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Volatility Spillovers Between BRIC and South African Stock Markets: Evidence from the COVID-19 and Russia-Ukraine Crises

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ABSTRACT

The aim of this study was to assess how global crises influenced volatility spillovers between BRIC and South African stock markets. In conducting the study, **the methods employed** are the generalized autoregressive conditional heteroskedasticity (GARCH) framework and the time-varying parameter vector autoregressive (TVP-VAR) Diebold-Yilmaz approach, based on a sample period segmented into pre-crisis, COVID-19, and Russia-Ukraine conflict phases. **The study results** revealed that volatility spillovers intensified during the COVID-19 pandemic due to economic disruptions and uncertainty. At the same time, the Russia-Ukraine conflict saw reduced spillovers due to geopolitical isolation and risk aversion. South Africa consistently emerged as a key volatility transmitter, particularly during crises. **The study concludes** that different global crises have distinct impacts on volatility transmission and should, therefore, be treated distinctly. **The key contribution** lies in enhancing the understanding of crisis-driven market integration, providing valuable insights for risk management and policy-making in interconnected financial systems.

Keywords: volatility spillovers; stock market; BRICS; Diebold-Yilmaz; COVID-19; Russia-Ukraine conflict

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ОРИГИНАЛЬНАЯ СТАТЬЯ

Перетоки волатильности между фондовыми рынками БРИК и Южной Африки: на примерах кризиса COVID-19 и российско-украинского конфликта

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АННОТАЦИЯ

Целью данного исследования была оценка влияния глобальных кризисов на перетоки волатильности между фондовыми рынками стран БРИК (Бразилия, Россия, Индия, Китай) и Южно-Африканской Республики (ЮАР). При проведении исследования использовались **методы** обобщенной авторегрессии с условной гетероскедастичностью (GARCH) и подход Дибольда-Йилмаза с векторной авторегрессией с переменными во времени параметрами (TVP-VAR), основанные на периоде выборки, сегментированном на фазы докризисного периода, COVID-19 и российско-украинского конфликта. **Результаты** исследования показали, что перетоки волатильности усилились во время пандемии COVID-19 из-за экономических потрясений и неопределенности, в то время как российско-украинский конфликт сократил перетоки из-за геополитической изоляции и неприятия риска. Южная Африка неизменно оказывалась ключевым передатчиком волатильности, особенно во время кризисов. **Выводы** исследования свидетельствуют о том, что мировые кризисы оказывают неодинаковое влияние на передачу волатильности и, следовательно, должны рассматриваться по-разному. **Ключевой вклад** работы заключается в улучшении понимания рыночной интеграции, вызванной кризисом, что дает ценные знания для управления рисками и разработки политики во взаимосвязанных финансовых системах.

Ключевые слова: перетоки волатильности; фондовый рынок; БРИКС; Diebold-Yilmaz; COVID-19; российско-украинский конфликт

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1. Introduction

Globalisation is an instance where international markets become more interconnected. This web of connectivity wields a substantial impact on volatility spillovers across markets [1]. Volatility, the fluctuations in asset prices over time, readily spills over to other markets as they become more connected, propelled by factors such as increased trade, cross-border investments, and the flow of information. Consequently, volatility spillovers, defined as the transmission of instability and risks from one market to another, have raised concerns for investors and policymakers [2].

Volatility spillovers can occur between distinct stock markets or different assets in a single market [3], where fluctuations in one market or asset can swiftly reverberate across others, amplifying market-wide volatility and risk perceptions. Such was the case during the 2008–2009 global financial crisis, as shocks from one market triggered reactions in related markets [1]. This illustrates how volatility spillovers can exacerbate market turmoil, highlighting the need for robust risk management strategies and coordinated policy responses to mitigate systemic risks and stabilise financial markets.

Thus, studying volatility and its spillovers is crucial for gaining insights into financial market behaviour, especially for emerging markets that are more sensitive to external shocks [2]. Despite their potential, emerging markets face challenges like weak financial institutions, limited financial depth, and high external debt. These challenges expose emerging markets to heightened vulnerability, particularly during periods of market turbulence and economic uncertainty, where their resilience is put to the test, often leading to significant market disruptions.

This vulnerability was apparent during the COVID-19 pandemic when financial markets experienced significant uncertainty and disruptions [4]. Similarly, markets were plagued by heightened geopolitical tensions and economic instability during the Russia-Ukraine conflict, exacerbating the already fragile situation initiated by the pandemic. Although not to the extent of the 2008–2009 global financial crisis, both periods highlight the interconnectedness of international markets and the critical role of understanding how volatility transmits across borders [1]. Accordingly, this study assessed the volatility spillovers between the South African and BRIC (Brazil, Russia, India, China) markets during the COVID-19 pandemic and the Russia-Ukraine conflict crises, juxtaposed with stable periods. The selection of BRICS (Brazil, Russia, India, China, South Africa) markets as the subjects of the analysis was driven by their growing prominence in the global economy and their significant impact on international financial markets [5]. Moreover, the focus on South Africa stemmed from its distinctive economic characteristics and market dynamics that render its markets unique and influential within the BRICS framework.

Further, while the pandemic and the Russia-Ukraine conflict crises resulted in disruptions, their effects may have differed. The pandemic primarily impacted global markets through widespread lockdown measures, supply chain disruptions, and economic slowdowns, leading to broad-based volatility and uncertainty [6]. Conversely, the conflict introduced geopolitical tensions and instability, potentially affecting specific industries and regions more acutely. Thus, understanding the nuanced differences is crucial for comprehending the intricacies of volatility spillovers across BRICS.

The rest of this study is organised as follows: Section 2 presents the theoretical framework employed as the foundation of the study, while Section 3 provides the empirical literature review of studies conducted on market connectedness and volatility spillovers before and during crises. Section 4 describes the methodology, while Section 5 contains the results and discussion. Section 6 concludes the study and provides implications of findings and recommendations for future studies on the subject.

2. Theoretical framework

In traditional finance, few theories have garnered as much attention as the efficient market hypothesis, which posits that markets are efficient due to the rapid assimilation of all available information into asset prices [7]. Investors are presumed rational, processing information per rational expectations [8]. This ensures that market prices adjust promptly to incorporate new information, leading to the accurate pricing of assets at any given time. Consequently, investors cannot consistently outperform the market through trading strategies based on publicly available information, as market participants swiftly correct any potential mispricing.

Various financial market phenomena, such as volatility spillovers, would not be expected to occur in efficient markets because all available information is rapidly and accurately incorporated into asset prices [9]. As a result, asset prices reflect their true underlying value. Any temporary imbalances are quickly corrected by rational arbitrageurs who exploit them. This process ensures that market prices remain efficient and any potential mispricing is promptly rectified across markets. Therefore, in theory, the hypothesis implies that volatility spillovers should be minimal or non-existent in truly efficient markets [8].

Yet, volatility spillovers have been ubiquitously reported across markets [10]. They present opportunities for profit-making that contradict the efficient market hypothesis. Volatility spillovers can only occur if markets are not perfectly efficient, as they entail delayed or incomplete incorporation of information into asset prices in these markets. If a group of investors can discern patterns or trends in volatility spillovers between connected markets, they can consistently outperform the market by leveraging the volatility information from one market to inform their trading decisions in another connected market.

Thus, volatility spillovers may be direct evidence against the efficient market hypothesis, like other abnormal patterns such as value, growth, size, momentum, and reversal effects [11]. They align with behavioural finance theory, a burgeoning strand of finance wherein market participants' psychological biases and irrational behaviours are acknowledged. Investors exhibit cognitive biases, leading to suboptimal decision-making and market inefficiencies. This perspective suggests that market inefficiencies can arise due to behavioural biases, leading to deviations from rational decision-making and the emergence of predictable patterns [12].

In this context, volatility spillovers reflect market interconnectedness and irrational investor behaviour, highlighting the limitations of the efficient market hypothesis in capturing the complexities of real-world markets [11]. Much evidence demonstrates that psychological biases such as herding behaviour and investor sentiment drive market volatility. Additionally, studies examining the relationship between market uncertainty and investor decision-making further underline the influence of behavioural factors on volatility spillovers, revealing the intricate interplay that exists in shaping financial market outcomes [13, 14].

Studies that provide evidence of intensified volatility spillovers during crises also fortify the argument about behavioural bias [15, 16]. During highly volatile periods, investors are more prone to emotional reactions such as fear and panic, which exacerbate market instability and amplify the transmission of volatility across interconnected markets [15, 17]. Additionally, heightened uncertainty and risk aversion may lead investors to overreact to new information or engage in irrational trading behaviour, further fuelling the propagation of volatility spillovers. This supports the notion that behavioural biases play a significant role in markets.

Overall, volatility spillovers and their alignment with behavioural finance theory challenge the rational expectations theories, signifying the need for a better understanding of market dynamics. This is more needful now since markets are increasingly getting connected. Investigating volatility spillover patterns in crises characterised by heightened uncertainty and stress provides valuable insights into the underlying mechanisms driving market behaviour. Understanding how volatility spillovers manifest during such extreme events can inform risk management strategies and enhance market participants' ability to navigate turbulent financial markets.

3. Empirical literature

3.1. Volatility spillovers before the crises

Several studies examined volatility spillovers and market interconnectedness across diverse markets. For example, [18] scrutinised BRIC countries' integration in regional and global equity markets between 1995 and 2004, uncovering significant integration within BRIC and other international markets. [19] explored BRICS capital markets post-2008 global crisis until 2013, revealing volatility spillovers with the US market, indicating the region's interconnectedness with international capital markets. [20] assessed volatility spillovers between the US and Latin American stock indexes from 2003 to 2016, identifying Brazil as a net transmitter of volatility in Latin American markets.

[21] investigated volatility spillovers between BRICS and G7 countries due to volatile oil prices from 1992 to 2015, highlighting the sensitivity to higher volatility and shocks in the oil market. [22] analysed spillover dynamics between the US and BRICS stock markets from 1998 to 2016, revealing shifts in the importance of net spillover in the different countries from the historical status quo. [23] examined volatility spillovers between BRICS and Japan from 2009 to 2019, discovering two-way relationships between foreign exchange and stock markets and emphasising the role of foreign exchange markets in influencing stock market volatility spillovers across different markets.

[3] explored volatility spillovers in BRICS countries from 2002 to 2019, highlighting increased spillovers during crises. [4] investigated returns and volatility spillovers in Indian markets compared to other countries from 2008 to 2019, revealing more significant volatility spillovers among Indian and Asian countries during expansion life cycles. [2] examined volatility spillovers in BRICS stock and foreign exchange markets from 1997 to 2018, identifying interdependence among BRICS markets, particularly during the 2008 global crisis, suggesting implications for coordinated policy responses and risk management strategies.

3.2. Volatility spillovers during the crises

Some other studies conducted similar studies, focusing on crisis periods. For instance, [10, 15] analysed volatility spillovers among BRIC and G7 countries, finding that G7 countries exported risk to BRIC countries, especially during crisis periods. [24] found heightened risk spillovers transmitted by China to its BRICS partners during the COVID-19 pandemic. [25] investigated volatility spillover effects influenced by COVID-19 on India's stock market. They found significant negative spillovers received by India from various global stock markets, particularly the US market. [24] found that connectedness and spillovers across China, America and Europe increased during the Russia-Ukraine conflict.

[26] revealed the significant roles played by the UK, Germany, the US, and France in transmitting risk to Japan and China during the Russia-Ukraine conflict. [27] noted an increase in total spillovers across markets during the Russia-Ukraine conflict, highlighting the influence of Russia in the volatility transmitted to global markets. [27] found that during the COVID-19 pandemic, the US, China, and Brazil exhibited the highest own volatility spillovers, with the US and Russia displaying the strongest long-term spillover effect. [28–30] noted that the Russia-Ukraine conflict had widespread global impacts observed since the 2008 financial crisis. Their study revealed intense interconnectedness among G7 and BRICS countries.

[31] revealed India and China as significant transmitters and receivers of stress spillovers during the COVID-19 pandemic. [32] found stronger connectedness and spillover effects among BRICS equity markets during the COVID-19 pandemic and the Russia-Ukraine conflict crises. [33] found notable contagion effects among BRICS countries, particularly heightened during the COVID-19 pandemic and the Russia-Ukraine conflict, notably with increased contributions from Russia. [34] found that volatility spillover among G7 and BRICS stock markets indexes increased during the Russia-Ukraine conflict and the pandemic. Additionally, the effect of geopolitical risk on spillovers varied over time.

Overall, the literature highlights the importance of examining volatility spillovers across markets. These studies consistently showed significant volatility spillovers among markets, including those involving BRICS countries, with crisis events amplifying these spillovers. Before the crises, some studies demonstrated dynamic shifts in spillover patterns influenced by economic phases. In contrast, heightened volatility transmission and interconnectedness were evident during crisis periods. These findings provide a compelling rationale for investigating volatility spillovers between BRIC and South African markets during the COVID-19 and Russia-Ukraine crises and stable periods.

4. Data and methodology

4.1. Data description

Daily closing prices on the BRICS broad market indices from January 2013 to 30 June 2023 from Bloomberg[1] were employed. Daily data offers a more efficient assessment of short-term price movements compared to lower frequencies, allowing for early detection of market trends [35]. The selection of broad market indices, as depicted in *Table 1,* ensured a good representation of a diverse range of stocks within each respective market [3, 2]. The returns on the broad market indices were then calculated as follows:

$$R_t = \text{In}\left(P_t / P_{t-1}\right)\times 100, \quad (1)$$

where: R_t are the index returns on day t, and P_t and P_{t-1} are the index prices on day t and $t-1$, respectively, in line with [35] and [3].

The study's sample, consistent with [2], excluded weekends and holidays for uniformity across BRICS economies, covering pre-crisis periods [25] and major events such as COVID-19 and the Russia-Ukraine conflict. It was divided into pre-crisis, COVID-19, and Russia-Ukraine conflict periods [36, 37], with the division justified by the distinct impacts each phase likely had on volatility spillovers between BRIC and South African stock markets. The pre-crisis period serves as a baseline of market behaviour under stable conditions, while the COVID-19 pandemic, marked by global economic disruptions and heightened uncertainty, may have amplified volatility spillovers.

In contrast, the Russia-Ukraine conflict, driven by geopolitical tensions, may have reduced spillovers due to market isolation and risk aversion. Thus, this segmentation allows the study to provide insights into the varying nature and transmission mechanisms of shocks across markets, captured using dummy variables for each period. Preliminary data analysis included stationarity tests [36], the Jarque-Bera test for normality, skewness, kurtosis statistics, and mean and standard deviation calculations. Autocorrelation and ARCH effects were assessed using the Ljung-Box [37] and the ARCH-LM tests, ensuring the GARCH model's suitability [23].

[1] Bloomberg Professional Services. Bloomberg terminal. Bloomberg. URL: https://www.bloomberg.com/professional/solution/bloomberg-terminal/ (accessed on 20.07.2023).

4.2. Method of analysis

4.2.1. GARCH models

To examine spillovers across the BRICS, this study employed both the GARCH (1,1), the TGARCH (1,1) and the EGARCH (1,1) in line with [23] and [2] to produce residuals to use in subsequent estimations. The GARCH models were chosen based on their ability to capture and model the time-varying volatility and leverage effects in financial markets. GARCH models are widely employed because they provide a robust framework for estimating volatility based on past values and errors. These are critical for understanding how market conditions evolve [36].

TGARCH and EGARCH models extend the standard GARCH by incorporating asymmetry and leverage effects, which are particularly relevant during periods of financial stress, as these models account for the fact that negative shocks may have a different impact on volatility compared to positive shocks [36]. These models allow the study to capture the complex and dynamic volatility patterns within the BRIC and South African markets, ensuring that the analysis reflects the true nature of market interconnections and spillovers during stable and crisis periods [2, 23].

The best model was selected using the Schwarz-Bayesian Information Criterion (SBIC) because it provides a reliable measure for model selection by balancing model fit and complexity. SBIC penalises the inclusion of unnecessary parameters, thus preventing overfitting while ensuring that the chosen model adequately captures the underlying volatility structure of the data. This criterion is particularly effective when comparing multiple models, as it consistently selects the model that optimises the trade-off between goodness of fit and parsimony, making it well-suited for choosing the most appropriate GARCH-based model for the study [36].

The mean equation — standard across the three models — was specified as:

$$y_t = \mu + \theta\left(\sigma_{t-1}\right) + \vartheta\left(y_{t-1}\right) + \nu\left(u_{t-1}\right) + u_t, \quad (2)$$

where:

ϑ captures the effect of previous returns, y_{t-1}, on current returns,

ν indicates the effect of past shocks, u_{t-1}, on current returns, and ·represents the risk premium on the standard deviation, σ_{t-1}.

Equations (3), (4), and (5) represent the variance equation specifications for the GARCH (1,1),

Table 1
BRICS broad market indices, 2013–2023

Countries	**Index**
Brazil	BOVESPA-Brazil Sao Paulo Equity Index
Russia	Russia Trading System Index
India	National Stock Exchange NIFTY 50 Index
China	Shanghai Stock Exchange Composite Index
South Africa	FTSE Johannesburg Stock Exchange All Share Index

Source: BRICS broad market indices, Bloomberg Terminal. URL: https://www.bloomberg.com (accessed on 21.04.2023).

TGARCH, and EGARCH models. Equation (3) improves on the ARCH model by reducing the likelihood of violating the non-negativity property, while Equations (4) and (5) go further by incorporating terms to capture leverage effects [2]. Of note is that the possibility of violating the non-negativity constraints on variance is entirely mitigated by the EGARCH. The specifications are as follows:

$$\sigma_t^2 = \omega_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2, \quad (3)$$

$$\sigma_t^2 = \omega_0 + \alpha_1 u_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta u_{t-1}^2 I_{t-1}, \quad (4)$$

where $I_{t-1} = 1$ if $u_{t-1} < 0$; and = 0 otherwise

$$\ln(\sigma_t^2) = \omega_0 + \alpha_1 \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right] + \beta \ln\sigma_{t-1}^2 + \delta \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} \quad (5)$$

where:

σ_t^2 is the conditional variance,

u_{t-1}^2 is the information about volatility in the previous period (the ARCH term) with

α_1 as the coefficient. The long-term mean is given by

ω_0 and the GARCH term is shown by

σ_{t-1}^2 with

β as the coefficient. Terms capture the leverage effects in Equations (4) and (5), respectively.

Subsequently, the models were examined to determine if they satisfy the stationarity and non-negativity conditions. The SBIC was then utilised to obtain the best models, and the residuals obtained from the selected models were transferred to the Diebold-Yilmaz model to examine volatility spillovers across BRICS markets.

4.2.2. Diebold-Yilmaz index

To explore spillover effects within BRICS, the study employed the Diebold-Yilmaz index [37, 38], known for its capability to quantify total and directional spillovers among financial markets. This index captures the overall interconnectedness of markets and distinguishes between the influence of individual markets as transmitters or receivers of volatility. Its dynamic framework allows for a comprehensive analysis of how shocks propagate across markets, particularly during periods of heightened uncertainty, thus ideal for examining the complex interrelations within the BRICS economies.

[28] and [1] advocate for incorporating a time-varying variation of the TVP-VAR model, as pioneered by [39]. The TVP-VAR model, which utilises Kalman filter estimation, effectively captures the evolving nature of spillovers over time, eliminating the constraints associated with fixed rolling window sizes and offering robustness against outliers. This approach allows for a more precise and flexible analysis of dynamic spillover effects, making it particularly suitable for assessing the interconnectedness of financial markets in this study. Therefore, the TVP-VAR model was specified as follows:

$$Y_t = \beta_t Y_{t-1} + \varepsilon_t,$$

$$\varepsilon_t \sim N(0, S_t) \quad (6)$$

$$\beta_t = \beta_{t-1} + \upsilon_t, \ \upsilon_t \sim N(0, R_t), \quad (7)$$

where: The variable vectors Y_t and $Y_t - 1$ are $N \times 1$, as is the error terms ε_t vector. Time-varying coefficients β_t, ν_t, and S_t are represented by $N \times N$ matrices, while the error variance-covariance matrix R_t has dimensions $N2 \times N2$. For connectedness measures, the TVP-VAR is transformed into a TVP-VMA as:

$$Y_t = \sum_{j=0}^{\infty} A_{jt}\varepsilon_{t-j}, \tag{8}$$

where: A_{jt} is a $N \times N$ matrix.

4.2.3. Generalised impulse response and variance decompositions

After that, the generalised impulse response function (GIRPF) and the generalised forecast error variance decomposition (GFEVD) were estimated to analyse how variables in the system respond to shocks, as they provide a comprehensive understanding of the dynamic relationships within the model [26]. GIRPF allows for assessing the magnitude and direction of variable responses to specific shocks without requiring orthogonalisation, thus maintaining the system's structural integrity. Meanwhile, GFEVD quantifies the proportion of each variable's forecast error variance attributed to shocks in other variables, offering insights into the influence and connectedness within the system.

Thus, together, these techniques enable a detailed exploration of the pathways and impacts of shocks across the variables, capturing the full extent of spillover effects in the studied financial markets. Following [40], the GIRPFs and GFEVDs were determined as:

$$\begin{cases} GIRF_t\left(h, \delta_{j,t}, F_{t-1}\right) = E\left(Y_{t+h} \mid \varepsilon_{j,t} = \delta_{j,t}, F_{t-1}\right) - E\left(Y_{t+h} \mid \varepsilon_{j,t} = F_{t-1}\right) \\ \psi_{j,t}^{g}(h) = S_{jj,t}^{-\frac{1}{2}} A_{h,t} S_t \varepsilon_{j,t}, \end{cases} \tag{9}$$

$$\begin{cases} GFEVD: \tilde{\theta}_{ij,t}^{g}(h) = \sum_{t=1}^{h-1} \psi_{ij,t}^{2,g}(h) \Big/ \sum_{j=1}^{N} \sum_{t=1}^{h-1} \psi_{ij,t}^{2,g}(h) \\ with \sum_{j=1}^{N} \tilde{\theta}_{ij,t}^{g}(h) = 1 \;\; and \;\; \sum_{i,j=1}^{N} \tilde{\theta}_{ij,t}^{g}(h) = N, \end{cases} \tag{10}$$

where:

h indicates the forecast horizon for equations (9) and (10), $\psi_{j,t}^{g}(h)$ shows variable j's GIRPFs and the selection vector is given by

$\delta_{j,t}$ which equals one for the element j and zero otherwise, and the information set is indicated by F_{t-1} until $t-1$.

The net spillovers of individual markets were assessed to ascertain whether they have acted as net receivers or transmitters of spillover effects. The total influence of shocks from all variables on the forecasted total error variance is referred to as the total spillover index (2:6). Additionally, the GFEVD, utilised in calculating the Total Connectedness Index (TCI), is provided by [25] as:

$$S_t^{g}(h) = \sum_{\substack{i,j=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij,t}^{g}(h) \Big/ \sum_{i,j=1}^{N} \tilde{\theta}_{ij,t}^{g}(h) \times 100, \tag{11}$$

where:

$S_t^{g}(h)$ denotes the total connectedness across the system.

In addition, per [1], directional spillovers are either transferred (Equation 12) or received (Equation 13) by the market i in the model in relation to the other markets, with the net spillovers being the difference (Equation 14). The latter determines whether a market is a net transmitter or receiver. The net pairwise directional spillovers are given by Equation 15, with a positive value indicating that i influences j, and vice versa for a negative value.

$$S_{,i}^{g}\left(h\right)=\sum_{\substack{j=1\\ i\neq j}}^{N}\theta_{ji,t}^{\sim g}\left(h\right)/\sum_{j=1}^{N}\theta_{ji,t}^{\sim g}\left(h\right)\times 100, \tag{12}$$

$$S_{i,}^{g}\left(h\right)=\sum_{\substack{j=1\\ i\neq j}}^{N}\theta_{ij,t}^{\sim g}\left(h\right)/\sum_{i=1}^{N}\theta_{ij,t}^{\sim g}\left(h\right)\times 100, \tag{13}$$

$$S_{i,t}^{g}\left(h\right)=S_{,i}^{g}\left(h\right)-S_{i,}^{g}\left(h\right), \tag{14}$$

$$NPDC_{ij}\left(h\right)=\theta_{ji,t}^{\sim g}\left(h\right)-\theta_{ij,t}^{\sim g}\left(h\right), \tag{15}$$

where: $NPDC_{ij}\left(h\right)$ indicates the net pairwise directional connectedness between market *i* and market *j*.

Overall, these estimations, primarily done in EViews, Excel and the David Gabauer online estimation platform, allowed for examining volatility spillovers among BRICS markets during the COVID-19 and Russia-Ukraine crises, providing insights into total, directional, and net spillovers, enabling a comprehensive analysis of BRICS interconnections.

5. Results and analysis

5.1. Preliminary data analysis

Figure 1, depicting the BRICS broad market indices, reveals a notable trend of volatility clustering during two major crises. This phenomenon, characterised by periods of heightened market fluctuations and sharper price movements, indicates a substantial increase in market uncertainty and risk. These findings align with those of [26], who observed increased volatility spillovers among BRICS markets during the COVID-19 pandemic due to economic disruptions and heightened investor uncertainty. Similarly, the pronounced impact of these crises on BRICS markets is consistent with [24], who found that geopolitical tensions during the Russia-Ukraine conflict led to significant market volatility, albeit with a differing spillover pattern due to the isolating effects of sanctions.

The observed volatility clustering underscores the interconnectedness and vulnerability of global financial systems to external shocks, as highlighted in previous studies on crisis periods [27]. Unlike earlier findings that suggested uniformly increased spillovers during crises, our results indicate that while the COVID-19 pandemic intensified interconnectedness, the Russia-Ukraine conflict led to reduced spillovers due to regional isolation, aligning with the conclusions of [17] that geopolitical disputes often result in market segmentation rather than integration. These insights emphasise the importance of robust risk management strategies to monitor and mitigate potential vulnerabilities in the face of such disruptions.

A preliminary analysis of BRICS broad market indices in *Table 2* reveals distinct characteristics. India boasts the highest mean daily return (0.0533%), while Russia experienced negative returns (–0.0217%) amidst geopolitical tensions. Russia also displays the highest volatility, followed by China, while India exhibits the least. Skewness and kurtosis values indicate non-normal return distributions, further confirmed by Jarque-Bera statistics. All indices exhibit stationarity in levels and significant ARCH effects, suggesting volatility clustering and serial correlation in residuals. These findings necessitate using GARCH models for accurate volatility analysis in the BRICS markets. These findings align with [20] in supporting the use of GARCH models.

The analysis of various GARCH models with different error distributions indicated that the optimal model varied among the BRICS nations. Although the EGARCH model with Student's t error distribution initially appeared suitable due to its low SBIC value, it failed to meet the stationarity condition. Consequently, TGARCH models were selected for Brazil and Russia, while standard GARCH models were deemed most appropriate for China, India, and South Africa, all utilising Student's t error distribu-

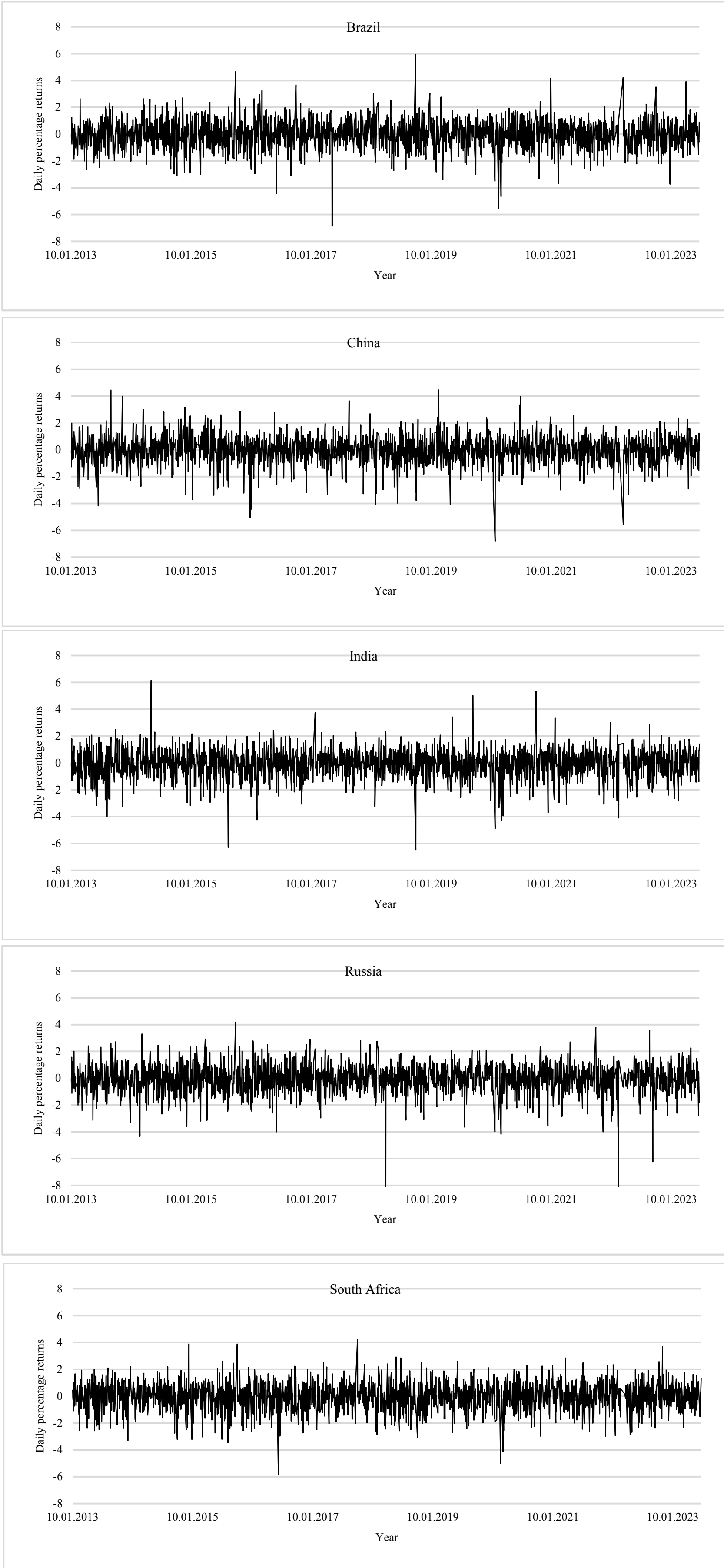


Fig. 1. **Broad market returns over the sample period**

Source: Authors' own depiction (2023).

Table 2
Preliminary tests and descriptive statistics

Test	rBzl	rRus	rInd	rChn	rSaf
Observations	2180	2180	2180	2180	2180
Mean (%)	0.0302	0.0217	0.0533	0.0157	0.0293
Std dev%	1.7154	2.3391	1.1688	1.4240	1.1697
Skewness	−0.7079	−4.0731	−1.1290	−0.8768	−0.5524
Kurtosis	15.2266	93.2108	18.5255	11.4267	10.2961
Jarque-Bera	13 760.63*	745 228.1*	22 357.67*	6729.294*	4946.183*
ADF t-stat	−49.0978*	−48.6743*	−46.4755*	−44.7242*	−45.6468*
KPSS lm-stat	0.0563	0.0555	0.02868	0.0417	0.0258
ARCH F-stat	985.5808*	115.0954*	83.1222*	69.7706*	156.4986*
Ljung-Box Q-stat	2119.9	148.92	1381.5	820.14	2277.7
Ljung-Box Q2-stat	59.882	52.644	80.017	48.652	28.454

Source: Authors' own computations (2023).

Note: * indicates the rejection at a 1% significance level.

tion. The residuals derived from these models were then employed to further analyse spillover effects and market interconnections within the BRICS countries using the Diebold-Yilmaz spillover index. The use of these tailored GARCH models allowed for a more precise capture of the unique volatility dynamics in each market.

5.2. Volatility spillover analysis

Table 3 reveals significant shifts in market dynamics across the sub-periods, as reflected in the TCI values. Before the crises, only 35.13% of market risk was attributed to spillovers, indicative of low interconnectedness, aligning with findings from previous studies that noted lower spillover levels during stable periods [15, 20]. However, during the pandemic, it surged to 54.14%, likely due to heightened correlations and contagion effects, as observed by [15, 26], who reported increased volatility transmission among BRICS markets during COVID-19. Conversely, it dropped to 22.05% during the Russia-Ukraine conflict, potentially due to sanctions imposed on Russia, which isolated the conflict's impact, consistent with [27]. These fluctuations highlight the sensitivity of financial markets to global events, a recurrent theme in the literature on crisis periods [24].

In the pre-crisis period, South Africa emerged as the primary transmitter at 36.46%, while China exhibited the lowest spillover transmission at 16.81%. South Africa also led in spillover reception at 35.03%, with China receiving the least at 20.50%, which aligns with findings that suggest regulatory frameworks significantly influence market dynamics during stable periods [13]. During the pandemic, total directional spillovers surged, with South Africa maintaining its dominance as the largest transmitter at 57.50% and China as the least transmitter at 23.06%, consistent with literature highlighting China's resilience due to strict capital movement restrictions during crises [26]. India exhibited increased transmission compared to Brazil, mirroring the findings noting India's growing interconnectedness during the pandemic [32].

Contrary to expectations, the Russia-Ukraine conflict decreased proportional connectedness and spillovers, with Russia transmitting and receiving minimal spillovers, reflecting findings by [28], who documented how sanctions created barriers that reduced Russia's market impact. Consequently, Russia became the lowest transmitter, while South Africa retained its status as the highest, a pattern similarly reported in studies on emerging markets' reliance on global trade [21]. South Africa's position as the largest receiver of shocks was likely due to its heavy dependence on international trade and commodity prices, highlighting the complexities of geopolitical conflicts on market dynamics, as supported by [32]. However, the analysis of net spillovers also unveils the shifting behaviour of BRICS markets in the subperiods.

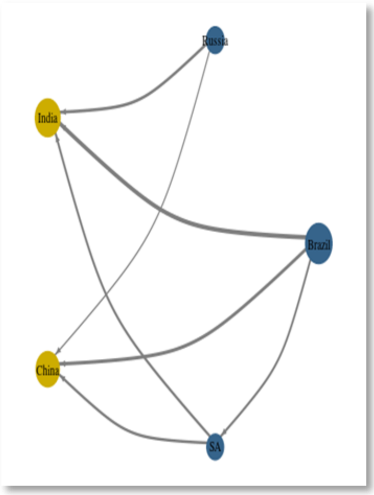


Fig. 2.a

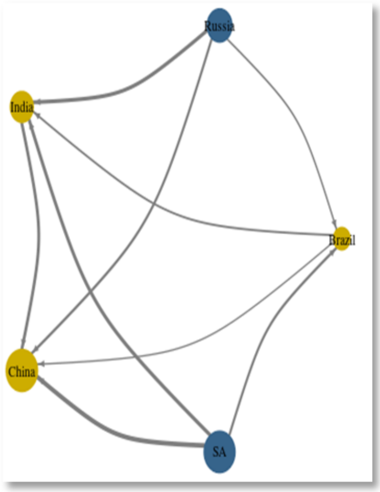


Fig. 2.b

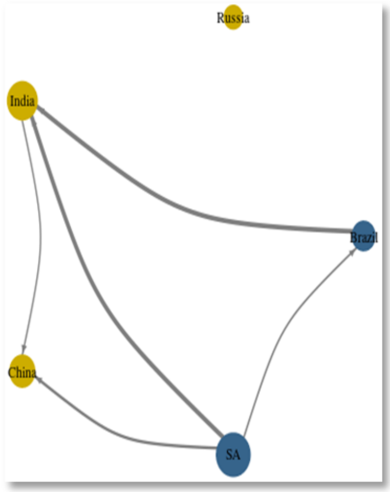


Fig. 2.c

Fig. 2. **Volatility spillover networks**

Source: Authors' own depiction (2023).

During the pandemic, Brazil shifted from being a net transmitter to a net receiver of volatility, likely due to its healthcare vulnerabilities and trade dependence, aligning with findings by [20]. In contrast, South Africa remained the largest net transmitter, consistent with findings by [3]. This pattern continued during the Russia-Ukraine conflict, where Russia, impacted by sanctions, became a net receiver, as observed by [17]. Pre-crisis, South Africa and Russia exhibited strong pairwise volatility spillovers. South Africa emerged as the most interconnected BRICS country during the pandemic, transmitting the most volatility to other members, as highlighted by studies on South Africa's role [32]. The Russia-Ukraine conflict saw Brazil, India, and China receiving more volatility from South Africa, reflecting its growing importance in global trade [28].

The net pairwise spillovers among BRICS countries during crises, analysed through volatility spillover networks in *Fig. 2*, reveal distinct patterns of volatility transmission across different periods. Before the crises (*Fig 2.a*), Brazil was the dominant source of volatility spillovers, while Russia and South Africa exhibited similar spillover behaviours, indicating a balanced yet interconnected market environment. During the COVID-19 pandemic (*Fig 2.b*), the dynamics shifted, with Russia and South Africa emerging as the primary transmitters of volatility, consistent with [26]. South Africa's significant role in transmitting shocks, particularly to India and China, stresses its growing influence within the BRICS bloc [16].

In contrast, Russia's role in volatility transmission was markedly diminished during the Russia-Ukraine conflict (*Fig 2.c*), likely due to trade restrictions and sanctions that isolated its market impact [27]. This shift left Brazil and South Africa as the primary drivers of volatility, with both countries significantly influencing India's market dynamics, which aligns with the findings by [17] and [13]. Overall, these findings emphasise the evolving nature of market interconnectedness within BRICS, demonstrating how South Africa, in particular, can exert substantial influence on the regional market landscape during periods of economic turbulence.

The limitations of static analysis in capturing the evolving nature of volatility spillovers prompted the adoption of a dynamic approach, as recent literature recommends, emphasising the importance of time-varying measures for understanding market interconnections [39]. Figure 3 below illustrates the dynamic TCI, which provides a better view of changes in market linkages over time. It notably surged above 50% during 2015–2016, coinciding with China's market crash, a period characterised by heightened global uncertainty and increased financial contagion, consistent with findings from [26]. The index peaked above 60% in early 2020, reflecting the severe impact of the COVID-19 pandemic on global financial interconnectedness, in line with documentation of significant increases in correlations during the pandemic [10].

Table 3
Static spillovers

	Market	Brazil	Russia	India	China	SA	FROM
Pre-crises	Brazil	76.66	11.11	3.80	1.59	6.84	23.34
	Russia	11.37	66.74	5.78	4.14	11.98	33.26
	India	5.70	7.11	71.62	5.13	10.44	28.38
	China	3.10	4.84	5.36	79.50	7.19	20.50
	SA	8.02	11.87	9.18	5.96	64.97	35.03
	TO	28.19	34.94	24.11	16.81	36.46	140.51
	Including Own	104.85	101.68	95.73	96.31	101.43	TCI =35.13
	NET	4.85	1.68	−4.27	−3.69	1.43	
	NPDC	4.00	2.00	1.00	0.00	3.00	
COVID-19 pandemic	Brazil	58.93	12.97	10.28	4.07	13.74	41.07
	Russia	11.82	52.21	11.12	4.91	19.94	47.79
	India	11.55	13.33	53.08	7.49	14.55	46.92
	China	5.02	6.60	9.66	69.45	9.28	30.55
	SA	12.07	19.30	12.26	6.59	49.78	50.22
	TO	40.46	52.21	43.32	23.06	57.50	216.55
	Including Own	99.39	104.42	96.41	92.51	107.27	TCI =54.14
	NET	−0.61	4.42	−3.59	−7.49	7.27	
	NPDC	2.00	3.00	1.00	0.00	4.00	
Russia-Ukraine conflict	Brazil	81.34	1.14	5.92	2.79	8.81	18.66
	Russia	1.29	95.47	0.20	2.13	0.92	4.53
	India	8.38	0.25	77.00	0.57	13.80	23.00
	China	3.19	1.77	1.52	84.89	8.62	15.11
	SA	7.75	0.81	11.31	7.04	73.09	26.91
	TO	20.61	3.98	18.95	12.53	32.15	88.22
	Including Own	101.95	99.44	95.95	97.42	105.24	TCI =22.05
	NET	1.95	−0.56	−4.05	−2.58	5.24	
	NPDC	3.00	1.00	1.00	1.00	4.00	

Source: Authors' own computations (2023).

Note: All figures in this table are percentages (%) and have been displayed without the % sign for brevity.

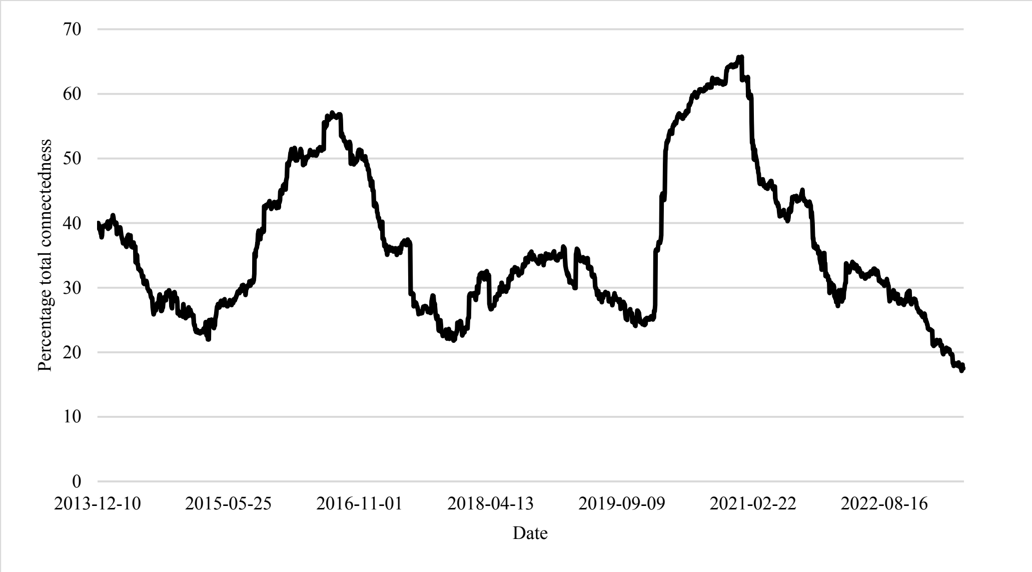


Fig. 3. **Dynamic total connectedness index**

Source: Authors' own depiction (2023).

Following the initial pandemic shock, the TCI gradually declined, likely due to improved pandemic management, economic adjustments, and monetary policy interventions aimed at stabilising markets, as observed by [29]. A renewed increase in the TCI in February 2022, followed by a gradual decline, underscores the impact of the Russia-Ukraine conflict on BRICS market interconnectedness, aligning with the literature that highlights how geopolitical events can abruptly alter market dynamics and volatility spillovers [1]. These findings reaffirm the critical need for dynamic analysis to capture better the temporal fluctuations in market connectedness driven by global economic and geopolitical developments. Otherwise, relying solely on static measures risks missing the real-time market behaviour and response shifts.

The dynamic directional spillovers in *Fig. 4* provide critical insights into the interactions between BRICS markets. During the crises, markets exhibited increased spillovers and connectedness, indicating contagion effects similar to those documented in previous studies [30]. China and India experienced predominantly negative net spillovers, likely due to their relatively insulated financial systems and stringent regulatory measures [10, 32]. In contrast, Brazil, Russia, and South Africa showed varying patterns, with South Africa frequently displaying positive net spillovers, particularly during the pandemic, demonstrating its role as a major volatility transmitter within the BRICS network, as shown by [16].

In *Fig. 5*, the net pairwise analysis reveals fluctuating volatility transmission between Brazil and Russia. Brazil generally received from Russia during the pandemic and the conflict, aligning with findings emphasising Russia's role as a volatility source during crises [32]. Brazil consistently transmitted volatility to India and China while receiving from South Africa, consistent with [32]. Russia transmitted volatility to India and China but was a net receiver from South Africa, particularly during the pandemic, aligning with [34]. The conflict marked a shift, with India and China transmitting to Russia and South Africa emerging as a net receiver, showcasing the dynamic nature of market linkages [35].

India consistently transmitted volatility to China and received it from South Africa. At the same time, China remained a net receiver from South Africa across both crises, highlighting their interconnected yet distinct roles within the network. These dynamics are further emphasised in *Fig. 6*. The continued economic integration means such patterns may become more prominent in future crises, reinforcing the necessity for vigilant market monitoring. A slight increase in connectedness observed following the Russia-Ukraine conflict reflects the broader impact of geopolitical tensions on global market dynamics, consistent with findings highlighting the ripple effects of geopolitical shocks on interconnected markets [1].

Spikes in connectedness also align with significant market events, such as the market crash in China, highlighting the heightened sensitivity of BRICS

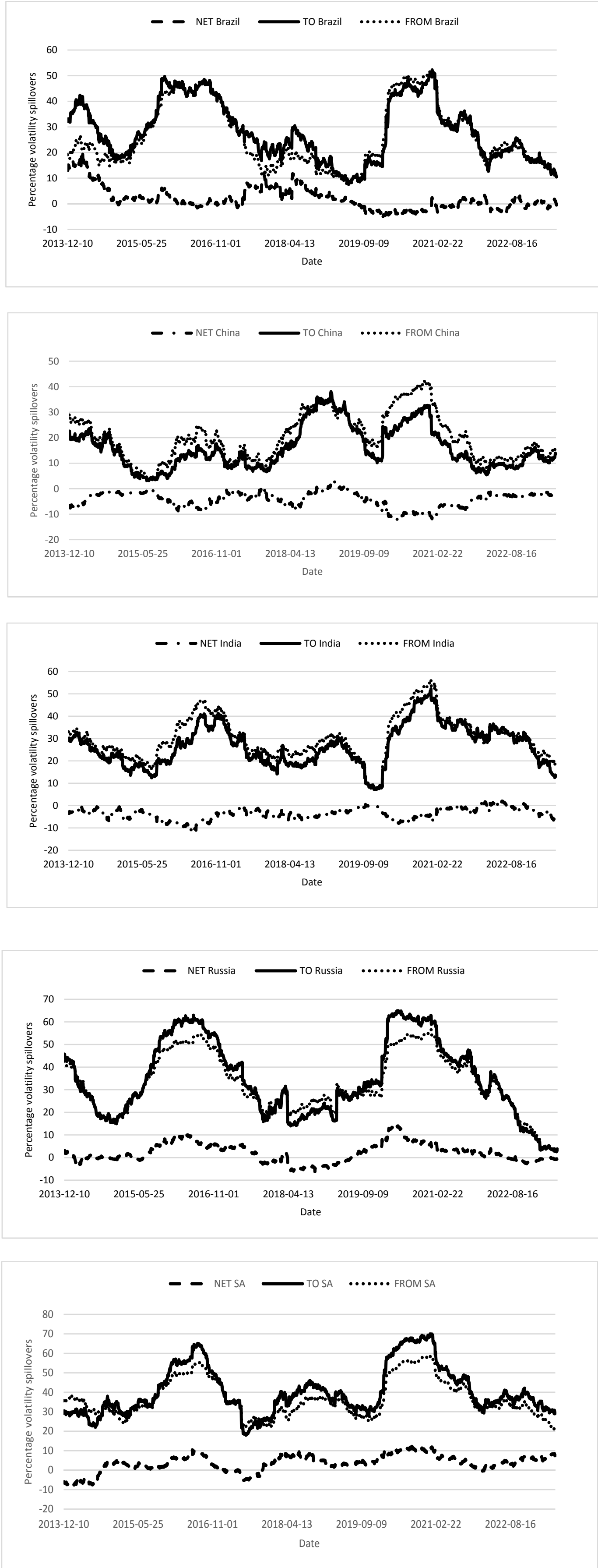
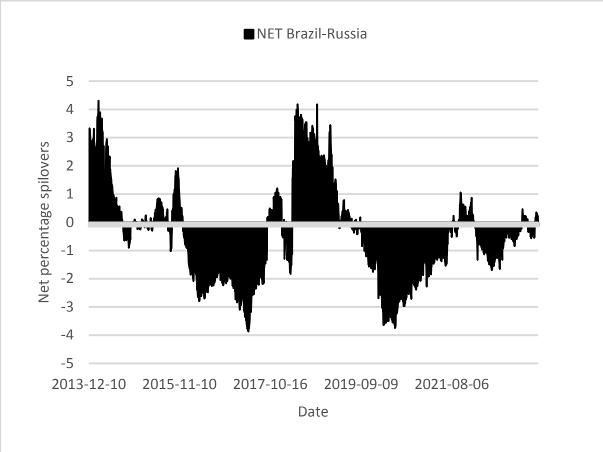


Fig. 4. **Directional dynamic spillovers**

Source: Authors' own depiction (2023).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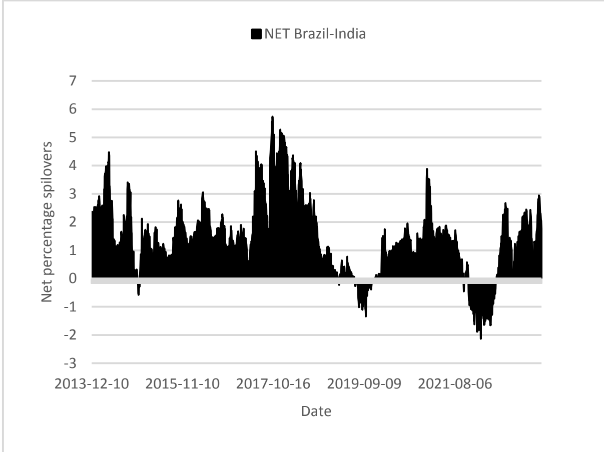
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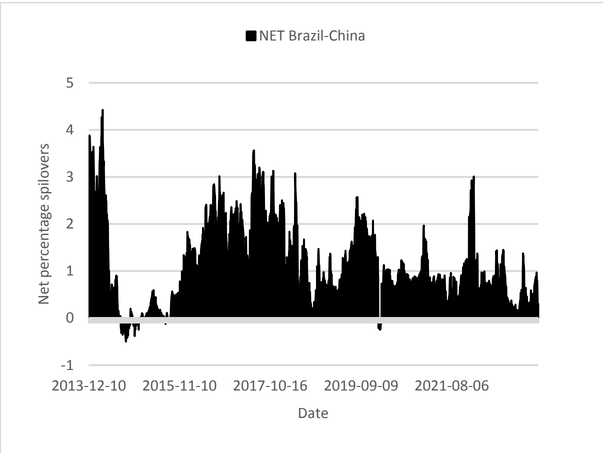
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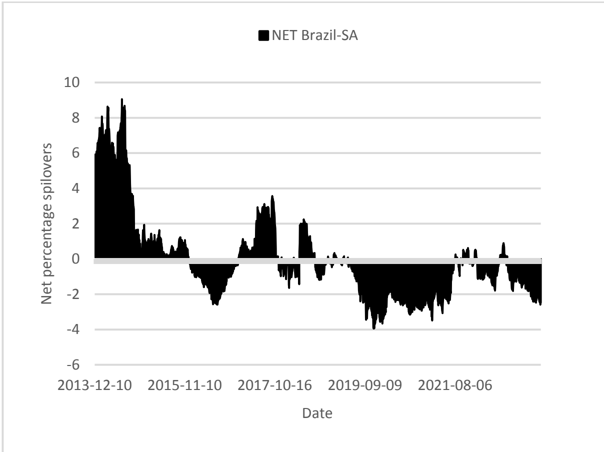
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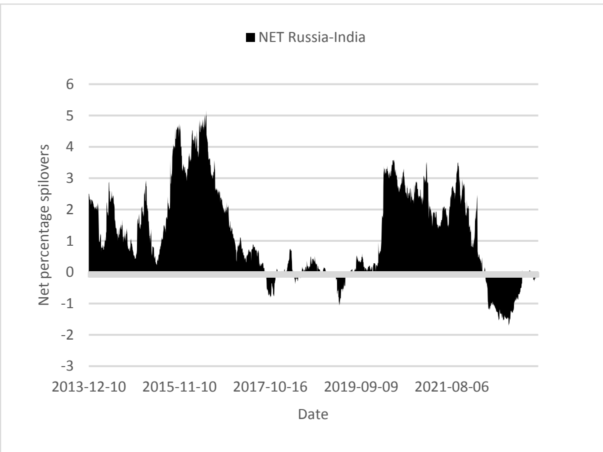
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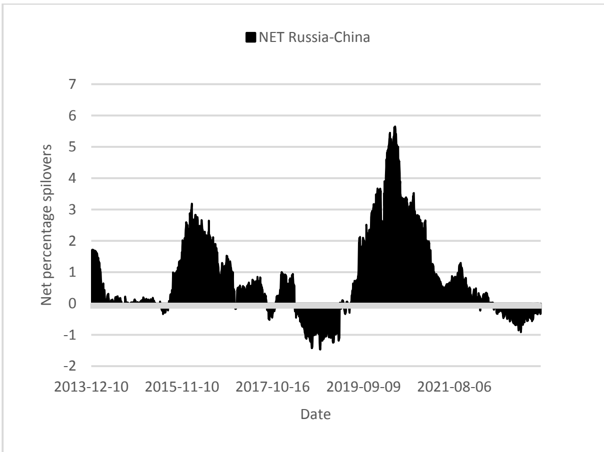
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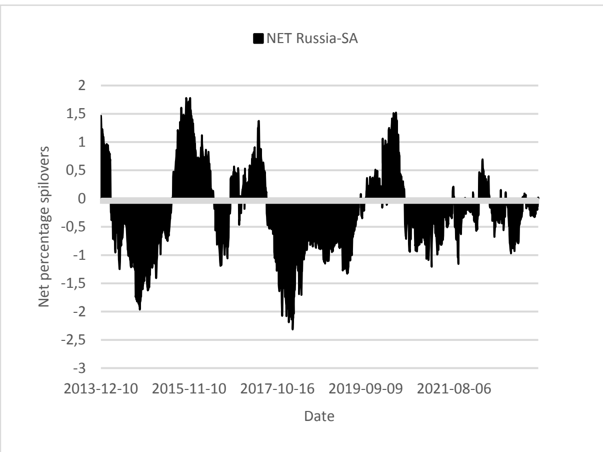
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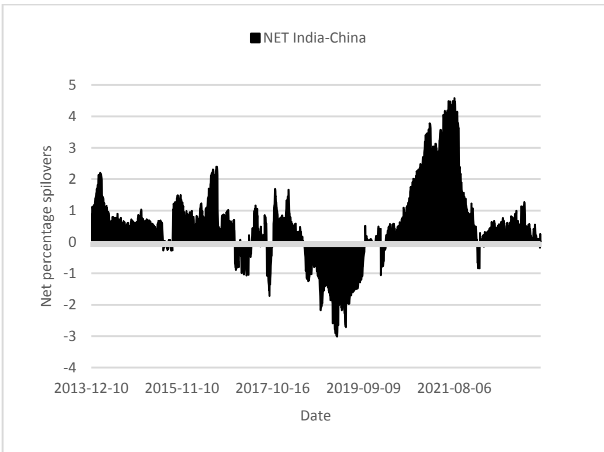
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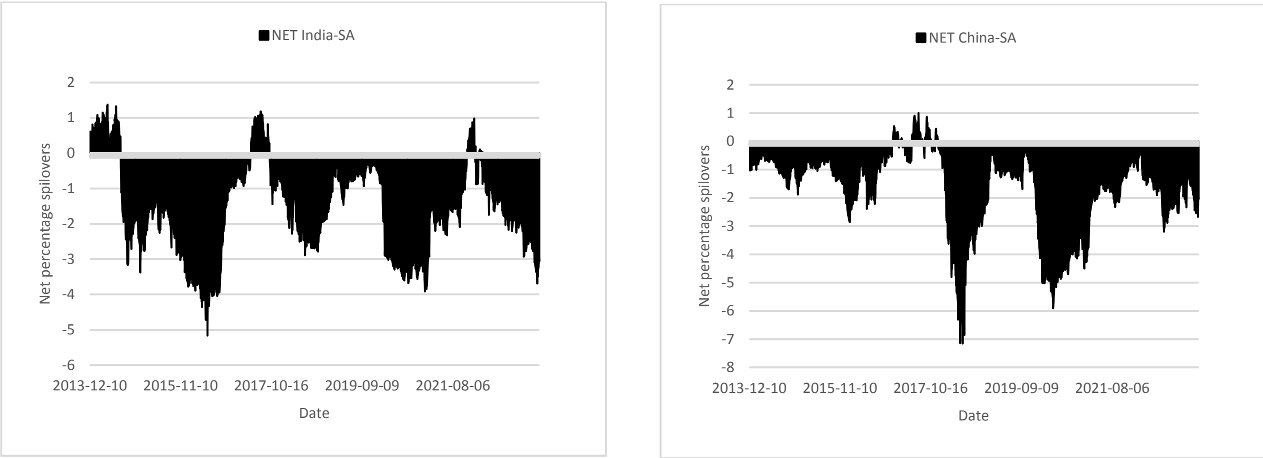
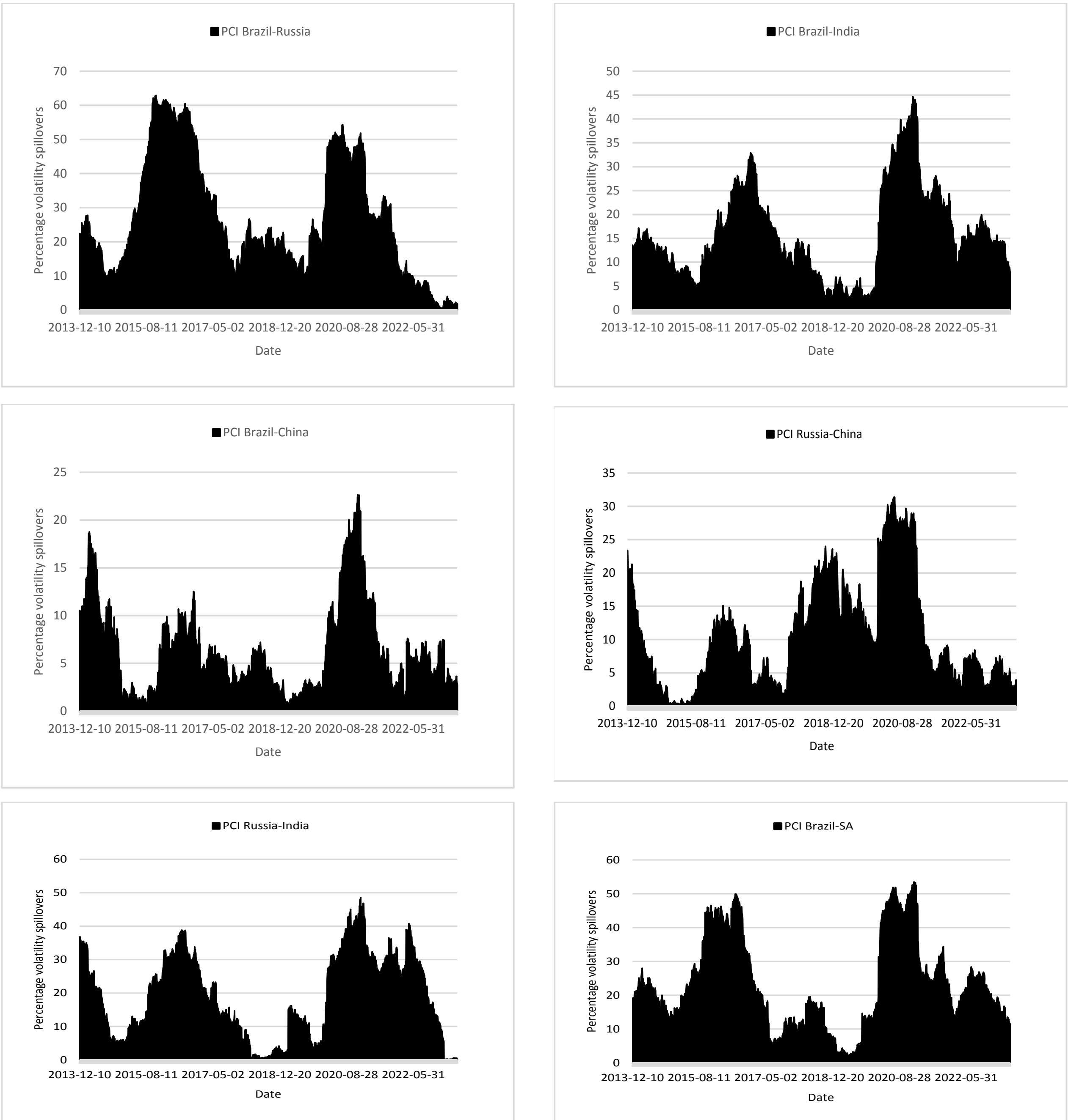


Fig. 5. **Dynamic net pairwise spillovers**

Source: Authors' own depiction (2023)



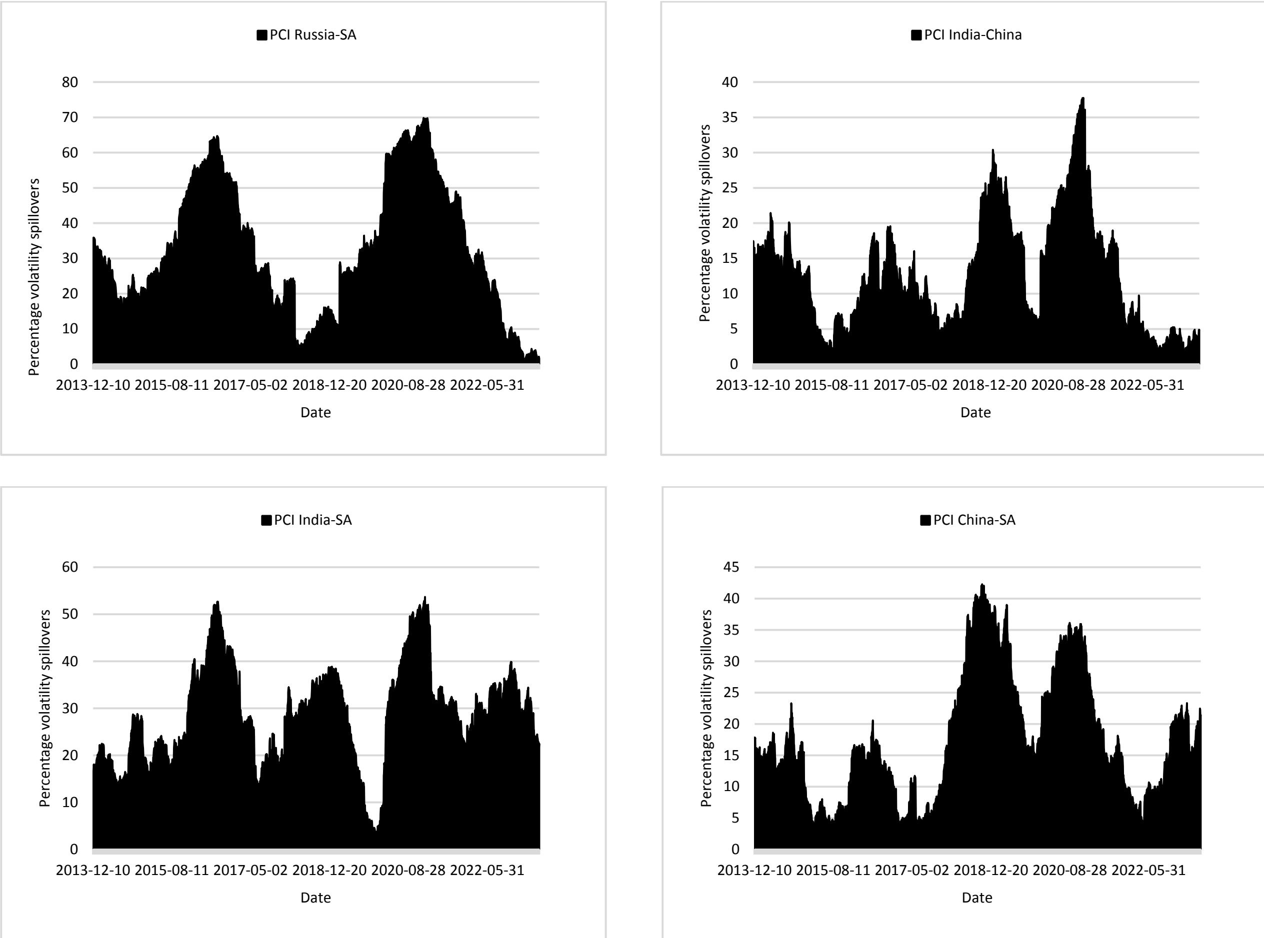


Fig. 6. **Pairwise Connectedness Index between BRICS countries over time**

Source: Authors' own depiction (2023).

markets to global disruptions and external shocks. These periods of increased volatility transmission underscore how quickly economic and geopolitical events can ripple through interconnected markets, affecting investor sentiment and market stability. Looking forward, it will be crucial to compare the impacts of the Russia-Ukraine conflict with those of ongoing geopolitical tensions, such as the current Middle East conflict, to understand how different types of crises influence market dynamics and interconnectedness.

Overall, the analysis reveals South Africa's consistent role as a transmitter of volatility across various crises. This prominence was particularly evident during the COVID-19 pandemic, where South Africa remained the top transmitter even as interconnectedness among BRICS nations declined. Interestingly, even the Russia-Ukraine conflict, which caused a decrease in overall spillovers, couldn't diminish South Africa's role as a primary transmitter. The reasons behind South Africa's unique role as a volatility transmitter warrant further investigation but could include its heavy reliance on global trade and possession of a financial system that might be more open and deregulated relative to the other BRICS.

6. Conclusion

This study examined the dynamics of volatility spillovers between the BRIC and South African stock markets across pre-crisis, COVID-19, and the Russia-Ukraine conflict periods. It highlighted substantial variations in spillover intensity across these phases, illustrating that crises and non-crisis periods impact market interconnectedness differently. These findings highlight the context dependency of market dynamics. Furthermore, different crises, such as the COVID-19 pandemic and the Russia-Ukraine conflict, also demonstrated unique impacts on market behaviours, reflecting the varying nature of economic disruptions and geopolitical tensions on volatility spillovers in interconnected markets.

During the COVID-19 pandemic, volatility spillovers increased significantly among BRICS markets, aligning with previous studies highlighting heightened contagion effects during global crises [3]. This spillover increase can be attributed to the widespread economic disruptions, lockdown measures, and heightened uncertainty that characterised the pandemic period [26]. In contrast, the Russia-Ukraine conflict saw a general decline in cross-market spillovers, mainly due to geopolitical isolation, sanctions on Russia, and reduced cross-border financial interactions, reflecting findings by [24] and [28].

South Africa consistently emerged as a key transmitter of volatility, especially during the COVID-19 pandemic. This dominant role may be attributed to its significant exposure to global commodity markets and relatively open financial system compared to other BRICS countries [16]. These findings suggest that market characteristics, such as openness to international trade and financial regulation, significantly influence the extent of spillover effects during crises. The persistent role of South Africa as a volatility transmitter aligns with [13], who found that emerging markets with higher integration into global financial systems are more likely to transmit shocks during periods of heightened uncertainty.

Interestingly, the study challenges initial assumptions that the Russia-Ukraine conflict would lead to heightened spillovers across BRICS markets, especially given the global economic disruptions typically associated with such geopolitical events. Contrary to expectations, spillover transmission decreased, indicating that geopolitical factors such as sanctions and regional isolation can reduce interconnectedness rather than intensify it [27]. This outcome aligns with the findings of [17], who noted that geopolitical conflicts often cause market segmentation rather than increased integration, highlighting how political tensions can disrupt regular market linkages and dampen cross-border volatility transmission.

These results have significant implications for policymakers, investors, and scholars. Policymakers should acknowledge that the nature of a crisis significantly influences market interconnectedness and the magnitude of spillover effects. Investors need to understand that financial markets react differently to various shocks, highlighting the importance of dynamic risk assessments. For scholars, these findings emphasise the need for continued research into crisis-specific market responses to refine predictive models. Overall, the evidence calls for tailored risk management and policy strategies that account for the unique characteristics of each crisis, enabling more effective navigation of market turbulence.

This study provides a valuable foundation for significant future research. Future studies could build on these findings by investigating sector-specific spillovers or incorporating additional variables, such as investor sentiment, to better capture the complex nature of volatility. Additionally, as BRICS expands and discussions about a new BRICS currency gain momentum, further research into these evolving market interconnections will be crucial for managing financial stability in an increasingly interconnected global economy. Such insights would deepen our understanding of crisis-driven market behaviour and inform strategies for risk management, investment decision-making, and policy formulation.

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