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Article *in* Journal of Finance & Economic Research · January 2018

DOI: 10.20547/jfer1803102

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Journal of Finance & Economics Research
Vol. 3(1): 23-42, 2018
DOI: 10.20547/jfer1803102

Time-varying Return and Volatility Spillover among EAGLEs Stock Markets: A Multivariate GARCH Analysis

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Abstract: *This study investigates the presence of return and volatility spillover across EAGLEs stock markets, namely China, India, Indonesia, Russia, Brazil, Turkey and Mexico. A multivariate GARCH DCC and BEKK frameworks are employed by classifying the total sample (i.e. from January 2002 to February 2017) into three sub-periods according to the 2008 Global financial crisis. The result shows a significant and positive spillover effect among stock markets in the pre-crisis and post-crisis periods. The transmission of spillover from external markets intensely influenced by US stock market. Furthermore, strong inter-connection and channel of spread observed among EAGLEs stock market during the post-crisis period.*

Keywords: Multivariate GARCH, conditional correlation, spillover effect, EAGLEs, stock markets

Introduction

As emerging markets undergone a remarkable economic and financial transformations, investment community sought to club markets together that will reflect the potential of emerging markets in the coming years. In this regard, Goldman Sachs introduced the term BRIC, which stands for Brazil, Russia, India and China, as part of economic modeling to forecast a shift in global economic power away from the current richest countries towards the emerging world over the next half-century. The endeavor to find the best grouping acronyms continues. New acronyms such as CIVETS coined by the Economist Intelligence Unit, to refer to Colombia, Indonesia, Vietnam, Egypt, Turkey, and South Africa.

In 2010, a Spanish bank BBVA [1] came up with a new term EAGLEs to identify key emerging markets based on their expected contributions to global GDP. The term EAGLEs is a dynamic concept to describe the emerging and growth-leading economies expected to lead the global economic growth in the next ten years.[2] The countries included in the EAGLEs membership is subject to annual revision and changes according to estimated potential growth of those countries relative to developed economies. According to annual report of BBVA (2016), member countries of EAGLEs group includes China, India, Indonesia, Russia, Brazil, Turkey, Mexico and other 8 countries that are expected

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[1]BBVA stands for Banco Bilbao Vizcaya Argentaria, S.A.
[2]EAGLEs contribution to global economic growth expected to be above the average threshold of G6 countries in the next ten years.

to contribute 64% of global growth between 2015-2025. In 2011, BBVA and Dow Jones Indexes have jointly started the Dow Jones BBVA EAGLEs Index, which measures the performance of 50 leading companies traded in EAGLEs. Although substantial studies examined the inter-linkage of developed and some emerging markets, to the best of our knowledge, no other paper investigate the dynamic of EAGLEs market as a group. This study focuses on examining the internal and external return and volatility spillovers among EAGLEs stock markets.

Most financial markets in developed and emerging countries have now liberalized and relaxed international capital flow barriers. The developments in information technologies as well as the fragmentation and electrification of markets play a significant role in the stock market integration process. When stock markets become mature and increasingly integrate with the other markets, they become more vulnerable to news and shocks originate from the rest of the world and their sensitivity to the return and volatility spillover increases. As a result, properly estimating the extent of transmission between the returns and volatilities among stock markets is important for a number of reasons. Firstly, investors are interested in the presence (absence) of spillover among stock markets in order to explore potential gains from portfolio diversification, because the design of a well-diversified portfolio remarkably relies on a proper understanding of how strongly stock markets are interrelated. A change in the spillover pattern of these markets calls for adjustment of portfolio allocation due to its inherent risk or arbitrage profit. Secondly, for policy makers, an increased role of the stock market in the economy has made analyzing transmission of shocks or spillovers across stock markets important in policy arrangements, thus the patterns and changes in the returns and volatility spillover of international stock markets affects economic policy. Furthermore, volatility spillover information is important in financial applications, such as option pricing, value at risk, portfolio optimization and hedging as they rely on estimation of conditional volatility.

A number of studies employ generalized autoregressive conditional heteroscedastic (GARCH) models to explore whether news and shocks originate from the rest of the world may influence local emerging markets (Lin, Engle, & Ito, 1994; Choudhry, 1996; Bekaert & Harvey, 1997; Kanas, 1998; Ng, 2000; Baele, 2005; Chiang, Chen, & Lin, 2013). R. F. Engle, Ito, and Lin (1990) and Hamao, Masulis, and Ng (1990) are among the prior studies to use univariate GARCH model to analyze the volatility spillover effect. For instance, Hamao et al. (1990) investigate the volatility spillover among US, UK and Japan stock markets, and observe volatility transmission from US and UK to Japan market. Theodossiou and Lee (1993) come up with a multivariate GARCH model to analyze US, UK, Japan, Canada and Germany stock markets, and reported the existence of mean spillovers from the US to other markets. Likewise, Booth, Martikainen, and Tse (1997) employed multivariate GARCH model to explore the volatility spillover dynamics among Scandinavian financial markets. In this article, we apply a multivariate GARCH model with the BEEK framework, which was proposed by R. F. Engle and Kroner (1995). This approach has been proven to be successful to explore the cross-market return and variances spillovers (Li & Majerowska, 2008; Beirne, Caporale, Schulze-Ghattas, & Spagnolo, 2010; Gilenko & Fedorova, 2014). Accordingly, we use BEKK-GARCH model which allows as to estimate return and variances spillovers among EAGLEs stock markets, as well as the influence of major economies (US, UK and German) on these markets. The contribution of this study to the existing literatures is three folds. First, it provides an explanation of conditional correlation, return and volatility spillovers by investigating EAGLEs stock market, which is a novel market group. Second, unlike most studies that uses multivariate GARCH model to explore the volatility spillover dynamics, this paper applies a multivariate GARCH dynamic conditional correlation (DCC) as well as BEEK frameworks. Moreover, it splits the sample period into three episodes to detect time-varying effect across markets. Third, the study not only capturer EAGLEs own and cross-market return and volatility effects, but it considers the influence of developed and other emerging countries on EAGLEs financial markets.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 describes the methodology used in this study. Section 4 presents the data set and descriptive statistics. Section 5 discusses empirical results. Section 6 offers some concluding remarks.

Related Literature

The transmission of returns and volatilities among stock markets draws the attention of many researchers in the last decades. A significant number of studies examined the spillovers effect among markets and provided a new perspective on the degree of such transmission. In this regard, studies that examine the spillover of volatility among developed markets (Hamao et al., 1990; Bae & Karolyi, 1994; Karolyi, 1995; Susmel & Engle, 1994; Koutmos & Booth, 1995; Lin et al., 1994; Kanas, 1998) and in the emerging and frontier markets (Choudhry, 1996; Bekaert & Harvey, 1997; Scheicher, 2001; Malik & Hammoudeh, 2007; Hammoudeh & Li, 2008; Li & Majerowska, 2008; Beirne et al., 2010; Gilenko & Fedorova, 2014) provides important insight in the explanation of volatility transmission across markets. Ng (2000) explore the spillover dissemination between US, Japan and various Pacific-Basin markets, and find evidence of volatility spillover from US and Japan to various Pacific-Basin markets. Hammoudeh and Li (2008) further estimate the volatility persistence of five GCC stock markets. They reported that greater the influence of the developed markets on most GCC stock markets than local and regional factors. Moreover, Beirne et al. (2010) examine the volatility and shock transmission mechanism among developed and 41 emerging market, and the result suggest the existence of spillovers from global and regional markets to vast majority of emerging stock markets.

The influence of US stock markets towards others have been investigated by numerous studies. Most of them find the major impact and a leading character of US market on other stock markets. For instance, Liu and Pan (1997) examine the interdependence between US and five Asian markets, and conclude that US stock market plays a dominant role in transmitting returns and volatilities spillovers to other four Asian markets than the Japanese market. The study of Chan, Gup, and Pan (1992) also indicates the significant influence of US and UKstock markets on Asian markets. Balios and Xanthakis (2003) examined the interdependence and dynamic linkage among US, five European countries and Japan stock market indices. They reported that US stock market is the most influential market in the world and the UK in Europe. Similarly, Wongswan (2006) investigates the influence of US and Japan markets information declaration on Korean and Thai stock market volatility. They could detect important feedback relationship between developed markets' information announcement and emerging markets' volatility in the short-run.

Studies that explore the interdependence of return and volatility across markets argue that the spillover effect among stock returns is not constant over time. Kearney and Lucey (2004) point out that any attempt to model the integration of stock markets without taking into account the time-variation may yield partial and confusing results. Moreover, Gallo and Velucchi (2009) highlight the existence of unstable volatility spillover effects across markets in the pre-crisis or post 1997 crisis. To handle this problem a verity of techniques have been suggested by researchers like using regime switching models, introducing dummy variables or splitting the sample period. For example, Bekaert and Harvey (1995) , Cumby and Khanthavit (1998) and Gallo and Velucchi (2009) introduced models that handles alteration in regime and time-varying effect across markets. In a similar fashion, Zheng and Zuo (2013) adopted a Markov-switching causality approach to model and test the potential instability of volatility transmission among US, UK, German, Japan and Hong Kong markets in tranquil and turmoil periods. Lagoarde-Segot and Lucey (2007) allow for regime switching in analyzing the interdependence of Middle East and North African (MENA) stock markets, and Lucey and Voronkova (2008) for European and Russian stock markets. While, R. Engle, Gallo, and Velucchi (2012) examines East Asian stock markets by introducing two dummy variables for the Asia crisis and the post-crisis periods. On the other hand, Choudhry and Jayasekera (2014) and Gilenko and Fedorova (2014) examined the across market return and volatility spillover by splitting the samples into sub-periods.

A considerable amount of studies assessed the degree of transmission in return and volatility among stock markets during stable and stress period. The divergence of linkage in the tranquil period and during or after market shocks further accentuates the measurement of spillover effect. Dickinson (2000) examined major European stock markets and reported the increase in the integration of European markets during the 1987 US stock market crash. The findings of King and Wadhwani (1990) also shows an increasing in international co-movement of US, UK and Japan stock returns, and Lee and Kim (1993) for 12 major stock markets since the US stock market crash of 1987. Leong and Felmingham (2003), Jang and Sul (2002) and Wong, Penm, Terrell, and Ching (2004) further documents that the correlation among Asian stock markets strengthened during Asian financial crisis, and between the developed and Asian stock markets since the 1987 US stock market crash and the 1997 Asian financial crisis. Similarly, Angkinand, Sawangngoenyuang, and Wihlborg (2010) argued the increase in the interdependence of US and many developed markets when the crisis emerged. Dufrénot and Keddad (2014) reported the existence of persistent volatility spillovers from US to Indian markets during the 2008 global financial crisis. Choudhry and Jayasekera (2014) also investigated the return, volatility and leverage spillover effects between developed (Germany, UK and US) and the less stressed European (Italy, Ireland, Greece, Spain and Portugal) stock markets, and found evidence of increase in the level and amount of spillover from developed markets to less stresses European markets during the 2008 global financial crisis.

Methodology

In this paper, the presence of mean and volatility spillover among stock returns assessed using both DCC and BEEK-GARCH models. These models allow to capture the time-varying spillover among stock returns, and the conditional variance and correlation is guaranteed to be positive. We represent the cross-market mean and volatility spillover among EAGLEs stock markets as well as the influence of developed economies on these markets using the following model:

$$r_{i,t} = \alpha + \beta_i r_{i,t-1} + \Psi_i \lambda_{i,t} + \Gamma_i h_{i,t} + \epsilon_{i,t} \epsilon_{i,t} \mid \Omega_{t-1} \sim N(O, H_{i,t}) \tag{1}$$

$$\sigma^2_{i,t} = \nu_i + \vartheta_i \epsilon^2_{i,t-1} + \xi_i \epsilon^2_{i,t} + \phi_i \sigma^2_{i,t} \tag{2}$$

Where $\gamma_{i,t}$ is a $nx1$ vector consisting of daily stock returns of EAGLEs country at time t for each market, $\gamma_{i,t-1}$ denotes a corresponding vector of lagged return. α and $\epsilon_{i,t}$ are a $nx1$ vector of constant and error terms. β_i is a nxn matrix of coefficients, capturing own and cross-market effects among EAGLEs stock index. Ψ_i represents a coefficient to consider the influence of developed countries on EAGLEs financial markets, and $h_{i,t}$ a vector of corresponding returns of US, UK and German markets index. Γ_i denotes a nxn matrix parameters of the GARCH-in-mean terms, and $H_{i,t}$ a $nx1$ column vector (i.e. diagonal $H_{i,t}$) of the conditional variance of the error, which allows to include the conditional variance of stock returns in each of EAGLEs, and developed markets mean equation. $\varepsilon_{i,t} \mid \Omega_{t-1}$ is $nx1$ vector of random errors at time t given all available market information at time $t-1$, which is supposed to pursue normal distribution with a mean of 0 and variance $H_{i,t}$. Whereas $H_{i,t}$ denotes the corresponding nxn conditional variance and covariance matrix.

Where $\sigma^2_{i,t}$ denotes the corresponding conditional volatility, and $\varepsilon^2_{i,t}$ is a proxy for a volatility shock during day t in market i. The parameters in the conditional variance equation shows that conditional volatility in a market specified as a linear function of constant (ν_i), its own and cross-market past volatility shock effects among EAGLEs markets (ϑ_i), the influence of developed countries past volatility shock on EAGLEs markets (ξ_i) and its own and cross-market past conditional variance (ϕ_i).

DCC-GARCH Model

The dynamic conditional correlation model (DCC), which was proposed by R. F. Engle (2002), allows modeling a multivariate time-varying conditional correlation matrix. This matrix decomposed into conditional standard deviation (D_t) and conditional correlation matrix (R_t). The DCC model is defined as:

$$H_t = D_t R_t D_t \tag{3}$$

Where $D_t = diag(h_{11t}^{1/2} ... h_{nnt}^{1/2})$ The conditional variance h_{iit} given by

$$h_{iit} = w_i + \sum_{p=1}^{q} \alpha_{ip} \alpha_{i,t-p}^2 + \sum_{p=1}^{j} \beta_{ip} h_{i,t-p}, i = 1, ..., n \tag{4}$$

The conditional correlation matrix R_t defined as following standardization:

$$R_1 = diag(q_{11t}^{-1/2}, ..., q_{nnt}^{-1/2}) Q_t diag(q_{11t}^{-1/2}, ..., q_{nnt}^{-1/2}), \tag{5}$$

Where $Q_t = (q_{ij,t})$ is the nxn symmetric positive definite matrix and has the form of

$$Q_t = (1 - a - b)\overline{Q} + a u_{t-1} u_{t-1}' + b Q_{t-1} \tag{6}$$

$\overline{Q}$ is the nxn unconditional variance matrix of u_t, with $u_t = \varepsilon_{it} / \sqrt{h_{iit}}$. a and b are non-negative scalar parameter satisfying $a + b < 1$. Parameter a captures the effect of previous shocks to the current conditional correlation, and parameter b measures the effect of own and cross-market past conditional correlation to the current conditional correlation.

The above standardization in equation (5) was challenged by McAleer and Christian Hafner (2014) that there is no clear explanation provided by R. F. Engle (2002) whether the matrix R_1 was the conditional covariance matrix or a conditional correlation matrix. McAleer and Christian Hafner (2014) suggest standardization of conditional covariance matrix to obtain conditional correlation. To specify

$$\varepsilon_t = \Gamma_t \eta_{t-1} \eta \Gamma_t \sim iid(\theta, \Phi) \ and \ \eta_t \sim iid(0, R) \tag{7}$$

Where, ε_t and η_t are $nx1$ vectors, Γ_t is nxn matrix of coefficients
The conditional covariance matrix given as

$$Q_t = R_t + \Phi' \varepsilon_{t-1} \varepsilon_{t-1}' \Phi \tag{8}$$

The scalar versions of DCC are

$$Q_t = R_t + \Phi' \varepsilon_{t-1} \varepsilon_{t-1}' \Phi + X Q_{t-1} X' \tag{9}$$

Where X is a diagonal or scalar matrix as in the case of BEKK model, Φ=$\phi^{1/2}$ and X= $X^{1/2}$. The standardize matrix of R_t in Equation 5 ensure that the definition of a matrix of correlation confident.

According to Engle (2002) estimation of DCC model parameters can be performed consistently in two-step approach. First, using Q_t to estimate conditional correlation:

$$\rho_{ij,t} = q_{ij,t} / \sqrt{q_{ii,t} q_{jj,t}} \tag{10}$$

Second, using $P_{ij,t}$ to estimate the conditional covariance

$$h_{ij,t} = \rho_{ij,t} \sqrt{h_{ii,t} h_{jj,t}} \tag{11}$$

Where the $h_{ii,t}(h_{ij,t})$ and $h_{ij,t}$ are the conditional variance and conditional covariance that generates though using univariate GARCH models.

As shown by R. F. Engle and Sheppard (2001), the likelihood function in the DCC model of R. F. Engle (2002) is the sum of two components, the mean and the volatility part, depending on a set of unknown parameter ψ_1s and the correlation term that depends on ψ_2 . Thus,

$$L1_t(\psi_1) = -\frac{1}{2}\sum_{i=1}^{T}\left[\sum_{i=1}^{n}\left(log(2\pi) + log(h_{iit}) + \frac{r_{i,t}^2}{h_{ii,t}}\right)\right] \tag{12}$$

$$L2_t(\psi_2 \mid \psi_1) = -\frac{1}{2}\sum_{i=1}^{T}\left(log \mid R_t \mid + u_t' R_t^{-1} u_t - u_t' u_t\right) \tag{13}$$

These two stage procedures help to predict the likelihood in DCC model.

BEKK-GARCH Model

The multivariate BEKK-GARCH model proposed by R. F. Engle and Kroner (1995), which guarantees the positive definiteness of matrix H_t and capture the behavior of conditional variance in the system. It takes the following form:

$$H_t = \wedge' \wedge + \Phi' \varepsilon_{t-1}\varepsilon_{t-1}' \Phi + \Omega' H_{t-1}\Omega \tag{14}$$

Where $\wedge$ is the nxn lower triangular matrix that contains constant parameters, while Φ captures the effect of own and cross-market previous shocks to the current conditional variance (ARCH effects), and Ω matrix measures the effect of own and cross-market past conditional volatility to the current conditional variance (GARCH effects).

The conditional log-likelihood function $L(\theta)$ given T observations and a vector of unknown parameters θ can be written as:

$$L(\theta) = \sum_{t=1}^{T} l_t(\theta) \tag{15}$$

$$l_t(\theta) = -\log 2\pi - \frac{1}{2}\log \mid H_t(\theta) \mid -\frac{1}{2}\varepsilon_t'(\theta) H_t^{-1}(\theta)\varepsilon_t(\theta) \tag{16}$$

The maximum likelihood estimates and the corresponding asymptotic standard errors are compute based on the Berndt, Hall, Hall and Hausman (BHHH) algorithm. The Ljung-Box Q statistics used to test the null hypothesis that the noise terms ϵ_t are uncorrelated, hence the model is properly specified.

Data

The data set includes daily stock indices of EAGLEs market, namely China, India, Indonesia, Russia, Brazil, Turkey and Mexico.[3] The sample period is from January 1, 2002

[3] The stock indices used in this study are as follow. China: Shanghai Stock Exchange A Share Index, India: S&P BSE SENSEX Index, Indonesia: Jakarta Stock Exchange Composite Index, Russia: Russian Trading System

to February 27, 2017, with a total of 3955 observations. We want to start from the period 2002, because it is characterized as a period of relative calm before the 2008 Global financial crisis, but after a slowdown in world economy due to "doc-com bubble", 9/11 attacks, the Turkish stock market crash and Brazilian stock market downturn. Hence, the sample span is conventional to assess the degree of transmission in return and volatility among stock markets during stable and stress periods. In ordered to consider the influence of developed markets on EAGLEs stock markets we incorporate the daily indices of US, UK and Germany stock markets. All market indices are obtained from DataStream.

To examine the conditional correlation of return and volatility spillovers across EAGLEs markets we split the total sample into three sub-periods according to the 2008 Global financial crisis: the pre-crisis period (January 1, 2002 to March 13, 2008), the crisis period (March 14, 2008 to April 23, 2009)[5] and the post-crisis period (April 24, 2009 to February 27, 2017). In this manner, the time-variation effect and any alteration in spillover from the pre-crisis to the recovery period can be assessed. The daily returns of each country stock index at time $t(r_{i,t})$ are computed as follows:

$$r_{i,t} = 1n\left(\frac{P_{i,t}}{P_{i,t-1}}\right) * 100 \tag{17}$$

Where $P_{i,t}$ and $P_{i,t-1}$ are the closing price of stock index i at time t and $t-1$, respectively. The returns for all stock markets are plotted in Figure 1. The first insurgence of volatility started in the early 2002, after "doc-com bubble" and 9/11 attack. It keeps US market at high volatility and began to influence UK and German stock markets that are closely connected with the US market. Moreover, in the aftermath of 2001 Turkish stock market crash and Brazilian stock market downturn, there was a considerable financial turbulence. For Russian market, the volatility surge started from late 2003. After a period of relative calm from 2003 to 2007, volatility in most financial markets increased following the collapse of Bear Stearns in March 2008 and Lehman Brothers on September 2008.

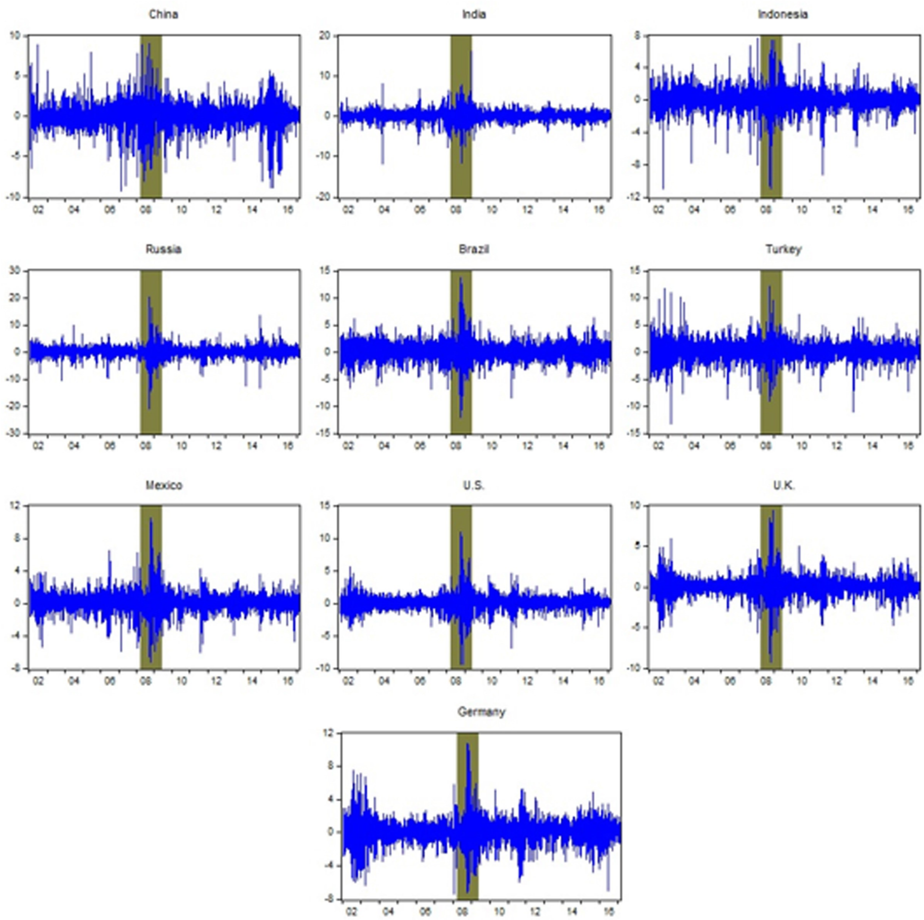
As can be seen from Figure 1, the Global financial crisis of 2008 influenced selected markets, even though the degree of impact varies across markets. The returns are more volatile during the crisis time as compared to the pre-crisis or post-crisis period. This is especially more noticeable for stock markets in Russia, Brazil, US and India. Starting from late 2011, the German stock market shows relatively high volatility following European sovereign debt crisis.

Cash Index, Brazil: Ibovespa Brasil Sao Paulo Stock Exchange Index, Turkey: Borsa Istanbul 100 Index, and Mexico: Mexican Bolsa IPC Index.

[5]We define March 14, 2008 as the beginning of crisis period. In this day the investment bank of Bear Stearns secure loan for additional funding from JPMorgan Chase in cooperation with the Federal Reserve Bank of New York. On March 16, 2008, the Bear Stearns collapsed and agreed to sell to JPMorgan Chase. While, the 23rd April of 2009 taken as end of global financial crisis, as US Federal Reserve releases annual financial statement and on 24th details of the stress tests that shows most banks have capital level more than the required amount.

Figure 1

Time series plot of daily stock return from January 1, 2002 to February 27, 2017, (the dark golden shaded area denotes the crisis period)



The descriptive statistics of stock indices for the three sub-periods are presented in Table 1. The annual mean return ranges from 0.4% (UK) to 12.8% (Russia) during the pre-crisis and from 0% (Russia) to 7.9% (Indonesia) in the recovery period. Furthermore, the mean return and volatility of EAGELs market exhibit relatively higher as compared to developed markets. The highest volatility during the pre-crisis period occurred in Turkey and Russia stock markets, as shown by high standard deviation. On the other hand, Indonesia stock market was much more volatile than other markets in the post-crisis period.

The post-crisis period characterized by a relatively low return and volatility for most EAGLEs stock markets as compared to the pre-crisis period. The mean return become negative in all stock markets and the volatility in return dramatically increase during the crisis period. Russia stock market yields the lowest mean returns and highest volatility in this period. Most return series exhibit considerably negatively skewed and excess kurtosis, which indicates they are not normally distributed. The Jarque'Bera normality test also rejects the normality of the stock returns in all markets. The Dickey'Fuller Generalized Least Squares (DF-GLS) unit root test indicates the non-stationary of most return series. The Ljung-Box statistics for both the returns and the squared returns suggests the presence of serial correlation in the series. ARCH test for conditional heteroscedasticity also supports the presence of ARCH effect in stock returns and warrants the application of multivariate GARCH-type model.

Table 1
Descriptive statistics of stock returns

	Mean	Median	Std. Dev.	Skewness	Kurtosis	JB	LB (12)	B2(12)	DF-GLS	ARCH (5)
Pre-Crisis Period										
China	0.054	0.000	1.525	-0.176	7.766	1539.927*	27.750*	125.35*	-39.944*	13.822*
India	0.097	0.112	1.414	-0.649	9.089	2613.500*	33.099*	496.28*	-4.652*	74.220*
Indonesia	0.111	0.092	1.359	-0.822	9.731	3236.947*	28.167*	199.85*	-1.919	24.905*
Russia	0.128	0.175	1.727	-0.683	7.134	1278.535*	22.452*	242.17*	-36.846*	32.157*
Brazil	0.093	0.071	1.692	-0.293	3.916	79.792*	26.370*	149.38*	-1.67	13.127*
Turkey	0.069	0.057	2.07	-0.051	5.65	1002.580*	16.274	220.98*	-2.212*	16.249*
Mexico	0.093	0.111	1.222	-0.145	5.65	459.452*	13.862	325.52*	-10.484*	24.039*
US	0.007	0.025	1.012	0.087	5.833	543.365*	16.19	1205.4*	-4.038*	78.561*
UK	0.004	0.006	1.098	-0.199	7.377	1302.767*	69.046*	1457.5*	-26.247*	87.104*
Germany	0.013	0.057	1.51	-0.064	6.816	983.091*	34.027*	1629.8*	-42.410*	85.728*
Crisis Period										
China	-0.165	0.000	2.643	0.171	3.931	11.904*	6.554	17.049	-2.155*	1.796
India	-0.113	0.000	2.673	-0.203	4.161	18.286*	16.244	137.75*	-0.76	11.027*
Indonesia	-0.139	0.000	2.192	-0.506	7.76	286.253*	35.534*	74.417*	-2.322*	5.301*
Russia	-0.313	0.000	4.2	-0.102	8.154	321.523*	30.733*	110.94*	-1.299	5.857*
Brazil	-0.097	0.000	3.177	0.188	6.044	113.717*	9.003	254.68*	-3.201*	16.062*
Turkey	-0.124	-0.032	2.561	0.115	5.697	88.594*	22.172*	38.592*	-0.734	2.774*
Mexico	-0.086	-0.046	2.274	0.51	6.325	146.250*	10.193	148.79*	-14.742*	5.996*
US	-0.136	0.002	2.675	-0.023	5.658	85.443*	21.283*	190.90*	-18.734*	14.547*
UK	-0.104	-0.040	2.324	0.087	6.181	122.693*	35.437*	149.75*	-0.831	8.159*
Germany	-0.111	0.000	2.404	0.484	7.011	205.791*	17.848	114.16*	-1.446	8.351*
Post-Crisis Period										
China	0.014	0.000	1.454	-0.962	8.563	2955.38*	32.336*	683.77*	-2.784*	54.488*
India	0.045	0.000	1.123	1.133	24.286	39248.1*	22.358*	70.905*	-9.957*	2.389*
Indonesia	0.059	0.057	1.129	-0.441	8.534	2678.08*	53.508*	430.61*	-3.551*	26.579*
Russia	0.014	0.000	1.19	-0.178	7.862	2027.37*	24.086*	492.40*	-2.007*	59.428*
Brazil	0.017	0.000	1.444	0.018	4.645	230.974*	12.694	207.69*	-2.262*	20.091*
Turkey	0.053	0.052	1.45	-0.453	6.811	1308.63*	18.116	156.61*	-21.122*	15.727*
Mexico	0.036	0.025	0.953	-0.283	5.963	776.259*	43.523*	288.53*	-0.972	25.207*
US	0.049	0.034	0.975	-0.396	6.985	1408.24*	49.082*	965.30*	-2.819*	69.984*
UK	0.027	0.029	1.000	-0.18	5.073	406.664*	15.168	658.81*	-42.450*	49.534*
Germany	0.045	0.069	1.291	-0.266	5.118	406.664*	15.638	597.09*	-40.782*	38.263*

Note: JB denotes Jarque-Bera normality test; LB (12) and LB2(12) are Ljung-Box statistics of autocorrelation test of returns and squared returns for 12 lags. DF-GLS is Dickey-Fuller Generalized Least Squares unit root test at level. ARCH (5) refers to LM test of conditional heteroscedasticity for 5 lags. * denotes rejection of the null hypothesis at 5% level.

Empirical Results

In this section, we estimate the extent of time-varying conditional correlation, mean and volatility spillover using DCC and BEKK GARCH models.

Results on Conditional Correlation

Table 2 presents the result of dynamic conditional correlation model for different time periods. In the DCC estimation the coefficient of the parameter a captures the effect of previous shocks to the current conditional correlation, while the parameter b indicates the degree of persistence of past conditional correlation.

Table 2
Dynamic conditional correlation

	DCC		
	Pre-Crisis Period	**Crisis Period**	**Post-Crisis Period**
Mean (China)	-0.001	-0.145	0.052*
Mean (India)	0.189*	-0.071	0.098*
Mean (Indonesia)	0.228*	-0.199	0.099*
Mean (Russia)	0.270*	-0.384	0.164*
Mean (Brazil)	0.235*	-0.076	0.119*
Mean (Turkey)	0.188*	-0.187	0.149*
Mean (Mexico)	0.189*	-0.054	0.108*
c (1)	0.073*	4.183	0.015*
c (2)	0.109*	3.659	0.025*
c (3)	0.271*	3.442	0.061*
c (4)	0.187*	11.381	0.068*
c (5)	0.106*	7.511	0.069*
c (6)	0.061*	7.247	0.150*
c (7)	0.099*	5.898	0.023*
a (1)	0.080*	0.172	0.046*
a (2)	0.111*	0.085	0.053*
a (3)	0.115*	0.141	0.090*
a (4)	0.084*	0.08	0.053*
a (5)	0.049*	0.269	0.074*
a (6)	0.038*	0.168	0.072*
a (7)	0.057*	0.140	0.063*
b (1)	0.894*	0.613	0.947*
b (2)	0.821*	0.633	0.922*
b (3)	0.708*	0.550	0.842*
b (4)	0.854*	0.581	0.931*
b (5)	0.906*	0.508	0.905*
b (6)	0.945*	0.383	0.856*
b (7)	0.838*	0.377	0.918*
DCC(a)	0.006*	0.136	0.006*
DCC(b)	0.992*	0.230	0.986*

Notes: * indicate significance at the 5% level.

The result of conditional correlation shows significant and positive effects in almost all markets during the pre-crisis and post-crisis periods, except for China stock market. The estimate of a , which is the impact of past shocks on current conditional correlation, and parameter b, the impact of past correlation, are statistically significant at 1% level. This implies that the conditional correlation is not constant. Hence, the DCC model is more appropriate than the constant conditional model (CCC), which assumes that a=b=0. The

DCC parameter a are small number as compared with b, and the sums of these parameters are close to one. For instance, the China stock market has a coefficient of a_1 = 0.08 and b_1 = 0.89, that shows conditional volatility persistence during the pre-crisis period. Similar results are also prevailed for other markets as well. The DCC parameter estimates during crisis period vary widely, which implies that the correlation dynamic differs across EAGLE markets.

To examine the time-varying propagation of return and volatility spillover across EAGLEs markets, GARCH framework with a BEKK representation are employed by classifying the total sample into three sub-periods according to the 2008 global financial crisis.

Results on Mean to Mean Spillover

Mean to mean spillover effects of stock returns are analyzed in two parts: internal spillover and external spillover. The results of internal mean to mean spillover effects (matrix B in mean Equation 1), gives emphasis on the simultaneous spillover of return among EAGLEs markets. While, the external mean to mean spillover effect (matrix Ψ in mean Equation 1) captures the influence of developed markets on EAGLEs financial markets. The result of mean to mean spillover effects are shown in Table 3.

Table 3
Mean to mean spillover effect

	Matrix B: Internal							Matrix Ψ: External		
	China	**India**	**Indonesia**	**Russia**	**Brazil**	**Turkey**	**Mexico**	**US**	**UK**	**Germany**
Pre-Crisis Period										
China	0.676*	-0.084*	-0.077	0.537*	0.326*	0.270*	-0.123*	0.098*	0.059*	0.064*
India		0.275*	-0.353*	-0.527*	-0.394*	-0.313*	-0.003	-0.049*	-0.062*	-0.047*
Indonesia			0.765*	-0.048	0.074*	0.176*	-0.131*	-0.021	0.015	0.006
Russia				0.221*	0.228*	0.048	0.008	0.076*	-0.003	-0.007
Brazil					0.311*	-0.096*	0.142*	0.113*	-0.037*	-0.035*
Turkey						0.043	0.034	0.005	0.008	0.014
Mexico							-0.006	-0.004	0.004	0.002
Crisis Period										
China	0.736*	0.231	-0.105	-0.263	-0.628*	0.172	-0.304*	-0.251*	-0.679*	-0.788*
India		-0.345*	0.208*	-0.149	0.133	-0.194	0.479*	0.333*	0.109	0.328*
Indonesia			0.019	-0.014	0.003	-0.018	0.061	0.053	-0.001	0.037
Russia				0.008	-0.056	0.024	-0.038	-0.015	-0.168	-0.128
Brazil					-0.003	0.034	-0.0944	-0.058	-0.138	-0.113
Turkey						0.027	-0.08	-0.067	-0.003	-0.057
Mexico								0.208*	0.134	0.225*
Post-Crisis Period										
China	0.004	0.036*	0.001	0.140*	0.031	-0.019	0.214*	-0.034*	0.142*	0.139*
India		0.160*	0.039	-0.161*	0.346*	-0.236*	0.266*	0.135*	0.289*	0.149*
Indonesia			0.116*	-0.147*	0.201*	-0.144*	-0.179*	0.031*	0.076*	0.029
Russia				0.208*	-0.120*	0.044	-0.041	-0.019	0.145*	0.129*
Brazil					0.209*	0.019	0.145*	0.094*	0.106*	0.088*
Turkey						0.225*	0.014	0.062*	-0.098*	-0.069*
Mexico							0.199*	-0.117*	-0.139*	-0.067*

Notes: * indicate significance at the 5% level.

During the pre-crisis period, the diagonal parameter of matrix B suggests that the return of China, India, Indonesia, Russia and Brazil stock markets are influenced by their first lags. On the contrary, the insignificant diagonal elements provide evidence that the returns of Turkey and Mexico stock markets are not influenced by their lagged returns. The off-diagonal element of matrix B measures the cross-market spillover effects among the EAGLEs markets. For instance, there is significant lagged returns spillover from India to China, and from Turkey to China, India, Indonesia and Brazil stock markets.

As to the crisis period, the mean volatility in Brazil and Mexico market found to have a significant impact on the stock return of China, as shown in Table 3. There is also evidence of mean spillover from Indonesia and Mexico to India. Moreover, the return of China and India stock market significantly influenced by their lagged returns. The overall result reveals a considerable drop in the mean spillover among EAGLEs stock market during the turbulence period.

The result of internal mean to mean spillover during the post-crisis period reveals a new insight. The return of all EAGLEs markets except Russia and Mexico are influenced by their lagged return, beside lagged mean return transmitted from other counterparts. For instance, the return of India and Indonesia markets are significantly impacted by the lagged return of Russia, Brazil, Turkey and Mexico markets. At the same time, Russia and Brazil markets also influenced by mean spillovers from Brazil and Mexico stock markets, respectively. These results support the fact that the increase in the integration of stock markets after the 2008 global financial crisis, and the returns are expected to be affected by not only on their own lagged return, but also by other market returns as well.

The external mean to mean spillover effect captures the influence of developed financial markets on EAGLEs markets, as exhibited in Table 3. The result of pre-crisis period shows a significant mean spillover from US, UK and Germany stock markets to China, India and Russia markets. While during turmoil period, US and German markets continue to influence the stock returns of China and India. At the same time, the UK stock market found to have a significant impact on the stock market of China. However, in this period the spread from developed to other EAGLEs stock market was weak.

The result of post-crisis period shows a new picture, apart from Russia, the return of all EAGLEs stock markets influenced by the spillover from US market. This indicates a strong connection of emerging markets with the US stock markets in the recovery period, as opposed to the pre-crisis period. Furthermore, we find evidence of significant mean spillover from UK and Germany stock market to almost all emerging markets.

Results on Conditional Variance Spillover

The above sub-section dealt with the mean to mean spillover among EAGLEs markets and the influence of external markets lagged return on these markets. In this part, we reveal the estimated results of time-varying conditional variance spillover effects. The estimated coefficients of matrix ϕ and matrix Ω in Equation 2 are reported in Table 4 and 5, respectively. The diagonal elements in matrix ϕ capture the effect of previous shocks i.e. own ARCH effect, whereas the diagonal elements in matrix Ω measures the historical conditional volatility to the current variance i.e. own GARCH effect. The off-diagonal element of these matrices captures the cross-market effect such as shock and conditional volatility spillovers among EAGLEs markets.

When we consider the shock transmissions within EAGLEs markets (as reported in Table 4) during the pre-crisis period, there is evidence of significant spillover from India, Brazil and Mexico to other emerging stock markets. Conversely, Turkey stock markets failed to have any substantial spillover effect on the returns of other EAGLEs markets. The diagonal element of China, India, Russia and Brazil stock markets indicate a strong self-shock spillover in the pre-crisis time.

During the crisis period, there is statistically significant shock transmission from Russia and Mexico to most EAGLEs stock markets. Turkey stock market also started to influence India, Brazil and Mexico stock markets. While, the shock transmission from China and India to other EAGLEs markets decline during this period.

Table 4
Conditional variance spillover effects. (ARCH matrix Φ)

	Matrix Φ: Internal							Matrix Φ: External		
	China	**India**	**Indonesia**	**Russia**	**Brazil**	**Turkey**	**Mexico**	**US**	**UK**	**Germany**
Pre-Crisis Period										
China	0.221*	-0.100*	-0.025	-0.047	-0.069*	0.033	-0.144*	0.106	0.027	-0.045
India	-0.061*	0.214*	0.044	-0.049*	-0.082*	-0.026	-0.017*	0.016	-0.143*	0.101*
Indonesia	0.086*	0.024	-0.019	-0.027	-0.066*	0.003	-0.015*	-0.255	-0.219*	0.065*
Russia	0.004	-0.067*	0.039	0.197*	-0.024	-0.037	-0.187*	-0.059	0.071	-0.037
Brazil	0.027	0.148*	-0.079*	0.003	0.094*	0.026	-0.088*	-0.187*	0.066*	-0.054*
Turkey	0.048*	0.011	-0.048	0.027	-0.025	0.008	-0.103*	-0.245*	0.229*	-0.107*
Mexico	0.028	0.099*	-0.053*	0.062*	-0.035*	0.004	-0.021	-0.041	-0.011	0.071*
Crisis Period										
China	-0.106*	0.102	-0.143*	0.054	0.109	-0.069	-0.240*	-0.161	-0.068	0.196
India	-0.031	-0.011	-0.029	0.137*	-0.098	0.143*	-0.128	-0.045	0.123	-0.051
Indonesia	-0.02	-0.023	0.112*	0.006	-0.194*	0.069	-0.242*	-0.002	-0.052	0.284*
Russia	-0.223*	0.212*	0.013	0.246*	-0.711*	-0.071	-0.850*	-0.113	-0.574*	1.155*
Brazil	-0.103*	-0.083	0.108	0.237*	0.039	0.285*	-0.271*	-0.570*	-0.376*	0.705*
Turkey	-0.033	0.177*	0.062	0.104*	-0.288*	0.055	-0.289*	-0.175*	-0.431*	0.506*
Mexico	0.018	-0.063	0.004	0.175*	-0.120*	0.086*	-0.209*	-0.225*	-0.125*	0.431*
Post-Crisis Period										
China	0.144*	-0.014	-0.026	-0.063*	0.029	0.017	-0.045	-0.091*	0.067*	0.052*
India	0.007	0.126*	-0.116*	0.004	-0.016	0.041*	-0.011	-0.188*	0.106*	-0.008
Indonesia	0.008	-0.051*	-0.163*	0.018	-0.028	0.063*	-0.049	-0.231*	0.129*	0.051*
Russia	-0.008	-0.125*	-0.005	0.173*	-0.096*	0.016	0.173*	-0.366*	0.027	0.103*
Brazil	0.017	0.094*	-0.171*	-0.063*	0.237*	0.071*	-0.045	-0.217*	0.262*	-0.014
Turkey	-0.065*	-0.065*	0.063*	0.056*	-0.007	0.099*	0.288*	-0.167*	-0.003	0.038
Mexico	-0.008	0.026	-0.106*	-0.072*	0.018	0.064*	0.023	-0.215*	0.224*	-0.047*

Notes: * indicate significance at the 5% level.

After the crisis period, the results relating to shock transmission reveals considerable interdependence among EAGLE markets, although the channel of spillover are different. For instance, the transmission of shocks from India and Indonesia have a negative influence on the return of most EAGLEs stock markets. On the other hand, Turkey stock market found to impact others positively. This shows the existence of different channels of shocks propagation within EAGLEs markets in the post-crisis period.

Regarding the influence of external markets, the distribution of shocks varies across periods. The spillover from US market was most evident for Brazil and Turkey during the tranquil period. While, during the 2008 global financial crisis, the shocks from US market started to impact Mexico market as well. After the crisis, there is persistent negative volatility spillovers from US to the return of all EAGLEs stock market. The transmission of shocks from UK market impacts the return of India, Indonesia, Brazil and Turkey markets in the pre-crisis period, and the returns of most stock markets during the post-crisis periods. The study of Chan et al. (1992) also indicates that US and UK stock markets had significant influence on the Asian markets. The level of spillover originates from German stock market declined from the pre-crisis to the post-crisis period; while the spillover from US and UK markets increased significantly over time.

From the perspective of volatility transmissions among emerging markets, the results reveal interesting insights. Table 5 reports a strong connection of cross-market volatility spillover among most EAGLEs stock markets. For instance, in the pre-crisis period there is a significant volatility spillover from China, India, Brazil and Mexico to all EAGLEs stock markets. Similarly, there is significant conditional volatility spillover from Indonesia and Russia stock market to the return of their counterparts, except for China and India respectively. The estimated diagonal elements are all statistically significant, indicating a strong self-volatility to volatility spillover.

As to the crisis period, cross-market volatility spillovers within the group of EAGLEs stock markets found significant. The result shows considerable volatility spillover from India and Brazil to all stock markets, from China to other stock markets except Brazil, and from Russia to all stock return apart from Indonesia.

Table 5
Conditional variance spillover effects. (GARCH matrix Ω)

	Matrix Ω: Internal							**Matrix Ω: External**		
	China	**India**	**Indonesia**	**Russia**	**Brazil**	**Turkey**	**Mexico**	**US**	**UK**	**Germany**
Pre-Crisis Period										
China	0.781*	0.071*	-0.015	-0.133*	-0.078*	-0.017	0.519*	-0.228*	-0.049*	0.02
India	-0.044*	0.885*	-0.095*	0.026	0.098*	-0.005	0.232*	-0.026	0.028*	-0.087*
Indonesia	-0.065*	0.229*	0.464*	-0.108*	-0.097*	-0.044*	0.345*	-0.029*	0.120*	-0.047*
Russia	-0.221*	0.149*	-0.161*	0.716*	-0.174*	-0.042*	0.571*	-0.222*	-0.008	0.039*
Brazil	-0.145*	-0.059*	-0.182*	-0.162*	0.849*	-0.034*	0.179*	-0.049*	0.053*	0.039*
Turkey	-0.168*	0.126*	-0.264*	-0.187*	-0.111*	0.949*	0.414*	-0.098*	-0.032*	0.047*
Mexico	-0.118*	-0.206*	0.036*	-0.071*	0.022*	-0.008*	0.927*	0.042*	0.050*	-0.026*
Crisis Period										
China	0.504*	-0.769*	0.853*	-0.091*	0.206*	0.476*	-0.066	0.041	-0.169	-0.268*
India	0.270*	0.475*	0.204*	-0.168*	0.121*	0.643*	-0.03	-0.190*	0.148*	-0.277*
Indonesia	-0.177*	0.136*	0.824*	-0.032	-0.091*	-0.172*	0.349*	-0.236*	0.059	0.168*
Russia	0.165*	-0.129*	-0.081	0.429*	-0.129*	-0.104	0.051	-0.494*	1.118*	-0.096
Brazil	-0.064	-0.146*	0.023	-0.147*	0.841*	0.161	-0.044	-0.187*	0.807*	-0.578*
Turkey	-0.223*	-0.179*	0.078	-0.147*	-0.107*	0.833*	0.013	-0.124*	0.235*	0.181*
Mexico	0.108*	-0.080*	-0.171*	-0.142*	0.123*	0.183*	0.727*	-0.209*	0.199*	0.037
Post-Crisis Period										
China	0.982*	0.007	0.014	0.017*	-0.005	-0.013*	0.031*	0.015	-0.067*	0.012
India	0	0.982*	-0.003	0.014*	0.004	0.008	-0.071*	0.137*	-0.163*	0.031*
Indonesia	-0.011*	0.019*	0.968*	-0.007	0.031*	-0.139*	0.063*	0.056*	-0.025	0.011
Russia	-0.013*	0.035*	0.067*	0.928*	0.110*	-0.069*	-0.137*	0.226*	-0.047*	-0.041*
Brazil	0.011*	-0.030*	-0.053*	0.094*	0.890*	0.074*	-0.003	0.083*	-0.465*	0.145*
Turkey	-0.012	-0.015	0.274*	-0.069*	0.083*	0.871*	-0.181*	0.267*	0.092*	-0.092*
Mexico	0.008	-0.011	0.037*	0.064*	-0.015*	0.068*	0.645*	0.285*	-0.397*	0.098*

Notes: * indicate significance at the 5% level.

Therefore, the volatility spillovers among most EAGLEs markets found to be bi- directional. This result supports the findings of Leong and Felmingham (2003) and Jang and Sul (2002) that the correlation among Asian stock markets strengthened during Asian financial crisis.

Considering the spillover effects in the post-crisis period, it is evident that transmission of volatility between the stock markets slightly decline. Especially, spillover spread from China and India to other markets. Furthermore, we also find evidence of weak transmission of volatility from Brazil to China and Indian stock markets. Therefore, as far as the volatility spillovers are concerned, the result shows a strong inter-connection and existence of channels of volatility transmission within the group of EAGLEs stock markets during the pre-crisis and crisis periods than post-crisis period.

Another finding is volatility spillover from developed markets to EAGLEs stock return. The propagation of volatility from US impacted most stock markets, except for India in the pre-crisis period. Numerous studies investigated the influence of US stock markets towards others markets and report the major impact and leading character of US market on emerging stock markets (Liu & Pan, 1997; Ng, 2000; Gilenko & Fedorova, 2014). Interestingly, UK and German markets also strongly interact with all EAGLEs markets before the 2008 Global financial crisis. During the crisis period, there is clear evidence of statistically significant volatility transmission from US to most EAGLEs stock markets. But, the influence of UK and German on other stock markets was less enunciated relative to U.S market. The post-crisis period reveals interesting result; the insurgence of volatility from US and U.K markets intensely impacts the stock return of all EAGLEs markets, except China and Indonesia respectively. This clearly indicates that volatility transmission and interdependence among markets increased significantly over time.

Conclusion

In this paper, we examined the return and volatility spillovers among EAGLEs stock markets for the sample period from 2002 to 2017. To considering the time-varying interdependence of return and volatility transmission among stock markets we split the total sample into three sub-periods: pre-crisis period, the crisis period and the post-crisis period. Then the propagation of mean and volatility spillover among stock returns assessed using both DCC and BEEK-GARCH models. We also investigated the influence of developed markets on EAGLEs financial markets.

The estimation result shows that conditional correlation and mean spillover are more persistent during the pre-crisis and post-crisis periods. While, strong volatility transmission among EAGLEs markets are prevalent in the pre-crisis and crisis periods than post-crisis period. The insurgence of spillovers from external markets, especially from US, intensely impacted the stock return of EAGLEs markets. The return and volatility spillovers varies across time, which is consistent with the findings of Kearney and Lucey (2004) and Gallo and Velucchi (2009).

Th findings of this study may have several implications for investors, policy makers and researchers. For instance, the presence (absence) of spillover among stock markets gives useful insight to investors to explore exploitable trading strategies and potential gain from international portfolio diversification. For policy makers, the patterns of returns and volatility spillover have an important implication in policy arrangements due to an increased role of stock market in the economy. For future research endeavor, this study can be extended by using different markets and analytical techniques.

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