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Dynamic Cross-Correlation Between BRICS Markets, Commodities and Green Bonds

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This paper evaluated the cross-correlation between the BRICS (Brazil, Russia, India, China and South Africa) markets with commodities and green bonds. For this purpose, the detrended moving-average cross-correlation coefficient (ρ_{DMCA}) was used, based on a sliding windows approach, with data covering a sample before the COVID-19 pandemic, during the COVID-19 pandemic and after Russia invaded Ukraine. The results show a positive cross-correlation between BRICS markets and commodities and green bonds after the COVID-19 pandemic, mainly for long time scales. This result can contribute to financial risk analysis, especially regarding hedge funds.

Keywords: BRICS; green bonds; cross-correlation.

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1. Introduction

The origin of the term BRIC (Brazil, Russia, India and China) was formulated by Goldman Sachs chief economist Jim O'Neill in a 2001 study entitled "Building Better Global Economic BRICs." In 2006, the concept gave rise to a grouping, properly speaking, incorporated into the foreign policy of Brazil, Russia, India and China. In 2011, during the Third Summit, South Africa became part of the group which adopted the acronym BRICS.

The BRICS nations play a crucial role in the global economy, significantly impacting key factors. Collectively, this group represents 40% of the world's population, 25% of the global GDP (equivalent to $16.039 trillion), 30% of the world's land coverage, 18% of global trade and a staggering $4 trillion in global foreign exchange reserves. These statistics underscore the immense influence and importance of the BRICS nations in shaping the economic landscape on a worldwide scale [1]. Concerning purchasing power parity, the GDP of the BRICS nations exceeds that of the USA and the European Union. Considering the most recent data from the International Monetary Fund (IMF), the sum of the GDP of the BRICS countries, including the new members, represents 29.1% of the global GDP, which is $30.7 trillion. China is currently the largest economy in the block, with a GDP of $19.37 trillion [2].

Given their economic and financial importance, impacts on these markets could affect the global financial system, contributing to an increase in systemic risk. Interestingly, some markets, such as commodities and green bonds, have increased their trading on stock exchanges and their returns could affect the BRICS countries, contributing to an increase in global systemic risk. Since commodities are basically raw materials, they are sold the way they are found in nature, without undergoing industrialization processes or with as little industrialization as possible.

Several studies analyzed the correlation between the commodities market and the BRICS stock exchanges. For example, Ji *et al.* [3] identified a correlation using networks between the BRICS markets and commodities. Additionally, Alam *et al.* [4] analyzed the effects of Russia's invasion of Ukraine on several markets (commodities and selected groups of countries). They discovered a correlation between all commodities and some stock exchanges corresponding to the G7 and BRICS nations. The results indicate that during Russia's invasion of Ukraine, gold, silver and the stock markets of the USA, Canada, China and Brazil were the recipients of the shocks from other commodities and markets. Ferreira *et al.* [5] examined the cross-correlation between the stock markets of 20 countries and the price of oil (WTI crude oil) before and after the 2008 crisis. These authors used the detrended cross-correlation coefficient (ρ_{DMCA}) and found a contagion effect between oil prices and stock markets.

The term commodity comes from English, which, when loosely translated, means goods. This term is attributed to commercialized products, such as soybeans, oil, iron ore, gold and others. Commodities are the raw materials and primary products produced by the agricultural, mineral and energy sectors and are important to the world economy. These products are traded on financial markets around the world, such as the Chicago Commodities Exchange (CME), the New York Commodities Exchange (NYMEX) and the São Paulo Commodities and Futures Exchange (BM&FBOVESPA), among others. Zhang and Hamori [6] found a less prevalent role for commodity markets, particularly oil, in conveying shocks to the American, Japanese and German stock returns during the recent COVID-19 pandemic. Using a multivariate DCC-GARCH model, Pinto-Ávalos *et al.* [7] showed that a correlation between commodities and other assets grows in times of crisis. Analyzing the possible impact of commodity prices in the main emerging economies can help identify possible financial risk situations, given that commodity volatility tends to be high over a given period. Furthermore, variations in oil returns could affect G20 countries 5].

Green bonds are like conventional fixed-income corporate bonds, except their proceeds are earmarked for environmentally friendly projects. Green bonds are issued mainly in US dollars and euros (around 80% of issuances) by private companies, the public sector (national government, local government or state entities) and supranational entities (e.g., the World Bank and European Bank of Investment) and have an average term of 5–10 years.[8] Several studies on the return transmission mechanism between green bond markets and global financial markets have emerged in the financial literature with some studies focusing on the links between the green bond market and other asset classes [8–12].

In this context, Broadstock *et al.* [11] found that the green bonds market moves weakly with the stock and energy raw materials markets (represented by the MSCI World Index and the S&P GSCI Energy Spot Index), with the degree of integration fluctuating simultaneously over time and in tails. Along these lines, Kanamura [13] examined the interrelationships between green bonds and other asset markets, including stocks, commodities, clean energy and conventional bonds, over 11 years from 2008 to 2019 and reported a low or negative correlation between green bonds, stocks and commodities.

The use of complex tool systems in economics has been called econophysics [14, 15]. In this context, econophysics has several subareas, one of which is the cross-correlation analysis between time series [16, 17]. The study of cross-correlation is based on statistics that relate one time series to another or several time series to each other [18]. Moreover, Kristoufek [19] created an alternative method to ρ_{DCCA} called detrended moving average cross-correlation coefficient (ρ_{DMCA}) to evaluate the cross-correlations between its non-stationary time series. Several authors applied the DCCA approach and its coefficient to assess the contagion effect [20–24] including in the cryptocurrency market [25, 26]. Notably, Quintino *et al.* [27] found that in the post-COVID-19 pandemic period, no correlation was identified between oil and natural gas prices, and Inacio *et al.* [28] used a dynamic cross-correlation approach to assess the impact of the war between Russia and Ukraine on energy prices. However, few studies have analyzed the influence of the commodities market and green bonds on the BRICS markets — a gap in the literature that we intend to fill with this research.

Methodologies like DCCA and DMCA, and the respective correlation coefficients, can handle stationary, non-stationary, nonlinear and non-normal signals and identify long-term memory and multifractal characteristics, allowing for understanding market dynamics [29–31]. Indeed, multifractal approaches based on detrended methodologies are commonly used in finance, as is exemplified, for example, in the studies that analyze the effect of COVID-19 in oil future markets [32] or analyze the cross-correlations between grains and oilseeds indices [33] among many others. As with other correlation coefficients, these detect the cross-correlation between two variables but cannot identify the origins of the correlations [34] As DCCA could also, in some cases, be affected by underlying trends that are not fully removed [34], DMCA has the advantage of having improved trend removal [35] and is adequate in reduced samples [36]. Considering these issues, both measures are sufficient for the purpose under analysis, with relevant properties reported by Zhao *et al.* [37]. However, as DMCA shows better performance [19], it was the chosen method in this paper.

The remainder of the paper is organized as follows: Section 2 presents the materials and methods used in the research; Section 3 presents the results, split into commodities and green bonds; Section 4 presents the discussion and the conclusion of the paper.

2. Materials and Methods

Given the increasing interconnectivity of financial markets, it is crucial to understand the cross-correlation dynamics between BRICS stock markets, commodities and green bonds. To achieve this, we employ the detrended moving-average cross-correlation coefficient (ρ_{DMCA}) to assess correlations in non-stationary time series. This study used data from May 1, 2013, to May 19, 2023, in a total of 2533 observations retrieved from www.yahoofinance.com (accessed on May 22, 2023). We selected this period because it encompasses critical economic and geopolitical phases that significantly impacted global financial markets, especially the BRICS commodities and green bonds markets, trying to fill the previously identified gap in the literature, i.e., the need to analyze the influence of the commodities and green bonds markets from BRICS markets. This period was chosen to capture the effects of major events like the COVID-19 pandemic (declared a pandemic by the World Health Organization on March 11, 2020) and the Russian invasion of Ukraine on February 21, 2022, both of which are recognized as having profound impacts on financial market dynamics. Recent literature highlights the importance of studying these phases to understand the patterns of correlation and contagion between different markets, as evidenced in previous analyses of global financial crises. The data are presented daily and correspond to the index's closing price. Daily closing prices are considered not only for data availability but also because they are prevalent in research examining market behavior and integration. These values provide a reliable, consistent and sufficiently granular dataset that accurately reflects market conditions and facilitates the analysis of market dynamics, correlations and risk.

The SP GSCI Global Commodities Index, the first major commodities index, was used for this study. It is one of the most widely recognized, broad-based, production-weighted benchmarks to represent the beta of the global commodities market. The S&P Green Bond Index is the global indicator for the green bond market. This pioneering index maintains strict standards only to include bonds whose proceeds are used to finance green projects. The BRICS indices (Table 1) were selected for several reasons, including that they are widely recognized and used in financial literature, comprehensively capture the financial performance of these countries and are well-established benchmarks that reflect the economic and financial activities of the underlying markets. Thus, they allow for a robust analysis of cross-market correlations.

Next, we define the ρ_{DMCA} [19]. Considering two series $\{x_t\}$ and $\{y_t\}$, on which we build two integrated series $X_t = \sum_{i=1}^{t} x_i$ and $Y_t = \sum_{i=1}^{t} y_i$, for $t = 1, 2, \ldots, T$, where T is the length of both series. From these integrated series, we built the fluctuation functions given by:

$$F_{x,\text{DMA}}(\lambda) = \frac{1}{T - \lambda + 1} \sum_{i=\lfloor \lambda - \theta(\lambda-1) \rfloor}^{\lfloor T - \theta(\lambda-1) \rfloor} (X_t - \widetilde{X}_{t,\lambda})^2, \tag{1}$$

$$F_{y,\text{DMA}}(\lambda) = \frac{1}{T - \lambda + 1} \sum_{i=\lfloor \lambda - \theta(\lambda-1) \rfloor}^{\lfloor T - \theta(\lambda-1) \rfloor} (Y_t - \widetilde{Y}_{t,\lambda})^2, \tag{2}$$

where $\lfloor \cdot \rfloor$ is the floor operator, λ refers to the length of the moving average window and θ is the style of moving average, which can take different values, as $\theta = 0$ (forward moving average), $\theta = 0.5$ (centered moving average) or $\theta = 1$ (backward moving average). In this paper, we use a centered moving average. Kristoufek [19] and Quintino *et al.* [27] report that this approach performs better than other options. The expressions $\widetilde{X}_{t,\lambda}$ and $\widetilde{Y}_{t,\lambda}$ corresponds to moving averages with a window length of λ. In its turn, the bivariate fluctuation function F^2_{DMCA} is a covariance function defined as

$$F^2_{\text{DMCA}}(\lambda) = \frac{1}{T - \lambda + 1} \sum_{i=\lfloor \lambda - \theta(\lambda-1) \rfloor}^{\lfloor T - \theta(\lambda-1) \rfloor} (X_t - \widetilde{X}_{t,\lambda})(Y_t - \widetilde{Y}_{t,\lambda}) \tag{3}$$

Table 1. BRICS countries and their respective indices analyzed.

Country	Index
Brazil	MSCI Brazil
Russia	Moex Russia
India	Nifty 500
China	Hang Seng
South Africa	MSCI South Africa

Thus, it is possible to construct the DMCA coefficient, (ρ_{DMCA}), in an analogous manner to the DCCA coefficient (ρ_{DCCA}) of Zebende [38], as follows:

$$\rho_{\mathrm{DMCA}}(\lambda) = \frac{F^2_{\mathrm{DMCA}}(\lambda)}{F_{x,\mathrm{DMA}}(\lambda)F_{y,\mathrm{DMA}}(\lambda)}. \tag{4}$$

$F_{x,\mathrm{DMA}}(\lambda)$ and $F_{y,\mathrm{DMA}}(\lambda)$ represent the detrended moving average fluctuation functions for the time series x_t and y_t, respectively. These functions quantify the local variance of the detrended integrated signals within a moving window of length λ, allowing for the assessment of cross-correlation between non-stationary time series at different time scales. The DMCA coefficient also has the desired properties of the ρ_{DCCA}, namely, $-1 \leq \rho_{\mathrm{DMCA}}(\lambda) \leq 1$. As illustrated by Fig. 1, in this analysis, the ρ_{DMCA} coefficient is calculated from sliding windows, which analyzes the correlation dynamically over time in windows of 1000 observations.

As shown in Table 2, to delimit the confidence interval of the $\rho_{\mathrm{DMCA}}(\lambda)$, we used the estimates prepared by Guedes [40], considering a sample of 1000 observations in different time scales. When conducting a sliding windows analysis, it is crucial to

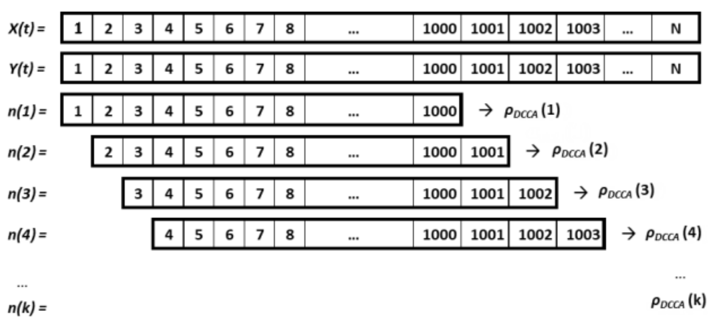


Fig. 1. Example of the sliding window procedure.

Note: (i) The sliding windows procedure was adapted from Tilfani *et al.* [24]; (ii) n(.) corresponds to the time scale and could take any value between $4 \leq n(\cdot) \leq w/4$, with w being the window size [39]. In our case $w = 1000$, consequently $4 \leq n(\cdot) \leq 250$.

Table 2. Critical values of the ρ_{DMCA} test considering 1000 observations at different time scales for a 95% confidence level, according to Guedes [40].

Time scale	Critical value
$n = 4$	0.0630
$n = 32$	0.1458
$n = 250$	0.4329

Note: The critical values of the ρ_{DMCA} test for the different time scales and considering a confidence level of 95% were obtained by Guedes [40].

consider the balance between capturing long-term trends and local features. Larger windows may overlook important local events such as crises or extreme financial shocks. Conversely, shorter windows can lead to biased estimations and limit the information available for longer time scales while increasing the time required for analysis. In this study, we have chosen a window size of 1000 observations, as reported previously [24, 41]. This window size is approximately four years as we work with daily data. By selecting this window size, we aim to balance capturing local events and maintain accuracy in our analysis.

Different time scales (short-term, medium-term and long-term) are crucial in cross-market correlation studies, as they allow for a more comprehensive understanding of market interactions. Short-term correlations, such as those observed over a 4-day scale, are typically weak and unstable, primarily influenced by immediate market reactions and high-frequency trading activities [42]. Due to market noise and rapid trading dynamics, these correlations can fluctuate significantly over days or weeks [43, 44]. They are particularly relevant for high-frequency traders and those seeking to capitalize on short-lived market movements [45]. Medium-term correlations, analyzed over a 32-day scale, exhibit greater stability than short-term correlations, yet they remain subject to fluctuations. These correlations often reflect market adjustments to new information, macroeconomic indicators and policy changes [42, 46]. Such correlations are particularly useful for swing traders and investors who adjust their portfolios based on quarterly or semi-annual market trends [47]. Long-term correlations, assessed over a 250-day scale, are generally stronger and more stable, capturing fundamental economic relationships and persistent market trends [48]. Over months to years, these correlations can reveal structural linkages between major global markets and long-term interactions between asset classes such as stocks and bonds. Understanding long-term correlations is essential for strategic asset allocation, risk management and assessing broader economic cycles [22, 49]. Analyzing correlations across different time horizons gives us a more nuanced perspective on how financial markets interact under various conditions. This differentiation allows us to distinguish between transient shocks and more stable market relationships, ultimately contributing to a deeper understanding of market behavior across different time scales.

3. Results

Table 3 summarizes the main descriptive statistics of the indices under analysis, calculated from daily returns, as follows: $r_{it} = \ln P_{i,t} - \ln P_{i,t-1}$, where r_{it} is the return of index "i" in period "t", and $P_{i,t}$ and $P_{i,t-1}$ refer to index values of "i" in period "t" and period "$t-1$", respectively. In the context of basic descriptive statistics, we did not analyze whether the indices are stationary. The DMCA correlation coefficient (and congeners such as DCCA) does not require the series to be stationary, as it allows the analysis of co-movements in both cases, which is different from traditional

Table 3. Summary statistics.

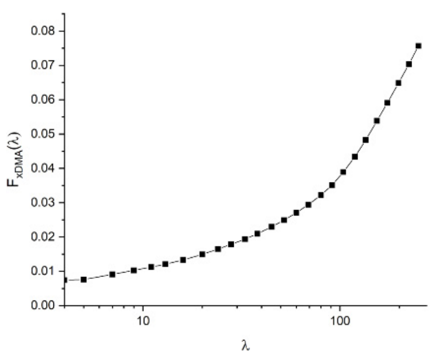
Index	Mean	Stdev	Skewness	Kurtosis
MSCI Brazil	0.0001	0.0154	−0.8939	13.9102
Moex Russia	0.0003	0.0156	−6.9021	191.3153
Nifty 500	0.0005	0.0105	−1.4807	18.1317
Hang Seng	−0.0002	0.0148	0.2684	4.1654
MSCI South Africa	0.0002	0.0126	−0.4953	5.6579
SP Green Bonds	−0.0001	0.0037	−0.3198	4.9032
SP GSCI	−0.0001	0.0141	−0.8400	8.2908

Source: Own results.

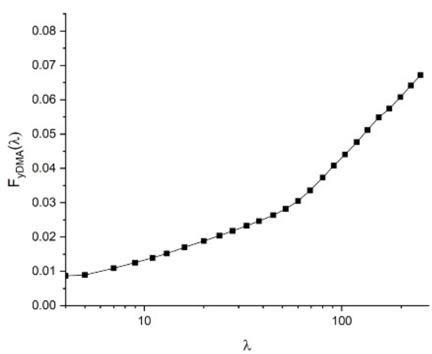
linear econometric techniques. Furthermore, such correlation coefficients are particularly useful when the series are nonlinear, as is common in financial indices.

On average, the indices presented positive returns, except for the Chinese index and green bonds, where negative returns were more frequent. The volatilities of the Brazilian, Russian, Chinese and South African indices and the commodities index were high and very similar. The volatility of the Indian index was considerably lower, and with a significant difference, green bonds also had low volatility. Regarding asymmetry, all indices showed negative asymmetry, except the Chinese index, meaning there were more extreme negative returns than positive ones. Regarding kurtosis, it appears that all indices showed more extreme variations compared to the normal distribution, especially the Russian index, followed by the Indian and Brazilian ones, which is a stylized fact about financial indices having heavier tails rather than a normal distribution.

Before the presentation of the results for the evolution of the DMCA correlation coefficients, Fig. 2 shows the process of the calculation of ρ_{DMCA}, with the fluctuation functions of $F_{x,\mathrm{DMA}}$ and $F_{y,\mathrm{DMA}}$ in panels (a) and (b), at the top of the figure, while

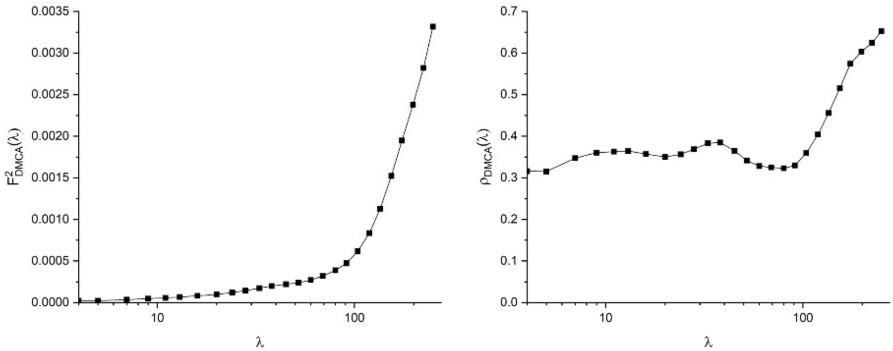


(a)



(b)

Fig. 2. Example of the ρ_{DMCA} calculation between the SP GSCI Global Commodities Index and the Brazilian stock market.



(c)

(d)

Fig. 2. (*Continued*)

panel (c) presents the absolute values of F^2_{DMCA} and panel (d) shows the ρ_{DMCA}, with all the figures having the length of λ in the horizontal axis (in a logarithmic scale). As we have a sliding windows approach, for that figure, we chose the first subsample of 1000 observations to measure the correlation between the S&P Green Bond Index (x) and the Brazilian index (y).

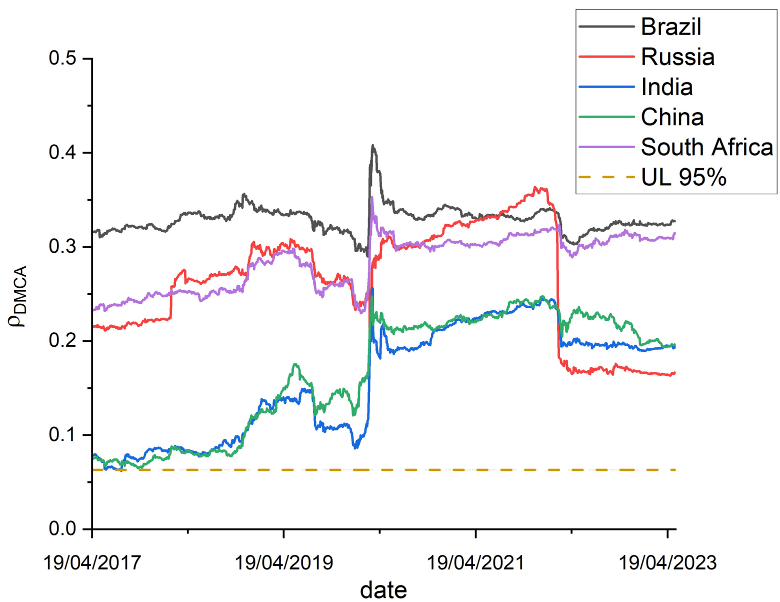


Fig. 3. Evolution of the ρDMCA between the SP GSCI global commodities index and the BRICS financial markets on a 4-day time scale.

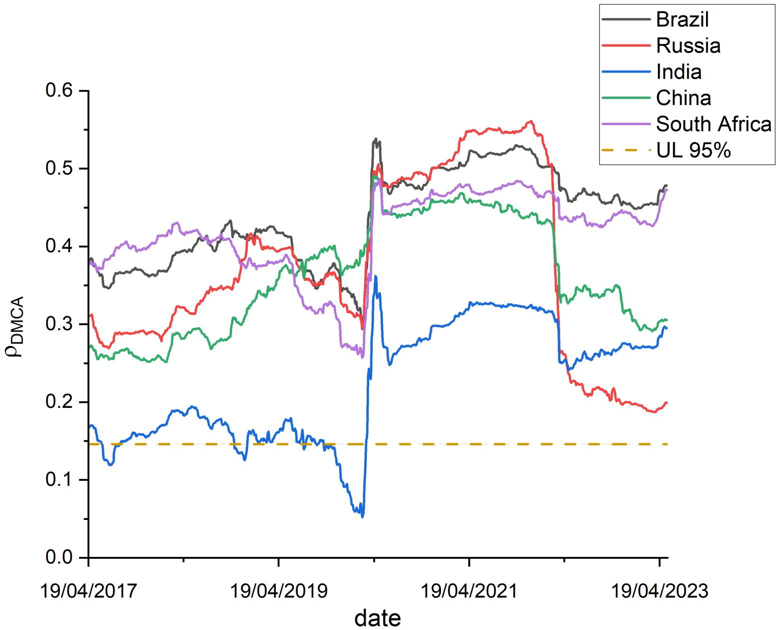


Fig. 4. Evolution of the ρ_{DMCA} between the SP GSCI Global Commodities Index and the BRICS financial markets on a 32-day time scale.

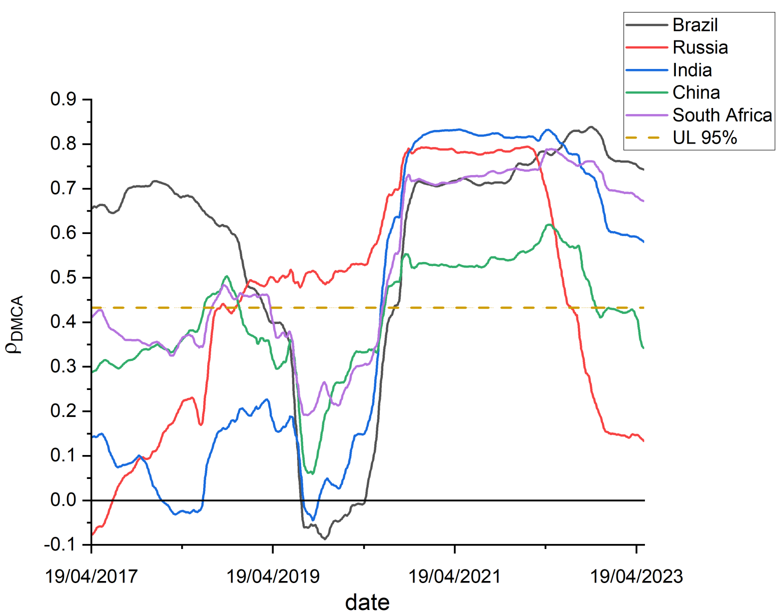


Fig. 5. Evolution of the ρ_{DMCA} between the SP GSCI commodities and the BRICS financial markets on a 250-day time scale.

3.1. *Commodities*

In Figs. 3–5, the cross-correlations between the SP GSCI commodities index and the BRICS financial indices between April 19, 2017, and April 19, 2023, were analyzed for the time scales of (4, 32 and 250 days, short-, medium- and long-run, respectively). The dotted lines correspond to the upper and lower limits of the confidence interval, with the yellow dotted line representing the upper limit of the 95% confidence level. The values between the dotted lines are not statistically significant [50]. The analysis periods included before the COVID-19 pandemic, during the COVID-19 pandemic and after the Russia–Ukraine war.

For the time scales of $n = 4$ and $n = 32$ (displayed in Figs. 3 and 4), after the start of the COVID-19 pandemic, the cross-correlation between the SP GSCI and the BRICS markets increased for all countries. In contrast, it decreased after the invasion of Ukraine by Russia. This result reveals that after the COVID-19 pandemic, the stock exchanges corresponding to the BRICS are moved by the commodities market, with an increase in correlation, which could signify a contagion effect. Several key economic and financial factors could explain the increased cross-correlation between the SP GSCI and BRICS markets during the initial phase of the COVID-19 pandemic, followed by a decrease after the Russian invasion of Ukraine. For example, during the pandemic, global markets experienced heightened uncertainty, leading to a contagion effect where the interconnectedness between commodities and BRICS stock markets intensified. This situation was driven by disrupted supply chains and a flight to safety in commodities, particularly those critical to BRICS economies. However, the geopolitical turmoil following Russia's invasion led to divergent impacts on BRICS markets, depending on each country's specific economic ties, energy dependencies, and exposure to the conflict. This divergence likely caused a decoupling effect, reducing the previously strong correlation as markets responded differently to the ongoing volatility and risks, reflecting the complex dynamics of investor behavior and market sentiment during these crises. Thus, the fluctuating cross-correlation between the SP GSCI and BRICS markets during these tumultuous times underscores the intricate relationship between global economic events and financial markets and highlights the importance of considering multiple factors, such as geopolitical events, economic dependencies and investor sentiment, when analyzing market behavior and trends.

For the time scale $n = 250$ (displayed in Fig. 5), after the COVID-19 pandemic, the cross-correlation between commodities and BRICS markets increased for all markets. On the other hand, cross-correlation decreased for all markets except Brazil after Russia invaded Ukraine. The increase in cross-correlation between commodity markets and the BRICS markets following the COVID-19 pandemic can be attributed to long-term adjustments and economic recovery strategies that have led to synchronized movements in global markets. As the BRICS economies, heavily reliant on commodities, gradually recovered, their markets became more aligned with global commodity trends. However, the subsequent decline in cross-correlation after Russia invaded Ukraine, except for Brazil, likely reflects the long-term differentiated impacts of the conflict on these economies. As a major commodities exporter, Brazil may have benefited from rising prices, particularly in agriculture and energy, leading to sustained correlation with commodities. At the same time, other BRICS nations experienced varying degrees of economic disruption and market divergence, possibly due to their specific geopolitical and economic ties.

Overall, a pattern can be observed between the SP GSCI and the BRICS financial indicators: the increase in cross-correlation for all time scales after the COVID-19 pandemic in 2020. Moreover, after Russia invaded Ukraine, the value of ρ_{DMCA} drops in all the time scales. The increase in cross-correlation between the SP GSCI and BRICS markets across all time scales after the COVID-19 pandemic could mean the impact of global economic upheavals and coordinated recovery efforts on the interconnected movement of commodities and BRICS markets. These economies rely heavily on commodity exports, which could explain the heightened correlation. However, the subsequent decline in ρDMCA following Russia's invasion of Ukraine indicates a divergence in market behaviors. This shift can be attributed to the varying effects of geopolitical instability, sanctions and disruptions in the supply chain on different BRICS nations. This divergence highlights how the pandemic initially fostered a sense of global economic unity, only to be disrupted by region-specific shocks brought about by the invasion. Consequently, this led to a reduction in the consistency of market responses across BRICS countries.

3.2. *Green bonds*

Figures 6–8 depict the cross-correlations between the SP Green Bonds index and the BRICS financial indices between April 19, 2017, and April 19, 2023, for the different time scales ($n = 4, n = 32, n = 250$) analyzed. The dotted lines correspond to the upper (yellow) and lower (blue) limits of the confidence interval for a 95% confidence level. The analysis periods were divided into the periods before the COVID-19 pandemic, during the COVID-19 pandemic, and after the Russia–Ukraine war.

Considering the $n = 4$ time scale (Fig. 6), there exists a positive and statistically significant cross-correlation between SP Green Bonds and BRICS after the start of the COVID-19 pandemic, with ρDMCA presenting a value of approximately 0.2. This scenario could likely reflect the initial market response to the pandemic. Investors increasingly turned to sustainable investments to hedge against economic instability during this uncertain time. The surge in interest in green bonds, fueled by global initiatives to integrate sustainability into recovery plans and the BRICS economies' exposure to international financial shifts, resulted in short-term co-movements between these markets. This modest correlation indicates that while similar economic factors influenced green bonds and BRICS markets during the pandemic, their link remained relatively weak. This result could be attributed to differing risk profiles and investment strategies associated with these assets.

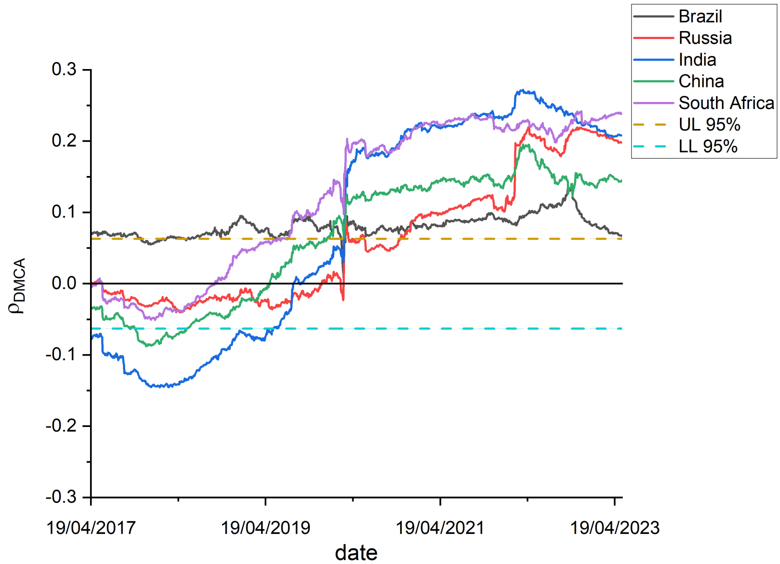


Fig. 6. Evolution of the ρ_{DMCA} between SP Green Bonds and BRICS financial markets on a 4-day time scale.

For the medium-run time scale ($n = 32$), Fig. 7 reveals an increase in the cross-correlation between green bonds and BRICS after the start of the COVID-19 pandemic. All the cross-correlations are statistically significant, emphasizing the Indian and South African markets. This evidence could indicate a growing alignment

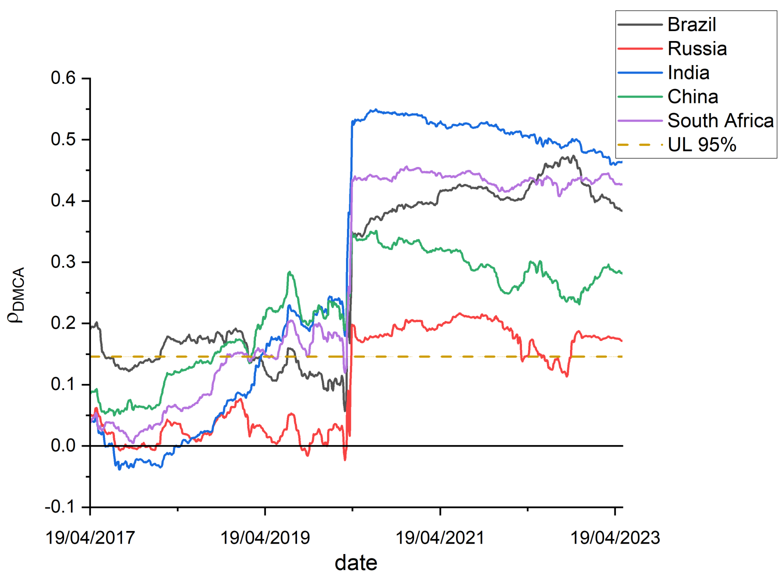


Fig. 7. Evolution of the ρ_{DMCA} between SP Green Bonds and BRICS financial markets on a 32-day time scale.

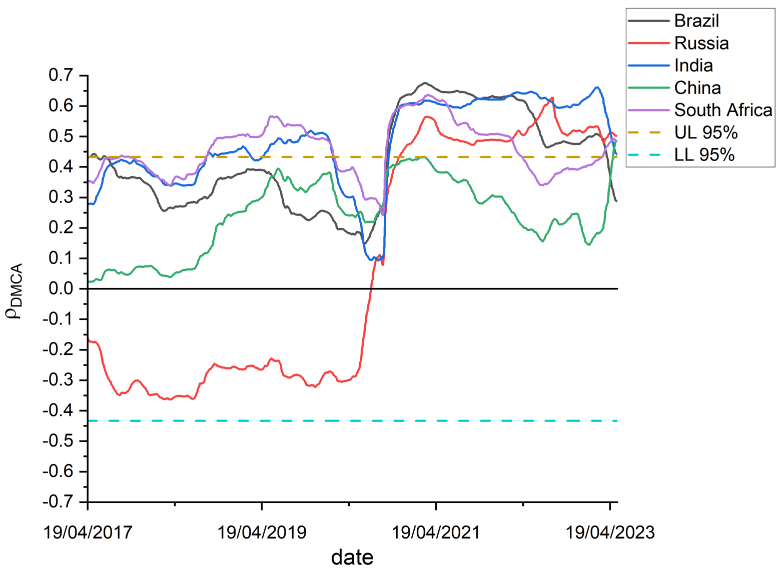


Fig. 8. Evolution of the ρDMCA between SP Green Bonds and BRICS financial markets on a 250-day time.

between these emerging markets and the global shift toward sustainable finance during the pandemic. The statistically significant correlations suggest that these economies, which faced considerable pressure to attract green investment for post-pandemic recovery, responded strongly to global trends in sustainable finance, driving closer co-movements between green bonds and their market indices.

For a long-run time scale, i.e., $n = 250$ days (Fig. 8), after the COVID-19 pandemic, there was generally a decrease in the cross-correlation, and all the cross-correlations were not statistically significant. During this period, divergent recovery paths and varying degrees of economic disruption across BRICS nations may have led to weaker and statistically insignificant correlations. However, the identified pattern changed, and after September 2020, there was an increase in the cross-correlations, with all of them becoming statistically significant, which may sign an increased focus on sustainable recovery.

For the short-run time scale, after COVID-19 and the beginning of the war between Russia and Ukraine, the cross-correlations between green bonds and the BRICS significantly increased (and are statistically significant) for all of them. This evidence could be justified by the immediate global financial turbulence that heightened investor focus on risk management and sustainable investments, leading to synchronized market movements. However, this pattern changed for the medium- and long-run time scales. For the medium-run time scale, after the COVID-19 pandemic, all the cross-correlations between green bonds and BRICS increased, but they remained stable after the beginning of the war between Russia and Ukraine. This evidence could mean that the impact of the Russia–Ukraine war introduced new geopolitical risks that left these correlations stable. For the long-run time scale, after the COVID-19 pandemic, the cross-correlations between green bonds and BRICS markets generally decreased, suggesting divergent economic trajectories and differing levels of integration into global green finance. However, after the war between Russia and Ukraine began, cross-correlations increased for the Indian and Russian markets. The unique economic ties to the conflict between these two countries could explain the observed pattern. However, for the remaining BRICS countries, the cross-correlation decreased. This evidence highlights the varied long-term responses to global instability and sustainability efforts.

3.3. *Robustness analysis*

The sliding windows approach used in this paper is a technique applied to the ρDMCA capable of capturing the continuous cross-correlation behavior between two variables. Although both the choice of window width and sliding length could be relevant for the analysis, as explained previously, it is necessary to analyze possible

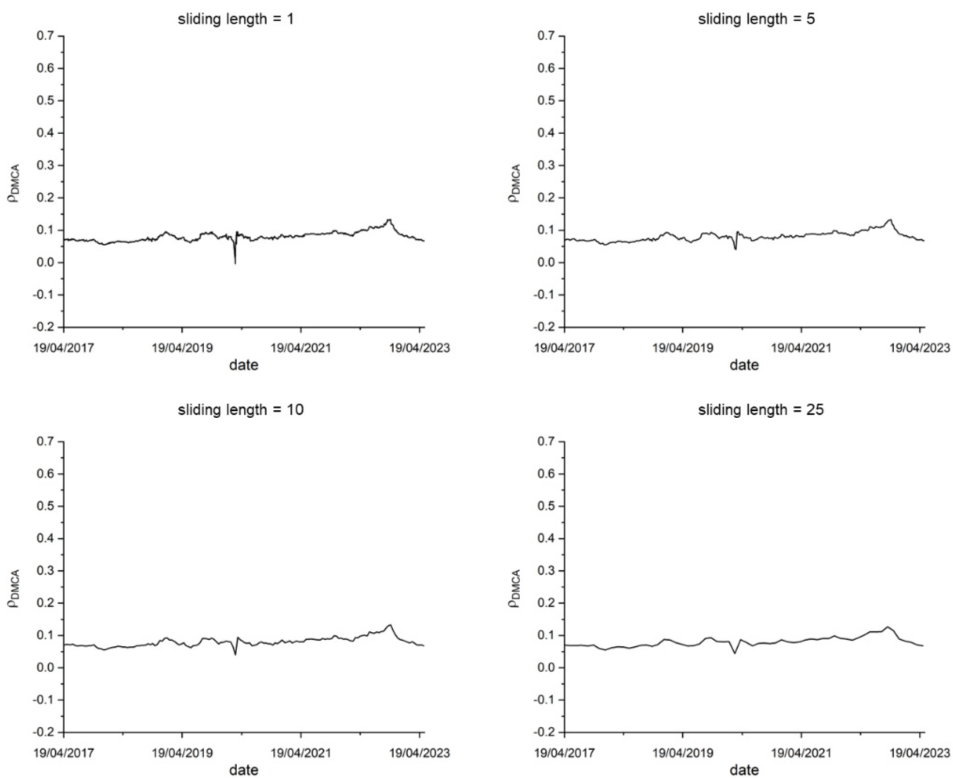


Fig. 9. Evolution of the ρ_{DMCA} between SP Green Bonds and the Brazilian stock market, for different sliding lengths, based on a 4-day time scale.

variations of those parameters for robustness. Thus, on the one hand, we will present an analysis with the application of sliding windows with different sliding lengths, avoiding possible redundant information. On the other hand, we perform the sliding windows analysis for a given pair of variables, using different window widths, trying to identify possible differences in the balance between long-term trends and local features.

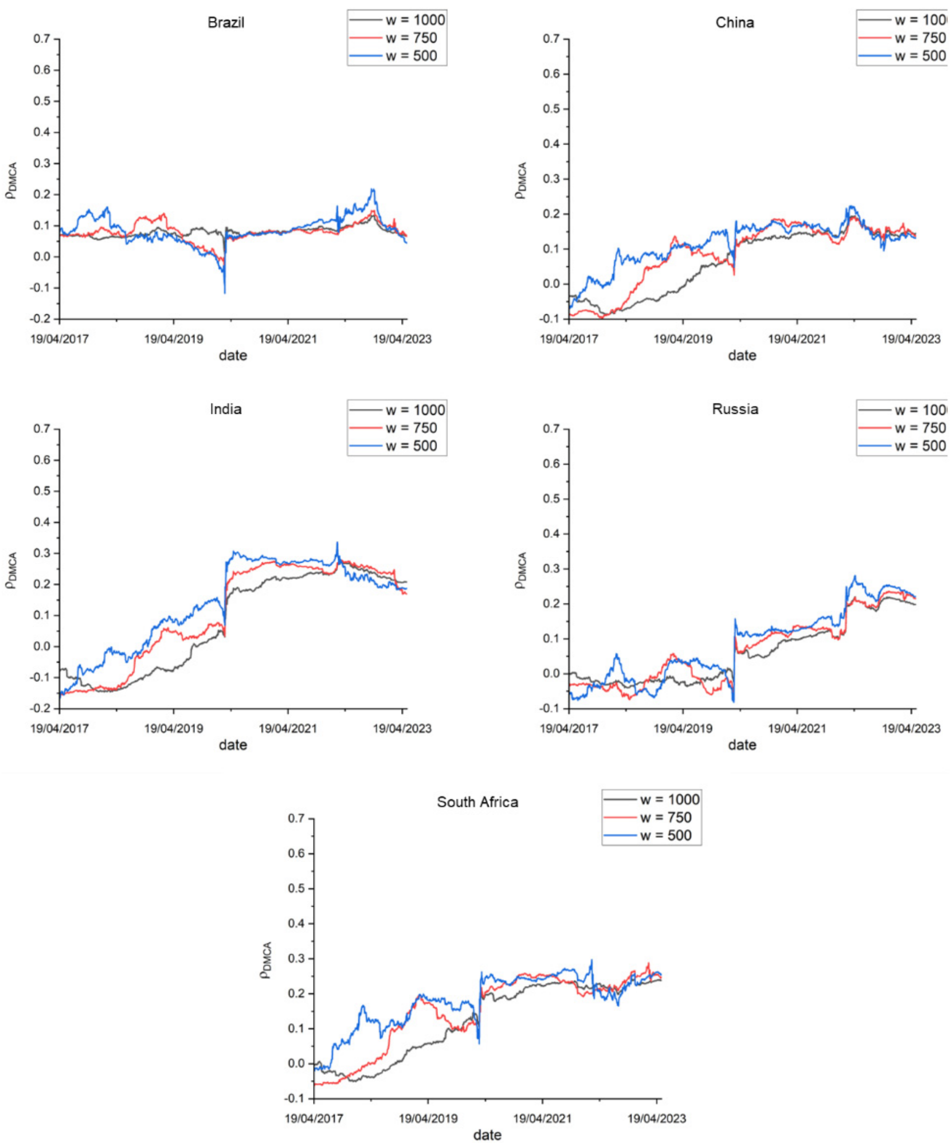


Fig. 10. Comparison of the different ρ_{DMCA} between SP Green Bonds and each of the BRICS financial markets, for various window size, based on a 4-day time scale.

Figure 9 shows the different ρDMCA between SP Green Bonds and the Brazilian stock market over time but with different sliding lengths: 1, 5, 10 and 25 days. In this case, regardless of the use of shorter or longer sliding lengths, results are qualitatively similar even though longer sliding lengths show a smoother evolution of the correlation coefficients, which is expected since it reduces some noise from the sample. In Fig. 9, we show the example of one of the pairs and scales, although the remaining are qualitatively similar. Due to space constraints, we cannot display the whole set of results, although they can be delivered upon request.

Complementarily, Fig. 10, which shows the evolution of the ρDMCA between SP Green Bonds and the chosen stock markets based on different window size (500, 750 and 1000 days) on a 4-day time scale, also demonstrates that the behavior of the various correlation coefficients has, in general, similar qualitative patterns, reinforcing the usefulness of the chosen method. In this case, sliding windows of different sizes would start on different days; however, for comparison purposes, we chose them to start on the same day based on the first correlation coefficient of the highest window. Once again, it just shows the example of a time scale of the correlation of the stock markets with one of the indices — with the remaining information being delivered upon request — considering the qualitative similarity of the results.

4. Discussion and Conclusion

The BRICS nations form the most important economic block of emerging countries. Therefore, analyzing the variables that influence the stock exchanges of these markets can be important in measuring global financial risk. Additionally, the commodities market plays a fundamental role in the worldwide economy by providing basic inputs for the automotive, automobile, electronics and other industries. Furthermore, green bonds are important for financing environmental projects, helping to combat global climate change.

In this study, a positive cross-correlation, which was statistically significant during most of the analyzed period, was identified between BRICS exchanges and SP GSCI commodities, indicating the influence of commodities in the main emerging markets have a strong presence of commodities in their export basket. This result agrees with Mezghani *et al.* [51] and Nguyen *et al.* [52]. The results showed that the COVID-19 pandemic caused an increase in cross-correlation for all time scales. On the other hand, after the Russia–Ukraine war, ρ_{DMCA} drops, particularly for smaller time scales. This situation could be justified by the increase in the price of commodities and the decrease in the price of some BRICS assets due to the war between Russia and Ukraine.

The cross-correlation between green bonds and BRICS increased after the start of the COVID-19 pandemic, especially in short- and medium-run time scales. In the long-run time scale, although ρ_{DMCA} decreased (and became not statistically significant) after the COVID-19 pandemic, this pattern was inverted after the middle of

2020, increasing and becoming statistically significant. These results allow us to conclude that the pandemic's beginning caused movement between the assets analyzed and the BRICS. The start of the Russia–Ukraine war did not change in terms of signal and cross-correlation between green bonds and BRICS markets, as it remained positive for all time scales and markets analyzed. However, in the long-run time scale, Brazil, China and South Africa registered a decrease in the cross-correlation.

The differences in how BRICS countries have responded to the Russia–Ukraine war and the varying impact of the pandemic on short-term cross-correlations can be attributed to several factors stemming from their unique economic structures, geopolitical positions and levels of integration with the global markets. For example, Russia's significant role as a global energy supplier directly influenced its market behavior following the invasion, with energy prices playing a crucial role in its economic resilience. On the other hand, countries like Brazil and South Africa, whose economies heavily rely on commodity exports, experienced increased volatility in response to fluctuating global demand, exacerbated by the pandemic's disruption of supply chains. Furthermore, the economic uncertainty brought about by the pandemic and the subsequent need for liquidity in financial markets led to short-term fluctuations in correlations as investors reassessed risks and reallocated assets, particularly in emerging markets. However, this dynamic was less pronounced in longer-term cross-correlations, as structural factors and gradual economic recovery helped to temper immediate market reactions. Thus, the responses of BRICS countries to global events and the impact of the pandemic on market correlations are complex and dynamic, reflecting the diverse economic landscapes and challenges each nation faces.

Our results affect several market participants, such as hedge funds, policymakers, investors and environmental and financial institutions. For hedge funds, the findings highlight their need to consider the changing dynamics of cross-correlations when designing risk management strategies, especially in response to global crises like pandemics or geopolitical events. Understanding these correlations for policymakers (governments and regulatory bodies) within BRICS countries can help design policies that stabilize financial markets during crises, particularly when considering the role of commodities and green finance. Institutional and individual investors should be aware of the shifting correlations between green bonds and BRICS markets, especially considering global crises, which can impact portfolio diversification and risk management strategies. Finally, for environmental and financial institutions, the increase in correlation between green bonds and BRICS markets during crises underscores the growing importance of sustainable finance, suggesting that institutions should prioritize green investments as part of their long-term strategies.

As a study limitation, we acknowledge that the findings are specifically tied to the BRICS nations, which limits their generalizability to other emerging or developed markets. Additionally, the use of particular time scales ($n = 4$, $n = 32$, $n = 250$), though common in such analyses, may overlook certain market dynamics that could be revealed through alternative or more granular time scales, potentially providing deeper insights into the behavior of these markets under varying conditions. The use of daily data could be another possible limitation of this study. While commonly employed in financial market analyses, it may not fully capture short-term market dynamics. High-frequency trading and intraday fluctuations could influence correlation patterns, particularly during periods of heightened market volatility. In this sense, higher frequency data (e.g., hourly or minute-by-minute) could provide deeper insights into the short-term behavior of cross-correlations, revealing patterns that may not be observable at a daily resolution. Finally, another potential limitation is the time frame of the data used. While the period considered was chosen to capture the effects of the two most recent economic and geopolitical events, such as the COVID-19 pandemic and the Russia–Ukraine war, extending the dataset further back in time could provide additional validation of the findings. A longer-term analysis could help determine whether the observed correlations are stable over time or specific to the analyzed period.

Future research could explore how different sectors within each BRICS country impact the correlations observed with commodities and green bonds, providing a more comprehensive understanding of market dynamics at a sectoral level. Additionally, expanding the analysis to encompass a wider array of financial assets, including currencies, government bonds and corporate bonds, will allow us to uncover whether comparable cross-correlation patterns exist across various asset classes. Future research could also explore the impact of using intraday data to refine the understanding of dynamic correlations, particularly in response to financial crises or sudden geopolitical shocks. Considering the last limitation acknowledged, future research could explore an extended dataset to assess the persistence of these cross-correlation patterns.

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Data Availability

The authors declare that all data used in this study will be available upon request from the correspondence author. The data used in this study are available at yahoofinance.com.

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