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Does oil price have similar effects on the exchange rates of BRICS?

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ABSTRACT

Motivated by the crucial status of oil price and exchange rates in world finance and economy, we apply daily data from August 2005 to February 2019 to investigate the impact of oil price shocks on the exchange rate of BRICS countries. This paper first adopts a new framework and EEMD method to decompose oil shocks and exchange rate series, respectively. With these econometric methods, the final research variables in this paper are constructed, including two types of oil shocks and three kinds of exchange rate series. The ARDL approach and VAR model are then employed to detect the influence of oil shocks on exchange rates in different frequencies, corresponding to the stationarity of series. The evidence, based on the original exchange rate series reveals that two oil price shocks can produce different effects on net oil-importing countries and net oil-exporting countries, while the results from different frequencies show that exchange rates will have a significant response to oil shocks only at a high frequency. It is worth noting that China is a unique case in BRICS, the relations between its exchange rate and oil price shocks is far insignificant than that of the other countries.

1. Introduction

Oil is one of the most strategic inputs in the production process, therefore traded assets and investment returns always tend to move together with oil price (Ji, Bouri, Roubaud, & Kristoufek, 2019). Since oil price has long been considered as a leading factor for the macroeconomy (Cavalcanti & Jalles, 2013; Gong & Lin, 2018; Lin & Xu, 2019;), fluctuations in oil price induce strong interest from investors (Ma, Ji, & Pan, 2019). The exchange rate is another key factor for investment, whose volatility may affect the price of final products, domestic countries' competitiveness in international trade, and even the stability of the economy (Antonakakis & Kizys, 2015). With the development of international trade and the prosperity of cross-border investment, frequent currency swaps are spreading, making it increasingly important to ensure the stability of exchange rates. Meanwhile, compared with other energy prices, exchange rates would be more sensitive to the oil price because oil has more characteristics of global marketization than coal, gas, or other fuels (Ma, Zhang, Ji, & Pan, 2019; Ji, Li, & Sun, 2019). With the prosperity of oil futures, oil prices can further influence exchange rates from within the financial system, thus many studies have probed the empirical relationship between oil prices and exchange rates ((Lin & Su, 2020)).

From a theoretical point of view, oil and exchange rates may be linked through several channels. The most accepted one is the trade channel (Amano & Van Norden, 1998; Habib, Bützer, & Stracca, 2016). This channel explains that exchange rates that rely heavily on oil in tradable sectors will be greatly affected by increment in oil price. (Beckmann & Czudaj, 2013). The second channel is the wealth channel, if oil price rises, oil exporters will gain wealth by exporting oil (Bénassy-Quéré, Mignon, & Penot, 2007). Hence, under this situation, oil-exporting countries experience currency appreciation while oil-importing countries face currency depreciation (Beckmann & Czudaj, 2013). The last one is the portfolio channel. It works similarly to the wealth channel but generates a longer-term effect. The strength of impact from this channel is related to two factors: (i) The superior position of the US to oil-exporting countries, which is represented by the quantum of oil imports and the share of exports, (ii) The relative preferences of oil-exporting countries for dollar assets (Beckmann, Czudaj, & Arora, 2017; Bénassy-Quéré et al., 2007; Coudert, Mignon, & Penot, 2008; Habib et al., 2016).

In light of these theoretical arguments, researchers explored the impacts of oil price on exchange rates using several empirical methods. An example is Amano and Van Norden (1998), they first employed a Johansen-Juselius cointegration test and found that there is a stable long-run relationship between domestic oil prices and the real effective exchange rate of the US dollar, high price leads the US dollar to appreciate and not vice versa. Coudert et al. (2008) adopted the same approach using international oil prices and got a similar result from

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1974 to 2004. Lizardo and Mollick (2010) constructed a VAR and VECM framework to capture the persistent long-run effect of oil price (WTI) on nominal exchange rates. They found that oil price has significant opposite effects on the US dollar when considering the oil exporters and importers as currency exchange country. Subsequently, more research gradually shifted the focus from the US dollar to other currencies. For example, Tiwari, Mutascu, and Albulescu (2013) adopted a discrete wavelet transform (DWT) approach and scale by-scale Granger causality tests to detect the case of Romania, which confirms that, similar to the United States, there is also a long-term and short-term relationship between oil price and real exchange rates. Tiwari and Albulescu (2016) further considered the non-linear correlation between oil price and the Indian real exchange rate and captured their symmetric and asymmetric co-movements. These results confirmed the existence of nonlinear, asymmetric, and indirect relationships between oil prices and exchange rates.

While many researchers focus on the effect of the oil price on exchange rates, most of them only pay attention to the situation in one country. A few studies employed comparative analysis for multiple exchange rate series to discuss their different responses to the oil price. BRICS is an association of five developing countries with rapid development and great potential, whose member states show many similarities with each other, such as fast economic growth, strong international capital attractiveness, and huge market potential (Ji, Liu, Zhao, & Fan, 2018). With the increasingly important role played by the BRICS in the world economic stage (Liu, Zhang, & Bae, 2017; Song, Zhang, Liu, & Fisher, 2013; Wang et al., 2016), it is necessary to analyze the effect of oil shocks on exchange rates from the perspective of BRICS countries and compare the differences in the impacts to provide some useful information for policymakers and international investors.

To address this issue, we apply the SVAR framework proposed by Ready (2018) to identify the oil supply and demand shock, which is more considerate of contemporaneous variation than the classical approach by Kilian (2009). In order to analyze the complex impact of oil price shocks, the ensemble empirical mode decomposition (EEMD) approach is also employed to decompose the original exchange rate series into high frequency and low-frequency components. Thus, the constructed variables include two kinds of oil shocks (supply shock and demand shock) and three kinds of exchange rate series of BRICS (original series, high frequency, and low-frequency components). Following the previous literature (Arfaoui, 2018; Singhal, Choudhary, & Biswal, 2019), the ARDL approach can be used regardless of the stationarity of variables; thus, this approach is used to capture the short-run and long-run dynamic impact when the variables are fractionally integrated. Meanwhile, for time series integrated with 0 order, we applied the VAR model and construct impulse response graphs to obtain the dynamic impact of oil shocks.

This study offers several noteworthy contributions. First, it investigates the effect of oil shocks on the BRICS exchange rates from a novel perspective, that is, the high-frequency and low-frequency components of exchange rates are used in the analysis to detect the complex impact path. Second, this study extends the works of existing researchers by adopting a new reasonable decomposed approach developed by Ready (2018). With this approach, oil supply and demand shocks can be constructed more appropriately, and this approach is more suitable for our daily data. Third, the BRICS countries are collectively served as the objects in our analysis, by comparing the differences for their cases, some general conclusions about the short-run and long-run impact of oil shocks can be drawn.

The remainder of this paper is organized as follows: (i) Section 2 introduces the literature review; (ii) Section 3 describes the research data and methodology; (iii) Section 4 reports the empirical results of this research; (iv) section 5 discusses the main conclusion and the implication of this study.

2. Literature review

For pioneer studies in this area, Amano and Van Norden (1998) found that oil price is a significant determinant of the US real effective exchange rate. Bénassy-Quéré et al. (2007), Coudert et al. (2008), Ciner, Gurdgiev, and Lucey (2013) and Cifarelli and Paladino (2010) found similar results. Among them, Bénassy-Quéré et al. (2007) adopted monthly data and found that exchange rates are highly sensitive to changes in oil price, showing that a rise in the oil price (10%), coincides with an appreciation of USD (43%) in the long run. Coudert et al. (2008) also verified that a statistically significant causality runs from oil prices to the exchange rate of USD. Cifarelli and Paladino (2010) also had similar results, they developed a process using a trivariate CCC-GARCH-M model and emphasized the crucial effect of speculation.

Several papers then moved the attention to other countries, like China, India, Japan, et cetera and reported some mixed findings. Huang and Feng (2007) estimated a four-dimensional SVAR model for the variables of real oil price, real industrial production, real exchange rates of CNY, and CPI. They found that a rise in the real oil price could weaken the exchange rate of CNY in the long run but only on a minor level. Ghosh (2011) detected a unidirectional causality from oil price to the exchange rates of Indian Rupee using the GARCH and EGARCH model, and concluded both positive and negative oil shocks have a similar impact on the Indian rupee. However, Tiwari, Dar, and Bhanja (2013) saw a different result for India. When discrete wavelet transforms and scale by-scale Granger causality tests are employed in the study, the causal relationship between variables will vary due to different frequency scales. Similar results can also be seen in the case of Japan (Uddin, Tiwari, Arouri, & Teulon, 2013), where the strength of co-movement always deviates over the time horizon. Then, Tiwari, Mutascu, and Albulescu (2013) analyzed the case of Romania, and also found that oil price has a strong influence in different frequencies for the exchange rate.

Several studies also focused on the comparative analysis for multiple countries. They revealed that there are two main reasons causing the oil shocks affect exchange rates varing from country to county: (i) the country's status of international oil trade; (ii) the exchange rate regime implemented by the states. Lizardo and Mollick (2010) presented an empirical analysis based on VAR and VECM model and concluded that a rise in real oil price might lead to a different impact on exchange rates of US dollar, which is depreciation against net oil exporters' currencies, and appreciation for the oil importers. Several studies also provide some findings in line with this paper (Beckmann, Berger, & Czudaj, 2016; Živkov, Njegić, & Balaban, 2019), suggesting that in the face of oil price shocks, exchange rates for oil-importing and oil-exporting countries may be affected differently. In addition, there are some discussions about the role of exchange rate restrictions in the process of oil price affecting exchange rates. Akram (2004) first argued that the interventions of the Norwegian government have resulted in a close relationship between the exchange rate and oil price. Lv, Lien, Chen, & Yu, 2018 adopted the data of 17 oil-exporting countries to demonstrate that the exchange rate regimes may affect the different response of exchange rates toward the oil market.

However, without decomposing the oil price shocks, there are still some limitations in examining the impact of oil price. The past analytical paradigms not only led to the existence of confusions such as reverse causality but also make it impossible to analyze specifically the diversified impacts of oil shocks under different driving forces. Some papers thus concentrated on the decomposed oil price shocks to investigate their impact on various financial assets, like stock (Basher, Haug, & Sadorsky, 2012; Sakaki, 2019; Hou, Mountain, & Wu, 2016; Nadal, Szklo, & Lucena, 2017; Tchatoka, Masson, & Parry, 2019), interest rates (Ioannidis & Ka, 2018), commodity prices (Shahzad, Rehman, & Jammazi, 2019; Wang, Wu, & Yang, 2014). Several studies also obtained the impact of decomposed oil price shocks on exchange rates (Atems, Kapper, & Lam, 2015; Basher, Haug, & Sadorsky, 2016; Habib et al., 2016). However, all these studies are based on a framework proposed by Kilian (2009), which neglects the impact of expected changes in demand or supply, thus acquiring some conflicting findings. For example, Habib et al. (2016) implied that both supply and demand shocks of oil price could affect exchange rates, but the latter is more influential; while Atems et al. (2015) and Basher et al. (2016) got a contrary conclusion that supply shocks failed to affect exchange rates. Considering the weakness of Killian's method, Ready (2018) improved it to provide a more accurate and efficient decomposition. Malik & Umar, 2019 firstly have applied this new framework in the area about oil shocks and exchange rates, and investigated the spillover relationships between them. However, they didn't focus on the complex impact of oil shocks, especially not considering long run and short run situation. Based on the literatures mentioned above, oil prices have different effects on exchange rates at different frequencies, therefore, it is still necessary to verify whether the same phenomenon exists for oil shocks decomposed by Ready's framework. Consequently, this paper analyzes the long-term and short-term influence caused by oil shocks and their complex impact on different exchange rate components, aiming to fill the related knowledge gaps.

3. Research data and methodology

3.1. Methodology

There are two main steps to conduct the estimation. First, we apply an SVAR framework to decompose oil price shocks and obtain the high and low-frequency components of the exchange rate series from the EEMD method. Subsequently, the ARDL approach and VAR model are utilized to model the effect of supply and demand shocks on three kinds of BRICS' exchange rate series.

3.1.1. Shocks construction

Based on Ready (2018), oil price changes should be explained entirely by supply shocks, demand shocks, and unexpected changes in the VIX index. Decomposed oil shocks can be captured following two steps. Firstly, from the ARMA (1,1) process, the unexpected changes in VIX is used as independent variables to regress production index of oil firms. The residual value from this procedure is defined as demand shocks. Similarly, supply shocks are constructed from the residuals of the regression of contemporaneous oil price changes, demand shocks, and unexpected changes in VIX, implying that supply shocks are orthogonal to other kinds of oil price shocks.

For the primary introduction of this approach, we also assume that supply shocks s_t, demand shocks d_t, and risk shocks v_t are defined in the following manner.

$$X_t \equiv \begin{bmatrix} \Delta p_t \\ R_t^{prod} \\ \xi_{VIX,t} \end{bmatrix}, Z_t \equiv \begin{bmatrix} s_t \\ d_t \\ v_t \end{bmatrix}, A \equiv \begin{bmatrix} 1 & 1 & 1 \\ 0 & a_{22} & a_{23} \\ 0 & 0 & a_{33} \end{bmatrix} \tag{1}$$

where Δp_t is changes in oil prices, R_t^{prod} is return on the index of global oil-producing firms, and $\xi_{VIX,\ t}$ represents unexpected changes to VIX.

Shocks can be effectively identified and mapped into observable variables in A matrix, so that

$$X = A * Z_t. \tag{2}$$

Supply shocks, demand shocks, and unexpected changes to VIX should be pairwise orthogonal. Therefore, to establish orthogonality, we further impose the following conditions.

$$A^{-1}\Sigma_x(A^{-1})^T = \begin{bmatrix} \sigma_S^2 & 0 & 0 \\ 0 & \sigma_d^2 & 0 \\ 0 & 0 & \sigma_V^2 \end{bmatrix} \tag{3}$$

In Eqn 3, Σ_x is the covariance matrix of observable X_t, while σ_s^2, σ_d^2 and σ_v^2 are the volatilities of a supply shock, demand shock, and unexpected changes to VIX, respectively.

In this process, instead of normalizing the volatility of the shocks to 1, the shocks are constrained to sum up to the total change in the oil price, which effectively defines the structural shocks in the SVAR model. Since the decomposed risk shock is an unexpected part of the panic in the international financial market, with the limited ability to explain the oil price, only the situation of oil supply shock and demand shock are discussed in the process of our empirical analysis.

3.1.2. EEMD modeling

EEMD is an upgrade of the empirical mode decomposition method (EMD), proposed by Wu and Huang (2009), which decomposes time series into independent components to inspect their internal behaviors and complex links with external shocks. Since the components decomposed by this model can reflect the local characteristics of the original sequence and help to understand the specific path of external impact factors, this study applied it to capture the high-frequency and low-frequency components of exchange rate series so as to provide an in-depth analysis of the differential effects of oil shocks under different spectra.

The exchange rate series ER_t can be expressed by intrinsic mode functions and one residual term,

$$ER_t = \sum_{j=1}^{n} c_j(t) + r_n(t) \tag{4}$$

where $c_j(t)$ represents the jth intrinsic mode functions, $r_n(t)$ represents the residual term, and n is the number of intrinsic mode functions.

The steps of EEMD are as follow:

(1) White noise with the mean of 0 and the constant standard deviation is added to the original series, that is,

$$Erate_i(t) = ER_t + w_i(t) \tag{5}$$

where $Ereate_i(t)$ are the series after adding white noise for the ith time and $w_i(t)$ is the corresponding white noise.

(2) The EMD decomposition is then performed on the new composited time series $Erate_i(t)$. The intrinsic mode functions obtained from this procedure are denoted by $c_{ij}(t)$, which means the jth intrinsic mode function decomposed after adding the white noise for the ith time.
(3) Adding different white noise series and repeating the above two steps until the obtained average curve tends toward zero, which means that the added white noise is sufficient to have mutually canceling characteristics.
(4) The overall average calculation is performed on the corresponding intrinsic mode functions in the above decomposition, and the final intrinsic mode functions are obtained. In general, the process of adding white noise can be controlled by the following rule

$$\varepsilon_n = {}^{\varepsilon}\!/\!\sqrt{N} \tag{6}$$

where N is the number of ensembles, and ε is the standard deviation of the added white noise series. In this research, N is set to 100, and ε is set to 0.2.

This study further used the t-test to check whether each extracted intrinsic mode function has a mean of zero. The functions that pass the significance test are classified as the high-frequency parts, and their sum is taken as the high-frequency component. The remaining intrinsic mode functions are classified as the low-frequency part, and the sum is taken as the low-frequency component, based on Bouoiyour, Selmi, Tiwari, and Olayeni (2016).

3.1.3. ARDL approach

Pesaran, Shin, and Smith (1996, 2001) proposed the ARDL approach as a classical method. It has always been used to simulate the relationship between variables in a single-equation time series setup. There are several econometric techniques to investigate long-run cointegrating relationship among the variables, but ARDL approach has some advantages over others. The main strength of this model is that it can estimate the long-term relationship, without restricting the variables cointegrated of the same order. Additionally, ARDL approach always provides fairly robust results even when all the variables are endogenous and can obtain short run and long run coefficients simultaneously. Taking into account the benefits of this approach, we construct the following ARDL model:

$$Erate_t = C_0 + C_1 t + \sum_{i=1}^{p} \varnothing_i \, Erate_{t-i} + \sum_{i=0}^{q} \beta_i' Shocks_{t-i} + u_t \tag{7}$$

where C_0, C_1, $\varnothing_i$, β_i', p, q and u denote the intercept, the coefficient of the time trend T, the coefficients of the lagged dependent variables, the coefficients of the lagged independent variables, the number of dependent and independent variables' lags, and the random error. The dependent variable is the series of BRICS' exchange rates, expressed by *Erate*. The independent variables are the lag terms of the *Erate* and the two types of oil price shocks, expressed by *Shocks*.

Some time series could be bound together due to equilibrium forces. To reveal cointegration among time series, we adopt the below ARDL bounds testing technique by which different time horizon dynamics can be extracted.

$$\Delta Erate_t = C_0 + C_1 t - \alpha (Erate_{t-1} - \theta Shocks_{t-1}) + \omega' \Delta Shocks_t + \sum_{i=1}^{p-1} \psi_{yi} Erate_{t-i} + \sum_{i=1}^{q-1} \psi_{xi}' Shocks_{t-i} + u_t \tag{8}$$

where $\alpha = 1 - \sum_{j=1}^{p} \varnothing_i$ represents the speed of adjustment to converge back to the long-run equilibrium, and this term should be negative, and should be between 0 and 1. $\theta = \frac{\sum_{j=0}^{q} \beta_j}{\alpha}$ are long-run coefficients, representing the equilibrium effects of the independent variables on the dependent variables. Short-run coefficients indicated by ψ_{yi}, ψ_{xi}, and ω, account for short-run fluctuations not due to deviations from the long-run equilibrium. Pesaran et al. (2001) named this equation, conditional ECM, and use the F-statistic to test the cointegrating relationship. This paper also follows the same approach.

3.1.4. VAR model

In order to analyze the dynamic relationship between stationary series, the VAR model and impulse response functions are used in this research. The mathematical expressions of the general VAR (P) model are as follows:

$$Y_t = A_1 Y_{t-1} + \ldots + A_p Y_{t-p} + \mu_t \tag{9}$$

where Y_t, $t = 1, \ldots, T$, is a K × 1 vector of time series, A_p is a K × K parametric matrix. μ_t represents the random error term.

3.2. Research data description

We first construct data sets related to oil price shocks. Following Ready (2018), three variables are required to decompose oil prices into supply and demand shocks. The first is unexpected changes in the VIX index, which represents the changes in risk. In order to isolate it, an ARMA (1,1) process is estimated on the VIX series and its residuals are used for the subsequent calculation. The second is an index of oil-producing firms. This research uses the World Integrated Oil and Gas Producer Index, the same as Ready (2018). The last is the oil price, WTI futures price is used as its proxy, since it is the main baseline of global crude oil price. For exchange rates, the amount of domestic currency equivalent to one US dollar is adopted as the indicator.

Table 1
Descriptive statistics for decomposed oil shocks and exchange rates.

	Mean	Std.Dev	Skewness	Kurtosis	Jarque-Bera
Supply shock	1.90E−10	0.19161	0.26331	11.0689	8938.70***
Demand shock	−3.61E−10	0.12409	0.41768	16.8580	26,348.0***
BRL	0.8482	0.2778	0.5111	1.966	289.00***
RUB	3.6153	0.3617	0.6459	1.7918	427.7***
INR	3.9788	0.1822	0.0208	1.537	292.6***
CNY	1.9097	0.0820	0.8598	2.7858	410.6***
ZAR	2.2373	0.2808	0.3055	1.6735	291.6***

*** Indicates statistical significance at the 5% and 1% level, respectively.

China reformed its exchange rate regime in 2005, considering this, only data post the reform is used in this research. A recent study by Bannigidadmath and Narayan (2016), pointed out that the daily data is better than the monthly data in the analysis process. As a result, 3281 samples of daily data from 1 August 2005 till 15 February 2019 are employed for this empirical research. All the data are available from the Wind database or Datastream. The exchange rates are indicated in their official currency code in latter sections.

3.2.1. Descriptive statistic for original series

We present the results of the descriptive statistics of all the series in Table 1. In the two types of oil price shocks, supply shock highlights positive mean values while demand shock highlights the negative mean value in the sample period. This indicates that the overall supply shock during the sample period is positive while the demand shock is the opposite. Moreover, the standard deviation of supply shock is greater than that of the demand shock, which indicates that supply shock fluctuates more intensely. The test of skewness and kurtosis reveal all seven series are positively skewed and have high kurtosis. According to the Jarque-Bera test, they also reject the null hypothesis of normal distribution at the 1% level.

3.2.2. Mode decomposition for exchange rates

This paper uses the EEMD method to decompose the exchange rate price series. Following the criteria, this model can constitute a data set that contains different intrinsic mode functions (for example, Fig. 1 shows the decomposed results of BRL exchange rates). They are arranged sequentially from small to large time scales, and the last one is the trend. Each of them significantly reflects the inherent fluctuation characteristics of the original series. According to the method mentioned in 3.1, all intrinsic mode functions are divided into two parts, high-frequency and low-frequency components. Figs. 2 and 3 example the case of BRL, which shows its high and low-frequency series, respectively. Comparing the two frequency components, the fluctuation of the high-frequency component is larger than that of the low-frequency component, and its fluctuation range is smaller, mainly surrounds the value of zero.

3.3. Research framework

To sum up, this study first uses Ready's approach to obtain both supply and demand oil shocks and uses the EEMD model to gain the exchange rate components of the high and low frequency. Table 2 provides the results of three traditional unit root tests for all variables. From this table, the original price series and low-frequency component series of BRICS exchange rates are I(1), while the oil shock series and the high-frequency components of the BRICS exchange rate series are I (0). Thus, When considering the effects of oil shocks on the original exchange rate price series and the low-frequency exchange rate series, there would be mixed order of integration for variables, ARDL approach

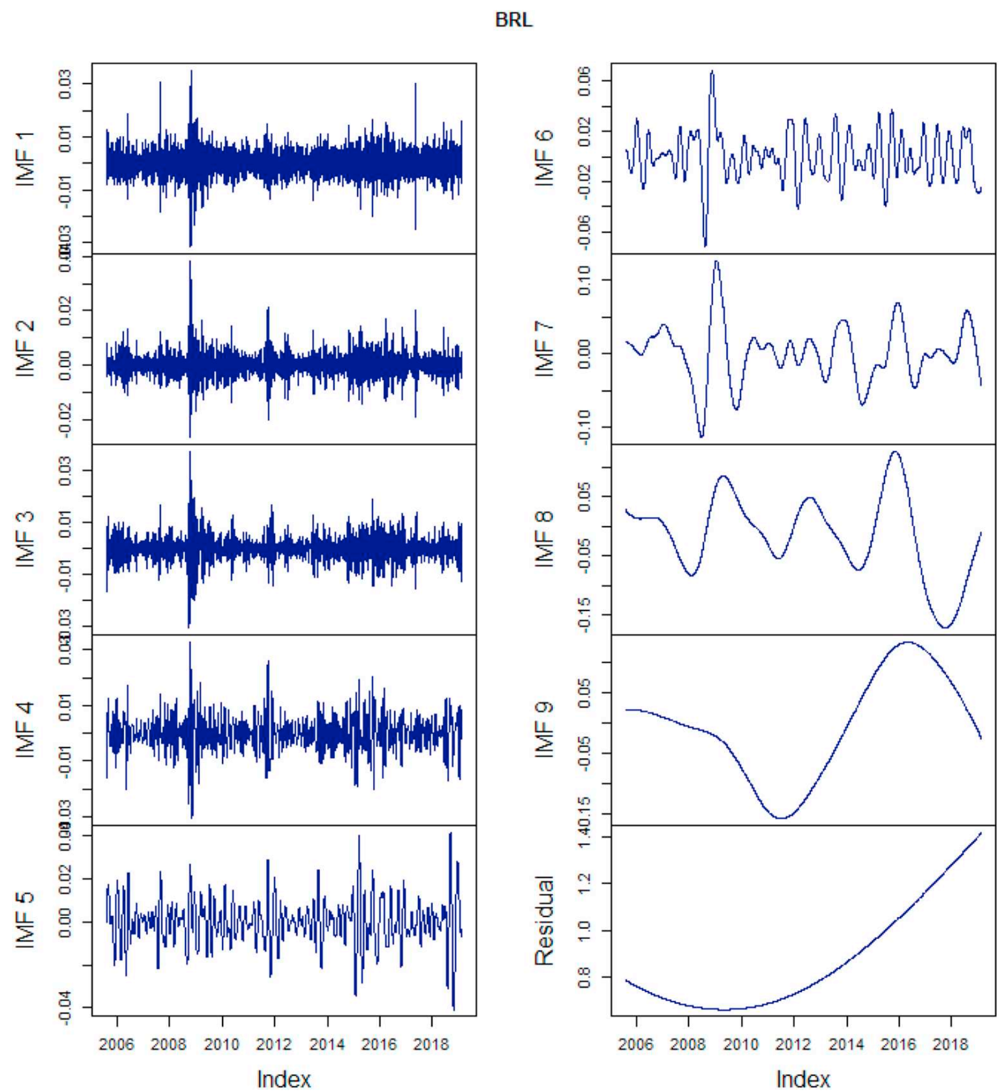

Fig. 1. Multi-time scale decomposition for BRL series.

is an effective way to deal with this situation. In contrast, since the high-frequency component series of exchange rates are stationary as the oil shocks series, the VAR model and its impulse response functions are preferred to show the relationships between variables. Summarizing the research ideas in this article can form a research framework diagram shown in Fig. 4.

4. Analysis of empirical results

4.1. Estimation for original exchange rate series

Based on the research framework of this study, ARDL approach is applied in this section to estimate how the oil shocks affect the original exchange rate price series. Following this methodology, we examine the

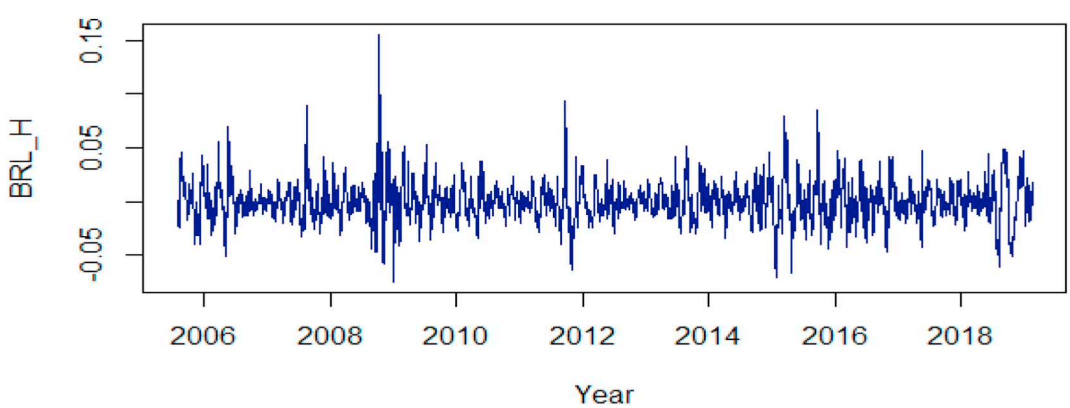

Fig. 2. High-frequency component time series for BRL.

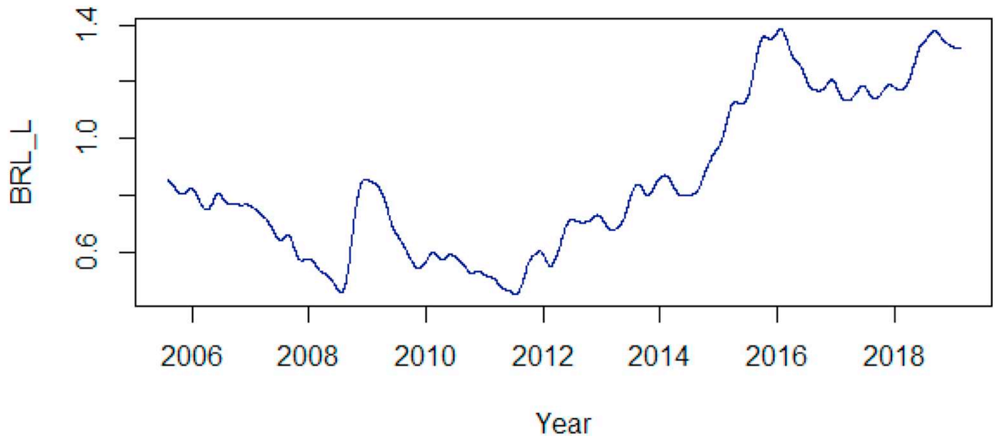

Fig. 3. Low-frequency component time series for BRL

Table 2
Unit root tests for all variables.

Variables	ADF test	KPSS test	PP test
Panel A. Unit root test for original exchange rates series			
BRL	−2.3620	22.236***	−6.3216
RUB	−2.2890	27.281***	−6.4041
INR	−2.6490	30.115***	−9.9653
CNY	−0.7210	19.100***	−0.9073
ZAR	−2.2570	27.801***	−11.932
d.BRL	−13.561***	0.3173	−2905.2***
d.RUB	−12.581***	0.2066	−3101.4***
d.INR	−13.601***	0.0826	−3380.3***
d.CNY	−13.251***	1.3340***	−3256.9***
d.ZAR	−15.746***	0.0469	−3133.2***
Panel B. Unit root test for high frequency exchange rates series			
BRL_H	−15.799***	0.0063	−606.28***
RUB_H	−15.405***	0.0060	−735.01***
INR_H	−15.771***	0.0091	−621.56***
CNY_H	−15.197***	0.0101	−881.48***
ZAR_H	−14.676***	0.0056	−626.80***
Panel C. Unit root test for low frequency exchange rates series			
BRL_L	−2.0968	22.338***	−3.0122
RUB_L	−2.1532	27.364***	−3.0568
INR_L	−2.5614	30.197***	−3.1665
CNY_L	−1.1317	19.128***	−0.2258
ZAR_L	−2.2213	27.918***	−2.2810
d.BRL_L	−6.6935	1.2220	−26.104***
d.RUB_L	−7.3078	0.6082	−25.487***
d.INR_L	−7.2302	0.3142	−30.992***
d.CNY_L	−6.0887	3.5083***	−22.145***
d.ZAR_L	−7.0213	0.2362	−30.350***
Panel D. Unit root test for demand and supply shock series			
Demand Shock	−15.664***	0.2681	−2982.0***
Supply Shock	−14.839***	0.0322	−3580.8***

Note: Table illustrates unit root test for all series in this study. The prefix d. represents the difference sequence, while the suffixes _H and _L represent the high-frequency and low-frequency component sequences of the exchange rates, respectively.

*** Means a significant reject null hypothesis in the 0.01 level.

critical F-statistics against their spective upper and lower bounds to detect whether there are long run cointegrating relations between decomposed oil shocks and the exchange rate prices of BRICS. The corresponding results are provided in Table 3. Before the estimation procedure, the optimum lag length of the model has been determined using the Akaike information criteria. Based on Pesaran et al. (2001), ARDL approach put forward a scheme to test cointegrated relations by calculating the value of F-statistics, namely ARDL-bounds test. If the calculated value is larger than the upper critical bound, there is a cointegrated relationship between the variables. If the calculated value is below the lower critical bound, the variables are not cointegrated. However, when the calculated value is between the upper and lower critical bounds, it is not clear whether cointegration exists between variables. As shown in this table, excluding CNY, the results of the F-statisitic are all larger than their upper critical values, which strongly proves long-term relations between oil price shocks and BRICS' exchange rates.

Based on the ARLD-ECM shown in Eq. (8), we can estimate long and short-run parameters of the model simultaneously. The estimations results are provided in Tables 4 to 8, these results reveal that there are significant relationships between oil shocks and exchange rate prices for all BRICS countries in short run but not always exist in the long run.

Specifically, from the perspective of the short-run situation, demand shock always produces a negative effect on exchange rates of BRICS, but the impact from supply shock will vary from country to country. In the cases of BRL, INR, and ZAR, the signs of supply shock's coefficients are positive, but they are negative when considering RUB or CNY; while the coefficients of demand shock are all negative, although not significant for RUB. From the perspective of a long-run situation, the results are basically consistent with the short-run; the only difference is that the impact from both shocks on CNY is not significant.

Reviewing the Ready's analysis for decomposing oil price shocks (Ready, 2018), supply shock reflects that it is more difficult to produce crude oil, which has a strong negative correlation with future international economic outputs. It can be concluded that net oil exporters can sell crude oil at a higher price to make more profits. Moreover, they can take advantage of oil resources to enhance their status in the world economy, and attract more international investors, which ultimately hedges devaluation risk on currency and even leads to an appreciation of their currencies (Yang, Cai, & Hamori, 2017). However, net oil importers can only passively accept the negative impact of oil supply shocks, resulting in currency depreciation (Filis, Degiannakis, & Floros, 2011). As a result, as the unique net oil exporter among BRICS, supply shock could bring obvious appreciate risks to the currency of Russia. In contrast, Brazil, India, and South Africa, as net oil importers, will suffer from currency devaluation. China, contrary to expectations when facing supply shock, its exchange rate experiences a strange insignificant influence. The possible reason we conclude is that a more effective managed-floating exchange rate system and the huge economy of China effectively hedges the risk of devaluation. There is a slight difference in our estimation compared with Basher et al. (2016). They find that the impact on exchange rates of Brazil, Russia, and India are not statistically significant when considering the supply oil shock. The most likely explanation seems to be that we adopt a new decomposing approach for oil price shocks.

Oil demand shock means that oil price rises as demand increases so that producers are able to sell more oil and are likely to obtain positive

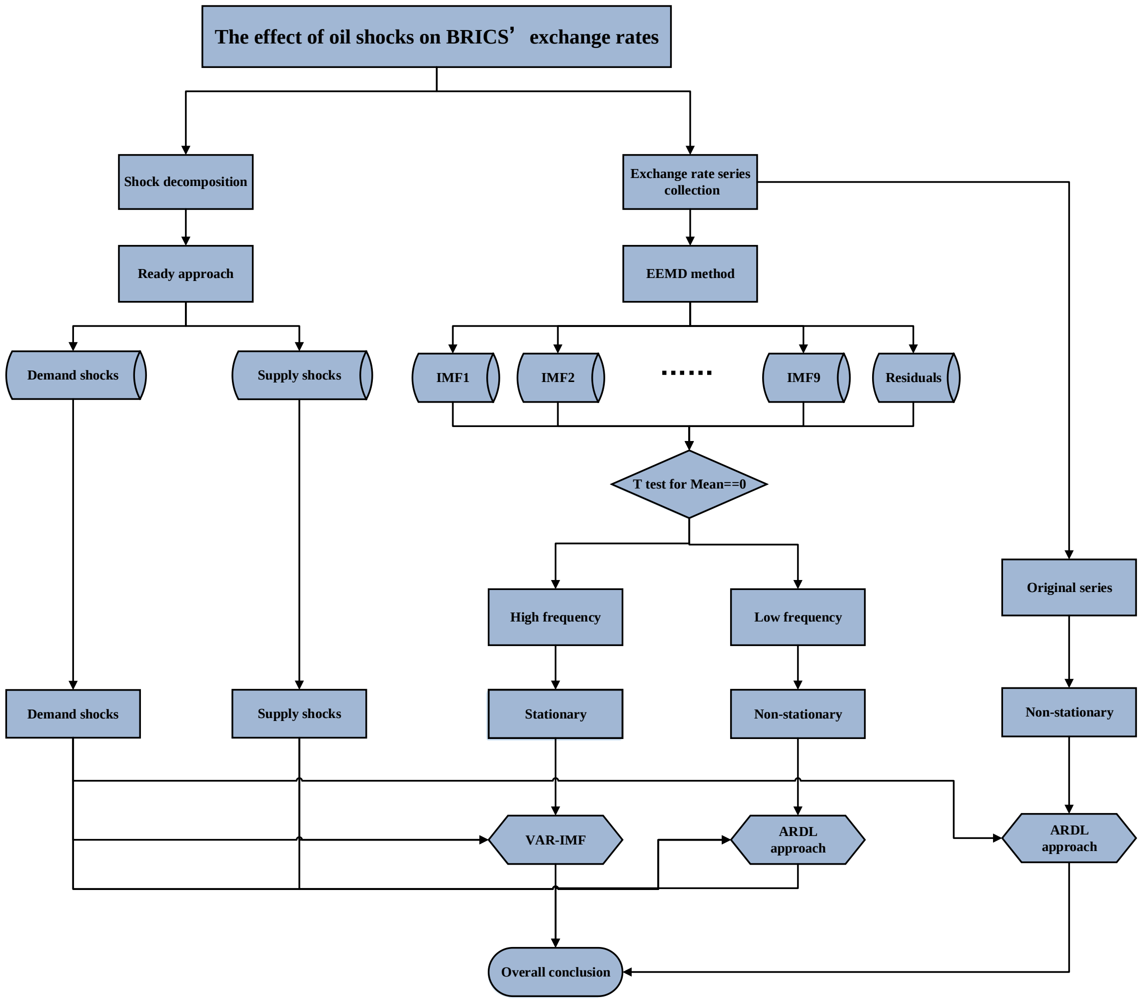

Fig. 4. Research framework of this study.

Table 3
Results of bounds test.

Critical bounds		99% lower bound	99% lower bound	95% lower bound	95% lower bound	90% lower bound	90% upper bound
BRL	106.1	6.34	4.87	5.85	4.19	5.06	7.52
RUB	30.8	6.34	4.87	5.85	4.19	5.06	7.52
INR	86.1	6.34	4.87	5.85	4.19	5.06	7.52
CNY	7.38	6.34	4.87	5.85	4.19	5.06	7.52
ZAR	139.2	6.34	4.87	5.85	4.19	5.06	7.52

Table 4
The short-run and long-run estimations for the case of BRL.

Regressor	Coefficient	Standard error	*Z*-ratio
Short run coefficients			
ΔSupply shock	0.000211***	0.000054	3.9
ΔDemand shock	−0.003518***	0.000123	−28.606
ECM $_{t-1}$	−0.001556***	0.000088	−17.602
Constant	0.001457***	0.000170	8.538
Long run coefficients			
Supply shock	0.11634*	0.05942	1.958
Demand shock	−2.05468**	0.65557	−3.134

*** Indicates statistical significance at the 1% level.
** Indicates statistical significance at the 5% level.
* Indicates statistical significance at the 10% level.

Table 5
The short-run and long-run estimations for the case of RUB.

Regressor	Coefficient	Standard error	*Z*-ratio
Short run coefficients			
ΔSupply shock	−0.0002419***	0.0000622	3.9
ΔDemand shock	−0.0000412	0.0001250	−0.329
ECM $_{t-1}$	−0.0006952***	0.0000884	−17.602
Constant	0.0027640***	0.0003451	8.009
Long run coefficients			
Supply shock	−0.5099***	0.1504	−3.391
Demand shock	−1.9885***	0.5555	−3.579

*** Indicates statistical significance at the 1% level.

Table 6
The short-run and long-run estimations for the case of INR.

Regressor	Coefficient	Standard error	Z-ratio
Short run coefficients			
ΔSupply shock	0.0001120***	0.0000303	3.702
ΔDemand shock	−0.0006982***	0.0000631	−11.07
ECM $_{t-1}$	−0.0024810***	0.0001698	−14.612
Constant	0.0100200***	0.0006807	14.724
Long run coefficients			
Supply shock	0.11831***	0.02486	4.758
Demand shock	−0.48106***	0.08118	−5.926

*** Indicates statistical significance at the 1% level.

Table 7
The short-run and long-run estimations for the case of CNY.

Regressor	Coefficient	Standard error	Z-ratio
Short run coefficients			
ΔSupply shock	−0.0000002***	0.00000922	−0.025
ΔDemand shock	−0.0000681***	0.00001917	−3.554
ECM $_{t-1}$	−0.0001810***	0.00002415	−7.494
Constant	0.0002947***	0.00005219	5.646
Long run coefficients			
Supply shock	−0.2281	0.3959	−0.576
Demand shock	−1.0809	1.8489	−0.585

*** Indicates statistical significance at the 1% level.

Table 8
The short-run and long-run estimations for the case of ZAR.

Regressor	Coefficient	Standard Error	Z-ratio
Short run coefficients			
ΔSupply shock	0.0003650***	0.0000647	5.64
ΔDemand shock	−0.0026070***	0.0001445	−18.04
ECM $_{t-1}$	−0.0037110***	0.0001875	−19.79
Constant	0.0085540***	0.0004582	18.67
Long run coefficients			
Supply shock	0.10136***	0.03105	3.264
Demand shock	−1.06982***	0.18857	−5.673

*** Indicates statistical significance at the 1% level.

returns. Thus, it is associated with international economic growth and stable oil production and consumption. As demand shocks occur, international investors will become more bullish on the world economy and more willing to invest in some risky non-dollar assets, and the currencies of the fast-growing BRICS will certainly be particularly favored. Corresponding to the theoretical conclusion, the estimation of ARDL-ECM similarly reveals that oil demand shock could affect BRICS' exchange rates in a negative way. Additionally, it is worth noting that CNY similarly receives an insignificant influence, which indicates that the CNY has a higher ability to cope with the oil price risks than other BRICS currencies.

4.2. Estimation for high-frequency components

This section considers how the high-frequency components of the exchange rate series respond to oil shocks. Since all-time series in this section are stationary, the VAR model is used to conduct the estimation, and we graph two impulse response diagrams to show their changes within 20 days after supply or demand shock. In order to ensure the robustness of the response, 1000 bootstrap calculations were done for each impulse response calculation process.

Fig. 5 shows the responses of the high-frequency components of the BRICS currencies on the impact of an oil supply shock. From the figure, the responses of BRL_H and RUB_H are negative, which means that the oil supply shock will have a negative impact on the high-frequency components of BRL and RUB. The responses of INR_H and ZAR_H are positive overall, meaning that high-frequency components of the Indian Rupee and the South African Rand would gain a positive effect of the supply shock. Notably, the CNY_H shows an extremely weak response, which indicates that the oil supply shock will hardly cause high frequency and rapid volatility of the CNY.

For the impulse from demand shock, Fig. 6 shows that it always has a negative impact on the high-frequency components of the exchange rates for BRICS, though the CNY still displays a weakly significant result. Comparing the response of different currencies, RUB_H is seen as the most sensitive to demand shock, which further matches the trade channel of the impact of oil price.

Considering the impact of supply and demand shocks on high-frequency components of the BRICS exchange rate, it is seen to fit the conclusion of the impact of oil shocks in the ARDL model. This effect will vary among oil-exporting countries and oil-importing countries. As net oil importers, the high-frequency components of India and South Africa are less affected by the two oil shocks, and these impacts will also be produced in opposite directions. As a net exporter of oil, the high-frequency component of the Russian ruble exchange rate is more sensitive than other currencies on oil supply and demand shock, and the effects of oil shocks are in the same direction. However, Brazil is a special case of net oil importers, that is, oil supply shock will have a positive impact on its original exchange rate, but its high-frequency components may occasionally respond negatively. The possible cause is that Brazil exports a large number of oil resources to obtain foreign currency exchange, which causes the real exchange rate of the BRL to show a different trend from its inherent high-frequency volatility. A comprehensive examination of the two shocks shows that the CNY generally lacks response, once more confirming the weak impact of the oil shock on it, especially for the supply shock.

4.3. Estimation for low-frequency components

Low-frequency components reflect the periodic fluctuations in exchange rates caused by obvious fundamental changes or significant events (Xu, Tan, He, & Liu, 2019). Although this component has a small volatility frequency, the amplitude is higher than the high-frequency component. It can be treated as a continuing impact of a major event on exchange rates.

On the basis of the ADF, KPSS, and PP test results, these decomposed low-frequency components are I(0) series. Thus, the basic ARDL estimation as in Eq. (7) is used to detect the basic linkages between variables.

Table 9 shows the basic ARDL estimation of oil shocks and low-frequency components of the BRICS exchange rates. From these results, no matter the oil demand or supply shocks, they would not significantly affect all BRICS exchange rates from the direction of the low-frequency components. In other words, oil shocks will not produce the periodic and large fluctuation cycle impact on the exchange rates of BRICS countries. Note that the analysis based on different frequency components reflects how oil shocks affect the exchange rates, so this result does not conflict with the estimation for the original exchange rate series. Specifically, the low-frequency components reflect the slow cyclical fluctuations, which are generally caused by significant events in the market, exchange rate policies, etc. (Xu et al., 2019; Zhang, Lai, & Wang, 2008). The insignificant impact on low-frequency components reflects that oil price volatility is not a significant event in currency markets; thus, the responses of BRICS exchange rates to oil shocks are mainly embodied through the high frequency and rapid fluctuations. These results are also in lined with some researches in this field, like Uddin et al. (2013) and Lin, Chen, and Yang (2016), who decomposed the time series by wavelet analysis.

5. Conclusion and implications

Whether and how oil price shocks affect exchange rates is a lasting topic, considerable literature has focused on this area. However, as developing countries with similar high speed and great potential in the economy, BRICS is rarely integrated into the investigation of the relationships between their exchange rates and oil price shocks to make an in-depth comparison. This study, therefore, attempts to empirically analyze whether the exchange rates of BRICS are affected by the oil price shocks and differences in high and low-frequency components.

In the process of the empirical estimation, we first employ a classification approach, developed by Ready (2018). On this basis, we further applied the ARDL approach to analyze the effect from two kinds of oil price shocks to the original exchange rate series. The findings

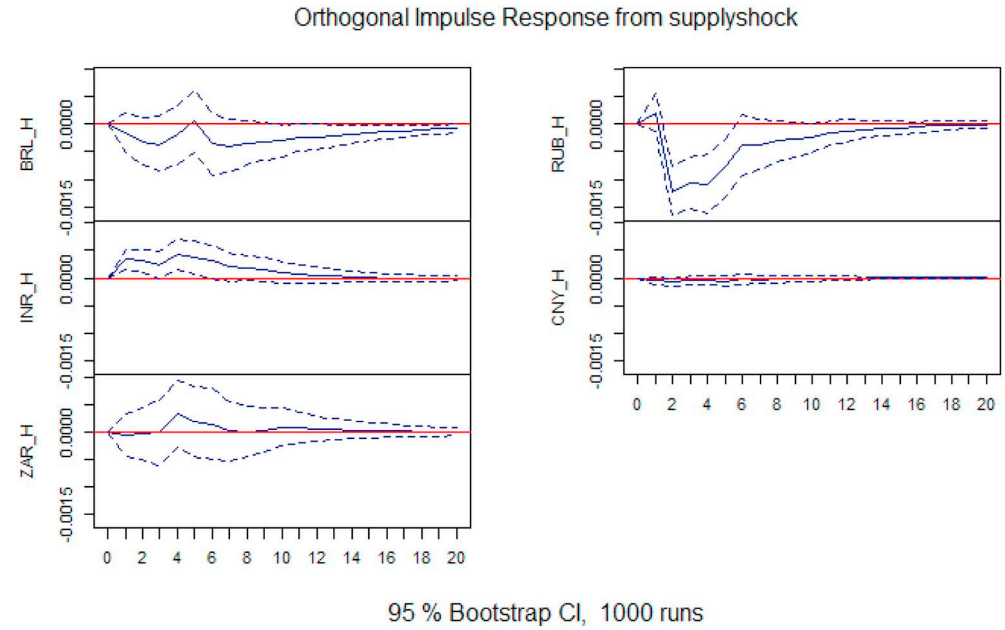

Fig. 5. Impulse response graph from a supply shock.

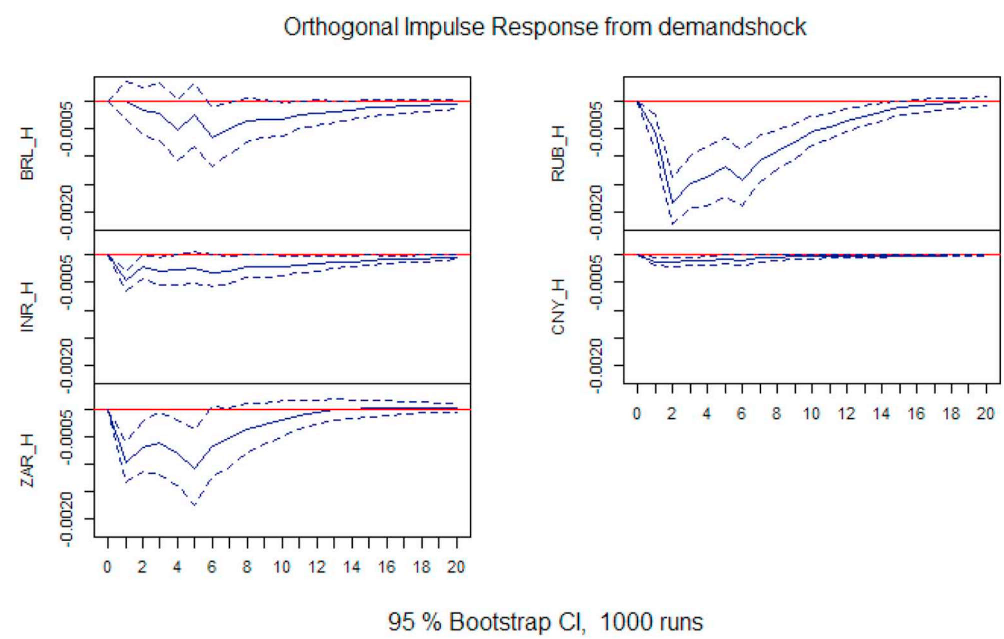

Fig. 6. Impulse response graph from a demand shock

Table 9
The estimation results for low-frequency components.

Dependent variable	BRL_L		RUB_L		INR_L		CNY_L		ZAR_L	
	Coefficient	T	Coefficient	T	Coefficient	T	Coefficient	T	Coefficient	T
C	0.0000***	6.19	0.0000***	8.18	0.0000***	9.72	0.0000***	6.51	0.0000***	10.24
Depvar(−1)	3.9920***	2746.77	3.9930***	2887.36	3.9910***	2705.52	3.9930***	2929.50	3.9920***	2864.58
Depvar(−2)	−5.9790***	−1372.88	−5.9830***	−1443.33	−5.9790***	−1352.34	−5.9840***	−1464.22	−5.9810***	−1431.92
Depvar(−3)	3.9840***	914.81	3.9870***	961.83	3.9840***	901.12	3.9890***	975.71	3.9860***	954.22
Depvar(−4)	−0.9960***	−685.68	−0.9967***	−720.97	−0.9961***	−675.39	−0.9977***	−731.40	−0.9968***	−715.25
Supply shocks	7.8310E−08	0.33	−4.6630E−08	−0.21	3.3770E−08	0.25	4.6000E−09	0.10	1.0990E−07	0.45
Demand shocks	−8.9240E−08	−0.24	−2.8790E−07	−0.84	−1.0040E−07	−0.48	−3.3670E−08	−0.48	1.5740E−07	0.42

Depvar(−n) means the n lag term of the dependent variable.
*** Indicates statistical significance at the 1% level.

confirm that the oil price shocks can affect BRICS' exchange rates both in the short-term and long-term, with the exception of the CNY, and these effects vary for oil-exporting and importing countries. Meanwhile, the lack of a relationship between oil shocks and exchange rates within frequency concerns motivated us to employ the EEMD method to construct frequency components of exchange rates. To correspond with their stationary conditions, we respectively applied the VAR method and the ARDL model to detect responses to oil shocks. The empirical results indicate that significant effects can be captured only when analyzing the high-frequency components of the exchange rates, showing that the oil shocks mainly affect the exchange rates by influencing their inherent irregular rapid fluctuation.

This study finds different impacts of decomposed oil price shocks and their remarkable short-run and long-run relationships with exchange rates of BRICS, and policymakers may use these results in formulating inflation stabilizing strategy. From the analysis based on exchange rate components, irregular fluctuation is the main path in the influence process of oil shocks. Thus, to avoid large, fast variations in exchange rates and achieve the stability of currencies, the BRICS' authorities should roll out efficient solutions to reduce the negative effects of the oil price shocks, for example, strengthening financial cooperation between countries and adjusting the current exchange rate regimes. All in all, these conclusions are important for optimizing investors' portfolios and reducing exchange rate risks in international trade and investment.

Declaration of competing interest

None.

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