (Russia) in equation (17).

$$\begin{aligned}
 r_t = & -0.0001 - 0.9998 * r_{t-1} + 0.0083 * \sigma_t + \varepsilon_t \\
 & + 1.0021 * \varepsilon_{t-1} + 0.0071 * IC_1 + 0.0057 * IC_2 \\
 & + 0.0025 * IC_3 - 0.0062 * IC_4,
 \end{aligned} \quad (17)$$

$$\begin{aligned}
 \sigma_t^{1.1540} = & 0.0002 + 0.1183 * (|\varepsilon_{t-1}| - 0.3823 * \varepsilon_{t-1})^{1.1540} \\
 & + 0.8720 * \sigma_{t-1}^{1.1540}.
 \end{aligned} \quad (18)$$

There are clear volatility spillovers from independent components (ICs) to RTS (Russia). According to the coefficients in Table 5, the four ICs can be ordered as follows: $IC_1, IC_4, IC_2,$ and IC_3 . The dominant source of volatility spillovers is INVSAF 40 (South Africa), followed by KOSPI (South Korea), IPC (Mexico), and Bovespa (Brazil), as shown in Figure 11.

One possible reason for the spillover transmission of South African and Brazilian markets towards the Russian market may be the increasing cooperation and win-win outcomes among BRICS countries in recent years. BRICS countries have been less impacted by the global financial crisis in light of the weak openness of their domestic financial markets; therefore, the volatility features of these

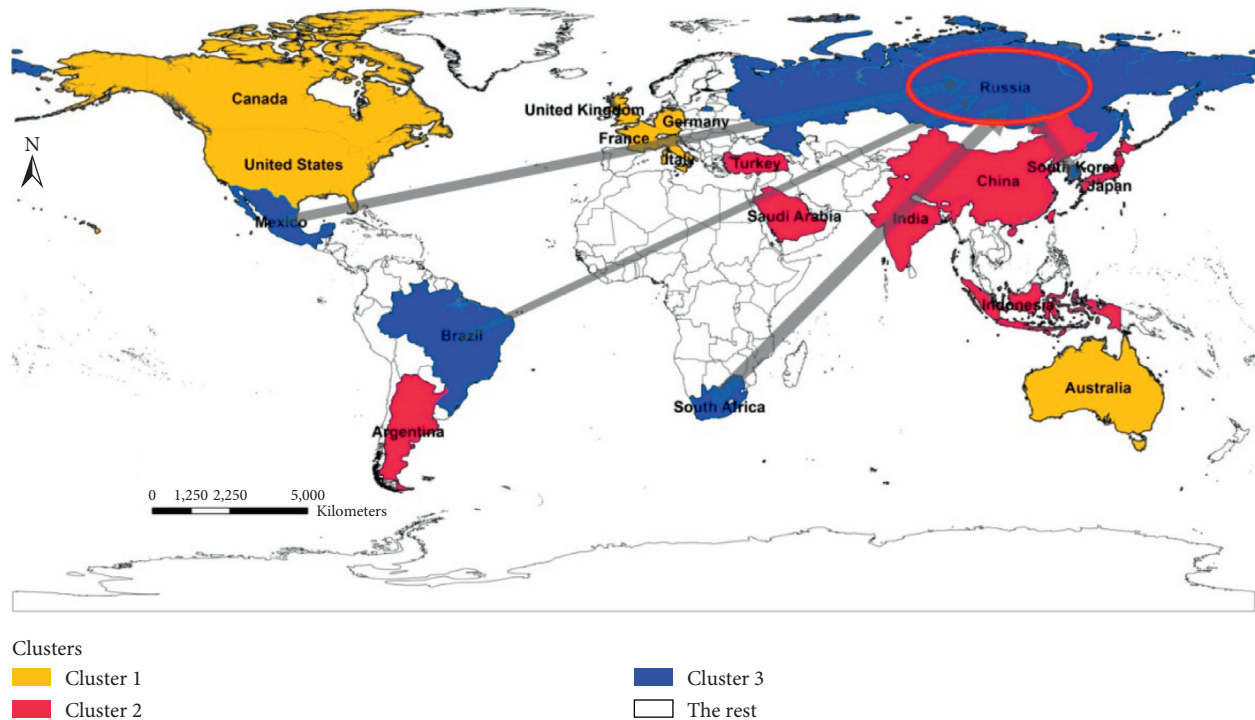


FIGURE 11: The volatility spillovers from Bovespa (Brazil), IPC (Mexico), INVSAF 40 (South Africa), and KOSPI (South Korea) to RTS (Russia).

markets are significantly different from those of the European and American markets in cluster 1.

5. Conclusion

In this study, the volatility similarity and spillover effects of G20 stock market comovements are examined using the ICA, ARMA-APARCH-M model, and fuzzy C-means clustering methods. This is a high-dimensional volatility problem of financial time series, involving nineteen financial markets. We cluster the G20 stock markets into three categories according to the volatility similarity and examine volatility spillover effects of the stock market comovements in each cluster.

The contribution of this study to the extant literature lies in three folds. First, an innovative method is adopted to examine the volatility spillover effects in G20 stock market comovements. This is due to the fact that financial volatility arises from some underlying factors representing the financial variables' comovements. Second, we can capture the common volatility spillovers from multiple markets to one as the comovements of financial variables. Third, this study has some implications for investors and policymakers in G20 stock markets. They are clustered into three categories, and there are spillover effects in stock market comovements of each cluster. Furthermore, the dominant source of volatility spillovers can be identified from multiple markets.

Some valuable findings can be drawn from the volatility similarity and spillover effects analysis on G20 stock market comovements, summarized as follows. First, we do confirm a striking feature of volatility similarity existing in the

comovements of G20 stock markets. Second, there exist spillover effects in stock market comovements group. Third, the dominant source can be identified from the spillover process. Furthermore, given that the changing interactions between stock markets are important reference for investment decision and policy making, our conclusion based on the proposed method provides practical implications to the participants of G20 financial markets.

The investors should be warned that it is becoming increasingly difficult to build portfolios to reduce systemic risk through real-time monitoring and tracking of major financial markets as the dynamic interactions among these heterogeneous agents increase. Investors seeking potential investment opportunities in complex financial systems should pay close attention to the interdependent dynamics among these comoving markets and adjust their investment strategies and asset allocation accordingly. They can identify cross-market volatility spillovers in advance and further seek the arbitrage opportunities to achieve the goal of improving their investment efficiency. For policy makers, risk regulation in the early stages of a financial crisis requires close attention to these heterogeneous, dynamic, and interactive financial markets. They can better formulate and implement strong relevant policy measures to stabilize the financial system by closely monitoring which are the dominant volatility transmitters.

For future study, we suggest conducting detailed explorations on the price risk caused by volatility spillovers of high-frequency trading data in stock markets. Quantifying the risk based on volatility is very important to investors and policy makers. Future work will help to effectively measure and monitor the risk of stock markets in real time.

Data Availability

The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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