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Economic Policy Uncertainty and Stock Market Co-Movements in BRIC Countries: Evidence from Wavelet Coherence and Rolling Bootstrap Granger Causality

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Abstract

Purpose: The relationship between economic policy uncertainty (EPU) and stock returns in the BRIC countries (Brazil, Russia, India, and China) is examined by analyzing both static and dynamic interactions across different time horizons, with particular attention to major global crises.

Design/methodology/approach: Monthly data from 2004 to 2022 are used, and wavelet coherence analysis is applied together with bootstrap rolling-window and full-sample Granger causality tests to assess the dynamic and causal links between EPU and stock returns.

Findings: The results show unidirectional causality from EPU to stock returns in Brazil, Russia, and India. In these countries, higher policy uncertainty reduces stock returns, while no significant causal relationship is found for China. Wavelet coherence results reveal strong short-term co-movements during crisis periods, medium-term synchronization in India and Russia, and persistent long-term correlations in China. The findings highlight the time-varying nature of the EPU–return relationship and its sensitivity to global shocks and institutional conditions.

Originality/value: By integrating wavelet coherence with bootstrap rolling-window Granger causality, the study provides a multi-scale and dynamic framework for analyzing the EPU–stock return nexus in BRIC economies, offering useful insights for portfolio management, risk assessment, and decision-making in the field of Decision Sciences.

Practical/Social implications: The results suggest that investors adopt horizon-sensitive investment strategies, while policymakers improve policy transparency and communication to limit market volatility. Opportunities for future sectoral and cross-market research are also highlighted.

Keywords: EPU; Stock Returns; Wavelet coherence; Bootstrap rolling window.

JEL Classifications: F21, C22.

1 Introduction

Following the global financial crisis, economic policy uncertainty has become a major determinant of financial markets' behavior and has attracted heightened attention from both scholars and policymakers (Baker et al., 2016; Marín-Rodríguez et al., 2025). A growing body of literature suggests that heightened policy uncertainty can significantly affect investor sentiment, resulting in greater volatility and lower returns in equity markets (Arouri et al., 2016; Nakhli et al., 2025). This relationship is particularly relevant for emerging economies such as the BRIC countries (Brazil, Russia, India, and China), which are characterized by considerable economic expansion and often volatile political landscapes. These nations are increasingly integrated into global financial systems, making them sensitive to both domestic and global policy shocks (Antonakakis & Kizys, 2015; Balcilar et al., 2017).

The BRIC nations represent some of the most dynamic emerging markets and collectively account for a considerable share of worldwide economic activity and investment flows. They collectively accounted for 21% of global GDP and were home to approximately 41% of the global population (World Bank, 2019). As key players in global economic governance, understanding the relationship between EPU and stock market performance in these countries is critical for investors, policymakers, and researchers. Given their sensitivity to both domestic policy changes and global uncertainty, especially from major economies such as the United States, shifts in EPU may have notable implications for equity returns in BRIC markets (Balcilar et al., 2017). Moreover, as shown in the literature, financial markets often react strongly to political and policy-related news (Pastor & Veronesi, 2013), and such reactions are amplified in environments where institutional frameworks are still maturing, as is often the case in emerging economies. Consequently, analyzing the co-movement and causal relationships between EPU and equity market returns in the BRIC countries offers valuable insights for risk assessment, portfolio diversification, and macroeconomic policy formulation (Hashmi et al., 2021).

The research contributes to the field of Decision Sciences by offering a robust methodological framework that supports portfolio managers and policymakers in making better-informed decisions under conditions of uncertainty. By demonstrating how economic policy uncertainty dynamically affects stock returns across multiple time horizons and during periods of crisis, the study provides actionable insights for optimizing asset allocation, enhancing hedging strategies, and designing timely and effective policy interventions.

Despite growing interest in the EPU–stock market relationship, most existing studies rely on time-domain models, which fail to capture its frequency-specific and time-varying nature. For instance, Aydin et al. (2022) apply asymmetric frequency-domain causality tests to BRIC countries, but their static framework overlooks temporal dynamics, especially during global crises. To address this gap, the study makes a distinct contribution by being the first to comprehensively investigate the dynamic interplay between economic policy uncertainty (EPU) and stock market returns in the BRIC countries using an integrated framework that combines wavelet coherence analysis with bootstrap rolling-window Granger causality tests. This dual-method approach allows for the uncovering of multi-scale co-movements and evolving causal linkages, capturing both the scale (investment horizon) and timing of interactions, particularly during episodes of market stress. Using monthly data from 2004 to 2022, the study provides a nuanced view of how EPU affects BRIC markets, highlighting both shared and country-specific dynamics. Supported by structural stability tests (Zeileis et al., 2005), the framework captures regime-dependent behavior across multiple crises. This contribution bridges theoretical, methodological, and empirical gaps, offering actionable insights for researchers and policymakers. For comparison, Sharif et al. (2020) demonstrate the value of wavelet coherence by showing strong short-term co-movements between COVID-19, EPU, and market volatility in the U.S. Likewise, Nakhli et al. (2022) employ a bootstrap rolling-window Granger causality framework to analyze the dynamic relationship between investor sentiment and momentum strategies, thereby addressing the limitations of static models.

In this line, the study makes a distinct and timely contribution by being the first to comprehensively examine the dynamic interplay between economic policy uncertainty (EPU) and stock market returns in BRIC countries through a novel methodological and empirical lens. Specifically, an integrated framework is adopted that combines wavelet coherence analysis (Ghosh & Adebayo, 2024; Soni et al., 2023) with bootstrap-based rolling-window Granger causality tests (Minlah & Zhang, 2021), thereby overcoming the limitations of traditional approaches that either neglect frequency-domain interactions (Rua & Nunes, 2009) or assume time-invariant relationships (Andrews, 1993). This dual methodology enables us to capture both the scale (investment horizon) and the timing of causal linkages between EPU and stock returns, particularly during episodes of market stress, including the Global Financial Crisis, the COVID-19 outbreak, and the Russia-Ukraine conflict (Rubbaniy et al., 2023).

By examining the BRIC economies, which is an area largely underexplored in the Economic Policy Uncertainty (EPU) literature, the study fills a critical gap and highlights notable cross-country heterogeneities alongside common market responses to uncertainty shocks. Unlike prior research focused on individual markets (Bagh et al., 2023; Nakhli et al., 2022), the comparative analysis offers practical insights for international investors seeking diversification and for policymakers dedicated to strengthening market resilience (Dumayiri et al., 2024; Hassan et al., 2019).

The study is organized as follows: Section 2 reviews the literature. Section 3 covers data and methods. Section 4 presents preliminary analysis. Section 5 discusses key findings. Section 6 concludes with policy implications.

2 Literature Review

2.1 Empirical Literature

Despite the existing research on the relationship between EPU and stock market returns, certain dimensions remain underexplored, particularly the frequency-specific dynamics of this relationship. Dew-Becker and Giglio (2016) advocate that the frequency domain provides a more appropriate framework for analyzing how shocks influence asset prices over time. Most current studies rely predominantly on time-domain methods, such as traditional Granger causality tests. While these approaches are valuable, they may overlook how EPU's effects differ across multiple time horizons. Understanding these variations is critical for both investors and policymakers, as shifts in uncertainty can produce distinct impacts depending on the time horizon. For example, short-term policy shocks might induce immediate market volatility, whereas long-term uncertainty may alter investment strategies and risk premiums. Recognizing this, Baruník and Křehlík (2018) suggest that causality should be examined in the frequency domain, as economic disturbances influence market variables differently across time scales. Since investors and institutions operate with varied investment horizons, ranging from high-frequency trading to long-term portfolio management, disentangling these effects is essential for informed decision-making, effective regulation, and robust risk management. Similarly, Marín-Rodríguez et al. (2025) explore EPU's dynamic linkages with external economic variables in Latin America, further highlighting the importance of analyzing policy uncertainty's evolving economic impacts over different time horizons.

Some studies have investigated the dynamic interactions between policy uncertainty and stock market behavior (M. A. Khan et al., 2020), highlighting temporal variations and market-specific responses (Bekiros et al., 2016). For instance, M. A. Khan et al. (2020) examine the impact of U.S. EPU on stock market performance using dynamic ARDL simulation and threshold modeling. Their findings reveal that increases in EPU significantly reduce stock prices in both the short and long run, while decreases in EPU have a positive long-term effect. The study also identifies threshold levels of EPU beyond which its impact on stock markets becomes more pronounced. Increased policy uncertainty may lead to declines in stock returns due to higher risk premia and lower investment confidence, while in certain contexts, stock markets might anticipate policy shifts and respond positively if the uncertainty is resolved (Xu et al., 2021). Given these complex and evolving interactions, there is a need for advanced analytical methods that can capture both the time-varying and frequency-dependent nature of the EPU-stock market nexus.

Recent literature has shown that international economic policy uncertainty, particularly from the U.S., exerts a dominant short-run effect on domestic equity returns, underscoring the significant influence of global events on local markets (Dumayiri et al., 2024). For instance, Dumayiri et al. (2024) employ a frequency-domain approach to analyze causal relationships between international EPU and equity returns in G20 countries. Their findings indicate that while domestic stock market volatility often increases domestic policy uncertainty, international EPU has stronger short-term predictive power over domestic equity returns. In the same line, Ghosh and Adebayo (2024) examine the influence of international policy uncertainty and geopolitical risk on Japan's export-driven growth, employing advanced wavelet-based methods; although their study does not address environmental or energy factors, it reinforces the utility of frequency-domain techniques in analyzing complex economic relationships.

Finally, Bagh et al. (2023) examine the impact of EPU on China's stock market index by applying a wavelet coherence methodology, revealing significant time-scale-dependent relationships. However, their analysis is limited to the Chinese context, underscoring the need for broader studies across emerging markets. Similarly, Aydin et al. (2022) investigate the relationship between EPU and stock prices in BRIC economies by employing asymmetric causality tests in the frequency domain, offering valuable insights into the directional and temporal asymmetries of EPU shocks. Nevertheless, the complexity of their methodology raises interpretive challenges and concerns about robustness and generalizability. In a related context, Nakhli et al. (2025) reveal a bidirectional causal relationship between investor sentiment and oil prices in G7 markets over the 2010–2022 period, with stronger interactions observed during periods of heightened uncertainty. Their time-varying framework shows that U.S. and U.K. markets exhibit the strongest feedback loops, particularly during the COVID-19 pandemic and the 2022 energy crisis. These findings reinforce the importance of dynamic causality models in capturing evolving market behavior under uncertainty.

To address these gaps, the study applies wavelet analysis combined with rolling Granger causality to examine the dynamic co-movements between EPU and stock markets across BRIC countries, aiming for a more comprehensive and robust understanding over multiple time horizons.

Building on the existing literature, the following hypotheses are proposed:

H1: *Economic Policy Uncertainty has a negative impact on stock market returns in BRIC countries.*

H2: *The impact of Economic Policy Uncertainty on stock market returns is time-varying and frequency-dependent across BRIC countries.*

2.2 Theoretical Background

The relationship between economic policy uncertainty (EPU) and stock market returns is grounded in several well-established economic and financial theories. These theories provide the conceptual foundation for understanding how policy-induced uncertainty influences investor behavior, asset pricing, and market dynamics, particularly in emerging economies such as the BRIC nations.

The Efficient Market Hypothesis (EMH) posits that asset prices fully reflect all available information (Fama, 1970). However, in the presence of heightened economic policy uncertainty, information becomes incomplete or ambiguous, leading to market inefficiencies. According to Information Asymmetry Theory (Akerlof, 1978), uncertainty exacerbates informational gaps between policymakers and investors, causing mispricing and increased volatility. In emerging markets, where information dissemination is often slower and less transparent, EPU can significantly distort price discovery mechanisms, leading to persistent deviations from fundamental values (Pastor & Veronesi, 2013).

On the other hand, the Risk Premium Channel suggests that Economic Policy Uncertainty (EPU) raises the required rate of return on equities due to increased risk aversion and heightened perceptions of systemic risk (Pastor & Veronesi, 2013). This mechanism can be formalized within an Intertemporal Capital Asset Pricing Model (ICAPM) framework:

$$E_t[\,R_{i,t+1}] = R_f + \gamma cov_t(R_{i,t+1}, \Delta EPU_{t+1}),$$

where R_f is the risk-free rate, γ is the coefficient of relative risk aversion, and $cov_t(R_{i,t+1}, \Delta EPU_{t+1})$ captures the conditional covariance between asset returns and innovations in EPU. In this setting, the covariance term reflects a time-varying beta, measuring exposure to EPU-related systematic risk. An increase in EPU amplifies this covariance, thereby increasing the required risk premium, leading to higher expected returns and lower current asset prices. Accordingly, higher levels of EPU are expected to exert a negative effect on stock market returns.

Finally, Behavioral Finance theories (Barberis & Thaler, 2003) highlight how cognitive biases and sentiment drive market outcomes under uncertainty. EPU can trigger herding behavior, overreaction, and loss aversion, leading to excess volatility and momentum effects. Investor sentiment, often measured through EPU indices, can amplify market swings, especially during crises (Baker et al., 2016).

3 Data

The paper explores the dynamic link between economic policy uncertainty and stock market returns in BRIC economies from January 2004 to December 2022. The data are collected at a monthly frequency, resulting in 228 observations for each country. The selection of BRIC countries is motivated by their significant role in the global economy. These nations dominate the group of emerging markets and attract a substantial share of global capital flows.

In addition, BRIC countries are chosen because they represent major emerging markets with significant global influence and diverse financial systems. Their varying levels of market development and sensitivity to policy shifts provide a strong foundation for assessing the influence of EPU on stock returns. Additionally, their frequent exposure to geopolitical tensions, regulatory changes, and macroeconomic volatility underscores their relevance. South Africa is not included due to its smaller economic scale and distinct financial context, which helps preserve consistency and comparability within the original BRIC framework.

EPU Data are obtained from www.policyuncertainty.com and rely on the index proposed by Baker et al. (2016). EPU is measured by a country-specific index, which quantifies policy-related uncertainty based on news coverage, tax code provisions, and economic forecaster disagreement. Stock market index data such as BOVESPA (Brazil), IMOEX (Russia), BSE (India), and SSE (China) are sourced from www.investing.com. Stock returns are computed using the following formula: R_t= 100* ln ($\frac{P_t}{P_{t-1}}$), where P_t and P_{t-1} denote the index values for the current and preceding month, respectively.

4 Methodology

The study examines the dynamic relationship between EPU and stock market returns in the BRIC countries using an integrated methodological framework that combines wavelet coherence analysis with bootstrap rolling-window Granger causality tests. Both variables are incorporated because they represent the central theoretical constructs of the analysis: EPU captures policy-related uncertainty that can influence investor behavior, while stock returns serve as indicators of market performance and risk-adjusted outcomes. Modeling these variables within a bivariate system enables the assessment of direct causal linkages while minimizing omitted variable bias, in line with established research on uncertainty and financial market dynamics (e.g., Arouri et al., 2016; Baker et al., 2016).

To operationalize this framework, the analysis proceeds in a stepwise manner as follows.

Step 1: Wavelet coherence analysis. Wavelet analysis offers distinct advantages over traditional time series methods, as it facilitates the decomposition of time series into different scales (frequencies), the identification of localized correlations, and the analysis of non-stationary data (Ghosh & Adebayo, 2024; Mensi et al., 2018, 2021; Reboredo et al., 2017). This approach allows for a deeper examination of the temporal dynamics governing the interaction between these variables. The Morlet wavelet is used as the mother wavelet to perform CWT (Rua & Nunes, 2009).

The Wavelet Power Spectrum (WPS) of a time series is given by the squared magnitude of its Continuous Wavelet Transform (CWT):

$$\mathrm{WPS}\ (\tau, \mathrm{s}) = \ |\mathrm{W}(\tau, \mathrm{s})|^2. \tag{1}$$

To analyze interactions between two series x(t) and y(t), the Cross-Wavelet Transform (XWT) is used:

$$W_{xy}(\tau, \mathrm{s}) = W_x(\tau, s)\ * W_y{}^*(\tau, s), \tag{2}$$

where * denotes the complex conjugate. The XWT highlights regions of high joint power in time-frequency space.

For a normalized measure of co-movement, Wavelet Coherence (WC) is defined as:

$$\mathrm{R}^2(\tau, \mathrm{s}) = \frac{\left|\mathrm{S}\left(\mathrm{s}^{-1} W_{xy}\ (\tau, \mathrm{s})\right)\right|^2}{\left[\mathrm{S}(\mathrm{s}^{-1}|W_x(\tau, \mathrm{s})|^2)\mathrm{S}\left(\mathrm{s}^{-1}\left|W_y\ (\tau, \mathrm{s})\right|^2\right)\right]}, \tag{3}$$

where S is a smoothing operator. WC values range from 0 (no correlation) to 1 (strong correlation), providing a localized measure of dependence (Mensi et al., 2018). This approach is particularly useful for detecting time-varying linkages between variables (Mishra et al., 2020).

Step 2: Rolling-window Granger causality analysis. Rolling-window Granger causality tests are implemented to examine evolving causal linkages, allowing the identification of time-varying relationships that conventional full-sample tests may fail to capture (Minlah & Zhang, 2021). To ensure robustness, a bootstrap procedure is used to infer the statistical significance of causality results under varying sample sizes and potential structural breaks. The rolling window Granger causality test is an econometric technique used to assess the dynamic causal relationships between two time series by estimating the parameters of a Vector Autoregressive (VAR) model within a bivariate context using sliding windows of data (Balcilar & Ozdemir, 2013). Since financial and economic series are frequently characterized by temporal variations, this method provides a valuable approach to analyze the evolving causal links between variables (Zeileis et al., 2005). The method involves resampling the data within these sliding windows to generate bootstrap samples, estimating Granger causality distributions for each window, and calculating the related confidence intervals. A bivariate VAR model allows for simultaneous estimation of the parameters for both variables, capturing their dynamic interactions (Balcilar & Ozdemir, 2013). Granger causality is assessed using the modified Wald test introduced by Toda and Yamamoto (1995) and applied by Minlah and Zhang (2021).

Step 3: Full-sample bootstrap Granger causality testing. The study conducts a bootstrap-based full-sample causality test (Balcilar & Ozdemir, 2013) to complement the rolling-window analysis. As in the rolling window approach, this test addresses concerns regarding the asymptotic distributions of conventional Granger causality statistics when applied to integrated or non-stationary series (Engle & Granger, 1987). The non-causality test examines whether past information from one variable improves the prediction of another within a bivariate VAR model.

The bivariate VAR model is specified as:

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \cdots . + \alpha_p y_{t-p} + \varepsilon_t, \quad t = 1,2, \ldots T, \tag{4}$$

where $y_t = (SR_t, EPU_t)'$ is a vector of the two variables (stock market returns (SR), and the economic policy uncertainty (EPU)), α_0 is a constant term, α_p are the coefficients for the lagged values of the variables, and ε_t is the error term. The lag length p is chosen based on the Schwarz Bayesian Information Criterion (SBIC).

Given the two sub-vectors, Equation 4 is written as follows:

$$\begin{Bmatrix} SR_t \\ EPU_t \end{Bmatrix} = \begin{Bmatrix} \alpha_{10} \\ \alpha_{20} \end{Bmatrix} + \begin{Bmatrix} \alpha_{11}(L) \alpha_{12}(L) \\ \alpha_{21}(L) \alpha_{22}(L) \end{Bmatrix} \begin{Bmatrix} SR_t \\ EPU_t \end{Bmatrix} + \begin{Bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{Bmatrix}, \tag{5}$$

where $\alpha_{ij}(L) = \sum_{k=1}^{p} \alpha_{ij,k} L^k$ and the lag operator (L) is expressed as: $L^k x_t = x_{t-k}$.

The directional causal relationships between economic policy uncertainty (EPU) and stock returns (SR) are then tested based on the following hypotheses:

H_0: $\alpha_{12}(L) = 0$ (EPU does not Granger-cause stock returns),

H_0: $\alpha_{21}(L) = 0$ (Stock returns do not Granger-cause EPU).

Step 4: Parameter stability and time-varying causality assessment. The study assesses the constancy of model parameters over the sample period to account for potential structural instability. In empirical analysis, Vector Autoregressive (VAR) model parameters are prone to instability when the full-sample data exhibits structural changes (C. W. Su et al., 2019). Indeed, Balcilar and Ozdemir (2013) emphasize that longer sample periods often include structural mutations within the component variables, leading to unstable interactions between the series. This is further supported by the finding that Economic Policy Uncertainty has been observed to affect stock market return and volatility differently under various heterogeneous market conditions (Kundu & Paul, 2022; Rubbaniy et al., 2023). To address concerns about instability, short-run parameter stability tests, namely Sup-F, Exp-F, and Mean-F (Andrews, 1993; Andrews & Ploberger, 1994), are employed alongside the long-run stability test Lc (Hansen, 1992).

Following the confirmation of parameter stability, a bootstrap sub-sample rolling-window causality test is implemented to capture finer time-varying causal dynamics, particularly in the presence of structural breaks or nonlinearities. Considering the limitations of full-sample analysis in the presence of parameter instability, a bootstrap sub-sample rolling-window Granger causality test is employed to assess the dynamic relationships between Economic Policy Uncertainty (EPU) and Stock Returns (SR). This approach, developed by Balcilar and Ozdemir (2013), divides the time series into subsamples based on a sliding window of width *l*, and estimates the impact of stock returns on EPU and EPU on stock returns using bootstrapped VAR models. By applying bootstrap techniques and considering that economic policy uncertainty and stock markets are related (Soni et al., 2023), this method incorporates the possibility of deviations in stability and is not limited by the structure of a model when changes happen. For a specific model and for a number of situations (Andrews, 1993; Andrews & Ploberger, 1994). In short, the ability to use economic policy uncertainty is what made this method ideal (Kido, 2018; Li et al., 2020).

The average of these estimates is calculated, and confidence intervals are constructed using the 5th and 95th percentiles of each estimate. Bootstrap p-values and likelihood ratios (LR) statistics are employed to detect temporal variations in the causal relationship between the two series. This approach accounts for changes in the causal structure and potential instability due to structural breaks. Specifically, to identify the average effects, the mean of the bootstrap estimates, denoted as N_b and $\widehat{\alpha}_{12,\mathrm{k}}$, is used, and confidence intervals are constructed based on the 5th and 95th percentiles of the distribution of estimates.

Formally, the average coefficients are expressed as:

$$N_b{}^{-1}\sum_{k-1}^{p}\widehat{\alpha}_{12,k}{}^{*} \text{ and } N_b{}^{-1}\sum_{k-1}^{p}\widehat{\alpha}_{21,k}{}^{*} \tag{6}$$

These represent the estimated coefficients from the b-th bootstrap replication for the k-th lag. Due to its ease of integration, this method is particularly well-suited to capturing dynamic relationships during periods of structural instability (Menzly et al., 2004).

Given that both EPU and stock returns series (SR) are integrated of order one, I(1) (as confirmed by unit root tests in **Table 2**), and may exhibit structural breaks, the Toda and Yamamoto (1995) approach is employed within a rolling-window bootstrap framework. This method is appropriate because it avoids pre-testing biases associated with cointegration analysis, and it accommodates structural breaks and time-varying parameters through rolling subsamples. The rolling-window bootstrap procedure is implemented as follows: Specify a bivariate VAR(p) model for EPU and SR, Select optimal lag length p using the Schwarz Bayesian Information Criterion (SBIC), Set rolling window width l=24 months to balance estimation efficiency and temporal sensitivity, For each rolling window t=l,l+1,…,T: (Estimate the

VAR(p) model using OLS, Compute the residuals $\hat{\varepsilon}_t$, Generate bootstrap samples by resampling residuals with replacement, Re-estimate the VAR(p) on each bootstrap sample, Compute the Wald statistic for Granger non-causality), Compute bootstrap p-values as the proportion of bootstrap statistics exceeding the observed statistic, and finally identify causal windows where p-values fall below the 10% significance level.

5 Empirical Results

5.1 Preliminary Analysis

Table 1. Descriptive Statistics of BRIC Stock Returns and EPU Series

			Stock Return (SR)			
	Mean	**Std-Dev**	**Skewness**	**Kurtosis**	**J-Bera**	**Observations**
RBOVESPA	0.7223	6.7001	-0.9920	7.0509	193.30***	228
RIMOEX	0.6117	7.5080	-1.2516	7.3678	240.77***	228
RBSESN	1.0272	6.2908	-0.7932	6.6497	150.45***	228
RSSE	0.4430	4.8965	-0.2097	3.1481	1.8810	228
			Economic Policy Uncertainty (EPU)			
	Mean	**Std-Dev**	**Skewness**	**Kurtosis**	**J-Bera**	**Observations**
EPU-BRAZIL	171.10	94.889	1.6208	7.1865	266.34***	228
EPU-RUSSIA	203.50	157.12	1.8667	7.0459	287.92***	228
EPU-INDIA	92.357	49.221	1.3570	5.0153	108.56***	228
EPU-CHINA	289.37	256.88	1.1011	2.9821	46.081***	228

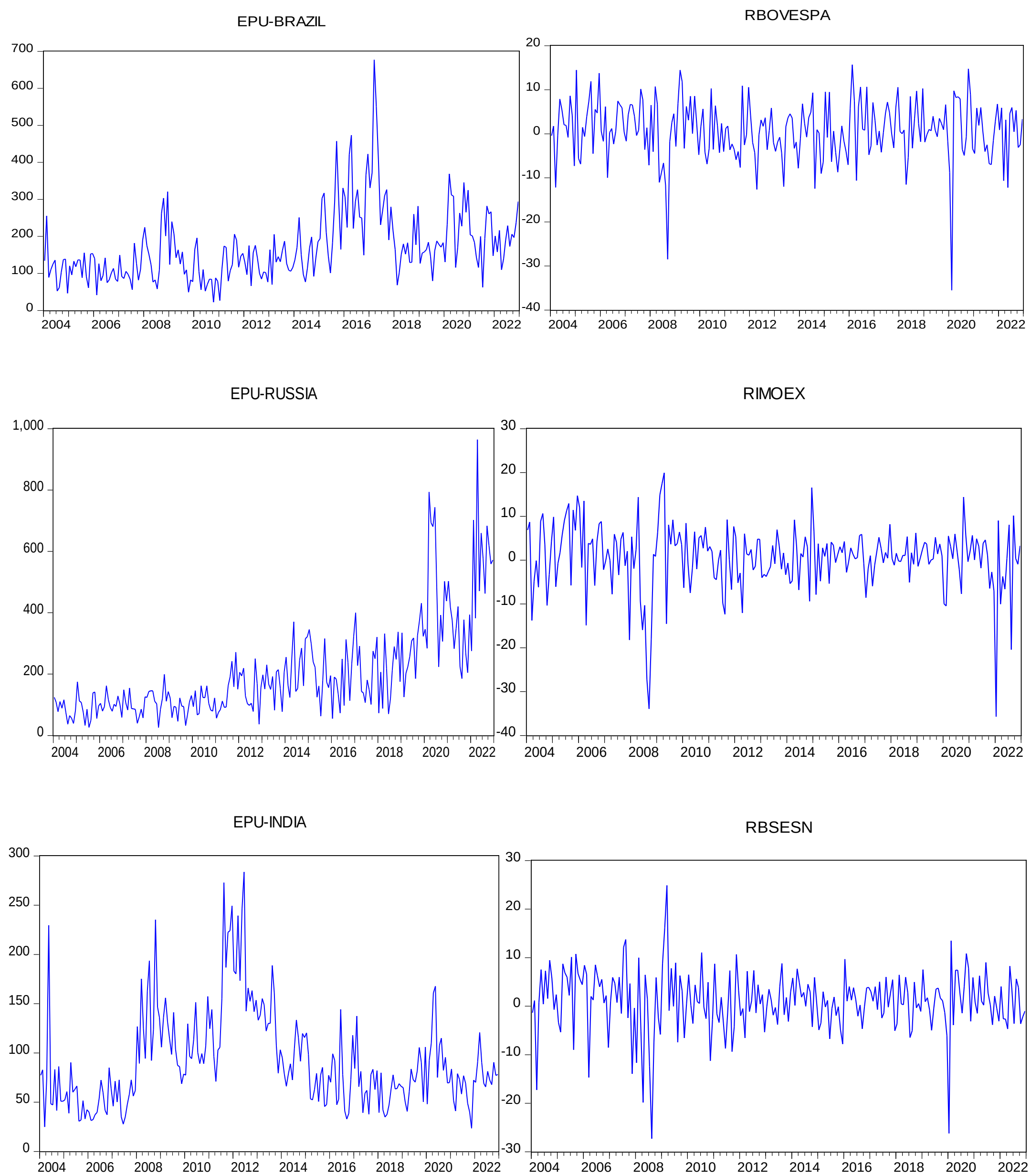
Notes: RBOVESPA, RIMOEX, RBSESN, and RSSE denote monthly stock returns of the BOVESPA (Brazil), MOEX (Russia), SENSEX (India), and SSE Composite (China) indices, respectively. EPU-BRAZIL, EPU-RUSSIA, EPU-INDIA, and EPU-CHINA represent the corresponding economic policy uncertainty indices. The sample period spans January 2004 to December 2022. The Jarque–Bera (J–B) test examines the null hypothesis of normality. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

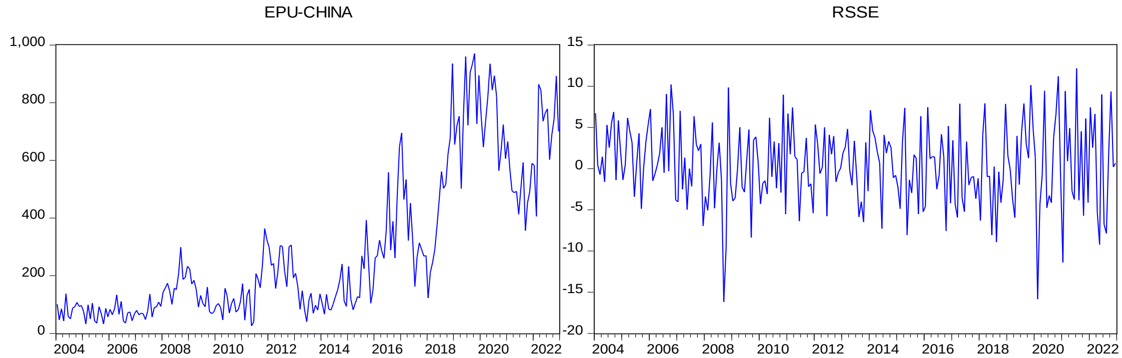
Table 1 presents the descriptive statistics for BRIC countries (Brazil, Russia, India, and China) stock market returns (SR) and economic policy uncertainty (EPU) indices. The results reveal that all stock return series exhibit positive mean values (ranging from 0.443% for China to 1.027% for India), indicating overall positive market performance during the observation period. However, their distributions display significant negative skewness (from -0.210 to -1.252) and leptokurtosis (kurtosis > 3), suggesting frequent extreme negative returns and heavier tails than a normal distribution. In contrast, the EPU indices show consistently positive skewness (1.101 to 1.867) and high kurtosis values, reflecting right-tailed distributions with periodic spikes in uncertainty.

The Jarque-Bera test rejects normality ($p < 0.01$) for all series except Chinese stock returns (JB = 1.881, $p > 0.10$), confirming non-Gaussian distributions. This, combined with high volatility (standard deviation ranging from 4.897 for Chinese stocks to 7.508 for Russian stocks) and leptokurtic tails (kurtosis > 3), necessitates robust analytical methods that accommodate non-normality and extreme values.

Figure 1 illustrates the monthly evolution of economic policy uncertainty (EPU, left axis) and stock market returns (right axis) for each BRIC country over the period January 2004 to December 2022. The shaded areas denote major global crisis episodes. Both series display pronounced volatility clustering, structural shifts, and notable co-movements during periods of economic turmoil.

Figure 1. Time Series of EPU and Stock Returns in BRIC Countries





Notes: This figure presents the monthly time series of Economic Policy Uncertainty (EPU) indices and stock market returns for BRIC countries over the period January 2004 to December 2022. Panels on the left report the EPU indices for Brazil, Russia, India, and China, while panels on the right display the corresponding stock market returns for the BOVESPA (Brazil), MOEX (Russia), SENSEX (India), and SSE Composite (China) indices. Stock returns are computed as logarithmic differences of stock price indices. The figure illustrates pronounced volatility clustering in stock returns and sharp spikes in EPU during major global events, such as the Global Financial Crisis, the COVID-19 pandemic, and recent geopolitical tensions. These observable features motivate the use of time-varying, nonlinear, and frequency-domain econometric methods in the subsequent analysis.

This figure illustrates the dynamic evolution of economic policy uncertainty (EPU) and stock market returns across BRIC countries, highlighting three key empirical regularities. First, both series display pronounced volatility clustering, where episodes of extreme fluctuations, such as 2008–2009 ($\sigma = 8.2\%$ for returns), are followed by more tranquil periods, for example, 2014–2016 ($\sigma = 3.1\%$). These patterns are directly observable from the figure and are characteristic of heteroskedastic behavior in financial time series. Second, persistent stochastic trends, confirmed by unit root tests (ADF $p > 0.1$ at levels, $p < 0.01$ after first differencing), indicate non-stationarity and I(1) behavior for both EPU and returns. Third, EPU series exhibit distinct structural breaks aligned with major global crises: (i) the 2008 Global Financial Crisis (EPU peak: 387 index points), (ii) the 2012 European Debt Crisis (+112% from baseline), (iii) the COVID-19 pandemic (maximum EPU: 529), and (iv) the 2022 Ukraine conflict ($\Delta EPU = +182\%$). These shocks coincide with sharp market downturns, with return deviations exceeding ±15% during crisis periods. The increase in rolling correlations between EPU and returns during crises ($\rho = 0.68$ vs. 0.21 in stable periods) further emphasizes the interconnectedness of uncertainty and market dynamics. These dynamics underscore the necessity for emerging market policymakers to develop and maintain adaptive risk management strategies that facilitate swift action in response to economic shocks.

5.2 Preliminary diagnostics: Residual tests and nonlinearity

Before conducting the wavelet coherence and causality analyses, a set of diagnostic tests is performed to assess the adequacy of the VAR specifications and to justify the application of nonlinear and dynamic methodologies. Specifically, the Jarque–Bera test is applied to the residuals of the bivariate VAR models for each BRIC country. As reported in **Table 2**, the results indicate that the residuals are largely non-normally distributed ($p < 0.01$ for Brazil, Russia, and India), underscoring the relevance of bootstrap-based inference to address potential biases arising from non-Gaussian error structures (Davidson & MacKinnon, 2004). In addition, the Durbin–Watson (DW) test is used to examine the presence of first-order autocorrelation in the VAR residuals. The DW statistics, also presented in **Table 2**, are close to the benchmark value of 2 (ranging from 1.85 to 2.12), indicating the absence of significant autocorrelation and confirming the suitability of the selected lag lengths.

To assess whether the relationship between economic policy uncertainty and stock returns displays nonlinear behavior, the nonlinearity test developed by Hui et al. (2017) is applied. As reported in **Table 2**, the test results strongly reject the null hypothesis of linearity for all BRIC countries ($p < 0.01$). This evidence supports the adoption of time-varying and frequency-domain methodologies such as wavelet coherence and rolling-window Granger causality, which are more effective in capturing nonlinear, regime-dependent dynamics in financial markets (Aydin et al., 2022; Mensi et al., 2021).

Table 2. Diagnostic Tests for VAR Residuals and Nonlinearity

Country	Jarque-Bera (Residuals)	Durbin-Watson	Hui et al. (2017) Nonlinearity Test
Brazil	18.34*** (p=0.000)	1.92	12.45*** (p=0.000)
Russia	22.17*** (p=0.000)	1.85	15.62*** (p=0.000)
India	14.89*** (p=0.001)	2.05	11.87*** (p=0.000)
China	3.21 (p=0.201)	2.12	9.34*** (p=0.002)

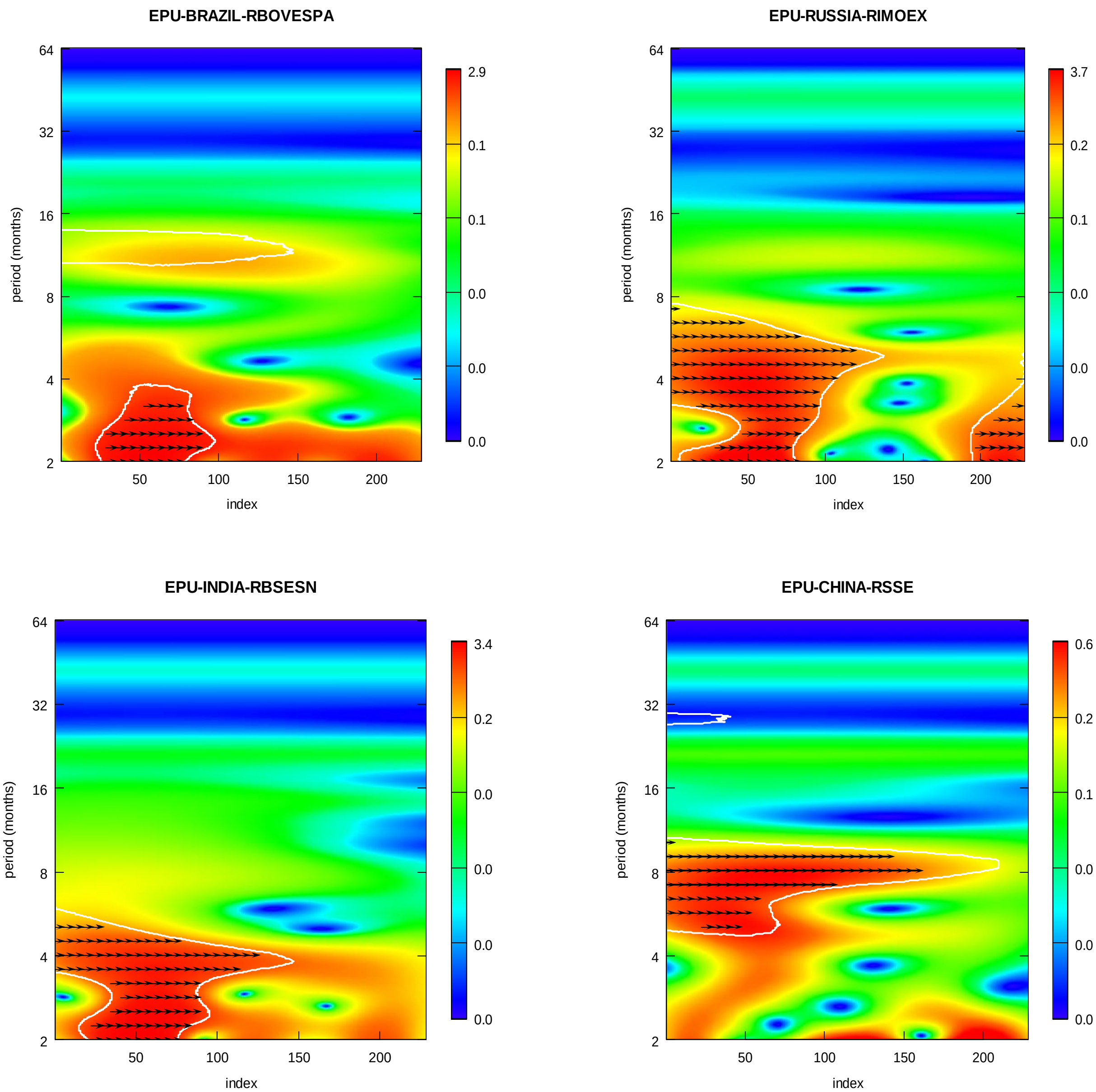
Notes: This table reports diagnostic tests based on residuals from the estimated VAR models for each country. The Jarque–Bera test examines the null hypothesis of normally distributed residuals. The Durbin–Watson statistic tests for first-order autocorrelation, with values close to 2 indicating no serial correlation. The Hui et al. (2017) test assesses the presence of nonlinear dependence in the EPU–stock return relationship. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

As shown in **Table 2**, the stock return and EPU series are I(1). Following methodological recommendations (Cheng et al., 2021, 2022; Wong et al., 2024; Wong & Pham, 2025; Wong & Yue, 2024), regressions involving non-stationary or mixed-integration series may produce spurious results if not properly addressed. To mitigate this risk, the Toda and Yamamoto (1995) modified Wald test is employed within the bootstrap Granger causality framework. This approach allows the estimation of VAR models in levels with an additional lag, ensuring valid inference even under potential integration, cointegration, and structural break issues. The bootstrap procedure further enhances robustness to non-normal errors and dynamic heterogeneity (Balcilar & Ozdemir, 2013). This methodology is widely adopted in studies involving I(1) financial and macroeconomic series (e.g., Minlah & Zhang, 2021; Y. Su et al., 2021).

5.3 Wavelet Coherence Analysis

Figure 2 illustrates the co-movements between BRIC stock market return volatilities and economic policy uncertainty using wavelet coherence. The analysis categorizes co-movements into short-term (2-8 months), medium-term (8-32 months), and long-term (beyond 32 months, up to 64 months) dynamics.

Figure 2. Wavelet analysis of Economic Policy Uncertainty and BRIC Stock Returns



Notes: This figure presents wavelet coherence plots between economic policy uncertainty (EPU) indices and stock market returns for Brazil, Russia, India, and China. The horizontal axis represents the time index, while the vertical axis denotes the period measured in months, capturing short-term (2 to 8 months), medium-term (8 to 32 months), and long-term (32 to 64 months) dynamics. The color scale indicates the strength of co-movement, ranging from blue (weak coherence) to red (strong coherence). The white contour lines enclose regions of statistical significance at the 5 percent level based on Monte Carlo simulations. The cone of influence delineates areas where edge effects become important, and results outside this region should be interpreted with caution. Arrows indicate the phase difference between the series. Arrows pointing to the right imply in-phase movement, arrows pointing to the left indicate anti-phase movement, and arrows pointing upward or downward suggest lead-lag relationships between EPU and stock returns.

The strength of the co-movement is represented by a color spectrum, ranging from weak correlation (blue, 0-0.25) to moderate correlation (green/yellow, 0.25-0.75) and strong correlation (red, 0.75-1). Statistically significant coherence at the 5% level during short- and medium-term horizons is identified by white contours. Right-pointing phase arrows indicate a positive correlation between EPU and stock returns (Vacha & Barunik, 2012).

The results reveal several key findings. First, BRIC stock markets demonstrate strong short-term co-movements with EPU, particularly during periods of heightened global uncertainty such as the 2008 Global Financial Crisis and the COVID-19 pandemic. Consistent with Brogaard and Detzel (2015), who report high correlation coefficients for developed markets during major policy shocks, this study finds comparable coherence in emerging markets, as evidenced by the high-intensity wavelet regions during these events. This highlights the vulnerability of BRIC markets to uncertainty spillovers, suggesting a similar or even stronger response to policy shocks compared to developed economies.

Second, a stabilization period is observed at medium-term frequencies (8–16 months), particularly in India and Russia. This suggests that policy interventions may help to restore market confidence and reduce volatility. This stabilizing pattern, which is less prevalent in developed markets (Baker et al., 2016), implies that the transmission and absorption of policy uncertainty varies across institutional contexts.

Third, China exhibits a distinct dynamic, with persistent and statistically significant coherence between EPU and stock market returns in the frequency band corresponding to cycles of approximately 20 to 28 months. This long-horizon relationship indicates that policy uncertainty affects the Chinese financial market over extended periods, in contrast to other BRIC countries, where the effects tend to be more immediate or medium-term. The wavelet coherence plots for China show relatively stable and sustained co-movement, especially during events like the U.S.-China trade tensions and the COVID-19 pandemic. This pattern likely reflects the unique characteristics of China's economic governance, including gradual policy adjustments and a regulated market environment (Wu et al., 2022). The persistence of this coherence suggests that investor responses to uncertainty are more prolonged, potentially due to lower transparency and slower information diffusion in China's financial system.

Overall, these results highlight the role of institutional and structural heterogeneity in assessing the impact of EPU on emerging markets. As **Figure 2** illustrates, Brazil (RBOVESPA), Russia (RIMOEX), and India (RBSESN) show strong short-term positive co-movements with EPU, especially during major systemic events, including the Global Financial Crisis and the COVID-19 pandemic.

Conversely, China (RSSE) exhibits both short and medium-term coherence, indicating a more sustained sensitivity to EPU shocks. From an economic perspective, this pattern lends support to the notion that stock markets can act as leading indicators, initially absorbing shocks from increasing uncertainty and subsequently influencing policy decisions. During periods of heightened uncertainty, such as those triggered by geopolitical tensions or global economic downturns, trade flows contract, firm profitability declines, and investor sentiment weakens, collectively depressing stock returns. Conversely, when uncertainty decreases, investor risk appetite typically increases, leading to market recoveries, increased volatility, and greater attractiveness for foreign direct investment (FDI).

5.4 Causality Analysis: Full Sample

Table 3. Unit Root Tests (ADF)

ADF-Test		
Variables	Statistic	Prob.
Stock Returns		
RBOVESPA	-13.0626***	0.0000
RIMOEX	-13.1962***	0.0000
RBSESN	-13.146***	0.0000
RSSE	-16.1338***	0.0000
Economic Policy Uncertainty		
EPU-BRAZIL	-7.5447***	0.0000
EPU-RUSSIA	-5.1534***	0.0001
EPU-INDIA	-3.2484*	0.0778
EPU-CHINA	-3.9993*	0.0801

Notes: Augmented Dickey–Fuller (ADF) tests are applied to examine the stationarity properties of the series at levels. The null hypothesis is that the series contains a unit root. Results indicate that stock returns and EPU indices are stationary in levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

As a preliminary step to the causality analysis, Augmented Dickey–Fuller (ADF) unit root tests are conducted on economic policy uncertainty (EPU) indices and stock market returns for Brazil (RBOVESPA), Russia (RIMOEX), India (RBSESN), and China (RSSE). The tests are applied to the level series in order to assess their stationarity properties prior to model estimation.

The results, reported in **Table 3**, indicate that all stock return series are stationary at levels at the 1% significance level. Similarly, the EPU indices for Brazil and Russia are stationary at the 1% level, while those for India and China are stationary at the 10% level. These findings suggest that all variables can be treated as stationary processes in levels.

Given the stationarity of the series, a bivariate VAR framework is employed to examine the causal relationships between EPU and stock market returns in each BRIC country. Following Balcilar and Ozdemir (2013), a rolling-window Granger causality approach with bootstrap inference is implemented to capture potential parameter instability, time variation, and nonlinear dynamics in the uncertainty–return relationship.

The optimal lag length is selected as one based on the Schwarz Bayesian Information Criterion (SBIC). A rolling window size of 24 observations is adopted to ensure reliable estimation, consistent with Pesaran and Timmermann (2005), who argue that excessively small windows may lead to imprecise autoregressive parameter estimates. Modified likelihood ratio tests based on rolling bootstraps are subsequently used to assess parameter stability and time-varying causality, with results interpreted on a country-by-country basis.

Table 4. Full Sample Granger Causality Tests: Bootstrap LR Test

Pair (RBOVESPA/EPU-BRAZIL)					
H0: RBOVESPA does not Granger-cause EPU-BRAZIL			**H0: EPU-BRAZIL does not Granger-cause RBOVESPA**		
	statistics	p-value		statistics	p-value
Bootstrap LR-Test	2.7471	0.2600	**Bootstrap LR-Test**	9.1631***	0.0000
Pair (RIMOEX/EPU-RUSSIA)					
H0: RIMOEX does not Granger-cause EPU-RUSSIA			**H0: EPU-RUSSIA does not Granger-cause RIMOEX**		
	statistics	p-value		statistics	p-value
Bootstrap LR-Test	0.6328	0.7200	**Bootstrap LR-Test**	6.4025***	0.0100
Pair (RBSESN/EPU-INDIA)					
H0: RBSESN does not Granger-cause EPU-INDIA			**H0: EPU-INDIA does not Granger-cause RBSESN**		
	statistics	p-value		statistics	p-value
Bootstrap LR-Test	2.2933	0.2800	**Bootstrap LR-Test**	22.3267***	0.0000
Pair (RSSE/EPU-CHINA)					
H0: RSSE does not Granger-cause EPU-CHINA			**H0: EPU-CHINA does not Granger-cause RSSE**		
	statistics	p-value		statistics	p-value
Bootstrap LR-Test	1.8141	0.4100	**Bootstrap LR-Test**	2.6341	0.2600

Notes: The table reports bootstrap-adjusted likelihood ratio (LR) tests for Granger causality. P-values are obtained from 1,000 bootstrap replications. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4 reports the results of the RB-based modified LR Granger causality tests with bootstrap-adjusted p-values (1,000 replications), ensuring robustness against non-normality and small-sample biases. The full-sample results reveal heterogeneous causal dynamics between economic policy uncertainty (EPU) and stock market returns across BRIC countries.

For Brazil, Russia, and India, statistically significant unidirectional causality running from EPU to stock returns is observed at the 1% level (Brazil: LR = 9.16, p = 0.000; Russia: LR = 6.40, p = 0.010; India: LR = 22.33, p = 0.000). These findings are consistent with the risk-premium channel proposed by Pastor and Veronesi (2013), whereby heightened policy uncertainty increases investor risk aversion and required returns, leading to lower equity prices. While risk pricing appears to be the dominant transmission mechanism, indirect effects through corporate investment and earnings expectations cannot be ruled out.

No evidence of reverse causality from stock returns to EPU is detected for any of the BRIC countries, suggesting limited feedback from financial markets to policy uncertainty. This contrasts with evidence from developed markets (Brogaard & Detzel, 2015), where market signals often influence policy decisions. In emerging economies, this asymmetry may reflect weaker institutional responsiveness or more insulated policy frameworks.

China represents a distinct case, as no statistically significant causality is detected in either direction ($p > 0.25$). This result aligns with Wu and Wu (2020), who emphasize the role of capital controls, state intervention, and limited market influence on policy formation. Extending this view, Khan et al. (2025) argue that the effects of EPU in China may operate through sector-specific channels that are not fully captured at the aggregate market level.

Overall, the full-sample evidence indicates a unidirectional causal relationship from economic policy uncertainty to stock returns in Brazil, Russia, and India, consistent with the risk-premium transmission mechanism. In contrast, no causal linkage is identified for China, highlighting the importance of institutional and structural differences across BRIC economies.

Table 5. Parameters stability tests

			Brazil			
	RBOVESPA equation		**EPU-BRAZIL equation**		**VAR System**	
	Statistics	**P-Value**	**Statistics**	**P-Value**	**Statistics**	**P-Value**
Sup-F	26.7505***	0.0006	36.3474***	0.0000	113.9477***	0.0000
Ave-F	2.8202	0.7038	12.9521***	0.0001	39.1891***	0.0069
Exp-F	8.3337***	0.0024	13.8252***	0.0000	52.8373	1.0000
Lc					1.4308***	0.0037
			Russia			
	RIMOEX equation		**EPU-RUSSIA equation**		**VAR System**	
		P-Value	**Statistics**	**P-Value**	**Statistics**	**P-Value**
Sup-F	3.9309	0.9853	26.4805***	0.0007	79.9270***	0.0000
Ave-F	2.1417	0.8772	9.5731***	0.0125	37.6833**	0.0222
Exp-F	1.1185	0.9298	8.7875***	0.0015	35.4761*	0.0552
Lc					8.3172***	0.0050
			India			
	RBSESN equation		**EPU-INDIA equation**		**VAR System**	
	Statistics	**P-Value**	**Statistics**	**P-Value**	**Statistics**	**P-Value**
Sup-F	8.1097	0.5917	27.0150***	0.0005	166.4732***	0.0000
Ave-F	3.7173	0.4763	9.5857**	0.0124	53.3522	1.0000
Exp-F	2.1275	0.5663	8.7386***	0.0016	78.3492	1.0000
Lc					6.2434***	0.0005
			China			
	RSSE equation		**EPU-CHINA equation**		**VAR System**	
	Statistics	**P-Value**	**Statistics**	**P-Value**	**Statistics**	**P-Value**
Sup-F	7.6161	0.6530	37.5809***	0.0000	386.3920***	0.0000
Ave-F	1.4916	0.9861	7.5744**	0.0488	171.4867***	0.0030
Exp-F	0.8985	0.9796	13.7196***	0.0000	188.7085***	0.0000
Lc					2.1816***	0.0000

Notes: Sup-F, Ave-F, Exp-F, and Lc denote parameter stability tests proposed by Zeileis et al. (2005). Sup-F is designed to detect sharp structural breaks, Ave-F captures gradual parameter instability, Exp-F emphasizes instability toward the end of the sample, and Lc tests for random walk behavior in the parameters. Reported p-values are based on 1,000 bootstrap replications. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5 reports the results of parameter stability tests based on the rolling-window framework of Zeileis et al. (2005), including the Sup-F, Ave-F, Exp-F, and Lc statistics. These tests assess whether the relationship between economic policy uncertainty (EPU) and stock returns is stable over time or subject to structural changes, which is particularly relevant for emerging markets where policy regimes and investor behavior may change abruptly.

For **Brazil**, strong evidence of parameter instability is found in both the RBOVESPA and EPU equations, as well as in the VAR system, with Sup-F and Exp-F statistics significant at the 1% level. The high Sup-F values indicate sharp structural breaks, while the Exp-F statistics suggest that recent observations play an important role in driving instability. These findings likely reflect episodic political crises, fiscal uncertainty, or major macroeconomic events (Aye, 2018). Although the VAR system exhibits weaker evidence of recent instability, the overall results suggest that Brazilian financial markets respond strongly to abrupt policy signals but gradually adjust over time.

For **Russia**, the stock return equation appears stable across all tests, whereas significant instability is detected in the EPU equation and the VAR system, particularly through the Sup-F and Exp-F statistics. This pattern is consistent with Apergis and Fahmy (2024), who argue that geopolitical risks and international sanctions have reshaped the transmission of uncertainty in Russian financial markets. The joint instability observed in the EPU equation and the VAR system suggests that policy uncertainty, largely driven by geopolitical developments, plays a central role in shaping market dynamics.

In **India**, the stock return equation remains stable, while the EPU equation exhibits significant structural breaks. The absence of strong instability in the VAR system, as indicated by the Ave-F and Exp-F tests, may reflect India's gradual institutional reforms and increasing market resilience (Mishra et al., 2020). Nevertheless, the detected instability in the EPU equation points to shifts in investor perceptions of policy risk, likely associated with regulatory changes or unexpected monetary policy actions.

A distinctive pattern emerges for **China**. While the RSSE return equation remains stable, the EPU equation and the VAR system display strong and consistent evidence of structural breaks across all tests ($p < 0.01$). This finding aligns with Wu and Wu (2020), who emphasize the evolving role of state intervention, capital controls, and policy opacity in shaping uncertainty transmission. The instability observed in the EPU equation may reflect changes in government priorities, regulatory tightening cycles, or external shocks such as U.S.–China trade tensions. The widespread significance of the stability tests underscores the importance of regime shifts in China's financial dynamics.

Finally, the Lc statistic is significant for all BRIC countries, indicating that VAR parameters follow a random walk process. This result confirms that the EPU–stock return relationship is inherently time-varying and nonlinear. Consequently, static full-sample models may be inadequate, supporting the use of dynamic approaches such as rolling-window Granger causality, wavelet coherence (Mensi et al., 2018; Reboredo et al., 2017; Wu et al., 2022), and dynamic connectedness frameworks (Aydin et al., 2022; Mensi et al., 2021).

In summary, **Table 5** provides strong evidence of structural instability in EPU equations and VAR systems across all BRIC countries, particularly in China. The significance of the Lc statistic confirms the time-varying nature of the relationship between economic policy uncertainty and stock returns. These findings highlight the regime-dependent impact of uncertainty, shaped by institutional characteristics, investor sentiment, and external shocks, and underscore the importance of transparent and predictable policy communication in mitigating financial market disruptions.

5.5 Time-varying Causality Analysis

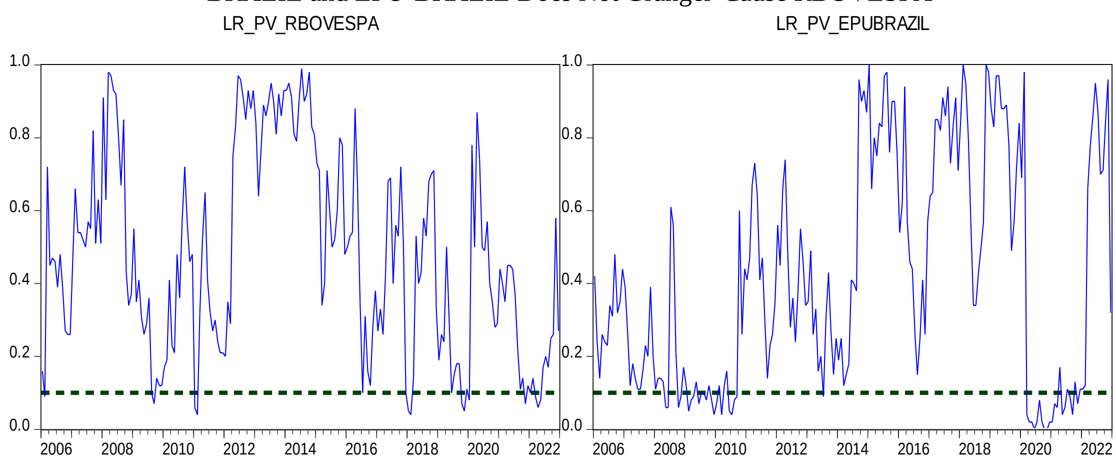
To evaluate the significance of the difference between models in the time-varying causality analysis, bootstrap p-values derived from the likelihood ratio (LR) test statistic are employed. The likelihood ratio test contrasts a simpler model with a more complex one, assessing which provides a superior fit to the data (Wilks, 1938). The bootstrap p-value quantifies the probability of observing a test p-value indicating the chance of observing a statistic as extreme as the observed value, assuming the null hypothesis is true (Efron & Tibshirani, 1994). A low bootstrap p-value suggests that the observed improvement in fit with the more complex model is unlikely due to chance, supporting the alternative hypothesis that it provides a significantly better representation of the underlying dynamics (Davidson & MacKinnon, 2004).

Bootstrap resampling, applied to each rolling window, entails repeatedly drawing samples with replacement from the original dataset to generate new datasets (Hall, 2013), estimating the distribution of the test statistic under the null hypothesis, and obtaining bootstrap p-values by comparing to the distribution. This allows us to capture the evolving nature of relations. These evolving relationships are visually presented **in Figures 3, 4, 5,** and **6**, which illustrate the bootstrap probability values, the direction, and the magnitude of the impacts of stock returns on EPU, and vice versa for the four BRIC countries.

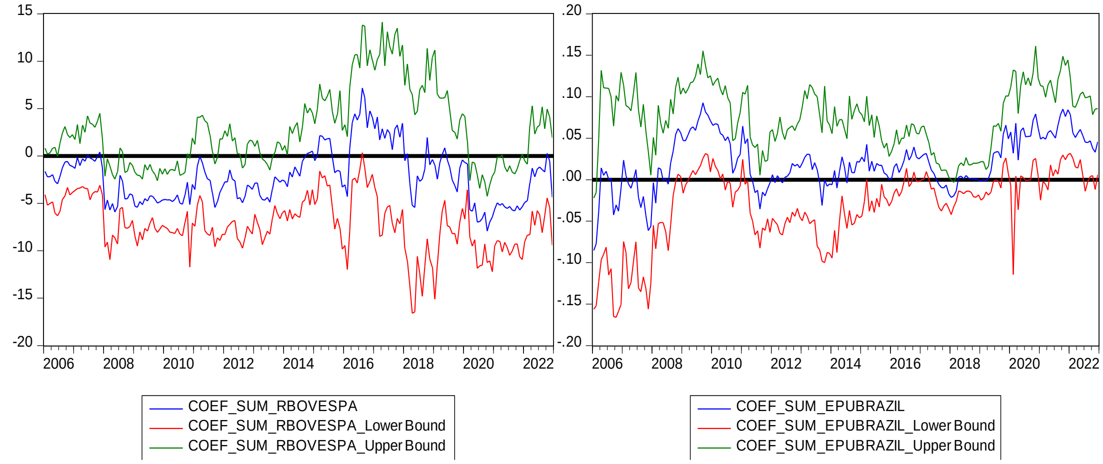
Figure 3. Rolling Window Estimation of the Dynamic Relationship between RBOVESPA and EPU-BRAZIL

Case of Brazil

Panel (A): Bootstrap P-values of the LR Test for the Null Hypotheses that RBOVESPA Does Not Granger-Cause EPU-BRAZIL and EPU-BRAZIL Does Not Granger-Cause RBOVESPA



Panel (B): Bootstrap Estimation of the Sum of Rolling Coefficients for the Effects of RBOVESPA on EPU-BRAZIL and EPU-BRAZIL on RBOVESPA



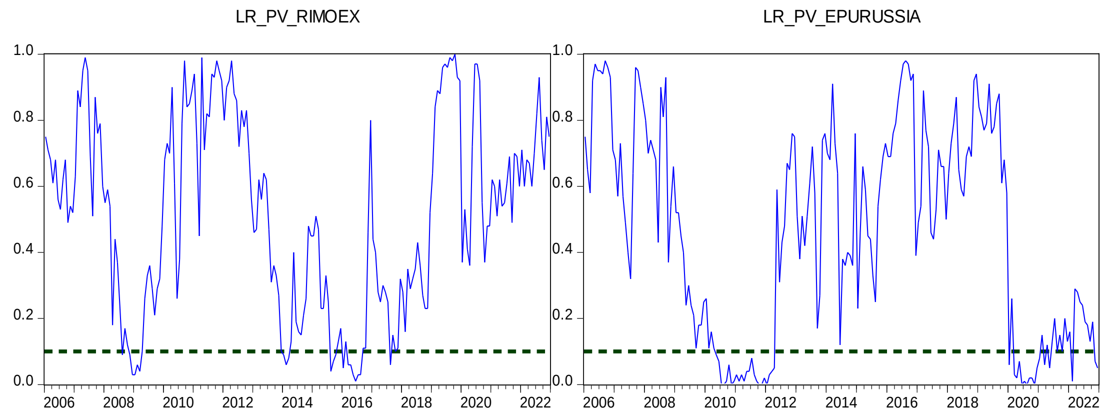
Notes: This figure consists of two panels: (a) bootstrap p-values for the null hypotheses of no Granger causality (solid line: stock → EPU; dashed line: EPU → stock), with a horizontal dotted line at 10% significance; (b) bootstrap estimates of the sum of rolling coefficients, indicating the direction and magnitude of effects. Shaded areas denote crisis periods.

Employing the bootstrap rolling-window Granger causality framework of Minlah and Zhang (2021), **Figure 3** illustrates the time-varying Granger causal relationship between the stock market (RBOVESPA) and economic policy uncertainty in **Brazil** (EPU-BRAZIL). Based on the 10% significance threshold indicated by the horizontal dotted line, the null hypothesis that RBOVESPA does not Granger-cause EPU-BRAZIL is rejected during the periods 2011M01–2011M02, 2018M01–2018M02, 2019M11–2020M01, and 2022M04–2022M06, suggesting that stock market performance may influence policy-related uncertainty in the short term. In the reverse direction, the hypothesis that EPU-BRAZIL does not Granger-cause RBOVESPA is rejected in 2008M04–2008M05, 2009M01–2010M10, and 2020M02–2022M11. These episodes coincide with major global crises, including the 2008 subprime crisis, the COVID-19 pandemic, and the Russia–Ukraine war. As Patel (2025) notes, financial markets are often highly sensitive to global turbulence, and such crises tend to reinforce uncertainty–return linkages. Additionally, the lower panel of **Figure 3** presents the bootstrap estimates of the sum of rolling coefficients. Periods with no significant causality typically correspond to negative or weak impacts of stock returns on uncertainty, and vice versa, while periods of significant causality are associated with positive and stronger effects. This time-varying behavior underscores the importance of capturing dynamic relationships in uncertainty–return interactions.

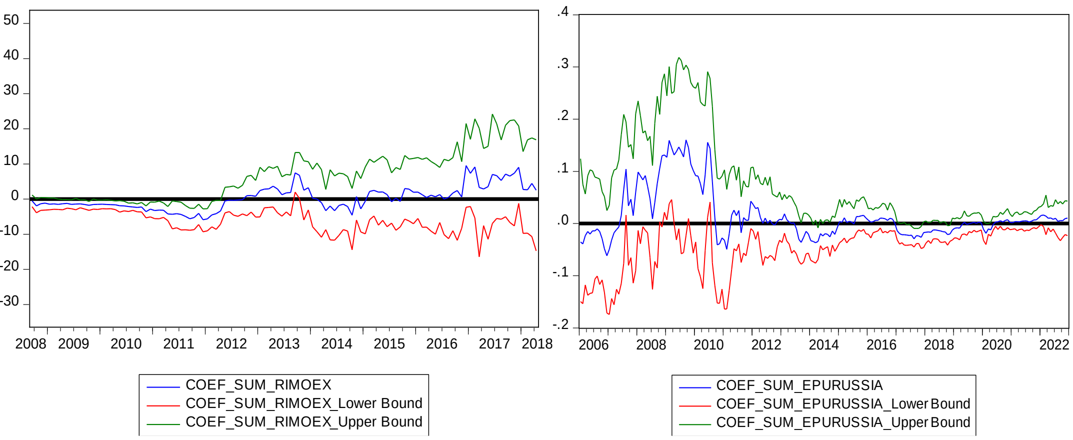
Figure 4. Rolling Window Estimation of the Dynamic Relationship between RIMOEX and EPU-RUSSIA

Case of Russia

Panel (A): Bootstrap P-values of the LR Test for the Null Hypotheses that RIMOEX Does Not Granger-Cause EPU-RUSSIA and EPU-RUSSIA Does Not Granger-Cause RIMOEX



Panel (B): Bootstrap Estimation of the Sum of Rolling Coefficients for the Effects of RIMOEX on EPU-RUSSIA and EPU-RUSSIA on RIMOEX



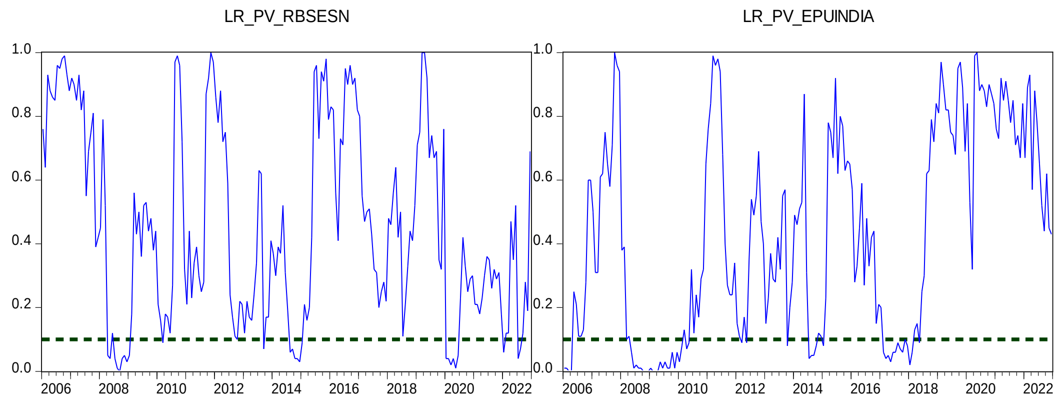
Notes: This figure consists of two panels: (a) bootstrap p-values for the null hypotheses of no Granger causality (solid line: stock → EPU; dashed line: EPU → stock), with a horizontal dotted line at 10% significance; (b) bootstrap estimates of the sum of rolling coefficients, indicating the direction and magnitude of effects. Shaded areas denote crisis periods.

In the case of **Russia**, the analysis of **Figure 4** of the Granger causal relationship between the Russian stock market index (RIMOEX) and EPU-RUSSIA reveals a nuanced picture. Bootstrap p-values from likelihood ratio tests show that RIMOEX typically Granger-causes EPU-RUSSIA, except during specific windows like 2007M07–2008M02, 2014M01–2014M02, and 2016M02–2016M08. Conversely, the hypothesis that EPU-RUSSIA does not Granger-cause RIMOEX cannot be rejected during 2010M04–2012M02 and 2020M02–2020M12. These periods of non-causality tend to coincide with major global and domestic shocks (the global financial crisis, the European sovereign debt crisis, and the COVID-19 pandemic), likely disrupting normal causal dynamics because of increased market intervention and overall uncertainty (Antonakakis et al., 2013). Consistent with these findings, the estimated cumulative rolling coefficients are generally negative during periods of no Granger causality, suggesting that changes in stock returns and uncertainty do not amplify each other. Notably, the impact of stock returns on economic policy uncertainty becomes positive during 2013M01–2013M12 and 2017M01–2018M12, potentially signaling increased investor confidence or policy responses to market conditions. Concurrently, policy uncertainty exerts a positive effect on stock returns during 2007M06–2010M10 and 2012M01–2012M04, suggesting that heightened uncertainty may correlate with increased stock return volatility or a greater investor risk appetite (Bekaert & Hoerova, 2016).

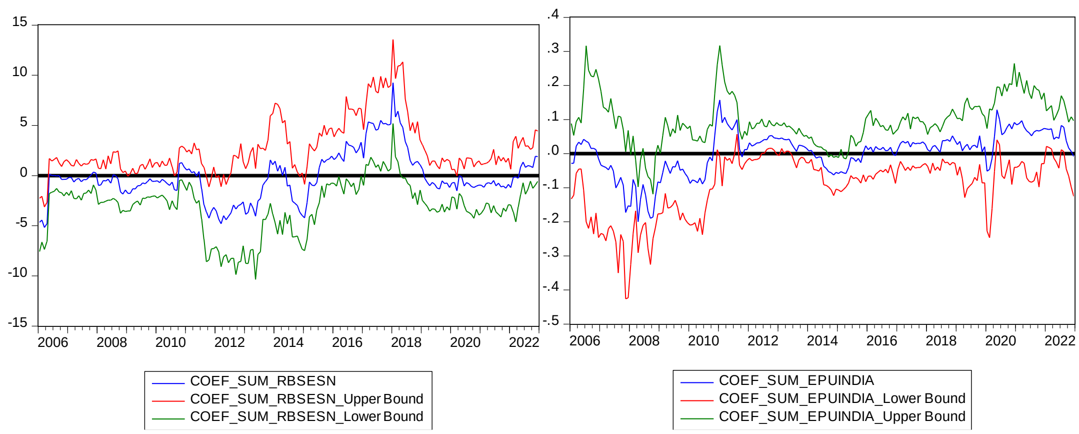
Figure 5. Rolling Window Estimation of the Dynamic Relationship between RBSESN and EPU-INDIA

Case of India

Panel (A): Bootstrap P-values of the LR Test for the Null Hypotheses that RBSESN Does Not Granger-Cause EPU-INDIA and EPUINDIA Does Not Granger-Cause RBSESN



Panel (B): Bootstrap Estimation of the Sum of Rolling Coefficients for the Effects of RBSESN on EPU-INDIA and EPU-INDIA on RBSESN



Notes: This figure consists of two panels: (a) bootstrap p-values for the null hypotheses of no Granger causality (solid line: stock → EPU; dashed line: EPU → stock), with a horizontal dotted line at 10% significance; (b) bootstrap estimates of the sum of rolling coefficients, indicating the direction and magnitude of effects. Shaded areas denote crisis periods.

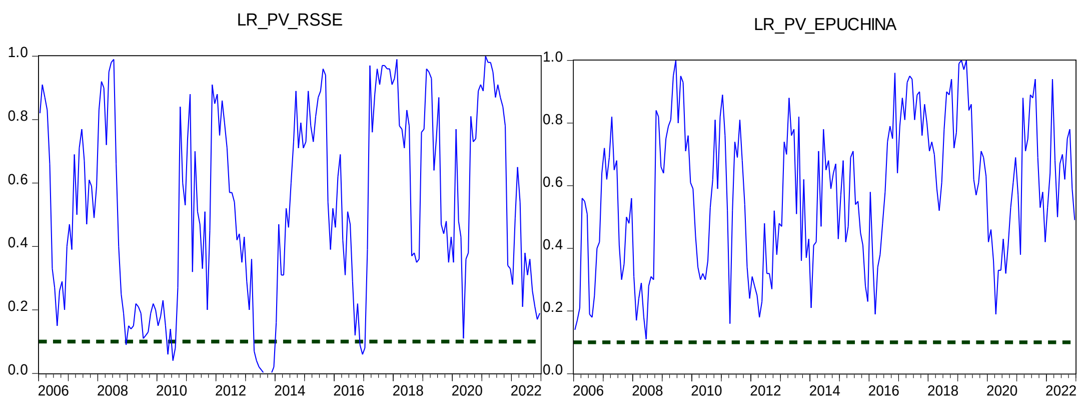
Figure 5 presents a rolling window estimation and bootstrap analysis of the dynamic relationship between the Bombay Stock Exchange Sensitive Index (RBSESN) and economic policy uncertainty in **India** (EPU-INDIA). Likelihood ratio tests indicate that RBSESN does not Granger-cause EPU-INDIA during 2008M02–2008M12, 2014M06–2014M12, 2020M01–2020M06, and 2022M06–2022M07. Similarly, EPU_INDIA does not Granger-cause RBSESN in the windows 2006M01–2006M05, 2008M02–2010M02, 2014M06–2014M12, and 2017M01–2018M02. These episodes correspond with major global and domestic disruptions, including the global financial crisis, India's general elections, and the COVID-

19 outbreak, which likely weaken traditional causal mechanisms due to increased uncertainty and policy interventions (Arouri et al., 2016). The bootstrap estimation of rolling coefficients suggests that the effects between RBSESN and EPU-INDIA are generally negative during these periods of no causality, implying a decoupling of the stock market and policy uncertainty. However, the impact of RBSESN on EPU-INDIA turns positive during specific periods, suggesting that rising stock returns may coincide with increased uncertainty, possibly reflecting market-driven expectations of policy change. Conversely, a positive effect of EPU-INDIA on RBSESN during other periods implies that higher uncertainty often leads to increased volatility or risk-adjusted returns in the stock market. This aligns with research highlighting uncertainty as a key driver of asset price dynamics (Antonakakis et al., 2013; Bekaert & Hoerova, 2016).

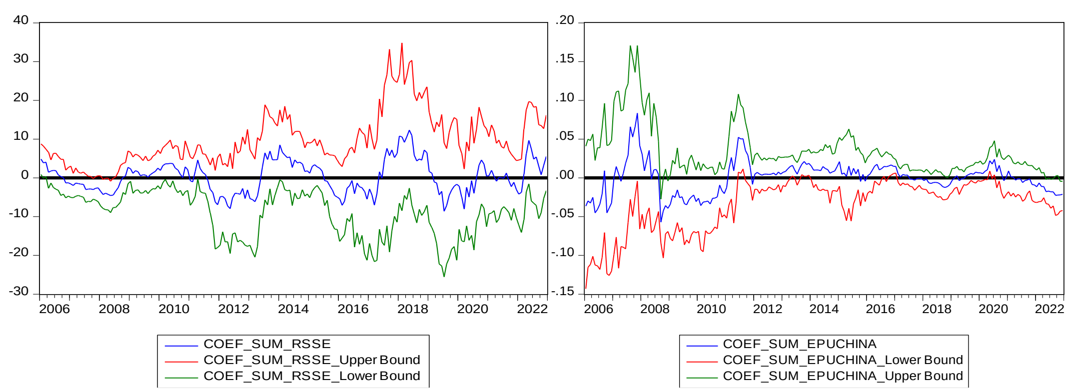
Figure 6. Rolling Window Estimation of the Dynamic Relationship between RSSE and EPU-CHINA

Case of China

Panel (A): Bootstrap P-values of the LR Test for the Null Hypotheses that RSSE Does Not Granger-Cause EPU-CHINA and EPUCHINA Does Not Granger-Cause RSSE



Panel (B): Bootstrap Estimation of the Sum of Rolling Coefficients for the Effects of RSSE on EPU-CHINA and EPU-CHINA on RSSE



Notes: This figure consists of two panels: (a) bootstrap p-values for the null hypotheses of no Granger causality (solid line: stock → EPU; dashed line: EPU → stock), with a horizontal dotted line at 10% significance; (b) bootstrap estimates of the sum of rolling coefficients, indicating the direction and magnitude of effects. Shaded areas denote crisis periods.

Finally, **Figure 6** examines the dynamic relationship between stock returns (RSSE) and EPU in **China**. Following Andrews and Ploberger's (1994) optimal testing approach, the analysis reveals that RSSE does not Granger-cause EPU-CHINA during specific sub-periods. This finding aligns with the notion that stock market fluctuations may not consistently predict policy shifts, possibly due to the government's proactive interventions in the stock market to maintain stability, as suggested by previous studies (e.g., Aydin et al., 2022). Conversely, EPU-CHINA demonstrates a significant Granger-causal effect on RSSE for most of the sample, supporting the established literature that policy uncertainty acts as a primary driver of stock market returns (Arouri et al., 2016). The negative (positive) cumulative coefficients observed during the "no-causality" windows for RSSE→EPU-CHINA (EPU-CHINA→RSSE) further suggest that decreasing (increasing) returns are associated with dampened (amplified) uncertainty, while heightened uncertainty tends to exert an uplifting effect on contemporaneous returns, potentially reflecting a risk-appetite channel as described by Bekaert and Hoerova (2016), where investors may seek riskier assets like stocks in response to increased uncertainty.

6 Conclusion and Policy Implications

Driven by the pivotal role of Economic Policy Uncertainty (EPU) in shaping financial markets, particularly in rapidly evolving emerging economies, this study sought to move beyond traditional static, time-domain approaches to investigate the complex, time-varying relationship between EPU and stock market returns in the BRIC countries, addressing gaps in the literature related to frequency-specific dynamics, dynamic causality, and changing market regimes during periods of major global crises.

The integrated methodological framework, combining wavelet coherence with bootstrap rolling-window Granger causality tests, produced several key findings. First, we found strong short-term co-movements between EPU and stock returns across the BRIC markets during periods of heightened global uncertainty. Second, we found that medium-term stabilization patterns emerged, particularly in India and Russia, suggesting potential moderating effects of policy interventions. Third, we showed that China exhibited a distinct pattern of persistent long-term coherence. Additionally, full-sample causality tests indicated unidirectional causality from EPU to stock returns in Brazil, Russia, and India, but not in China. The time-varying analysis confirmed that the causal links are dynamic and dependent on market regimes.

These findings have significant implications for both academics and practitioners. For researchers, the study demonstrates the effectiveness of integrating time-frequency and dynamic causality methods to analyze complex market interactions, offering a more robust framework for examining uncertainty transmission. For investors and portfolio managers, the results emphasize the importance of horizon-specific and country-differentiated strategies, recognizing that the impact of policy uncertainty varies across investment timeframes and national institutional contexts. As such, this study contributes to the literature by providing a novel and methodologically rigorous analysis of the EPU–stock return relationship in BRIC economies. It is among the first to simultaneously employ wavelet coherence and rolling-window Granger causality tests, capturing both multi-scale correlation patterns and dynamic, time-varying causal linkages, which are often overlooked in traditional static analyses. These contributions advance both the theoretical understanding of uncertainty transmission in emerging markets and the practical toolkit available to policymakers, investors, and financial risk managers.

Despite these contributions, certain limitations point to avenues for future research. First, our study is conducted at an aggregate market level, and sector-specific studies could uncover heterogeneous exposures to EPU shocks. Extending the comparative framework to other emerging or frontier markets would help generalize the findings. In addition, incorporating behavioral factors and investor sentiment measures could further illuminate the channels through which policy uncertainty influences financial decisions in the economies.

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