Volatility Spillover Between Chinese Stock Market and Selected Emerging Economies: A Dynamic Conditional Correlation and Portfolio Optimization Perspective

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Abstract
This paper examines the spillover effect from Chinese stock market to select emerging economies to check the diversification opportunities. The study analysed the data in three different periods including full period from January 3, 2000 to February 7, 2020; first sub period from January 3, 2000 to October 18, 2009 and second sub period from October 19 to February 7, 2020. We applied Granger Causality and Dynamic Conditional Correlation Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) to investigate the spillover between Chinese and emerging economies. Referring to the Granger causality, it reveals that there is bi-directional causality between China and Indonesia only in full period. Further, DCC-GARCH indicates that there is spillover effect from the Chinese market to the Indonesian stock market in full period of observations both in the short run and long run. There is no spillover effect from China to emerging economies in first and second sub periods. We recommend that portfolio managers investing in Chinese economy may explore emerging economies as possible destinations to diversify their risk.

Keywords Volatility spillover · Dynamic conditional correlation · Emerging economies · Portfolio diversification · Causality

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1 Introduction

After financial liberalization and globalization in the 1990s, the world economies have been interlinked. Due to the interconnectedness of the markets, it has found a high spillover originated from the developed countries to developing countries. Some countries are moving in tandem while other countries are showing negative correlation; there is evidence of neutral interrelations too (Bekaert, 1995; Huang et al., 2000; Lucey et al., 2010, Beirne et al., 2010, Liang, C et al., 2015). The dynamic linkages or spillover among different markets provides ample opportunities to build international portfolios instead of restricted to sectors of an individual nation. Building up global portfolio motivates investors by investing in various countries which furnishes a hedge to their portfolio against a country-specific risk. Within the paradigm of international portfolio diversification, the studies show that the investment in emerging economies has been increasing from the last two decades (Delios, A. & Henisz, W.I., 2017). Investing in emerging countries markets are the most attractive avenues for investments among the foreign portfolio investors (Bekaert, G. & Harvey, C.R., 2003). Further, the importance of emerging countries in the portfolio of foreign investors reflects the enormous scope to do research and suggest robust strategies to manage portfolio (2001). Behind that, it has analyzed the fascination of FPIs, specifically in emerging economies which is derived due to the pattern of the growth perceived after liberalization (World Bank, 2001). Thus, emerging economies are promising high returns subject to high risk. On this note, it is imperative to examine the spillover effect of volatility from Chinese to select emerging market.

However, return and risk go hand in hand. Emerging economies are more prone to international vulnerability, especially, financial crisis, macro factors, political and other tangible and intangible events. FPIs are always sensitive to market efficiencies and macro-economic factors while investing in emerging countries. Thus, FII’s acted as a strong determinant of stock prices in emerging countries (Sultana, S.T. & Pardhasaradhi, S., 2012; Kumar, S.S, 2010). Because of high returns and linkages with developed nations, studies already done on emerging economies and portfolio optimization among indices or stocks of developing countries. Some studies supplement the emerging economies with other asset class like crude oil, gold, cryptocurrencies, etc. We consider emerging economies as these countries are coming up with various economic/financial reforms to speed up the growth and maintain sustainable growth rate. Adoption of economic and financial reforms in these economies is reflecting specific structural changes. Because of strong linkages, these economies have been affected by the international financial crisis, which reflects structural changes in the economy. This structural change causes structural breaks in data considered for the present study. In the context of structural change, large numbers of studies have already done on the spillover effect of financial liberalization and financial crisis on emerging markets. Studies related to the impact of liberalization on the stock markets (Cunado, J., Biscarri, JG., et al., 2006, Rejeb, A.B., & Bougrara, A., 2013) and the studies on the volatility transmission of the financial crisis among the emerging markets (Dimitriou et al., 2013, Kim., et al., 2015; Gulzar et al., 2019).

The existing studies already analyzed the linkages between developed counties and emerging or in between emerging countries. However, this paper examines the
linkages between China and other emerging countries during the financial crisis. China considered being the world second-largest economy after the U.S. and the largest economy in developing countries. According to the IMF Report (2020), the world GDP is around $90.84 trillion where the US has contributed $ 21.44 trillion. As the second-largest economy, the Chinese economy has added $ 13.37 trillion to the world GDP. The emerging economies are contributing around 80% to the world GDP, where China is standalone contributing $14.41 trillion. Hence, China considered as the strongest and one of the fascinating countries among emerging nations along with most lucrative destinations to invest (Carmen Stoian 2013).

Source: International Monetary Fund (IMF).

The purpose of this paper is to analyse the spillover effect of China with rest of the four emerging economies namely China, India, Indonesia, Brazil and Mexico. We consider the data extending from January 3, 2000 to February 7, 2020. Further this period is divided into two sub-periods; first sub-period extends from January 3, 2000 to October 18, 2009, and second sub-period extends from October 19, 2009 to February 7, 2020. For empirical analysis, Granger Causality and Dynamic Conditional Correlation (DCC) have been employed. The result obtained from Granger causality depict that there is bi-directional causality between China and Indonesia only in full period while DCC reveals that there is spillover effect from the Chinese market to the Indonesian stock market in full period of observations both in the short run and long run. Further, it is evident that there is no spillover effect from China to emerging economies in first and second sub periods. Thus, the paper covered the vast scope and suggested the portfolio strategy in various scenarios. The results of the paper are best suited to foreign portfolio investors (FPIs), who have always kept a close eye/bird’s eye view on indices or stocks of emerging economies for investments. This paper contributes to existing studies in threefold: first, it investigates the spillover effect of volatility from Chinese stock market to other four emerging countries. Second, divides the data of this study in two different periods to curb the structural break points in form of financial crisis. Third, this paper employs Granger causality
and dynamic conditional correlation (DCC) simultaneously to validate the result of spillover among these constituent markets.

The rest of the sections are structured as follows: section two provides the extent literature on spillover among various assets class. Section 3 discusses the data and econometric models employed in this paper. Further, section four furnishes the empirical results followed by conclusion and policy implication.

2 Review of literature and rationale of the study

The advent of liberalization in financial markets provides significant evidence of linkages of financial markets. Enormous studies have been done post liberalization on inter-linkages of economies. Thus, after liberalization of financial markets and with the advent of international portfolio diversification in 1974, a wide range of opportunities of investment in international portfolios is provided. Several studies found mid-seventies on international portfolios. In the early-mid-seventies studies shows negative, weak linkages among various markets (Hilliard, 1979). The weak linkages among countries provide lucrative opportunities to diversify. Afterwards, this linkage converges to positive because of the globalization and free trade among the nations. Later on, the financial crisis had shown significant evidence via various studies of the volatility transmission from the US to various countries. In the light of portfolio diversification, emerging countries are showing enormous growth, and thus it takes the significant chunk in international investor’s portfolio. The study is on the spillover effect of China being the dominant economy on various emerging countries. Further, the study considered the spillover effect among them pre and post-financial crisis. Thus, the literature review of the paper has been segregated into various segments, i.e. studies related to spillover from developed countries to emerging countries and portfolio optimization. Emerging countries and other asset class portfolio strategies. Broadly, the literature further extends to the spillover effect of the Chinese market on emerging and other markets as below.

2.1 Studies with respect to emerging countries and other assets class

Balli et al., (2015) identified the return volatility of emerging countries and the spillover from developed to emerging markets. They analyzed that the twenty emerging countries having significant spillover from developed markets. Brana, S., Djigbenou, M.L. & Prat, S., (2012) examined the accommodating monetary policy creating liquidity and vulnerability in emerging markets in a panel VAR data modelling. The paper identified the spillover effect of excess liquidity on developing countries. Majdoub & Mansour (2014) investigated the conditional correlation between the US and five Islamic emerging countries employing three models like multivariate GARCH BEKK, CCC and DCC. They found a weak correlation among the US and Islamic countries. This study provides significant insight into international portfolio investors. Abbas et al. (2013) undertook a study on spillover of volatility among Asian countries. Li, Y. & Giles, D.E., (2014) studied the long and short run linkages between stock market of USA, Japan and six Asian countries. The study identified the
strong unidirectional linkages from the USA to Asian countries by applying asymmetric multivariate GARCH models. Additionally, it finds bidirectional spillover between them during the Asian financial crisis. Zaid & Ahmed (2011) analysed the spillover effect of US and UK on the selected emerging markets. The study found that Egypt and Israel are significantly linked with US stock market. Beirne, J. et al., (2013) undertook a study on the volatility and contagion from developed to emerging markets. In the same tandem, the several studies were done on spillover among emerging countries or in between developed and emerging markets (Graham et al., 2012, Tsa, I.C., 2014, Qiu, S., Kundu, S. & Sarkar, N., 2016, Ahmed et al., 2017, Vardar, G., Coskun, Y., & Yelkenci, T., 2018).

Extent literatures are available on volatility of markets and other assets class. These studies provide diversification and hedging strategies. Chkili (2012) examined the dynamic correlation between the exchange rate and stock markets of emerging countries. This paper applied BEKK-MGARCH models and found the spillover between these two assets class. Additionally, the study also provides insight to the international portfolio managers and currency risk hedging strategies. In the similar direction, authors investigated the dynamic connectedness to check the diversification opportunities. While doing connectedness or spillover from one market to other, they employed symmetrical dynamic conditional correlation among various assets class like crude oil, stock markets, metal, bullion and other assets class (Awartani, B., et al., 013; Boubaker, H., and Raza, S.A, 2017; Bouri, E. et al., 2018(a)). Further helps institutional investors to diversify their portfolios in various assets class that provides hedge from probable risk.

2.2 Studies with respect to emerging countries during the financial crisis and chinese market

Studies on the financial crisis are restricting the opportunities to invest in international markets because of high cointegration among the world financial markets during the time of crisis, i.e. Asian Crisis or US financial crisis. These studies reveal positive conditional correlation among the countries and their different assets class. Therefore, the positive relationship among the markets is against the general hypothesis of portfolio diversification. On this note, it has been very crucial for international portfolio investors before allocating the corpus among countries. Gulzar, S., (2019) investigated dynamic linkages between Asian emerging markets and volatility diffusion during financial crisis among these countries. The study considered three window periods, i.e. pre, during and post-financial crisis. With an application of Johansen and Juselius cointegration & VECM model, it has been noticed that there is long term association among these assets class. Hwang, E. et al., (2013) analyzed the spillover of financial crisis on the Asian countries employing conditional correlation of financial markets returns during the financial crisis.

Moon, G.H., and Yu, W.C., (2010) studied symmetric and asymmetric volatility spillover among US and China with particular reference to structural break test and Multivariate GARCH. Similarly, Raghunathan, V., and Brooks, R.D., (2010) studied the volatility of Chinese stock markets. Zhang, B., et al., (2014) investigated the spillover among oil markets and the Chinese markets. They found that there is to and
fro spillover among these markets. Additionally, it reveals that the volatility largely flows from world oil market to Chinese market. On this note, it could be inferred that the influence of the Chinese market has the least impact on world oil markets. In continuation, Zhuo Huang et al., (2018) investigated the macroeconomic vulnerability among US and China. The study concluded that the macroeconomic vulnerabilities in both the US and China have significant impact on the Chinese economy. LIAO Shi-guang (2010) studied the spillover effect among Chinese and Hong Kong stock market within the paradigm of subprime crisis. Xiangyi Zhou et al., (2010) corroborates the LIAO Shi-guang (2010) undertaking a study on spillover among Chinese equity market and world equity markets. Further, Majdoub, J. et al., (2017); Shamila A., et al., (2011) investigated dynamic spillover among Chinese and emerging Asian Islamic equity indices and found spillover among these indices.

Wang and Wang (2019) studied the frequency dynamics of volatility spillovers of crude oil and China’s stock markets employing BK (2017) test. They observed the total volatility spillover driven mainly in short run compared to long run. Additionally, heterogeneity in net pairwise (frequency) spillovers is found from oil to sector markets. S. Ashok et al., (2022) investigated whether energy markets are better informed than equity markets or not. For this purpose, they employed dynamic conditional correlation on before and after COVID-19 data. The study concluded that Chinese equity markets is slower than international energy markets to respond the COVID-19 gravity. In this tandem, crude oil reaction to COVID-19 has been studied considering the US, Japan, and Germany (Zhang and Hamori, 2021). Similarly, Umar et al. (2021) examined the dynamic return and volatility encompassing the agricultural and livestock commodity along with coronavirus indices.

In sum, there is sufficient literature to investigate the volatility spillover from one market to another or one asset class to another. The existing literature attracts attention of various stakeholders like investors, policy makers and portfolio managers who keep an eye on diversification opportunity and their hedging. As per extent literature, very few studies are on Chinese and other emerging market with respect to sub-sample of entire observations. Additionally, investors want to mitigate the portfolio risk considering equity market of China and emerging market. Hence, it is imperative to carry on this study to check either there is spillover or not.

3 Data and Econometric Models

3.1 Data description

We attempt to unravel the spillover effect of Chinese stock exchange with select stock exchanges of emerging economies like Indian stock exchange, the Indonesian stock exchange, Brazilian stock exchange and Mexican stock exchange. The proxies of sample countries are return on Shanghai Stock Exchange (RSSE) located in China, return on Bombay Stock Exchange (RBSE) located in India, return on Jakarta Stock Exchange (RJKSE) located in Indonesia, return on Sao Paulo Stock Exchange (RBVSP) located in Brazil and return on Mexican Stock Exchange (RMEXICAN) located in Mexico. Each stock has 4661 total observations in the present study. The
adjusted daily prices of these stocks have been considered extending from January 3, 2000, to February 7, 2020. After receiving the data, these stocks have converted into daily log return ($R_{it}$) applying $=\log(P_{1}/P_{0})$, in which $P_{1}$ and $P_{0}$ are two successive daily closing prices of $i^{th}$ stock indices. Further, we analyzed and interpreted the results containing a full period (January 3, 2000, to February 7, 2020), first sub-period (January 3, 2000, to October 18, 2009) and second sub-period (October 19, 2009, to February 7, 2020).

3.2 Econometric Models

We employ Granger causality and dynamic conditional correlation to investigate the spillover effect from Chinese stock market to select emerging economies. Granger causality helps to know whether the change in one series causes another series and dynamic conditional correlation (DCC) is one of best tools to capture the transmission of information or spillover from one market to another (Yadav and Pandey, 2020). These models are briefly explained as below:

3.2.1 Granger Causality Test

Granger (1969) proposed “Granger Causality Test” to identify the causal relationship among variables. It helps to know whether the change in one series affects the change in another series to check the causality direction. Broadly, in the Granger Causality, $x$ is a cause of $y$, if it considered as a crucial determinant of $y$. Here, “crucial” means that $x$ is having a potential to improve the predictive value of $y$ with respect forecast considering past values of $y$.

$$X_{(t)}=\sum_{j=1}^{p}A_{11,j}; X_{(t-j)} + \sum_{j=1}^{p}A_{12,j}; Y_{(t-j)} + \epsilon_{1(t)}................. (4)$$

$$Y_{(t)}=\sum_{j=1}^{p}A_{21,j}; X_{(t-j)} + \sum_{j=1}^{p}A_{22,j}; Y_{(t-j)} + \epsilon_{2(t)}................. (5)$$

Where, $p$ denoted as the maximum number of lagged observations considered in the model.

The benefit of the Granger Causality is that it allows researchers to identify directional influence of one series on another without any a priori hypothesis. This test is based on two basic principles, first, cause takes place prior to its effect, and second, cause consists of unique information about future values. It is applied on stationary series; hence, if the two or more than two series are stationary at level values then it is applied on I(0) otherwise non stationary is converted into stationary and then Granger Causality is applied.

3.2.2 DCC GARCH Model

In financial econometric literature, to measure the volatility, there are univariate and multivariate models. After liberalization of markets, it has recognized that financial spillover moves with time among markets and across assets. Understanding this interdependency could be captured through multivariate models, rather univariate models. Multivariate models are versatile applications that provide better decision making in the financial world, i.e. asset pricing, optimization of portfolio, hedging and risk management. One of the prominent papers of Engle (1982), the traditional
time series tools based on mean, i.e. autoregressive moving average (ARMA) models (Box and Jenkins, 1970) has been stretched. Similarly, for forecasting and measuring the volatility of time series, i.e. ARCH models (Bollerslev et al., 1992) have been used. This study considers the volatilities of China and four other emerging countries; thus, the most obvious application, i.e. MGARCH (multivariate GARCH) model, has been applied. In the financial econometric literature, there are four types of multivariate GARCH Models namely VECH model of Bollerslev et al., (1988) followed by BEKK model, and DCC model.

VECH model is a direct generalization of the univariate GARCH to multiple dimensions. The BEKK (1995), has reduced the parameter dimension of the VECH model. DCC (2002) which had further simplified the BEKK model and thus reduced the unknown parameters of the BEKK model. DCC model considered to be the superior model over BEKK (Huang et al., 2010). Thus, this study considers the DCC model to capture the volatility transmission between China and four emerging countries. In the estimation of DCC, the variance-covariance matrix presented as follows:

\[ K_t = D_t L_t D_t \]

Where, \( D_t = \text{diag}\{\sqrt{K_{\text{emerging market}}}, \sqrt{K_{\text{chinese market}}}\} \), emerging market= emerging markets

\[ K_{ii, t} = \omega_{i,o} + \lambda_{ii} \varepsilon_{t-1} + m_{ii} K_{ii, t-1}, i = \text{emerging markets, chinese market} \]

\[ L_t = (\text{diag}\{\phi_t\})^{-1/2} \phi_t (\text{diag}\{\phi_t\})^{-1/2} \]

Where, \( \omega_{i,o} \), \( i = \text{emerging markets, Chinese market} \), represents the constant term. \( \lambda_{ii} \) and \( m_{ii} \) are ARCH and GARCH coefficients respectively. \( \lambda_{ii} \) is capturing own ARCH effect that explains the short-term perseverance and \( m_{ii} \) reflects the own GARCH effects that infers the long-term perseverance. For \( i \neq j \), the coefficients of ARCH & GARCH account the volatility and spillover between Chinese market and four emerging markets. The DCC parameters are given as:

\[ \phi_t = (1 - \delta_1 - \delta_2) \phi_0 + l \pi_{t-1} \pi_{t-1} + \delta_2 \phi_{t-1} \]

\[ \phi_t = \phi_{11,t} \phi_{12,t} \phi_{21,t} \phi_{22,t} \]

Where, \( \phi_t \) shows the time varying conditional correlation between Chinese market and four emerging markets. \( \delta_1 \)estimates the lagged shock on current dynamic conditional correlation (\( DCC_t \)) & \( \delta_2 \)accounts the lagged dynamic conditional correlation (\( DCC_{t-1} \)) on current dynamic conditional correlation (\( DCC_t \)). The vector of standardized residuals \( \pi_t = (\pi_{\text{emerging market}}, \pi_{\text{chinese market}}) \) is \( 2 \times 1 \), where \( \pi_t = \varepsilon_t / \sqrt{K_t} \), \( \phi_0 \) that is matrix of unconditional correlation.
The objective of this paper is to examine the volatility spillover between Chinese stock market (SSE) and four emerging countries, i.e. Indian stock market (BSE), Indonesian stock market (JKSE), Brazilian stock market (BVSP) and Mexican stock market (MEXICAN). We present the empirical result in three window periods; full coverage of the period (January 3, 2000, to February 7, 2020), first sub-period: pre period of financial crisis (January 3, 2000, to October 18, 2009) and second sub-period: post period of financial crisis (October 19, 2009 to February 7, 2020). Table 1 panel encapsulated the descriptive statistics of three respective window periods. As regards with Table 1(a), RBSE realized the highest return (15.99%) followed by RBVSP (13.68%) and RMEXICAN (10.44%) while the positive lowest return is witnessed by RJKSE (7.62%). The return distributions of these five countries are negatively skewed, which depicts the low probability of high yield. Each series has leptokurtic distribution having high kurtosis of RBSE (8.17). It implies that the stock market may generate either very large or very small future returns. The volatility of stock return measured by standard deviation is high for RSSE (1.6). The Jarque-Bera test confirms that these returns not normally distributed as it rejects the null hypothesis of normality.

Further, stationarity of log return is tested applying Augmented Dickey-Fuller (ADF) test, which shows that each series is stationary at level. It means the series can be forecasted and generalizable. In a bid to check the volatility clustering, ARCH-LM test has been applied, that confirms the volatility clustering in each log series as their p-value is less than 5%. Further, summary statistics of the first sub-period (January 3, 2000, to October 18, 2009) has been captured in Table 1b., the average return of RSSE is 0.04% which is less than other stock exchanges. RBSE is more volatile during the first sub-period because its standard deviation is high (1.87) even than RSSE (1.80). The log return of each series is negatively skewed, but highest skewness is observed in total period comparatively. ADF test and ARCH-LM test confirm that the series is stationary and contains volatility clustering.

Similarly, the descriptive statistics of second sub-period extending from October 19, 2009 to February 7, 2020 is presented in Table 1(c). In this period, the average

| Table 1 (a) Descriptive Statistics (January 3, 2000 to February 7, 2020) | RSSE | RBSE | RJKSE | RBVSP | RMEXICAN |
|---|---|---|---|---|---|
| Nobs | 4661 | 4661 | 4661 | 4661 | 4661 |
| Minimum | -0.0926 | -0.1181 | -0.1131 | -0.1457 | -0.0839 |
| Maximum | 0.0940 | 0.1599 | 0.0762 | 0.1368 | 0.1044 |
| Mean | 0.0002 | 0.0004 | 0.0005 | 0.0004 | 0.0004 |
| Stdev | 0.0160 | 0.0148 | 0.0135 | 0.0180 | 0.0132 |
| Skewness | -0.3257 | -0.2221 | -0.6835 | -0.1441 | -0.0764 |
| Kurtosis | 5.0527 | 8.1748 | 6.9709 | 4.4713 | 5.7778 |
| Jarque Bera | 5047 | 13,032 | 9812 | 3904 | 6496 |
| sig. value | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| ADF Test | 0.0100 | 0.0100 | 0.0100 | 0.0100 | 0.0100 |
| ARCH-LM-test | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

Source: Authors own calculation
return is highest for the RJKSSE (0.0005) followed by RBVSP (0.0004) and REMICAN (0.0004). RSSE realized the lowest average return. RBVSP is riskier (0.0144) followed by RSSE (0.0140). Each return series witnessed with negative skewness. SSE has the highest, and RBVSP has the lowest kurtosis. Jarque-Bera confirms that no series is normally distributed in this second sub-period because of significant (less than 0.05) p-value. Further, stationarity of each series has been tested applying ADF test, which confirms that log return of each stock exchange is stationary at level. Further, the ARCH-LM test has been applied to check the arch effect. It firmly rejects the hypothesis of no arch effect and confirms the presence of arch effect in each series. After descriptive statistics, we apply Granger-causality to check the information flows across stock exchanges.

We apply Granger Causality to test the information flows across stock exchanges considered in study. It helps to identify the direction of volatility transmission from one economy to another (Gupta & Guidi, 2012; Huang et al., 2000). Table 2(a), Table 2(b) and Table 2(c) encapsulated the results of Granger Causality consisting total period, first sub-period and second sub-period respectively. As regards the entire

### Table 1 (b) Descriptive Statistics (January 3, 2000 to October 18, 2009)

| Descriptive Statistics | RSSE | RBSE | RJKSE | RBVSP | RMEXICAN |
|------------------------|------|------|-------|-------|-----------|
| Nobs                   | 2234 | 2234 | 2234  | 2234  | 2234      |
| Minimum                | -0.0926 | -0.1181 | -0.1131 | -0.1457 | -0.0839  |
| Maximum                | 0.0940 | 0.1599 | 0.0762 | 0.1368 | 0.1044    |
| Mean                   | 0.0004 | 0.0005 | 0.0006 | 0.0006 | 0.0006    |
| Stdev                  | 0.0180 | 0.0187 | 0.0164 | 0.0210 | 0.0146    |
| Skewness               | -0.0166 | -0.2324 | -0.6720 | -0.1531 | 0.0144    |
| Kurtosis               | 3.9275 | 5.6208 | 5.4982 | 3.9456 | 3.8687    |
| Jarque Bera            | 1440 | 2969 | 2990 | 1462 | 1398      |
| sig. value             | 0.00 | 0.00 | 0.00 | 0.00 | 0.00      |
| ADF Test               | 0.0100 | 0.0100 | 0.0100 | 0.0100 | 0.0100    |
| ARCH-LM Test           | 0.00 | 0.00 | 0.00 | 0.00 | 0.00      |

**Source:** Authors own calculation

### Table 1 (c) Descriptive Statistics (October 19, 2009 to February 7, 2020)

| Descriptive Statistics | RSSE | RBSE | RJKSE | RBVSP | RMEXICAN |
|------------------------|------|------|-------|-------|-----------|
| Nobs                   | 2427 | 2427 | 2427  | 2427  | 2427      |
| Minimum                | -0.0887 | -0.0612 | -0.0930 | -0.0850 | -0.0781  |
| Maximum                | 0.0641 | 0.0519 | 0.0701 | 0.0639 | 0.0429    |
| Mean                   | 0.0000 | 0.0004 | 0.0004 | 0.0002 | 0.0001    |
| Stdev                  | 0.0140 | 0.0098 | 0.0105 | 0.0144 | 0.0094    |
| Skewness               | -0.9335 | -0.0324 | -0.5830 | -0.1295 | -0.6101   |
| Kurtosis               | 6.1849 | 1.9948 | 5.9378 | 1.7815 | 4.8377    |
| Jarque Bera            | 4231 | 404  | 3712  | 329   | 2524      |
| sig. value             | 0.00 | 0.00 | 0.00 | 0.00 | 0.00      |
| ADF Test               | 0.0100 | 0.0100 | 0.0100 | 0.0100 | 0.0100    |
| ARCH-LM Test           | 0.00 | 0.00 | 0.00 | 0.00 | 0.00      |

**Source:** Authors own calculation
sample, the Granger Causality test has applied on the total period, the study finds evidence of unidirectional causality from China (RSSE) to India (RBSE) which says causality flows from Chinese stock market to the Indian stock market. But, the evidence shows no causality flows from the Indian stock market to the Chinese stock market. It also found that there is bidirectional Granger Causality at 5% significance level running from Indonesia (RJKSE) to China (RSSE) and China to Indonesia. It has been analysed that causality is not rolling from Brazil and Mexico to China and vice versa. In the case of first sub-period (January 3, 2000, to October 18, 2009) presented in Table 2(b), there is no existence of bidirectional causality across stock exchanges of sample countries. However, there is a unidirectional flow of information from Indonesia (RJKSE) to China (RSSE)

| Table 2 (a) Result of Granger Causality Test (January 3, 2000 to February 7, 2020) |
|---------------------------------|-----------------|-----------------|
| Null Hypothesis (H0)           | F-value         | P-value         |
| No Granger Causality flows from RBSE to RSSE | 2.7916 | 0.0614 |
| No Granger Causality flows from RSSE to RBSE | 2.3047 | 0.0317* |
| No Granger Causality flows from RJKSE to RSSE | 2.6030 | 0.0077** |
| No Granger Causality flows from RSSE to RJKSE | 3.4982 | 0.0018** |
| No Granger Causality flows from RBVSP to RSSE | 0.5030 | 0.6802 |
| No Granger Causality flows from RSSE to RBVSP | 1.6282 | 0.1350 |
| No Granger Causality flows from RMEXICAN to RSSE | 0.6182 | 0.6495 |
| No Granger Causality flows from RSSE to RMEXICAN | 1.9019 | 0.0767 |

**Source:** Authors own calculation

| Table 2 (b) Result of Granger Causality Test (January 3, 2000 to October 18, 2009) |
|---------------------------------|-----------------|-----------------|
| Null Hypothesis (H0)           | F-value         | P-value         |
| No Granger Causality flows from RBSE to RSSE | 2.6455 | 0.0711 |
| No Granger Causality flows from RSSE to RBSE | 2.0893 | 0.0514 |
| No Granger Causality flows from RJKSE to RSSE | 2.1270 | 0.0303* |
| No Granger Causality flows from RSSE to RJKSE | 1.8440 | 0.0869 |
| No Granger Causality flows from RBVSP to RSSE | 0.3140 | 0.8153 |
| No Granger Causality flows from RSSE to RBVSP | 1.1882 | 0.3095 |
| No Granger Causality flows from RMEXICAN to RSSE | 0.1812 | 0.9482 |
| No Granger Causality flows from RSSE to RMEXICAN | 2.0301 | 0.0585 |

**Source:** Authors own calculation
Table 3 (a). DCC-GARCH Parameters of sample countries’ returns (January 3, 2000 to February 7, 2020)

| Variables | Estimates | $\mu$  | $\omega$  | $A$  | $B$  | DCC $\alpha$ | DCC $\beta$ |
|-----------|-----------|-------|-------|-----|-----|-------------|-------------|
| RBSE      | Coef.     | 0.0009| 0.0000| 0.0937| 0.8978| 0.0193       | 0.3419       |
|           | Sig-Value | 0.0000| 0.3923| 0.0055| 0.0000| 0.2016       | 0.4094       |
| RJKSE     | Coef.     | 0.0008| 0.0000| 0.1063| 0.8838| 0.0225       | 0.8191       |
|           | Sig-Value | 0.0000| 0.1950| 0.0000| 0.0000| 0.0098       | 0.0000       |
| RBVSP     | Coef.     | 0.0007| 0.0000| 0.0617| 0.9217| 0.0000       | 0.9200       |
|           | Sig-Value | 0.0048| 0.6805| 0.0000| 0.0000| 1.0000       | 0.0745       |
| RMEXICAN  | Coef.     | 0.0005| 0.0000| 0.0749| 0.9180| 0.0247       | 0.0000       |
|           | Sig-Value | 0.0086| 0.9272| 0.7073| 0.0000| 0.2193       | 1.0000       |

Source: Authors own calculation

Table 3 (a) to Table 3 (c) encapsulated the outcome of Dynamic Conditional Correlation–Generalized Autoregressive Conditional Heteroscedasticity (DCC-GARCH) of sample countries’ stock return. Table 3 (a) depicts DCC-GARCH parameters of the full period (January 3, 2000, to February 7, 2020) to inspect the time-varying correlation between Chinese Market (RSSE) to Indian stock market (RBSE), Indonesian stock market (RJKSE), Brazilian stock market (RBVSP) and Mexico (RMEXICAN). The table contains overall mean ($\mu$), constant ($\omega$), ARCH term ($\alpha$), GARCH term ($\beta$), DCC$\alpha$ and DCC$\beta$. Alpha ($\alpha$) indicates the ARCH coefficient calculated based on previous squared residual and Beta ($\beta$) signifies GARCH coefficient that forecasts the volatility based on past conditional variance. As depicted, $\alpha$ and $\beta$ of the Indian stock market (RBSE) are significant, which confirms the persistence of volatility. Similarly, there is the persistence of buoyancy in the case of the Indonesian market (RJKSE) and Brazilian market (RBVSP) as their $\alpha$ and $\beta$ are significant. Mexican stock market (RMEXICAN) witnessed with insignificant $\alpha$ and significant $\beta$, which indicate that conditional volatility, can be forecasted considering the past volatility rather than squared residual. Further, the summation of $\alpha$ and $\beta$ of these constituent series is less than 1; it signifies decay in volatility persistence over time. Broadly,
it evaluates information transmission from the Chinese Market (RSSE) to rest of sample countries’ market. DCC α and DCCβ are spillover parameters displayed in Table 3(a). It noticed that there is no transmission of information or spillover from the Chinese market to Indian, Brazilian and Mexican market as their DCC α and DCCβ are insignificant. In contrast, the spillover parameters of Indonesian market is significant; it confirms the spillover effect from the Chinese market to the Indonesian market. As can be seen, one can diversify their portfolio in the Indian market, Brazilian and Mexican market as they not influenced by the Chinese market.

Table 3(b) presents the result of the DCC model for first sub-period extending from January 3, 2000, to October 18, 2009. Individually, we observe volatility persistence witnessed by every stock market except the Mexican stock market as its p-value of ARCH is insignificant. It depicts that each stock volatility is forecasted by squared residual along with past variance. However, the volatility of the Mexican market has predicted by only previous variance. In case of spillover from the Chinese market to Indian stock market (RBSE), Brazilian stock market (RBVSP) and Mexican stock market (RMEXICAN), there is no spillover or transmission of information (DCC parameters, i.e. DCCα and DCCβ are insignificant). As regards from the Chinese stock market to Indonesian market (RJKSE), DCC α and DCCβ is significant, implying the transmission of information.

Further, the result of the DCC model for the second sub-period from October 19, 2009, to February 7, 2020, encapsulated in Table 3(c). The conditional volatility of
Indian stock market forecasted by its past variance while the conditional heteroscedasticity of rest of the markets (Indonesian, Brazilian and Mexican) are predicted by the previously squared residuals ($\alpha$) and prior variance ($\beta$) as they are significant. We observe that DCC$\alpha$ of each aforesaid stock market is insignificant. It implies that, in the short run, there is no spillover effect from the Chinese stock market to the rest of the stock markets while there is a spillover effect in the long term. It indicates that there is no transmission of information in short runs, whereas the transfer of information is possible in the long run.

Figures 1, 2 and 3 plots the conditional correlation between the Chinese stock market to the Indian market, to the Indonesian market, to the Brazilian market and the Mexican market. It contains a full period, first sub-period and second sub-period. As depicted in Fig. 1, the conditional correlation of Indian market, the Indonesian market, the Brazilian market vary from $-0.1$ to $0.3$, $-0.1$ to $0.3$, $0.022$ to $0.023$ and $-0.4$ to $0.1$ respectively. Further, the conditional correlation of the first sub-period and second sub-period are plotted in Figs. 1 and 3. We observe that the pattern of stock market correlation varies over time, and it has reverted to a long term mean. This study is similar to Sehgal et al., (2019) and Kee et al. (2016).

5 Conclusion and policy implication

We examine the volatility spillover between Chinese stock market and four emerging economies (Indian stock market, the Indonesian stock market, the Brazilian stock market and Mexican stock market). Emerging economies, due to their similarity, can furnish diversification benefits to investors. The study examines transmission of vola-
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We begin empirical analysis through descriptive statistics and Granger Causality. It is observed that there is bidirectional causality between Chinese and Indonesian market whereas unidirectional causality flows from Chinese to Indian stock market in full observations. Further, it is found that there is unidirectional flow of causality from Indonesian market to Chinese market in first sub-period. Next, in

Fig. 2 Plot of Dynamic Conditional Correlation (January 3, 2000 to October 18, 2009)

Fig. 3 Plot of Dynamic Conditional Correlation (October 19, 2009 to February 7, 2020)
the second sub-period, the causality flows from China to the Indonesia and from the Mexico market to China. There is no bidirectional causality in the first and second sub-period. It implies that Chinese market is affecting high in total period of observations rather than first and second sub-period to emerging economies considered in this study. Additionally, DCC-GARCH has been applied to examine the transmission of information or spillover. We find DCCα and DCCβ of Chinese and Indonesian market to be significant in the total period while DCCα of first sub-period and DCCβ of second sub-period are significant. It indicates that there is a spillover effect from Chinese market to the Indonesian stock market in the comprehensive period both in the short period and long period. In the first sub-period, there is the transmission of information in the short run while in the second sub-period; the transmission of the information found in the long run.

Our findings have implications for academia as well as portfolio managers. Broadly, portfolio managers want to optimize their returns and minimize their risk diversifying through investments. Volatility spillover is one of the techniques to examine the integration among markets. We find diversification opportunity of investment in India, Brazil and Mexico as there is no evidence of transmission of information from Chinese stock market. This provides opportunity to diversify portfolio among these countries. Due to the integration or communication of information between the Chinese stock market Indonesian market, there are no benefits in diversifying their investments. In future, a study can be explored considering various other economies like ASIAN, BRICS, MINT and other economies. Similarly, we can also employ wavelet analysis, and Copula GARCH.

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