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OIL PRICE SHOCKS, MARKET EFFICIENCY, AND VOLATILITY SPILLOVERS: EVIDENCE FROM BRICS COUNTRIES

Abstract

This study examines the impact of crude oil price shocks on stock market efficiency and volatility spillovers across BRICS countries (Brazil, Russia, India, China, and South Africa) using 6,275 daily observations from April 1999 to March 2024. The results from unit root and Lo-Mackinlay variance ratio tests show that only Russia and India exhibit weak-form efficiency, while Brazil, China, and South Africa display inefficiencies, indicating scope for abnormal returns. Granger causality analysis confirms strong short-term interlinkages, with Brazil emerging as a leading market for Russia, India, and South Africa. Johansen's cointegration test reveals long-term relationships among BRICS markets and with crude oil prices, suggesting limited diversification opportunities. ARCH-GARCH models and impulse response functions show significant volatility spillovers triggered by oil price shocks, lasting 2-6 trading days. Crude oil volatility affects all markets except South Africa, reflecting varying energy dependencies. These findings underscore the interconnectedness and systemic risk exposure of BRICS financial systems, with critical implications for international investors and policymakers in managing portfolio strategies and stabilizing markets.

Keywords stock market efficiency, interlinkages, volatility spillovers, crude oil, cointegration

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INTRODUCTION

Financial markets have become increasingly interconnected, with economic shocks and asset price movements in one region often rippling across global markets. This is particularly true for emerging economies like Brazil, Russia, India, China, and South Africa (BRICS), which play a growing role in global finance. Understanding the efficiency of these markets and their susceptibility to external shocks, such as fluctuations in crude oil prices, is crucial for investors, policymakers, and financial regulators. The Efficient Market Hypothesis (EMH) suggests that stock prices fully reflect all available information, making it difficult for investors to earn abnormal returns. However, in emerging economies, factors such as regulatory changes, market sentiment, and macroeconomic conditions often lead to deviations from efficiency. If BRICS markets do not exhibit weak-form efficiency, it implies opportunities for speculative gains but also raises concerns about market integrity and investor protection. A major factor driving market interdependence is the increasing trend of international cross-listing, which has intensified the co-movement of global stock markets and crude oil prices. A shock in one market often spills over into others, leading to volatility transmission across financial systems. While financial integration allows for better capital allocation, risk diversification, and strengthened market structures, it also heightens the risk of rapid financial instability spreading across interconnected markets.

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Another critical issue is the impact of crude oil price fluctuations on financial markets. Oil is a key input for industrial production and transportation, making its price movements a significant economic driver. Given the varying levels of energy dependency among BRICS nations, the relationship between oil prices and stock market volatility is not uniform. While research indicates that oil price shocks can influence stock market volatility, the extent and persistence of these effects in BRICS economies remain uncertain. This study provides empirical insights into how BRICS stock markets function within the broader global financial system by investigating these key financial dynamics market efficiency, volatility spillovers, and inter-linkages. Addressing these questions is critical for portfolio management and formulating regulatory policies that enhance market stability and resilience in emerging economies.

1. LITERATURE REVIEW

Researchers have debated whether emerging markets behave like their developed counterparts, particularly regarding efficiency and reaction to external shocks. This section reviews previous research of the similar areas investigated related to stock market efficiency in the emerging market, volatility spillover and market efficiency between crude oil and BRICS stock market.

The Efficient Market Hypothesis (EMH) suggests that financial markets reflect all available information, making asset prices unpredictable (Fama, 1970). According to the weak form of EMH, stock prices reflect all past information, making it impossible to earn abnormal returns through historical price analysis (Fama, 1965). However, empirical research on stock market efficiency in emerging markets has produced mixed findings. Studies on Brazil (Gupta & Basu, 2007; Ji et al., 2018) indicate more evidence of weak-form efficiency, suggesting that its market behavior aligns more closely with theoretical expectations. In contrast, research on India (Ramesh et al., 2023; (Maharana et al., 2024) reveals deviations from the random walk hypothesis, pointing to inefficiencies. Similarly, studies on Russia and China (Li & Su, 2020; Chen & Sun, 2023; Jarrett, 2008) suggest market inefficiencies, while findings on South Africa remain inconclusive.

Researchers use various econometric models to analyze volatility spillovers, including the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, Vector Autoregression (VAR), and wavelet analysis, which help in understanding the time-varying effects of oil price changes on stock market volatility (Boubaker & Raza, 2017; Hao et al., 2023). Studies consistently show that crude oil price volatility has a significant impact on BRICS stock markets, with markets reacting differently to positive and negative price shocks (Bagchi, 2017; Bouslama, 2023). Post the 2008 financial crisis, these spillovers intensified, highlighting the growing interdependence between global commodity markets and emerging economies (Boubaker & Raza, 2017; Liu et al., 2011). Wavelet analysis further shows that these spillovers vary over time, becoming more pronounced during periods of economic instability (Hao et al., 2023).

Among BRICS nations, oil-exporting countries like Russia and Brazil are more susceptible to oil price volatility than oil-importing nations such as China and India (Khan, 2010; Lo & MacKinlay, 1988). It highlights the direct macroeconomic influence of crude oil on stock markets in resource-dependent economies. The studies confirm that Russia's stock market reacts strongly to Brent crude price movements, while China's stock market shows weaker long-term linkages to oil prices (Hanif et al., 2024; Lee & Huang, 2014).

Economic downturns tend to amplify volatility spillovers. The 2008 financial crisis and the COVID-19 pandemic significantly increased oil price-related market instability, with Russia's market being most affected due to its dependency on oil exports (Bouslama, 2023; Abid et al., 2024). Additionally, financial market integration studies suggest that stock markets exhibit strong linkages, particularly during crises (Hammoudeh et al., 2014; Sehgal et al., 2017). The research on BRICS economies highlights the presence of significant co-movements, suggesting that market shocks in one country can have widespread effects (Bagchi, 2017; Batondo & Uwilingiye, 2022). According to the EMH, stock prices should follow a random pattern in an efficient market. However, empirical research using unit root tests and autocorrelation analyses suggests that BRICS stock markets deviate from this principle due to prolonged volatility spillovers from crude oil (Mensi et al., 2021). Studies on stock market integration and cointegration tests, such as Johansen's test, suggest that BRICS markets are not entirely independent, as short-term causal links and long-term interdependencies exist between them (Makhija & Raghukumari, 2015; Gokmenoglu & Fazlollahi, 2015; Lee, 1992).

Emerging markets often face inefficiencies due to information asymmetry, speculative trading, and regulatory challenges (Yan et al., 2022; Chen et al., 2022). The studies indicate that India and China's stock markets are less efficient than Brazil and South Africa, owing to higher levels of government intervention and weaker market transparency (Ogbuabor et al., 2022; Leng et al., 2015). The existing research provides mixed evidence regarding market efficiency, volatility spillovers, and stock market interlinkages in emerging economies. While some studies confirm weak-form efficiency, others highlight persistent inefficiencies, allowing for possible return predictability. Market integration and volatility transmission have been well established, with crude oil playing a crucial role in influencing stock market behavior. However, further research is needed to understand how these dynamics affect Brazil, Russia, India, China, and South Africa. This growing financial interconnectedness underscores the importance of understanding how information transmission and volatility spillovers shape BRICS markets in the context of global finance.

The insights from these studies collectively suggest that, while offering potential investment opportunities, BRICS stock markets remain susceptible to external shocks such as currency fluctuations and crude oil price volatility. The degree of integration among these markets also implies that financial stability policies and risk management strategies must account for domestic and global economic conditions. Understanding these financial dynamics is essential for investors, portfolio managers, and policymakers seeking to enhance market resilience in emerging economies. This study explores the efficiency, interconnectedness, and volatility spillovers of stock markets in Brazil, Russia, India, China, and South Africa, particularly emphasizing the influence of crude oil price fluctuations. The study tests the following hypotheses:

H1: *The stock markets of BRICS exhibit weak-form efficiency.*

H2: *There are significant short-term interlinkages among the stock indices of BRICS countries.*

H3: *BRICS stock markets share long-term relationships among the stock indices of BRICS countries.*

H4: *Crude oil price volatility significantly influences stock market fluctuations in BRICS nations.*

2. METHODOLOGY

To ensure consistency, research has included only trading days when all five stock markets were operational, resulting in a final dataset of 6,275 observations. In analyzing the weak-form efficiency and interconnections among BRICS nations, research has included West Texas Intermediate (WTI) crude oil prices alongside daily stock indices from the Brazil Stock Exchange, Moscow Stock Exchange, National Stock Exchange of India, Shanghai Stock Exchange, and Johannesburg Stock Exchange from April 1, 1999, to March 31, 2024, from the Bloomberg database.

The analytical tests employed in this study include:

2.1. Assessment of stock market efficiency

A time series is stationary if its mean, variance, and autocovariance (at different lags) remain constant. In such a series, values revert to the mean, and the variance stays uniform. The researchers often use unit root tests along with the MacKinlay variance ratio test to assess the stationarity of time series data.

$$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \sum_{i=1}^{p} \delta_i \Delta Y_{t-i} + \varepsilon_t, \tag{1}$$

where ΔY_t represents the first difference of the series, capturing changes over time. The coefficient γ is tested for stationarity, where if γ=0, the series

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has a unit root and is non-stationary. The term εt denotes the white noise error, accounting for random fluctuations in the data. Also this study have used Lo and MacKinlay variance ratio test which is a statistical method used to evaluate the efficiency of financial markets, specifically in testing the weak form of market efficiency, which suggests that stock prices fully reflect all available information, including past prices. The test is based on the premise that if the price series follows a random walk, the variance of returns over a q-period interval should be q times greater than the variance of returns over a single period. It is expressed mathematically as the variance of the difference between X_t and X_{t-q} being equal to q times the variance of the return over one period. A significant deviation from this expected ratio would indicate that the market does not conform to the random walk hypothesis, thus suggesting inefficiencies in the market. The test is particularly valuable in analyzing market behavior and determining whether historical price movements can predict future movements. This relationship is expressed in the following equation:

$$VR(q) = \frac{\sigma^2(q)}{\sigma^2(1)}, \tag{2}$$

where the term $\sigma^2(q)$ represents the variance of returns over a multi-period interval of length q, while $\sigma^2(1)$ denotes the variance of returns over a single-period interval. These values are used to assess the relationship between return variances over different time horizons, particularly in tests of market efficiency.

2.2. Long-term and short-term interlinkages

In a bivariate framework, variable Y_1 Granger causes variable Y_2 if the inclusion of past values of Y_1 enhances the predictive accuracy of Y_2. The Granger causality test is widely used for empirically analyzing causal relationships between variables.

$$Y_t = \alpha_0 + \sum_{J=1}^{p} \alpha i Y_{t-i} + \sum_{j=1}^{q} \beta j X_{t-j} + \varepsilon_t. \tag{3}$$

If βj≠0, variable X Granger-causes Y. This model is used to evaluate whether lagged values of oil prices or other BRICS indices help predict current stock prices.

Cointegration occurs when two or more variables of the same order form a stationary linear combination. The Johansen cointegration test assesses the presence of cointegration by determining how many independent linear combinations within a time series lead to stationarity. The Johansen test is susceptible to lag length selection, making determining a suitable lag structure crucial. The lag selection is done using the Akaike Information Criterion (AIC), Schwarz Criterion (SC), and Likelihood Ratio (LR) test. The represented equation is as follows:

$$\Delta Y_t = \mu + \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma i \Delta Y_{t-1} + \varepsilon_t, \tag{4}$$

(VECM form)

where Y_t represents BRICS stock indices and oil prices. The cointegration matrix Π=αβ′ captures long-run relationships, where α is the adjustment speed and β contains cointegration vectors. The short-run adjustments are modeled by Γ_i, while ε_t represents error terms capturing external shocks.

A stable Vector Autoregression (VAR) model, represented by a Vector Moving Average (VMA) process, forms the basis for analyzing the Impulse Response Function (IRF). The IRF illustrates how a shock to one variable propagates through all other variables within the VAR model over time. By conducting impulse response analysis, to evaluate how stock market indicators in one country react to shocks originating from another country's market.

$$Y_t = \mu + \sum_{i=1}^{\infty} \Psi i \varepsilon_{t-i}, \tag{5}$$

(IRF Form)

where Ψi represents the matrix of impulse responses at horizon i, which measures the dynamic effect of a shock on the system over time. ε_{t-i} denotes the structural shocks at lag i, capturing unexpected disturbances that influence the system's behavior in previous periods.

Moreover, these models suggest that the variance of the error term in the current period is affected by squared error terms from prior periods. This results in volatility clustering, a widely observed pattern in financial markets where high volatility phases are often followed by similar periods of instability. To effectively model such time-dependent volatility in financial time series data, the Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models are widely applied. Mathematically it can be represented as:

ARCH(1) is

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2, \tag{6}$$

whereas

GARCH(1,1) is

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{7}$$

where α_0 is the long-run average volatility (constant), α_1 is the ARCH term (impact of recent shocks), and β_1 is the GARCH term (effect of past volatility). ε_{t-1} represents the previous period's error, while σ_t^2 is the current conditional variance (volatility).

3. RESULTS

Table 1 illustrates the average stock returns for Brazil (0.035%), Russia (0.0008%), China (–2.1774%), India (–0.7315%), and South Africa (–0.0002%), respectively. Research computed daily continuously compounded returns for each index by taking the first difference of their natural logarithms. A normal distribution has zero skewness, which measures the asymmetry of the distribution around the mean. The analysis revealed that the stock markets of BRICS are positively skewed, except for India and Russia, which displayed negative skewness. Furthermore, the kurtosis values for all variables exceeded 3, indicating a leptokurtic distribution with fat tails, a finding corroborated by the Jarque-Bera statistics. Brazil exhibited the highest average returns, while China had notably lower returns.

Following the summary statistics, assessing the correlation among the stock indices considered in this study becomes essential. The findings reveal that all five countries exhibit a significant positive correlation, suggesting a strong contemporaneous relationship. This positive correlation can largely be attributed to advancements in technology, globalization, and the widespread availability of Internet services, which have enabled investors to trade online and invest in foreign markets more efficiently.

The substantial correlations among the examined variables necessitate the application of further econometric techniques. Clarifying that a high or low correlation does not establish or negate causality is essential. Instead, it reflects the two variables' positive or negative linear relationship. Following the correlation analysis, it is essential to assess the time series by employing unit root tests such as the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, alongside the nonparametric Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test. Table 3 presents the findings of the unit root tests, showing that the null hypothesis, which indicates the presence of a unit root in the time series, could not be rejected for most of the countries analyzed, excluding Brazil, Russia, and South Africa at the 5% significance level. This outcome is consistently supported by the ADF, PP, and KPSS tests. However, after applying first-order differencing, all series were found to be stationary, as the null hypothesis of non-stationarity was rejected at the same significance level, ensuring the feasibility of the modeling process.

Table 1. Summary of key statistical metrics for BRICS stock indices (1999-2024)

Series	Mean	Median	Minimum	Standard deviation	Skewness	Kurtosis	Jarque-Bera	Probability
Brazil	0.0306	0.0000	–0.1465	0.1746	5.3154	29.565	179607	0.0000
China	0.0008	–0.0003	–0.0985	0.0371	22.15	596.07	775938	0.0000
India	–2.1774	–0.0003	–5842.9	113.28	–51.28	2630.7	0.0000	0.0000
Russia	–0.7315	–0.0002	–2264	38.134	–53.51	2933.5	0.0000	0.0000
South Africa	–0.0002	–0.0006	–0.0707	0.0182	31.4653	1724.17	0.0000	0.0000
WTI	0.0305	0.0000	–0.1465	38.134	–53.51	2933.5	0.0000	0.0000

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Table 2. Correlation analysis between BRICS stock indices and crude oil

	Brazil	China	India	Russia	South Africa	WTI
Brazil	1.0000					
	–					
China	.0251*	1.0000				
	.0682	–				
India	.0022*	-.0029**	1.0000			
	.0698	.0283	–			
Russia	.0056***	-.0043*	-.0003*	1.0000		
	.0033	.0503	.0789	–		
South Africa	.0583***	.2686***	.0003*	.0020*	1.0000	
	.0000	.0000	.0810	.0527	–	
WTI	.0854**	.6585***	.0036**	.0300*	.0300*	1.0000
	.0000	.0752	.0368	.0362	.0458	–

Note: *** denotes significance at 1%, ** at 5%, and * at 10% levels.

Table 3. Results of ADF, PP, and KPSS unit root tests

Variable	At level			At first difference		
	ADF	PP	KPSS	ADF	PP	KPSS
Brazil	–26.9321	–41.5177	5.1977**	–36.1478***	–55.2565**	6.2616***
Russia	–72.5798**	–72.5798	0.2994	–89.8563*	–72.6258***	0.5689***
India	–11.5508	–76.1946**	0.1536**	–26.8451***	–92.2154***	0.8565***
China	–32.5204	–51.3318	0.0528	–42.5689***	–75.1245***	0.1254***
South Africa	–109.2093	–109.7231	0.1458**	–155.5263***	–115.2548***	0.2546***
WTI	–1.550	–60.1986*	0.1558**	–52.5685***	–114.2154***	0.5566***

Note: *** denotes significance at 1%, ** 5%, and * 10% levels.

The unit root test results support the null hypothesis, suggesting that most stock index series exhibit non-stationary behavior, except those from Russia, Brazil, India, and South Africa. It suggests that these series follow a random walk process, aligning with the characteristics of weak-form market efficiency.

The study applied the variance ratio test to assess whether Brazil, Russia, India, China, and South Africa stock markets adhere to a random walk and exhibit weak-form efficiency. The results in Table IV reveal that only the Russian and Indian markets demonstrate weak-form efficiency, as indicated by their variance ratios being below one and statistically insignificant Z-values. In contrast, the Brazilian, Chinese, and South African stock markets do not follow a random walk, suggesting inefficiencies allowing greater price predictability. In brief, Russia and India appear to have efficient markets, while the other three markets show signs

Table 4. Results of Lo and Mackinlay's variance ratio test

Variable	Lags	At (2)	At (4)	At (8)	At (16)
BRAZIL	Variance ratio	.9064	.4701	.2397	.1214
	Z-statistics	–4.2300***	–4.2300***	–8.5533	–7.5920
RUSSIA	Variance ratio	.5001	.2502	.1253	.0628
	Z-statistics	–1.3387	–1.3387	–1.3387	–1.3387
INDIA	Variance ratio	.5001	.2502	.1253	.0628
	Z-statistics	–1.4137	–1.2242	–0.9895	–0.8929
CHINA	Variance ratio	.7730	.4470	.2256	.1128
	Z-statistics	–23.1900***	–3.7403***	–2.9694***	–2.7625***
SOUTH AFRICA	Variance ratio	.5080	.2597	.1288	.0652
	Z-statistics	–31.2088***	–26.3434***	–20.4242***	–25.3937***
WTI	Variance ratio	.7730	.4470	.2256	.1128
	Z-statistics	–53.1900***	–13.7403***	–20.9694***	–21.7625***

Note: *** significant at 1% level.

Table 5. Granger causality test of crude oil and BRICS countries (log-adjusted)

(Lag1)	Brazil	China	South Africa	WTI
Brazil	–	–	** (Bidirectional)	** (Unidirectional)
Russia	** (Unidirectional	–	–	** (Bidirectional)
India	** (Bidirectional)	–	–	** (Unidirectional)
South Africa	** (Bidirectional)	–	–	** (Unidirectional)
China	–	–	–	** (Bidirectional)

Note: ** represents significance at 5% level.

of inefficiency. As a result, *H1* is only partially rejected, confirming efficiency in Russia and India but not in the other markets.

The selection of the optimal lag length for the Granger causality test relies on the Akaike Information Criterion (AIC) and the Schwarz Information Criterion (SIC), as the test's accuracy is significantly affected by the choice of lags for the endogenous variables. This study selects a lag length of one, reflecting the dynamic nature of stock markets. Given that stock prices tend to exhibit short-term memory, it is generally expected that the influence of past prices on future movements remains relevant only for one or two periods, making longer lags unnecessary for this type of analysis.

The Granger causality relationships in Table 5 reveal that the Brazilian stock market is a leading indicator for Russia, India, and South Africa. A unidirectional causality is observed between Brazil and Russia, while a bidirectional causality exists between Brazil, India, and South Africa, with these markets also leading Brazil. Moreover, WTI exhibits a one-way relationship with Brazil, India, and South Africa while demonstrating a two-way relationship with Russia and China.

The Granger causality test was conducted to analyze the short-term interconnections among BRICS stock indices (*H2*). The findings indicate strong positive correlations as per Pearson's correlation between all five stock markets, implying a high degree of co-movement. Brazil emerged as a leading indicator for Russia, India, and South Africa, while China and Russia exhibited bidirectional causal relationships, meaning they influence each other's market movements. These results confirm that stock markets in BRICS economies are not independent, and price changes in one market often trigger reactions in others. Consequently, hypothesis *H2* is accepted, reinforcing the view that BRICS markets are significantly interlinked in the short run.

Figure A1 (see Appendix A) presents the response of various stock market indicators. A positive correlation is found in four stock markets, excluding Brazil, which is affected by shocks from Russia, India, China, and South Africa. The markets of India, China, South Africa, and Russia share a similar dynamic to Brazil's. It concludes that all BRICS nations are interconnected in their market responses. Thus, any significant news, whether positive or negative, will influence the overall economy for approximately 2 to 6 days, indicating a short-term impact.

Study analyze long-run relationships using the Johansen cointegration test and the Trace and Maximum Eigenvalue statistics. The study evaluates five models, each with distinct intercept and trend specifications. These models include: (1) no intercept, no trend; (2) intercept, no trend; (3) linear intercept, no trend; (4) linear intercept with trend; and (5) quadratic intercept with trend, with results interpreted accordingly.

Table 6 presents the results of Johansen's cointegration test, applying both the Trace and Max-Eigen approaches. The findings reveal a long-term relationship among all BRICS nations. Additionally, the data highlights a significant long-term connection, at the 5% significance level, between these countries and among their stock market indices and crude oil. It suggests that portfolio diversification across these markets may offer long-term benefits. The Johansen cointegration test confirms that BRICS stock markets share long-term relationships (*H3*), meaning their prices move together, and deviations are temporary. It limits long-term portfolio diversification as market movements are interconnected. Thus, hypothesis *H3*

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is accepted, confirming sustained co-movement among BRICS indices.

This paper have also investigated the volatility spillovers in Brazil, Russia, China, India, and South Africa. The Auto-Regressive Conditional Heteroscedasticity (ARCH) model requires meeting two key conditions. First, there should be evidence of volatility clustering. Second, the ARCH test for residual diagnostics should confirm the presence of heteroscedasticity by rejecting the null hypothesis. In this study applied the ARCH model separately to each of the five stock markets.

This study considers Russia, India, China, and South Africa as exogenous variables to evaluate their impact on Brazil's market volatility. The study can also extend this framework to assess its effects on other countries. Table 7 presents the ARCH and GARCH analysis, which provides insights into volatility dynamics. The findings indicate that ARCH and GARCH coefficients are statistically significant across all examined nations except South Africa. The ARCH coefficient shows that past returns affect current returns, while the GARCH coefficients indicate that previous volatility impacts future market fluctuations. Interestingly, Brazil's market volatility is shaped by movements in all the other economies included in this study, while Russia, India, and China exhibit similar interdependencies. However, in South Africa, volatility is primarily influenced by Russia and China, with a significance level of 10%.

The complete data for this study can be found at Marathe (2025).

The reasons for such volatility are nothing but today's market itself. Such volatility is due to globalization and the faster spillover of information. We can see the impact of a small news company on the immense volatility in the market in terms of negative or positive volatility. There is also a reason, including the faster developments in the global market, which leads to volatility in developing and underdeveloped countries. Therefore, from the above, no ARCH effect exists in the model at a significance level of 5% and 10%. The ARCH-GARCH model and Impulse Response Function (IRF) confirm that volatility spillovers persist for 2-6 trading days (*H4*), meaning financial shocks in one BRICS

Table 6. Results of Johansen cointegration test (log series)

Test type	Model	WTI Brazil	WTI Russia	WTI India	WTI China	WTI South Africa	WTI (BRICS countries)
Trace statistics	No intercept, no trend	I	I	I	I	I	0
Max-Eigen statistics		I	I	I	I	I	III
Trace statistics	Intercept, no trend	I	I	I	I	I	III
Max-Eigen statistics		I	I	I	I	I	III
Trace statistics	Linear and intercept, no trend	I	I	I	I	I	0
Max-Eigen statistics		I	I	I	I	I	III
Trace statistics	Linear intercept and trend	I	I	I	I	I	III
Max-Eigen statistics		I	I	I	I	I	III
Trace statistics	Quadratic intercept and trend	I	I	I	I	I	0
Max-Eigen statistics		I	I	I	I	I	III

Table 7. Results of ARCH- GARCH model

Dependent variable/ coefficients	$e^2_{(t-1)}$ previous error term	Garch(–1) previous volatility	Volatility – Brazil	Volatility – Russia	Volatility – India	Volatility – China	Volatility – South Africa	Volatility – WTI
Brazil	34.49**	–27.42**	–	9.29**	68.58**	31.25**	29.56*	56.29**
Russia	53.14**	39.04**	668.43	–	187.90**	37.49**	–119.32**	63.56*
India	26.62**	–5.45**	77.24**	9.23**	–	27.77**	262.44**	77.24**
China	9.04**	–1.72**	4.92**	–	7.64**	–	6.99**	8.06**
South Africa	40.21	–2.00*	21.23	668.43	317.01	17.12*	–	83.23*
WTI	53.14**	39.04**	668.43	–	–	27.77**	262.44**	–

Note: ** represents significant at 5% level, * 10% level.

market affect others for a short duration. It reinforces market interconnectedness and the transmission of financial instability. Thus, hypothesis *H4* is accepted.

Therefore, the study confirms the hypothesis that strong short-term interlinkages (*H2*), long-term relationships (*H3*), and persistent volatility spillovers among BRICS markets. However, market efficiency is only present in Russia and India (*H1*: partially rejected), and crude oil affects all markets, except South Africa (*H4*: partially accepted), highlighting integration and inefficiencies.

4. DISCUSSION

The findings of this study provide valuable insights into stock market efficiency, interlinkages, and volatility spillovers among Brazil, Russia, India, China, and South Africa. The results indicate that while Russia and India exhibit weak-form efficiency, Brazil, China, and South Africa remain inefficient, suggesting price predictability. It aligns with past studies on emerging markets, such as Gupta and Basu (2007); Kang et al. (2014) highlighting inefficiencies due to lower market maturity and investor behavior. The short-term interconnections among BRICS stock indices, confirmed by Granger causality and correlation analysis, further reinforce the high degree of market interdependence, with Brazil leading Russia, India, and South Africa. The long-term relationships identified through Johansen's cointegration test confirm that these markets move together, limiting portfolio diversification opportunities, which is consistent with prior findings by Agmon (1972).

The findings of this study indicate that fluctuations in crude oil prices significantly influence the stock markets of Brazil, Russia, India, and China. However, the South African stock market is mainly unaffected, suggesting varying degrees of economic dependence on oil across these nations. While this finding supports previous studies like Khan (2010) the weaker impact on South Africa suggests that its energy diversification reduces oil price sensitivity. Furthermore, the ARCH-GARCH model and Impulse Response Function (IRF) confirm that volatility spillovers persist for 2-6 trading days, meaning financial shocks rapidly transmit across BRICS economies, reinforcing systemic risks. This finding is consistent with Bagchi (2017), who observed similar volatility patterns in emerging markets. The results highlight the need for investors and policymakers to monitor these interlinkages carefully, as financial instability in one BRICS country can quickly spread to others. Future research should consider incorporating other emerging markets, analyzing crisis periods, and exploring macroeconomic factors that influence stock market behavior.

Future research could address these limitations by expanding the scope of analysis to include additional countries, regions, and financial markets. Moreover, incorporating structural break analysis, advanced econometric models, and high-frequency data could provide deeper insights into the evolving relationships between stock markets and crude oil prices. Such research would offer a more comprehensive understanding of global financial dynamics and support more informed decision-making by investors, policymakers, and financial institutions operating in these interconnected markets.

CONCLUSION

This study examined the efficiency, interlinkages, and volatility spillovers in the stock markets of BRICS countries Brazil, Russia, India, China, and South Africa by analyzing the effect of crude oil price changes over a 25-year period from 1999 to 2024. Using daily data and applying various statistical and econometric tools such as unit root tests, Lo and Mackinlay variance ratio tests, Granger causality, Johansen cointegration, and ARCH-GARCH models, the study provides several important findings.

The results show that the stock markets of Russia and India follow weak-form efficiency, meaning that past price information cannot be used to predict future stock movements in these countries. However, the markets in Brazil, China, and South Africa are not efficient, as prices in these markets can be predicted to some extent using historical data. This suggests that not all BRICS countries have fully developed or transparent financial markets.

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The study also finds strong short-term relationships among BRICS markets. Brazil appears to influence other markets like Russia, India, and South Africa. In addition, some countries show mutual relationships in terms of how market movements affect each other. These findings indicate that stock markets in BRICS countries are closely connected and that events in one country can have a quick impact on the others. The cointegration results confirm that these markets also move together in the long run. This means that although there may be short-term differences, their stock prices tend to follow a common trend over time. Because of this, it may be difficult for investors to reduce risk by investing in multiple BRICS markets, as they are likely to move together in response to major events. Volatility analysis using the ARCH and GARCH models shows that oil price changes affect market volatility in Brazil, Russia, India, and China, but not in South Africa. The impact of such volatility tends to last for 2 to 6 trading days. This confirms that oil price shocks are an important factor influencing market stability in many BRICS countries, especially those that are more dependent on oil imports or exports.

In summary, the study highlights that BRICS markets are partly efficient, highly interconnected, and sensitive to oil price changes. These results have practical importance for investors, who need to consider both regional and global risks when making investment decisions. Policymakers should also focus on improving market transparency and building financial systems that can better handle external shocks such as changes in oil prices.

Future research could include more countries, consider other economic factors like interest rates and inflation, or use more detailed data to better understand the relationships between global commodity prices and financial markets. Such studies would help improve investment strategies and guide policy decisions in emerging economies.

AUTHOR CONTRIBUTIONS

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Writing – review & editing: Shripad Ramchandra Marathe, Sanjeeta Parab.

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APPENDIX A

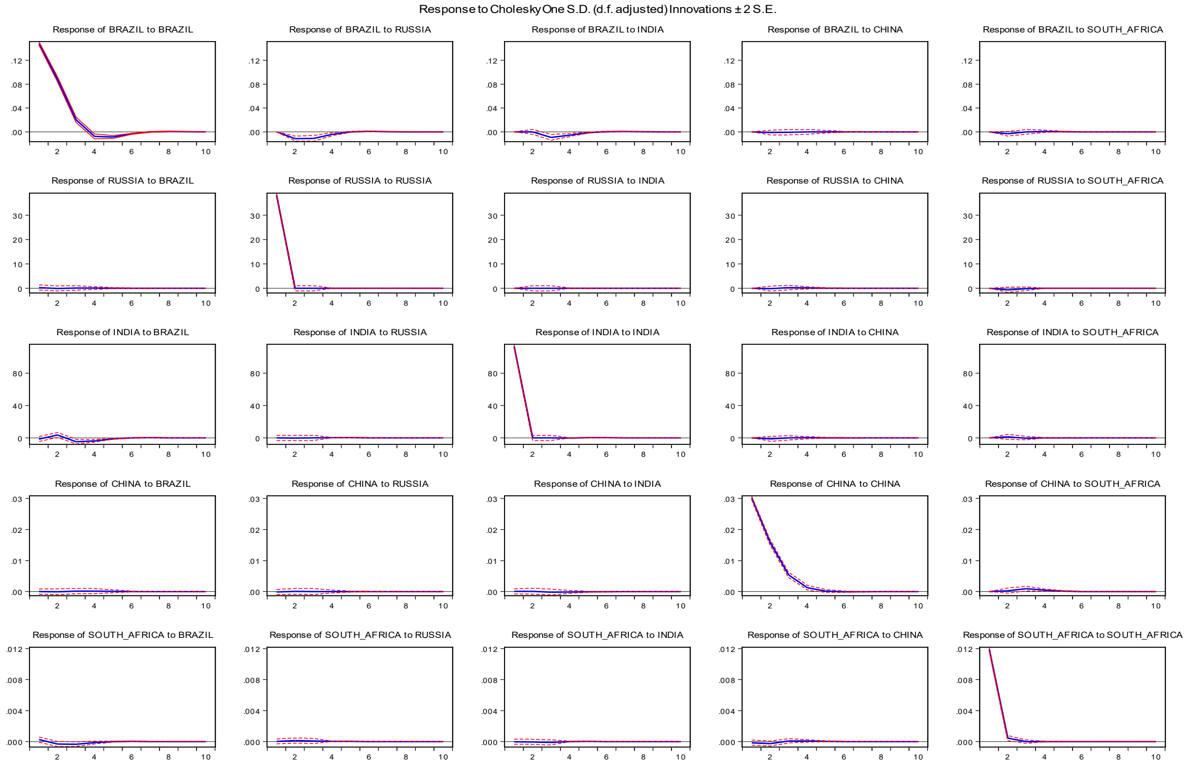

Figure A1. Results of impulse response analysis

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