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Granger Causality and Hierarchical Transmission Patterns in BRICS Currency Markets

Chajar Matari Fath Mala[1*], Sapto Jumono[2]
[1]Universitas Pembangunan Jaya, Tangerang Selatan, Indonesia, chajar.matari@upj.ac.id
[2]Universitas Esa Unggul, Jakarta, Indonesia, sapto.jumono@esaunggul.ac.id

[*]Corresponding Author: chajar.matari@upj.ac.id[1]

Abstract: The short-run causal links and the multistage transmission order among BRICS (Brazil, Russia, India, China, and South Africa) currencies against the US dollar are studied from November 2019 to May 2025. We utilise daily exchange rate returns and employ a multinivariate VAR-Granger causality framework with a lag length of eight to account for short-run interactions during periods encompassing multiple global shocks, such as the COVID-19 pandemic and the Russia-Ukraine war. The pre-estimation diagnostics (ADF unit root test, stability checks and LM serial correlation tests) are strong evidence of the soundness of the model. Granger causality tests, on the other hand, reveal a specific asymmetric, hierarchical structure. A set of players, including the Russian ruble (RUB) and the Indian rupee (INR), are primarily transmitting shocks. At the same time, a second group, e.g., featuring the Chinese yuan (CNY) and South African rand (ZAR), acts as a shock absorber. This novel contribution to the literature uncovers short-run causality behaviors in BRICS forex markets during a previously unprecedented multi-crisis period. It offers new insights into the foreign exchange policy coordination and exchange risk management.

Keywords: BRICS currencies, Granger causality, VAR model, exchange rate dynamics, short-run transmission, hierarchical structure.

INTRODUCTION

Over the past decade, Brazil, Russia, India, China, and South Africa have emerged as a major collective force within the global financial system. Acting as a counterweight to traditional economic powers, the BRICS bloc has witnessed a surge in cross-border capital movements and international trade. Recent scholarship indicates that the internal hierarchy of monetary influence within the group is undergoing transformation. For instance, Kyriazis (2025) finds that although Russia continues to occupy a central position, the roles of Brazil, China, and South Africa within the BRICS monetary network have strengthened considerably, signaling an evolving pattern of transmission leadership. This function is especially prominent in the multi-crisis phase of 2019–2025, which includes the COVID-19 pandemic, the worldwide energy crisis, and the Russia-Ukraine war. Focusing on this episode, we find significant turmoil in the foreign exchange markets, and the links between BRICS currencies and US dollar shocks have become more volatile. Given this, a fundamental question is whether all the BRICS currencies are equally important in transmitting shocks or whether there exists some preferential hierarchy among the exchange rate network of these countries.

On the theoretical side, the overshooting model of Dornbusch (1976) and the network approach by Diebold and Yilmaz (2012; 2014) provide justifications as to how monetary shocks and expectations can cause asymmetric relationships across currencies, some acting primarily as dominant shock transmitters while others functioning predominantly as shock absorbers. Based on this theoretical framework, Kerbeg et al. (2025) show that home interest rate shocks largely influence BRICS exchange rates, and they stress the involvement of monetary channels in short-run transmission dynamics. Nevertheless, extant literature on BRICSC exchange rate dynamics suffers from several notable shortcomings. The first available evidence from single-episode crisis scenarios does not capture the complexity of multiple crises. Second, most empirical investigations are based on impulse response functions or variance decomposition; however, relatively little is known about the nature of short-run causal structures derived solely from Granger causality tests. Third, the use of longer lags in VAR models to capture lagged short-run transmission mechanisms has been constrained, despite being particularly important for emerging markets with frictions and slower information adjustment.

This theoretical perspective is consistent with prior empirical research. Antonakakis et al. (2011), and Tiwari et al. (2019) discovered that connectivities are strongest in BRICS currency markets, with the Russian ruble and Indian rupee often serving as leading drivers. Antonakakis et al. (2016) found that the BRICS currency networks strengthen in turbulent times, with Russia and India playing a central role in transmission. Bekiros (2014) also points to the non-linear and regime-dependent character of cross-currency relationships, indicating that some dynamic model is necessary to describe these implications. Phiri (2018) and other studies also indicate that the ruble (RUB) and rupee (INR) usually dominate short-run dynamics, while the Chinese yuan (CNY) tends to replicate global fluctuations. Hence, Inagaki (2006) finds unidirectional causality from the yen to the US dollar for developed economies. Newer evidence adds further complexity, such as Nach (2024) empirically evaluates BRICS as a potential optimum currency area and that, while responses to external shocks may be only partially symmetric, there continues to be significant heterogeneity across members; Umoru et al. (2025) demonstrate that exchange rate volatility strongly affects BRICS equity returns in the short term, highlighting the relevance of high-frequency dynamics. Taken as a whole, these results emphasise the degree of interconnectedness among currency markets through trade, financial, and policy linkages (e.g., Dornbusch and Fischer, 1980), with rational expectations and monetary policy playing central roles in determining cross-currency relationships. Despite these valuable contributions, several areas in the literature have been overlooked. The majority of research looks at single-crisis events and does not account for the 6-year, multi-crises scenario developed between 2019 and 2025.

Most empirical analysis instead has focused on impulse response functions (IRF) or variance decomposition (FEVD), and the scope for pure short-run causality structures using Granger tests is relatively limited. Very few studies use longer VAR lags to reveal significant lagged short-run transmissions in emerging markets with slow information interpretations. Furthermore, few studies have focused on the hierarchical structure among RUB, INR and other BRICS currencies in a multivariate system. Empirical evidence at high-frequency daily data over a long horizon is minimal, even though such evidence can be of significant importance for the monetary authorities of BRICS countries to develop coordinated exchange rate policies and manage external disturbances.

Considering these factors, the present study aims to determine the direction of short-run causality and the hierarchical structure of shock transmission among BRICS currencies vis-à-vis the US dollar during the 2019–2025 multi-crisis period. In particular, the paper investigates how short-run causal linkages are established and diffused across BRICS currencies, how these currencies play a dominant role in spreading shocks and act as either a net receiver or a donor, and what kind of hierarchical causality structure emerges under persistent global shocks. With a recent change in BRICS monetary leadership (Kyriazis, 2025) and the resurgence of interest rate channels (Kerbeg et al), this analysis is timely and policy-related. What is distinctive about this study is the combination of a long multi-crisis period, an eight-period lag length to capture short-run dynamics of delay effects, and a focus solely on short-run pair-wise Granger-causality relationships, as well as the detection of hierarchy among BRICS foreign exchange market areas that are relatively underexplored in extant studies. These findings are likely to contribute valuable empirical evidence and policy implications for exchange rate coordination and stabilisation policies in emerging economies.

METHOD

This work adopts a quantitative research design by using multivariate time series econometrics to study the short-run causal relationships among returns of BRICS/USD exchange rates. We consider five major BRICS currencies, which are RUB, CNY, BRL, INR, and ZAR, relative to the US dollar. A VAR representation and associated Granger causality tests are used in detecting the long-run orientation and structure of determination for a given pair. This method, proposed by Sims (1980), is especially appropriate for modelling dynamic relationships among several variables without any a priori structural constraints.

We took daily secondary data from 5 November 2019 to 12 May 2025. This period includes several significant global shocks, such as the COVID-19 pandemic, the global energy crisis and the Russia–Ukraine War. Daily high-frequency data enables a more accurate identification of short-term causality and quick market responses. The variables are the daily log returns of BRICS currencies with respect to the US dollar. Data are extracted from reliable international websites such as Bloomberg, Investing.com, and the Federal Reserve Economic Data (FRED).

The key variable is the daily log return of each exchange rate, calculated as the first natural logarithmic difference of the spot exchange rate between day t and t−1. For currency i at time t, the return is computed as:

$$RET_{i,t} = \triangle\, ln(ER_{i,t}) = \ln\left(ER_{i,t}\right) - \ln\left(ER_{i,t-1}\right)$$

When expressed in percentage terms, the daily return for each currency is obtained by multiplying the logarithmic change by 100, as follows:

$$RET_{i,t} = 100\ x \triangle\, ln\left(ER_{i,t}\right) = 100\ x\ \ln\left(ER_{i,t}\right) - \ln\left(ER_{i,t-1}\right)$$

The variable ERit refers to the spot exchange rate of currency i against the U.S. dollar at time t, while ln(·) denotes the natural logarithm. The expression Δln(Erit) captures the logarithmic change in the exchange rate, representing daily returns. With this transformation, exchange rate movements can be reported in percentages for more straightforward interpretation and consistency with established empirical finance literature. This strategy gives a strong basis for studying high-frequency financial time series. By using log returns instead of raw exchange rate data, we can gain several empirically documented advantages. It stabilizes variance in the presence of heteroskedasticity, takes away deterministic trends from the level series, and permits consistent temporal aggregation of returns at various horizons (Campbell, Lo, and MacKinlay 1997; Antonakakis et al. 2016). For these purposes, logreturn changes are popular in the literature on foreign exchange market behavior and propagation of financial shocks (Diebold and Yilmaz 2014; Bekiros 2014).

The empirical examination begins with testing the stationarity of all variables using the Augmented Dickey-Fuller (ADF) procedure. Each series is considered stationary at a level with a constant deterministic component, and in each case, the lag length was determined using the Schwarz Information Criterion (SIC). Critical values and associated p-values are computed using MacKinnon (1996). Only level stationary variables, I(0), were retained in the Vector Auto-Regression (VAR) and Granger causality setting. This additional first step is necessary to make sure the model is identified and not encumbered by spurious statistical correlations. After ensuring that the series are stationary, the amount of lag for the VAR model is determined by using several standard information criteria: Akaike (AIC), Final Prediction Error (FPE), Schwarz SC, and Hannan-Quinn HQ. Although AIC and FPE indicate a lag structure of two, the article uses a longer one of eight. This decision reflects conventions in the literature on cross-market financial linkages (Antonakakis et al. 2016; Diebold and Yilmaz 2014) and accommodates the need to capture both short-term feedback mechanisms and more complex transmission dynamics among the BRICS currencies during turbulent periods. The VAR(8) model is then estimated for the BRICS/USD return system.

Rather than focusing on individual parameter estimates, the VAR serves as the backbone for testing short-run causality and ensuring dynamic stability. Stability is assessed by examining the roots of the characteristic polynomial, which must all lie strictly inside the unit circle. Once this condition is satisfied, Granger causality is investigated using the Block Exogeneity Wald test, which evaluates whether lagged values of one currency significantly improve the prediction of another. Rejecting the null hypothesis of no joint lagged effect provides statistical evidence of Granger causality. The findings are presented both as detailed pairwise statistics and in a concise summary matrix, making it possible to detect the principal transmitters and receivers of shocks within the BRICS currency network.

To verify the robustness of the specification, a full set of diagnostic checks is performed. Stationarity is re-confirmed through ADF testing, stability is verified by root analysis, and residual serial correlation is examined using the LM test. A summary of these diagnostics is presented in Table 1. These checks validate the VAR(8) model and provide a solid foundation for subsequent causality analysis. Overall, the empirical procedure follows a systematic and transparent sequence: data transformation, unit root testing, lag selection, VAR estimation, model diagnostics, and causality testing—culminating in the interpretation of results and drawing of policy-relevant insights. This structured methodological design ensures internal consistency and enhances the credibility of the inferences regarding short-run causal interactions among the BRICS foreign exchange markets.

RESULTS AND DISCUSSION

Prior to testing for Granger causality, a set of pre-estimation diagnostic checks is conducted to test the validity of the VAR model. The Augmented Dickey–Fuller (ADF) stationarity test results suggest that the BRICS/USD returns are stationary at level, I(0), at a 1 percent MacKinnon significance level. This implies that the data no longer need to be differenced further, thus fulfilling the most important precursor for the AN application of VAR. The selected lag length is not the same under different selection criteria. The LR test diagnoses the length of lag as eight, while the AIC and FPE criteria suggest a lag length of two. Finally, both SC and HQ suggest a lag length of zero. When we use high-frequency financial data, the appropriate lag length is eight since the LR criterion is more sensitive to complicated short-run dynamics. This aligns with the suggestions of Lütkepohl (2005) and Kilian & Lütkepohl

(2017), which emphasise the necessity of employing longer lags better to capture short-run autocorrelations in daily financial time series.

Table 1. Overall Assessment of VAR Pre-Estimation Diagnostics (Lag 8)

Diagnostic Aspect	Test Results	Decision / Key Findings
Stationarity (ADF Test)	All BRICS/USD return series are stationary at level (I(0)) at the 1% MacKinnon significance level.	No differencing is required; the series meet the stationarity requirement.
Optimal Lag Selection	LR test selects **lag 8**, whereas AIC and FPE suggest lag 2, and SC & HQ favor lag 0. Lag 8 is adopted following the LR criterion, which is more sensitive to short-run dynamics in high-frequency financial data.	Lag 8 strikes a balance between model fit and the need to absorb short-run autocorrelation structures.
VAR Stability (Roots Test)	All roots of the characteristic polynomial lie inside the unit circle.	The VAR(8) model satisfies the dynamic stability condition, allowing for valid Granger causality testing.
Serial Correlation (LM Test)	LM test up to lag 8 shows no serious violation of the no serial correlation assumption. Only lags 3, 4, and 6 show mild significance ($p < 0.05$), but not in a systematic way. Joint tests (lags 1–8) yield p-values between 0.17–0.32.	No serious residual autocorrelation issues remain; lag 8 adequately captures short-run dynamics in the data.
Sample Size	1,336 daily observations (05 November 2019 – 12 May 2025).	The sample size is sufficiently large for a high-dimensional VAR with long lags.
Suitability for Further Analysis	All pre-estimation requirements—stationarity, stability, lack of serial correlation, and sufficient sample size—are met.	The VAR(8) model is suitable for **Granger causality tests** in subsequent analysis.

Note: The choice of lag 8 follows the LR criterion, which is particularly recommended in high-frequency financial applications because it is more responsive to short-run dynamics (Lütkepohl 2005; Kilian and Lütkepohl 2017).

Source: Authors' calculations using EViews 12.

The stability test results demonstrate that all roots of the characteristic polynomial lie inside the unit circle, implying that the VAR(8) system meets the dynamic stability condition. This is to avoid potential bias in the Granger causality test and further dynamic analyses due to model instability. The results of the LM test up to the eighth lag indicate that there is no evidence of a serious violation of the non-autocorrelation assumption. While mild significance is evident at lags 3, 4 and 6 ($p < 0.05$), the evidence is not systematic, and the joint test for lags from 1 until eight results in p-values between \$0.17\$ and \$0.32\$. As such, the leftover residual autocorrelation can be interpreted as small when a long lag structure is used to capture short-run dynamics.

The sample size is large enough to estimate a five-variable model with the VAR(8) structure using 1,336 daily observations. In general, the pre-estimation diagnostic results indicate that all major assumptions; stationarity, systems stability, no significant residual autocorrelation and sufficient sample sizes—are well met. Therefore, the VAR(8) model can be a good specification for the following Granger causality analysis. Having confirmed the appropriateness of the VAR(8 model) based on various diagnostic checks, we proceed to test for the direction of short-run causal linkages between BRICS/USD currency return using Granger Causality (Block Exogeneity Wald) tests. The purpose of these tests is to find out whether previous movements in one currency can predict the fluctuations of other currencies according to the VAR framework (Sims, 1980; Lutkepohl, 2005).

The aggregate and multicountry results in Table 2 show whether several statistically significant causal links exist. At 5% level of significance, previous RUB and CNY returns have significantly affected the INR (p=0.0180 and p=0.0250, respectively). INR and ZAR UPTs are influenced by RUB (p = 0.0087 and p = 0.0061) return (p-values of 0.0086, respectively). Notably, causal relationships are generally unimportant with respect to CNY and ZAR, though there is weak evidence of causality running from ZAR to INR (p = 0.0515). This finding indicates that RUB and INR serve as the key shock givers in the short term of the BRICS foreign exchange return system, while CNY and ZAR are more like shock receivers. This evidence agrees with prior studies that found both Russian and Indian markets may possess a higher level of volatility settings and could generate information spillover to the other BRICS exchange rates (refer, for example, Antonakakis et al. 2016; Bekiros, 2014).

Table 2. Pairwise Granger Causality / Block Exogeneity Wald Tests (Lag 8)

Dependent Variable	Excluded Variable	Chi-sq	df	Prob.	Decision (5%)
RETRUB	RETCNY	10.03	8	0.2627	Not significant
	RETBRL	12.88	8	0.1161	Not significant
	RETINR	20.47	8	0.0087	**Significant**
	RETZAR	21.42	8	0.0061	**Significant**
	All	68.23	32	0.0002	Jointly significant
RETCNY	RETRUB	6.97	8	0.5394	Not significant
	RETBRL	7.40	8	0.4945	Not significant
	RETINR	10.24	8	0.2484	Not significant
	RETZAR	13.36	8	0.1002	Not significant
	All	37.78	32	0.2219	Jointly not significant
RETBRL	RETRUB	20.50	8	0.0086	**Significant**
	RETCNY	8.32	8	0.4027	Not significant
	RETINR	7.90	8	0.4435	Not significant
	RETZAR	6.98	8	0.5393	Not significant
	All	44.22	32	0.0737	Jointly marginally significant
RETINR	RETRUB	18.46	8	0.0180	**Significant**
	RETCNY	17.54	8	0.0250	**Significant**
	RETBRL	8.75	8	0.3640	Not significant
	RETZAR	5.45	8	0.7090	Not significant
	All	47.47	32	0.0384	Jointly significant
RETZAR	RETRUB	7.36	8	0.4985	Not significant
	RETCNY	7.37	8	0.4978	Not significant
	RETBRL	8.28	8	0.4062	Not significant
	RETINR	15.42	8	0.0515	Marginally significant
	All	38.15	32	0.2100	Jointly not significant

Note: The table reports Chi-squared statistics for pairwise Granger causality/block exogeneity Wald tests using lag 8, with 1,336 daily observations from 05 November 2019 to 12 May 2025. A rejection of the null indicates that the excluded variable Granger-causes the dependent variable at the 5% level.
Source: Authors' calculations using EViews 12.

In summary, the main results of the Granger causality analysis show that short-run shock spillovers between BRICS currencies and USD are mainly transmitted via RUB and INR. Strong causal endpoints are found from INR to RUB and from ZAR to RUB, indicating that India and South Africa play an important role in the short-run shaping of the Russian currency dynamics. Also, there is strong causality running from RUB to BRL because the Russian market is closely related to that of Brazil, mainly through commodity price spillovers and global capital flows. RUB and CNY also have a significant causal influence on INR; that is, changes in the Russian and Chinese payee currencies are important contributors to the behaviour of the Indian rupee. In contrast, CNY and ZAR are relatively inactive because fewer important causal relationships serve as explanatory variables within the system. Meanwhile, the links from BRL to the other currencies are one-way, as BRL is only significantly driven by RUB without substantial feedback effects. This general pattern confirms the presence of an elastic system in the BRICS exchange rate network, where some currencies play a central role as disseminators and others act predominantly as absorbents.

To clarify the pattern of short-run causal relationships among BRICS/USD currency returns, the results of the Granger causality tests presented in Table 4.2 are summarized in a more intuitive format in Table 3. This table displays the direction of causality in a concise and accessible manner, with rows representing the causal variables and columns representing the affected variables. A checklist symbol indicates the presence of a statistically significant Granger causality relationship at the 5% level, cross symbol indicates the absence of a significant causal relationship, and cross (0.051) denotes a marginal relationship that is close to the 5% significance threshold.

Table 3. Summary of Pairwise Granger Causality among BRICS/USD Returns (Lag 8)

From \ To	RUB	CNY	BRL	INR	ZAR
RUB	—	✖	✓	✖	✖
CNY	✖	—	✖	✓	✖
BRL	✖	✖	—	✖	✖
INR	✓	✖	✖	—	✖
ZAR	✓	✖	✖	✖ (0.051)	—

- ✓ = indicates a statistically significant Granger causality relationship ($p < 0.05$)
- ✖ = indicates no statistically significant Granger causality relationship
- ✖ (0.051) = indicates a marginal relationship (close to the 5% significance level)
- The direction of causality is read from the row (cause) → column (affected)

Source: Authors' calculations using EViews 12, daily data from 5 November 2019 to 12 May 2025.

Table 3 provides a concise overview of the direction of causal relationships among BRICS currencies. It clearly shows that the Russian ruble (RUB) and the Indian rupee (INR) act as the primary shock transmitters within the BRICS/USD exchange rate system. This is reflected in the significant causal links running from INR to both RUB and ZAR, as well as from RUB to BRL. Moreover, a bidirectional relationship is observed between INR and RUB, where INR exerts a significant influence on RUB. At the same time, the Russian ruble (RUB) influences the Indian rupee (INR) in an indirect manner, operating through its effects on the Brazilian real (BRL) and several other currencies within the system. By contrast, Chinese yuan (CNY) and South African rand (ZAR) have a relatively peripheral role in this chain of causation. The CNY has a strong effect on the INR and is relatively independent of other currencies—both features are consistent with the controlled floating exchange rate regime in China (He et al. 2020; Zhang et al. 2021). The rand has only a near-causal relationship with the INR ($p \approx 0.051$), and is effectively irrelevant elsewhere in the network. By contrast, the BRL serves a predominantly buffering role, cushioning shocks, particularly from RUB.

This pattern highlights the strong transmission channels linked to commodity prices and internationally mobile capital flows, which are rapidly adjusted to signals from Russian financial markets. Kerbeg et al. (2025) report that their short-run pass-through is driven by domestic interest rate differentials, in particular RUB and INR-based pairs. Nach (2024) emphasises partial symmetry and continued heterogeneity among BRICS countries, while Umoru et al. (2025) present challenging empirical results showing how changes in exchange rates have quick impacts on financial markets and reinforce the leadership of high-volatility and deep market currencies. Overall, these results substantiate the ‘asymmetric and hierarchical’ characterisation of the BRICS exchange-rate network (with RUB and INR as leaders, CNY-ZAR-BRL as followers) for both bull and bear segments.

The Granger causality tests provide a clear picture of short-run transmission patterns among BRICS/USD currency returns over the period from 5 November 2019 to 12 May 2025. Overall, the results reveal an asymmetric and hierarchical structure in which certain currencies function as primary transmitters of shocks, while others behave more passively as shock absorbers. These empirical insights are critical because they provide concrete evidence of the flow of information and short-run shock transmission within the increasingly interconnected BRICS financial system. More specifically, the results indicate that RUB and INR hold dominant positions as the primary sources of short-run shock transmission. INR returns significantly influence movements in RUB ($p = 0.0087$) and ZAR ($p = 0.0061$), while RUB significantly affects BRL ($p = 0.0086$). Conversely, INR is itself significantly affected by movements in RUB ($p = 0.0180$) and CNY ($p = 0.0250$), indicating the presence of bidirectional causality between INR and RUB. CNY acts as a predictor of INR but is not significantly influenced by other currencies, reflecting the tightly managed nature of China’s exchange rate regime (He et al., 2020; Zhang et al., 2021). BRL functions primarily as a shock receiver, especially from RUB, highlighting the importance of global commodity price channels and portfolio capital flows—particularly in energy markets—in shaping its dynamics.

The dominance of RUB and INR within the system aligns closely with the findings of international literature. Antonakakis et al. (2016) and Bekiros (2014) emphasise that Russian and Indian financial markets are characterised by high volatility and strong international linkages, particularly during periods of global turmoil. However, recent empirical studies by Hussain et al. (2024) exhibit high volatility and return connectedness among stocks and exchange rates in BRICS, particularly highlighting the linkages between Russia and India. Within the BRICS context, cross-currency interactions often reflect transmission channels operating through commodity prices, global bond markets, and international portfolio investment flows (Reboredo, 2012; Wang et al., 2021). Ahmed, Siddiqui, and Naushad (2025) also depict strong co-movements between oil prices and exchange rates, as well as equity prices, in BRICS countries, indicating that both RUB and INR are sensitive to global energy shocks. Singh (2024) investigates risk–return and volatility spillovers in BRICS and finds that there is clustering around big transmitters, especially during stress periods. Qabhobho (2023) examines the dynamics of realised volatility connectedness among BRICS foreign exchange markets and shows that spillover patterns fluctuate significantly over time, with notable intensification during periods of crisis. The analysis highlights Russia’s pivotal role as a transmitter of energy-related shocks, consistent with its position as a major global commodity exporter. In contrast, India emerges as an important financial conduit within the region, reflecting its status as one of South Asia’s largest emerging economies and a key destination for international capital flows.

These findings are also in line with conventional models of international macroeconomics and time series econometrics. Sims (1980) introduced the vector autoregression (VAR) model to capture dynamic interactions among economic variables without imposing strong a priori structural restrictions. This method is especially convenient for detecting short-run causal relationships in complex financial systems. Granger (1969) introduced the notion of Granger causality by testing whether past values of one variable offer additional predictive power for another. This approach forms the basis for causality tests in this study.

In addition, Lucas (1976) and Mundell (1961) emphasised the significance of rational expectations and international market integration in cross-border movement of shocks and policies. In this context, the RUB-INR causality regimes detected here are areas of shared market expectations between these economies. CNY and ZAR being somewhat meh makes sense at a theoretical level as well. For the Chinese yuan (CNY), this pattern echoes with China's exchange rate regime of managed-floating, in which the central bank frequently interferes to mitigate potential shocks in the short run (Zhang et al. 2021). On the other hand, even within a relatively financially liberal system, the South African rand (ZAR) tends to function mainly as a shock absorber (Antonakakis et al. 2015). This role may stem from the smaller size of South Africa's economy and its greater sensitivity to global economic conditions. The real from Brazil (BRL), which is a leading commodity exporting economy, experiences the RUB to be a distinct spread of Russia, also being heavily influenced by this currency, which claims to cover the BOURI71576 model but within commodity markets and financial market transmission, as evidenced by that in line with (Reboredo et al. 2018).

These causality patterns could be understood in terms of the exchange rate overshooting model of Dornbusch (1976), which posits that short-run overreactions immediately follow monetary or external expectation shocks for the exchange rate, and are then subsequently corrected to long-run equilibria. The high volatility of the RUB and INR, in turn, accelerates the transmission of such shocks to currencies like the BRL and ZAR through expectations-driven channels. In the current integrated global financial system, these channels are magnified by increased capital market interdependencies (Diebold and Yilmaz 2014) and investor movements that react instantaneously to cross-border information transmission. In combination, the Granger causality results provide not only statistical evidence but also economic content. First, the sequence of summits is readily distinguishable in terms of short-term leadership in the BRICS foreign exchange network, and RUB and INR play a predominant role. Second, a hierarchy arises in which some currencies mainly transmit the shock, while others take on a more passive absorbing role. Third, these results are in close accord with the existing theoretical models and empirical literature in international finance.

CONCLUSION

The stratified diagnostic test results assure the appropriateness of the VAR 8 specification. These econometric prerequisites, particularly stationarity, dynamic stability, and the absence of significant residual autocorrelation, confirm that the operational conditions for GCA are met. The causality test's outcomes readily indicate an evident asymmetry and hierarchy in the short-term propagation of shocks through the BRICS markets and economies. This implies an uninhibited propagation behavior by the Russian ruble and Indian rupee, with a passive shock-receiving functionality observed for the Chinese yuan and South African rand. Especially interesting is the BRl, which is heavily dependent on RUB's behavior and was exposed by the shock analysis. This can be theoretically explained by the excessive use of rents and capital flows between markets associated with Russian natural resources, particularly regarding pricing. The outcomes thus present evidence consistent with the existing literature, emphasizing the pivotal role of the Russian and Indian markets within BRICS and even at the interface of global finance. The Russian and Indian markets lead in spreading both mirroring and informational-content-related volatility to the rest of BRICS and even to the global financial system.

From a policy standpoint, the significance of RUB and INR as core short-run transmitters suggests that closer coordination between exchange rates and more transparent communication around monetary policy will be needed—particularly in times of elevated financial turbulence. Such initiatives might contribute to market stability and contain the spread of shocks within the BRICS currency network. Countries with shock-absorbing currencies (CNY and ZAR) would need to upgrade their policy arsenal to ease short-term external repercussions via targeted FX interventions and macroprudential policies. For international traders, the findings show that the RUB and INR could be lead indicators for the dynamics of other BRICS countries. This is of great significance for the investors in terms of hedge strategy and portfolio diversification, particularly during commodity price shocks and global risk scenarios. Regionally, from a policy perspective, the hierarchical order of short-run causal linkages underscores the urgency to strengthen regional policy coordination mechanisms, such as BRICS forums or regional swap deals. These plans can improve the stability of the BRICS rate system and help respond collectively to cross-market shock spillovers.

However, this paper limits the investigation of short-run causality in a linear VAR model, indicating further scope for research in several directions. At the same time, upcoming research could use nonlinear or regime-switching VAR models to account for potential shifts in causal dynamics between crises and non-crises. Furthermore, the inclusion of external factors like international commodity prices or uncertainty indices may facilitate the detection of third-factor effects in the exchange rate transmission amongst BRICS. The use of Impulse Response Functions (IRF) and Forecast Error Variance Decomposition (FEVD) could also provide more comprehensive information regarding the size and duration of exchange rate shocks. Methodological extensions of this kind would enhance the literature on BRICS exchange rate transmission mechanisms in an ever more sophisticated and integrated global financial system.

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