Linear and nonlinear linkage of conditional stochastic volatility of interbank interest rates: Empirical evidence of the BRICS countries

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Abstract

The purpose of this article is to detect a possible linear and nonlinear causal relationship between the conditional stochastic volatility of log return of interbank interest rates for the BRICS countries in the period from January 2015 to October 2018. To extract the volatility of the analyzed time series, we use a stochastic volatility model with moving average innovations. To test a causal relationship between the estimated stochastic volatilities, two steps are applied. First, we used the Granger causality test and a vector autoregressive model (VAR). Secondly, we applied the nonlinear Granger causality test to the raw data to explore a new nonlinear causal relationship between stochastic volatility time series, and also applied it to the residual of the VAR model to confirm the causality detected in the first step. This study demonstrates the existence of some unidirectional/bidirectional linear/nonlinear causal relationships between the studied stochastic volatility time series.

Keywords: conditional stochastic volatility; stochastic volatility model with moving average innovations; nonlinear Granger causality test.

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Introduction

BRICS is a group of countries (Brazil, Russia, India, China, and South Africa) that have agreed to establish an economic entity that opposes the Western economic entities represented in the International Monetary Fund and the World Bank and includes a new global banking credit system excluding the unipolar policy pursued by the United States of America, which control the world's resources through economic exploitation and restrictions on developing countries of the third world. The BRICS countries occupy 26% of the world's land area, account for about 22% of the total global product, and have more than 4 trillion dollars in cash reserves. The BRICS group has the fastest economic growth in the world, and its total population of 2.83 billion people constitutes 42% of the world's population. The major challenges facing the BRICS group are, first of all, differences in economic policies pursued by the countries participating in the group. Another problem is cultural and historical differences and financial policies pursued by each country separately, as well as the overlap of several economic systems of varying sizes and exchange rates of different currencies in one economic system. Another challenge worth mentioning is the group's desire to develop a strategy for economic cooperation between these five countries. This can be done through finding appropriate conditions to accelerate economic development, enhancing the ability of these countries to compete, expand and diversify trade and monetary relations, and secure interaction for innovative growth.

Similarity or dependence between the monetary policies of the BRICS countries may reflect the fact that these countries have overcome the problem of the difference between these monetary policies and gives an idea of the level of economic cooperation between them. The interbank interest rate constitutes an important variable when studying a country's monetary policy. This variable represents an interest rate at which banks borrow and lend their funds in the money market in the short-term. It contains information on whether the market is tight or is in excess of liquidity. This interest rate provides key signals for the central bank to understand the situation in the currency market. In a liberal economy, the interbank interest rate is closely linked to other market interest rates. Consequently, many central banks adjust their monetary policies so that the interbank interest rate does not deviate significantly from the policy rate. In this respect, understanding the volatility of interbank interest rates is very important for the central bank to determine whether the pressure on interbank interest rates is due to demand, supply or exogenous factors, and whether market intervention is necessary.

Moreover, in the interbank market, the volatility of the interbank interest rate is a tool used by market participants to control risks. These risks may be related to uncertainty in the interbank market, to the monetary policy adopted by the central bank, or to the evolution of the interbank interest rate itself. In this respect, liquidity risk is the most studied risk. Generally, the volatility of the interbank interest rate is influenced by certain factors, namely structural factors, as well as cyclical factors that are linked to the macroeconomic environment. In this context, the analysis and modeling of the volatility of interbank interest rates is of extreme importance.

The objective of this study was to test possible causal relationships between volatility time series in the interbank markets of the BRICS group. The Granger causality test, the

VAR model, and the non-linear causality test were used for finding causal relationships. The VAR model and causality tests were applied to the volatility of the interbank interest rates estimated by the stochastic volatility model with moving average innovations. To the best of our knowledge, at the time of this writing, there were no studies that were interested in the same objective.

1. Data and methodology

The data analyzed in this study were conditional stochastic volatility time series of interbank interest rates of the BRICS countries. All the used time series were collected in the period from July 22, 2015 to August 31, 2018 in the form of 753 observations. The data are downloaded from different websites (Table 1).

Table 1. Studied interbank interest rates time series

Country	Internet site
Brazil	https://www.bcb.gov.br/en
China	https://www.bank-of-china.com/en/
Russia	http://www.cbr.ru/eng/
South Africa	http://www.resbank.co.za
India	https://www.centralbankofindia.co.in

Source: compiled by the authors.

The interbank rates time series comprising the sample are all annual daily overnight rates (for 252 working days) and are converted to daily rates per working day (used as daily returns), calculated as follows:

$$y_t = (1+x_t)^{1/252} - 1,$$

where y_t represents the interbank interest rate of a working day, and x_t is the overnight interbank interest rate.

In this study, we focus on the analysis the conditional stochastic volatility of such time series as y_t. To estimate the stochastic volatility, we use the stochastic volatility model with moving average innovations (SVM-MA) (Chan & Grant, 2016), as there are different studies that reject the use of ARCH or GARCH models to estimate volatility time series. (See, for example: Small & Tse, 2003; Chan & Grant, 2016; Dhifaoui, 2021.) We remind that the SVM-MA is given by:

$$\begin{cases} y_t = \mu + \varepsilon_t^y \\ \varepsilon_t^y = u_t + \psi u_{t-1} \end{cases}, \tag{1}$$

where u_t is a normal random variable with zero mean, and having $\exp(h_t)$ as a variance, $u_0 = 0$ and $|\psi| < 1$. On the other hand, it is assumed that the log volatility h_t follows the autoregressive process as:

$$h_t = \mu_h(1-\phi_h) + \phi_h h_{t-1} + \varepsilon_t^h, \tag{2}$$

where the error term ε_t^h is a normal random variable with zero mean and variance w_h^2, and is also independent of the error term ε_t^y. The estimation method for fitting the model given by equations 1 and 2 is detailed in Chan and Grant (2016). The estimation of stochastic volatility time series is denoted by $\hat{h}_t^i$, where i is the first capital letter of Brazil, China, India, Russia, and South-Africa, respectively. Some descriptive statistics of the studied stochastic volatility time series are given in Table 2, and all these time series are illustrated in Figures 1 and 2.

Table 2. Descriptive statistics of studied time series

|	$\hat{h}_t^B$	$\hat{h}_t^C$	$\hat{h}_t^I$	$\hat{h}_t^R$	$\hat{h}_t^S$
Mean	0.984	−1.254	−8.772	0.182	−1.044
Standard deviation	0.727	0.675	0.660	0.604	0.646
Skewenes	−2.013	−1.603	−0.364	−1.020	−0.622
Kurtosis	7.44	5.735	2.161	3.433	2.669
J.B test	1126.008∗∗∗	556.521	38.639∗∗∗	136.339∗∗∗	52.00∗∗∗
Correlation matrix					
$\hat{h}_t^B$	1				
$\hat{h}_t^C$	0.835	1			
$\hat{h}_t^I$	0.437	0.347	1		
$\hat{h}_t^R$	0.8	0.673	0.433	1	
$\hat{h}_t^S$	0.236	0.327	−0.084	0.346	1

Note: ∗∗∗ — denotes *p-value* statistical significance at 1%.
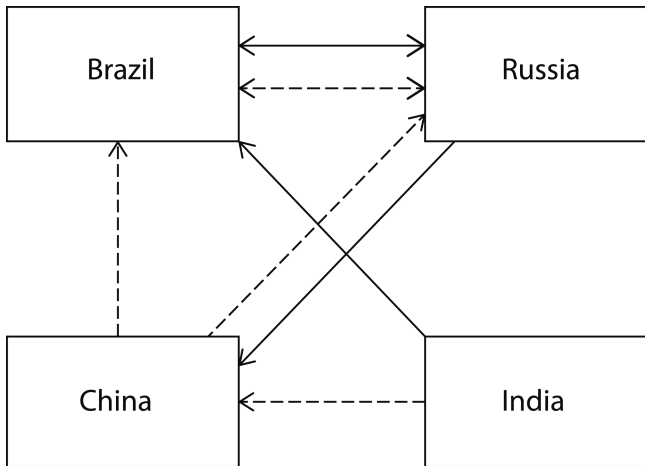*Source:* compiled by the authors.
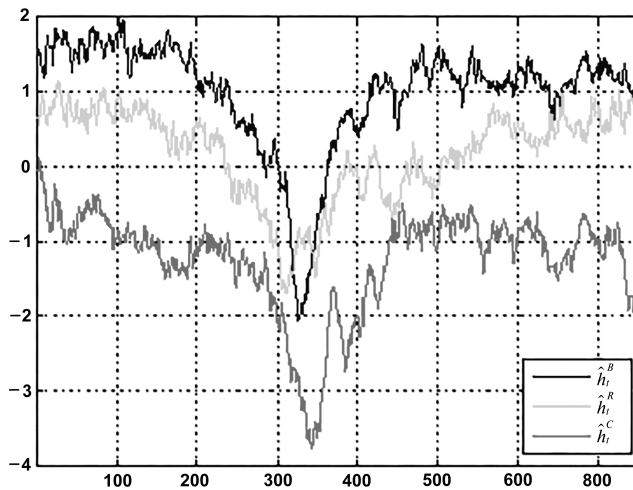
Source: compiled by the authors.
Figure 1. Volatility of interbank interest rates in the interbank markets of Russia, Brazil, and China
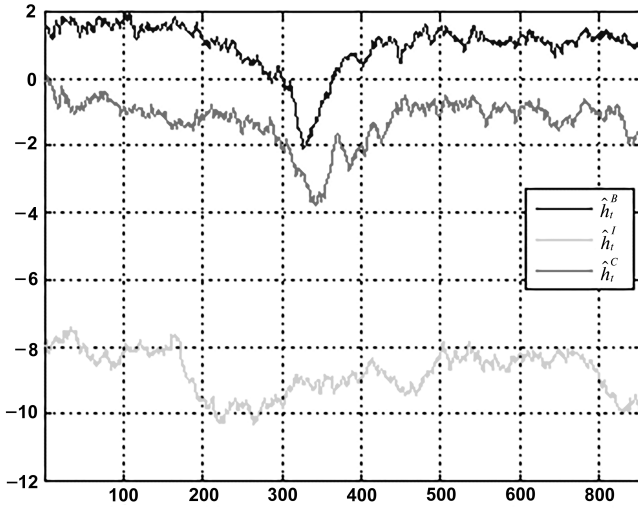
Figure 2. Volatility of interbank interest rates in the interbank markets of Russia, India, and China

Note: One arrow: unidirectional causality. Double arrow: bidirectional causality. Dashed arrow: linear causality and continue arrow: nonlinear causality.
Source: compiled by the authors.
Figure 3. Detected causal relationship of interbank interest rates

To test the direction of causality between different conditional stochastic volatility time series, a two-stage procedure was applied: in the first stage, the linear Granger causality test (Granger, 1969) was adapted to identify a linear relationship between variables. For this goal, the augmented Dickey-Fuller (ADF) unit root test (Dickey & Fuller, 1979) and the Phillips-Perron (PP) test (Phillips & Perron, 1988) were used to explore the stationarity characteristics of conditional stochastic volatility time series. We used both tests in order to check the robustness of the results. One advantage of the PP test over the ADF test

is that the former is resistant to general forms of heteroscedasticity in terms of standart error. On the other hand, the Akaike information criterion (AIC) was used to select the lag length in the ADF test, while the Newey-West Bartlett kernel was used to select the bandwidth for the PP test. At this stage, if all the variables are integrated in the same order, then a long-run equilibrium relationship is investigated using a cointegration technic, and a vectorial correction error model can be applied to investigate the short-run and long-run causal relationship between variables. If not, the vector autoregressive (VAR) model proposed by Sims (1980) can be used for the linear Granger causality test. In the same first stage, the nonlinear Granger causality test developed by Diks and Panchenko (2006) (DP test) is applied to the raw data in order to investigate a nonlinear relationship between the studied variables. In the second stage of our analysis, we investigated a possible persistence of the causality discovered in the first step by applying the DP test to the residuals of the VAR model estimated in the first step. Another causality may also appear.

2. Results and discussion

The results of the stationarity tests are given in Table 3, where the values in parentheses indicate the optimal order and bandwidth number for the ADF and PP tests, respectively.

Table 3. Results of the ADF and PP unit root tests

Variables	ADF test		PP test	
	Raw-data	First difference	Raw-data	First difference
$\hat{h}_t^B$	−1.312(0)	−27.459(0)***	−1.3(5)	−27.462(4)*
$\hat{h}_t^C$	−2.335(0)	−25.954(0)***	−0.545(8)	−25.919(7)*
$\hat{h}_t^I$	−1.73(0)	−27.892(0)***	0.667(5)	−27.902(4)*
$\hat{h}_t^R$	−2.177(0)**	−28.655(0)***	−1.834(23)	−30.038(27)*
$\hat{h}_t^S$	−2.267(0)	−25.862(0)***	−1.204(6)	−25.965(5)*

Note: *, **, *** — denote the statistical significance of the *p-value* at 10%, 5%, and 1%, respectively.
Source: compiled by the authors.

According to Table 3, the raw time series $\hat{h}_t^R$ is stationary in level, thus, it is integrated of order 0 ($I(0)$), while all other time series are stationary in the first difference, and then they are integrated of order 1 ($I(1)$). Afterwards, we proceed to estimate the Vector Autoregressive (VAR) model of order q for stationary time series, but before this step we must test the linear causal relationship between the studied time series, using the Granger causality test. The results of the Granger causality test, illustrated in Table 4, show the existence of a unidirectional linear causal relationship running from $\Delta \hat{h}_t^C$ to $\hat{h}_t^R$.

Table 4. Results of the linear Granger causality test

Source of causality	Dependent variable				
	$\Delta \hat{h}_t^B$	$\Delta \hat{h}_t^C$	$\Delta \hat{h}_t^I$	$\hat{h}_t^R$	$\Delta \hat{h}_t^S$
$\Delta \hat{h}_t^B$	—	0.953	0.952	0.365	0.512
$\Delta \hat{h}_t^C$	0.1	—	0.17	0.003***	0.428
$\Delta \hat{h}_t^I$	0.904	0.291	—	0.474	0.819
$\hat{h}_t^R$	0.158	0.543	0.234	—	0.592
$\Delta \hat{h}_t^S$	0.399	0.996	0.464	0.882	—

Note: *** — denotes the *p-value* statistical significance at 1%.
Source: compiled by the authors.

The estimation of the VAR(q) model was performed without a constant and trend, and by choosing q=1 according to the AIC criteria as the order of the model. Therefore, we estimated the following model for stationary time series:

$$\Delta \hat{h}_t^B = \beta_{12}\Delta \hat{h}_{t-1}^B + \beta_{13}\Delta \hat{h}_{t-1}^C + \beta_{14}\Delta \hat{h}_{t-1}^I + \beta_{15}\hat{h}_{t-1}^R + \beta_{16}\Delta \hat{h}_{t-1}^S + \eta_{1t},$$

$$\Delta \hat{h}_t^C = \beta_{22}\Delta \hat{h}_{t-1}^C + \beta_{23}\Delta \hat{h}_{t-1}^B + \beta_{24}\Delta \hat{h}_{t-1}^I + \beta_{25}\hat{h}_{t-1}^R + \beta_{26}\Delta \hat{h}_{t-1}^S + \eta_{2t},$$

$$\Delta \hat{h}_t^I = \beta_{32}\Delta \hat{h}_{t-1}^I + \beta_{33}\Delta \hat{h}_{t-1}^B + \beta_{34}\Delta \hat{h}_{t-1}^C + \beta_{35}\hat{h}_{t-1}^R + \beta_{36}\Delta \hat{h}_{t-1}^S + \eta_{3t},$$

$$\hat{h}_t^R = \beta_{52}\hat{h}_{t-1}^R + \beta_{53}\Delta \hat{h}_{t-1}^B + \beta_{54}\Delta \hat{h}_{t-1}^C + \beta_{55}\Delta \hat{h}_{t-1}^I + \beta_{56}\Delta \hat{h}_{t-1}^S + \eta_{4t},$$

$$\Delta \hat{h}_t^S = \beta_{62}\Delta \hat{h}_{t-1}^S + \beta_{63}\Delta \hat{h}_{t-1}^B + \beta_{64}\Delta \hat{h}_{t-1}^C + \beta_{65}\Delta \hat{h}_{t-1}^I + \beta_{66}\hat{h}_{t-1}^R + \eta_{5t},$$

where Δ is the first difference operator and η_{it} for $i = 1,\ldots,5$ denotes the error terms. The estimation results are shown in Table 5.

Table 5. Results of the estimation of the VAR(1) model

Dependent variable	Independent variables	VAR(1) estimates	
		Coefficient	t-statistic
$\Delta \hat{h}_t^B$	$\Delta \hat{h}_{t-1}^C$	0.066	1.971*
	$\Delta \hat{h}_{t-1}^I$	0.0112	0.311
	$\hat{h}_{t-1}^R$	0.0217	2.407*
	$\Delta \hat{h}_{t-1}^S$	0.0340	1.174
$\Delta \hat{h}_t^C$	$\Delta \hat{h}_{t-1}^B$	−0.00002	−0.0006

Table 5. Continued

Dependent variable	Independent variables	VAR(1) estimates	
		Coefficient	t-statistic
$\Delta \hat{h}_t^I$	$\Delta \hat{h}_{t-1}^I$	0.0636	1.621*
	$\hat{h}_{t-1}^R$	0.0048	0.485
	$\Delta \hat{h}_{t-1}^S$	0.006	0.168
	$\Delta \hat{h}_{t-1}^B$	0.0075	0.200
	$\Delta \hat{h}_{t-1}^C$	−0.036	−1.046
$\Delta \hat{h}_t^R$	$\hat{h}_{t-1}^R$	−0.0140	−1.510
	$\Delta \hat{h}_{t-1}^S$	0.023	0.682
	$\Delta \hat{h}_{t-1}^B$	0.069	1.809*
	$\Delta \hat{h}_{t-1}^C$	0.056	1.602*
	$\Delta \hat{h}_{t-1}^I$	0.008	0.214
$\Delta \hat{h}_t^S$	$\Delta \hat{h}_{t-1}^S$	−0.018	−0.524
	$\Delta \hat{h}_{t-1}^B$	0.046	1.169
	$\Delta \hat{h}_{t-1}^C$	−0.044	−1.234
	$\Delta \hat{h}_{t-1}^I$	0.014	0.387
	$\hat{h}_{t-1}^R$	−0.003	−0.278

Note: * — denotes the *p-value* statistical significance at 10%.
Source: compiled by the authors.

Based on the results reported in Table 5, the coefficient β_{13} is statistically significant. This implies that there exist a unidirectional causal relationship running from $\Delta \hat{h}_t^C$ to $\Delta \hat{h}_t^B$. Besides, the coefficient β_{15} is statistically significant, which implies the existence of a unidirectional causal relationship running from $\hat{h}_t^R$ to $\Delta \hat{h}_t^B$ and confirms the unidirectional linear causal relationship detected by the Granger causality test shown in Table 2. Moreover, the coefficient β_{24} is statistically significant, which implies the existence of a unidirectional causal relationship running from $\Delta \hat{h}_t^I$ to $\Delta \hat{h}_t^C$. Finally, coefficients β_{53} and β_{54} are statistically significant, which implies that there exists a unidirectional causal relationship running from $\Delta \hat{h}_t^B$ and $\Delta \hat{h}_t^C$ to $\hat{h}_t^R$.

Now, in order to test a nonlinear causal relationship between the studied stochastic volatility time series, we used the DP test (Diks & Panchenko, 2006). The results of this

test, using $l_X = l_Y = 1$ and $\varepsilon_n = 1.6$ as a bandwidth, are presented in Table 6, where we noticed the existence of a unidirectional nonlinear causal relationship running from $\Delta\hat{h}_t^I$ to $\Delta\hat{h}_t^B$, from $\hat{h}_t^R$ to $\Delta\hat{h}_t^B$, and from $\hat{h}_t^R$ to $\Delta\hat{h}_t^C$.

Table 6. Results of the nonlinear Granger causality test (ε_n=1.6)

Source of causality	Dependent variables				
	$\Delta\hat{h}_t^B$	$\Delta\hat{h}_t^C$	$\Delta\hat{h}_t^I$	$\hat{h}_t^R$	$\Delta\hat{h}_t^S$
$\Delta\hat{h}_t^B$	—	0.588(0.278)	−0.636(0.737)	0.412(0.34)	−1.308(0.904)
$\Delta\hat{h}_t^C$	−0.041(0.516)	—	0.866(0.193)	0.930(0.176)	−0.084(0.533)
$\Delta\hat{h}_t^I$	2.077(0.018)**	0.560(0.287)	—	−0.740(0.77)	−0.432(0.666)
$\hat{h}_t^R$	2.759(0.002)***	2.813(0.002) ***	0.160(0.436)	—	−0.417(0.661)
$\Delta\hat{h}_t^S$	0.335(0.368)	−0.114(0.545)	−1.562(0.94)	0.616(0.268)	—

Note: **, *** — denotes the *p-value* statistical significance at 5% and 1%, respectively.
Source: compiled by the authors.

In order to detail our analysis, we applied the DP test to the residual of the VAR(1) model estimated in the last steep. For this purpose, we also used $l_X = l_Y = 1$ and $\varepsilon_n = 1.6$. The results of the DP test to the residual of the VAR(1) model are shown in Table 7.

Table 7. Results of the nonlinear Granger causality test for the VAR(1) residual (ε_n=1.6)

Source of causality	Dependent variables				
	$\Delta\hat{h}_t^B$	$\Delta\hat{h}_t^C$	$\Delta\hat{h}_t^I$	$\hat{h}_t^R$	$\Delta\hat{h}_t^S$
$\Delta\hat{h}_t^B$	—	0.839(0.2)	−0.973(0.834)	1.921(0.027)**	−1.147(0.874)
$\Delta\hat{h}_t^C$	−0.426(0.664)	—	0.629(0.264)	0.276(0.391)	−0.390(0.651)
$\Delta\hat{h}_t^I$	2.220(0.013)**	0.769(0.22)	—	0.166(0.433)	−0.277(0.609)
$\hat{h}_t^R$	1.170(0.121)	0.167(0.433)	0.115(0.454)	—	−0.117(0.546)
$\Delta\hat{h}_t^S$	0.416(0.338)	−0.146(0.558)	−1.273(0.898)	0.467(0.320)	—

Note: ** — denotes the *p-value* statistical significance at 5%.
Source: compiled by the authors.

Based on the fact that the application of the DP test to the residual of the VAR model serves to ensure that each detected causal relationship is nonlinear, we noticed in this step

the persistence of the causal relationship between $\Delta \hat{h}_t^B$ and $\hat{h}_t^R$, as well as the appearance of a non-linear causal relationship running from $\Delta \hat{h}_t^I$ to $\Delta \hat{h}_t^B$. All detected causal relationships (linear and nonlinear) are illustrated in Figure 3.

There are general effects that can explain the existence of unidirectional and bidirectional causal relationships between the volatility of interbank interest rates in the BRICS group. It should be remembered that there are three participants in the interbank market, which are the supervisory authorities, including the central bank, issuers such as commercial banks, cooperative banks, financial companies or specialized financial institutions, and investors. Therefore, any intervention by any participant can affect the magnitude of the change in the interbank interest rate.

The general effects may explain the interbank dependence between the BRICS countries. We recall that at the Durban summit in 2013, the BRICS countries signed two agreements in the framework of interbank cooperation: one on co-financing of infrastructure in Africa, and the other on financing the green economy and combating climate change. Furthermore, in April 2010, the Brazilian Development Bank, the State Bank for Development and Foreign Economic Affairs of Russia, the Export-Import Bank of India, and the Development Bank of China established an interbank cooperation mechanism. In 2014, the BRICS group announced the creation of the New Development Bank (NDB) and an emergency reserve fund (ERF). The BRICS governments promoted the NDB and the ERF as alternatives to the World Bank and the International Monetary Fund, respectively. The mission of the NDB is to invest in infrastructure and sustainable development in emerging markets and developing countries.

Although in 2015, Brazil's monetary policy was marked by a pause, since 2016, the Central Bank has eased its monetary policy by lowering its policy rate. This reduction is accused in a context favorable to easing (implicit inflation under control, easing of monetary policies in developed economies) and weak growth. In 2017, the Central Bank of Brazil accelerated the easing of its monetary policy by reducing its policy rate five times in a row to reach a rate of 11.25% by the end of the year. This decline continued in 2018 and stabilized at 6.5%.

The same behavior has been adopted by Russia since 2015, when the Central Bank decided to reduce its policy rate from 11.5% to 11% to fight against the ongoing and faster-than-expected decline in inflation, to stimulate the economic situation in a recession and control the evolution of the rouble. Having kept the policy rate at 11% in 2016, the Central Bank of Russia lowered it to 8.25% in 2017 in order to cope with the persistent inflation risks. This decrease continued in 2018, in view of the weak economic growth and uncertainty in the world financial markets, and reached 7.25%. This similarity between the evolution of the policy rate of the Central Bank of Brazil and that of the Central Bank of Russia is a factor explaining the bidirectional causal relationship detected between the volatility of their interbank interest rates.

Since 2014, China and Russia have started the process of replacing the US dollar (de-dollarization). These two countries are especially targeted by the United States: China is in the midst of a trade war with them, and Russia has been subject to numerous sanctions

since the annexation of Crimea in 2014. The two countries created a trade hub to be able to make transactions between them either in rubles or in yuan. In addition, Russia implemented a dollar exit strategy that depleted its greenback reserves by more than two-thirds and replaced it with the euro and ruble. Russia's main trading partners have already agreed to trade in these currencies. For example, three-quarters of Russia's transactions with India are conducted in rubles. The bidirectional causal relationship detected between the volatility of interbank interest rates can be interpreted as a result of these trade and monetary exchanges between the two countries.

On the one hand, China is Brazil's largest trading partner, and Chinese banks play an important role in this relationship. In this respect, several Chinese banks have already set up their subsidiaries, such as the Industrial and Commercial Bank of China (ICBC), China Construction Bank (CCB) and Bank of Communications (BoCom) in Brazil, to enhance the Chinese contribution to the Brazilian economy. The participation of these Chinese banks will unlock many infrastructure projects that have been delayed or even paralyzed, such as railways for exporting soybeans produced in the central-western and north-eastern regions of Brazil. To this end, funds worth 50 billion will be created by the ICBC and Brazil's Federal Economic Fund (CEF).

On the other hand, China has just announced the abolition of investment quotas under the Qualified Foreign Institution Investor (QFII) and Renminbi Qualified Foreign Institution Investor (RQFII) programs. The development of market access for foreign investors is an ongoing process, as China has undertaken structural reforms of its financial markets and given foreign companies greater control over their assets. This development follows the recent decision to allow foreign financial companies to hold a majority stake in joint ventures. In this context, Indian businessmen have succeeded in establishing themselves in the Chinese business community. Moreover, as most Indian investment is concentrated in the services sector, Hong Kong remains a favorite destination for Indian investors. These Indian investments and the bilateral trade relations may explain the bidirectional causal relationship between the volatility of Indian and Chinese interbank interest rates.

Since 2014, Brazil has entered a period of economic crisis, aggravated by political uncertainties and structural blockages. To solve this problem, Brazil motivated its free trade relationship with India, and as a consequence, a significant number of Indian companies began to invest in Brazil, for example, Tata Consultancy Services. On the investment side, Indian investment has been strong in Brazil. Sterlite Group won 800 million euros in the project of the electricity transmission line (Sterlite Group usually invested 2 billion US dollar in Brazil), UPL invested 150 million US dollar in its new plants in Sao Paulo. India's total investment in Brazil is estimated at 8 billion US dollars.

In addition, Brazil is one of India's most important trading partners in the entire Latin American and Caribbean region. Bilateral India-Brazil trade has grown considerably over the past two decades. However, the global decline in commodity prices and the economic recession in Brazil that began in 2014 have affected Brazil's overall trade. As a result, the negative impact was also felt in bilateral trade when it declined to 7.9 billion US dollars and 5.64 billion US dollars in 2015 and 2016, respectively. However, with a slight recovery

of the Brazilian economy in 2018, bilateral trade between India and Brazil reached 7.57 billion US dollars. Indian exports to Brazil are valued at 3.66 billion US dollars. In 2018, India was the 11th largest exporter to Brazil. This trade relationship and the increase in Indian investments in Brazil may explain the causal relationship between the volatility of their interbank interest rates.

Conclusion

This article analyzes the interbank relationships between the countries of the BRICS group. For this purpose, the magnitude of the evolution of the interbank interest rate yield was analyzed to test possible associations that may exist between the interbank markets of this group of countries. The search for unidirectional and bidirectional causality relationship was carried out using the Granger causality test, the VAR model, and the non-linear Granger causality test. These causalities tests are applied to the volatility of the interbank interest rate return extracted by the SVM model with moving average innovations. The results obtained show the existence of some bidirectional and unidirectional relationships, confirming the existence of some triangular relationships between the BRICS countries, i.e., the existence of blocks of countries within this group. For example, the BIC group formed by Brazil, India and China, or also the BRC group formed by Brazil, Russia and China. Furthermore, the results show the absence of South Africa in these causal relationships. The econometric results confirm the use of local currency and borrowing by financial institutions of the BRICS members to facilitate economic growth until this period. Moreover, trade and investment within the BRICS countries have increased rapidly in recent years as a result of wider use of local currency in the settlement of transactions. This use of the local currency is one of the factors that creates interbank dependence between these countries. This interbank dependence was one of the objectives of BRICS to facilitate foreign trade and investment and to promote the diversified development of the international monetary system. In this sense, a mechanism of interbank cooperation of the BRICS countries was established to find ways and models for extending credits in the local currency in order to build a more open and efficient financial services system. For example, in April 2010, the Development Bank of Brazil, the State Bank for Development and Foreign Economic Affairs of Russia, the Export-Import Bank of India, and the Development Bank of China established an interbank cooperation mechanism. The Development Bank of South Africa joined this mechanism in 2013.

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