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Following the leaders? A study of co-movement and volatility spillover in BRICS currencies

Suman Das[a,*], Saikat Sinha Roy[b]

[a] Department of Economics, Jadavpur University, Kolkata, India
[b] UGC Centre for Advanced Studies, Department of Economics, Jadavpur University, Kolkata, India

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A B S T R A C T

The paper investigates return co-movement and volatility spillover among the currencies of Brazil, Russia, India, China, and South Africa (the BRICS member countries) and four major developed countries from April 2006 to October 2019. Using Bloomberg daily data on exchange rates, the study employs a flexible multivariate generalized autoregressive conditional heteroskedasticity (MGARCH)–dynamic conditional correlation (DCC) model and a vector autoregressive (VAR)–based spillover index, as the empirical strategy. Along with evidence of exchange rate volatility in BRICS currencies, among which the Russian ruble and the Chinese yuan are explosive, the econometric estimation results show the presence of significant return co-movement and volatility spillover among the foreign exchange markets across different countries. The currency markets in developed countries, as leaders, are found to transmit volatility mostly to BRICS currency markets, which are net receivers. The degree of spillover, however, varies across countries, with Brazil and Russia passing on volatility to the developed countries whereas India, China, and South Africa receive volatility from their developed counterparts.

1. Introduction

This paper examines the currency connectedness (in terms of return co-movement and volatility spillover) among Brazil, Russia, India, China, South Africa, the member countries of BRICS, and the developed countries, whose currencies are most traded globally. As BRICS economies have progressively adopted a floating exchange rate regime and are increasingly integrated into the global financial market, volatility in currency markets is expected to increase manifold. The extent and persistence of this volatility could evolve into a crisis, adversely affecting, directly or indirectly, many key policy variables, including interest rate and return on investment, apart from posing a downside risk to export competitiveness, international investment portfolios, international reserves, the currency value of debt payment, and economic stability and growth.[1] Managing currency volatility is a major challenge for individual central banks as they formulate monetary policy in these emerging market economies.

* Corresponding author.
E-mail addresses: sumandas.eco@gmail.com (S. Das), saikat.sinharoy@jadavpuruniversity.in (S.S. Roy).

[1] However, Kose et al. (2009), reviewing evidence on developing countries, find little systemic evidence that financial globalization leads to "deeper and more costly" growth crises.

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A study on volatility in the BRICS currency markets is important, as these countries accounted for 24% of global output in 2019 compared with 11.8% in 2006 (IMF, 2019).[2] Total exports from BRICS more than doubled, from US$1.6 trillion in 2006 to US$3.5 trillion in 2019, increasing their combined share of global exports from 14.6% to 20.7%. The trade surplus of these countries also increased, from US$369.8 billion to US$436.9 billion over the same period. In addition, the BRICS countries experienced staggering growth in the flow of foreign direct investment (FDI), with the share of these countries in world FDI increasing from 9.2% in 2006 to 19.7% in 2019. As a result, according to the database of the Federal Reserve Bank of St. Louis, foreign exchange reserves, excluding gold, for the BRICS as a whole increased from US$1.35 trillion to US$4.39 trillion over this period. The improving economic prospects of the BRICS attracted investors and portfolio managers and increased their participation in the BRICS foreign exchange markets.

According to the Bank for International Settlements (BIS), the foreign exchange market turnover in April 2019 was US$71 billion for Brazil, US$72 billion for Russia, US$113 billion for India, US$284 billion for China, and US$72 billion for South Africa, accounting for 9.3% of the global foreign exchange turnover (BIS, 2019). However, the standard deviation of returns for the Brazilian real, Russian ruble, Chinese yuan, Indian rupee, and South African rand is 0.0104, 0.0089, 0.0045, 0.0016, and 0.0110, respectively. These currencies (except the Chinese yuan and Indian rupee) are also more volatile than their developed country counterparts. This low volatility in the Indian rupee and Chinese yuan is possibly due to extensive intervention in the foreign exchange markets by the irrespective monetary authorities. The emerging importance of BRICS in the global economy and the volatility observed in these currencies should not obscure the potential for volatility spillover in the global economy.

A large body of emerging literature exists on volatility in currency markets and volatility clustering in developing economies.[3] Some studies are on volatility transmission in currency markets in both developed and developing economies. For instance, Engle et al. (1990) find supporting evidence for the effects of “heat waves” and “meteor showers.” Currency markets have instances of apparent spillover effects, as shown by Ebrahim (2000). Melvin and Melvin (2003), while examining volatility spillovers of the deutsche mark–US dollar and yen–US dollar exchange rates across regional markets, find volatility in one region to be a function of both prior-period volatility in that region (heat wave effect) and volatility in other regions (meteor shower effect), with the former more dominant than the latter.[4] Andersen et al., (1999) find normality-inducing volatility transmission, high contemporaneous correlation across volatilities, pronounced and persistent temporal variation in both volatility and correlation, indicating long memory dynamics in both volatility and correlation.

Although Inagaki (2007), using a residual cross-correlation function, finds evidence of unidirectional volatility spillover between the euro and the pound, Hong (2001) shows bidirectional causality of spillover between the two currencies. Kearney and Patton (2000) point to both direct and indirect volatility transmission within the European Monetary System. Further, some developed country currencies exhibit higher dependence during periods of joint appreciation than during periods of joint depreciation (Tamakoshi and Hamori, 2014).[5] It is further argued that markets are more likely to transmit volatility in active phases than in calm ones (Andersen and Bollerslev, 1998). Gomez-Gonzalez and Rojas-Espinosa (2019) show that extreme foreign exchange market co-movement of 12 Asian-Pacific countries depend primarily on the degree of interdependence among them.[6] Niyitegeka and Tewari (2020) show unidirectional volatility spillover from the euro to the rand during the eurozone crisis and post-crisis periods. Moreover, volatility spillover and time-varying correlations increase during crisis, indicating financial contagion among the markets.

In addition to ascertaining the existence and nature of volatility spillovers, it is also important to identify currencies that are net receivers or transmitters of volatility. Antonakakis (2012), in a dynamic conditional correlation (DCC) and vector autoregressive (VAR) framework, finds that the euro is a net transmitter of volatility whereas the pound is a net receiver of volatility. Moreover, cross-market volatility spillovers are found to be bidirectional, and the highest spillovers occur between European markets.[7] Kocenda and Moravcova (2019) show that conditional correlation between the new European Union (EU) exchange rates and the US dollar decreases during crisis periods and increases after the crisis. The cross-currency volatility spillover is bidirectional and is highest during global financial crises. The literature discussed above gives evidence on return co-movement and volatility spillover across currencies. However, these studies largely concentrate on the foreign exchange markets of developed countries with little evidence on sources of volatility and volatility spillover in the currency markets of BRICS countries.[8] On the whole, the studies reviewed show co-

[2] According to the International Monetary Fund, the four BRICS countries are among the top ten economies in the world in terms of the purchasing power parity–adjusted nominal gross domestic product (GDP).

[3] See, e.g., Chong et al. (2002), Erdemlioglu et al. (2012), Johnston and Scott (2000), Kocenda and Valachy (2006), Narayan et al. (2009), Niyitegeka and Tewari (2020), and Sandoval (2006).

[4] Several other studies, including Bollerslev (1990), show that the co-movement between currencies were significantly higher before the European Monetary System than afterward, with free floating currencies. Other studies covering volatility transmission in developed country currency markets include Ebrahim (2000), Inagaki (2007), Kearney and Patton (2000), Hong (2001), McMillan and Speight (2010), Kitamura (2010), Antonakakis (2012), and Kocenda and Moravcova (2019). Recent studies, such as Black and McMillan (2004), Calvet et al. (2006), Perez-Rodrìguez (2006), Nikkinen et al. (2006), Kitamura (2010), and McMillan and Speight (2010), find evidence of volatility spillovers and return co-movement among currency exchange rates.

[5] In contrast, Patton (2006), Chiang et al. (2007), and Boero et al. (2011) demonstrate higher correlations during periods of depreciation than in periods of appreciation.

[6] Some studies, e.g., Sahoo (2012), Ghosh (2014), and Lee (2010), show volatility transmission from other currencies and financial markets to developing country currency markets.

[7] Similar conclusions are arrived at by Chowdhury and Sarno (2004) using the generalized autoregressive conditional heteroscedasticity [GARCH (1,1)] method.

[8] One exception might be Chuliá et al. (2018), which shows that the most liquid currencies are net transmitters of volatility during periods of US

movement in foreign currency returns and cross-country volatility in which some currencies are identified as net transmitters of volatility whereas others are net receivers. The transmission of volatility is likely to be greater during crises than in phases with relative stability. However, no studies have been conducted on return co-movement and volatility spillover in BRICS currency markets.[9]

This study investigates the extent of return co-movement and volatility spillover in BRICS currency markets.[10] Given the recent evidence of no contagion in currency markets (Gomez-Gonzalez and Rojas-Espinosa, 2019), this paper avoids analysis of contagion. It focuses, instead, on volatility spillover among currencies in 2006–2019, without splitting the full sample period into crisis and non-crisis sub-periods. For this purpose, we consider several developed country currencies: the euro, Japanese yen, British pound, and Australian dollar.[11] Using the DCC model and VAR methods, the analyses show the presence of significant return co-movement and volatility spillover between foreign exchange markets, in which the BRICS markets are net receivers of volatility and developed markets are net transmitters of volatility. The study, however, estimates volatility spillover in a rolling-sample framework that identifies currency market volatility during periods of relative turmoil and tranquility. Our key contribution to the literature is in examining return co-movement and volatility spillover in the BRICS foreign exchange markets, unlike the existing studies, which are on only developed country currency markets.

The structure of the paper is as follows.

Section 2 presents some stylized facts on currency movement in BRICS and other developed countries.

Section 3 delineates the econometric methodology and the data used in the study. Section 4 presents the empirical results.

Section 5 concludes with a summary of the major findings and policy implications.

2. Stylized facts on currency movement: BRICS and selected developed countries

The exchange rates of BRICS currencies (Brazilian real, Russian ruble, Indian rupee, Chinese yuan, and South African rand) with respect to the US dollar have fluctuated since 2006 (Fig. 1). The descriptive statistics on the return series of the Brazilian real, Russian ruble, Indian rupee, Chinese yuan, South African rand, euro, Japanese yen, British pound, and Australian dollar for the period 2006–2019 are presented in Table 1.[12] It is evident that the variations in currency returns, as measured by standard deviation, are the highest for the South African rand, followed by the Brazilian real, Russian ruble, Indian rupee, and the Chinese yuan.

The variations in the returns are lower for the Indian and Chinese currencies than for the currencies of advanced countries, indicating significant interventions by the respective central banks (Das and Sinha Roy, 2021). The time pattern of volatility for BRICS currency returns shows that the amplitude of fluctuations in the return series is larger for BRICS countries except China (Appendix Fig. A1), thus confirming the findings in Table 1. Volatility seems to have clustered in 2008, 2009, 2011, 2015, 2016, 2018, and 2019 for the Brazilian real, Russian ruble, Chinese yuan, and the South African rand, whereas for the Indian rupee, volatility clustering occurs in 2008, 2009, 2011–2013, 2018, and 2019.[13]

The returns series of BRICS currencies as well as for developed country currencies are found to be leptokurtic, implying that currency returns follow a non-normal distribution. Further, the significance of Jarque–Bera statistics also indicates non-normality of the currency returns series. This analysis uses a normal distribution for the maximum likelihood estimation (MLE), although it is a standard practice to use Student's *t* or generalized Gaussian distribution when ε_t follows a fat-tailed and asymmetric distribution (Bollerslev, 1986, 1987; Hsieh, 1989; Nelson, 1991). However, this technique can produce inconsistent estimators if the distribution of innovation is misspecified. In contrast, the Gaussian MLE or Gaussian quasi-maximum likelihood estimation (QMLE) produces consistent estimator (Elie and Jeantheau, 1995) and is asymptotically normal if a finite fourth moment of the innovation exists, even when the true distribution is far from normal (Berkes et al., 2003; Hall and Yao, 2003).

Table 1 also reports the Ljung–Box Q and the Q^2 statistics for all return series and the squared return series. The Q statistic results demonstrate that none of the series follow a random-walk process, and the augmented Dickey–Fuller test shows that all the return series are I(0).[14] However, Q^2 is significant for each return series, showing the presence of higher-order serial correlation and

(*footnote continued*)
dollar appreciation and net receivers during periods of turbulence whereas the least liquid currencies are always net receivers of volatility. However, in the event of tail spillovers, the most liquid currencies are net receivers of shocks, but those in the least liquid quartiles are net transmitters. However, Gomez-Gonzalez et al. (2020) show dynamic connectedness and predictive causality between oil prices and exchange rates. The existing literature on BRICS primarily focuses on stock and bond market volatility spillovers. See, e.g., Walid et al. (2011), Zhang et al. (2013), Abbas et al. (2013), Syriopoulos et al. (2015), Chkili (2016), Yarovaya and Lau (2016), Mensi et al. (2016, 2017), Kocaarslan et al. (2017), and Ahmad et al. (2018)].

[9] Sandoval (2006) deals with return co-movement in emerging markets, and Chuliá et al. (2018), Niyitegeka and Tewari (2020) study volatility spillovers between developed and emerging market economies.

[10] Contagion is defined as a significant increase in cross-market co-movement after a shock to one country or a group of countries (Forbes and Rigobon, 2002). On contagion among foreign exchange markets, see Loaiza-Maya et al. (2015a, 2015b).

[11] According to the BIS (2019), these developed country currencies are the most traded.

[12] The return on each foreign exchange is calculated by taking the first logarithmic differences in the exchange rate, denoted as: $\Delta \ln S_t = \ln S_t - \ln S_{t-1}$.

[13] However, in the developed country foreign exchange markets, volatility clustering appears to occur in the entire period, with a higher magnitude for the euro, followed by the British pound, the Japanese yen, and the Australian dollar.

[14] The Phillips-Perron and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test statistics are also consistent with the augmented Dickey–Fuller test

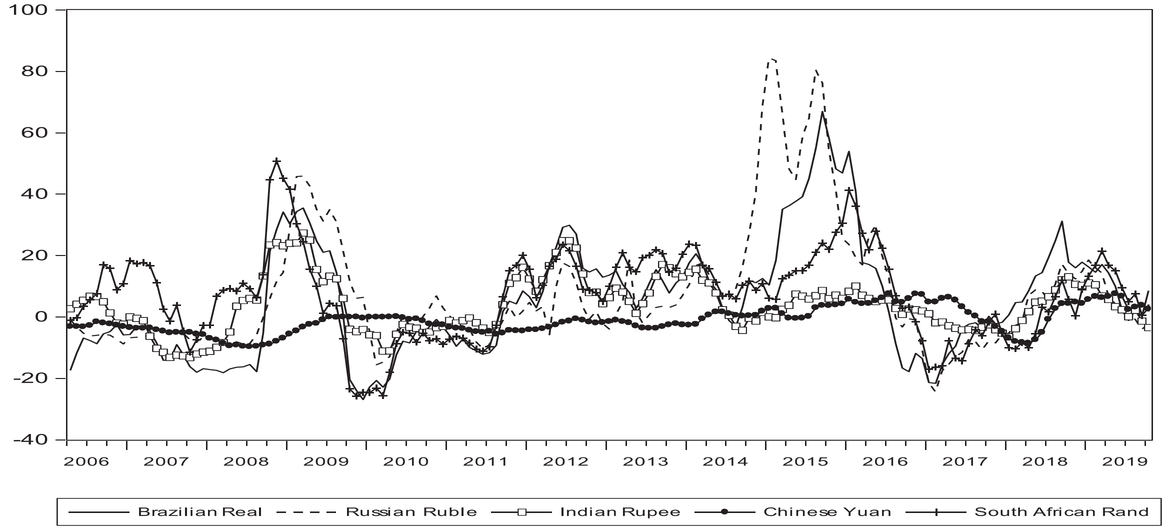

Fig. 1. Movement in monthly exchange rate returns in the BRICS (year-on-year % change).
Source: Exchange rate data from the Federal Reserve Bank of St. Louis

nonlinearity among the variables. These series, on the whole, exhibit non-randomness, volatility clustering, and autoregressive conditional heteroskedasticity (ARCH) effects, which are suggestive of modeling exchange rate returns volatility in a generalized ARCH (GARCH) framework.

3. Methodology and data

3.1. Methodology

In the literature, although the notion of correlation captures the degree of interdependence among currencies, an understanding of volatility spillover helps in identifying the proliferation of shocks from one currency market to another. Volatility in financial markets, including stock and foreign exchange markets, can be measured in many ways.[15] The analysis of volatility in financial markets has been widely studied with the ARCH–GARCH framework, à la Engle (1982) and further developed by Bollerslev (1986) and Nelson (1991). The ARCH–GARCH family of models, include the fractionally integrated GARCH model (FIGARCH), exponential GARCH model (EGARCH), the threshold GARCH model (TGARCH), and the power ARCH model (PARCH).[16] Several studies—for instance, Mundaca (1991), Chong et al. (2002), McKenzie and Mitchell (2002), Narayan et al. (2009), and Erdemlioglu et al. (2012)—show the superiority of GARCH family models over ARCH for understanding currency volatility. In this paper, in sharp contrast to the constant conditional correlation model, return co-movement among the foreign exchange markets is investigated using an MGARCH–DCC model.[17]

The DCC model, as proposed by Engle (2002), explicitly captures both conditional and unconditional time-varying relations among the markets, not constant correlations.[18] The model has two steps. In the first step, the individual conditional variances are specified as univariate GARCH processes, and the correlation among the series is presented in the second step. The model has a computational advantage over other MGARCH models in that the number of parameters to be estimated in the process is independent of the number of series correlated. As a result, very large correlation matrixes can be estimated. Additionally, an $AR(1)$ term is included to correct for possible autocorrelation. The DCC model, following Engle (2002), is represented as:

$$r_t = \mu_t + \gamma_1 r_{t-1} + \epsilon_t, \quad \text{where} \quad \epsilon_t \mid \Omega_{t-1} \sim N(0, H_t) \tag{1}$$

$$\epsilon_t = H_t^{1/2} u_t, \text{ where } u_t \sim N(0, I)$$

(*footnote continued*)
(ADF) results. The results are available upon request from the authors.

[15] The volatility of an economic variable includes both anticipated variability and unanticipated uncertainty, and the latter is said to constitute a “shock.” Volatility in the exchange rate, according to Engel and Hakkio (1993), is explained in terms of volatility in market fundamentals, changes in expectations due to new information, and speculative “bandwagons.”

[16] Econometric inquiry in this field is carried out, among others, by Johnston and Scott (2000), Sandoval (2006), and Kocenda and Valachy (2006).

[17] Perez-Rodrìguez (2006), Kitamura (2010), Antonakakis (2012), Kocenda and Moravcova (2019), and Gomez-Gonzalez and Rojas-Espinosa (2019) use this modeling strategy to decipher return co-movement in currency markets. Cappiello et al. (2006), Wang and Moore (2012), Kang et al. (2016), Roy and Roy (2017), and Ngene et al. (2018) use this method for estimating return co-movement in other financial markets.

[18] See also Bauwens et al. (2006).

Table 1
Descriptive Statistics: BRICS and most traded currency return series (with respect to US dollar).

	Brazilian real	Russian ruble	Indian rupee	Chinese yuan	South African rand	Euro	Yen	Pound	Australian dollar
Mean	0.00017	0.00024	0.00013	-0.00004	0.00025	0.00002	-0.00002	0.00008	0.00001
Std. Dev.	0.0104	0.0089	0.0045	0.0016	0.0110	0.0059	0.0063	0.0060	0.0083
Skewness	0.27	0.56	0.22	0.67	1.04	-0.08	-0.04	0.98	0.36
Kurtosis	8.56	19.78	9.32	17.15	16.54	5.29	8.06	16.29	14.28
ADF Test	-63.7	-56.5	-43.8	-59.8	-59.9	-59.0	-61.1	-57.3	-63.0
JarqueBera	4610.3 (0.00)* **	41,782.6 (0.00)* **	5916.9 (0.00)* **	29,815.4 (0.00)* **	27,690.7 (0.00)* **	777.6 (0.00)* **	3779.7 (0.00)* **	26,665.5 (0.00)* **	18,848.8 (0.00)* **
Q(30)	65.4 (0.00)* **	128.0 (0.00)* **	85.5 (0.00)* **	112.3 (0.00)* **	45.3 (0.03)* *	21.1 (0.00)* **	56.5 (0.00)* **	53.9 (0.00)* **	84.3 (0.00)* **
$Q^2(30)$	4584.6 (0.00)* **	4607.3 (0.00)* **	2029.9 (0.00)* **	477.34 (0.00)* **	878.8 (0.00)* **	2168.6 (0.00)* **	1094.4 (0.00)* **	401.16 (0.00)* **	6405.7 (0.00)* **
Obs.	3544	3544	3544	3544	3544	3544	3544	3544	3544

Notes: *** and ** significant at 1% and 5%, respectively. *p*-values are in parentheses. Q(1) and $Q^2(1)$ are the Ljung–Box statistics for serial correlation in return series and squared return series, respectively.

$$H_t = D_t R_t D_t \tag{2}$$

where $r_t = (r_{it}......y_{nt})'$ is a nx1 vector of exchange rate returns,

$\mu_t = (\mu_{it}, ..., \mu_{nt})'$ is the conditional nx1 mean vector of r_t, H_t is the conditional covariance matrix,

$D_t = diag(h_{iit}^{1/2}......h_{nnt}^{1/2})'$ is a diagonal matrix of square root conditional variances, with h_{iit} being defined as any univariate GARCH-type models,

and $R_t$contain comprises the time-varying conditional correlations defined as

$$R_t = diag \quad (q_{ii,t}^{-1/2}...q_{nn,t}^{-1/2})Q_t diag(q_{ii,t}^{-1/2}...q_{nn,t}^{-1/2}) \text{or} \rho_{ij,\quad t} = \rho_{ji,\quad t} = \frac{q_{ij,\quad t}}{\sqrt{q_{ii,\quad t}q_{jj,\quad t}}} \tag{3}$$

where $Q_t = (q_{ij,t})$ is annxn symmetric positive definite matrix given by

$$Q_t = (1 - \alpha - \quad \beta)\bar{Q} + \alpha u_{t-1}u'_{t-1} + \quad \beta Q_{t-1} \tag{4}$$

where $u_t = (u_{1t}, u_{2t}, ...u_{nt})'$is the nx1 vector of standardized residuals, $\bar{Q}$ is the (nxn) unconditional correlation matrix of u_t, and α and β are nonnegative scalar parameters that satisfy $\alpha + \beta < 1$.[19]

To study volatility spillover among the foreign exchange markets, we use the generalized VAR structure (Koop et al., 1996; Pesaran and Shinn, 1998, referred to as KPPS henceforth), as it leads to variance decomposition, which is invariant to the ordering of the variables. The generalized VAR approach allows correlated shocks and accounts for them accurately using the historically observed error distribution. Because the shocks to each variable are not orthogonalized, the contributions to the variance of the forecast error do not necessarily add up to one. Likewise, Diebold and Yilmaz (2009), in a VAR framework, find indications of contradictory performance in the dynamics of return spillovers and volatility spillovers in the context of 19 global equity markets.[20]

For a $p - order\, N - variable$VAR,

$$x_t = \sum_{i=1}^{p} \varphi_i x_{t-1} + \quad \epsilon_t, \tag{5}$$

where $x_t = (x_{it}, ...x_{nt})$ is a vector of endogenous variables, $\epsilon_t \sim (0, \Sigma)$ is a vector of independently and identically distributed (i.i.d.) disturbance. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \epsilon_{t-1}$, where the NxN coefficient matrices A_i obey the recursion $A_i = \varphi_1 A_{i-1} + \varphi_2 A_{i-2} + ...+\varphi_p A_{i-p}$, with A_0 being an NxN identity matrix and $A_i = 0$ for $i < 0$. Denoting the Koop, Pesaran, Potter, and Shin (KPPS) H-step-ahead forecast error variance decomposition as

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e_i)} \tag{6}$$

where Σ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the j^{th} equation, and e_i is the selection vector with one as the i^{th} element, and zero otherwise. As mentioned above, the sum of each row of the variance decomposition matrix does not equal one, so each variable of the matrix is normalized by the row sum, so that the resulting row sum of the variables equals one, as follows:

$$\widetilde{\theta}ijg(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N} \theta_{ij}^{g}(H)} \tag{7}$$

with $\sum_{j=1}^{N} \widetilde{\theta}ijg(H) = 1$ and $\sum_{i,j=1}^{N} \widetilde{\theta}ijg(H) = N$ by construction.

Using these results, we can construct the total volatility spillover index, which is

$$S^g(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \widetilde{\theta}ijg(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}ijg(H)} {*}100 = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{N} \widetilde{\theta}ijg(H)}{N} {*}100 \tag{8}$$

This index measures the contribution of spillovers of volatility shocks across five markets to the total forecast error variance. Additionally, the directional spillovers received by market i from all other markets j are defined as

$$S_{i<}^{g}(H) = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{\theta}ijg(H)}{\sum_{i,j=1}^{N} \widetilde{\theta}ijg(H)} {*}100 = \frac{\sum_{\substack{j=1 \\ j \neq i}}^{N} \widetilde{\theta}ijg(H)}{N} {*}100 \tag{9}$$

Then, the directional spillovers transmitted by market i to all other markets j are defined as

[19] Kuruvila et al. (2012) and Sekhar (2003) find this condition to hold true in order for economic time series to be non-explosive.

[20] See Diebold and Yilmaz (2012), Chuliá et al. (2018), and Gomez-Gonzalez et al. (2020).

$$S^g_{i>}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \widetilde{\theta} jig(H)}{\sum_{i,j=1}^{N} \widetilde{\theta} jig(H)} *100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \widetilde{\theta} jig(H)}{N} *100 \tag{10}$$

and, finally, the net volatility spillover from market i to all other markets j is defined as

$$S^g_i(H) = S^g_{i>}(H) - S^g_{i<}(H) \tag{11}$$

The net volatility spillover shows how much each market, on average, contributes to the volatility of other markets and vice-versa.[21]

On the whole, Eq. (3) estimates the DCC indicating co-movement, whereas Eq. (11) shows net volatility spillover between currencies.[22]

3.2. The data

This study is carried out using the daily exchange rate series of developed countries including the euro, Japanese yen, British pound, and Australian dollar vis-à-vis the US dollar, along with that of the Brazilian real, Russian ruble, Indian rupee, Chinese yuan, and South African rand for the period 2006–2019. These exchange rate series are obtained from the Bloomberg database.

The initial period in the study is 2006 for the following reasons. First, in July 2005, China moved to a managed floating exchange rate regime with reference to a basket of currencies. Second, the formation of BRIC as a regional group was initiated in September 2006 at the first meeting of the leaders of Brazil, Russia, India, and China to enhance development cooperation among these countries. Later, in April 2011, South Africa was added to the group, forming the BRICS.

The choice of developed-country currencies such as the euro, Japanese yen, British pound, and Australian dollar is based on the Bank for International Settlements (BIS)Triennial Central Bank Survey (2019),which finds them to be the world's top-five-most-traded currencies (BIS, 2019). The BIS Triennial Central Bank Survey shows that in 2019these currencies had turnover of all transactions, including spot transactions, outright forwards, foreign exchange swaps, currency swaps and foreign exchange options, totaling US$2.129 trillion, US$1.108 trillion, US$844 billion, and US$445 billion, respectively.

4. Empirical results

In this section, the empirical analysis is set out with the estimation of time-varying conditional correlation by applying the DCC model followed by an analysis of volatility spillover among the BRICS and developed country currency markets. In this analysis, the focus will be primarily on BRICS foreign exchange markets.

4.1. Estimation of return co-movement

The analysis on static correlation among the currency return variables of different countries reveals the degree of association between any two return series. Table 2 shows that returns on the Brazilian real, Russian ruble, Indian rupee, and South African rand have a significantly positive correlation with returns on the euro, British pound, and Australian dollar and a significantly negative correlation with the Japanese yen whereas the Chinese yuan is positively correlated with all four developed country currencies. It is also important to note here that returns on the BRICS currencies have the highest positive correlation with that of Australian dollar. The results indicate that returns on all BRICS currencies appreciate with appreciation in the British pound, Australian dollar, and euro and vice-versa, but an appreciation in the BRICS currencies, except for the Chinese yuan, is associated with depreciation in the Japanese yen. The findings on unconditional correlation of return series are compared and contrasted with those from using MGARCH–DCC(1,1).

The DCC model is estimated separately for each BRICS currency market to arrive at univariate GARCH estimates as well as to understand the co-movement of the respective currencies with that of any developed country currency. The statistically significant estimated DCC parameters indicate that the second-order moments of exchange rate returns are time varying. In the case of univariate GARCH estimation of currency returns of individual BRICS economies, as seen in Table 3 (Panel A), whereas the AR(1) term, (γ_1), is significant for the Brazilian real and the Russian ruble, it is insignificant for the Chinese, Indian, and South African currencies. Table 3 also shows significant volatility persistence, given by the sum of the ARCH(α) and GARCH(β) coefficients, in the foreign exchange markets of the respective BRICS country currencies. The exceptions to this pattern are the Russian ruble and the Chinese yuan, which

[21] In this context, it is also important to mention net pair-wise volatility spillover between markets i and j, which is defined as the difference between the gross volatility shocks transmitted from market i to market j and vice-versa. It is different from the concept of net volatility spillover in the sense that the former is at a more disaggregated level, i.e., from one market to another and not to all other markets. Net pairwise volatility spillover, which, for example, reveals volatility that spills over between each developed country and BRICS foreign exchange markets, is represented as:

$S^g_{ij}(H) = \left(\frac{\widetilde{\theta} jig(H)}{\sum_{i,k=1}^{N} \widetilde{\theta} ikg(H)} - \frac{\widetilde{\theta} ijg(H)}{\sum_{j,k=1}^{N} \widetilde{\theta} jkg(H)} \right) *100 = \left(\frac{\widetilde{\theta} jig(H) - \widetilde{\theta} ijg(H)}{N} \right) *100$. The result is available upon request from the authors.

[22] However, the network framework developed by Diebold and Yilmaz (2014) is a better method for measuring connectedness.

Table 2
Unconditional correlation of BRICS currency returns.

	Euro	Yen	Pound	Australian dollar
Brazilian real	0.319 (0.000)* **	-0.099 (0.000)* **	0.284 (0.000)* **	0.506 (0.000)* **
Russian ruble	0.281 (0.000)* **	-0.038 (0.023)* *	0.240 (0.000)* **	0.350 (0.000)* **
Indian rupee	0.186 (0.000)* **	-0.076 (0.000)* **	0.193 (0.000)* **	0.264 (0.000)* **
Chinese yuan	0.133 (0.000)* **	0.050 (0.000)* **	0.149 (0.000)* **	0.146 (0.000)* **
South African rand	0.426 (0.000)* **	-0.093 (0.000)* **	0.382 (0.000)* **	0.599 (0.000)* **

Note: *** and ** indicate significance at 1% and 5%, respectively. *p*-values are in parentheses.

Table 3
Dynamic conditional correlation of BRICS.

Panel A					
	Mean Equation	Variance Equation			Status of the series
	γ_1	α	β	$\alpha + \beta$	
Brazilian real	-0.086 * ** (0.015)	0.126 * ** (0.012)	0.864 * ** (0.012)	0.99	Volatility persists for a long time
Russian ruble	0.037 * ** (0.013)	0.110 * ** (0.008)	0.907 * ** (0.006)	1.017	Explosive
Indian rupee	-0.001 (0.016)	0.068 * ** (0.008)	0.923 * ** (0.009)	0.991	Volatility persists for a long time
Chinese yuan	-0.005 (0.018)	0.019 * ** (0.001)	0.983 * ** (0.001)	1.002	Explosive
South African rand	-0.005 (0.012)	0.064 * ** (0.007)	0.929 * ** (0.009)	0.993	Volatility persists for a long time

Panel B: Multivariate DCC Equation: Individual BRICS vis-à-vis ***developed country currency returns***					
	Brazilian real	Russian ruble	Indian rupee	Chinese yuan	South African rand
DCC(A)	0.029 * ** (0.002)	0.029 * ** (0.002)	0.027 * ** (0.002)	0.027 * ** (0.002)	0.028 * ** (0.002)
DCC(B)	0.961 * ** (0.003)	0.971 * ** (0.002)	0.964 * ** (0.003)	0.966 * ** (0.003)	0.963 * ** (0.002)

Notes: ** and * denote significance at the 1% and 5% level, respectively. Standard errors are in parentheses. To conserve space, only the DCC estimates of the BRICS countries are presented. The full DCC estimates portraying the variation in individual BRICS currencies with that of individual developed country currencies are available upon request from the authors.

are explosive in nature,[23] and tend to move away from the mean value. On the whole, volatility in currency returns of individual BRICS countries tends to persist for a long period. However, the sum of the estimated DCC(1,1) parameters (shown in Panel B) is significant but less than 1in all cases, indicating that the model is well specified, with considerable time-varying co-movement among the foreign exchange markets.

The explosive nature observed in the returns on the Russian ruble can be attributed to the series of political and financial events that occurred during the period of our study. Even though the monetary authorities intervened and changed the exchange rate regimes about five times to address the conditions, it was not enough to tamp down currency volatility. The State Duma elections in 2011, the Ukrainian–Russian conflict of 2014 and the accession of Crimea then, the large fall in global oil prices in 2014, and foreign exchange policy, including devaluation of the Russian ruble in 2016, probably contributed to the turmoil in the foreign exchange market. The policy of the Russian Central Bank to continuously increase exchange rate flexibility and gradually move to a fully floating regime also added to the explosive nature of the Russian ruble. At the same time, the explosive nature of the Chinese yuan might be due to the change in the exchange rate regime from a preannounced crawling peg and a defacto moving band narrower than or equal to $+/-$ 1% of the de facto crawling peg. The global financial crisis in 2008, the eurozone debt crisis in 2011, and the US federal government shutdown in 2013 did not have a significant effect on volatility of the Chinese yuan, as the monetary authority intervened to minimize the adverse effect of these events on the Chinese foreign exchange market. However, the change in the exchange rate regime to a defacto crawling peg in December 2014 and, thereafter, the Brexit referendum in 2016, the European general election in first half of 2017, and the emergence of a US–China trade war in 2018 and its continuation in 2019 affected the volatility of the yuan by inducing it to move away from the mean value. In addition, depreciation of the yuan in 2015 was followed by huge capital outflows, purchases of foreign assets by domestic residents, and reduction in the foreign exchange reserves, which might have made the exchange rate series more explosive.

The conditional correlation graphs (in Fig. 2) report evidence of significant DCC between individual BRICS markets and developed country markets. Fig. 2 shows a high positive correlation between individual BRICS country currencies with the Australian dollar, the euro, and the British pound, but the degree of correlation with the Chinese yuan, though positive, is small. The graphs show that the correlation is positive and has a high magnitude for the full sample period. The correlation with the Japanese yen does not turn out to be of much importance.

This increase in correlations is indicative of extreme episodes, such as large capital outflows from emerging markets after the Federal Reserve signaled in 2006 that it would increase the federal funds interest rate, the global financial crisis started in

[23] A return series is explosive when the sum of ARCH (α) and GARCH (β) coefficient is greater than one. (Kuruvila et al., 2012).

Fig. 2. Conditional correlation of BRICS currencies with developed country currencies.

2007–2008, the eurozone debt crisis in 2011, the Russian financial crisis in 2014, the deep plunge in oil prices from mid-2014–2016, the Brexit referendum in 2016, and the US–China trade war in 2018.

Nonetheless, the correlation illustrations demonstrate that the BRICS currencies comove with the euro, the pound, and the Australian dollar. On the whole, they show that volatility in the euro, the pound, and the Australian dollar has a significant

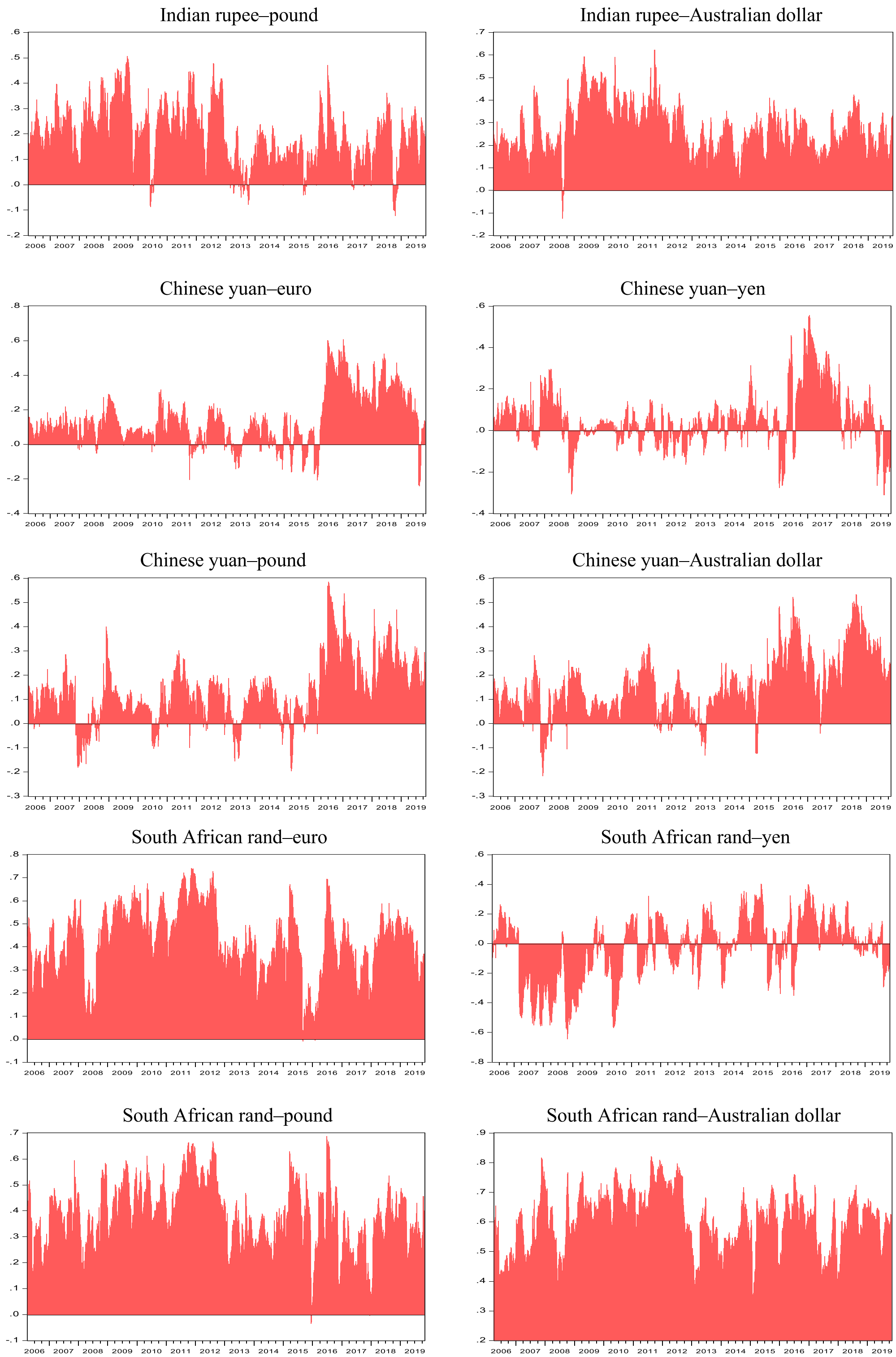

Fig. 2. (*continued*)

Table 4
VAR-based spillover index: BRICS currencies and major foreign exchange markets.

Panel A: Volatility Spillover to/from BRICS currencies

To	From									
	Brazilian real	Russian ruble	Indian rupee	Chinese yuan	South African rand	Euro	Yen	Pound	Australian dollar	Contribution from others
Brazilian real	79.763					3.212	3.914	0.968	12.143	20.237
Russian ruble		93.210				3.050	1.559	0.558	1.623	6.790
Indian rupee			94.038			1.496	1.979	0.168	2.320	5.962
Chinese yuan				98.247		0.692	0.267	0.434	0.360	1.753
South African rand					76.359	2.045	2.991	3.888	14.718	23.641
Euro	4.166	3.404	0.200	0.116	2.557					
Yen	2.655	2.059	0.626	0.178	3.509					
Pound	1.809	1.190	0.287	0.375	4.624					
Australian dollar	12.630	1.247	1.148	0.146	8.116					
Contributions to others	21.261	7.899	2.261	0.814	18.806					
Contributions including own	101.023	101.109	96.299	99.062	95.165					
Net Spillover	**1.024**	**1.109**	**-3.701**	**-0.939**	**-4.835**					

Panel B: Spillover Index of BRICS with major developed country currencies

Brazilian real	*Russian ruble*	*Indian rupee*	*Chinese yuan*	*South African rand*
26.604%	21.403%	20.619%	19.708%	26.607%

Notes: The estimates reported are the variance decomposition based on 10-step-ahead forecasts. The VAR lag length of order 1 was determined by the Hannan-Quinn criterion. Only within-and cross-market volatility spillovers among the BRICS currencies and developed country currencies are presented here. However, the full results of the VAR-based spillover index, showing the within and cross-market volatility spillover between individual BRICS currencies and individual developed country currencies are not presented here. It is available upon request from the authors.

impact on volatility in the BRICS currency returns. The following section presents a discussion on volatility spillovers across currencies.

4.2. Volatility spillover

In this section, volatility spillover between the BRICS and developed country foreign currency markets is estimated using the VAR process. Specifically, the variance decomposition technique is used to measure volatility spillover. The results of the degree and direction of volatility spillovers within and across BRICS economies are shown in Table 4 (Panel A).[24] Before we present and analyze the results, we need to explain the rows and columns in the spillover table. The diagonal results measure the intra-market, or within-market, volatility spillover and the off-diagonal results measure the inter-market, or cross-market, volatility spillover. The off-diagonal column sum and row sum, respectively, are the "to" (contributions to others) and "from" (contributions from others) volatility spillovers in each market and the difference between them is the net volatility spillover from one market to another. In addition, the 'contribution including own' row shows the sum of intra-market and inter-market volatility spillover to the respective BRICS currencies. The total volatility spillover index, expressed as a percentage, shows the grand sum of off-diagonal columns (rows) relative to the grand sum of columns (rows), including diagonals.

Some interesting results appear. Within-market volatility spillover is found to be the highest for all currency returns. The highest volatility spillover to the Brazilian real, the Indian rupee, and the South African rand is from the Australian dollar, whereas the highest volatility spillover to the Russian ruble and the Chinese yuan is from the euro. Further, the Brazilian real, the Indian rupee, and the South African rand pass on the maximum volatility to the Australian dollar, whereas the Russian ruble and the Chinese yuan pass on the maximum volatility to the euro and the pound, respectively. There no single developed market currency plays a dominant role in volatility transmission to the BRICS currency markets. The volatility transmission from BRICS currency markets to their developed counterparts also varies. The dynamics of volatility transmission are supported by the unconditional positive correlation between BRICS currencies with the euro, the yen, the pound, and the Australian dollar. It is important to undertsand that there is very less currency trading happening between individual BRICS currencies and the developed country currencies. In this context, such volatility transmissions between currencies take place through a common currency, the USD in this case.

The "contribution to others" row and "contribution from others" column in Table 4 demonstrate that the BRICS currency markets, except Brazil and Russia, show a similar pattern. The foreign exchange markets of India, China, and South Africa contribute less volatility to developed markets and absorb more volatility from them, whereas it is just the reverse for the Brazilian and Russian currency markets. Further, the Indian, Chinese, and South African currencies are found to be net receivers of volatility whereas the developed market currencies are net transmitters of volatility.[25] The highest receiver of volatility is the South African rand, followed by the Indian rupee and the Chinese yuan. The Brazilian and Russian foreign exchange market are net transmitters of volatility, and the developed country markets are net receivers.

Table 4 shows that the volatility of the Brazilian real explains 21.261% of the forecast error variance (FEV) of the other currencies as a whole, whereas 20.237% of the Brazilian real volatility is captured by other currencies in the VAR. In particular, the Brazilian real contributes 12.630% to the FEV of the Australian dollar, which is the highest contribution to FEV among the developed country currencies. At the same time, the Australian dollar accounts for 12.143% of the FEV of the Brazilian real, the highest spillover to the Brazilian currency among the developed country currencies. Similarly, the South African rand explains most of the FEV of the Australian dollar (8.116%), and the Australian dollar accounts for the highest spillover to the FEV of the South African rand (14.718%). Table 4 also reflects that the volatility of the South African rand explains 18.806% of the FEV of the other currencies, whereas 23.641% of the South African rand volatility is captured by other currencies in the VAR.

Table 4 further shows that the Russian ruble contributes 3.404% to the FEV of the euro, which is higher than that of the yen, the pound, and the Australian dollar. In contrast, the euro accounts for 3.050% of the FEV of the Russian ruble, the highest spillover to the Russian currency among the developed country currencies. Furthermore, the volatility of the Russian ruble explains 7.899% of the FEV of the other currencies as a whole, whereas the other currencies explain 6.790% of the FEV of the Russian ruble in the VAR. The Indian rupee explains 1.148% of the FEV of the Australian dollar, which is the highest. Alternatively, the Australian dollar accounts for 2.320% of the FEV of the Indian rupee, the highest spillover to the Indian currency among the developed country currencies. The volatility of the Indian rupee explains 2.261% of the FEV of the other currencies, but 5.962% of the Indian rupee volatility is captured by other currencies in the VAR. Table 4 also reveals that the Chinese yuan contributes the most to the FEV of the pound (0.375%). However, the highest contribution to the FEV of Chinese yuan is by the euro (0.692%). Moreover, the table shows that the volatility of the Chinese yuan explains 0.814% of the FEV of the other currencies, whereas 1.753% of the Chinese yuan volatility is captured by other currencies in the VAR.

Overall, most BRICS currencies are found to be net receivers of volatility. The Indian rupee, the Chinese yuan, and the South African rand are net receivers of volatility from the developed country currencies, and the developed country currencies are net transmitters. In contrast, the Brazilian real and the Russian ruble are net transmitters of volatility to the developed country currencies. Further, the spillover index (Table 4 Panel B) is the highest for the South African rand (26.607%) followed by the Brazilian

[24] Note that cross-market volatility spillover among the foreign exchange markets of BRICS countries is not significant.

[25] Net transmitter or receiver indicates whether the contribution of volatility of a particular currency to all other currencies is greater or less than the transmission of volatility from other currencies to that particular currency. This result is primarily derived from the directional volatility spillover analysis (see Yarovaya et al., 2016; Palanska, 2018; Balcilar et al., 2021).

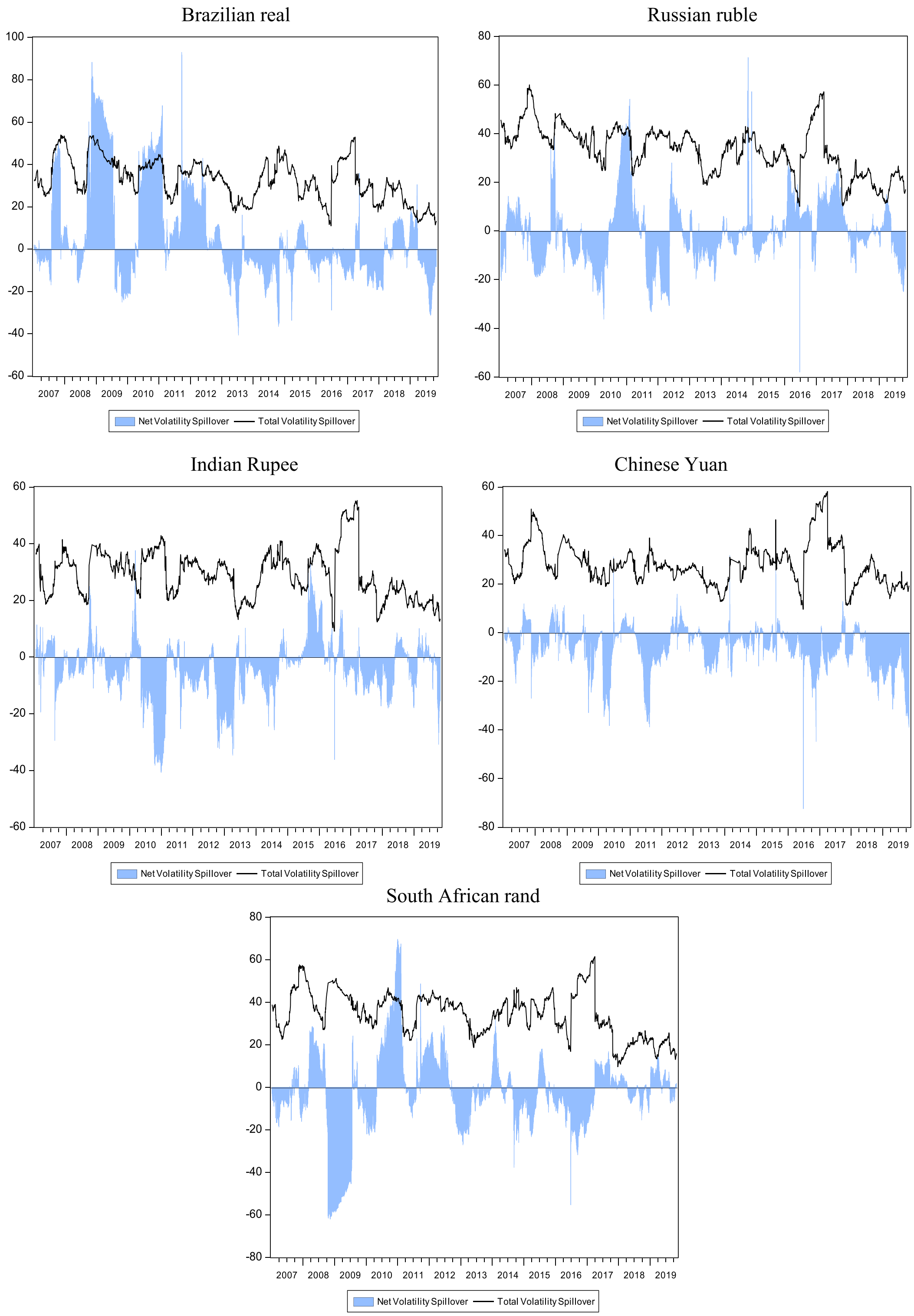

Fig. 3. Total and net volatility spillover, 200-day rolling window.

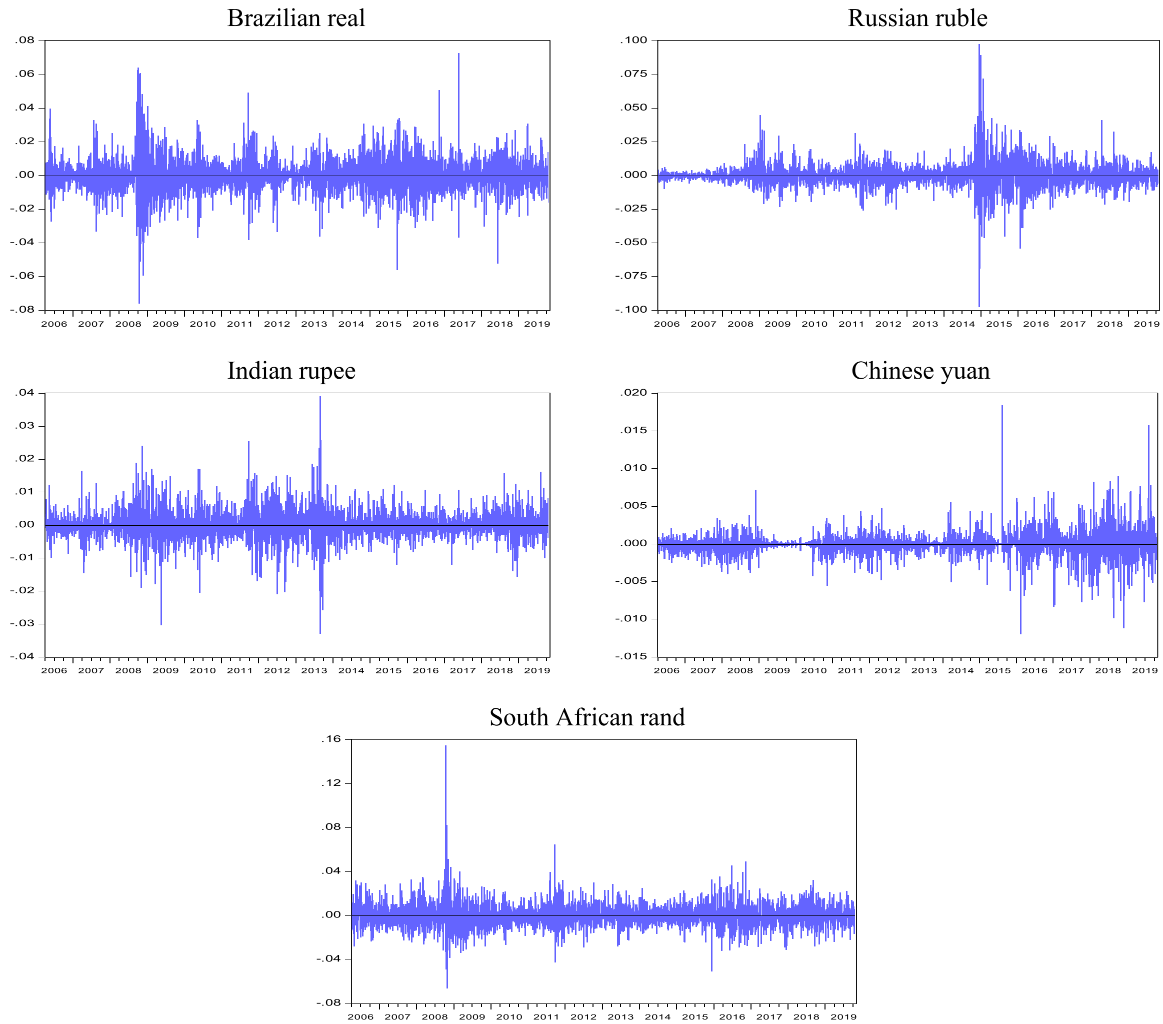

Fig. A1. Return series: BRICS and developed economies currencies.

real (26.604%), the Russian ruble (21.403%), the Indian rupee (20.619%), and the Chinese yuan (19.708%). This result corroborates our earlier observation that, among the BRICS countries, the South African rand and the Brazilian real have the highest variance.

The observed linkage between individual BRICS and individual developed country currencies might be due to greater trade and foreign investment linkages between these pairs of countries, exchange rate policies/regimes, large foreign exchange reserves, interventions by the central bank as well as the importance of individual foreign currencies in portfolios held by residents/investors and the respective central bank in these emerging market economies. This result suggests that the investors, monetary authorities, and policy makers in the BRICS countries must monitor developments in the foreign exchange markets of the respective developed countries, as fluctuations in their currencies influence the foreign exchange markets in BRICS countries. For instance, the Brazilian and South African monetary authorities need to keep an eye on events in the Australian foreign exchange market, as variation in the Australian dollar affects the Brazilian real and the South African rand.[26] Accordingly, Russia, India, and China should follow the events in the foreign exchange markets for the euro, the Australian dollar, and the pound, as volatility in these markets influences volatility in their own foreign exchange markets.

The spillover index summarizes the behavior of foreign exchange markets, but it does not necessarily capture the impact of several global crises during the period of analysis. To address this issue, we estimate volatility spillover using a 200-day rolling sample to understand the enormity and the character of the spillovers. Fig. 3 plots the total volatility spillover for the BRICS foreign exchange markets, which demonstrates their actions to economic events, such as debt crises, a stock market crash, and currency crises.

Total volatility for all the BRICS currencies peaked in mid-2007, 2008, 2010, 2012, 2014, 2016, and 2018. This is probably due to the aftermath of the US dollar crisis in 2005, the capital outflow from emerging market economies in 2006, the global financial crisis

[26] By contrast, Raputsoane (2008) shows significant negative spillovers between the rand and the euro.

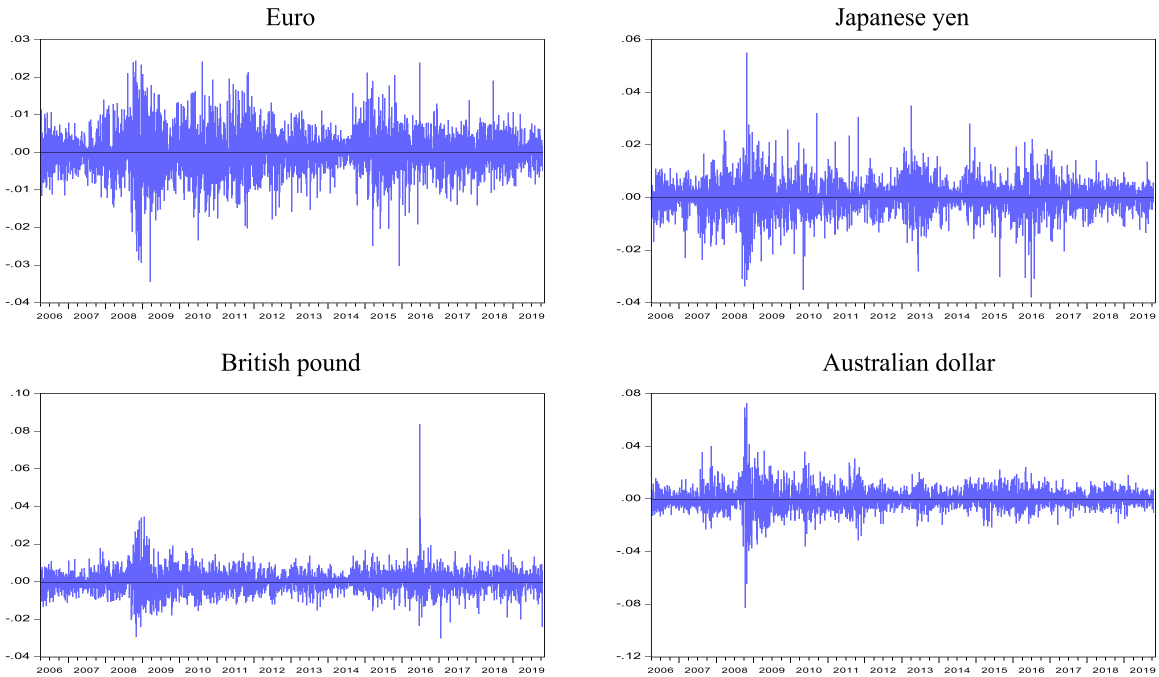

Fig. A1. (*continued*)

in 2007–2008, the eurozone debt crisis in 2011, the large decline in oil prices in 2014, the Brexit referendum in 2016, the US presidential election in 2016, the European general elections in early 2017, and the US–China trade war in 2018. The net volatility spillover of the BRICS foreign exchange markets (in Fig. 3), determined by estimating Eq. (11) using a 200-day rolling sample, supports the earlier evidence showing that the BRICS currencies, except the Brazilian real and Russian ruble, are net receivers of volatility. Among the BRICS markets, the South African rand is the highest receiver of volatility, as shown by the magnitude of spillover, from developed economies, followed by the Indian rupee and the Chinese yuan.

Developed country currencies as a whole have significant volatility spillover to BRICS foreign exchange markets. This result is in line with Ozkan and Unsal (2012), which states that volatility is likely to spillover to emerging markets because of trade linkages among the countries. Niyitegeka and Tewari (2020) show persistent volatility spillover between the euro and the rand.[27] Most of these emerging country currency markets are net receivers of volatility, with the degree of spillover varying across currencies. Further, these spillovers show large variations over time, which are necessarily synchronous with the global economic trajectory. As Ross (1989) notes, this volatility is an important source of information on the financial markets. The first channel for volatility spillover is news, which affects a set of financial variables simultaneously (Bollerslev et al., 1992), and the second channel operates through information spillover caused by cross-market hedging (Ederington and Lee, 1993). In addition to trade and financial linkages between countries, the extent of volatility transmission might depend on cross-country portfolio diversification, shifts in foreign institutional investment, excess demand for foreign currency, an economic or political crisis that originates in these countries, and interaction between individual BRICS currency markets and those in developed countries.

5. Conclusions and policy implications

This paper investigates return co-movement and volatility spillover among the currencies of the BRICS and four developed countries (the euro, yen, pound, and Australian dollar) in 2006–2019. It is observed in the existing literature that since currencies across countries have become market determined, the magnitude of volatility has increased, with the potential for volatility transmission across currency markets. This necessitates a detailed econometric analysis of return co-movement and volatility spillover.

Our econometric analysis identifies significant return co-movement in the foreign exchange markets and indicates that the volatility in the foreign exchange markets of Brazil, India, and South Africa tends to be persistent, whereas the foreign exchange markets of Russia and China are explosive in nature compared to those of the developed economies. Our analysis also shows that the Brazilian real, the Indian rupee, and the South African rand are influenced more by the Australian dollar, whereas the Russian ruble and the

[27] Few studies show volatility spillover between currencies across countries. However, some studies examine volatility spillover between developed country stock markets and BRICS foreign exchange markets (Sui and Sun, 2016; Naresh et al., 2018), between BRICS foreign exchange markets and stock markets (Mroua and Trabelsi, 2020), internal and external spillover effects of BRIC stock markets (Gilenko and Fedorova, 2014), currency linkages between Brazil, Russia, India, and South Africa (BRIS) and 15 emerging market economies (Mittal et al., 2019), and spillover between stock markets and foreign exchange markets of selected Asian economies (Jebran and Iqbal, 2016).

Chinese yuan are influenced more by the euro and the pound. In addition, the BRICS foreign exchange markets, other than Brazil and Russia, are net receivers of volatility, whereas the developed country markets are net transmitters of volatility. The investigation further reveals that the South African rand is the highest receiver of volatility among the BRICS foreign exchange markets. These findings also show that the BRICS economies follow the global leaders with regard to exchange rate movement during 2006–2019. This proposition is further supported by the spillover index and the graphs using a 200-day rolling sample. Further, dynamic correlations and volatility spillovers show large variability, which is necessarily synchronous with extreme economic episodes, including the global recession. This analysis, however, does not include identification of these movements with major turning points in the global economy.

Nonetheless, these results suggest that central banks in emerging market economies, specifically the BRICS economies, should concentrate more on designing policies to reduce volatility in foreign exchange markets. Any such misalignment in the equilibrium exchange rate requires intervention in the exchange market through appropriate exchange rate policy, along with monetary and fiscal policies to ensure currency market stability, to maintain economic stability and growth. The individual BRICS economies have intervened in the respective currency markets to check excess volatility from time to time. Further, because of greater global integration of the BRICS countries, our evidence on return co-movement and volatility spillovers can be of use to investors who wish to participate in currency trading and manage risk through portfolio diversification as well as to policy makers in initiating effective measures to tackle volatility in foreign exchange markets.

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Appendix A

See Fig. A1.

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