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Islamic stocks, conventional stocks, and crude oil: Directional volatility spillover analysis in BRICS

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ABSTRACT

This paper uses threshold GARCH (TGARCH) and generalised forecast error variance decomposition to compute time domain and frequency domain volatility spillover. The spillover technique is then applied to Islamic and conventional stock indices and crude oil in BRICS countries (Brazil, Russia, India, China, and South Africa), thus informing investors about the magnitude and speed of the volatility spillover. We find that the total volatility spillover is driven mainly by a long-term component. Accordingly, these assets are suitable for investors with short- and medium-term investment horizons. However, analysis reveals that volatility spillover magnitude and speed increase substantially during the global financial crisis, suggesting that investors in Brazil, Russia, and South Africa with stocks in their portfolio should rebalance promptly. Dynamic covariance analysis shows that covariance between Islamic and conventional stock index returns is the highest and exhibit a significant increase during the crisis period.

1. Introduction

While developed countries and conventional stocks have been able to satisfy investors' risk-tolerance or risk-aversion, developing countries and Islamic stocks offer a unique set of assets to diversify or complement portfolios. However, determining these assets' return risk profiles is not trivial; rather, it is a costly exercise, so screening and selection of potential indices and stocks must be made prudently. Researchers and practitioners have provided evidence that BRICS (Brazil, Russia, India, China, and South Africa) and Islamic stocks warrant consideration for potential inclusion in an efficient international portfolio; see, for example, Reza et al. (2016).

Ansari and Sensarma (2019) justify the selection of BRICS for this purpose based on their population, economic growth, and interconnectedness. Similarly, Gusarova (2019) supports the selection and includes the prominent role played by BRICS in agricultural production, world trade, and global services. Goldman Sachs and the World Bank concur with the importance of BRICS in the world economy. While Steinbock (2019) presents a more measured and subdued assessment of BRICS' challenging developing economies, their leadership among developing and emerging economies is undisputed.

Studies have demonstrated that oil has an important effect on economies, and a more thorough analysis has shown that the impact differs depending on a country's economic development and whether it is an oil importer or oil exporter (Demirer et al., 2015; Silvapulle et al., 2017). By focusing on BRICS, we can explore this nexus more fully. Among BRICS, the oil importers are China, India, and South Africa and the oil exporters are Russia and Brazil.

Islamic stocks and indices have emerged as an avenue for investors to form portfolios cognisant of their religious beliefs. The importance of these stocks and indices as an investment increased when researchers showed that Islamic stock could also satisfy investors' risk-tolerance or risk-aversion, especially during the global financial crisis. Ejaz and Khan (2014) note that the Islamic financial sector exhibited resilience during the global financial crisis, which they consider to be the

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outcome of a built-in risk-sharing feature in the contract design for Islamic securities. However, whether Islamic stocks provide a safeguard or insurance for investors during a crisis period has not been unambiguously resolved.[1]

Volatility spillover provides the opportunity to examine this issue further and is particularly relevant for portfolio investors. Empirical research has also demonstrated significant volatility linkage between crude oil and stock returns (Singh et al., 2019; Zhang, 2017; Feng et al., 2017; Khalfaoui et al., 2015). Since oil plays an important role in BRICS countries, its inclusion in the portfolio is merited.

The extent of volatility or risk transmission between oil and stock markets guides an investor in designing superior investment strategies. Based on the relationship between oil and stock, several studies have computed optimal hedge ratios between the two, which can be used for managing the risk of an oil–stock portfolio. Some wavelet-based studies analyse the link between crude oil and stock returns with different wavelet components or time scales; see, for example, Reboredo and Rivera-Castro (2014); Madaleno and Pinho (2014); Khalfaoui et al. (2015); Huang et al. (2016); Boubaker and Raza (2017). These studies analyse the impact of oil price fluctuation on stock price or volatility spillover between the two from higher to lower frequencies. However, they do not provide any information on how the magnitude of total volatility spillover is decomposed into different frequencies.

Since previous wavelet-based studies do not provide such guidance, we coalesce these strands of research by considering Islamic indices associated with BRICS. We further exploit the global financial crisis to examine investment horizons using time and frequency domain volatility spillover. Notably, according to Lehkonen and Heimonen (2014), large investment banks may be interested in short-term dynamics, while individuals, insurance companies, and superannuation funds may be more interested in long-term dynamics. In practice, if most volatility spillover takes place in the short run, an investor interested in short-term dynamics may avoid holding these assets in their portfolio. However, investors may include these assets in their portfolio in the short run if most of the spillover occurs in the long term.

The present paper contributes to the literature in the following ways. This is the first study on volatility spillover in the frequency domain between crude oil and stock return in the context of BRICS.[2] Despite the extensive literature on the oil–stock nexus, the topic of volatility spillover between oil and stock returns in BRICS is an issue yet to be explored. Existing studies on BRICS or individual countries included in BRICS examine different aspects of the oil–stock relationship. Zhu et al. (2016) and You et al. (2017) employ quantile regression to examine the relationship between oil and stock in China while Ghosh and Kanjilal (2016) employ nonlinear cointegration tests for India. Fang and You (2014) use vector autoregression (VAR) for China, India, and Russia, whereas Ding et al. (2016) employ a causality test for China, Hong Kong, Korea and Japan. Jain and Biswal (2016) apply dynamic conditional correlation (DCC) for India, and Wei and Guo (2017) apply local projection VAR for China.

The most recent papers that parallel our research are those of Hassan et al. (2019) and Wang and Wang (2019). Hassan et al. (2019) consider total volatility spillover for BRIC countries, while Wang and Wang (2019) use frequency domain volatility spillover but for sector industries operating in China. What is critical is the magnitude and speed of the total spillover. Hassan et al. (2019) focus on the magnitude of the total spillover. Wang and Wang (2019) focus on the spillover's magnitude and speed for industry sectors specific to China. The present study provides information for international investors on portfolio construction for Islamic indices operating in BRICS countries. Interestingly, Kocaarslan et al. (2018) note that different investors, depending on their risk-tolerance or risk-aversion, consider different investment horizons, confirming the importance of computing spillover time periods. Frequency-based total spillover decomposition will provide useful information to investors with different investment horizons and different risk-tolerance degrees.

The second contribution relates to the inclusion of Shariah-compliant or Islamic stocks. Islamic stocks have gained popularity in recent times, in particular, since the 2008–09 global financial crisis and 2011–12 European debt crisis. Several studies argue that Islamic stocks perform better than their conventional counterparts during periods of financial stress (Al-Khazali et al., 2014; Ho et al., 2014; Hkiri et al., 2017). Kenourgios et al. (2016) suggest that Islamic stocks provide better portfolio diversification benefits for BRIC countries than for developed markets. Despite their potential role in portfolio diversification, few empirical studies on volatility spillover exist between Islamic stocks and crude oil in BRICS countries. Relevant studies are largely confined to developed markets. For example, Mensi et al. (2017) cover the United States (US), and Shahzad et al. (2017) cover the US, United Kingdom (UK), and Japan. To the best of the present authors' knowledge, Hassan et al. (2019) is the only study to analyse volatility spillover between crude oil and Islamic equities in BRIC countries.

The rest of the paper is organised as follows. The literature related to the present study is reviewed in section 2. Section 3 discusses the econometric methods applied and the data used in empirical estimation, which is followed by a discussion of empirical results in Section 4. The implications of the empirical findings are discussed in Section 5, followed by robustness tests in Section 6. The paper concludes in Section 7.

2. Literature review

An extensive body of research has focused on the link between crude oil and stock markets following the early work of Jones and Kaul (1996) and Sadorsky (1999). Since then, this oil-stock nexus has been investigated in almost all major stock markets around the globe.

Among BRICS countries, the Chinese stock market receives the closest attention in regard to the empirical investigation of the oil–stock relationship. China has recorded impressive economic growth over the last couple of decades to become the world's largest emerging economy. As a result, the Chinese stock market also grows significantly, both in size and volume of investment (Xiao et al., 2019). According to the US Energy Information Administration (EIA, 2014), China is the second-largest oil consumer and the largest net oil importer in the world. Given the development of the Chinese stock market and China's position in world oil consumption, an increasing number of researchers are investigating the oil–stock market nexus in the context of the Chinese economy. An early study by Cong et al. (2008) does not find any statistically significant oil effect on Chinese stock market indices. However, Li et al. (2012) find evidence of a positive long-run impact of real oil prices on Chinese sectoral stock indices. Broadstock et al. (2012) also note that oil prices and Chinese energy sectoral stocks are correlated, and more strongly so following the 2008 global financial crisis. Chen and Lv (2015) document a similar finding, reporting positive

[1] Some studies conclude that Islamic stocks perform better than their conventional counterparts during the financial crisis (see, e.g., Al-Khazali et al., 2014; Ho et al., 2014; Hkiri et al., 2017); while Sensoy (2016) conclude that systematic risk of Islamic stocks during a financial crisis is not lower than that of conventional stocks and hence they do not offer superior diversification benefits. Similarly, Hassan et al. (2020) conclude that Islamic stocks are not immune to crises in financial markets.

[2] This study focuses on Brazil, Russia, India, China, and South Africa, popularly known as BRICS, which occupy a significant global economic position. These five countries combined produced 21.50% of world Gross Domestic Product (GDP) (constant 2010 US dollar) in 2017. BRICS countries are also considered a major source of world economic growth. It was predicted that GDP growth in these countries in 2018 (2019) would be 1.4% (2.4%), 1.7% (1.8%), 7.3% (7.4%), 6.6% (6.2%) and 0.8% (1.4%) respectively (International Monetary Fund, 2018). Goldman Sach's report predicts that by 2050, BRIC's nominal GDP (excluding South Africa) will reach $128 trillion, while the nominal GDP of G7 countries will be only $66 trillion (Kumar et al., 2018). By 2030, BRIC stock markets are predicted to account for more than 40% of the world's stock market capitalisation, and by that time, China's stock market capitalisation is predicted to exceed that of the United States. (Mensi et al., 2014). Several studies add S (for South Africa) to the acronym BRIC to give its current form of BRICS (see, for example, Liu et al., 2013; Zhang et al., 2013; Mensi et al., 2017).

extremal dependence between the Chinese stock market and the world crude oil market, which exhibits an increasing trend during the global financial crisis period.

Zhu et al. (2016) show that the impact of real crude oil price varies across the conditional distribution of Chinese real industry stock returns. They find that the dependence is positive and significant at the lower quantile only. Wei and Guo (2017) examine the effects of oil price shocks on the Chinese stock market and find that oil price shock has a more substantial effect on stock return than on stock volatility. Zheng and Su (2017) examine the effects of oil price shocks on the Chinese stock market's liquidity. They find that stock market liquidity increases when the shock comes from the oil-specific demand side; however, liquidity moves in the opposite direction when the shock comes from the oil supply side or the aggregate demand side.

Li and Li (2019) document asymmetric dependence between West Texas Intermediate (WTI) crude oil and Chinese energy sector stocks. Also, Xiao et al. (2019) observe that changes in the implied volatility index of the oil market positively influence changes in the implied volatility index of the Chinese stock market, and this impact becomes stronger during bearish markets. Wang and Wang (2019) examine frequency domain volatility spillover between crude oil and Chinse sectoral stock markets and conclude that total volatility spillover is dominated mainly by a short-term component.

Some studies examine the oil–stock nexus in the context of other countries in BRICS. Fang and You (2014) examine the impact of an oil price change on stock prices in China, India, and Russia and conclude that oil price has heterogeneous impacts on stock prices in these three newly industrialised economies. In India, the oil price negatively impacts stock price unless oil price change is not caused by oil consumption demand. In Russia, stock returns are positively affected by oil price change only if Russian oil-specific supply shocks cause the change. In China, oil price change has a negative effect on stock returns if the change comes from China's oil-specific demand shocks. Ghosh and Kanjilal (2016) explore the long-run equilibrium relationship between oil prices and the Indian stock market. They do not find any significant cointegrating relationship between the two over the period 2003–11. However, when they split their data for this period into three subperiods—pre-crisis, crisis, and post-crisis—their empirical results show a cointegrating relationship between oil and stock for the post-crisis period only.

Boubaker and Raza (2017) investigate the mean and volatility spillover between crude oil and BRICS stock markets. Using ARMA-GARCH and wavelet methods, they document the existence of significant mean and volatility spillover effects between the two.

Over the past two decades, Islamic or Shariah-compliant stocks (SCSs) have become an attractive investment alternative to their conventional counterparts. Consequently, in addition to conventional stocks, some studies investigate the relationship between crude oil and SCSs. Mensi et al. (2017) examine the risk spillover between crude oil, gold, global indices of conventional stocks, and Islamic aggregate and sectoral stocks. Using a multivariate spillover framework (see Diebold and Yilmaz, 2012), Mensi et al. find that energy, financial, technology, and telecommunication sectors of SCSs are net receivers. In contrast, materials, consumer services, consumer goods, healthcare, industrial, and utilities sectors of SCSs are net transmitters of volatility to the system.

Shahzad et al. (2017) examine volatility spillover between oil and five Islamic stock markets: the Islamic Market World Index, and Islamic indices of the US, UK, Japan, and Islamic financial sectors. Their study concludes that there is lower tail dependence and bi-directional spillover between oil and Islamic stocks. Very recently, Hassan et al. (2019) examine the dynamic correlation and volatility relationship between crude oil and Islamic stock markets in BRIC. Their study finds that dynamic correlation increases during the global financial crisis for India and China, but not for Brazil and Russia. They also report that volatility spillover increases during the global financial crisis.

This review of previous studies of the oil–stock nexus identifies two significant research gaps. First, no study has examined the volatility spillover among Islamic stocks, conventional stocks, and crude oil in BRICS; second, no research has analysed volatility spillover among Islamic stock, conventional stocks, and crude oil from a frequency domain perspective by decomposing total spillover into short-, medium- and long-term components. This decomposition is important since investors differ in their investment horizons. From these viewpoints, our study is related closely to that of Hassan et al. (2019), who examine volatility spillover between Islamic stock and crude oil in BRIC, and Wang and Wang (2019), who examine volatility spillover between crude oil and the stock market in the frequency domain in China.

3. Methods of analysis

3.1. Calendar anomaly

It is argued that calendar anomalies disappear after evidence of such anomalies is reported. This is because investor competition to exploit these anomalies with the expectation of making abnormal profit helps achieve market efficiency. However, empirical research continues to report calendar and seasonal anomalies in stock returns (see, e.g., Keef and Roush, 2005; Marquering et al., 2006; Lim et al., 2010). In particular, stock markets in emerging countries exhibit a weak form of inefficiency (Hu and Zhao, 2018; Hiremath and Kumari, 2015).

We, therefore, do not ignore the possibility of such anomalies in our weekly data. Each return series is filtered for any week-of-the-month effect by running a regression of the following form:

$$r_t = \gamma_1 D1_t + \gamma_2 D2_t + \gamma_3 D3_t + \gamma_4 D4_t + u_t \tag{1}$$

where r_t is our return series; $D1_t$ is a dummy variable that takes the value of 1 for week 1 of each month and 0 otherwise. Similarly, D2, D3, and D4 are dummy variables for week 2, week 3, and week 4 of each month, respectively. The problem of multicollinearity or dummy variable trap arises if we include an intercept term and all four dummy variables in the equation. To avoid this problem, we should either include an intercept and three dummy variables or all four dummy variables with no intercept term (Brooks, 2014). Accordingly, in Eq. (1), we include four dummy variables and no intercept term. If any of the dummy variable coefficients are found to be significant, the residual is used for subsequent estimation; otherwise, the original return series is used.

3.2. Volatility spillover analysis

3.2.1. Volatility estimation

It is observed that negative shocks and bad news have larger impacts on the volatility of equity returns than positive shocks and good news of equal magnitude. To accommodate this asymmetry, we estimate a threshold GARCH (TGARCH) model to derive the underlying return series volatilities. The conditional variance equation of a TGARCH model is given as follows:

$$h_t = \gamma_0 + \sum_{i=1}^{p} (\gamma_i + \vartheta_i d_{t-i}) u_{t-i}^2 + \sum_{j=1}^{q} \delta_j h_{t-j} \tag{2}$$

where d_t takes the value of 1 for $u_t < 0$ and 0 otherwise. The coefficient γ represents the impact of positive shock or good news, while $\gamma + \vartheta$ represents the impact of negative shock or bad news. A statistically significant $\gamma > 0$ value represents asymmetry in volatility. We take the log of variance series for our subsequent volatility spillover analysis.

3.2.2. Volatility spillover in the time domain

To measure volatility spillover in the frequency domain, we follow the approach recently proposed by Baruník and Křehlík (2018), which is an extension of the time domain-based volatility spillover approach

of Diebold and Yilmaz (2012). Both approaches are based on generalised forecast error variance decomposition (GFEVD) from an estimated VAR model. In frequency dynamics of volatility spillover, the spectral representation of variance decomposition is considered based on frequency response to shock instead of impulse responses to shocks (Baruník and Křehlík, 2018).

Let $\mathbf{x}_t$ be a covariance stationary vector of endogenous variables. The moving average (MA) representation of VAR then takes the following form: $\mathbf{x}_t = \Psi(L)\boldsymbol{\varepsilon}_t$, where, $\Psi(L)$ is the matrix of infinite lag polynomials, which needs to be approximated with MA coefficients Ψ_h calculated at $h = 1, \ldots, H$ horizons. Variance decomposition, which involves the transformation of Ψ_h, is the key to measurement of the contribution of shocks to the system. The standard method to calculate variance decomposition is Cholesky factorisation; however, the limitation of this approach is that it depends on the ordering of the variables in the VAR. As a remedy, Pesaran and Shin (1998) propose generalised variance decomposition, which is independent of variable ordering in VAR. The generalised variance decomposition is given as follows:

$$(\theta_H)_{j,k} = \frac{\sigma_{kk}^{-1}\sum_{h=0}^{H}\left((\Psi_h\Sigma)_{j,k}\right)^2}{\sum_{h=0}^{H}\left(\Psi_h\Sigma\Psi_h'\right)_{j,j}} \tag{3}$$

where $(\theta_H)_{j,k}$ is the contribution of the kth variable to the forecast error variance of the element j, at horizon h; Σ is a covariance matrix; and $\sigma_{kk} = (\Sigma)_{k,k}$. Since the row sums of $(\theta_H)_{j,k}$ are not necessarily equal to 1, each entry of the variance decomposition matrix $(\theta_H)_{j,k}$ is normalised by the respective row sums to obtain:

$$\left(\widetilde{\theta}_H\right)_{j,k} = \frac{(\theta_H)_{j,k}}{\sum_{k=1}^{N}(\theta_H)_{j,k}} \tag{4}$$

Here, $\left(\widetilde{\theta}_H\right)_{j,k}$ is a measure of pairwise spillover from j to k at horizon H. Summing up this pairwise connectedness, we can obtain the total spillover of the system. Diebold and Yilmiz (2012) define the volatility spillover (VS) measure (sometimes called a 'connectedness' measure) as the ratio of the sum of the off-diagonal elements to the entire matrix given in Eq. (3) and expressed as follows:

$$VS_H = 100.\frac{\sum_{j\neq k}\left(\widetilde{\theta}_H\right)_{j,k}}{\sum\widetilde{\theta}_H} = 100.\left(1-\frac{Tr\left\{\widetilde{\theta}_H\right\}}{\sum\widetilde{\theta}_H}\right) \tag{5}$$

where $Tr\{\bullet\}$ is the trace operator; $\sum_{j\neq k}\left(\widetilde{\theta}_H\right)_{j,k}$ is the sum of off-diagonal elements (i.e., the total variance in the forecasts contributed by error other than own errors); and $\sum\widetilde{\theta}_H$ is the total variance in the forecasts contributed by errors. In short, spillover is the relative contribution to the forecast variances that come from other variables in the system.

3.2.3. Volatility spillover in the frequency domain

The volatility measure described above tells us the relative contribution of the forecast error variance of a variable that comes from other variables in the system over the specific time horizon. This may be useful to understand how the volatility of an asset's returns is affected by the volatility of other asset returns of an investor's portfolio over a certain period. However, an investor may be more interested in knowing the extent of volatility that is spilled over, say, within a week or a month. Frequency domain volatility spillover measures provide such information and help plan more effective portfolio diversification. This goal can be achieved through the spectral representation of variance decomposition based on frequency response to shocks. The Fourier transform of the coefficients of the matrix Ψ_h gives us the following frequency response function at frequency ω: $\Psi(e^{-i\omega}) = \Sigma_h e^{-i\omega h}\Psi_h$, where $i = \sqrt{-1}$. The spectral density of $\mathbf{x}_t$ at frequency ω is defined as the Fourier transform of a MA-filtered series and is expressed as follows:

$$\boldsymbol{S}_{\mathbf{X}}(\omega) = \sum_{h=-\infty}^{\infty} E\left(\mathbf{x}_t\mathbf{x}_{t-h}'\right)e^{-i\omega h} = \Psi\left(e^{-i\omega}\right)\Sigma\Psi'\left(e^{+i\omega}\right) \tag{6}$$

where the power spectrum $\boldsymbol{S}_{\mathbf{x}}(\omega)$ describes how the variance of $\mathbf{x}$ is distributed over ω. The frequency domain counterparts of variance decomposition over frequencies $\omega \in (-\pi, \pi)$ is derived from the spectral representation for covariance[3] as follows:

$$(f(\omega))_{i,k} \equiv \frac{\sigma_{kk}^{-1}\left|\left(\Psi(e^{-i\omega})\Sigma\right)_{j,k}\right|^2}{\left(\Psi(e^{-i\omega})\Sigma\Psi'(e^{+i\omega})\right)_{j,j}} \tag{7}$$

where the Fourier transform of the impulse response Ψ_h is denoted by $\Psi(e^{-i\omega}) = \Sigma_h e^{-i\omega h}\Psi_h$. The portion of the spectrum of the jth variable at a given frequency ω that is due to shocks in the kth variable is indicated by $(f(\omega))_{i,k}$ in Eq. (5) above.

However, it is more useful for investors to assess volatility spillover in the short, medium or long run, than at a given single frequency ω; that is, it is more useful to work with frequency bands rather than a single frequency. Therefore, the variance decomposition on a frequency band d[4] is defined as:

$$(\theta_d)_{j,k} = \frac{1}{2\pi}\int_d \Gamma_j(\omega)(f(\omega))_{i,k}d\omega \tag{8}$$

The estimation of volatility measure depends on the precise estimation of the VAR. GFEVD is computed from the estimated VAR, and Fourier transforms are used to estimate the spectral quantities.

Baruník and Křehlík (2018) define two connectedness measures over frequency band d: within connectedness and frequency connectedness. The within connectedness measures the spillover effect that takes place within the frequency band, weighted by the power of the series on the given frequency only and defined as follows:

$$C_d^W = 100 \times \left(1-\frac{Tr\left\{\widetilde{\theta}_d\right\}}{\sum\widetilde{\theta}_d}\right) \tag{9a}$$

In simple terms, within connectedness splits the total volatility spillover into different frequencies, such as short-, medium- and long-term spillover. Frequency connectedness decomposes the overall connectedness into distinct parts that sum to the original connectedness measure (C_∞), defined as follows:

$$C_d^F = 100 \times \left(\frac{\sum\widetilde{\theta}_d - Tr\left\{\widetilde{\theta}_d\right\}}{\sum\widetilde{\theta}_\infty}\right) \tag{9b}$$

Since our goal is to assess the amount of spillover that takes place in the short, medium and long term, the relevant measure is within connectedness.

3.3. Data and summary statistics

Our stock data include weekly Islamic and conventional stock indices from Morgan Stanley Capital International (MSCI) from the first week of June 2002 to the second week of March 2017. Weekly data are used to bypass the problems associated with daily data, such as day-of-the-week effect or missing data for non-trading days. Both conventional and Islamic MSCI stock data are collected from Datastream. WTI and Brent crude oil prices are collected from the US EIA website

[3] Spectral representation of covariance is given by $E(\mathbf{x}_t\mathbf{x}_{t-h}') = \int_{-\pi}^{\pi}\boldsymbol{S}_{\mathbf{X}}(\omega)e^{i\omega h}d\omega$

[4] Frequency band $d = (a,b)$: $a,b \in (-\pi, \pi)$, $a < b$.

(www.eia.gov). WTI data are used in our main analysis, while Brent crude oil data are used for robustness tests. The return series (r) is calculated as $r = [\log(x_t) - \log(x_{t-1})] \times 100$.

Table A1 in Appendix A reports summary statistics for the data. The statistics reveal several stylised facts for the financial return series. Islamic stock, conventional stock, and crude oil returns are negatively skewed in all countries. In other words, all return series exhibit asymmetric behaviour about the mean as indicated by skewness values. The kurtosis values are all substantially greater than 3, indicating that all series have fat tails. Return asymmetry, together with fat tail distribution, supports the stylised fact of non-normality of financial returns, which is also evidenced by highly significant Jarque–Bera statistics.

We also examine the mean reversion property of all return series using the widely used Augmented Dicky–Fuller test and find that all series are $I(0)$. Lee and Strazicich (2003, 2013) tests are employed to ensure that stationarity properties of the time series under study are not affected by any structural breaks that may occur.[5] Table A2 reports the estimation results for Eq. (1). The results indicate that there is some week-of-the-month effect present in the data. Accordingly, the filtered return series are used in subsequent analysis.

4. Empirical results and analysis

4.1. Volatility estimation

For volatility, we estimate the TGARCH model as specified in Eq. (2). The results are reported in Table A3 in Appendix A. The F-statistic for the ARCH-LM test reported in the rightmost column of Table A3 indicates that all estimated models are free from the ARCH effect. The asymmetry coefficients ($\gamma_i + \upsilon_i$) indicate that asymmetric responses to bad and good news do not hold across the asset classes and markets. In Brazil, bad news has a more substantial effect than good news on the volatility of both Islamic and conventional index returns. However, in Russia and India, the coefficients are not significant, implying symmetric responses to bad and good news. In China (South Africa), we see that conventional (Islamic) stock index returns respond more to bad news than to good news. The high and significant values of δ_i indicate a high persistence of volatility in each asset class. The log of estimated volatility from TGARCH models is used in the subsequent volatility spillover analysis.

Before analysing the volatility spillover in terms of frequency bands, we examine the total volatility spillover index and its dynamic counterparts in the time domain to assess these assets' connectedness.

4.2. Time domain total spillover analysis

In this section, we discuss volatility spillover results in the time domain; however, to clarify specific spillover tables' specific elements, an interpretation is presented. The $(i,j)^{th}$ element in each table is the estimated contribution to the forecast error variance of variable i, which comes from innovations to the variable j. The diagonal elements ($i = j$) measure own-variable volatility spillover and off-diagonal elements ($i \neq j$) measure cross-variable volatility spillover. The total spillover index is reported in the lower right cell in each panel in percentage points. The Akaike Information Criterion (AIC) is used to determine the optimal VAR lag length.[6] All results are based on generalised variance decomposition of 100-week-ahead forecast errors.

Table 1 reports Diebold and Yilmaz (2012) total volatility spillover results. The figures in percentages in column 4 indicate the overall volatility spillover of the system. The results show that Brazil has the highest (32.35%) spillover or connectivity with the system, while spillover in Russia, India, China, and South Africa is close to each other, being 17.67%, 17.65%, 19.49%, and 21.80%, respectively. Further, the estimated contribution of the conventional MSCI (MSCIC) to the forecast error variance of the Islamic MSCI (MSCII) is 35.04, and MSCII own-volatility spillover is 60.04.

Table 1
Time domain total volatility spillover.

	MSCII (1)	MSCIC (2)	WTI (3)	From other (4)
Brazil				
MSCII	60.04	35.04	4.92	39.96
MSCIC	36.09	58.25	5.60	41.75
WTI	5.78	9.55	84.67	15.33
To others	41.87	44.59	10.58	97.04
Total spillover				32.35%
Russia				
MSCII	69.73	22.46	7.81	30.27
MSCIC	16.38	81.86	1.76	18.14
WTI	4.15	0.44	95.41	4.59
To others	20.53	22.90	9.57	53.00
Total spillover				17.67%
India				
MSCII	71.23	27.53	1.24	28.77
MSCIC	18.60	77.78	3.63	22.23
WTI	0.40	1.56	98.04	1.96
To others	19.00	29.09	4.87	52.96
Total spillover				17.65%
China				
MSCII	76.66	19.68	3.66	23.34
MSCIC	19.27	75.94	4.79	24.06
WTI	3.28	7.78	88.94	11.06
To others	22.55	27.46	8.45	58.46
Total spillover				19.49%
South Africa				
MSCII	77.62	14.70	7.68	22.38
MSCIC	19.48	71.55	8.96	28.44
WTI	9.54	5.05	85.41	14.59
To others	29.02	19.75	16.64	65.41
Total spillover				21.80%

Note: (a) MSCII, MSCIC and WTI represent MSCII Islamic stock index, MSCI conventional stock index and West Texas Intermediate crude oil respectively. Figures in the off-diagonal cells represent the volatility that goes from column-head to row-head. For example, in Brazil the value 36.09 along MSCII column and MSCIC row indicates MSCIC receives 36.09% of its volatility from MSCII, while the value 35.04 along MSCIC column and MSCII row indicates MSCII receives 35.04% of its volatility from MSCIC; (b) 'To others' and 'From others' are volatility transmitted to others and received from others. For example, in Brazil, 41.87 is the value of volatility that is transmitted by Islamic stock index (MSCII) to others, that is, to Conventional stock index (MSCIC) and crude oil (WTI). Similarly, volatility received by MSCII from others, that is, conventional stock index and crude oil are 39.96.

Concerning individual asset classes, crude oil (WTI) is least connected with MSCII and MSCIC stocks since it has the highest own-variable spillover, with a minimum value of 84.67 (Brazil) and a maximum value of 98.04 (India). This finding is consistent with those of Hassan et al. (2019), who document a low level of volatility spillover between Islamic stocks and crude oil in BRIC countries. A similar finding is reported in Mensi et al. (2017) between Islamic stock and crude oil in the US market. Shahzad et al. (2017) report somewhat similar results for the global Islamic financial sector and crude oil.

Another observation that emerges from the results in Table 1 is that connectedness between Islamic and conventional stocks is substantially higher than each stock's individual connectedness with crude oil. The lowest spillover index between Islamic and conventional stock is 14.70 in South Africa, and the highest is 36.09 in Brazil. This result is in line with previous studies on the relationship between Islamic and conventional stocks. Ajmi et al. (2014) document a significant causal link between Islamic and conventional stocks in the US, Europe, and Asia. Hammoudeh et al. (2014) also document significant dependence between Islamic and conventional stocks in the US, Europe, and Asia. Hkiri et al. (2017) find similar results for Islamic and conventional stocks in Asia, Russia, Argentina, Brazil and the US.

[5] Unit root test results are not reported but are available from the authors upon request.
[6] The optimal VAR lag length selected by AIC for Brazil, Russia, India, and South Africa is 2; while for China, it is 1.

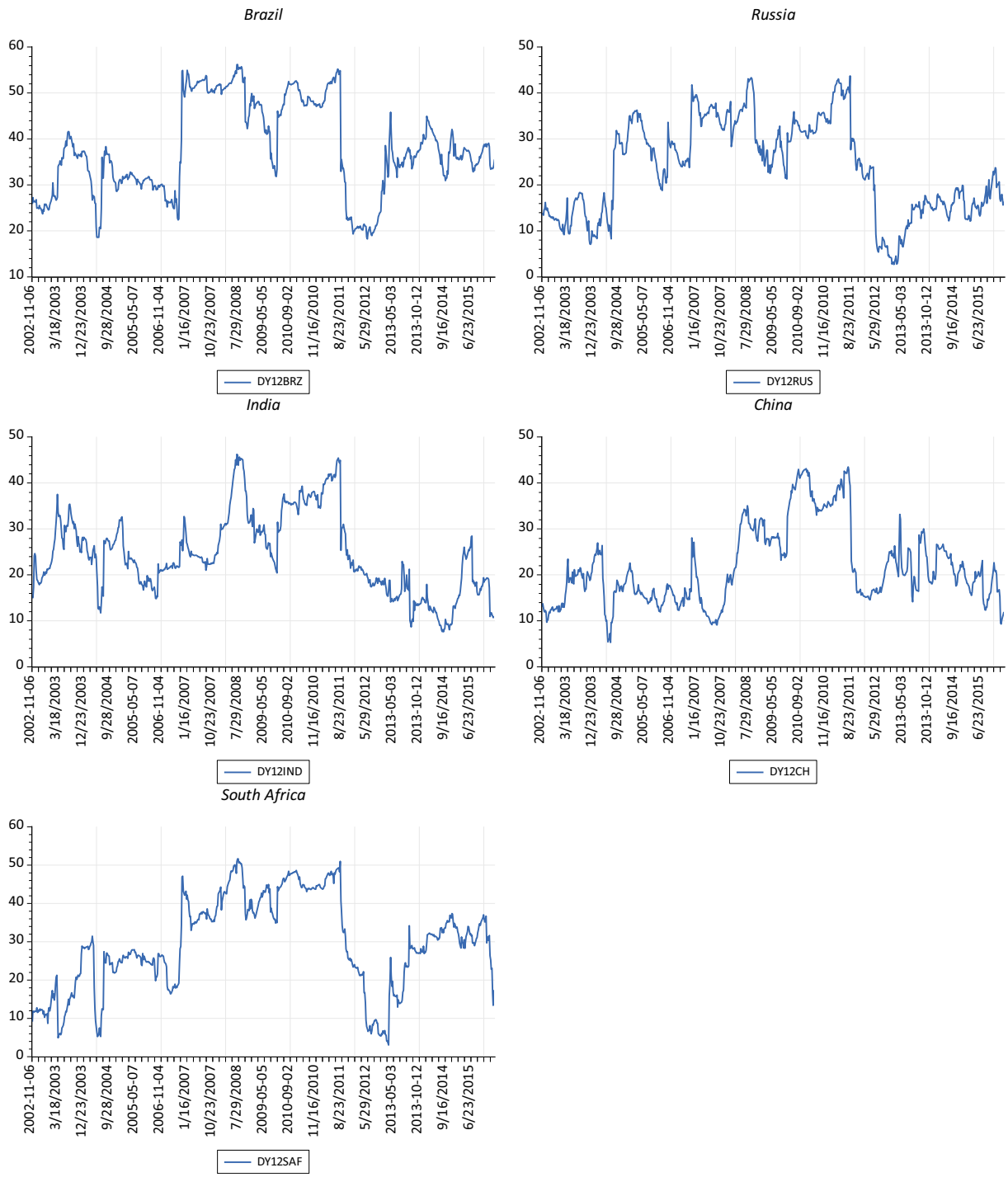

Fig. 1. Rolling window total spillover indexes.

4.3. Time domain rolling window total spillover analysis

The spillover indices in Table 1 can be suitably termed as stemming from a static spillover analysis. This generates an average picture of spillover for the entire sample period. To obtain a dynamic picture of spillover, we estimate a rolling window spillover index. In doing so, we use a 100-week rolling window and analyse the total volatility spillover.

Plots of the rolling window total spillover index are presented in Fig. 1. The spillover value exceeds 50% for Brazil and South Africa and 40% for Russia, India, and China. The spillover plots show that the system experiences high connectedness during the global financial and European debt crisis periods. This finding is consistent with previous studies, such as Broadstock et al. (2012) on China and Naifar and Dohaiman (2013) on Gulf Cooperation Countries.

4.4. Frequency domain volatility analysis

For the purpose of frequency domain analysis, we decompose the total spillover into four frequency bands. These comprise up to 1 month, 1 month to one quarter, one quarter to 6 months, and 6 months to 1 year computed as S_d^F on the bands corresponding to $d_1 \in [1,4]$,

Table 2
Frequency-based volatility spillover table.

	1–4 weeks				4–12 weeks				12–24 weeks				24–48 weeks			
	MSCII	MSCIC	WTI	From other	MSCII	MSCIC	WTI	From other	MSCII	MSCIC	WTI	From other	MSCII	MSCIC	WTI	From other
Brazil																
MSCII	7.13	3.86	0.17	1.34	15.02	7.77	0.71	2.83	17.57	9.16	1.09	3.42	23.11	12.46	1.97	4.81
MSCIC	4.46	7.90	0.31	1.59	8.67	13.93	1.16	3.28	10.06	16.00	1.48	3.84	13.08	20.85	2.10	5.06
WTI	0.05	0.14	10.01	0.06	0.32	0.52	21.58	0.28	1.02	1.60	25.09	0.87	2.84	4.46	32.36	2.44
To others	1.51	1.33	0.16	**3.00%**	3.00	2.76	0.62	**6.38%**	3.69	3.59	0.86	**8.13%**	5.31	5.64	1.36	**12.30%**
Russia																
MSCII	11.86	1.46	0.32	0.59	21.30	3.17	1.10	1.43	22.48	3.86	1.43	1.76	25.35	5.54	2.11	2.55
MSCIC	1.51	9.96	0.05	0.52	3.29	19.52	0.09	1.13	3.85	23.31	0.21	1.35	5.23	32.35	0.61	1.95
WTI	0.06	0.01	10.71	0.02	0.18	0.06	23.36	0.08	0.58	0.11	27.39	0.23	1.53	0.25	35.76	0.59
To others	0.52	0.49	0.12	**1.14%**	1.16	1.08	0.40	**2.63%**	1.48	1.32	0.55	**3.35%**	2.25	1.93	0.91	**5.09%**
India																
MSCII	10.12	1.04	0.04	0.36	19.25	3.18	0.06	1.08	22.31	4.93	0.13	1.69	29.24	9.30	0.41	3.24
MSCIC	1.34	9.989	0.03	0.46	3.32	19.88	0.16	1.16	4.09	23.26	0.37	1.49	5.85	30.77	0.95	2.27
WTI	0.04	0.04	10.77	0.03	0.14	0.08	23.62	0.07	0.23	0.06	27.88	0.10	0.46	0.05	36.63	0.17
To others	0.46	0.36	0.02	**0.85%**	1.15	1.09	0.07	**2.31%**	1.44	1.66	0.17	**3.27%**	2.10	3.12	0.45	**5.67%**
China																
MSCII	10.30	2.04	0.10	0.71	19.26	3.87	0.24	1.37	22.26	4.69	0.46	1.72	29.05	6.64	1.09	2.58
MSCIC	2.57	12.40	0.23	0.93	4.64	21.97	0.48	1.71	4.91	21.99	0.73	1.8	5.69	23.07	1.32	2.33
WTI	0.15	0.18	11.52	0.11	0.35	0.62	21.56	0.32	0.61	1.56	25.09	0.72	1.21	3.61	33.53	1.61
To others	0.91	0.74	0.11	**1.76%**	1.66	1.50	0.24	**3.40%**	1.84	2.08	0.40	**4.32%**	2.30	3.42	0.80	**6.52%**
South Africa																
MSCII	10.52	1.65	0.53	0.73	18.76	2.98	1.80	1.59	21.68	3.59	2.18	1.92	28.34	5.10	2.88	2.66
MSCIC	1.52	9.66	0.46	0.66	3.86	17.97	1.78	1.88	4.80	20.63	2.32	2.37	6.88	26.72	3.40	3.43
WTI	0.31	0.18	9.87	0.16	1.05	0.41	21.53	0.49	1.72	0.80	25.38	0.84	3.47	1.87	33.40	1.78
To others	0.61	0.61	0.33	**1.55%**	1.64	1.13	1.19	**3.96%**	2.18	1.46	1.50	**5.14%**	3.45	2.32	2.09	**7.86%**

Note: This table reports volatility spillover among MDCII, MSCIC and WTI in four different frequency bands. For example, in Brazil, overall spillover among three assets in 1–4 weeks frequency band is 3%. Off-diagonal elements represent directional spillover among the assets (please see Table 1, Note (a) for a detailed description for off-diagonal values).

$d_2 \in [4,12]$, $d_3 \in [12,24]$ and $d_4 \in [24,48]$ weeks, where the lowest frequency is bounded by window length at each time point. The results from these analyses are presented in Table 2.

From Table 2, it is apparent that Brazil has the highest spillover or connectivity that comes from the system, while spillover in Russia, India, China, and South Africa is similar. Visibly, India has the lowest total spillover for the 1–4-week period while Russia exhibits the lowest spillover for the 24–48-week period. Consistent with Table 1, WTI is least connected with MSCII and MSCIC stocks, since it has the highest own-variable spillover. Notably, the connectedness between Islamic and conventional stocks is substantially higher than their individual connectedness with crude oil.

Importantly, an investor needs to consider the magnitude and persistence of the total spillover and the investment horizon. If the total spillover is low and the magnitude is essentially time-invariant, then the necessity for portfolio rebalancing is low. As a result of total volatility partitioned on the different periods, MSCIC, MSCII, and WTI associated with BRICS have low connectedness. Since the total spillover is persistently low, then the need to rebalance portfolios comprised of these assets is negligible. Russia and India have total spillover of less than 3.5% up to 6 months. In contrast, after the 6-month period, Brazil and South Africa have total spillover over 7.5%; hence it would be prudent for an investor to consider rebalancing their portfolio. Noticeably, the spillover associated with MSCIC, MSCII, and WTI for BRICS behaves monotonically with each frequency domain contributing incrementally to the system's aggregate connectedness.

To visualise the differences between spillover indices at four different frequencies, we plot total volatility indices in Fig. 2. The plots indicate that spillover increases with an increase in the frequency band. To ascertain the extent to which the total spillover is realised within 48 weeks, the decomposed total spillover is summed over that period and compared with the total spillover over the entire period in Table 3. As shown in Table 3, more than 90% of total spillover is realised within 48 weeks in Brazil, more than 80% is realised in China and South Africa, while approximately 70% of total spillover is realised within 48 weeks in Russia and India.

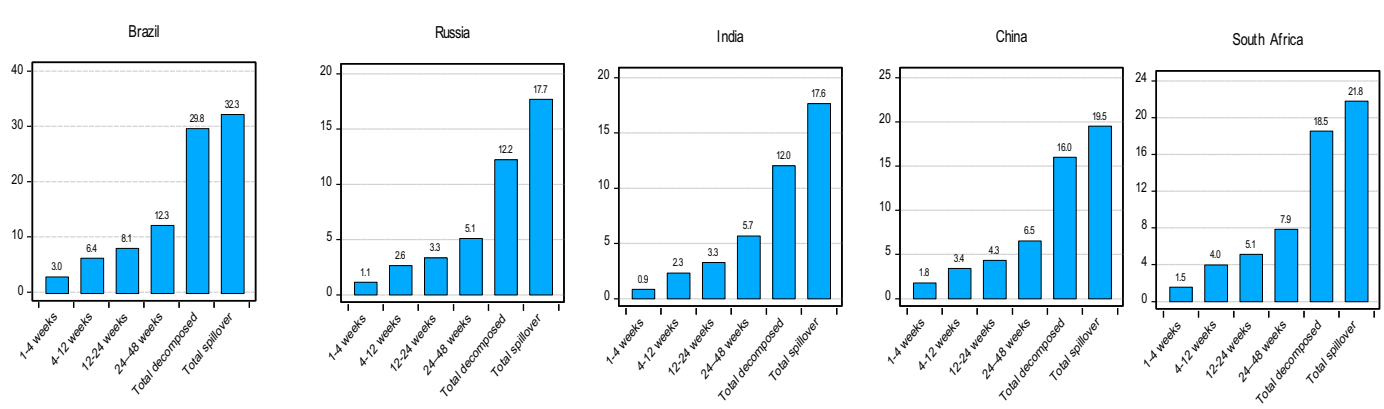

Fig. 2. Frequency domain total volatility spillover indexes.

Table 3
Decomposition of total volatility spillover into four frequency bands.

	1–4 weeks (1)	4–12 weeks (2)	12–24 weeks (3)	24–48 weeks (4)	Total decomposed (5) = (1)+ (2)+ (3)+ (4)	Total spillover (6)	Total decomposed as a percentage of total spillover [(5)/ (6)=7)
Brazil	3.00 (9.3%)	6.38 (19.7%)	8.13 (25.1%)	12.30 (38.0%)	29.78	32.35	92.06%
Russia	1.14 (6.5%)	2.63 (14.9%)	3.35 (19.0%)	5.09 (28.8%)	12.21	17.67	69.10%
India	0.85 (4.8%)	2.31 (13.1%)	3.27 (18.5%)	5.67 (32.1%)	12.04	17.65	68.22%
China	1.76 (9.0%)	3.40 (17.4%)	4.32 (22.2%)	6.52 (33.5%)	16.00	19.49	82.09%
South Africa	1.55 (7.1%)	3.96 (18.2%)	5.14 (23.6%)	7.86 (36.1%)	18.51	21.80	84.91%

Note: Percentage figures in columns (1) through (4) the share of total decomposed spillover reported in column (7) in each frequency band. For example, in Brazil, total decomposed spillover is 92.06%, which is the sum of its component shares in 1–4 weeks (9.3%), 4–12 weeks (19.7%, 12–24 weeks (25.1% and 24–48 weeks (38.0%).

Our findings contradict those of Wang and Wang (2019) concerning crude oil and several conventional sectoral indices in China. The 11 sectoral indices they used are telecommunication, real estate, consumer discretionary, industrial, utility, financials, energy, consumer staples, information technology, healthcare, and materials. Wang and Wang (2019) find that the total volatility spillover is dominated by spillover in a 1–4-week frequency band. In their 12-variable system, 11 variables are sectoral indices, and the other is crude oil. Therefore, the total spillover measure primarily comes from the spillover among the 11 sectoral indices, which may be why our results differ from those of Wang and Wang (2019). Our study is more of a macro-type, while that of Wang and Wang (2019) is more of a micro-type study.

This spillover pattern provides useful information for investors with different investment horizons and degrees of risk-aversion. For BRICS countries, and considering assets comprised of MSCII, MSCIC, and WTI, investors with high risk-aversion and short investment horizon could hold these assets in their portfolio for around 1 month since minimum spillover takes place in a 4-week frequency band. However, for Russia and India, the spillover magnitude persists at a low level so that an investor with moderate risk-aversion could hold their portfolio for the 12–24-week frequency band. Investors with a high degree of risk-aversion and longer investment horizon should hold these portfolios for more than 48 weeks, since most of the spillover is realised in four frequency bands.

4.5. Rolling window frequency domain volatility analysis

The dynamics of spillover over time for different frequencies are captured with rolling window total volatility spillover plots. Spectral decomposition of variance decomposition is used to extract the time frequency dynamics of volatility spillover. Similar to time domain plots, we use a 100-week moving window to compute rolling spillover indices. The indices are plotted in Fig. 3, which allows for some interesting observations.

First, spillover in all bands shows noticeable variability, and this variability becomes more pronounced as the frequency band decreases; that is, the least variability is observed in the 1–4-week band, while the most variability is observed in the 24–48-week band. This indicates that the market's information processing takes time, and hence, any shock in the market is least reflected in the highest frequency; however, as time elapses, the market processes information, which is reflected in lower frequencies.

Second, volatility spillover in all frequency bands exhibits significant responses to the global financial crisis. Before the start of the crisis in 2007, all spillover indices in all bands exhibit a simultaneous sharp rise, as indicated by the first shaded area in all graphs. The second shaded area shows a simultaneous fall in spillover indices in all frequency bands in the late 2011 and early 2012. Although the financial crisis ends in early 2009 (Nowak et al., 2011; Akhtar and Jahromi, 2015; Hassan et al., 2019), a simultaneous fall in spillover index in all frequency bands takes place in late 2011.

In short, spillover indices behave proactively before the start of a crisis (i.e., bad news). Some exhibit inertia in responding to the end of the crisis (i.e., good news), which is an indication of asymmetric responses to bad and good news—not in terms of the magnitude of responses, but in terms of timing of responses. This may reflect a 'wait and see' strategy employed by markets (Balcilar et al., 2017).

4.6. Financial crisis and volatility spillover

4.6.1. Time domain volatility spillover

Research suggests that volatility spillover and dependence between oil and stock markets are more pronounced after the 2008 financial crisis. For example, Chen and Lv (2015) document a dramatic increase in dependence between China's oil and the stock market during the financial crisis. Wen et al. (2019) find that volatility spillover between oil and the US stock market increases after the 2008 financial crisis. Although Fig. 1 shows some indication of increased spillover during the crisis period, we examine this effect more closely by splitting our sample into three sub-periods: pre-crisis, crisis, and post-crisis. We follow Nowak et al. (2011), Akhter and Jahromo (2015), and Hassan et al. (2019) to mark 1 June 2007 and 31 March 2009 as the beginning and end of the financial crisis, respectively. Accordingly, our pre-crisis sample spans from the first week of June 2002 to the fourth week of May 2007; the crisis period spans from the first week of June 2007 to the fourth week of March 2009; and the post-crisis period spans from the first week of April 2009 to the third week of January 2018. We first estimate the time domain volatility spillover index.

The results for the three sub-periods are reported in Table 4. To visualise the differences in spillover during the pre-crisis, crisis, and post-crisis periods, we plot the total volatility spillover index in Fig. 4. The plots show that the volatility spillover index in all countries during the crisis period increases almost twice over their pre-crisis levels. This finding is consistent with the stylised fact that financial asset returns become more correlated during the turmoil period. Another observation that can be made from Fig. 4 is that in all countries except India, markets become more connected after the crisis compared with their pre-crisis levels. The volatility spillover index during the post-crisis period is higher than its corresponding value in the pre-crisis period for all countries; however, the highest connectedness takes place in China. A similar finding is documented in Broadstock et al. (2012), who find that connectedness between crude oil and energy-related stock in China becomes stronger after the 2008 financial crisis.

In addition to overall spillover, Table 4 presents insightful information regarding the pairwise connectedness between the variables during the three sub-periods. First, MSCII and MSCIC stocks have higher connectedness across the three sub-periods; however, this

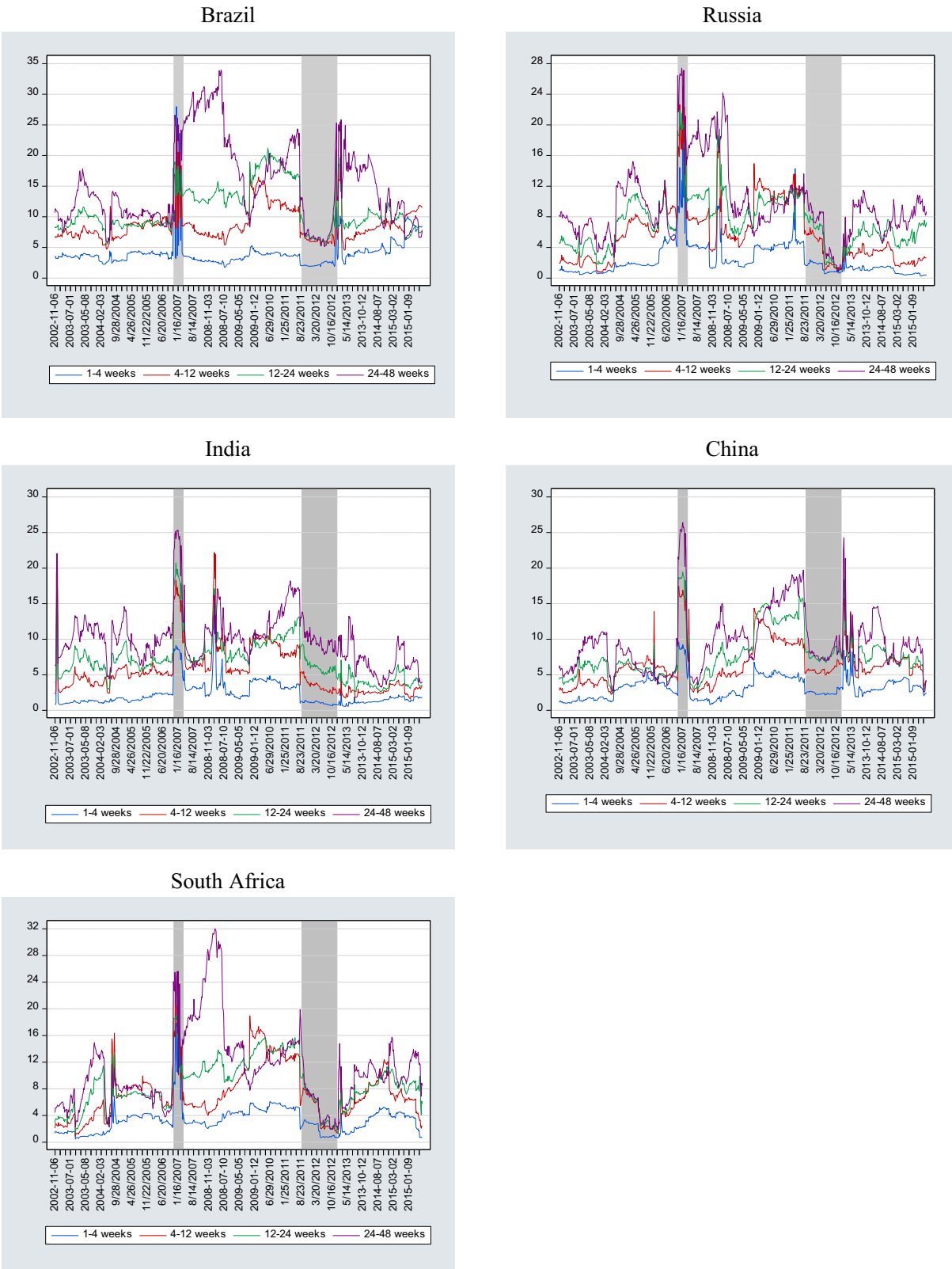

Fig. 3. Rolling window frequency domain volatility spillover plots.

connectedness increases substantially during the crisis period in all countries except China. This result of higher connectedness between Islamic and conventional stocks is consistent with previous studies on other constituents, such as the US, Europe, and Asia (Ajmi et al., 2014). Hammoudeh et al. (2014) document a similar result for global Islamic and conventional stocks. However, unlike Ajmi et al. (2014), we do not find a unanimous effect of influence from one stock on the other during the pre-crisis and crisis periods.

Table 4
Time domain total volatility spillover during pre-crisis, crisis and post-crisis period.

	Pre-crisis period				Crisis period				Post-crisis period			
	MSCII	MSCIC	WTI	From other	MSCII	MSCIC	WTI	From other	MSCII	MSCIC	WTI	From other
Brazil												
MSCII	68.03	28.02	3.95	10.66	45.09	38.79	16.13	18.30	41.58	31.17	27.24	19.47
MSCIC	29.60	62.45	7.94	12.52	38.82	44.78	16.40	18.41	27.29	52.56	20.16	15.81
WTI	2.14	8.13	89.73	3.42	31.98	43.91	24.11	25.30	3.78	14.11	82.11	5.96
To others	10.58	12.05	3.96	**26.60%**	23.60	27.56	10.84	**62.01%**	10.36	15.10	15.80	**41.25%**
Russia												
MSCII	72.07	27.27	0.66	9.31	55.46	22.73	21.82	14.85	51.49	25.21	23.30	16.17
MSCIC	22.03	77.89	0.08	7.37	38.73	54.33	6.94	15.22	5.42	80.60	13.99	6.47
WTI	3.59	8.47	87.94	4.02	42.68	13.51	43.81	18.73	1.11	2.48	96.41	1.20
To others	8.54	11.91	0.25	**20.70%**	27.14	12.08	9.59	**48.80%**	2.17	9.23	12.43	**23.83%**
India												
MSCII	67.22	25.15	7.63	10.93	37.99	27.56	34.45	20.67	75.74	15.10	9.16	8.09
MSCIC	22.73	73.66	3.61	8.78	11.40	42.56	46.04	19.15	13.98	67.29	18.74	10.90
WTI	15.50	1.76	82.74	5.75	0.24	0.29	99.47	0.18	0.51	1.68	97.81	0.73
To others	12.74	8.97	3.75	**25.46%**	3.88	9.28	26.83	**39.99%**	4.83	5.60	9.30	**19.72%**
China												
MSCII	78.47	17.19	4.34	7.18	53.43	14.47	32.10	15.52	63.37	18.57	18.06	12.21
MSCIC	12.05	84.37	3.58	5.21	4.17	47.90	47.93	17.37	15.79	66.71	17.50	11.10
WTI	4.42	2.75	92.83	2.36	0.16	10.10	89.74	3.42	2.40	3.66	93.94	2.02
To others	5.49	6.65	2.64	**14.78%**	1.44	8.19	26.68	**36.31%**	6.06	7.41	11.85	**25.33%**
South Africa												
MSCII	80.80	4.95	14.25	6.40	36.47	49.42	14.11	21.18	66.80	11.10	22.10	11.07
MSCIC	14.75	82.59	2.66	5.80	12.93	67.56	19.52	10.81	16.13	54.53	19.34	11.82
WTI	4.38	5.77	89.85	3.38	8.15	52.40	39.45	20.18	5.22	3.24	91.53	2.82
To others	6.38	3.57	5.64	**15.58%**	7.03	33.94	11.21	**52.17%**	7.12	4.78	13.81	**25.71%**

Note: The whole sample is split into three sub-periods, pre-crisis, crisis and post-crisis; and volatility spillover during these three sub-periods are reported in this table. The results show that the highest spillover take place during the crisis period in all five BRICS countries.

Second, oil is the least connected with both Islamic and conventional stocks before the crisis. During the pre-crisis period, the maximum pairwise spillover index value for crude oil (WTI) is 15.50, which is with Islamic stocks in India, while the minimum value is 2.14, which is also with Islamic stocks, but in Brazil. In the crisis period, oil's overall connectedness with both Islamic and conventional stocks increase significantly. It is observed that crude oil's pairwise spillover reaches 52.40 with conventional stocks in South Africa. In the post-crisis period, oil's connectedness with Islamic and conventional stocks falls; however, on average, it is higher than in the pre-crisis period.

From Table 4, we can obtain the direction of net pairwise volatility spillover. Thus, to compute the net pairwise volatility spillover for MSCII and MSCIC for the pre-crisis period, we observe that the MSCIC's estimated contribution to the forecast error variance of MICII is 28.02, and the MSCII's estimated contribution to the forecast error variance of MSCIC is 29.06. Accordingly, we conclude that MSCII transmits more volatility to MSCIC than it receives from MSCIC. The results of these computations are reported in Table 5. It can be seen that during the post-crisis period, Islamic stocks are the net receiver of volatility spillover in all countries, except South Africa. Overall, the results suggest that Islamic stocks are not immune from risk originating in conventional stock markets. Our results are in line with Hammoudeh et al. (2014), who also note that Islamic stocks are not very different from conventional stocks. From a portfolio point of view, Islamic stocks may not be able to contribute significantly to reducing portfolio risk. Table 5 also indicates that during the post-crisis period, crude oil dominates both

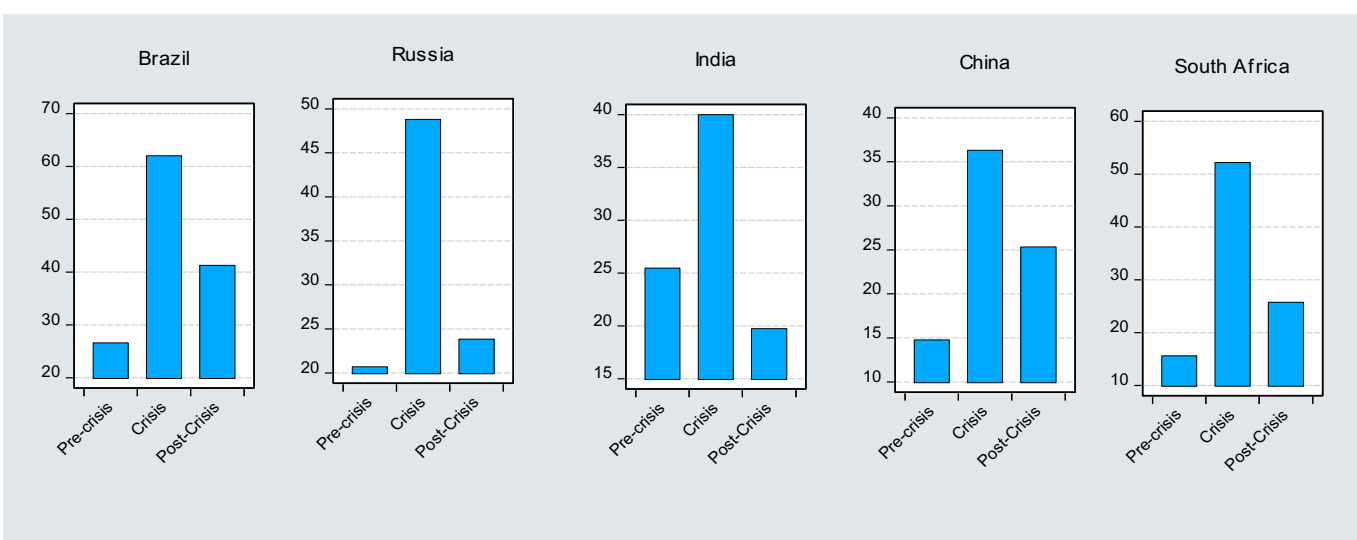

Fig. 4. Time domain total volatility spillover index during pre-crisis, crisis and post-crisis periods.

Table 5
Directions of net pairwise volatility spillover.

	Pre-crisis			Crisis			Post-crisis		
Brazil	MSCII	→	MSCIC	MSCII	→	MSCIC	MSCIC	→	MSCII
	MSCIC	→	WTI	MSCII	→	WTI	WTI	→	MSCII
	WTI	→	MSCII	MSCIC	→	WTI	WTI	→	MSCIC
Russia	MSCII	→	WTI	MSCII	→	MSCIC	MSCIC	→	MSCII
	MSCIC	→	MSCII	MSCII	→	WTI	WTI	→	MSCII
	MSCIC	→	WTI	MSCIC	→	WTI	WTI	→	MSCIC
India	MSCII	→	WTI	MSCIC	→	MSCII	MSCIC	→	MSCII
	MSCIC	→	MSCII	WTI	→	MSCIC	WTI	→	MSCII
	WTI	→	MSCIC	WTI	→	MSCII	WTI	→	MSCIC
China	MSCIC	→	MSCII	MSCIC	→	MSCII	MSCIC	→	MSCII
	MSCII	→	WTI	WTI	→	MSCIC	WTI	→	MSCII
	WTI	→	MSCIC	WTI	→	MSCII	WTI	→	MSCIC
South Africa	MSCII	→	MSCIC	MSCIC	→	MSCII	MSCII	→	MSCIC
	MSCIC	→	WTI	MSCIC	→	WTI	WTI	→	MSCII
	WTI	→	MSCII	WTI	→	MSCII	WTI	→	MSCIC

Note: (a) MSCIC = MSCI Conventional index; MSCII = MSCI Islamic index; WTI = Crude oil; (b) → indicates the direction of net volatility spillover, for example, MSCII → MSCIC indicates net directional spillover runs from MSCII to MSCIC, that is, MSCII transmits more volatility to MSCIC than it receives from MSCIC. For example, in Table 4, in Brazil's pre-crisis panel, the pairwise volatility index 29.60 represents volatility transmission from MSCII to MSCIC, while the value 28.02 represents volatility received by MSCII from MSCIC, that is, MSCII transmitting more volatility to MSCIC than it receives from MSCIC. This result is indicated by MSCII→MSCIC for Brazil in the above table during the pre-crisis period. Rest of the bi-directional results are obtained similarly.

Islamic and conventional stocks; that is, in all five countries, crude oil is the net transmitter of volatility to both Islamic and conventional stocks. Also, during the post-crisis period, the conventional stock is the net transmitter of volatility to Islamic stock in all countries except South Africa. This reinforces our conclusion that Islamic stocks cannot be used as an alternative to conventional stocks.

4.6.2. Frequency domain volatility spillover

This section considers the volatility spillover pattern in four frequency bands during the pre-crisis, crisis, and post-crisis periods, which are reported in Table 6. The figures in Table 6 suggest that spillover realised in four frequency bands is highest during the crisis period in all countries except China, where only 31.60% volatility is realised within 48 weeks; that is, approximately 70% is realised in frequency above 48 weeks. Another observation is that of the four frequency bands, the highest spillover occurs in the frequency band 24–48 weeks (except in China). This slow information processing may be attributed to the low degree of market efficiency, as indicated by previous research on emerging markets, in particular on BRIC countries (see, e.g., Fiedor, 2014; Mobarek and Fiorante, 2014; Singh, 2014). Overall, investors with a shorter investment horizon will benefit the most by investing between 1 and 12 weeks during the global financial crisis period.

The aggregation of total spillover, albeit partitioned into the four frequency bands, masks important portfolio construction parameters, as is evident when the pre-crisis, crisis, and post-crisis periods are considered. For the pre-crisis and post-crisis periods, the spillover associated with MSCIC, MSCII, and TWI for Brazil, Russia, and India aggregate connectedness of the system is driven by the 24–48-week band. In contrast, for China and South Africa, the aggregate connectedness of the system behaves monotonically, with each frequency domain contributing incrementally to connectedness. For the crisis period, the spillover associated with MSCIC, MSCII, and TWI for Brazil, Russia, and South Africa aggregate connectedness of the system is driven unambiguously by the 24–48-week band. In contrast, for China and India, the aggregate connectedness of the system is driven almost equally for each frequency band.

The spillover pattern changes dramatically when the pre-crisis, crisis, and post-crisis periods are examined. Considering the crisis period, for Brazil, Russia, and South Africa, the most pronounced spillover occurs in the 24–48-week period, which contributes about half of the total spillover. In contrast, for India and China, a monotonic increase in each band occurs, but the increment is gradual, yielding a total realised spillover of only 56.6% and 31.6%, respectively.

5. Implications for portfolio diversification

The empirical analysis presented above provides some useful portfolio diversification guidelines in relation to crude oil, Islamic and conventional stocks in BRICS. The results indicate that these three assets are suitable for a typical risk-averse investor with an investment horizon of 1–4 weeks or longer than 48 weeks. The results also indicate that connectedness between Islamic and conventional stocks is higher than the

Table 6
Volatility spillover in four frequency bands during pre-crisis, crisis and post-crisis period.

	1–4 weeks (1)	4–12 weeks (2)	12–24 weeks (3)	24–48 weeks (4)	Total realised (5) = (1) + (2) + (3) + (4)	Total spillover (6)	Total realised (%) (7) = ((5)/ (6)) *100
				Brazil			
Pre-crisis	3.12	5.76	6.54	8.52	23.94	26.60	90.00
Crisis	2.97	6.55	14.30	35.49	59.31	62.01	95.64
Post-crisis	3.64	9.97	9.58	13.57	34.76	41.25	84.27
				Russia			
Pre-crisis	0.58	1.55	2.86	5.09	10.08	20.70	48.69
Crisis	4.32	7.99	10.32	17.43	40.06	48.80	82.09
Post-crisis	1.34	2.61	3.36	5.17	12.48	23.83	52.37
				India			
Pre-crisis	0.58	1.73	3.43	6.26	12.00	25.46	47.09
Crisis	2.89	5.60	6.61	7.53	22.63	39.99	56.59
Post-crisis	1.10	2.54	3.30	5.14	12.08	19.72	61.25
				China			
Pre-crisis	1.88	3.47	3.80	4.34	13.49	14.78	91.27
Crisis	1.59	2.93	3.18	3.77	11.47	36.31	31.60
Post-crisis	2.79	5.11	5.63	6.93	20.46	25.33	80.77
			South Africa				
Pre-crisis	1.28	3.73	3.88	4.39	13.28	15.58	85.24
Crisis	2.85	5.70	9.59	17.70	35.84	52.17	68.70
Post-crisis	2.23	5.27	6.19	7.90	21.59	25.71	83.97

Note: Table 6 reports volatility spillover in four frequency bands in column (1) through column (4), while column (5) reports total volatility spillover that take place in 48 weeks, which is the sum of column (1) through (4). Column (6) reports total volatility spillover during three sub-periods, which correspond to Fig. 4, while column (7) examine the proportion of total spillover that is realised in 48 weeks.

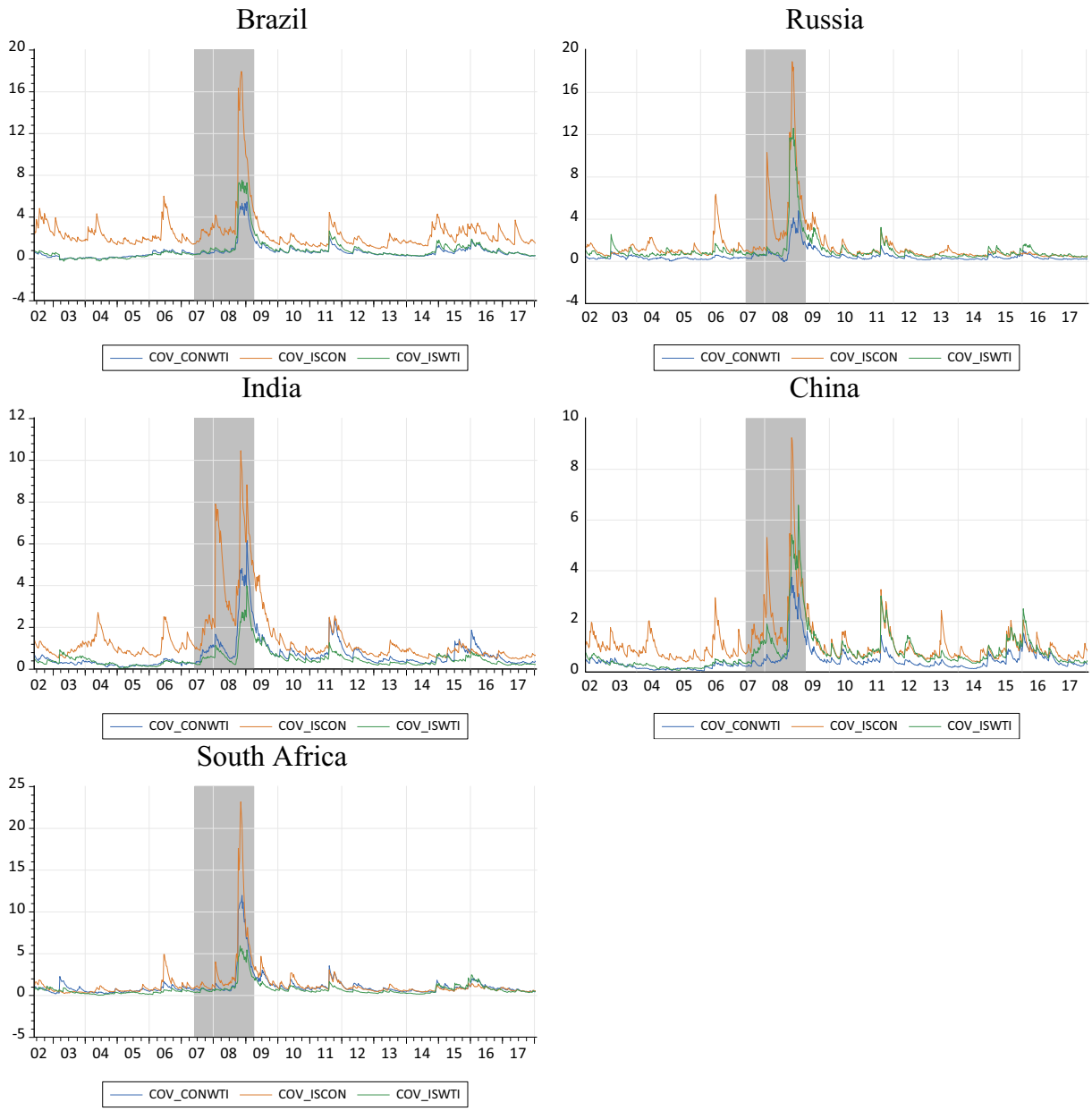

Fig. 5. Dynamic covariances. Note: (a) The shaded area in each plot represents the crisis period, that is, from 1 June 2007 to 31 March 2009. (b) COV_CONWTI, COV_ISCON, and COV_ISWTI represent covariances between conventional stock and crude oil, Islamic stock and conventional stock and Islamic stock and crude oil respectively.

connectedness of oil with either of these two stocks, which implies lower diversification benefits with Islamic and conventional stocks. This result also suggests that Islamic stocks cannot be treated as an alternative to conventional stocks during a crisis period.

To substantiate this aspect further, we analyse the dynamic covariance between each pair of asset returns. Covariance between two return series determines the extent of risk reduction of a portfolio, as shown in the following fundamental portfolio risk equation: $\sigma_P^2 = w_1^2\sigma_1^2 + w_2^2\sigma_2^2 + 2w_1w_2COV(r_1,r_2)$. This equation shows that it is the covariance between the return series that determines whether the portfolio risk will be higher or lower than the weighted average of their individual risks. To derive the dynamic covariance series, we first estimate the DCC model of Engle (2002) with crude oil, Islamic, and conventional stock index returns.[7] The DCC estimates the dynamic correlation between each pair of returns and the dynamic variance for each return series, from which we calculate dynamic covariance using the formula $COV(r_{1,\,t}, r_{2,\,t}) = \rho_{12,\,t} \times \sigma_{1,\,t} \times \sigma_{2,\,t}$.

The dynamic covariance between each pair of return series for each country is plotted in Fig. 5. The plots in Fig. 5 show that three covariance series exhibit significant positive spikes during the crisis period as represented by the shaded areas. Of the three covariance series, the covariance between Islamic and conventional stocks in all countries exhibits the highest increase during the crisis period. This indicates that conventional and Islamic stocks move very closely during the crisis period, and hence Islamic stocks cannot provide an effective safeguard against financial crisis.[8]

[7] We estimate the TGARCH-DCC model. The resulting TGARCH estimations results are reported in Table A3 and are used to extract volatility measures for the underlying series; however, we do not discuss the DCC model in detail, to save space.

[8] Several studies employ DCC models to show crisis period co-movements of financial asset returns; for example, Filis et al. (2011), Sadorsky (2014), Hassan et al. (2017 & 2019). Comparing covariance plots in Figure 5 and correlation plots in Figure 6, we see that dynamic correlations do not exhibit any sharp change during the crisis period, while the covariances in Figure 5 clearly show a significant increase during the crisis period.

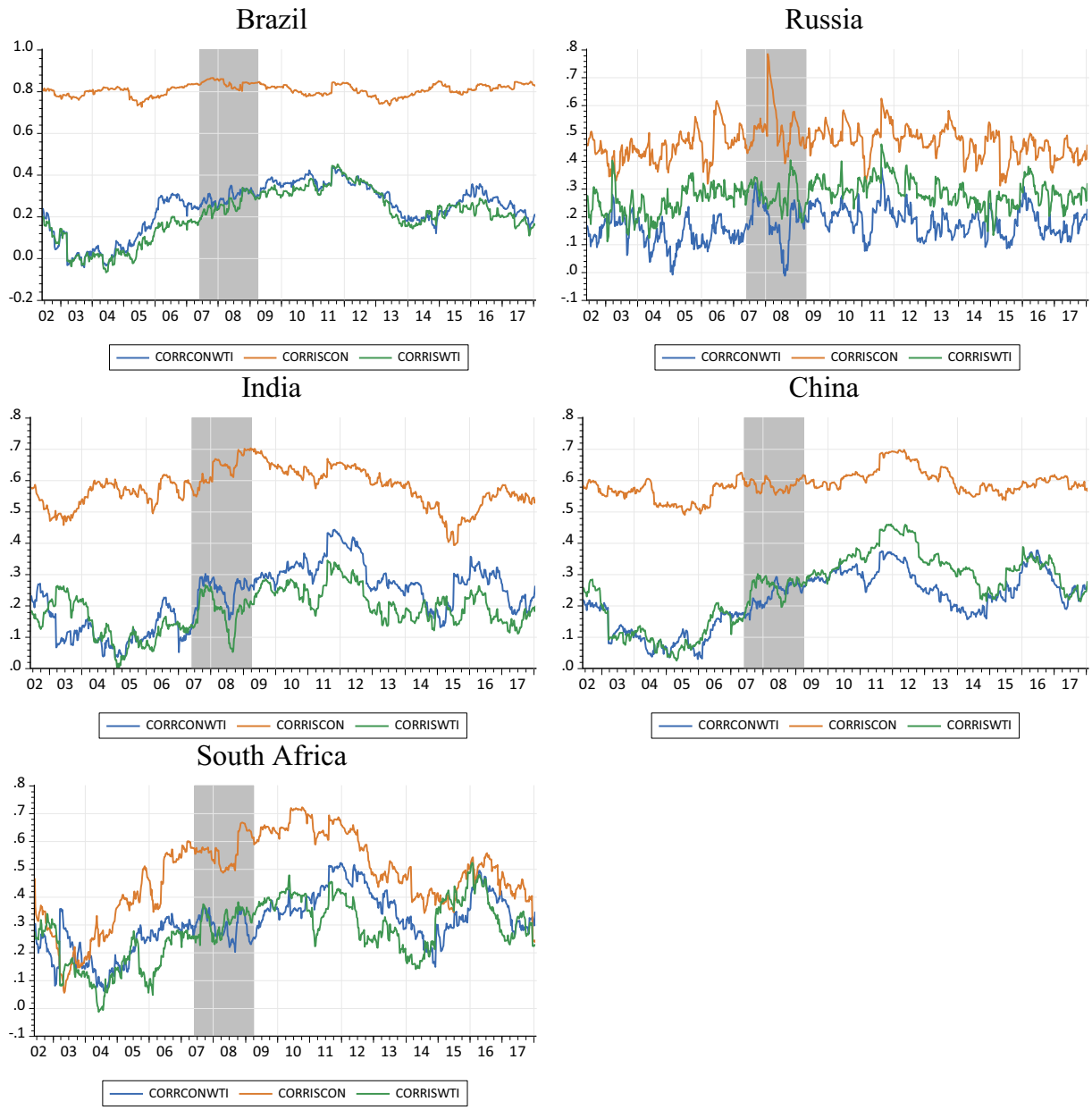

Fig. 6. Dynamic conditional correlations. Note: (a) The shaded area in each plot represents the crisis period, that is, from 1 June 2007, to 31 March 2009. (b) CORRCONWTI, CORRISCON and CORRISWTI represent dynamic conditional correlations between conventional stock and crude oil, Islamic stock and conventional stock and Islamic stock and crude oil respectively.

Another observation from Fig. 5 is that across all BRICS countries, the dynamic covariance between Islamic and conventional indices is the highest among the three dynamic covariance series over the whole sample period. The dynamic correlation between Islamic and conventional stock index returns is also the highest, as shown in Fig. 6.

6. Robustness test

To ensure the robustness of our findings, we perform two alternative estimations. First, we apply a 75- and a 125-week rolling window to estimate the spillover index. Similar robustness tests are applied in previous studies, such as those of Kang et al. (2015); Kang et al. (2017). Following Bai and Koong (2018), we use a different global crude oil benchmark in our second robustness test, namely Brent crude oil.

The results do not change qualitatively.[9] All results of robustness tests indicate that the findings reported and analysed in this paper are not sensitive to the choice of rolling window or a different crude oil benchmark.

7. Conclusion

The current paper's objective has been to analyse the volatility spillover among crude oil, Islamic stocks and conventional stocks in BRICS. While analysing volatility spillover, we pay particular attention to decomposing the total volatility spillover into various frequency bands. This decomposition is important since different investors have different investment horizons.

[9] The results are not reported but are available from the authors upon request.

Our empirical results provide some concrete outcomes. First, the results show that there is moderate volatility spillover among Islamic stock, conventional stock and crude oil—own-variable volatility spillover being the dominant element. The highest volatility spillover index is 32.35% for Brazil, while the lowest is 17.67% for India.

Second, crude oil is least connected with Islamic and conventional stocks, making it a potential candidate to include in a portfolio with either of the stocks. Third, among these three assets, Islamic and conventional stocks exhibit higher connectedness in terms of volatility spillover. Dynamic covariance and the DCC between these two is also higher compared with their dynamic covariance and DCC with crude oil. This implies that Islamic stocks cannot be used as an alternative to conventional stocks. Also, they are not suitable for inclusion in the same portfolio.

Fourth, volatility spillover increases significantly during the financial crisis of 2007–09 compared with the pre-crisis period in all countries and also during the post-crisis period, except for in China. The covariance among the assets also increases sharply during the crisis period indicating higher portfolio risk with these assets.

The frequency decomposition of total volatility spillover indicates an approximately linear positive relationship between spillover and frequency bands; spillover increases with an increase in frequency bands. The highest frequency band (1–4 weeks) has the lowest spillover, while the lowest frequency (24–48 weeks) has the highest spillover; that is, the lowest frequency band dominates the other bands. Frequency decomposition also suggests that most of the volatility spillover is realised within the four frequency bands covering 48 weeks (approximately 1 year).

The findings of our study convey useful messages to investors considering BRICS markets for their investment diversification. First, Islamic stocks cannot be taken as a safeguard against financial turmoil, since there is substantial volatility spillover and covariance between Islamic and conventional stocks. Second, our study provides specific information for investors having different degrees of risk-aversion and different investment horizons. Investors with high risk-aversion coefficients and short-run investment horizons should consider investing for 1 month. In contrast, investors with high risk-aversion and long investment horizons should consider investing for more than 48 weeks (i.e., approximately 1 year).

Credit authorship contribution statement

Kamrul Hassan: Conceptualisation, method design, estimation, formal analysis, writing – original draft.

Ariful Hoque: Conceptualization, formal analysis.

Dominic Gasbarro: Method design input, formal analysis, revision coherence;

Muammer Wali: Data curation, interpretation consistency.

Note: The first four columns represent total spillover decomposition into four frequency bands, the fifth column represents total spillover decomposed in four frequency bands within a year (48 weeks), while the last column represents total volatility spillover index as reported in percentage form in Table 1.

Appendix A. Appendix

Table A1
Summary statistics.

	Mean	Std deviation	Skewness	Kurtosis	Jarque-Bera
Brazil					
MSCI Islamic	−1.0063	2.0271	−0.7785	7.0753	647.1167***
MSCI Conventional	−0.0831	1.4915	−0.3370	6.6078	458.0057***
Russia					
MSCI Islamic	0.0701	2.1008	−0.9501	15.0847	5943.919***
MSCI Conventional	−0.0065	1.4622	−0.7039	8.0482	933.8414***
India					
MSCI Islamic	−0.0207	1.4657	−0.8978	8.9568	1316.079***
MSCI Conventional	−0.0134	1.6280	−0.6755	7.8005	845.8528***
China					
MSCI Islamic	0.0129	1.7098	−0.5684	7.2067	645.6218***
MSCI Conventional	−0.0166	1.1488	−0.1782	5.4828	213.9226***
South Africa					
MSCI Islamic	0.0344	1.3208	−0.3285	6.4840	427.3726***
MSCI Conventional	0.0659	2.0583	−0.8661	15.9712	5822.639***
Crude oil	0.0680	1.8053	−0.2310	6.2299	361.9622***

Note: Descriptive statistics reveal some stylised facts of financial time series, such as, all series exhibit asymmetric distribution as indicated by negative skewness and fat-tailed distribution as indicated by the kurtosis values. Negative skewness and fat-tailed distribution are further supported by highly significant Jarque-Berta test statistics.

Table A2
Week-of-the-month effect result.

	γ_1	γ_2	γ_3	γ_4
Brazil				
MSCIC	0.2630**	0.1446	−0.1257	0.0572
	(2.5146)	(1.3828)	(−1.2021)	(0.5468)
MSCII	0.3047**	0.1968	−0.1077	−0.0507
	(2.1429)	(1.3845)	(−0.7574)	(0.1422)
Russia				
MSCIC	0.2033**	0.0504	−0.0342	0.2604**
	(1.9826)	(0.4915)	(−0.3332)	(2.5395)
MSCII	0.0312	0.2262	−0.0559	0.0787
	(0.2122)	(1.5371)	(−0.3799)	(0.5348)
India				
MSCIC	0.3215***	0.2165*	−0.2006*	0.0408
	(2.8153)	(1.8960)	(−1.7566)	(0.3576)
MSCII	0.1630	0.0606	−0.0423	0.2376**

Table A2 (*continued*)

	γ_1	γ_2	γ_3	γ_4
	(1.5858)	(0.5900)	(−0.4116)	(2.3114)
China				
MSCIC	−0.2114***	0.0588	−0.0066	0.0636
	(2.6327)	(0.7325)	(−0.0832)	(0.7946)
MSCII	0.3333***	0.2144*	−0.2272*	0.0063
	(2.7794)	(1.7881)	(−1.8952)	(0.0527)
South Africa				
MSCIC	0.0421	0.2217	−0.0307	0.0305
	(0.2924)	(1.5373)	(−0.2133)	(0.2119)
MSCII	0.1980**	−0.0029	−0.0929	0.0195
	(2.1372)	(−0.0314)	(−1.0032)	(0.2103)
WTI	0.2279*	−0.0682	−0.1455	0.1896
	(1.7998)	(−0.5386)	(−1.1494)	(1.4976)

Note: ***,** and * indicate significant at 1%, 5% and 10% level respectively. The results show the presence of the week-of-the-month effect in data. In particular first week of the month has more pronounced effect than other weeks either stock markets in BRICS. These effects are taken into consideration and the filtered series are used in further analysis.

Table A3
Estimation results of threshold GARCH model.

	γ_i	$\gamma_i + \vartheta_i$	δ_i	ARCH-LM test (*F*-stat)
Brazil				
MSCII	0.0451	0.0623*	0.8960***	0.3473
	(0.0324)	(0.0321)	(0.0302)	(0.555)
MSCIC	0.0375	0.0686*	0.8597***	1.910
	(0.0320)	(0.0358)	(0.0464)	(0.1673)
Russia				
MSCII	0.1115**	0.0375	0.8182***	0.4656
	(0.0510)	(0.0542)	(0.0416)	(0.4952)
MSCIC	0.0623**	0.0382	0.9007***	0.0011
	(0.0291)	(0.0341)	(0.0245)	(0.9730)
India				
MSCIII	0.0637**	0.0109	0.9035***	0.0328
	(0.0299)	(0.0331)	(0.0260)	(0.8563)
MSCIC	0.0875**	0.0098	0.8788***	0.1159
	(0.0360)	(0.0364)	(0.0332)	(0.7336)
China				
MSCI	0.0827**	0.0574	0.8402***	0.0003
	(0.0382)	(0.0423)	(0.0457)	(0.9871)
MSCIC	−0.0005	0.2298***	0.8171***	0.0271
	(0.0248)	(0.0572)	(0.0397)	(0.8692)
South Africa				
MSCII	0.0286	0.1391***	0.8580***	0.1879
	(0.0263)	(0.0443)	(0.0331)	(0.6647)
MSCIC	0.1008**	0.0600	0.8116***	0.2374
	(0.0488)	(0.0526)	(0.0413)	(0.6262)
WTI	0.0292	0.1193***	0.8774***	0.2128
	(0.0265)	(0.0379)	(0.0270)	(0.6447)

Note: (1) Figures in the parentheses are standard errors, except ARCH-LM test, where figures in the parentheses are probability values; (2) Null hypothesis of ARCH-LM test is that there is no ARCH effect in the residuals; (3) ***,** and * indicate significant at 1%, 5% and 10% level respectively.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2020.104985.

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