ESG Uncertainty and Volatility Spillovers among BRICS Markets

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ABSTRACT

This study investigates the two-way relationship between ESG uncertainty and volatility spillovers across BRICS stock markets over the period November 2002 to March 2025. Conditional volatilities are modelled using an E-GARCH framework, while spillover dynamics are assessed through a Time-Varying Parameter VAR model. Granger causality tests are then employed to explore how ESG uncertainty interacts with market interconnectedness. The results reveal significant yet asymmetric volatility spillovers, with BRICS market connectedness intensifying during episodes of elevated ESG uncertainty. Short-run spillovers exert a strong influence on ESG uncertainty, whereas the opposite effect is comparatively weaker, suggesting that financial markets act as forward-looking indicators of sustainability-related risk perceptions. Evidence of bidirectional causality between ESG uncertainty and bilateral spillovers further underscores the importance of major BRICS economies in shaping ESG dynamics. Overall, the findings provide valuable implications for portfolio allocation, regulatory design, and ESG risk management within BRICS markets.

Keywords: BRICS markets; ESG uncertainty; volatility spillovers; E-GARCH; TVP-VAR; Granger causality; market connectedness; sustainability risk; asymmetric spillovers; financial integration.

INTRODUCTION

Over the past decade, sustainable investment has attracted growing attention from financial market participants. In particular, ESG stocks that comply with Environmental, Social, and Governance criteria have been widely adopted as a tool to mitigate the negative externalities associated with climate change and as an impact absorber of crisis events in financial markets. This positions ESG stocks as strong competitors to traditional asset classes in financial markets. Investors of all sizes now routinely incorporate Environmental, Social, and Governance (ESG) criteria into portfolio selection and risk management. However, the rapid growth of rating agencies, modelling techniques, and reporting standards has created significant uncertainty about a firm's true sustainability profile, as well as the ambiguity surrounding a firm's actual ESG standing. Without standardized methodologies, different ESG scores can mislead market participants, distort perceived risk, and ultimately impact asset prices.

Although companies in emerging markets, including the BRICS (Brazil, Russia, India, China, and South Africa) group, have recently increased their ESG investments, the positive effects on financial performance remain uncertain. This uncertainty is mainly due to institutional, legal, cultural, and structural differences with developed markets, which make ESG initiatives more expensive, less transparent, and sometimes seen as opportunistic. In particular, BRICS markets are vulnerable to global ESG uncertainty since doubts about the credibility or effectiveness of ESG practices can lead to risk-averse behaviors among international investors. This leads to increased financial volatility in these markets and spillover effects between them, intensified by their growing integration and shared exposure to global ESG risk perceptions.

Since Environmental, social, and governance (ESG) issues have taken a central place in economic and financial decisions, their uncertainty (not their level, but their instability, their unpredictability) now constitutes a systematic risk in financial markets. This explains the new direction of research in the ESG context. Recently, studies have attempted to detect and measure ESG risk using various methods and to examine its impact on financial markets. Despite the contributions of these studies in answering the question of ESG risk, they remain limited. For investors, policymakers, and academics, it is crucial to study the bidirectional relation between ESG uncertainty and traditional financial markets, especially in the BRICS group. BRICS economies account for nearly 40 percent of the world's population and over one-quarter of global GDP. Their equity markets, characterized by higher volatility and sensitivity to both global shocks and domestic policy shifts, present fertile ground for examining the transmission of volatility spillovers. Although prior research has documented time-varying and frequency-specific spillovers among BRICS markets, it has largely overlooked how ESG uncertainty may amplify or attenuate these dynamic linkages.

This highlights the contribution of the present study, as we analyse the bidirectional relationship between ESG uncertainty and dynamic volatility spillovers in BRICS stock markets. First, we examine daily dynamic volatility spillovers among BRICS stock markets from November 01, 2002, to March 31, 2025, using a Time-Varying Parameter Vector Auto regression (TVP-VAR) model by Antonakakis, Chatziantoniou, and Gabauer (2020). Second, we identify the ESG-Based Sustainability Uncertainty Index (ESGUI) across two indices proposed by Ongan, Gocer, and Isik (2025): The Global Equal Weighted Index and the Global GDP Weighted Index. Third, we analyse the bidirectional relationship between volatility spillovers in BRICS markets and the ESG uncertainty index using Granger causality tests over multiple lags.

Our objective is motivated by: First, sustainability is not only a reputational issue but also a significant financial risk factor. Policy shifts toward decarbonisation, changing disclosure standards, green taxonomies, stranded-asset risks, and social/governance shocks (such as labour standards and corruption events) all generate uncertainty about future cash flows, regulation, capital costs, and investor flows. This leads markets to increasingly incorporate sustainability information, though these signals are often noisy, incomplete, and vary across countries. Therefore, measuring sustainability uncertainty helps identify this information risk, which can disrupt valuations, expand risk premiums, and cause rebalancing in global portfolios. Second, volatility does not remain confined within a single market. Through capital mobility, index co-membership, shared investor bases, derivatives linkages, and macro-financial channels, shocks in one equity market can influence risk perceptions and volatility in others. Measuring volatility spillovers uncovers how financial stress spreads, the level of market integration, and the potential for contagion or risk insulation. For risk management, understanding who "exports" versus "imports" volatility helps inform hedging strategies and portfolio decisions. Third, examining dynamic volatility spillovers across the BRICS markets, especially, is important because the BRICS economies are large, systemically important emerging markets with increasing influence in global portfolios and real-economy demand. However, they vary significantly in financial market development, governance quality, regulatory depth, commodity reliance, and ESG policy directions. These differences create a natural laboratory to examine asymmetric cross-market risk transmission: who takes the lead, who absorbs shocks, and how disruptions spread when fundamentals and institutional qualities differ. Because international investors often combine BRICS exposures (fund mandates, benchmarks, ETFs), the interconnectedness is economically significant. Studying BRICS markets is particularly relevant not only for emerging economies but also for developed markets, hence the global economy. Recent evidence suggests a gradual convergence between BRICS and G7 economies (BenMabrouk & HadjMohamed, 2022). The strong performance of BRICS countries has been largely driven by substantial foreign direct investment in their private sectors, which has enhanced trade integration with the rest of the world (Mensi et al., 2014; Ruzima & Boachie, 2018). Furthermore, several studies indicate that BRICS nations have the potential to rival the G7 in the coming decades, with projections suggesting they could surpass G7 countries by 2050 (Golam & Monowar, 2015; Naik et al., 2018; Plakandaras et al., 2019). Fourth, linking sustainability uncertainty and dynamic volatility spillovers in BRICS markets helps to ask a central question in finance: Does rising (or falling) sustainability uncertainty change the strength, direction, or net balance of volatility transmission across BRICS? This captures a policy-relevant systemic risk dimension: sustainability shocks may not stay idiosyncratic, but they can reshape regional or global market co-movements, affecting diversification benefits and amplifying financial instability. Fifth, detecting and studying volatility spillovers between BRICS markets by using a TVP-VAR (Time-Varying Parameter VAR) model is a choice. ESG regulation and investor preferences have accelerated and evolved unevenly across the BRICS. Therefore, to study sustainability, it is necessary to use a dynamic model that allows for market relationships to evolve. TVP VAR model by Antonakakis, Chatziantoniou Gabauer (2020) captures evolving relationships over time, offers a dynamic analysis of interconnected financial variables, and is suitable for markets influenced by external shocks such as BRICS markets. Sixth, testing causality (Granger Causality tests) between sustainability uncertainty and spillovers allows us to test the direction of causality: if sustainability uncertainty explains volatility spillovers across BRICS markets or the other way around, or both directions of causality are present. Furthermore, using multiple lag lengths accommodates differences in information diffusion speeds across BRICS and allows us to detect short- vs. long-horizon predictive channels. Seventh, the choice of ESGUI by Ongan et al. (2025) over other existing uncertainty indices, such as the Sustainable Policy Uncertainty (SPU) or the ESG-related Economic Policy Uncertainty (EPU-ESG), is both theoretically and empirically motivated. Unlike SPU or EPU-ESG, which mainly derive from newspaper data and concentrate on economic or policy uncertainty, ESGUI directly measures uncertainty within the ESG framework itself. Additionally, ESGUI uses the same standardized source (EIU reports) as the World Uncertainty Index (WUI), ensuring international consistency and reducing methodological differences. By including data from 25 countries and providing monthly observations, ESGUI offers greater temporal and geographical detail, making it suitable for dynamic analyses like volatility transmission and spillover effects among emerging markets. Furthermore, ESGUI demonstrates empirical robustness; Ongan et al. (2025) found strong correlations between it and established uncertainty measures (WUI, EUI, and EPU), supporting the reliability and interpretive value of ESGUI as a hybrid indicator of sustainability risk. By incorporating textual signals of ESG risk perception into a quantitative tool, ESGUI provides a comprehensive, market-relevant measure of sustainability-related uncertainty, making it especially useful for studying its transmission to financial volatility in the BRICS context, which explains its importance for sustainable finance. The eighth motivation is the studied period spanning from November 01, 2002, to March 31, 2025. This period covers several critical events: (2002-2003) Enron, Sarbanes-Oxley Act, and Corporate governance scandals, (2007-2009) Global Financial Crisis, Lehman collapse, and Occupy Wall Street, (2010-2011) BP Oil Spill, Fukushima Disaster, and Arab Spring, (2015-2019) Paris Agreement, Volkswagen Emissions Scandal, and Black Lives Matter, (2020-2023) COVID-19 pandemic, Green recovery efforts, Extreme weather events, and ESG reporting mandates. This rich set of structural breaks helps identify how sustainability uncertainty interacts with evolving inter-market risk transmission.

This study contributes to the literature on sustainability, ESG, and the interconnectedness of financial markets in several ways. First, several studies have focused on ESG profiles as a refuge during crisis periods; however, few have studied ESG uncertainty as a systematic risk in financial markets. Despite their growing importance for portfolio allocation and systemic risk (Nguyen et al., 2021), ESG and sustainability uncertainty have rarely been analysed as triggers for financial contagion or spillovers. This paper is the first to examine whether ESG uncertainty enhances volatility spillover across markets. Second, analysing the bidirectional relationship between ESG uncertainty and volatility spillover across markets is crucial for a better understanding of this connectedness. Understanding whether this relationship runs from ESG uncertainty to financial markets instability, the reverse, or both ways, adds valuable insights to ESG-finance and contagion research. It also offers practical benefits, such as improving sustainability regulations, stabilizing markets, and helping investors optimize their portfolios. Third, to examine emerging markets' interconnectedness, previous studies focused on economic uncertainty and macro shocks (Bouri et al., 2018), oil shocks (Tiwari et al., 2025), crisis events (Hsiao et al., 2024), and geopolitical conflicts (Ijaz et al., 2025), but they didn’t examine the impact of sustainability uncertainty. Linking sustainability uncertainty to spillover dynamics, especially for BRICS markets, is another contribution explaining otherwise instability and interconnectedness in these markets, as all emerging markets are more vulnerable to ESG uncertainty. Fourth, through the period studied (2002-2025), we can detect how sustainability uncertainty interacts with volatility spillovers under different conditions. This can offer theoretical and practical implications.

This study has numerous theoretical and practical implications. Theoretically, it advances the literature on sustainable finance and emerging market dynamics. This research clearly contributes to understanding the complex relationships between ESG uncertainty and financial volatility in the BRICS emerging economies. The results highlight the bidirectional and heterogeneous relationships between ESG uncertainty and market volatility, suggesting that conventional models must integrate ESG dimensions to better capture risk dynamics. Moreover, the analysis with multiple lags shows that effects are not immediate but can develop over several periods, highlighting the importance of dynamic studies in modelling sustainability-related financial risks. For the efficient markets theory and ESG, the discovery that financial volatilities precede changes in ESG uncertainty could raise questions about how markets integrate ESG information, suggesting that it is not yet fully assimilated into price formation. Practically, for investors, this study supports decision-making. Understanding that volatility spillover influences ESG uncertainty helps investors to anticipate periods of high ESG risk based on market dynamics and adapt their sustainable portfolio management strategies. Furthermore, this study clarifies ESG policy direction and helps to improve sustainability regulations. For policymakers in BRICS countries, our results help to better align their ESG strategies with regional financial dynamics by identifying "influencer" countries (e.g., China, Brazil, India) that could play a pivotal role in ESG stability. For corporate finance, this study strengthens corporate risk management. By integrating changes in inter-market volatility as a leading indicator of changes in the ESG environment, companies can improve their ESG risk management. More importantly, this paper adds to the development of ESG monitoring tools. The methodology used in this study can be incorporated into automated risk monitoring systems to continuously monitor the interactions between financial markets and sustainability uncertainties. For investors, policymakers, and regulators, this can detect early warning signals of ESG-driven volatility transmission. Moreover, this encourages the integration of ESG criteria into financial analyses.

The remainder of the paper is organized as follows. Section 2 exposes previous studies in a literature review. Section 3 presents the methodology. Section 4 describes the data used and shows the summary statistics. Section 5 reports the empirical evidence. We conclude the paper in Section 6.

LITERATURE REVIEW

Several studies have demonstrated the success of ESG profiles in financial markets. For instance, Hoepner et al. (2019) suggested that engagement with ESG issues reduces downside risk. Furthermore, Ilhan et al. (2019) showed that firms with poor ESG profiles, measured by higher carbon emissions, have higher tail risk. Moreover, Albuquerque et al. (2020) developed a theoretical framework showing how firms can reduce systematic risk exposure by using CSR investments to enhance product differentiation and diversify their product portfolios. Otherwise, He et al. (2023) found that ESG rating significantly improves stock liquidity in the Chinese stock market. Similarly, Zhang et al. (2024) demonstrated that ESG ratings have a positive impact on stock market performance.

Following the outbreak of the 2008 global financial crisis and the increasing deterioration of the global environment in recent decades, sustainability and stability studies are urgent issues for the interest of policymakers and market regulators. This explains why some studies have examined the success of ESG profiles during crisis periods. For instance, Cornett et al. (2016) demonstrated that during the Global Financial Crisis (GFC), the financial performance of U.S. banks is positively related to their ESG score. Similarly, Lins et al. (2017) found that U.S. non-financial firms with high ESG scores have better financial performance than other firms during this period. Furthermore, Singh (2020) examined the spillover effects across the three different long-short portfolio indices during the COVID-19 pandemic, and they found that investors become more attentive to corporate fundamentals, causing capital to flow away from the defensive and stocks from Europe, Australasia, and the Far East (EAFE) portfolios to the ESG portfolio during crisis periods. They suggested that investors find refuge in the ESG approach as it focuses on the long-run sustainability of firms. Furthermore, by exploiting the new Morningstar ESG risk indicators introduced at the end of 2019, Ferriani & Natoli (2021) analysed how investors receive these signals during phases of high uncertainty. They found that low ESG risk funds attract more inflows during the COVID-19 crisis, with a marked importance of environmental risks relative to social or governance risks. Moreover, Broadstock et al. (2021) investigated the role of ESG performance during the COVID-19 pandemic. They found that ESG performance lowers financial risk during a crisis, and high-ESG (performance) portfolios generally outperform low-ESG portfolios. However, by using data of the constituents of the MSCI USA ESG leader index, Rubbaniy et al. (2021) investigated the herding behavior in the US ESG stocks and found a significant herding behavior in the US ESG leader stocks during both bear and bull market conditions. They documented evidence of market-wide herding during the global financial crisis, COVID-19, lockdown, and post-lockdown episodes. Confirming the success of ESG profiles, Boubaker et al. (2022b) highlight the role of responsible investments in reducing the adverse impacts of COVID-19-related externalities. Furthermore, Liu et al. (2023) showed that ESG serves as a systemic stabilizer in financial markets. They examined the relationship between sustainability (through ESG investments) and financial stability by evaluating whether including ESG in stock indices reduces volatility spillovers among Chinese financial markets. They found that when the ESG index is used, volatility contagion effects (total, directional, bilateral) decrease across the financial system, suggesting that ESG investments mitigate shock transmissions between markets.

The frequency, ambiguity, and sometimes contradiction of sustainability regulatory changes, the rapid evolution of investor expectations regarding sustainability, environmental, and social shocks (e.g., COVID-19, war in Ukraine, natural disasters), and the divergence of ESG ratings explain why lately, there is growing interest in studies to detect and measure sustainability uncertainty and to examine its impact on financial markets.

By proposing a partial approach, Ardia et al. (2023) used the Media-based Climate Change Concerns Index (MCCC) as a daily aggregated score based on climate change news articles and the Unexpected Changes in MCCC (UMC) extracted as the surprise (shock) component, after filtering for financial, energy, and macroeconomic factors. This sustainability index captures unexpected variations in climate change concerns in the American media (2003-2018) and primarily focuses on climate risk (not comprehensive ESG). Focusing on the uncertainty linked to divergences between ESG rating agencies, Zeng et al. (2024) investigated the impact of ESG rating uncertainty on sustainability uncertainty to examine its effect on institutional investor decisions in China. They found that this uncertainty has a negative effect on institutional investment and weakens the influence of ESG ratings on investment. Similarly, Sun et al. (2025) measured this risk by ESG rating disagreements to study its effect on stock performance in the Chinese A-share market, focusing on immediate and short-term market reactions and the risk of future stock price crashes. They found that higher levels of ESG divergence significantly increase the risk of future stock price crashes. In the same vein, Zhang et al. (2025) focused on the widespread confusion among investors regarding Environmental, Social, and Governance (ESG) rankings assigned by rating agencies has underscored a critical issue in sustainable investing. They provided a methodological framework enabling investors to make more informed decisions in the face of uncertainty related to ESG ratings. Unlike other, more generic uncertainty indices (such as the World Uncertainty Index or the Economic Policy Uncertainty Index), Ongan et al. (2025) developed a new ESG-based Sustainability Uncertainty Index (ESGUI) for 25 countries by employing text mining techniques on the Economist Intelligence Unit's monthly country reports, analysing the frequency of ESG-related keywords and uncertainty indicators. This captures uncertainty directly linked to ESG issues, contrary to previous measures, ensuring a better theoretical fit with research on the dynamics of sustainability, governance, or responsible investment and avoiding informational noise linked to irrelevant forms of uncertainty (e.g., monetary, fiscal). Based on the Economist Intelligence Unit (EIU) reports and economically relevant documents covering 25 countries, ESGUI of Ongan et al. (2025) enriched with text mining techniques and corrected by the World Uncertainty Index (WUI). This combination creates a robust index, contextualized at both the national and global levels, guaranteeing strong informative value for financial markets, particularly for assessing sustainability risks. Torri et al. (2025) provided a valuable methodological contribution to the construction of ESG indicators by developing an axiomatic approach to measuring the risk and performance of sustainable investments, taking into account not only financial returns, but also environmental, social, and governance (ESG) criteria. However, from a macroeconomic and empirical perspective aimed at studying the impact of ESG uncertainty on financial markets, the ESGUI of Ongan et al. (2025) stands out as a dynamic, global, and operational measure.

As it is important to study ESG perspectives, it is very important to examine ESG risks in financial markets. The literature demonstrated that the success of ESG profiles is related to informational symmetry. Consequently, ESG risk is explained by informational asymmetry, resulting in uncertainty and instability of financial markets.

By investigating the impact of ESG disclosures and institutional ownership on market information asymmetry for 683 firms listed on the New York Stock Exchange, Siew et al. (2016) suggested that there is a statistically significant negative relationship between ESG disclosures and bid-ask spread as a measure of market information asymmetry. Using a Covalence EthicalQuote database, Capelle-Blancard (2019) studied market reaction to positive and negative ESG information in environmentally sensitive industries. They demonstrated a negative market reaction when negative ESG information circulates (via companies, media, NGOs), which underlines the importance of transparency and reliability of ESG information. Furthermore, Avramov et al. (2022) analysed the implications of uncertainty on the ESG profile of companies, and they found that higher uncertainty leads to a higher market premium, reduced demand for shares, an increase in CAPM alpha, and effective beta. It illustrates how ESG uncertainty constitutes an obstacle to sustainable investment.

Other studies attributed ESG uncertainty to crisis periods. For instance, Yi et al. (2021) applied the event study method and econometric models to investigate the impacts of COVID-19 on China's green bond market for the first time. They found significant impacts of the COVID-19 pandemic on China's green bond market by increasing the cumulative abnormal return (CAR) of the green bonds greatly, signalling that these assets have not functioned as a shield against financial turmoil. Similarly, Liu (2022) examined the risky side of the green bond market by measuring their reaction to extreme negative shocks (e.g., COVID-19), assessing and forecasting the volatility of this market, and identifying the determining factors of this volatility. They found a high instability of the green bond market during the pandemic; hence, the green characteristics of a financial instrument do not mitigate risk under extreme conditions. They added that green bond volatility is primarily influenced by the traditional bond market, followed by foreign exchange, equity, and green infrastructure investments, and markets with higher spillover effects allow for better volatility forecasts, but accuracy decreases when correlations become unstable.

Although companies in emerging markets, including the BRICS, have recently increased their ESG investments, the positive effects on financial performance remain uncertain. This uncertainty is mainly due to institutional, legal, cultural, and structural differences with developed markets, which make ESG initiatives more expensive, less transparent, and sometimes seen as opportunistic. This explains why some studies suggest that ESG uncertainty is greater in emerging markets than in developed markets. According to Feng et al. (2022), the growth of ESG investment in emerging markets, particularly in China, faces challenges stemming from weak regulation and low transparency. Confirming by He et al. (2022), emerging markets like China have a less developed institutional and regulatory framework. In these markets, investor protection is weaker, laws and regulations related to governance and transparency remain incomplete, and fraud control and sanction systems are less stringent, reducing the incentive to adopt high-quality ESG. He et al. (2022) noted that in emerging markets, ESG is sometimes used as a camouflage tool to conceal opportunistic behavior or mismanagement. Similarly, Hao & He (2022) presented several indices of ESG uncertainty in emerging markets such as China. A recent regulation, high information asymmetry, strategic use of CSR, and variable quality of reports are ESG uncertainty indices.

Despite the significant contribution of these studies, all of them have focused on the unidirectional link from ESG uncertainty to the financial market and have overlooked the reverse direction of this relationship.

Motivated by these previous studies, we examine the bidirectional relationship between sustainability uncertainty and instability in emerging markets. For this, we connect ESG uncertainty with dynamic volatility spillover across BRICS markets in two directions over a period spanning November 01, 2002, to March 31, 2025.

METHODOLOGY

To examine the relationship between sustainability uncertainty and dynamic volatility spillovers across BRICS markets, we implement a three-stage approach. First, we apply the E-GARCH model to estimate the daily conditional volatility of each BRICS market, allowing us to capture the persistence and asymmetry of market shocks. Second, we use a Time-Varying Parameter Vector Autoregression (TVP-VAR) model to investigate how volatility spillovers between markets evolve, capturing dynamic interconnections that may change due to external shocks. Finally, we conduct Granger causality tests to examine whether ESG-based sustainability uncertainty can predict changes in market volatility, and vice versa.

E-GARCH model

The Exponential Generalized Autoregressive Conditional Heteroscedasticity (E-GARCH) model, introduced by Nelson (1991), extends the standard GARCH model by allowing for asymmetries in volatility. This means that negative shocks (“bad news”) may affect market volatility differently than positive shocks (“good news”). The E-GARCH(p,q) model expresses the logarithm of the conditional variance σ_t^2 as a function of past shocks and past variances, ensuring that volatility is always positive. We choose E-GARCH because it effectively models the high persistence and leverage effects commonly observed in financial markets. The E-GARCH(p,q) model expresses the logarithm of the conditional variance σ_t^2 as:

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$$\ln(\sigma_t^2) = \omega + \sum_{i=1}^{p} \beta_i \ln(\sigma_{t-i}^2) + \sum_{j=1}^{q} \alpha_j \left(\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} - E\left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}}\right]\right) + \sum_{j=1}^{q} \gamma_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}} \quad (1)$$

The return series is defined as $r_t = \mu + \varepsilon_t, \quad \varepsilon_t = z_t \varepsilon_t$, where $z_t \sim N(0,1) i.i.d$

ω is a constant term. β_i measures volatility persistence (ARCH effects). α_j captures the symmetric impact of past shocks (shock magnitude). The parameter γ_j captures the asymmetric impact of shocks. If $\gamma_j < 0$, negative shocks (bad news) increase volatility more than positive shocks of the same magnitude. Since the logarithm of variance $\ln(\sigma_t^2)$ is modelled, the conditional variance σ_t^2 is always positive. The model captures persistent volatility and shock aggregation often observed in financial markets.

TVP-VAR model

The Time-Varying Parameter Vector Autoregression (TVP-VAR) model (Antonakakis, Chatziantoniou, & Gabauer, 2020) allows us to examine how the relationships between BRICS market volatilities change over time. Unlike standard VAR models, TVP-VAR accommodates structural shifts and evolving interconnections among markets. This is important because volatility transmission between markets is not constant and can be affected by external shocks. The model estimates how shocks in one market influence other markets over time, providing a dynamic map of risk transmission.

Mathematically, the model can be represented as $Y_t = A_t z_{t-1} + \varepsilon_t$, where the coefficients A_t vary over time to capture changing relationships. To analyze the spillover effects, we transform the model into a Vector Moving Average (VMA) representation, which enables the computation of Generalized Impulse Response Functions (GIRF) and Generalized Forecast Error Variance Decompositions (GFEVD). These tools measure the directional impact of shocks from one market to another and the total connectedness within the BRICS market system. Positive values indicate a market acts as a risk transmitter, while negative values indicate it is a risk receiver.

Their time-varying parameters and systemic perspective make the TVP-VAR exceptional models. TVP-VAR permits the coefficients that describe how one variable affects another to evolve across time; this explains how we chose this model to study risk transmission across BRICS markets. Indeed, the TVP-VAR model allows us to follow and control the evolution of risk transmission and interconnectedness between BRICS markets. The TVP-VAR model can be formulated as follows:

$$Y_t = A_t z_{t-1} + \varepsilon_t, \qquad \varepsilon_t | \Omega_{t-1} \sim N(0, \textstyle\sum_t)| \quad (2)$$

$$vec(A_t) = vec(A_{t-1}) + \zeta_t, \qquad \zeta_t | \Omega_{t-1} \sim N(0, \Xi_t)| \quad (3)$$

With $z_{t-1} = \begin{pmatrix} Y_{t-1} \\ Y_{t-2} \\ \vdots \\ Y_{t-p} \end{pmatrix} \qquad A'_t = \begin{pmatrix} A_{1t} \\ A_{2t} \\ \vdots \\ A_{pt} \end{pmatrix}$

Where Ω_{t-1} represents all information available until t-1. Y_t and z_{t-1}represent m×1 vectors respectively. A_t and A_{it} are, respectively, m×mp and m×m dimensional matrices. ε_t is an m×1 vector. ζ_t is with dimension (m^2p×1). The time-varying variance-covariance matrices $\sum_t$ and Ξ_t are, respectively, m×m and $m_p^2 \times m_p^2$ dimensional matrices. Furthermore, $vec(A_t)$ is the vectorization of A_t, which is $m_p^2 \times 1\ dimensional$ vector.

To investigate dynamic behavior, the TVP-VAR model transforms into a Vector Moving Average (VMA) representation. VMA representation facilitates the computation of both the Generalized Impulse Response Function (GIRF) and the Generalized Forecast Error Variance Decomposition (GFEVD). The GIRF represents the responses of all variables j, following a shock in the variable i. This representation incorporated a specified forecast horizon for forward-looking analysis. In turn, the GFEVD represents the pairwise directional connectedness from j to i and illustrates the influence variable j has on variable i in terms of its forecast error variance share. These variance shares are then normalized, so that each row sums up to one, meaning that all variables together explain 100% of the variable i's forecast error variance. This is calculated as follows:

$$\theta_{ij,t}(H) = \frac{\sum_{t=1}^{H-1} \Psi_{ij,t}^2}{\sum_{j=1}^{m} \sum_{t=1}^{H-1} \Psi_{ij,t}^2}$$

With $\sum_{j=1}^{m} \theta_{ij,t}(H) = 1$ and $\sum_{i,j=1}^{m} \theta_{ij,t}(H) = m$. The denominator illustrates the cumulative effect of all the shocks, while the numerator shows the cumulative effect of a shock in the variable i. Based on the GFEVD, the Total Connectedness Index (TCI) is represented as follows:

$$S_t(H) = \frac{\sum_{i,j=1}^{m}, i \neq j\ \theta_{ij,t}\ (H)}{m} \times 100$$

This connectedness approach shows how a shock in one variable is transmitted to other variables. We explain the connectedness approach in three steps: in the first step, we look at the case where variable i transmits its shocks to all other variables j, which is called total directional connectedness to others and is defined as:

$$S_i \to j, t(H) = \frac{\sum_{j=1}^{m}, i \neq j\ \theta_{ij,t}\ (H)}{\sum_{j=1}^{m}\ \ \theta_{ij,t}\ (H)} \times 100$$

In the second step, we calculate the directional connectedness variable i receives from variable j, which is called total directional connectedness from others and is defined as:

$$S_i \leftarrow j, t(H) = \frac{\sum_{j=1}^{m}, i \neq j\ \theta_{ij,t}\ (H)}{\sum_{i=1}^{m}\ \ \theta_{ij,t}\ (H)} \times 100$$

In the third and final step, we calculate the net total directional connectedness by subtracting the total directional connectedness to others from the total directional connectedness from others. The net total directional connectedness can be interpreted as the influence variable i has on the analysed network.

$$S_{i,t} = S_i \to j, t(H) - S_i \leftarrow j, t(H)$$

If $S_{i,t}$ is positive, this means that variable i influences the network more than it is influenced by itself (variable i is a transmitter of risk). Conversely, if $S_{i,t}$ is negative, meaning variable i is driven by the network (variable i is a receiver of risk).

Finally, we break down the net total directional connectedness even further to examine the bidirectional relationships by computing the net pairwise directional connectedness NPDC: $\mathrm{NPDC}_{ij}(H) = (\ \theta_{ji,t}\ (H) - \theta_{ij,t}\ (H)) \times 100$

$$\text{If } \mathrm{NPDC}_{ij}(\mathrm{H})>0 \text{ , it means that i dominates variable j. Conversely, if } \mathrm{NPDC}_{ij}(\mathrm{H}) < 0, \text{it means that variable j dominates variable i}$$

Granger causality tests

Granger causality tests (Granger, 1969) were conducted to clarify the direction of causality between ESG Uncertainty Indices (ESGUI) and BRICS volatility spillovers. In simple terms, the test examines whether past values of one variable (e.g., ESGUI) can help predict another variable (e.g., market volatility). We test whether ESG uncertainty "causes" changes in volatility spillovers and whether volatility spillovers can "cause" changes in ESG uncertainty.

Data and descriptive statistics

Date

The data includes daily closing prices of BRICS market indices (Brazil, Russia, India, China, South Africa), which are, respectively, BM & FBovespa, IMOEX, BSE Sensex, Shanghai Composite, and TOP40. They are collected from DATASTREAM. BRICS returns are calculated as follows: $R_{it} = ln\frac{P_{it}}{P_{i,t-1}}$

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The ESG uncertainty indices (ESGUI) of Ongan et al. (2025) are collected from the website of economic policy uncertainty (http://www.policyuncertainty.com/). ESGUI indices are Global Equal Weighted and Global GDP Weighted. Our data covers the period from November 1, 2002, to March 31, 2025.

ESG-Based Sustainability Uncertainty Index (ESGUI)

The ESG-based Sustainability Uncertainty Index (ESGUI), developed by Ongan, Gocer, and Isik (2025), represents the first global composite measure specifically designed to quantify uncertainty related to sustainability and ESG factors. The index provides a systematic way to capture how uncertainty stemming from environmental (E), social (S), and governance (G) dimensions is reflected in macroeconomic dynamics and investment behavior. Its construction integrates the conceptual framework of the World Uncertainty Index (WUI) by Ahir et al. (2022) with ESG-related textual indicators, thereby filling a methodological gap in the literature on sustainability risk measurement.

The ESGUI is constructed using text mining techniques applied to the Economist Intelligence Unit's (EIU) monthly country reports for a panel of 25 developed and developing economies covering the period 2002M11–2024M09. These reports were selected due to their standardized structure, regular frequency, and global comparability, reducing ideological and linguistic inconsistencies across countries. The construction of ESGUI involves three main steps:

First step: Building the ESG sub-index

Separate indices are computed for environmental (E), social (S), and governance (G) dimensions based on the relative frequency of selected ESG-related keywords within each monthly Economist Intelligence Unit EIU report.

The keywords were extracted through natural language processing (NLP) using the PyMuPDF (Fitz) and Natural Language Toolkit NLTK libraries. Common stop words were removed, and advanced models such as Latent Dirichlet Allocation LDA and Bidirectional Encoder Representations from Transformers BERT were tested but rejected in favor of a transparent keyword-based approach to maintain interpretability and replicability.

For each report, the frequency of ESG-related terms is divided by the total number of words in the text, producing normalized monthly series:

$$E_t = \frac{Frequency\ (E\ keywords)}{Total\ words},\ \ S_t = \frac{Frequency\ (S\ keywords)}{Total\ words},\ \ G_t = \frac{Frequency\ (G\ keywords)}{Total\ words}$$

These three dimensions are equally weighted to form the composite ESG sub-index:

$$ESG_t = \frac{1}{3}(E_t + S_t + G_t)$$

Each sub-series is normalized using a Min–Max scaler (range 0–100), following the approach of Dang et al. (2023) and Chung et al. (2022), to ensure comparability over time and across countries.

Second step: Building the Uncertainty sub-index (UI)

Following Ahir et al. (2022), the uncertainty component is derived from the frequency of the words "uncertain," "uncertainty," and "uncertainties" within the same reports:

$$UI_t = \frac{Frequency\ (Uncertainty\ keywords)}{Total\ words}$$

Third step: Constructing the ESGUI composite

The final index integrates the ESG and uncertainty components with equal weights:

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$$ESGUI_t = \frac{1}{2}ESG_t + \frac{1}{2}UI_t$$

The global ESGUI is then computed in two forms:

(i) Equally weighted, giving the same importance to each country, and

(ii) GDP-weighted, using each country's share in the total GDP of the 25-country sample.

Descriptive statistics

Table 1 provides a statistical summary of the daily returns in the BRICS markets and the ESG Uncertainty Indices (Global Equal Weighted and Global GDP Weighted) of Ongan et al. (2025).

Table 1 shows that the average returns are positive for all markets considered. This indicates that all markets are profitable, although the Russian market is the least profitable among them. The Jarque-Bera test rejects the null hypothesis of normality at the 1% significance level for all series (p-value = 0). The skewness and kurtosis values support the non-normality of the series, with non-zero skewness and high kurtosis. Most return distributions exhibit significant deviations from normality, with extreme kurtosis values for Russia (~758), indicating heavy tails. Additionally, skewness values reveal strong asymmetries in the Russian market.

The ARCH-LM test (Engle, 1982) reveals a significant ARCH effect in Brazil, India, China, and South Africa, but not in the Russia series. Although the ARCH-LM test revealed no statistically significant ARCH effect for the Russian stock market series, we adopt the Exponential GARCH (E-GARCH) framework (Nelson, 1991) for all BRICS markets for several methodological and theoretical reasons. First, the absence of a significant ARCH effect based on a preliminary diagnostic test does not rule out the presence of conditional heteroscedasticity in a more flexible model such as E-GARCH. Unlike traditional GARCH models, the E-GARCH specification captures asymmetric volatility effects (also called leverage effects), which are common in financial time series, even when symmetric ARCH-type behavior is not identified. Second, E-GARCH models the logarithm of the conditional variance, which relaxes the non-negativity constraint on variance parameters. This feature provides extra flexibility and robustness, especially during volatile market conditions or structural breaks. Third, for consistency and comparability across the BRICS markets, it is methodologically sound to use the same volatility modeling framework for all series. Applying a unified model enables consistent examination of volatility dynamics and cross-market spillovers, which is especially important in a multivariate or systemic context. Therefore, using the E-GARCH model for all BRICS countries is justified by its statistical robustness and driven by the research goals, including capturing asymmetric volatility responses to shocks and maintaining coherence in cross-market analysis.

The Augmented Dickey–Fuller (ADF) unit root test of Dickey & Fuller (1981) and the Phillips–Perron (PP) unit root test of Peter et al. (1988) indicate that all return series are stationary. Nevertheless, Global Equal Weighted is not stationary according to the ADF and PP tests. Hence, we use the first difference for this series to obtain a stationary series, as indicated by the ADF and PP tests.

Table 1 Descriptive statistics of BRICS and ESGU indices

Index	N	Mean	Max	Min	Std.Dev	Skew	Kurt	J-B stat	LM-stat	ARCH effect	ADF-stat	PP-stat
BRAZIL	5853	0.0004	0.1344	-0.1577	0.0158	-0,4581	13,3100	$26127,4193^{***}$	1732.3(<2.2e-16)	Yes	-17.422^{***}(0.01)	-5931.2^{***}(0.01)
RUSSIA	5853	0.0002	1.1306	-0.4047	0.0248	14,8457	757,7373	$139133118,0418^{***}$	1.5252 (0.9999)	No	-23.808^{***}(0.01)	-5746.4^{***}(0.01)
INDIA	5853	0.0005	0.1642	-0.1374	0.0132	-0,4080	16,3398	$43559,8721^{***}$	721.07 (<2.2e-16)	Yes	-16.425^{***}(0.01)	-5594.1^{***}(0.01)

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CHINA	5853	0.0004	0.1404	-0.1283	0.0153	-0.0408	10.8949	15202,06***	6502.2 (<2.2e-16)	Yes	-3.1749***(0.01)	-1493.1***(0.01)
SOUTH AFRICA	5853	0.0003	0.0723	-0.0948	0.0123	-0,3043	7,4575	4936,0055***	1453.1 (<2.2e-16)	Yes	-18.946*** (0.01)	-5157.5*** (0.01)
Global Equal Weighted	5853	28.6600	46.8000	17.6100	4.9900	0,4597	4,4950	751,2540***	-	-	-2.2935 (0.4541)	-8.6829 (0.6256)
Global GDP Weighted	5853	27.6700	51.1200	16.6900	5.8000	1,0332	4,5381	1618,2625***	-	-	-3.5393**(0.0385)	-21.966**(0.0466)

Note: Table 1 presents descriptive statistics of BRICS indices' daily returns and ESG Uncertainty indices (Global Equal Weighted and Global GDP Weighted) of Ongan, Serdar, Gocer, Ismet, and Isik, Cem (2025), and preliminary tests for the used data. The data range is from November 01, 2002, to March 31, 2025. *** Indicates statistical significance at the 1% level through the Jarque-Bera (JB) test. ADF and PP denote the statistics of Augmented David et al. (1981) and Peter et al. (1988) unit root tests, respectively. ***and ** indicate the stationary level at 1% and 5%.

Source: Author's work

Empirical evidence

The conditional volatility estimation

Table 2 shows the estimates of the E-GARCH (1,1) model for BRICS returns. The results indicate a very high β_1 for all series, suggesting that all BRICS markets exhibit strong volatility persistence. This means that volatility shocks have long-lasting effects, which is important for spillover analyses. γ_1 is positive and significant for all series, indicating that negative news increases volatility more than positive news in all BRICS markets. We note that Russia and India present the strongest asymmetry, reflecting high political or macroeconomic risk sensitivity. α_1, which indicates shock sensitivity, shows that South Africa and Russia respond the most to the size of past shocks. However, China has the lowest α_1, indicating a more stable volatility response to events. Furthermore, all markets (except South Africa) show positive and significant mean returns, reflecting higher growth potential or risk premiums in these markets above all in India and China.

These premium results motivate us to understand volatility transmission dynamics among BRICS and to examine the relationship between ESG uncertainty (ESGUI) and this spillover. This is the objective of the following section.

Table 2 E-GARCH model estimates

$$\ln(\sigma_t^2) = \boldsymbol{\omega} + \beta_1 \ \ln(\sigma_{t-1}^2) + \ \alpha_1 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \gamma_1 \ \frac{\varepsilon_{t-j}}{\sigma_{t-j}}$$

$$r = \mu + \varepsilon_t, \qquad \varepsilon_t \sim N(0, \sigma_t^2)$$

Markets	μ	ω(ct)	α (ARCH)	β (GARCH)	γ (Asymmetry)
BRAZIL	0.0003***	-0.1664***	-0.0554 ***	0.982 ***	0.126***
RUSSIA	0.0004***	-0.3092***	-0.0854***	0.962***	0.2046***
INDIA	0.0006***	-0.133***	-0.0731 ***	0.980 ***	0.170 ***
CHINA	0.0005***	-0.4775***	-0.0278***	0.984***	0.167***
SOUTH AFRICA	0.0002	-0.2019***	-0.0944 ***	0.979 ***	0.119 ***

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Note: Table 2 presents the estimates of the E-GARCH model (Nelson, D.B. 1991) that is presented as follows: $\ln(\sigma_t^2) = w + \sum_{i=1}^{p} \beta_i \ln(\sigma_{t-i}^2) + \sum_{j=1}^{q} \alpha_j \left(\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}} - E\left[\frac{|\varepsilon_{t-j}|}{\sigma_{t-j}}\right]\right) + \sum_{j=1}^{q} \gamma_j \frac{\varepsilon_{t-j}}{\sigma_{t-j}}$. *** indicates the significance level at 1%.

Source: Author's work

BRICS volatilities and ESGU indices

Figure 1 shows BRICS volatilities and ESGUI indices (Global Equal Weighted and Global GDP Weighted) from November 01, 2002, to March 31, 2025. Analysing this figure, we observe several key points.

The period spanning 2002 to 2003 is characterised by a peak in ESGUI and generally a high volatility in BRICS markets. This peak in volatility is more marked in India and China, but less marked in Brazil and South Africa, and it is negligible in Russia. This simultaneity in BRICS volatilities and ESGUI behavior can be explained as follows. Enron, Sarbanes-Oxley Act, and corporate governance scandals (2002-2003) events that are marked in Ongan et al. (2025) can be an explanation. A crisis of confidence caused by corporate governance scandals such as Enron, WorldCom, and Tyco explained this peak on ESGUI. These events revealed major failures in internal control and financial transparency systems, leading to a major regulatory reaction with the adoption of the Sarbanes-Oxley Act in 2002. This American law increases the perceived ESG uncertainty in emerging economies such as the BRICS, leading investors to be more afraid about their future cash flows, hence increasing market volatility. These observations confirm the work of Capelle-Blancard (2019) and Siew et al. (2016), who highlight that the dissemination of negative information on governance increases uncertainty and volatility via an increase in information asymmetry. They also agree with Avramov et al. (2022) that increased uncertainty about governance raises the risk premium and reduces demand for shares.

Between 2008 and 2009, a high level of volatility was observed in all BRICS markets. This peak is higher in China, Brazil, India, and South Africa, and relatively higher in Russia. Simultaneously, a sudden rise in ESGUI is detected. This period covers the Global Financial Crisis, leading to financial markets becoming more volatile. During this period, uncertainty about financial governance, corporate accountability, and regulatory reform has reached unprecedented levels. Emerging markets such as the BRICS were particularly affected by the global capital flight and the collapse in commodity demand. As ESG concerns intensify, investors have re-evaluated the institutional risk of developing economies, increasing market volatility. These observations are consistent with Cornett et al. (2016), Lins et al. (2017), and Broadstock et al. (2021), who show that ESG plays a relatively stabilizing role, but that increased uncertainty about corporate governance and responsibility in times of crisis amplifies volatility. Also, they align with Liu et al. (2023), suggesting that in times of high uncertainty, if ESG is not integrated or perceived as credible, volatility spillovers remain strong.

During 2010-2011, due to ongoing instability from the global financial crisis, the developing Eurozone sovereign debt crisis, increasing geopolitical tensions such as the Arab Spring, the explosion of the Deepwater Horizon rig, and a major nuclear disaster resulting in radioactive leaks, ESG uncertainty stayed high. These events raised concerns about political and institutional risks, especially in emerging economies. As ESG frameworks developed, uncertainty about the direction and enforcement of sustainability-related regulations also increased investor caution. This leads BRICS markets to experience renewed volatility, which was aggravated by external shocks and fluctuations in commodity markets. These observations are in line with Yi et al. (2021) and Liu (2022), who show that "green" or ESG-strong assets do not always neutralize risk under extreme shocks, particularly in emerging markets like the BRICS group.

By observing the period from 2015 to 2016, we note a peak in ESGUI, which is attributed to policy risk stemming from regulatory shifts, such as the Paris Agreement, as well as reputational and legal risks (as seen in the Volkswagen case), and social unrest and governance concerns (as exemplified by Black Lives Matter activism). Faced with this uncertainty, BRICS markets, often perceived as riskier, experienced capital withdrawals, portfolio adjustments, and increased responsiveness to ESG information, leading to higher conditional volatility. This aligns with Zeng et al. (2024), Sun et al. (2025), and Zhang et al. (2025) that the negative impact of ESG divergences and controversies on investment decisions increases perceived risk and volatility.

Between 2020 and 2025, Figure 1 shows that sustainability uncertainty has experienced a continuous increase, explained by several critical events such as the COVID-19 pandemic, Black Lives Matter, Green Recovery Efforts, Extreme weather events, and ESG reporting mandates. This contributed to higher volatility levels across BRICS financial markets through capital flows, investor sentiment, and global supply chains. These observations converge with Ferriani & Natoli (2021), Broadstock et al. (2021), and Boubaker et al. (2022), who show that ESG perception strongly influences capital flows in times of high uncertainty, but also with Hao & He (2022) and Feng et al. (2022), who highlight that in the BRICS, institutional weakness amplifies these effects.

Fig. 1 BRICS volatilities and ESGU indices

Note: Figure 1 presents E-GARCH Conditional volatility of BRICS markets returns and ESGU indices that are Global Equal Weighted and Global GDP Weighted by Ongan, Serdar, Gocer, Ismet, and Isik, Cem (2025) from November 2002 to March 2025.

Source: Author's work

Volatility spillover among BRICS markets

In this paragraph, we examine volatility spillovers among BRICS markets by applying the TVP-VAR model of Antonakakis, Chatziantoniou, & Gabauer (2020). Table 3 presents ADF and PP stationarity tests of BRICS volatilities. The results demonstrate that all BRICS volatility series are stationary.

Table 3 Stationarity tests of BRICS volatilities

Market volatility	ADF	PP
BRAZIL	-7.779994***	-110.96670***
RUSSIA	-6.242132***	-344.74825***
INDIA	-8.248202***	-148.19730***
CHINA	-6.305515***	-95.65445***
SOUTH AFRICA	-7.971513***	-143.15921***

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Note: Table 3 reports the results of the ADF and PP stationarity tests for BRICS volatilities. *** indicates the stationarity of the series at 1% level.

Source: Author's work

Figure 2 presents the Total Connectedness Index (TCI) across BRICS markets' volatilities. As illustrated in Fig. 2, the TCI value exhibits significant temporal variation throughout the observation period. A Strong interconnectedness of BRICS markets during the period spanning 2003 to 2004, since TCI has an extremely high level (>75%) following the accounting crisis (post-Enron), in a context of governance reforms. The period spanning 2007 to 2009 shows another peak of TCI (~ 65%), tracing the effect of the global financial crisis. New peaks of TCI are observed between 2011 and 2012 that are linked to the Eurozone sovereign debt crisis, geopolitical tensions (Arab Spring), and Fukushima, confirming studies of Hsiao et al. (2024) that crisis events explain markets' interconnectedness, and confirming Ijaz et al. (2025) that geopolitical conflicts enhance the spillover effect.

A strong peak of TCI is detected in the period spanning 2020 to 2022 (~ 70%), reflecting the impact of the COVID-19 pandemic and ESG uncertainty resulting from Green recovery and ESG mandates. Our finding emphasizes a new role, ESG uncertainty, which is added to health crises to fuel spillovers. This aligns with Ongan et al. (2025), who state that new ESG obligations and the "green recovery" have added a new channel of uncertainty. Between 2023 and early 2025, the TCI index first declined, then recovered. This is due to a gradual decline following the COVID crisis (normalization effect) in 2023 (Diebold & Yilmaz, 2012), but in 2024–2025, a clear recovery is visible. This rebound is linked to the resurgence of geopolitical tensions (such as the prolonged Russia-Ukraine war), the acceleration of ESG policies, and increasing extreme weather events. This recovery aligns with work showing that geopolitical uncertainty and climate risks become lasting catalysts for spillovers (Broadstock & Zhang, 2021; Nguyen et al., 2023; Ijaz et al., 2025). These results motivate us to explore the dynamic relationship between ESG uncertainty and BRICS connectedness within the volatility context. That is the objective of the following sections.

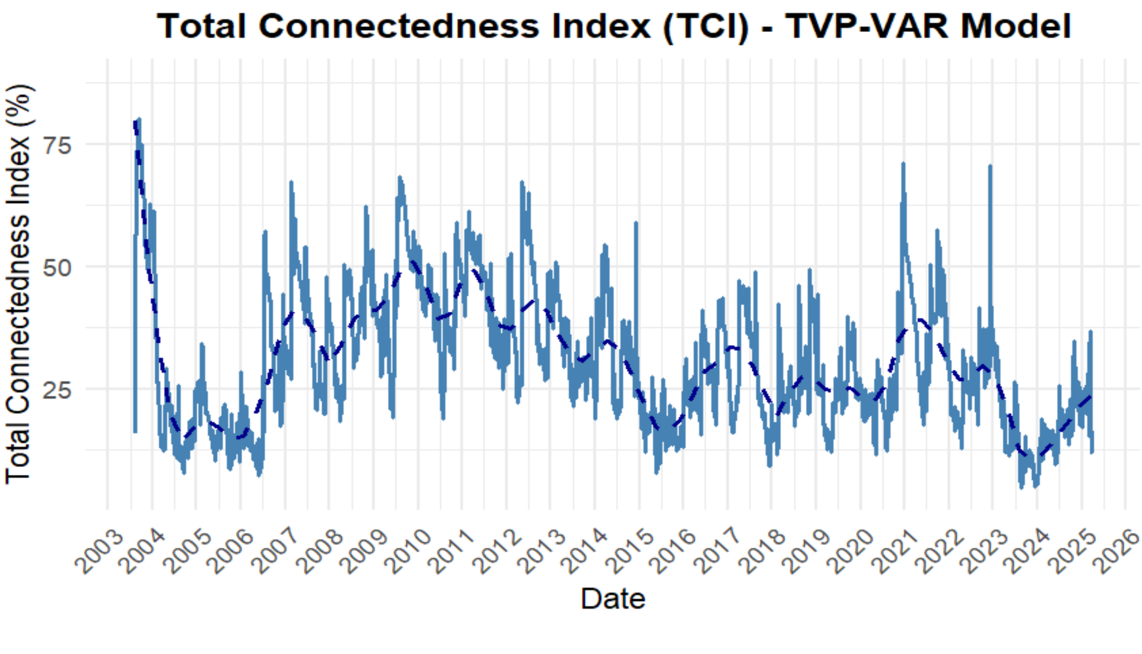

Fig.2. Dynamic Total Connectedness (TVP–VAR (0.99,0.99) with three lags and a 12-step-ahead forecast)

Note: Figure 2 presents the Dynamic Total Connectedness Index (TCI), which is estimated using a Time-Varying Parameter Vector Autoregression (TVP–VAR) model with forgetting factors set at 0.99 for both the state and covariance equations, incorporating 3 lags and a 12-step-ahead forecast horizon. This specification captures the evolving spillover effects and connectedness dynamics among the BRICS markets over the sample period.

Source: Author's work

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Table 4 presents averaged connectedness measures. Diagonal elements denote idiosyncratic shocks, while off-diagonal elements signify interdependencies between variables. Analysis of each BRICS series indicates that the majority of market volatility fluctuations (> 67%) originate from internal shocks. This suggests that BRICS markets remain largely self-determined in terms of volatility, confirming Diebold & Yilmaz (2012) that emerging markets, although interconnected, retain a high proportion of self-generated volatility, often linked to domestic factors (monetary policy, institutional instability, market structure).

Table 4 shows that China and South Africa transmit, respectively, 32% and 33% volatility to other markets, indicating that they are the main emitters of volatility in the BRICS group. However, Russia, India, and Brazil are the weakest emitters (29%, 28%, and 28% respectively). Due to its dependence on raw materials and its high financial integration, South Africa is often a source of shocks. Despite capital controls, China influences the BRICS through its economic size and trade ties (Mensi et al., 2014, and Bouri et al., 2020). Russia, South Africa, and Brazil receive, respectively 38%, 37%, and 35% of the volatility from other markets. They are the most vulnerable markets to external shocks, while India and, above all, China are less affected (27% and 12%). Analysing the results of net spillover (TO-FROM), we suggest that Russia, Brazil, and South Africa (+9%, +7%, and +4% respectively) are net volatility issuers, but China and India (- 20% and -1% respectively) are net volatility receivers. This shows that China and India appear as volatility dampeners rather than catalysts, confirming Mensi et al. (2014). However, Russia appears as a net contributor, especially during episodes related to sanctions or energy volatility, justifying the results of Tiwari et al. (2025) that markets highly exposed to commodity prices (such as oil and gas for Russia) and geopolitical tensions often act as structural sources of volatility.

Table 4 Average Connectedness Table

	BRAZIL	**RUSSIA**	**INDIA**	**CHINA**	**SOUTH AFRICA**	**FROM**
BRAZIL	0.72	0.10	0.06	0.03	0.10	0.28
RUSSIA	0.09	0.71	0.06	0.03	0.11	0.29
INDIA	0.08	0.08	0.72	0.03	0.09	0.28
CHINA	0.06	0.09	0.08	0.68	0.08	0.32
SOUTH AFRICA	0.11	0.11	0.07	0.04	0.67	0.33
TO	0.35	0.38	0.27	0.12	0.37	1.49
NET(TO-FROM)	+ 0.07	+ 0.09	- 0.01	- 0.20	+ 0.04	

Note: Table 4 shows the averaged connectedness results obtained from TVP–VAR (0.99,0.99) with three lags and a 12-step-ahead forecast. Diagonal elements denote idiosyncratic shocks, while off-diagonal elements signify interdependencies between variables.

Source: Author’s work

To conclude, Table 4 shows a significant but asymmetric interconnectedness of volatility among the BRICS, with China acting as the net receiver (absorbing shocks), Russia as a major source of volatility, and the other countries playing more balanced roles. Asymmetric connectedness is a well-documented phenomenon (Baruník et al., 2017), reflecting differences in market size, financial openness, and risk profile.

Figure 3 traces a network of BRICS volatility spillover. Visual inspection of Fig. 3 reveals that Brazil transmits high volatility to South Africa. This confirms Brazil's position as a net transmitter, observed in the table (Net = +0.07). Russia also transmits a lot to South Africa. This reinforces its status as the largest net emitter of volatility (Net = +0.09). These two dominant relationships place South Africa in a major receiver position, which perfectly corresponds to the fact that South Africa has a high FROM (0.33), confirming that it receives more volatility than the others. However, the dynamic connectedness between other markets is less intense.

Figure 3 visually confirms what the Average Connectedness Table reveals numerically. Russia and Brazil are the main emitters of volatility, but South Africa is the main receiver, with strong links from both countries. This can be explained on one side by the strong dependence of Russia and Brazil on raw materials, which have highly volatile prices and are more vulnerable to global shocks. This can be a trigger of market risk, hence sources of regional and international contagion. Furthermore, the period studied covers several critical events that help to explain volatility spillovers, such as the war of Russia-Ukraine, the COVID-19 pandemic, and other uncertainty sources (Bouri et al., 2021; Tiwari et al., 2025). We must note also that Brazil, as a large emerging market in Latin America, is often a regional proxy for investors. Consequently, a shock in Brazil can trigger chain reactions in other BRICS markets. On the other hand, South Africa is a relatively small and open economy, more dependent on foreign investment and international trade, explaining its vulnerability to external shocks (Mensi et al., 2014, and Baruník et al., 2017), particularly those coming from major trading partners such as Russia and Brazil. What makes the South African market more sensitive to external shocks is its significant public debt and recurring social tensions (inequalities, strikes, political instability). China is relatively isolated as a net receiver. Several reasons can explain this result. The Chinese market is still partially closed to foreign capital, with controls on financial flows and the exchange rate, limiting the transmission of its volatility to the external market (low spillover "TO") (Diebold & Yilmaz, 2014). Furthermore, the Chinese economy is more diversified and run by the state, which absorbs the magnitude of shocks to financial markets. However, China remains exposed to external shocks (notably via global trade), which explains why it receives more volatility than it transmits (net = –0.20 in the table). Consequently, overall dynamic interconnectedness is moderate, but some bilateral relationships are dominant and asymmetric (Diebold & Yilmaz, 2012; Baruník et al., 2017). These results are consistent with the literature on shock transmission in emerging markets, which highlights that countries rich in natural resources or exposed to geopolitical tensions are often emitters of volatility, while more fragile or dependent economies are receivers.

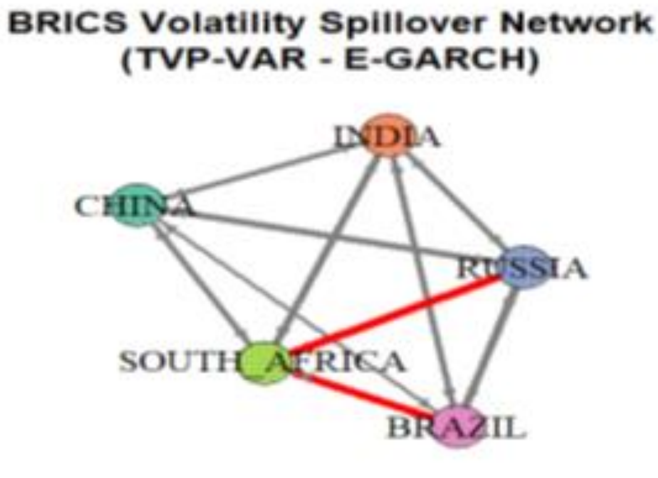

Fig. 3. A network of Volatility spillover

Note: Figure 3 illustrates the directed interactions within a network of BRICS market volatilities. Node size represents the magnitude of net pairwise directional connectedness.

Source: Author's work

We continue this investigation by quantifying total directional connectedness to differentiate between net transmitters (positive index values) and net receivers (negative index values) of volatility (risk) shocks over the time series. Figure 4 shows this characterization. Notably, the Brazilian market is a highly volatile emitter during several periods (2008, 2010-2012, post-2018). We note also that it transmits more volatility than receives, reflecting its role as a shock propagator, particularly during crises (global financial crisis, local political

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instability, pandemic). Concerning the Russian market, we note a one-time net contributor, but it often tends to be close to zero. In 2022, the peaks could be explained by the war in Ukraine and sanctions. The Indian market shows an alternation between the role of transmitter and receiver, without clear dominance. A strong volatility transmission of this market is detected in 2008, 2013, 2020, and 2022-2023, linked to the financial crisis, the COVID-19 pandemic, its growing integration into global markets, and ESG tensions. However, the Chinese market presents a volatile role. More frequently, it is a net receiver until 2015, with occasional emitter episodes during specific stresses (stock market crisis of 2015-2016, trade tensions with the US) (Baruník et al., 2017). For the South African market, we observe an almost constant net emission of volatility, with very significant peaks (2008, 2020), reflecting its structural sensitivity to external and ESG shocks. The South African market plays a pivotal role in transmitting volatility within the BRICS. These asymmetric results call for differentiated hedging strategies across BRICS markets.

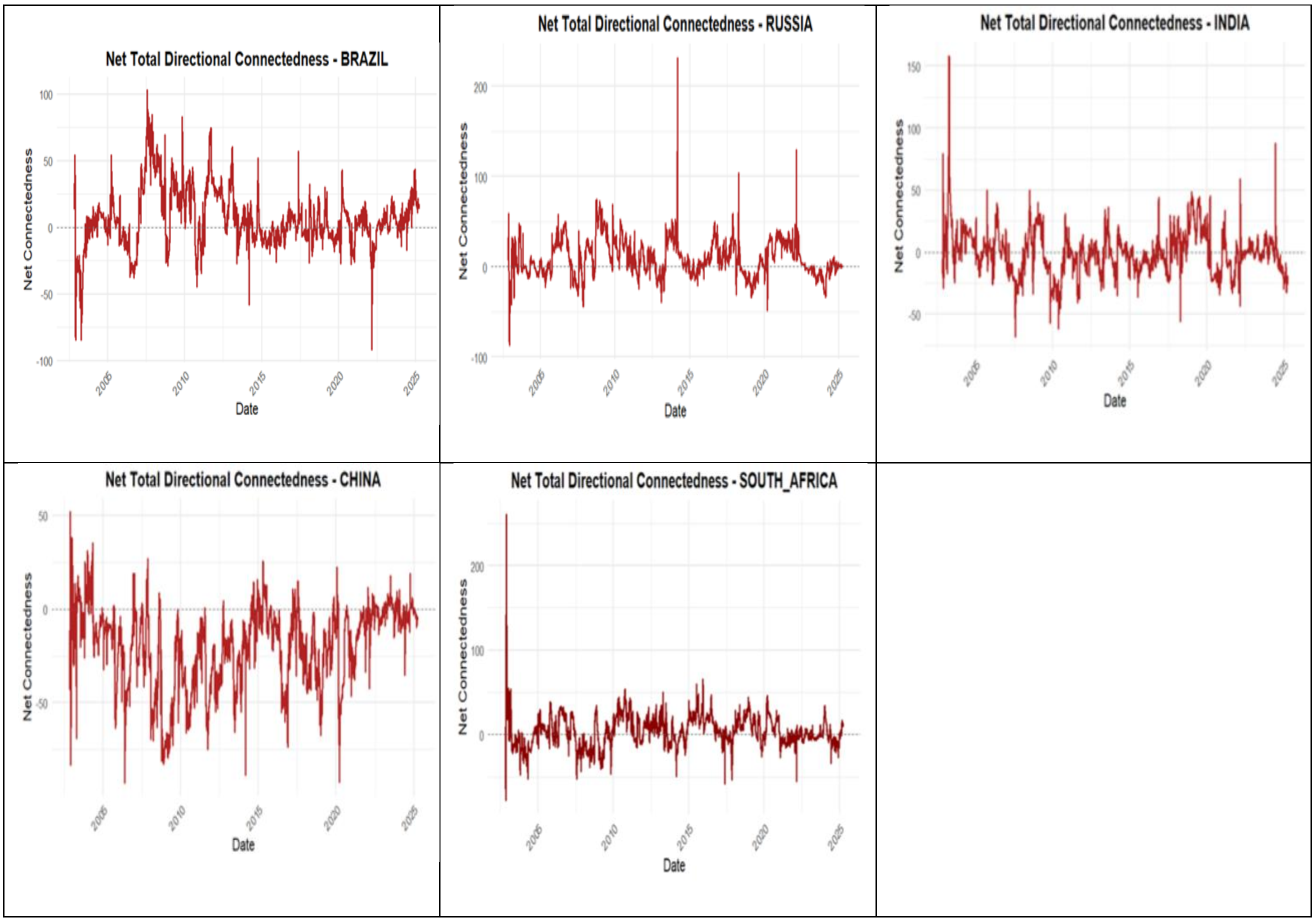

Fig. 4. Dynamic net total directional connectedness

Source: Author’s work

Note: Fig. 4 shows the dynamic net total directional connectedness between BRICS volatilities in a period separately from November 01, 2002, to March 31, 2025

Source: Author’s work

To analyse the impact of market i on market j, we use Net Pairwise Directional Connectedness among BRICS markets. Figure 6 shows the results of this measurement. The Brazilian market experienced several peaks of volatility transmission to the Russian market (in 2003, 2006, 2009, 2014, 2018, 2023). Conversely, during these times, the Russian market was a strong receiver of risk. Several key events explain this pattern, such as the global financial crisis and commodity crisis. However, volatility spillover between Brazil and India seems more contained. Episodes where Brazil becomes a net emitter are evident around 2008, 2013 (taper tantrum), and 2020 (COVID). Looking at the Brazil-China dynamic through volatility shows moderate variability but generally stays around zero, indicating a balanced bilateral relationship. Between Brazil and South Africa, spillover is highly

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volatile, especially around 2008, 2011, and 2020, suggesting Brazil often acts as a net transmitter of volatility to South Africa. Similarly, for the Russia-India relationship, Russia appears to be a net transmitter during certain periods. However, the Russia-China dynamic remains relatively stable, with some significant dips during times of geopolitical crisis. High directional volatility between Russia and South Africa during 2008, 2014, and 2020; periods when Russia appears to be a net emitter of shocks. The India-China net directional connectivity varies greatly, especially between 2005 and 2015. India often appears to be a net transmitter, except during periods of crisis when this reverses. Between India and South Africa, a strong asymmetry (very positive peaks) in directional connectedness is observed, indicating that India appears to play a dominant role as a net transmitter of volatility to South Africa, especially around 2008 and 2020. The net pairwise directional connectedness between China and South Africa is highly volatile, with periods where China receives a significant amount of risk (negative values around 2003-2004 and 2008). After 2010, China became a net transmitter more frequently.

Generally, these results show that Brazil, India, and China often appear as net sources of volatility for the other BRICS. However, South Africa is frequently a net receiver. Russia plays a mixed role, but often appears to be a net receiver during periods of geopolitical tension. These findings suggest that periods of global crises (2008, 2011, 2020) generally amplify directional connectivity and reveal structural roles.

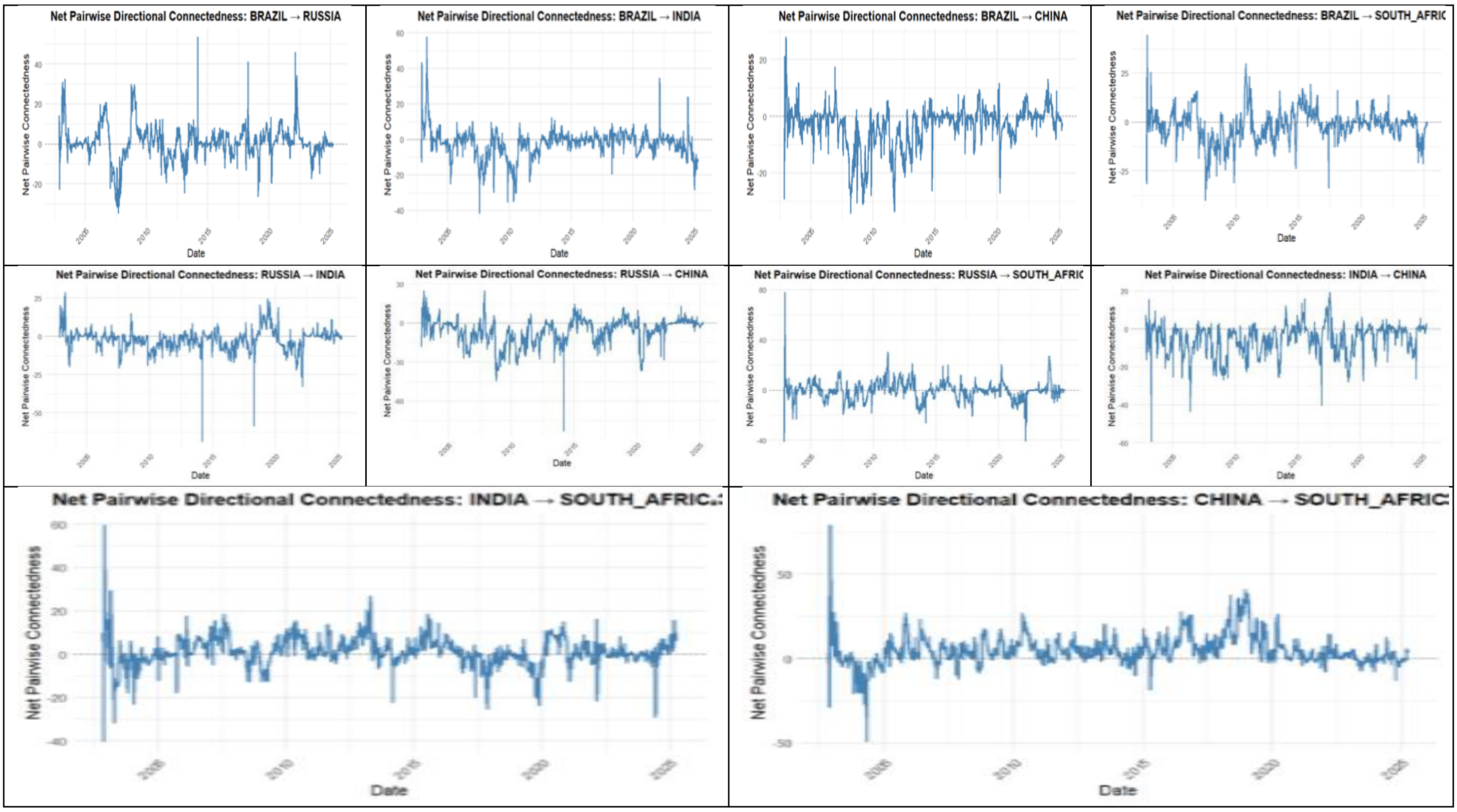

Fig. 5. Net Pairwise Directional Connectedness.

Note: Fig. 5 shows the net pairwise directional connectedness between BRICS volatilities in a period separately from November 01, 2002, to March 31, 2025.

Source: Author's work

ESG Uncertainty and Volatility Spillover

To examine the relationship between ESG Uncertainty and Volatility Spillover among BRICS markets, we apply the Granger causality tests for several lags. First, we test the relationship between the Global Equal Weighted, as an index of ESG uncertainty (Ongan et al., 2025), and the Total Connectedness Index TCI, as a measure of spillover, for several lags. Second, we test the relationship between the Global GDP Weighted, as a second index of ESG uncertainty (Ongan et al., 2025), and the Total Connectedness Index TCI for several lags. Third, we apply Granger causality tests between the Global Equal Weighted and the Net Pairwise Directional Connectedness for several lags.

The results of these tests are shown in Tables 5 and 6. First, Table 5 reveals a unidirectional causality from BRICS TCI to ESG Uncertainty (Global Equal Weighted) for a one lag, suggesting that changes in BRICS volatility connectivity influence global ESG uncertainty in the very short term. This supports the idea that regional financial turmoil can lead to an immediate reassessment of global ESG risks (market reactions, investor repositioning, etc.). However, there is no causality from ESGUI to TCI for any lag, indicating that changes in global ESG uncertainty do not seem to predict or directly affect volatility dynamics between BRICS markets, at least not in the following days. Similarly, the Granger causality tests between the Global GDP Weighted and the TCI (Tests 3and 4) show that TCI causes ESG uncertainty (GDP Weighted) only at lag 5, but no significant causality from ESG uncertainty (GDP weighted) to TCI for all lags tested.

These findings suggest no strong evidence that ESG uncertainty indices cause spillover volatility (TCI). This result doesn’t confirm Sun et al. (2025), who found that higher levels of ESG uncertainty, measured by ESG divergence, significantly increase the risk of future stock price crashes, increasing their share volatility and volatility spillover. However, TCI appears to influence ESGUI, indicating that the dynamics of interconnected volatility in BRICS markets could affect sustainability uncertainty. This is consistent with the view that financial markets, as barometers of the real economy and the political environment, can trigger a rapid reassessment of extra-financial risks (He et al., 2023). Thus, a high volatility contagion reflects a climate of instability that fuels the perception of uncertainty regarding sustainability.

We interpret these results as follows. The TCI reflects the intensity and spread of risks and uncertainties among BRICS markets. When the interconnected volatility increases, this can create fear and uncertainty among BRICS investors that are connected to global investors, and this reveals a deterioration or overall economic instability, prompting stakeholders to reassess ESG risks and thus modify the ESGUI indices. Furthermore, ESGUI doesn’t react to TCI can be explained by its slower reactivity. ESG uncertainty indices are often constructed from indicators, reports, aggregated data, or surveys that do not react instantly. In contrast, financial markets are highly sensitive and reactive to events, creating a time lag where market volatility precedes and statistically "causes" the change in the ESGUI. Moreover, these results can be specific to BRICS markets. Knowing that the sustainability concept in BRICS markets is being developed in comparison to developed markets, these emerging markets are slowly integrating ESG information. Furthermore, BRICS markets are subject to more immediate economic, political, and geopolitical influences than ESG concerns (Feng et al., 2022; Hao & He, 2022). This can explain why ESG's effect on spillovers may be weak or delayed. These findings imply that BRICS markets play the role of an ESG risk "barometer" and the need to improve ESG integration in BRICS asset prices as an opportunity to improve transparency, disclosure, and the consideration of ESG factors in investment decisions. This is consistent with Liu et al. (2023) and Boubaker et al. (2022b) that it is crucial to integrate ESG data into financial decision-making to better anticipate and mitigate the spread of systemic risks.

To search: what is the Pairwise Directional Connectedness that causes ESG uncertainty? We apply in Table 6 the Granger causality tests between Global Equal Weighted and Net Pairwise Directional Connectedness for lags from 01 to 05.

Table 5. Granger causality tests between ESGUI and TCI

Test 1: Global Equal Weighted does not Granger-cause BRICS Total Connectedness	
Lag	F-Stat
1	0.5682
2	0.5080
3	0.3437

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4	0.2910
5	1.0033
Test 2: BRICS Total Connectedness does not Granger-cause Global Equal Weighted	
Lag	F-Stat
1	**5.4535********
2	1.8199
3	1.0541
4	1.0442
5	1.6993
Test 3: Global GDP Weighted does not Granger-cause BRICS Total Connectedness	
Lag	F-Stat
1	0.3770
2	1.1892
3	0.8911
4	1.1379
5	1.2513
Test 4: BRICS Total Connectedness does not Granger-cause Global GDP Weighted	
Lag	F-Stat
1	0.9368
2	2.0147
3	1.6819
4	0.9978
5	**3.6316********

Note: Table 5 presents the Granger causality test results between ESGUI (Global Equal Weighted) and BRICS Total Connectedness Index from 1 to 5 lags (Test 1 and Test 2), and the Granger causality test results between ESGUI (Global GDP Weighted) and BRICS Total Connectedness Index from 1 to 5 lags (Test 3 and Test 4). *** indicates significance of F-statistic at 1% level and reject H_0 that Global Equal Weighted does not Granger-cause Net Pairwise Directional Connectedness

Source: Author's work

Table 6 presents the results of Granger causality tests between Global Equal Weighted and Net Pairwise Directional Connectedness for lags from 01 to 05. Table 5 shows several significant causal relationships (p <

0.05) between ESGUI and certain pairwise directional connectedness. Bidirectional volatility spillovers between Brazil-China, Russia-India, Russia-China, and China-India significantly cause ESG uncertainty. This reflects the dominant influence of major economies, principally China and Russia, and to a lesser extent India and Brazil, on sustainability concerns. Furthermore, the significance of Granger causality tests is bidirectional, suggesting a strong interdependence in ESG dynamics and financial risks. This result echoes the work of Liu et al. (2023) and Zhang et al. (2025), who emphasize the importance of understanding the complex interactions between financial volatility and ESG risks, particularly in emerging markets where sustainability is still under institutional construction.

These findings help investors to better anticipate ESG risk transmissions between markets, thus guiding diversification and risk management. Understanding which countries are major sources of ESG risk can guide financial and environmental oversight policies, particularly in the context of sustainable transition.

Table 6. Granger causality tests between ESGUI and Net Pairwise Directional Connectedness

Test 5: Global Equal Weighted does not Granger-cause Net Pairwise Directional Connectedness		
FROM	**TO**	**F-Stat**
BRAZIL	RUSSIA	0.7628
BRAZIL	INDIA	1.2988
BRAZIL	**CHINA**	**18.4527*****
BRAZIL	SOUTH AFRICA	0.8070
RUSSIA	BRAZIL	0.7628
RUSSIA	**INDIA**	**5.2152*****
RUSSIA	**CHINA**	**12.8702*****
RUSSIA	SOUTH AFRICA	0.0008
INDIA	BRAZIL	1.2988
INDIA	**RUSSIA**	**5.2152*****
INDIA	**CHINA**	**8.0164*****
INDIA	SOUTH AFRICA	0.0576
CHINA	**BRAZIL**	**18.4527*****
CHINA	**RUSSIA**	**12.8702*****
CHINA	**INDIA**	**8.0164*****
CHINA	SOUTH AFRICA	0.4317
SOUTH AFRICA	BRAZIL	0.8070
SOUTH AFRICA	RUSSIA	0.0008
SOUTH AFRICA	INDIA	0.0576
SOUTH AFRICA	CHINA	0.4317

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Note: Table 6 presents the Granger causality test result between ESGUI (Global Equal Weighted) and Net Pairwise Directional Connectedness of BRICS markets from 1 to 5 lags (Test 5). *** indicates significance of F-statistic at 1% level and reject H_0 that Global Equal Weighted does not Granger-cause Net Pairwise Directional Connectedness.

Source: Author's work

CONCLUSIONS, IMPLICATIONS, AND LIMITATIONS

Conclusions

This study examines the bidirectional relationship between ESG-based sustainability uncertainty (ESGUI) and dynamic volatility spillovers among BRICS stock markets from November 2002 to March 2025. To forecast BRICS' conditional volatilities, we utilize the E-GARCH model. We also explore a Time-Varying Parameter Vector Autoregression (TVP-VAR) framework to analyze the dynamic volatility spillovers across BRICS markets, and conduct Granger causality tests to investigate the relationship between ESG uncertainty indices of Ongan, Gocer, and Isik (2025) and the dynamic volatility spillover. The goal is to provide new evidence on how sustainability-related uncertainty and financial market interconnectedness interact in emerging economies.

Our empirical results reveal several key findings:

- **Volatility spillovers in BRICS markets:** There are substantial but asymmetric spillovers. Brazil, Russia, and South Africa generally act as net transmitters of volatility, while China and India tend to be net receivers. These roles, however, fluctuate over time.

- **Impact of ESG uncertainty:** Volatility interconnectedness peaks during periods of heightened ESG uncertainty, coinciding with major global crises, such as the 2002–2003 corporate governance scandals, the 2008–2009 global financial crisis, the 2010–2011 Eurozone debt crisis and Fukushima disaster, the 2015–2016 Paris Agreement period, and the COVID-19 pandemic.

- **Causality patterns:** Granger causality tests indicate that volatility spillovers (TCI) significantly influence ESG uncertainty in the short term, whereas the reverse effect is generally absent. This suggests that financial market turbulence in BRICS can act as a leading indicator of sustainability risk perceptions, while ESG uncertainty reacts more slowly due to reliance on aggregated reports and surveys.

- **Bilateral relationships:** At the pairwise level, bidirectional causality between ESGUI and specific volatility transmissions (notably Brazil–China, Russia–India, Russia–China, and China–India) highlights the dominant role of larger BRICS economies in shaping ESG risk dynamics.

Implications

Our findings expand the literature on the interaction between ESG factors and financial contagion, particularly in emerging markets. The asymmetric volatility spillovers indicate that market size, resource dependence, and exposure to geopolitical risks shape risk transmission. Moreover, the causal link from market interconnectedness to ESG uncertainty suggests that financial markets can act as early indicators of sustainability risks.

Regulatory implications: Volatility spillovers intensify during periods of high ESG uncertainty, highlighting the need for macroprudential monitoring. Regulators should integrate ESG-based uncertainty indicators into early warning systems, promote harmonized ESG reporting standards, enhance transparency, and encourage cross-border data sharing among BRICS countries. These measures can reduce contagion risks driven by ESG uncertainty.

Implications for investors and portfolio managers: Identifying net transmitters and receivers of volatility provides actionable insights for risk diversification. Investors can dynamically adjust portfolio allocations based on spillover intensity and ESG uncertainty trends. Understanding that volatility often precedes changes in ESG uncertainty enables portfolio managers to anticipate ESG shocks and optimize sustainable investment strategies.

Implications for policymakers and corporates: ESG uncertainty and financial volatility are interlinked, calling for integrated sustainability and financial stability policies. Cooperation among major BRICS markets (e.g., China, Brazil, India) and integration of sustainability metrics into financial supervision can strengthen resilience against global ESG shocks.

Consequently, ESG uncertainty is not only an environmental or social issue—it is a financial stability concern. By monitoring ESG uncertainty and volatility spillovers, regulators and investors can make informed decisions to manage risk and enhance market stability.

Limitations

Despite the theoretical and practical implications, several limitations should be acknowledged.

Limitations of the ESGUI index: The ESGUI, as developed by Ongan et al. (2025), has inherent methodological constraints. First, it relies on English-language EIU reports, which introduces a language bias and may reduce accuracy for non-English-speaking countries, including some BRICS members. Second, the index covers a limited set of 25 countries, potentially underrepresenting smaller or less-documented emerging economies, creating a geographical bias. Third, the equal weighting of the three ESG pillars (Environmental, Social, Governance) may oversimplify their relative importance in different national contexts. Fourth, the keyword-based text-mining approach imposes contextual and semantic limitations: it may miss nuances such as tone, irony, negation, or emerging sector-specific ESG issues. Finally, institutional and cultural heterogeneity implies that ESG-related uncertainty may manifest differently across regulatory and market environments. Future research could address these limitations by incorporating multilingual sources, sentiment-aware or contextual NLP models, and disaggregated ESGUI measures at sectoral or regional levels.

Limitations of empirical methods: While the TVP-VAR and Granger causality frameworks are effective for detecting dynamic relationships, they do not fully account for potential non-linearities, structural breaks, or higher-order network effects that may further influence the ESG-volatility relationship.

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