Volatility Spillover from the Chinese Stock Market to E7 and G7 Stock Markets

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Abstract

Purpose – The purpose of this paper is to examine volatility spillover from the Chinese stock market to E7 and G7 stock markets. Using the estimated results, the authors also analyze the optimal weights and optimal hedge ratios for the portfolios including stocks from E7 and G7 countries.

Design/methodology/approach – The authors employed generalized vector autoregressive-generalized autoregressive conditional heteroskedasticity approach, developed by Ling and McAleer (2003), in order to analyze daily data on the national stock indices. Considering the late establishment of some E7 stock markets, the sampling covers the period from 1995 through 2015.

Findings – The findings indicate significant volatility spillover from the Chinese stock market to E7 and G7 stock markets. In particular, the Chinese stocks highly co-move with the stocks of countries within a same geographical region. While the highest volatility spillover occurs between China and India among E7 countries, the highest volatility spillover occurs between China and Japan among G7 countries. Furthermore, the examination of optimal weights and hedge ratios suggest that investors should hold more stocks from G7 countries than E7 countries for their portfolios.

Originality/value – To the best of the authors' knowledge, this is the first study which investigates the volatility spillover in the stock markets of G7 and E7 countries. Moreover, the current study contributes particularly to the existing limited literature on the Chinese stock market. Since the Chinese stock market is not fully integrated to other markets and it is subject to intense government interventions, there is a widely accepted belief that the contagion effects from the Chinese stock market to other stock markets are not influential. This view discourages and limits the prospect studies. However, the findings of this paper refute this view and indicate significant interaction among the Chinese stock market and E7 and G7 stock markets.

Keywords China, Volatility spillover, G7, E7, Hedge ratio, VAR-GARCH

Paper type Research paper

1. Introduction

In spite of some advantages, financial integration and globalization carry some risks. Contagion of the financial crisis is the most serious disadvantage of increased interdependence. This effect was particularly obvious in the advent of the 2007–2009 financial crisis during which the vulnerability of both developed and developing markets increased. The linkages between developed markets and emerging markets have thus become a hot topic of debate.

The recent financial crisis not only hit the financial markets but also accelerated the shift in economic power from developed to emerging economies. While the emerging countries weathered the storm well, the developed economies suffered and remained vulnerable even long time after the crisis. During this period, the developing economies proved themselves as true competitors to the developed economies and they reinforced an argument that the

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global economic axis will be shifted from Group of 7 (G7) countries to Emerging 7 (E7) countries in the following decades (PWC, 2011)[1].

The primary objective of this study is to examine volatility spillover from the Chinese stock market to G7 and E7 stock markets. We employed vector autoregressive-generalized autoregressive conditional heteroskedasticity (VAR-GARCH) approach, developed by Ling and McAleer (2003), to analyze daily data on the stock prices of national indices over the period from 1995 through 2015. We test the volatility spillover from the Chinese equity market to E7 and G7 countries. In recent years, the world markets view the Chinese economy as a barometer of the world economy rather than an indicator of China's domestic economy itself. News about the Chinese economy affects the economies of other countries significantly (Baum *et al.*, 2014). Although the Chinese financial markets are relatively isolated from the international markets, regulatory reforms over the last decade have done much to improve the functioning of the financial markets. In recent years, the Chinese stock market gradually becomes more integrated with other markets as a result of the relaxation of restrictions on capital controls such as the unlocking of state-owned shares, the introduction of the Qualified Foreign Institutional Investor program, minority shareholder protection, dividend policy and disclosure. The ongoing reforms in the Chinese financial markets are not enough but promising to investigate whether or not there is a spillover effect from the Chinese stock market to other stock markets.

Our findings indicate significant volatility spillover from the Chinese stock market to E7 and G7 stock markets. In particular, the Chinese stocks highly co-move with the stocks of countries within a same geographical region. While the highest volatility spillover occurs between China and India among E7 countries, the highest volatility spillover occurs between China and Japan among G7 countries. Furthermore, the portfolio analysis suggests that the inclusion of G7 countries stocks to a well-diversified portfolio of the Chinese stocks may improve the risk-adjusted performance of portfolios.

The current study contributes to the existing literature in three folds. The foremost of the contributions is that while the existing studies focus mostly on one or two developed countries and few emerging markets, the current study specifically focuses on the E7 and G7 countries. To the best of the authors' knowledge, this is the first study which investigates the volatility spillover in the stock markets of G7 and E7 countries. Moreover, the current study contributes particularly to the existing limited Chinese literature. Since the Chinese stock market is not fully integrated to other markets and it is subject to intense government interventions, there is a widely accepted belief that the contagion effects from the Chinese stock market to other stock markets are not influential. This view discourages and limits the prospect studies. Therefore, this paper is an attempt to test whether the Chinese stock market has a volatility spillover effect or not.

This paper is organized as follows; Section 2 describes literature review. Section 3 depicts data and methodology used in this paper in order to analyze the volatility spillover effects between G7 and E7 countries. Section 4 highlights the empirical results and discussion. Section 5 summarizes the concluding remarks.

2. Literature review

Empirical literature has focused on the transmission of volatility from one country to another country which is referred to as volatility spillover effect. Since volatility spillover is a function of financial integration and financial crisis, investors have great interest in determining the volatility spillover in order to develop hedging strategies to reduce their risk and vulnerability. A number of studies presented the evidence of significant volatility spillover across developed stock markets (Hamao *et al.*, 1990; Ng, 2000; Miyakoshi, 2003; Baele, 2005; Giannellis *et al.*, 2010; Jawadia *et al.*, 2015; Li and Giles, 2015; Akca and Ozturk, 2016).

In recent years, emerging markets have received a great attention due to high risks associated with high returns in these markets. In MENA region, Abou-Zaid (2011) investigated volatility spillover from the USA and UK to selected MENA emerging markets. The author also showed a significant transmission of daily stock index volatility movements from the USA to Egypt, Israel and Turkey. In a recent paper, Ozturk and Volkan (2015) examined the stock return volatility spillovers within the MENA region and from the USA to the MENA region. They used daily data between 2008 and 2012. Their findings show that there is a significant volatility spillover in MENA stock returns. The highest (lowest) return volatility spillover occurs in the banking and financial sectors (oil and gas sectors).

In Asia, Lee (2009) used the VAR-GARCH model to examine the volatility spillover among six Asian countries including India, Hong Kong, South Korea, Japan, Singapore and Taiwan. The author also found significant volatility spillover among these stock markets. The existence of high volatility spillover in Asian stock markets suggests limited hedging choices available for investors. In another study, Sok-Gee and Karim (2010) examined five ASEAN countries with the USA and Japan, and employed multivariate EGARCH model. The results of EGARCH model show significant volatility spillover effects between the USA and Japan. Furthermore, the Philippines and Thailand are more sensitive to past shocks. Abbas *et al.* (2013) investigated the presence of volatility spillover among the stock markets of Pakistan, China, India and Sri Lanka. Their findings show that trade and investment links among countries play crucial roles in volatility transmission. A closer inspection of their analyses suggests that volatility spillover among the four countries is mostly from a larger market to a smaller market. The volatility transmission among Pakistan, India and Sri Lanka is due to economic fundamentals rather than herd behavior. Therefore, the investors should better not intensify their stock investments, where the correlation levels are high in order to diversify the risk of their portfolios. More recently, Yarovaya *et al.* (2016) investigated volatility transmission across stock index futures in six major developed and emerging markets (Hong Kong, Singapore, Japan, China, Taiwan and South Korea) in Asia. Their results show strong transmission, indicating that the stock returns are sensitive to both negative and positive volatility shocks. Their findings suggest that South Korea is a recipient of volatility from Singapore, China and Taiwan and it is the source of negative volatility shocks for Hong Kong and Taiwan, respectively. For investors, it is important to understand the source of cross-country volatility spillover in order to adopt appropriate risk management technics and hedging strategies. Once the investors attempt to measure the volatility spillover, it would be easier for them to calculate optimal weights and hedge ratios for their portfolios.

Focusing on China, Li (2007) investigated the stock markets of China, Hong Kong and the USA to measure the linkages among these markets by using MV-GARCH model. Their results show no direct linkage between the Chinese and the US stock markets. The outcomes of the study also suggested low volatility spillovers between the stock markets of China and Hong Kong. Moreover, Bhar and Nikolova (2009) employed an EGARCH model to examine the volatility spillover between the USA and BRICS stock markets. Their findings showed volatility transmission effects between the USA and BRICS markets. Furthermore, Moon and Yu (2010) investigated spillover effects by employing structural breaks and symmetric and asymmetric GARCH models between China and USA from 1999 through 2007. They found a strong evidence of symmetric and asymmetric volatility spillover from the USA to China. In recent past, Abidin and Zhang (2011) studied major Asian markets to investigate the volatility spillover effect over a period from 2004 to 2010. They found significant volatility spillover between the Australian and Chinese stock markets. Syriopoulos *et al.* (2015) investigated the sectors of BRICS' stock markets by using VAR-GARCH model from 2005 to 2013. Their findings show significant volatility spillover between the USA and BRICS countries and negative correlation between the USA and China. The low and negative correlation between the USA and China suggests certain portfolio gains to be expected from asset diversification. In particular, past US industrial sector volatility affects industrial sector volatility in all BRICS markets, except China. This result can be associated with the gradual integration of China into the world economy. Furthermore, their results indicate low hedging ratios for US–BRIC portfolios. This suggests that the hedging effectiveness on the BRIC and US sector indices is very satisfactory. In another study, Nishimura *et al.* (2016) explored return and volatility spillover between the Chinese and Japanese stock markets during the periods, where trading hours of these countries overlap. Their findings show the unidirectional impact of the Chinese stock market on the Japanese stock returns. This finding can be attributed to restrictions on foreign investment in the Chinese stock market, and insufficiently diversified international portfolios held by the Chinese investors.

More recently, Majdoub and Sassi (2017) examined volatility spillover between the Chinese and Asian stock markets including China, India, Malaysia, Indonesia, Korea and Thailand. They applied bivariate VARMA-BEKK-AGARCH model for the period of 2011–2016. Further, they computed the effectiveness of portfolio diversification based on the conditional volatility of returns series. Their results show a significant positive and negative return spillover from China to selected Asian Islamic stock markets and bidirectional volatility spillovers among the stock markets of China, Korea and Thailand. For international portfolio diversification and hedging strategies, they suggest that investors in Asia should hold more stocks in the Chinese market than other stock markets in Asia in order to reduce the risk without lowering the anticipated returns of their portfolios.

3. Data description and methodology

3.1 Data

The data include daily closing prices of market indices for G7 and E7 countries. The data were taken from Thomsan Reuters Datastream over a period from September 1, 1995 to March 3, 2015 except for Italy due to the non-availability of earlier three-year data. Among the E7 stock markets, the Russian stock market was established later than other stock markets. Therefore, we chose data sample from 1995. Using daily prices enabled us to have relatively large observations. Since we deal with 14 countries in total, we had to drop some data due to non-matching trading days of E7 and G7 countries. It is important to note that time horizon of a portfolio is a sensitive issue for an investor. In the presence of short time horizon or long time horizon, a portfolio may drift from its target allocation and this may require portfolio rebalancing.

We matched the trading days of the sample countries. Since the data of 14 countries do not match with each other due to different trading days, we dropped non-trading and non-matched days. This induced reduction in the number of observations. However, the use of daily data enables us to deal with relatively a large sample size. In their studies, Mensi *et al.* (2013), Abbas *et al.*, Li and Giles (2015) and Syriopoulos *et al.* (2015) used daily closing prices in order to avoid more reductions in their sample.

The stock market indices of E7 include Shanghai Composite index of China, S&P BSE 100 index BSE 100 index of India, BOVESPA index of Brazil, BOLSA index of Mexico, RTS index of Russia, JSX Composite index of Indonesia and BIST 100 index of Turkey. The G7 stock indices include S&P/TSX Composite Index of Canada, CAC 40 index of France, DAX 30 index of Germany, FTSE MIB index of Italy, Nikkei 225 of Japan, and FTSE ALL SHARE index of the UK and S&P 500 index of the USA.

The daily returns are computed by using the following equation (Bali *et al.*, 2016):

$$R_t = (P_t - P_{t-1})/P_{t-1}, \tag{1}$$

where P_t is the current closing price of index and P_{t-1} the previous closing price of index.

3.2 Methodology

We employed bivariate VAR-GARCH (1, 1) model, proposed by Ling and McAleer (2003), to explore volatility spillover effects. The strength of the model rests on its flexibility to explore the conditional volatility and conditional correlation cross-effects with meaningful estimated parameters. The ability of the VAR-GARCH model to capture cross-market volatility interactions has been tested and confirmed in the recent studies (Hammoudeh *et al.*, 2009; Arouri *et al.*, 2011; Mensi *et al.*, 2013). In VAR-GARCH model, the conditional mean and variance are as follows:

$$R_t = \mu + \Phi R_{t-1} + \varepsilon_t, \tag{2}$$

$$\varepsilon_t = H_t^{1/2}\eta_t, \tag{3}$$

where R_t is the return of stock market index, ε_t the residual terms of the mean equation, η_t the random vectors and H_t the conditional variances.

Bollerslev's (1986) constant conditional correlation (CCC) model assumes that the conditional variance for each return, h_{it}, $i = 1, \ldots, m$, follows a univariate GARCH process:

$$h_{it} = \omega_i + \sum_{j=1}^{r} \alpha_{ij}\varepsilon_{i,t-j}^2 + \sum_{j=1}^{s} \beta_{ij} h_{i,t-j}, \tag{4}$$

where α_{ij} represents the ARCH effects, or the short-run persistence of shocks to return i, and β_{ij} represents the GARCH effects, or the contribution of shocks to return i to long-run persistence, namely $\sum_{j=1}^{r}\alpha_{ij} + \sum_{j=1}^{s}\beta_{ij}$.

The conditional correlation matrix of CCC is $\Gamma = E(\eta_t\eta_t'|F_{t-1}) = E(\eta_t\eta_t')$, where $\Gamma = \{p_{ij}\}$ for $i, j = 1, \ldots, m$. From (1), $\varepsilon_t\varepsilon_t' = D_t\eta_t\eta_t'D_t$, $D_t = (diagQ_t)^{1/2}$ and $E(\varepsilon_t\varepsilon_t'|F_{t-1}) = Q_t = D_t\Gamma D_t$, where Q_t is the conditional covariance matrix. The conditional correlation matrix is defined as $\Gamma = D_t^{-1}Q_tD_t^{-1}$, and each conditional correlation coefficient is estimated from the standardized residuals. Ling and McAleer (2003) proposed a VARMA specification of the conditional mean and the following specification for the conditional variance:

$$H_t = W + \sum_{i=1}^{r} A_i \vec{\varepsilon}_{t-i} + \sum_{j=1}^{s} B_j H_{t-j}, \tag{5}$$

where $H_t = (h_{1t}, \ldots, h_{mt})'$, $\vec{\varepsilon} = (\varepsilon_{1t}^2, \ldots, \varepsilon_{mt}^2)'$ and W, A_i for $i = 1, \ldots, r$ and B_j for $i = 1, \ldots, s$ are $m \times m$ matrices defined as:

$$A = \begin{pmatrix} \alpha^2_{\text{China }1} & \alpha^2_{\text{China }2} \\ \alpha^2_{\text{Index }2} & \alpha^2_{\text{Index }1} \end{pmatrix}, \quad B = \begin{pmatrix} \beta^2_{\text{China }3\ 1} & \beta^2_{\text{China }2} \\ \beta^2_{\text{Index }2} & \beta^2_{\text{Index }1} \end{pmatrix},$$

$$h_t^{\text{Index}} = C_{\text{Index}} + \alpha_{\text{Index}}\left(\varepsilon_{t-1}^{\text{Index}}\right)^2 + \beta_{\text{Index}} h_{t-1}^{\text{Index}} + \alpha_{\text{China}}\left(\varepsilon_{t-1}^{\text{China}}\right)^2 + \beta_{\text{China}} h_{t-1}^{\text{China}},$$

$$h_t^{\text{China}} = C_{\text{China}} + \alpha_{\text{China}}\left(\varepsilon_{t-1}^{\text{China}}\right)^2 + \beta_{\text{China}} h_{t-1}^{\text{China}} + \alpha_{\text{Index}}\left(\varepsilon_{t-1}^{\text{Index}}\right)^2 + \beta_{\text{Index}} h_{t-1}^{\text{Index}}.$$

The conditional covariance was modeled as:

$$h_t^{\text{Index, China}} = \rho \times \sqrt{h_t^{\text{Index}} \times h_t^{\text{China}}}, \tag{6}$$

where ρ is the conditional correlation coefficient.

This model allows both the conditional mean and volatilities between E7 and G7 countries to capture the interdependence and spillover effect.

The log likelihood function L was optimized by BFGS algorithm for a sample of T observations:

$$L = \sum_{t=1}^{T} L_t,\ \ L_t = \ \ln(2\pi)n/2-1/2\ln|H_t|-1/2\varepsilon_t' H_t^{-1}\varepsilon_t. \tag{7}$$

4. Empirical results

Table I describes the summary statistics of the stock returns for E7 and G7 countries. In general, the findings show that the stock returns of E7 countries are higher than those of G7 countries. The unconditional volatility, as measured by standard deviations, is higher for the E7 countries in comparison with G7 countries. The findings imply that emerging markets are riskier but provide higher returns than developed economies. The kurtoses of all countries are greater than 3 indicating that all stock return series are leptokurtic. The Jarque–Bera test rejects the null hypothesis of normality for both E7 and G7 stock return series. The L–B test results indicate the evidence of autocorrelation in return series of E7 and G7 stock markets.

The detailed inspection of developed and developing countries is given in Panel A and in Panel B, respectively. For E7 countries, the Russian stock market has the highest volatility, as approximated by a standard deviation of 2.67 percent, followed by the Turkish stock market (2.53 percent). The negatively skewed returns are found in China and India, while the positively skewed returns are found in other countries.

Figures 1 and 2 exhibit stock return behaviors for E7 and G7 countries. It is obvious in Figure 1 that while the volatility increased in Indian and Indonesian markets during the Asian crisis, the stock returns of Brazil and Mexico were affected from the 1994 Mexican financial crisis. The Russian and Turkish markets seem highly volatile during 1990s. All the countries have experienced a high volatility in their returns during the 2007–2009 subprime financial crisis. Further, there are large spikes in the volatilities of stock returns in response to the global financial crisis. In their paper, Syriopoulos *et al.* (2015) found similar volatility clustering patterns for BRICS countries during the recent global financial crisis.

Table II documents six bivariate VAR-GARCH (1, 1) models for testing the volatility spillover between China and the remaining E7 markets. The one-period lagged returns of the Chinese stock market affect the current returns of other E7 stock returns positively. Brazil and Mexico are reported as the most influenced markets with the coefficients of 0.062 and 0.045, respectively. This implies the fact that the Chinese past market returns can be used to predict other emerging markets stock returns. Inversely, with the exception of Russia, past stock returns of E7 have no impact on the Chinese stock returns. The impact of Russian stock market is significant and negative with an estimated coefficient of −0.045.

From the variance equation perspective, the ARCH and GARCH coefficients which are used to estimate shocks and volatility independence in the conditional variance equations are highly significant in most cases. The empirical findings show that past own volatility is important in determining future volatility. This conclusion is in line with previous studies on stock market volatility (Hammoudeh *et al.*, 2009; Joshi, 2011; Li and Giles, 2015). The past shocks of the Chinese stock market, $(\varepsilon_{t-1}^{\mathrm{China}})^2$, affect the return dynamics of Indonesia and Mexico. The past volatility of the Chinese stock market, represented by h_{t-1}^{China}, has no significant impact on the E7 countries. As for the opposite direction, the impact of past conditional volatility of emerging markets, h_{t-1}^{Index}, on the conditional volatility of the Chinese stock market is statistically significant. The reported outcome indicates that past conditional volatility of E7 countries can be modeled to estimate future volatility. To capture

Table I.
Descriptive statistics for E7 and G7 countries

Country	Brazil	China	India	Indonesia	Mexico	Russia	Turkey
Panel A: statistics for E7 countries							
Mean	0.00073	0.000455	0.000617	0.000629	0.000708	0.000813	0.001403
SD	0.021172	0.016765	0.016289	0.016161	0.015041	0.026662	0.025268
Min.	−0.15809	−0.099113	−0.112515	−0.119549	−0.133366	−0.191031	−0.181093
Max.	0.33419	0.09857	0.167544	0.140283	0.129231	0.223896	0.19451
Skewness	0.820706	−0.0323	−0.025532	0.042570	0.223517	7.448929	0.419964
Kurtosis	18.24559	4.91953	6.292764	7.795450	7.026080	249.63146	6.551686
J–B	66,909.4 (*0.00*)	4,826.06 (*0.00*)	7,895.54 (*0.00*)	12,117.27 (*0.00*)	9,882.14 (*0.00*)	10,910.72 (*0.00*)	8,698.74 (*0.00*)
ARCH–LM	118.011	331.664	246.266	271.373	284.202	437.36	441.545
LB–Q (12)	62.733 (*0.00*)	34.731 (*0.00*)	71.983 (*0.00*)	149.971 (*0.00*)	43.305 (*0.00*)	99.025 (*0.00*)	38.536 (*0.00*)
LB–Q (24)	265.44 (*0.00*)	248.00 (*0.00*)	247.61 (*0.00*)	365.33 (*0.00*)	218.27 (*0.00*)	350.56 (*0.00*)	210.61 (*0.00*)
No. of Obs	4,785	4,785	4,785	4,785	4,785	4,785	4,785
Panel B: statistics for G7 countries							
Country	Canada	France	Germany	Italy	Japan	UK	USA
Mean	0.000314	0.000311	0.00046	0.000099	0.000122	0.000224	0.00035
SD	0.011128	0.01487	0.015462	0.015941	0.015147	0.011269	0.01239
Min.	−0.093242	−0.090368	−0.080405	−0.082389	−0.114064	−0.083414	−0.09035
Max.	0.098233	0.111762	0.11402	0.114905	0.141503	0.092106	0.1158
Skewness	−0.037742	0.107039	0.013955	0.051152	−0.103019	−0.108523	−0.071296
Kurtosis	7.397226	4.660497	4.352830	4.111586	5.667508	6.105943	7.970654
J–B	10,910.72 (*0.00*)	4,339.60 (*0.00*)	3,777.73 (*0.00*)	2,964.46 (*0.00*)	6,412.51 (*0.00*)	7,442.59 (*0.00*)	12,670.61 (*0.00*)
ARCH–LM	457.996	408.596	495.685	319.394	869.922	569.356	619.056
LB–Q (12)	99.025 (*0.00*)	54.714 (*0.00*)	22.114 (*0.00*)	47.882 (*0.00*)	20.228 (*0.00*)	74.219 (*0.00*)	60.447 (*0.00*)
LB–Q (24)	307.06 (*0.00*)	293.91 (*0.00*)	252.53 (*0.00*)	234.52 (*0.00*)	157.53 (*0.00*)	343.72 (*0.00*)	280.68 (*0.00*)
No. of Obs	4,785	4,785	4,785	4,785	4,785	4,785	4,785

Notes: *p*-values are in parentheses. JB is the empirical statistics of the Jarque–Bera test for normality based on skewness and excess kurtosis. ARCH refers to the empirical statistics of the statistical test for conditional heteroskedasticity of order 6. LB is the empirical statistics of the Ljung–Box tests for autocorrelations

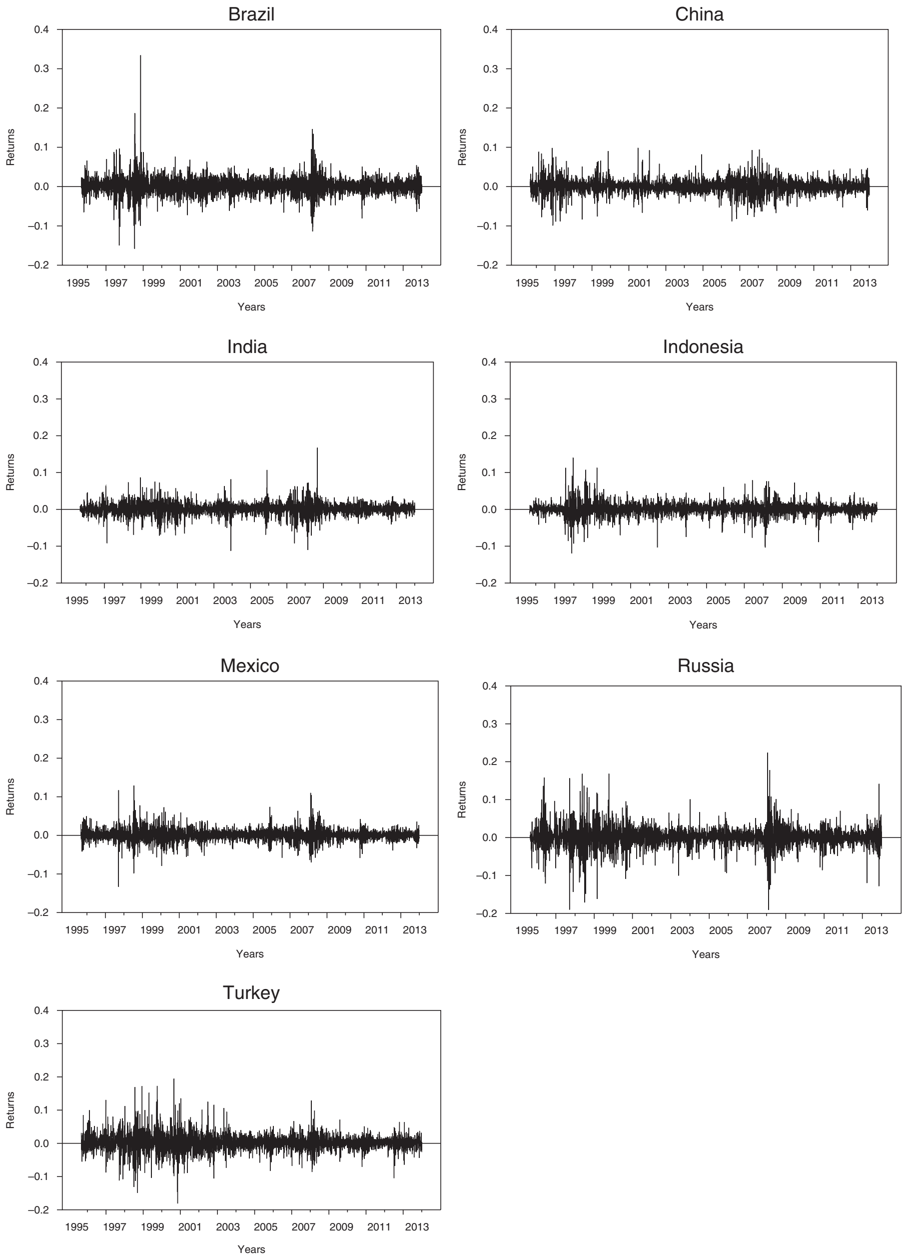

Figure 1.
Daily stock returns for E7 countries

persistence in the conditional variance of stock returns, GARCH (1.1) is sufficient. The estimates of CCC present mixed results. While the CCC values are positive and significant for Brazil and India, the coefficients are negative and significant for Mexico and Russia. There is no significant constant correlation observed for the markets of Indonesia

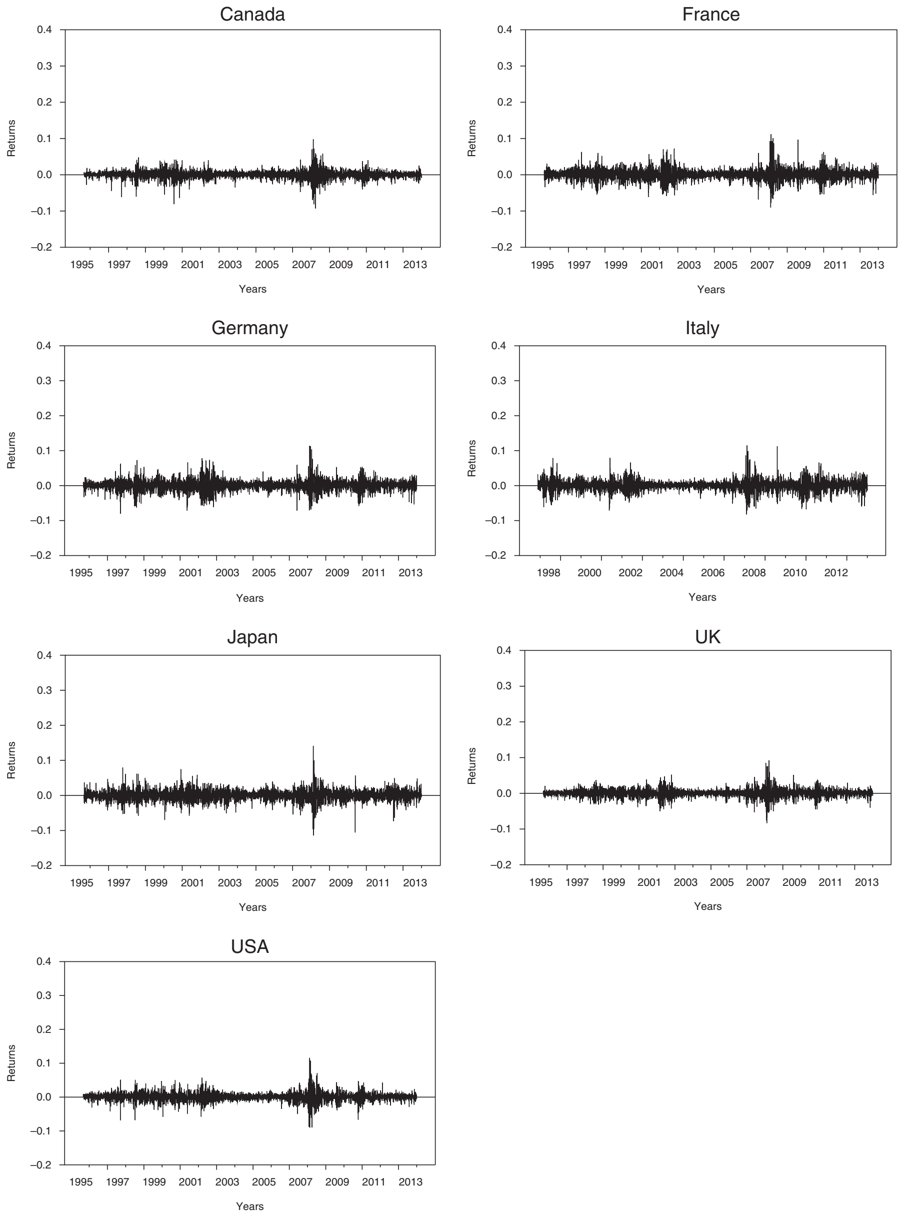

Figure 2.
Daily stock returns for G7 countries

and Turkey. The results show that the highest CCC is between China and India. This is consistent with the findings of Joshi (2011), who analyzed the volatility dynamics in six Asian stock markets and found volatility spillover from the Chinese stock market to the Indian stock market.

According to mean equation in Table III, the impact of one-period lagged returns of the Chinese stock market on G7 markets is positive and significant at 1 percent. There is no

Table II. Estimates of VAR(1)-GARCH(1) model for China and E7

	Brazil		India		Indonesia	
Mean eq.	China	Brazil	China	India	China	Indonesia
China(1)	−0.0009 (*0.95*)	0.062*** (*0.00*)	−0.001 (*0.92*)	0.034*** (*0.01*)	0.001 (*0.91*)	0.025** (*0.04*)
Index(1)	0.007 (*0.60*)	0.007 (*0.62*)	−0.004 (*0.72*)	0.094*** (*0.00*)	−0.011 (*0.21*)	0.125*** (*0.00*)
Variance equation						
C (10) ^{5}	0.360*** (*0.00*)	0.621*** (*0.00*)	0.301*** (*0.00*)	0.233*** (*0.00*)	0.337*** (*0.00*)	0.409*** (*0.00*)
$(\varepsilon_{t-1}^{\text{China}})^2$	0.060*** (*0.00*)	−0.001 (*0.69*)	0.062*** (*0.00*)	−0.0008 (*0.89*)	0.059*** (*0.00*)	0.010* (*0.08*)
$(\varepsilon_{t-1}^{\text{Index}})^2$	−0.040*** (*0.00*)	0.097*** (*0.00*)	0.006 (0.39)	0.098*** (*0.00*)	−0.012 (*0.11*)	0.113*** (*0.00*)
h_{t-1}^{China}	0.932*** (*0.00*)	−0.057 (*0.11*)	0.923*** (*0.00*)	0.042 (*0.21*)	0.930*** (*0.00*)	3.308 (*0.36*)
h_{t-1}^{Index}	0.268*** (*0.01*)	0.874*** (*0.00*)	0.184*** (*0.00*)	0.871*** (*0.00*)	−6.54*** (*0.00*)	0.871*** (*0. 00*)
CCC China and Index	0.077*** (*0.00*)		0.129*** (*0.00*)		−0.0007 (*0.24*)	
Log like	25,765		26,910		27,077	
AIC	−9.895		−10.194		−10.355	
H–Q	−9.865		−10.153		−10.323	
	Mexico		Russia		Turkey	
Mean eq.	China	Mexico	China	Russia	China	Turkey
China(1)	0.003 (*0.75*)	0.045*** (*0.00*)	0.004 (*0.79*)	0.033*** (*0.00*)	0.001 (*0.94*)	0.029*** (*0.00*)
Index(1)	0.011 (*0.20*)	0.088*** (*0.00*)	−0.045*** (*0.00*)	0.112*** (*0.00*)	−0.019 (*0.24*)	0.035*** (*0.01*)
Variance equation						
C (10) ^{5}	1.600*** (*0.00*)	0.400*** (*0.00*)	0.309*** (*0.00*)	0.992*** (*0.00*)	0.318*** (*0.00*)	0.390*** (*0.00*)
$(\varepsilon_{t-1}^{\text{China}})^2$	0.119*** (*0.00*)	0.057*** (*0.00*)	0.062*** (*0.00*)	0.002 (*0.62*)	0.061*** (*0.00*)	−0.002 (*0.53*)
$(\varepsilon_{t-1}^{\text{Index}})^2$	0.0004 (*0.86*)	0.171*** (*0.00*)	−0.066*** (*0.00*)	0.114*** (*0.00*)	−0.004 (*0.68*)	0.086*** (*0.00*)
h_{t-1}^{China}	0.821*** (*0.00*)	−27.4*** (*0.00*)	0.925*** (*0.00*)	−1.27 (*0.40*)	0.928*** (*0.00*)	−0.216 (*0.91*)
h_{t-1}^{Index}	−22.22*** (*0.00*)	0.820*** (*0.00*)	−18.76*** (*0.00*)	0.860*** (*0.00*)	−9.427 (*0.23*)	0.906*** (*0.00*)
CCC China and Index	−0.0003*** (*0.00*)		−0.001*** (*0.00*)		−0.0009 (*0.32*)	
Log like	27,273		24,857		24,846	
AIC	−10.534		−9.375		−9.429	
H–Q	−10.502		−9.343		−9.397	

Notes: The bivariate VAR(1)–GARCH(1, 1) model is estimated for each E7 country from September 1, 1995 to March 3, 2015. The Index refers E7 countries. The *p*-values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H–Q information criteria. *,**,***Significant at 10. 5 and 1 percent levels, respectively

Table III.
Estimates of VAR(1)–GARCH(1) model for China and G7 countries

	Canada		France		Germany		Italy	
Mean eq.	China	Canada	China	France	China	Germany	China	Italy
China(1)	−0.0008 (*0.95*)	0.133*** (*0.00*)	0.0002 (*0.98*)	0.077*** (*0.00*)	−0.0008 (*0.95*)	0.074*** (*0.00*)	0.006 (*0.70*)	0.085*** (*0.00*)
Index(1)	−0.013** (*0.04*)	0.056*** (*0.00*)	−0.012 (*0.22*)	−0.021 (*0.18*)	−0.008 (*0.38*)	−0.021 (*0.14*)	−0.004 (*0.69*)	−0.028* (*0.09*)
Variance equation								
C (10)^5	0.354*** (*0.00*)	0.104*** (*0.00*)	0.395 (*0.00*)	0.186*** (*0.00*)	0.403*** (*0.00*)	0.265*** (*0.00*)	0.429*** (*0.00*)	0.093* (*0.06*)
$\left(\varepsilon_{t-1}^{China}\right)^2$	0.060*** (*0.00*)	0.001 (*0.88*)	0.061*** (*0.00*)	−0.002 (*0.65*)	0.060*** (*0.00*)	−0.004 (*0.50*)	0.070*** (*0.00*)	−0.0008 (*0.90*)
$\left(\varepsilon_{t-1}^{Index}\right)^2$	−0.009** (*0.05*)	0.089*** (*0.00*)	0.011* (*0.06*)	0.079*** (*0.00*)	0.002 (*0.66*)	0.094*** (*0.00*)	0.005 (*0.47*)	0.090*** (*0.00*)
h_{t-1}^{China}	0.932*** (*0.00*)	−0.220 (*0.12*)	0.933*** (*0.00*)	−0.180** (*0.03*)	0.934*** (*0.00*)	−0.155*** (*0.01*)	0.915*** (*0.00*)	2.746 (*0.50*)
h_{t-1}^{Index}	0.069 (*0.40*)	0.900*** (*0.00*)	0.062 (*0.40*)	0.908*** (*0.00*)	0.023 (*0.752*)	0.893*** (*0.00*)	−10.6*** (*0.00*)	0.901*** (*0.00*)
CCC China and Index	0.036*** (*0.00*)		0.052*** (*0.00*)		0.061*** (*0.00*)		−0.0007 (*0.12*)	
Log like	29,037		27,398		27,311		24,146	
AIC	−11.111		−10.442		−10.353		−10.349	
H–Q	−11.070		−10.411		−10.321		−10.312	

	Japan		UK		USA	
Mean eq.	China	Japan	China	UK	China	USA
China(1)	0.003 (*0.79*)	0.009 (*0.48*)	−0.001 (*0.93*)	0.118*** (*0.00*)	0.003 (*0.85*)	0.115*** (*0.00*)
Index(1)	−0.006 (*0.53*)	−0.019 (*0.23*)	−0.010 (*0.15*)	0.004 (*0.76*)	−0.002 (*0.74*)	−0.029* (*0.07*)
Variance equation						
C (10)^5	0.411 (*0.00*)	0.372*** (*0.00*)	0.393*** (*0.00*)	0.123*** (*0.00*)	0.355*** (*0.00*)	0.099*** (*0.00*)
$\left(\varepsilon_{t-1}^{China}\right)^2$	0.602*** (*0.00*)	−0.002 (*0.65*)	0.060*** (*0.00*)	0.004 (*0.56*)	0.061*** (*0.00*)	−0.001 (*0.90*)
$\left(\varepsilon_{t-1}^{Index}\right)^2$	0.005 (*0.42*)	0.083*** (*0.00*)	−0.0004 (*0.93*)	0.101*** (*0.00*)	−0.014*** (*0.00*)	0.086*** (*0.00*)
h_{t-1}^{China}	0.936*** (*0.00*)	−0.082** (*0.04*)	0.934*** (*0.00*)	−0.219** (*0.02*)	0.933*** (*0.00*)	−0.547 (*0.31*)
h_{t-1}^{Index}	0.053 (*0.16*)	0.892*** (*0.00*)	0.022 (*0.68*)	0.888*** (*0.00*)	0.689 (*0.26*)	0.893*** (*0.00*)
CCC China and Index	0.137*** (*0.00*)		0.062*** (*0.00*)		0.016 (*0.23*)	
Log like	27,077		28,944		28,451	
AIC	−10.596		−11.079		−10.805	
H–Q	−10.565		−11.047		−10.773	

Notes: The bivariate VAR(1)–GARCH(1, 1) model is estimated for each G7 country from September 1, 1995 to March 3, 2015. The Index refers G7 countries. The *p*-values are given in parentheses. The optimal lag order for the VAR model is selected using the AIC and H–Q information criteria. *,**,***Significant at 10. 5 and 1 percent levels, respectively significant impact reported for Japan. The findings further show that G7 countries have no significant impact on the Chinese stock market.

The past conditional volatility of G7 markets is helpful to predict future volatility. In variance equation, it is reported that there is no significant impact of past shocks of the Chinese market, $\left(\varepsilon_{t-1}^{\text{China}}\right)^2$, on the conditional volatility of G7 countries stock returns. On the other hand, the past volatility of the USA, Canada and France stock markets has a significant impact on the stock return volatility of China. The findings further suggest that the past volatility of the Chinese stock market, h_{t-1}^{China}, affects market volatility in France, Germany, Japan and the UK.

Turning out to the estimates of the CCC, we find that the Chinese stock market returns are positively correlated with the stock returns in Canada, France, Germany, Japan and the UK. The magnitude of the correlation is generally very low suggesting a weak spillover. This can be attributed to segmented equity markets rather than integrated equity markets. The highest correlation occurs between China and Japan (0.137).

The findings can be valuable in terms of risk diversification and portfolio choice. Indeed, the conditional correlations are very low, suggesting that the Chinese market is not a channel of transmission of shocks and volatility spillover to G7 and E7 countries. This result can be attributed to the nature of the Chinese stock market, which is not fully integrated with the other financial markets. However, the investors should be careful while investing in the Chinese and other Asian stock markets simultaneously. The findings show relatively high correlations between the Chinese, Japanese and Indian stock markets. The geographical proximity and trading relations of these countries would be the reason of relatively high correlations among Asian stock markets.

4.1 Portfolio management and hedging strategies

The findings of VAR(1)–GARCH(1) show a significant volatility spillover from the Chinese stock market to E7 and G7 stock markets. According to Kroner and Ng (1998), the optimal weight of the Chinese stocks in one dollar portfolio of Index, China at time t is given as:

$$W_t^{\text{Index, China}} = \frac{h_t^{\text{China}} - h_t^{\text{Index, China}}}{h_t^{\text{Index}} - 2h_t^{\text{Index, China}} + h_t^{\text{China}}},$$

and:

$$\begin{cases} & 0 \text{ if } W_t^{\text{Index, China}} < 0 \\ W_t^{\text{Index, China}} & \text{if } 0 \leqslant W_t^{\text{Index, China}} \leqslant 1 \\ & 1 \text{ if } W_t^{\text{Index, China}} > 1 \end{cases},$$

where $W_t^{\text{Index, China}}$ refers to the weight of stocks of E7 (G7) countries in one US dollar portfolio of the two assets portfolio of Index–China at time t. h_t^{China}, h_t^{Index} and $h_t^{\text{Index, China}}$ are the conditional variances and conditional covariances at time t. The weight of China stocks in supposed portfolio is $1 - W_t^{\text{Index, China}}$.

As to the optimal hedge ratios, it is important to know how much a long position of one dollar on the index returns of E7(G7) countries can be hedged by the short position of $\beta_t^{\text{Index, China}}$ dollar on the Chinese stocks. Kroner and Sultan (1993) proposed the hedge ratio as follows:

$$\beta_t^{\text{Index, China}} = \frac{h_t^{\text{Index, China}}}{h_t^{\text{China}}}.$$

Table IV demonstrates the summary statistics for the portfolio weights, $W_t^{\text{Index, China}}$, and hedge ratios, $\beta_t^{\text{Index, China}}$, produced by the VAR(1)–GARCH(1, 1) model. The highest average weight of portfolio including the Chinese stocks is 70 percent for the portfolio that includes stocks of Canada and China. This implies that for one dollar portfolio, 70 cents should be invested in the Canadian stock market and 30 cents should be invested in the Chinese stock market. The optimal portfolio weights indicate that investors should hold more stocks from G7 countries than E7 countries. Any change in the prices of the emerging market stocks could lead to unfavorable effects on the performance of the portfolios. Therefore, it would be better for the investors to have more stocks from developed markets to minimize risk in their portfolios.

The average optimal hedge ratios are generally low for the portfolios including the Chinese stocks. The low hedge ratios suggest that investment risk can be hedged by taking short positions in the Chinese stock market. The results on China are in the same line with the previous studies, suggesting that there is a gradual integration of the Chinese market into the world economy (Bhar and Nikolova, 2009; Syriopoulos *et al.*, 2015). The largest ratio is obtained for the portfolios of Japan–China and India–China with the hedge ratios of 16 and 15 percent, respectively. This suggests that one dollar long position in the Chinese stock market should be hedged with a short position of 16 cents in the Japanese and 15 cents in the Indian stock markets.

Overall, there is no generally accepted optimal asset allocation. However, in the presence of time-varying volatility, investors may rebalance their portfolios in order to reduce the fluctuation of the asset class weightings around the target allocations. Considering G7 and E7 stock portfolios, investors should better overweight their portfolios with the stocks from developed countries in order to minimize the risk without lowering their expected returns. While doing this, the Chinese stocks can help investors to diversify their portfolio risk due to low correlations with G7 and E 7 stocks. Furthermore, the Chinese stocks can be an integral part of a diversified portfolio of stocks and help investors to increase the risk-adjusted performance of the hedged portfolios. However, it is important to note that investors should be careful while pairing the Chinese stocks with other Asian stocks in their portfolios. Geographic proximity, the absence of time difference and close cultural familiarity among China and other major Asian markets may help to disseminate investment opportunities and information.

5. Conclusion

The main purpose of this study is to investigate the volatility spillover from the Chinese stock market to E7 and G7 stock markets over the period between 1995 and 2015. Daily closing prices of national stock indices were analyzed using the recent VAR (1)–GARCH (1) model.

	$W_t^{\text{Index, China}}$	$\beta_t^{\text{Index, China}}$
Brazil–China	0.41	0.07
India–China	0.53	0.15
Indonesia–China	0.53	0.14
Mexico–China	0.57	0.06
Russia–China	0.33	0.06
Turkey–China	0.34	0.05
Canada–China	0.70	0.09
France–China	0.57	0.07
Germany–China	0.56	0.08
Italy–China	0.55	0.07
Japan–China	0.54	0.16
UK–China	0.70	0.11
USA–China	0.65	0.02

Note: The table reports average optimal weights and hedge ratios for all stock markets

Table IV.
Summary statistics for the portfolio weights and hedge ratio

The results of this model are then used to construct portfolio designs and to calculate the optimal hedge ratios.

The results show that volatility spillover from the Chinese stock market to G7 countries is more obvious than the E7 countries. For the opposite direction, volatility spillover from G7 countries to China is stronger than the volatility spillover from E7 countries to China. This finding implies a fact that in spite of low openness and liberalization of the Chinese financial markets, the Chinese stock market is somehow more integrated with G7 stock markets than E7 stock markets.

The estimates of CCC show that the pairs of China with G7 and E7 countries exhibit statistically significant but low correlations. In the presence of low conditional correlation and volatility transmission, it can be argued that the investors may have opportunities for international portfolio diversification. In this context, investing in the Chinese stock market may help international investors to manage risk exposure in their portfolios. In another words, the Chinese stocks can be an integral part of both G7 and E7 stock portfolios and help investors to increase the risk-adjusted performance of their hedged portfolios. However, it is important to note that there is a relatively high volatility spillover from China to its neighbors such as Japan and India. The geographic proximity, the absence of time difference and close cultural familiarity between China and these major Asian markets may play crucial roles to disseminate the information. Therefore, international investors should better monitor the correlation levels in the stock returns of G7 and E7 countries.

Furthermore, the examination of optimal weights and hedge ratios suggests that investors should hold more stocks from G7 countries than E7 countries. In light of the above-mentioned issues, our results are crucial for portfolio managers and policy makers for building an optimal portfolio and forecasting stock return volatility. The findings may enable investors to take well-informed decisions. For the future research avenue, it would be interesting to extend this study by examining the volatility spillover between G7 and other major emerging stock markets.

Note

1. The Group of 7 (G7) is a bunch of countries including the USA, Canada, the UK, Germany, France, Japan and Italy. These countries represent the majority of the net global wealth. The emerging 7 (E7) is a bunch of countries including Mexico, Turkey, Russia, China, Indonesia, India and Brazil. These countries present the major emerging economies according to their wealth.

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