FORECASTING VOLATILITIES OF CURRENCY EXCHANGE RATES OF EMERGING MARKET ECONOMIES

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Abstract

The degree of nation-to-nation interaction brought on by internationalization has sparked concerns over the possibility of shocks crossing boundaries. The paper forecasted the volatility of exchange rates of currencies in Brazil, Russia, India, China, and South Africa (BRICS) using asymmetric models. Based on the findings, the patterns of predicted volatility indicate that BRICS economies face greater currency risk when doing business abroad in the future. Inflation, previous currency exchange rate volatility, and hikes in interest rate differential are some of the factors contributing to the increased volatility. Due to the interconnectedness of volatility shocks, businesses should employ hedging strategies to lower their exposure to currency market risks. The priors of Bayesian vector autoregression (VAR) demonstrate that the response of consumer price inflation to shocks in volatilities of exchange rates of BRICS declines first and thereafter begins to rise persistently over time. Positive shock to interest rates differential causes the consumer price inflation to rise, stabilizing in the eighth quarter. The findings are further validated by the results' continued robustness under various prior definitions. BRICS need protection against the spillover effect of the volatility in their exchange rates. These findings emphasize the impact of creating monetary policies that help reduce inflationary risks brought on investors by exchange rate swings.

Keywords: Consumer Price Inflation, Bayesian VAR, Exchange Rate Volatility, Foreign Exchange

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1. INTRODUCTION

The shock to the global oil price frequently amplified the effects of multiple shocks, including the credit restrictions and liquidity freezes currently strangling emerging economies. The emerging economies, such as those of Brazil, Russia, India, China, and South Africa (BRICS), are highly sensitive to changes in the price of oil and currency exchange rate variations. All emerging economies suffer from the cumulative negative effects of amplified shocks. Shocks to the economy can affect fundamental indicators of a country's economic health. Shocks to the economy can cause unanticipated shifts in total supply and demand, which could necessitate the implementation of macroeconomic policy. Foreign currency earnings often fall when countries experience a drop in commodity prices, having established a baseline typically in dollars for their annual budgets and development plans based on those revenues. This has an unsettling effect on exchange rates and makes it tough to implement annual budgets and development projects, which in turn accounts for the massive infrastructural deficit and the inability to attain sustainability. This is the main reason why the exchange rate between the currencies of developing countries and international currencies is so high. Certainly, the exchange rate becomes unpredictable, and when it does, it affects the entire economy. The reactions are more intense when the vulnerability is higher. As the global financial shock began, Zulkefly and Karim (2016) report that the currencies of around seven major emerging countries experienced significant losses. Most regional currencies have depreciated against the US dollar, as reported by the World Bank (2024).

Several emerging countries have used foreign debt markets to help pay for infrastructure and social programs after experiencing volatilities of currency exchange rates and this resulted in unexpected economic setbacks. A depreciated currency can have a wide range of negative effects, including higher prices for imported capital goods and operating costs, higher interest rates in dollars, and wider spreads on bonds. It is therefore not surprising that many emerging nations are deeply in debt. This research specifically forecasted the volatility of the exchange rates of the currencies of BRICS in relation to the US dollar. Despite the extensive empirical literature on the relationship between internationally transmitted shocks and the domestic economy, most studies by researchers have focused on the influence of oil price volatility without devoting attention to the volatilities of exchange rates of the currencies. This indicates a gap in the literature, particularly as it relates to non-oil volatility and its effect on consumer pricing in BRICS.

The paper contributes to the literature on the volatility of currency exchange rate dynamics. Given that the dollar has a considerable influence on international transactions, remittances, and domestic inflation rates, and hence domestic prices, policymakers in BRICS countries can take advantage of the volatility prediction of their currencies to execute favourable policy choices as it relates to exchange rate stability. Relatively, the fact that the volatility in the exchange rate of a country can affect investment in that country by creating an uncertain business environment for investment in that country makes forecasts of the volatility of the exchange rates of BRICS to the US dollar useful for valuing currency options. The paper contributed to the importance of volatility forecasting, which is essentially needed to evaluate all foreign-denominated cash flows in terms of exchange risks and gains or returns connected to international transactions. The effects of shocks in exchange rates are asymmetric. Understanding that currency exchange rates are characterized by asymmetrical volatility risk, the paper outlined the policy requirement for BRICS businesses and investors to effectively implement a hedging strategy against currency exchange risk that impacts transactions on the foreign exchange (FX) market. The study highlights the need for BRICS to uphold international competitiveness in foreign markets to forestall market fluctuations by implementing a hedging scheme. The foreign exchange market does not always follow a predicted pattern of volatility. This paper contributed to the literature on the volatility of currency exchange rates of emerging market economies.

The rest of the study is structured as follows. Section 2 presents a theoretical and empirical review of the literature. Section 3 describes the research methodology. Section 4 provides the results. Section 5 discusses the main findings. Section 6 concludes the paper.

2. LITERATURE REVIEW

Numerous studies have been conducted on the subject of exchange rate volatility and its forecasting. Nonetheless, we have chosen to restrict the concise review to the most recent studies. These include Sönmez and Birim (2024), Alwadeai et al. (2024), Umoru, Effiong, Umar, Ugbaka, et al. (2023), Khaliq (2022), Umoru and Amedu (2022), Umoru and Shaibu (2022), Sugita (2022), Ho et al. (2022), Wan et al. (2021), Dai et al. (2020), Liu et al. (2020), Engel et al. (2019), and Habibi and Lee (2019). The aforementioned studies have all found effects of the volatility of currency exchange rates. Based on the evaluation of different models, the bi-long short-term memory (LSTM) and gated recurrent units (GRUs) models were found by Sönmez and Birim (2024) to be the best models for forecasting exchange rates, especially when the period is characterized by high volatility. Alwadeai et al. (2024) found that high reserves-to-GDP (gross domestic product) ratios cannot be relied upon for the stability of exchange rate volatility and its forecasting in the presence of economic sanctions. The volatility of the exchange rate affects stock prices asymmetrically, foreign reserves asymmetrically, industrial production, and oil prices (Umoru, Effiong, Umar, Ugbaka, et al., 2023). In particular, Umoru, Effiong, Umar, Okpara, et al. (2023) established the presence of a volatility spillover effect in exchange rates, implying the transmission of harmful volatility effects from one country to another.

In another recent study, Umoru, Effiong, Umar, Ugbaka, et al. (2023) forecasted exchange rate dynamics in emerging countries and reported that the Ghanaian exchange rates exhibited upward movements in the variance curve and were projected to rise significantly. The authors also reported a highly persistent exchange rate for Nigeria, whereby the forecasting model took into account 98% of the unsystematic error. Khaliq (2022) established that domestic risks influenced the forecasting and stability of Indonesia's currency exchange rate in relation to US dollar volatility. Umoru and Amedu (2022) deployed the dynamic generalized method of moments (GMM) approach to establish that volatility in the exchange rate had positive effects on commodity prices in Africa. In a similar study, Umoru and Shaibu (2022) reported a significant negative impact of exchange rate devaluation on consumption spending in Sub-Saharan Africa (SSA). According to Sugita (2022), iterated forecasts with models based on stochastic search variable selection prior are better off for out-of-sample performance.

According to Ho et al. (2022), the smooth transition exponential smoothing (STES) models with realized variance as the transition variable surpassed *ad hoc* methods and generalized autoregressive conditional heteroskedasticity (GARCH) models under the root mean square error (RMSE) evaluation criteria. The study by Wan et al. (2021) for the Malaysia Mutual Fund Indices established that the STES method surpassed the GARCH model. According to Dai et al. (2020), the variations in the RMB/USD exchange rate in China significantly increase the volatility forecasting performance of empirical models. According to Liu et al. (2020), the STES surpassed the exponential smoothing and GARCH techniques in forecasting eight stocks even in the presence of outliers in forecasting. In their research, Engel et al. (2019) observed that the essentials of the Taylor rule influence forecast changes in US dollar exchange rates outside of the sample. Similar results were obtained by Habibi and Lee (2019). For Malaysian real estate stocks, Gooi et al. (2018) established that the STES technique surpassed the GARCH forecasting approach.

3. RESEARCH METHODOLOGY

The countries covered in this study include Brazil, Russia, India, China, and South Africa. These are emerging countries widely known as BRICS. The BRICS are prominent emerging nations with common bilateral relations piloted based on equality, non-interference, and common benefit. Before the estimation, we begin with the unit root test. We also proceeded to obtain a co-integrating link among the variables. There are alternative forecasting techniques, namely Autoregressive integrated moving average (ARIMA) forecasting techniques, fuzzy network models of forecasting, structural panel Bayesian VAR (SPBVAR), STES, exponential smoothing forecasting methods, and moving average forecasting techniques that could be utilized in forecasting exchange rate volatility. Numerous forecasting methods can be used to analyze exchange rate volatility. Fuzzy models can recognize complex patterns, but they also require a lot of data and processing capacity to generate predictions. Although it relies on prior distributions, which may introduce bias, SPBVAR performs well for dynamic panel connections. STES, exponential smoothing, and moving average forecasting are good at finding trends, but they cannot foresee abrupt shifts in the market.

In light of preceding drawbacks, the GARCH family of models which includes GARCH model credited to Bollerslev (1986) and Glosten et al.'s (1993) Threshold GARCH (GJR-GARCH) model were employed in this study to realistically reflect the asymmetric nature of exchange rate swings and also in consideration of the asymmetric nature of the forex market. According to Nugroho et al. (2019), the GJR-GARCH models have enhanced performance over the GARCH model. Nevertheless, we choose to specify both the GJR-GARCH and the GARCH models and determine the best model based on the performance measures, namely, mean absolute error (MAE), root mean square error (RMSE), Theil inequality coefficient, and mean absolute percent error (MAPE), to forecast the volatility of the exchange rates of the currencies of BRICS. The GARCH and GJR-GARCH equations are specified in Eq. (1) and Eq. (2), respectively:

Bollerslev (1986) independently expounded the autoregressive conditional heteroskedasticity (ARCH) model and developed the GARCH model. GARCH (p, q) and (1, 1) models of conditional variance are specified thus:

$$\partial_t^2 = \vartheta + \sum_{i=1}^{p} \omega_i \epsilon_{t-i}^2 + \sum_{j=1}^{q} \tau_j \partial_{t-j}^2 \quad (1)$$

$$\partial_t^2 = \vartheta + \omega_i \epsilon_{t-1}^2 + \tau_i \partial_{t-1}^2 \quad (2)$$

The GARCH process is stationary if $\omega_i + \tau_j < 1$. If the stationarity condition is fulfilled the conditional variance converges towards the unconditional variance $\vartheta/1 = (\omega + \tau)$. Thus, $\vartheta > 0, \omega_i \geq 0, i = 1,2,3 \dots p, \tau_j \geq 0, j = 1,2,3 \dots q$. The ω_i coefficient captures market news. In particular, the ω_i explains how fast the model reacts to news on the market while τ_j explains how persistent the conditional variance is over time. The GJR-GARCH (p, q) model is defined as:

$$\partial_t^2 = \emptyset + \sum_{i=1}^{q}\left(\pi_i \in_{t-i}^2\right) + \sum_{i=1}^{q}\left(\gamma_i d(\in_{t-i} < 0) \in_{t-i}^2\right) + \sum_{j=1}^{p}\left(\omega_j \partial_{t-j}^2\right) \quad (3)$$

where $I(\epsilon_t < 0)$ is an indicator function, which takes the value one if the corresponding lagged unconditional standard deviation is less than zero. The GJR-GARCH (1, 1) model is defined as: $\partial_t^2 = \rho + \omega + \in_{t-1}^2 + \theta_1 I(\in_t < 0) \in_t^2 + \tau_1 \partial_t^2$.

The alternative specification is given by Eq. (4):

$$\partial_t^2 = \phi + (\mu_i + \vartheta \mathbb{I}_{t-i})\epsilon_{t-i}^2 + \tau_i \partial_{t-i}^2, \quad \vartheta_i > 0, \tau_i > 0 \quad (4)$$

$$\begin{cases} I_{t-i}(\in_{t-i}) = \in_{t-i} \ \forall \in_{t-i} > 0 \\ I_{t-i}(\epsilon_{t-i}) = 0, otherwise \end{cases}$$

where ∂_t^2 is the volatility in the present period, ϕ is constant, τ_i are the coefficients of volatility in the previous period, I_{t-i} is the indicator function, and ϑ_i are the squared error coefficients. The paper also analyzes the response of cpi to shocks in global oil prices, currency volatility, and interest rate differentials using the Bayesian VAR modelling technique. In line with Oladunni (2019), we adopt the Normal-Wishart prior specification, the Litterman/Minnesota prior and stochastic search variable selection (SSVS) to assess the level of sensitivity in our findings. The Bayesian VAR model is thus specified as:

$$Z_t = B_0 + B_1 Z_{t-1} + B_2 Z_{t-2} + \cdots + B_p Z_{t-p} + u_t \quad (5)$$

where $Bi \sim$ normal (bi, Vi) for $\forall\, i = 0$ representing the priors for the coefficients.

The Z — variables can be explained as cpi_t is consumer price inflation, *cvol* is the volatility of the exchange rates of the currencies of BRICS (of the Brazilian Real/USD, Rubble/USD, Rupee/USD, Yuan/USD, and Rand/USD exchange rate), a proxy for global currency volatility; *indff* is interest rate differential, measured as the difference in the interest rates of each BRICS country and the US rate; and *oilp* is international oil price volatility. The specifications ARIMA model were as follows:

$$AR(p)\colon cvol_t = \emptyset + b_1 cvol_{t-1} + \cdots + b_p cvol_{t-p} + u_t \quad (6)$$

Using lag operator, the general AR(p) model of government expenditure becomes:

$$AR(p) = \left(1 - \sum_{i=1}^{p} \alpha_i L^i\right) cvol_t = \left(1 - \sum_{i=1}^{p-d} \varphi_i L^i\right)(1 - L)^d \quad (7)$$

$$MA(q)\colon cvol_t = \gamma + d_0 \in_t + \alpha_1 \in_{t-1} + \cdots + \alpha_q \in_{t-q} \quad (8)$$

$$ARMA(p,q)\colon cvol_t = \vartheta + \sum_{i=1}^{p} \theta_i cvol_{t-i} + \rho_0 \in_t + \sum_{j=1}^{q} \rho_j \in_{t-j} \quad (9)$$

ARIMA (p, d, q) can be specified for different values of d. These are given in Eq. (10) and Eq. (11):

$$cvol_t = \emptyset + \sum_{i=1}^{p} \in_i (cvol_t - cvol_{t-d})_{t-i} + \rho_0 \in_t + \sum_{j=1}^{q} \rho \in_{t-j} \text{ for } d = 1 \quad (10)$$

$$cvol_t = \emptyset + \sum_{i=1}^{p} \in_i (cvol_t - 2cvol_{t-1} + cvol_{t-d})_{t-i} + \rho_0 \in_t + \sum_{j=1}^{q} \rho_j \in_{t-j} \text{ for } d = 2 \quad (11)$$

Using lag operator, the general ARIMA model of government expenditure becomes:

$$ARIMA\ (p,d,q) = \left(1 - \sum_{i=1}^{p} \varphi_i L^i\right)(1 - L)^d cvol_t = \left(1 + \sum_{i=1}^{q} \theta_i L^i\right) \in_t \quad (12)$$

where p is the lag of *cvol*, q is the lag of error terms, $\in$ is an error term, $\emptyset$, γ, ϑ, are constants, d is the order of integration (number of times the model is differenced). The *cpi* was sourced from World Development Indicators, and interest rate differentials were sourced from the World Bank database. The world oil prices were obtained from the International Energy Agency (IEA). The exchange rates are averages of quarterly exchange rate series. The volatilities were measured by calculating the standard deviation series of the variances of the Brazilian Real/USD, Rubble/USD, Rupee/USD, Yuan/USD, and Rand/USD exchange rate changes around the mean from the exponential generalized autoregressive conditional heteroscedasticity (EGARCH) model. Interest rate differential was calculated as the difference in the interest rates of each BRICS country and US rate; each variable had a range of values from 1990Q1 to 2023Q4. Interest rate differentials were calculated as the difference between the foreign interest rate and the domestic interest rate. Specifically, it was calculated as the difference between the US interest rate and interest rates in Brazil, Russia, South Africa, India, and China. To interpret in percentages, all the variables were converted into logarithmic form.

4. RESULTS

The panel unit root test results presented in Table 1 indicate that *lncpi* (log of *cpi*) are stationary at the level and first differenced with the inclusion of an intercept. This result is not true for the Breitung unit root test, which indicates the *lncpi* is not stationary when assumed to have an intercept and trend. In the log of global oil prices based on the Levin, Lin, and Chu test, the variable is stationary at a level and first difference. The same result is evidence for the Breitung test for panel integration.

Table 1. Panel unit root test results

Variables	*Method*	*Statistics-levels*	*Probability*	*Statistics-difference*	*Probability*
		-2.83	0.00	-10.49	0.00
lncpi	llc t*	0.25	0.60	-10.10	0.00
	B t-stat	1.28	0.90	0.88	0.81
	llc t*	-3.25	0.00	-18.05	0.00
lnoilp	llc t*	-2.21	0.01	-15.13	0.00
	B t-stat	-1.62	0.05	-2.13	0.02
	llc t*	-0.14	0.45	-14.68	0.00
lncvol	llc t*	3.71	1.00	-14.12	0.00
	B t-stat	-1.64	0.05	-11.72	0.00
	llc t*	1.48	0.93	-12.43	0.00
lnindff	llc t*	-1.85	0.03	-10.74	0.00
	B t-stat	-7.96	0.00	-8.56	0.00

Note: llc = Levin, Lin & Chu t, B = Breitung.*

The log of *cpi* is only stationary at the first difference. Including trends in the data-generating process, the variable is non-stationary. This later analysis of non-stationary is applicable when considering the Breitung test. The exchange rate of BRICS currencies to dollars and interest rate differentials are both stationary at the level and first difference. Irrespective of whatever, with or without trend, the results of the Breitung test corroborate the results of the Levin, Lin, and Chu tests.

The estimated conditional standard deviation is stationary at first, without trend. The latter result is corroborated by the Breitung test. The panel-co-integrating relationship is presented in Table 2. From the results, the Pedroni co-integration indicates the weak presence of a panel co-integrating relationship. Nevertheless, judging by augmented Dickey-Fuller (ADF) statistics, we could potentially accept the presence of a co-integrating association at a 0.05 significance level. We also examine the panel co-integrating relationship, and the results are presented in Table 4. The Kao residual co-integrating relationship is only present at a 0.10 significance level. The Fisher panel co-integrating relationship indicates the presence of one co-integrating relationship at a 0.05 significance level. This study further examines the dynamic relationship between shocks in global oil prices, the volatility of the exchange rates of the currencies of BRICS, the interest rate differential, and the response of *cpi* in BRICS using the Bayesian VAR model.

Table 2. Pedroni co-integration results

Test methods	*Statistic*	*Prob.*	*Statistic*	*Prob.*
Panel v-Statistic	-2.55	0.99	-4.05	1
rho-Statistic	1.72	0.96	2.29	0.99
PP-Statistic	-0.75	0.23	0.44	0.67
ADF-Statistic	-0.77	0.22	-2.33	0.01

In terms of model selection, a better model should have the smallest SIGMA, smallest SIC, and smallest AIC, while adjusted R^2 should be higher, and the number of significant coefficients should be higher. The total number of significant coefficients should be higher. The higher the SIGMA value, the higher the volatility. For Brazil, Table 3 shows that for ARIMA (1, 1, 2), the adjusted R^2 is higher, AIC has the smallest value (6.579), and SIGMA is the smallest (1.03). The ARIMA (1, 1, 2) model is therefore chosen for the Brazilian economy as the best model for residual diagnostics, such as residual correlograms, tests for SC (Lung-box test), tests for heteroskedasticity (ARCH test statistic), and finally estimation of ARCH and GARCH models before forecasting. Similarly, ARIMA (2, 1, 2), ARIMA (2, 1, 1), ARIMA (4, 1, 2), and ARIMA (2, 1, 3) models were chosen for Russia, India, China, and South Africa, respectively. These models are well fitted considering the low values of AIC and SC, respectively. We did an out-of-sample forecast from 2022Q1 to 2030Q4.

Table 3. Results of model selection for BRICS countries

		Brazil		
Statistics	*ARIMA (1, 1, 2)*	*ARIMA (4, 1, 9)*	*ARIMA (6, 1, 2)*	*ARIMA (6, 1, 9)*
SIGMA	1.034	5.782	3.671	2.675
Adj. R^2	0.295	0.072	0.056	0.026
AIC	6.579	9.304	9.549	10.655
SIC	0.092	1.268	0.193	2.179
Significant coefficients	3	3	3	3
		Russia		
Statistics	*ARIMA (2, 1, 2)*	*ARIMA (4, 1, 9)*	*ARIMA (6, 1, 2)*	*ARIMA (6, 1, 9)*
SIGMA	0.014	0.578	1.047	0.157
Adj. R^2	0.589	0.4702	0.012	0.386
AIC	4.301	4.501	5.159	6.255
SIC	0.012	1.023	0.103	1.124
Significant coefficients	3	3	3	3
		Indian		
Statistics	*ARIMA (4, 1, 2)*	*ARIMA (2, 1, 1)*	*ARIMA (6, 1, 2)*	*ARIMA (6, 1, 9)*
SIGMA	1.034	0.123	2.671	1.675
Adj. R^2	1.476	0.5025	0.056	0.126
AIC	3.468	1.104	6.424	3.655
SIC	0.012	0.068	0.593	2.692
Significant coefficients	3	3	3	3
		China		
Statistics	*ARIMA (4, 1, 2)*	*ARIMA (4, 1, 9)*	*ARIMA (6, 1, 2)*	*ARIMA (6, 1, 9)*
SIGMA	0.154	2.209	1.345	1.665
Adj. R^2	0.269	0.130	0.136	0.271
AIC	0.034	1.564	1.450	1.566
SIC	0.011	0.302	0.127	1.359
Significant coefficients	3	3	3	3
		South Africa		
Statistics	*ARIMA (4, 1, 2)*	*ARIMA (4, 1, 9)*	*ARIMA (6, 1, 2)*	*ARIMA (2, 1, 3)*
SIGMA	0.035	0.182	1.271	0.075
Adj. R^2	0.035	0.390	0.256	0.426
AIC	0.560	1.004	0.579	0.465
SIC	0.192	3.180	0.259	1.210
Significant coefficients	3	3	3	3

An inspection of the correlogram of residuals reported in Table 4 shows that all values of autocorrelation function (ACF) and partial autocorrelation function (PACF) are less than unity (1) for the volatility of the Brazilian Real/USD, Rubble/USD, Rupee/USD, Yuan/USD, and Rand/USD exchange rates. The p-values for the greater part of the analysis are significant. In effect, the residual correlogram for ARIMA models, namely, ARIMA (1, 1, 2), ARIMA (2, 1, 2), ARIMA (2, 1, 1), ARIMA (4, 1, 2), and ARIMA (2, 1, 3) are stationary. Nevertheless, the Lung-box test reported in terms of the Q-statistic is highly significant, with the implication that serial correlation is present in the models.

Table 4. Residual correlogram of BRICS currencies/US dollar volatility rate

ARIMA (4, 1, 2) residual correlogram for R$/US$ volatility — Brazil				
Lags	***ACF***	***PACF***	***Q-Stat***	***Prob.***
1	-0.0000	-0.0012	3.0003	0.3460
2	0.0493	0.0479	2.7913	0.0000
3	-0.0075	-0.0071	4.356	0.0000
4	-0.2469	-0.2413	5.0283	0.0080
5	-0.0388	-0.0382	13.174	0.620
6	0.0049	0.0046	14.589	0.8790
7	-0.0639	-0.0617	17.468	0.6890
8	-0.0018	-0.0019	20.518	0.9470
9	0.0034	0.0036	23.475	0.2650
10	-0.0016	-0.0015	25.168	0.4670
11	-0.0200	-0.0123	25.153	0.3560
12	-0.0010	-0.0019	26.780	0.7540
ARIMA (4, 1, 2) residual correlogram for Rubble/US$ volatility — Russia				
1	-0.0000	-0.0112	3.579	0.0000
2	0.0293	0.0579	5.794	0.0000
3	-0.0175	-0.0135	2.237	0.0000
4	-0.2169	-0.2133	22.497	0.4980
5	-0.0318	-0.0382	23.174	0.6120
6	0.0454	0.0246	24.189	0.3579
7	-0.0652	-0.0217	27.068	0.5509
8	-0.0218	-0.0139	30.118	0.2354
9	0.0234	0.0246	34.475	0.4450
10	-0.0216	-0.2455	29.128	0.4670
11	0.1534	0.2546	14.985	0.3650
12	-0.2306	-0.7955	15.588	0.2170
ARIMA (4, 1, 2) residual correlogram for Rupee/US$ volatility — India				
1	-0.0000	-0.0462	4.5346	0.0000
2	0.0233	0.0203	2.3463	0.0000
3	-0.3815	-0.004	22.356	0.0000
4	-0.2329	-0.2204	1.0283	0.0000
5	-0.0353	-0.0132	41.174	0.2568
6	0.0394	0.0156	10.189	0.7693
7	-0.0602	-0.0671	17.268	0.4590
8	-0.0261	-0.0230	20.418	0.3870
9	0.0024	0.2436	63.075	0.3350
10	-0.0126	-0.3610	44.068	0.7670
11	0.3454	0.1350	24.233	0.52 89
12	-0.0009	-0.3247	41.785	0.2100
ARIMA (4, 1, 2) residual correlogram for R$/US$ volatility — China				
1	-0.0000	-0.0012	12.459	0.2434
2	-0.0421	0.0479	2.7945	0.0000
3	-0.2817	-0.0071	10.126	0.6843
4	-0.5290	-0.2413	21.023	0.4980
5	-0.0882	-0.0382	1.1468	0.0000
6	0.0491	0.0046	10.520	0.8790
7	-0.2395	-0.0617	1.2398	0.0000
8	-0.018	-0.0019	2.648	0.0000
9	0.0342	0.0036	3.5475	0.0000
10	-0.0285	-0.0015	5.1268	0.4670
11	-0.0390	-0.0123	5.1523	0.3590
12	-0.0465	-0.0019	6.7806	0.7320
ARIMA (4, 1, 2) residual correlogram for R$/US$ volatility — South Africa				
1	-0.0000	-0.0012	2.0461	0.0000
2	0.0003	0.0129	2.7024	0.0000
3	-0.0120	-0.0261	4.3610	0.0000
4	-0.0216	-0.2303	5.063	0.0000
5	-0.0018	-0.0412	10.234	0.6120
6	0.0019	0.0296	4.589	0.0000
7	-0.0209	-0.0307	5.468	0.0000
8	-0.0388	-0.0129	1.518	0.0000
9	-0.0390	0.0106	20.475	0.2650
10	-0.0361	-0.0350	15.168	0.4670
11	-0.0160	0.1157	19.125	0.5680
12	-0.0181	-0.0409	11.180	0.4589

Also, the results of the ARCH-LM test results of Table 5 provided evidence in favor of the presence of the ARCH effect in the volatilities of all the BRICS currencies to dollar. The implication here is that the variance coefficient increases over time.

Table 5. ARCH-LM test results for residuals of BRICS currencies/US dollar volatility rate

Brazil, Real/US$ volatility			
LM F-stat	***Obs. R^2***	***Prob (F-value)***	***Prob. (Chi^2)***
38.973	38.029	0.0000	0.0000
Russia, Ruble/US$ volatility			
20.120	21.056	0.0000	0.0000
India, Rupee/US$ volatility			
24.09	32.685	0.0000	0.0000
China, Yuan/US$ volatility			
17.35	23.47	0.0000	0.0000
South Africa, Rand/US$ volatility			
40.15	47.28000	0.000000	0.000000

Table 6 contains the results of the ARCH and GARCH models estimations, respectively. In Table 8, all the variance equations had significant ARCH and GARCH coefficients as well as a significant intercept. The sum of ARCH (1) and GARCH (1, 1) < 1. This meets the requirement of parameter constraint with evidence of high volatility.

Table 6. Results of model estimation for BRICS countries (Part 1)

Results of the GJR-GARCH model for Brazil			
Variables	***Coefficient***	***z-statistic***	***Probability***
Mean equation			
c	0.0371	12.300	0.0000
ar(1)	-0.1490	-9.583	0.0000
ma(1)	0.0397	0.481	0.4681
ma(2)	0.0245	14.568	0.0000
Variance equation			
c	1.0255	100.379	0.0000
arch(1)	0.0247	110.346	0.0000
garch(1)	0.9236	192.589	0.0000
gamma (1)	-0.0785	-196.794	0.0000
aic	2.0068	SC	2.0179
dw	2.1190	Log-likelihood	-1234.85
Results of the GARCH model for Brazil			
Mean equation			
c	1.0372	10.357	0.0000
ar(1)	-0.0190	-6.520	0.0000
ma(1)	0.0210	123.579	0.0000
ma(2)	0.3358	140.132	0.0000
Variance equation			
c	1.0821	4.3781	0.0000
arch(1)	0.2251	164.768	0.0000
garch(1)	0.7636	112.529	0.0000
aic	2.0000	SC	2.0005
dw	2.0090	Log-likelihood	-1034.69
Results of the GJR-GARCH model for Russia			
Mean equation			
c	1.2790	20.457	0.0000
ar(1)	-0.1562	-7.659	0.0000
ma(1)	0.0140	20.349	0.0000
ma(2)	-0.0190	-27.468	0.0000
Variance equation			
c	-1.0930	-11.058	0.0000
arch(1)	0.3109	13.689	0.0000
garch(1)	0.6671	184.103	0.0000
gamma (1)	-0.0254	-122.021	0.0000
aic	0.0221	SC	1.0200
dw	1.9900	Log-likelihood	-113.60
Results of the GARCH model for Russia			
Mean equation			
c	-1.0837	-23.479	0.0000
ar(1)	-0.1793	-17.501	0.0000
ma(1)	0.2836	1390.57	0.0000
ma(2)	1.0023	100.038	0.0000
Variance equation			
c	0.4618	50.479	0.0000
arch(1)	0.3354	200.489	0.0000
garch(1)	0.5731	209.476	0.0000
aic	1.390	SC	1.4578
dw	2.0145	Log-likelihood	-1255.95

Table 6. Results of model estimation for BRICS countries (Part 2)

Results of the GJR-GARCH model for India			
Variables	***Coefficient***	***z-statistic***	***Probability***
Mean equation			
c	1.3410	25.687	0.0000
ar(1)	-0.5471	-40.568	0.0000
ma(1)	0.0082	16.137	0.0000
ma(2)	0.0011	29.851	0.0000
Variance equation			
c	0.1039	97.034	0.0000
arch(1)	0.0821	89.012	0.0000
garch(1)	0.7652	134.568	0.0000
gamma (1)	-0.0381	-170.457	0.0000
aic	0.3750	SC	0.0150
dw	2.0349	Log-likelihood	-28410
Results of the GARCH model for India			
Mean equation			
c	-0.2827	-19.368	0.0000
ar(1)	0.4032	46.781	0.0000
ma(1)	0.6840	145.600	0.0000
ma(2)	0.2710	189.037	0.0000
Variance equation			
c	-0.9370	-170.587	0.0000
arch(1)	0.3183	150.129	0.0000
garch(1)	0.6581	126.508	0.0000
aic	0.1787	SC	0.1048
dw	2.1470	Log-likelihood	-1209.45
Results of the GJR-GARCH model for China			
Mean equation			
c	-0.3781	-100.289	0.0000
ar(1)	0.2390	123.578	0.0000
ma(1)	0.0715	162.679	0.0000
ma(2)	0.1039	1456.69	0.0000
Variance equation			
c	1.5237	367.578	0.0000
arch(1)	0.2589	134.100	0.0000
garch(1)	0.6670	200.476	0.0000
gamma (1)	-0.1630	-234.028	0.0000
aic	0.376	SC	0.6759
dw	2.530	Log-likelihood	-1873.5
Results of the GARCH model for China			
Mean equation			
c	0.3475	561.578	0.0000
ar(1)	-0.0378	-90.488	0.0000
ma(1)	0.0941	146.096	0.0000
ma(2)	0.1270	165.986	0.0000
Variance equation			
c	0.5789	293.578	0.0000
arch(1)	0.1256	136.210	0.0000
garch(1)	0.7851	124.596	0.0000
aic	0.1376	SC	0.5670
dw	2.0000	Log-likelihood	-1357.6
Results of the GJR-GARCH model for South Africa			
Mean equation			
c	1.6590	130.851	0.0000
ar(1)	-0.3497	199.586	0.0000
ma(1)	0.0266	1457.12	0.4681
ma(2)	0.0167	1987.69	0.0000
Variance equation			
c	-0.5782	-130.419	0.0000
arch(1)	0.2114	179.127	0.0000
garch(1)	0.8013	245.457	0.0000
gamma (1)	-0.0245	-111.193	0.0000
aic	0.0420	SC	0.4569
dw	2.2476	Log-likelihood	-1054.10
Results of the GARCH model for South Africa			
Mean equation			
c	-0.3545	-110.970	0.0000
ar(1)	-0.0231	-3456.34	0.0000
ma(1)	0.0475	293.782	0.0000
ma(2)	0.0327	160.345	0.0000
Variance equation			
c	0.7124	203.587	0.0000
arch(1)	0.2760	150.416	0.0000
garch(1)	0.7035	187.652	0.0000
aic	0.4560	SC	0.4655
dw	1.897	Log-likelihood	-1894.65

Table 7 contains the results of the ARCH-LM tests. The comparison between the two models of volatility is made in Table 9. Accordingly, the values of the LM statistic differ with respect to each currency.

Table 7. ARCH-LM test results for the residuals currency exchange rate volatility

Statistic	GARCH	GJR-GARCH
Real/US$ volatility		
LM-statistic	0.6542	0.8942
Obs. R^2	0.6501	0.8560
Prob. (F-value)	0.5314	0.5010
Prob. (Chi^2)	0.5762	0.5012
Rubble/US$ volatility		
LM-statistic	0.5326	0.1942
Obs. R^2	0.3480	0.6560
Prob. (F-value)	0.9234	0.6670
Prob. (Chi^2)	0.5659	0.4892
Rupee/US$ volatility		
LM-statistic	0.5142	0.4642
Obs. R^2	0.6201	0.5260
Prob. (F-value)	0.5414	0.5410
Prob. (Chi^2)	0.3562	0.2730
Yuan/US$ volatility		
LM-statistic	0.2243	0.3542
Obs. R^2	0.3705	0.2460
Prob. (F-value)	0.2214	0.7910
Prob. (Chi^2)	0.5862	0.2412
Rand/US$ volatility		
LM-statistic	0.5320	0.9242
Obs. R^2	0.5490	0.5360
Prob. (F-value)	0.3214	0.2780
Prob. (Chi^2)	0.7262	0.3325

The results of Table 8 show that the forecasting ability of the relevant models was ascertained based on performance measures such as mean absolute error (MAE), root mean square error (RMSE), Theil inequality coefficient, and mean absolute percent error (MAPE). As revealed in Table 10, the GJR-GARCH model yielded the smallest performance values for measuring prediction errors. The implication is that the asymmetric model provides enhanced forecasting performance of the forex market dynamics following the presence of a leverage effect. In effect, there are asymmetric effects of the Brazilian Real/USD, Rubble/USD, Rupee/USD, Yuan/USD, and Rand/USD exchange rate volatility in all the countries of the BRICS. This indeed validated the results obtained from the nonlinear autoregressive distributed lag (NARDL) estimation.

Table 8. Forecast performance results of estimated models for BRICS countries

Forecast measures	GARCH	GJR-GARCH
Brazil		
RMSE	0.7239	0.5589
MAE	0.5624	0.5352
MAPE	0.5914	0.5470
Theil inequality coefficient	0.0012	0.0001
Russia		
RMSE	0.3539	0.2701
MAE	0.3424	0.3152
MAPE	0.5946	0.4260
Theil inequality coefficient	0.0056	0.0023
India		
RMSE	0.2839	0.2370
MAE	0.2424	0.2352
MAPE	0.1710	0.1470
Theil inequality coefficient	0.0082	0.0059
China		
RMSE	0.3831	0.3189
MAE	0.3624	0.3521
MAPE	0.4670	0.4710
Theil inequality coefficient	0.0032	0.0002
South Africa		
RMSE	0.2480	0.1289
MAE	0.3740	0.3652
MAPE	0.2390	0.2370
Theil inequality coefficient	0.0042	0.0003

Table 9 reports the out-of-sample forecast results for the quarters of 2020, 2021, and 2022. The forecasted volatility is close to the actual. The bias in prediction, as denoted by the deviation between forecasted and actual volatilities, lies within the range of $0.078 < \text{error} < 0.322$ for Brazil, Russia, India, China, and South Africa, respectively. Given that no bias was up to 1, the robustness of the forecasted GJR-GARCH model is established.

Table 10 below presents out-of-sample forecasts. Table 11 provides a summary of the forecasted values for currency exchange rate variations in BRICS.

Table 9. In-sample forecast results for volatility in the exchange rates of currencies

Brazil			
Real/US$ volatility	***Forecasted value (%)***	***Actual value (%)***	***Error (%)***
1st Quarter 2020	2.356	2.344	-0.012
2nd Quarter 2020	0.278	0.256	-0.022
3rd Quarter 2020	1.560	1.585	0.025
4th Quarter 2020	0.247	0.242	-0.005
1st Quarter 2021	0.356	0.354	-0.002
2nd Quarter 2021	1.278	1.256	-0.022
3rd Quarter 2021	1.560	1.585	0.025
4th Quarter 2021	3.247	3.252	0.005
1st Quarter 2022	1.356	1.034	-0.322
2nd Quarter 2022	2.278	2.356	-0.078
3rd Quarter 2022	5.120	1.585	-3.535
4th Quarter 2022	1.247	1.042	-0.205
Russia			
Rubble/US$ volatility	***Forecasted value (%)***	***Actual value (%)***	***Error (%)***
1st Quarter 2020	1.563	1.463	-0.100
2nd Quarter 2020	0.781	0.771	-0.010
3rd Quarter 2020	1.602	1.322	-0.280
4th Quarter 2020	1.477	1.577	0.100
1st Quarter 2021	1.569	1.469	-0.100
2nd Quarter 2021	1.783	1.883	0.100
3rd Quarter 2021	2.602	0.502	-2.100
4th Quarter 2021	1.452	1.371	-0.081
1st Quarter 2022	1.560	1.260	-0.300
2nd Quarter 2022	1.749	1.989	0.2400
3rd Quarter 2022	1.625	1.523	-0.102
4th Quarter 2022	1.475	1.375	-0.100
India			
Rupee/US$ volatility	***Forecasted value (%)***	***Actual value (%)***	***Error (%)***
1st Quarter 2020	0.564	1.504	0.9400
2nd Quarter 2020	0.783	1.736	0.9530
3rd Quarter 2020	1.602	0.665	-0.9370
4th Quarter 2020	2.471	2.472	0.0010
1st Quarter 2021	0.562	0.534	-0.0280
2nd Quarter 2021	1.783	1.756	-0.0270
3rd Quarter 2021	1.604	1.665	0.0610
4th Quarter 2021	0.472	0.452	-0.0200
1st Quarter 2022	1.563	1.564	0.0010
2nd Quarter 2022	2.781	2.856	0.0750
3rd Quarter 2022	1.608	1.665	0.0570
4th Quarter 2022	1.475	1.472	-0.0030
China			
Yuan/US$ volatility	***Forecasted value (%)***	***Actual value (%)***	***Error (%)***
1st Quarter 2020	2.560	2.534	-0.0260
2nd Quarter 2020	3.789	3.756	-0.0330
3rd Quarter 2020	3.609	3.685	0.0760
4th Quarter 2020	2.475	2.342	-0.1330
1st Quarter 2021	1.065	1.534	0.4690
2nd Quarter 2021	1.784	1.956	0.1720
3rd Quarter 2021	1.602	1.685	0.0830
4th Quarter 2021	1.473	1.442	-0.0310
1st Quarter 2022	3.562	3.434	-0.1280
2nd Quarter 2022	1.581	1.756	0.1750
3rd Quarter 2022	4.601	4.685	0.0840
4th Quarter 2022	2.413	2.442	0.0290
South Africa			
Rand/US$ volatility	***Forecasted value (%)***	***Actual value (%)***	***Error (%)***
1st Quarter 2020	0.356	1.034	0.6780
2nd Quarter 2020	0.278	0.356	0.0780
3rd Quarter 2020	1.560	1.685	0.1250
4th Quarter 2020	1.371	1.242	-0.1290
1st Quarter 2021	1.026	1.034	0.0080
2nd Quarter 2021	1.278	1.356	0.0780
3rd Quarter 2021	1.560	1.685	0.1250
4th Quarter 2021	1.237	1.242	0.0050
1st Quarter 2022	3.356	3.034	-0.3220
2nd Quarter 2022	6.278	6.356	0.0780
3rd Quarter 2022	2.560	2.685	0.1250
4th Quarter 2022	5.265	7.123	1.8580

Table 10. Forecast results for volatility in the exchange rates of BRICS currencies

Brazil	
Real/US$ volatility	***Forecasted value (%)***
1st Quarter 2024	2.047
2nd Quarter 2024	3.168
3rd Quarter 2024	3.190
4th Quarter 2024	3.257
1st Quarter 2025	3.206
2nd Quarter 2025	4.198
3rd Quarter 2025	5.120
4th Quarter 2025	5.109
1st Quarter 2026	5.287
2nd Quarter 2026	5.310
3rd Quarter 2026	6.150
4th Quarter 2026	6.197
Russia	
Rubble/US$ volatility	***Forecasted value (%)***
1st Quarter 2024	1.034
2nd Quarter 2024	2.124
3rd Quarter 2024	2.370
4th Quarter 2024	2.357
1st Quarter 2025	5.136
2nd Quarter 2025	5.123
3rd Quarter 2025	5.138
4th Quarter 2025	6.127
1st Quarter 2026	6.130
2nd Quarter 2026	6.235
3rd Quarter 2026	7.129
4th Quarter 2026	7.197
India	
Rupee/US$ volatility	***Forecasted value (%)***
1st Quarter 2024	0.657
2nd Quarter 2024	1.234
3rd Quarter 2024	2.155
4th Quarter 2024	2.987
1st Quarter 2025	3.245
2nd Quarter 2025	3.268
3rd Quarter 2025	3.468
4th Quarter 2025	4.139
1st Quarter 2026	4.227
2nd Quarter 2026	4.309
3rd Quarter 2026	4.351
4th Quarter 2026	4.389
China	
Yuan/US$ volatility	***Forecasted value (%)***
1st Quarter 2024	3.350
2nd Quarter 2024	3.359
3rd Quarter 2024	3.456
4th Quarter 2024	5.039
1st Quarter 2025	5.061
2nd Quarter 2025	5.040
3rd Quarter 2025	5.398
4th Quarter 2025	5.503
1st Quarter 2026	5.208
2nd Quarter 2026	6.379
3rd Quarter 2026	6.451
4th Quarter 2026	7.430
South Africa	
Rand/US$ volatility	***Forecasted value (%)***
1st Quarter 2024	1.052
2nd Quarter 2024	1.210
3rd Quarter 2024	2.150
4th Quarter 2024	2.319
1st Quarter 2025	2.015
2nd Quarter 2025	3.031
3rd Quarter 2025	3.160
4th Quarter 2025	3.037
1st Quarter 2026	4.136
2nd Quarter 2026	4.078
3rd Quarter 2026	5.160
4th Quarter 2026	5.365

Source: Authors' results from EViews.

Table 11. Forecasted volatility trends (2024–2026)

Country	***Forecasted volatility trend***
Brazil	Rising from 2.047% (2024Q1) to 6.197% (2026Q4)
Russia	Increasing from 1.034% (2024Q1) to 7.197% (2026Q4)
India	Peaking at 4.389% (2026Q4)
China	Climbing from 3.35% (2024Q1) to 7.430% (2026Q4)
South Africa	Rising from 1.052% (2024Q1) to 5.365% (2026Q4)

Figure 1. Impulse response using Litterman/Minnesota priors

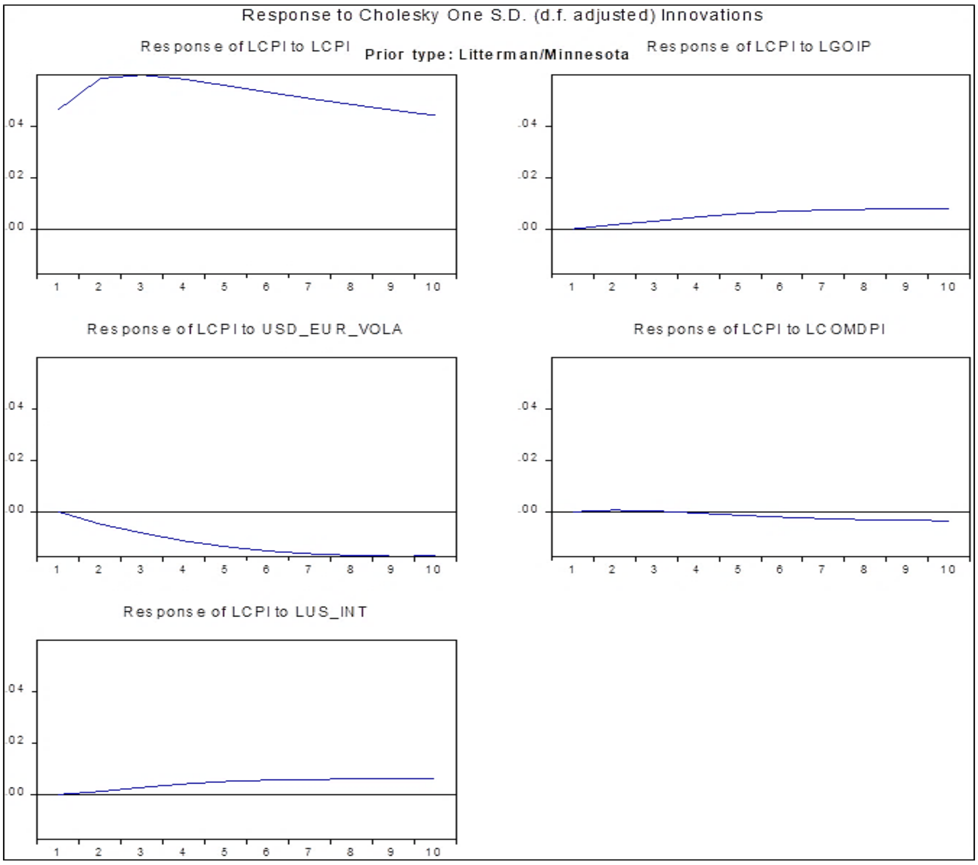
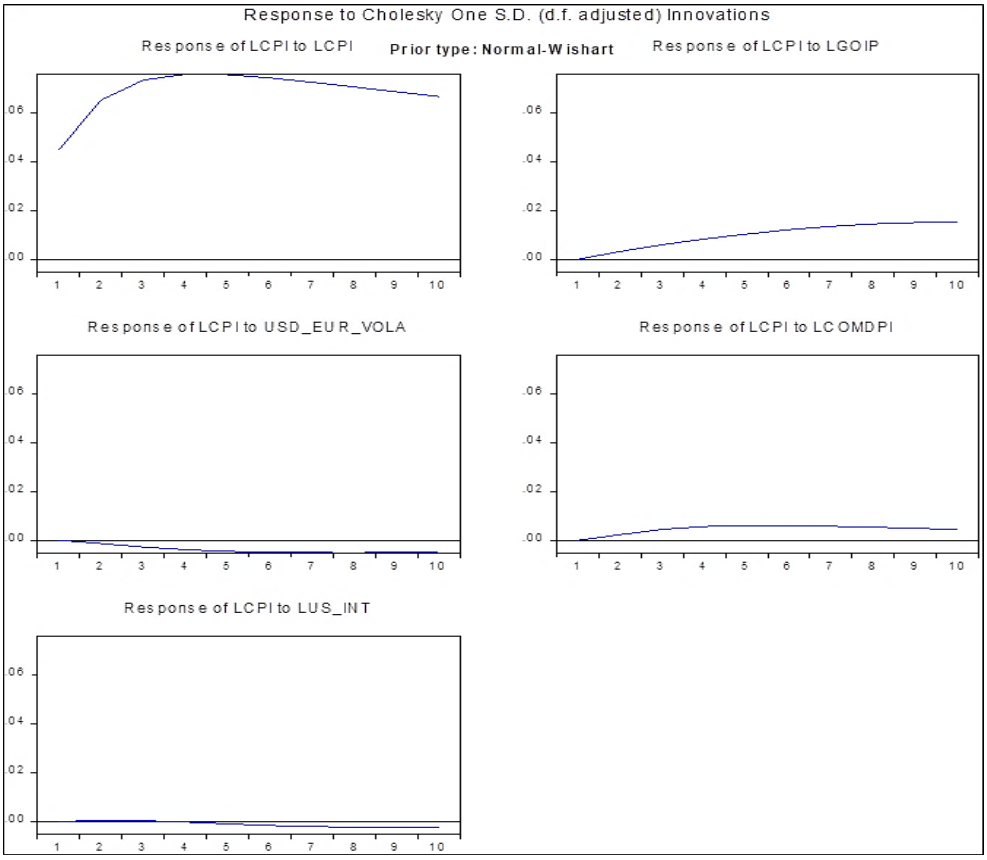


Figure 2. Impulse response using Normal Wishart prior



5. DISCUSSION

According to our forecast, the volatility of the Brazilian real/USD exchange rate is trending upwards from 2024 through 2026, starting from a threshold of 2.047% in the first quarter of 2024 and reaching a peak of 3.257% by the end of the year. In 2025Q1, the volatility was 3.206% and rose to 5.120% at 9 months. In 2026Q2, the volatility stood at 5.310% while it got to its peak at 6.197%. The volatility of the rupee/USD exchange rates exhibits a rising trend between 2024 and 2026, beginning from a threshold of 1.034% in the first quarter of 2024 to 2.124% at 6 months and attaining a peak of 2.357% by the end of the year. In 2025Q1, the volatility of the rupee/USD exchange rates was 5.136% and rose to 6.127% in Q4. In 2026Q1, 2026Q2, and 2026Q4, the volatility stood at 6.130% and 6.235%, while it reached its peak at 7.197% in 2026Q4.

The volatility of the rupee/USD exchange rate has also trended upward, with a threshold of 0.657% in 2024 Q1 and reaching a peak of 2.987% by 2024 Q4. In 2025Q1, the volatility was 3.245% and rose to 3.468% in the third quarter. In 2026Q1, the volatility stood at 4.227%, while it reached its peak at 4.389% at the end of the year. The volatility of the Yuan/USD exchange rate demonstrated a rising trend, beginning with a threshold of 3.35% in the first quarter of 2024 and reaching a peak of 5.039% by the end of the year. In 2025Q1, 2025Q2, and 2025Q3, the volatility was 3.245% and 3.268%, respectively. In 2026Q1, the volatility stood at 4.227%, while it rose to 4.389% in 2026Q4. The volatility of the Rand/USD exchange rates also revealed a rising trend between 2024 and 2026, beginning from a threshold of 1.052% in the first quarter of 2024 to 2.150% at the end of six months and attaining a topmost of 2.319% by the end of the year. In 2025Q1, the volatility of the Rand/USD exchange rates was 2.015% and rose to 3.037% in Q4. In 2026Q1, the volatility stood at 4.136%, while it reached its peak at 5.365% in 2026Q4.

The volatility of the Brazilian Real/USD, Rubble/USD, Rupee/USD, Yuan/USD, and Rand/USD exchange rates is trending upwards between 2024 and 2026. The implication is that, in the coming years, 2024, 2025, and 2026, international businesses in Brazil, Russia, India, China, and South Africa will endure the operation in a highly unpredictable business setting that is predisposed to currency risks. In effect, a rising trend in the volatility forecast is strongly indicative of the impending negative consequences that the evolution of the volatility of currencies could have on firms that process international payments in BRICS. The volatility of the exchange rates had been predisposed by several major factors, namely, the level of inflation, the COVID-19 pandemic, the Russia-Ukraine war, the British pound flash crash of September 2022, and hikes in US interest rates. This corroborates the empirical fact that exchange rates are extensively exposed to global shockwaves, speculations, and market sentimentalities (Bahmani-Oskooee & Gelan, 2018; Sugiharti et al., 2020). Moreover, the FX is the most globally integrated, highly decentralized, and liquid financial market (Kinyo, 2020). All these demonstrate the extent to which volatility shocks do not exist in isolation. They are interconnected. Knowing that volatilities asymmetrically characterize currency exchange rates and are interdependent, businesses and investors need to adequately execute a hedging policy against currency exchange risks that affect FX market transactions. Hence, for all BRICS countries to maintain international competitiveness in foreign markets, they need to anticipate market fluctuations and imbibe a hedging strategy.

The Bayesian VAR results with Litterman/Minnesota and Normal Wishart priors are shown in Figures 1 and 2, respectively. The response of *cpi* to the shock in the volatility of the currencies of the BRICS to the dollar exchange rate is based on a negative analysis of the Litterman/Minnesota priors. A shock to the volatility of the exchange rates of the currencies of the BRICS produces a drop in the *cpi*. In addition, the impact of the shock does not die out as time passes; rather, it negatively builds up over time. There is no apparent instantaneous impact on the domestic price level. Nonetheless, in the long run, from the 5th period on, the domestic *cpi* decreases before stabilizing at the tail end of the horizon. For a positive shock in the US interest rate, consumer prices build up before stabilizing in the eighth period. This indicates volatility in the interest rate differential transmitted to the growing *cpi* in Africa. We further assess the sensitivity of our results to changes in priors' specifications. The results indicate a positive shock to the global oil price level; the response of the domestic *cpi* is robust to whichever prior was adopted.

The response of *cpi* to its innovation shock is sensitive to the nature of prior adoption. Though the same positive impact was observed, the response of *cpi* to its innovation never returned to its instantaneous impact value. The response of *cpi* to the shock in the volatility of the exchange rates of the currencies of the BRICS is robust to prior adoption. Whereas the response of the domestic price level to a shock in the interest rate differential is sensitive to prior adoption, the Normal Wishart prior specification indicates the absence of instantaneous impact from the shock. Subsequently, the *cpi* gradually declines. The response of the *cpi* is sensitive to the prior specification as well. The response from the Normal Wishart prior indicates that the volatility shock index of the exchange rates of the currencies of BRICS had a growing negative impact on the *cpi* in BRICS. From the results presented in Figure 2, the response of *cpi* to shocks in global oil price volatility is persistent throughout the horizon. A positive global oil price shock had a positive impact on consumer prices in the BRICS. This substantiates the findings of Otoakhia (2021). The response of *cpi* to a shock to its innovation is instantaneous and persistent up to the four periods. Subsequently, the response declines but never dies off. In short, the volatility of the exchange rates of the currencies of the BRICS had a hump-shaped impact on the cpi.

The study emphasizes the necessity of efficient monetary policies and interventions by highlighting the crucial role that exchange rate volatility plays in determining the dynamics of inflation in the BRICS countries. The study implies that to stabilize currency rates and lessen inflationary pressures, governments will be better equipped to employ tactics like managing foreign exchange reserves. Since currency shocks continue to have inflationary impacts, proactive measures are required to preserve economic stability. The results show that the volatility of exchange rates in the BRICS economies is influenced by macroeconomic variables, interest rate differences, and shocks to the price of oil. The findings support the monetary model of exchange rate setting since the effects of these important variables align with existing theories. To provide a theoretical justification of the results of the study, the Bayesian VAR results show that consumer price inflation increases in response to shocks to oil prices, supporting the cost-push inflation theory, which maintains that higher oil prices increase production costs and inflation. This result is also in line with earlier empirical studies that found a comparable relationship between oil prices and inflation (Olamide et al., 2022). The exchange rate pass-through hypothesis, which holds that changes in currency value have a gradual impact on domestic price levels, is supported by the cpi's initial decline before stabilizing in reaction to exchange rate volatility. Erstwhile empirical studies (Zakaria et al., 2021) have also supported this, showing that exchange rate shocks have a delayed impact on inflation. The study also finds that increases in US interest rates raise consumer prices in the BRICS, supporting theories that higher global interest rates could lead to capital flight and currency devaluation, which would raise inflationary pressures.

The anticipated rise in exchange rate volatility for the BRICS countries between 2024 and 2026 aligns with previous empirical studies that underscore the role of exogenous shocks like inflation, geopolitical worries, and shifts in monetary policy in causing exchange rate fluctuations. Empirical research on the behaviour of financial time series is supported by the models' strong ARCH effects, which validate the existence of volatility clustering (Sugita, 2022). Asymmetric volatility theory and earlier studies that highlight the nonlinear character of exchange rate fluctuations are in accord with the GJR-GARCH model's superior ability to capture asymmetric exchange rate movements. The findings also cast doubt on the long-held acceptance that holding sizable foreign capital reduces exchange rate volatility. The results are in line with Alwadeai et al. (2024), who contend that reserves by themselves might not be sufficient to lower volatility in the face of severe economic conditions, even though some models suggest that large reserves serve as a buffer against shocks. Because of the interconnectedness of the world's financial systems, the BRICS economies are nevertheless susceptible to external shocks even though they have sizable reserves.

In terms of implications of the study for policy makers, investors, and regulators, and the contributions of the study to the existing literature, it could be stressed that the results indicate the significance of considering currency rate risks when making investment decisions. As inflation reacts to volatility asymmetrically, investors ought to protect themselves from future price spikes, especially in industries that are susceptible to inflation. By strengthening currency market frameworks and lowering excessive volatility, regulators can improve market stability. In other words, policymakers could enhance market stability by improving forex market institutions and reducing extreme volatility through targeted interventions. This study advances existing literature by providing empirical evidence on the asymmetric impact of exchange rate volatility on inflation in BRICS nations. Using GARCH and Bayesian models, it builds on prior research, affirming that currency fluctuations have lasting inflationary effects.

6. CONCLUSION

In this research, we attempted to forecast the volatility rate of the currencies of BRICS to the dollar exchange rate, based on interest rate differential, and oil price volatility shock. The study uses Bayesian VAR to analyze shifts in dynamic responses and volatility of the exchange rates. The study uses the GARCH models for forecasting the volatility of exchange rates. We observed Bayesian VAR plots for shocks to international oil prices; own values of currency volatility and consumer price inflation's own values are robust to prior specifications adopted. The volatilities of the BRICS's exchange rates in relation to the dollar are trending upwards. By implication, in the coming years, international businesses in BRICS will operate in a highly unpredictable business atmosphere that is susceptible to currency risks. In effect, a rising trend in the volatility forecast is strongly indicative of the impending negative consequences that the evolution of the volatility of currencies could have on firms that execute transnational payments in BRICS. The volatility of the exchange rates had been predisposed by several major factors, namely, the level of inflation, previous currency volatility, rising differential in interest rates of BRICS and the US rate. Particularly, consumer pricing is one of the sources of the rising volatility in currency exchange rates of BRICS with respect to the US dollar. This corroborates previous findings. The patterns of forecasted volatility suggest that increased currency risk is a problem for the BRICS economies as they participate in international businesses. Largely, consumer prices react asymmetrically to the volatility in the exchange rates of all the currencies in the BRICS. The response of consumer prices to shocks in interest rate differentials also depends on the priors adopted. The volatility shock to global oil prices had a positive and permanent impact on the consumer price level, depending on the specific priors adopted.

With the knowledge that volatilities asymmetrically characterize currency exchange rates, businesses and investors need to adequately execute a hedging policy against currency exchange risks that affect foreign exchange market transactions. Therefore, for all BRICS countries to uphold international competitiveness in foreign markets there is an urgent policy need to forestall market instabilities and execute a hedging strategy. There is a need to protect the local economies of BRICS against internationally transmitted shocks in the price of oil and, in particular, the spillover effect of the volatilities in their exchange rates as well as the spillover of interest rate differential that threatens price stability in BRICS. The foreign exchange market does not always follow a predicted pattern of volatility. The reason is that data-based forecasting alone cannot provide a hundred percent valid prediction because volatility is caused by other factors such as inflation uncertainty, government regulations or politics, regime shifts, as well as transition variables. Further researchers should incorporate these variables in an STES model to improve forecasts. The sample period of this research has been marked by the outbreak of the health pandemic and supply chain disruptions. These events can unexpectedly impact exchange rates, interest rates, and oil prices. Consequently, the present research findings could be influenced by these extraordinary circumstances, limiting their applicability to more stable periods. Impending research should consider the effects of these external shocks and unforeseen events.

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