Modern Finance

Article

Understanding crisis spillovers: US-BRICS market interdependence in times of turmoil

Mariem Bouzguenda [1,*], **and Anis Jarboui** [2]

[1] Faculty of Economics and Management Sciences of Sfax, Tunisia, email: mariembouzguenda@hotmail.fr
[2] High Institute of Business Administration of Sfax, Tunisia, email: anisjarboui@yahoo.fr
* Correspondence: mariembouzguenda@hotmail.fr

Abstract: This study investigates the interconnectedness of stock returns between the U.S. and BRICS economies over the period 2016 - 2023, using daily data and integrating quantile and frequency-based methodologies. The analysis provides a comprehensive assessment of short- and long-term dynamics, with particular attention to tail dependencies and crisis episodes. The findings reveal heightened spillovers during the COVID-19 pandemic and the Russia-Ukraine war, with the U.S. and Brazil identified as the predominant net transmitters of shocks. Their roles, however, fluctuate across time and quantiles, underscoring the evolving and asymmetric nature of global linkages. These insights offer guidance for investors, policymakers, and risk managers.

Keywords: dynamic spillover effects; volatility transmission; BRICS-US stock market interdependence; quantile connectedness approach; frequency-domain analysis; financial crises; COVID-19; Russia-Ukraine war; 2023 banking crisis

JEL classification: E44; E62; F65; G11; G18; H62

Citation: Bouzguenda, M., & Jarboui, A. (2025). Understanding crisis spillovers: US-BRICS market interdependence in times of turmoil. *Modern Finance*, 3(4), 46-65.

Accepting Editor: Adam Zaremba

Received: 7 August 2025
Accepted: 15 November 2025
Published: 19 November 2025

1. Introduction

Global financial markets have been repeatedly disrupted by major crises in recent years, including the COVID-19 pandemic, the Russia–Ukraine war, and the 2023 banking turmoil. These episodes have generated unprecedented uncertainty, heightened volatility, and systemic repercussions across the global economy. The COVID-19 outbreak, officially declared a global health crisis by the WHO in March 2020, triggered severe market instability and economic losses (Jeribi et al., 2021; Bouzguenda & Jarboui, 2025a; Zhang et al., 2024). Two years later, Russia's invasion of Ukraine further destabilized global markets, marking the most significant European conflict since World War II and amplifying financial contagion (Karkowska & Urjasz, 2023; Beraich et al., 2022; World Bank, 2023). More recently, the collapse of Silicon Valley Bank and related institutions in March 2023 underscored the fragility of the banking system and its systemic implications (Lyócsa et al., 2023; Naveed et al., 2024). Collectively, these crises have shaken investor confidence, disrupted capital flows, and intensified the need to understand how shocks propagate across markets.

Against this backdrop, a growing body of research has examined volatility transmission and spillovers across global markets. Studies have shown that uncertainty in U.S. economic policy generates short-term volatility spillovers to BRICS stock returns, while long-term correlations remain time-varying (Dakhlaoui & Aloui, 2016; Lan et al., 2023; Oral and Özkan, 2024; Zhang et al., 2025). Other contributions highlight the asymmetric role of developed and emerging economies, with Brazil and Russia often acting as transmitters of volatility. At the same time, India, China, and South Africa tend to absorb shocks (Das and Roy, 2023). More recently, research has begun to address the 2023 banking crisis, showing that the collapse of Silicon Valley Bank had significant global repercussions, particularly for financial institutions in the U.S., Europe, and Asia (Aharon et al., 2023; Yousaf & Goodell, 2023). However, the literature remains fragmented, with few studies providing a comprehensive view of how multiple crises jointly reshape global financial connectedness.

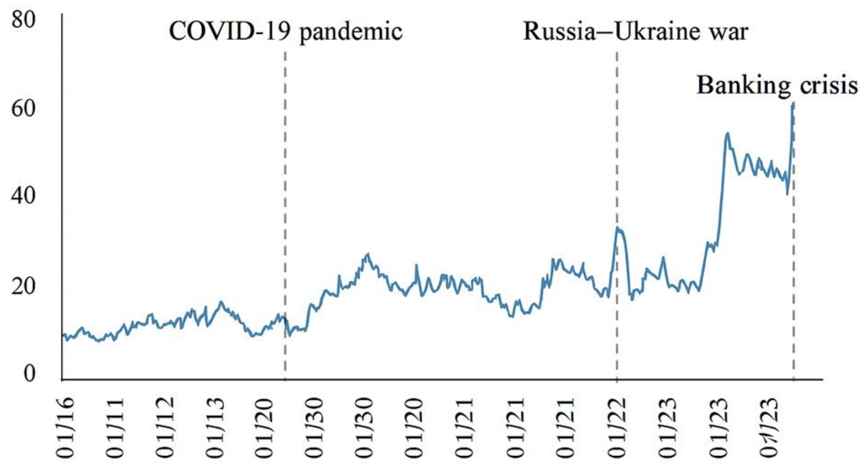
This paper addresses this gap by investigating the dynamic connectedness of stock index returns between the U.S. (S&P 500) and major BRICS economies (China, Russia, India, Brazil, and South Africa). Using both static and dynamic approaches, we analyze volatility transmission and spillover effects during crisis episodes. We further distinguish between markets acting as net transmitters or receivers of shocks, thereby mapping the evolving structure of global financial interdependence. Our contributions are twofold. First, we extend the literature by jointly examining three major crises: the COVID-19 pandemic, the Russia–Ukraine war, and the 2023 banking collapse, providing a comprehensive view of shock transmission channels. Second, we account for the asymmetric and nonlinear features of U.S. BRICS linkages, offering more profound insights into volatility dynamics under extreme conditions.

The empirical results have important implications for investors, policymakers, and portfolio managers by identifying the markets most exposed to systemic risk and highlighting the channels through which volatility spreads. Ultimately, our findings underscore the evolving, crisis-sensitive nature of global financial connectedness. To illustrate our main finding, Figure 1 depicts the dynamic connectedness index over the sample period, highlighting sharp increases during the COVID-19 pandemic, the Russia-Ukraine war, and the 2023 banking crisis. This visual evidence underscores the crisis-sensitive nature of global financial interdependence.

Our main findings can be summarized as follows. First, as seen in Figure 1, the dynamic connectedness between U.S. and BRICS stock markets intensifies markedly during crisis episodes, with the COVID-19 pandemic and the Russia-Ukraine war generating the most persistent and widespread spillovers. The 2023 banking turmoil, while shorter in duration, triggered sharp volatility transmission, particularly affecting Brazil and South Africa.

Second, the U.S. and Brazil emerge as predominant net transmitters of shocks, whereas China and India tend to act as net receivers, confirming the asymmetric nature of global financial linkages. These roles, however, fluctuate across time and quantiles, underscoring the evolving structure of market interdependence.

Figure 1. Dynamic Connectedness among US and BRICS Markets during Major Global Crises



Third, short-term dynamics dominate the transmission process, especially in extreme quantiles, revealing heightened sensitivity to immediate disturbances. The inverse relationship between short- and long-term connectedness at specific quantiles highlights the importance of monitoring tail risks and adapting investment strategies accordingly.

By integrating quantile- and frequency-based methodologies, our approach captures both immediate contagion effects and more profound structural shifts in return-risk connectedness. These insights offer practical guidance for investors, portfolio managers, and policymakers seeking to mitigate systemic risk and enhance financial resilience under turbulent conditions.

The remainder of the paper is structured as follows. Section 2 reviews the related literature. Section 3 outlines the methodology. Section 4 describes the data. Section 5 presents and discusses the results. Section 6 concludes.

2. Literature Review

The phenomenon of globalization has intensified the interdependence and interconnectedness of countries and global markets, a trend that becomes particularly evident during periods of crisis (Zaremba et al., 2019; Spierdijk & Umar, 2014). This interlinkage has increased correlations across economies, especially in times of turmoil, and has proven particularly damaging for emerging markets (Kenourgios et al., 2011; Syriopoulos et al., 2015; Jareño et al., 2023). Recent crises have extended across all sectors of the global economy, producing destructive effects more severe than those of the 2007–2008 financial crisis (Goodell, 2020). Although emerging economies often face weaker institutional frameworks and higher financial and social risks (Bretas & Alon, 2020; Hevia & Neumeyer, 2020; Zhang et al., 2024; Neto, 2025), the adverse effects of crises have sometimes been less pronounced in these markets compared to developed ones. Among emerging economies, the BRICS countries are of particular interest given their significant share of global GDP and population (Bretas & Alon, 2020). Several studies have highlighted the impact of the COVID-19 pandemic on BRICS stock markets (Jareño et al., 2023; Zhang et al., 2024), while others have examined spillover effects during the Russia-Ukraine conflict (Wiseman, 2022; Karkowska & Urjasz, 2023; Yousaf et al., 2023). More recently, research has begun to address the 2023 banking crisis and its global repercussions (Aharon et al., 2023; Naveed et al., 2024; Bouzguenda & Jarboui, 2025a).

Understanding the role of BRICS equity markets, their risk-return dynamics, and their interactions with mature markets such as the U.S. remains a crucial issue for international investors and policymakers (Zhang et al., 2025). The literature consistently shows that extreme events affect stock markets (Arin et al., 2008; Chen & Siems, 2007; Boungou & Yatié, 2022; Kumari et al., 2022; Oral and Özkan, 2024). However, evidence on the degree of dependence and spillover effects between BRICS and developed markets remains mixed (Aloui et al., 2011; Kenourgios et al., 2011; Dimitriou et al., 2013; Zhang et al., 2013; Syriopoulos et al., 2015; Bhuyan et al., 2016; Mensi et al., 2016, 2017a, 2017b; Bekaert & Harvey, 2017). Syriopoulos et al. (2015) identified significant return and volatility transmission dynamics between the U.S. and BRICS, with Brazil and India most affected by U.S. shocks. Similarly, Mensi et al. (2016) found that Brazil, India, China, and South Africa were strongly impacted by the Global Financial Crisis, supporting the hypothesis of financial recoupling.

Beyond these findings, numerous empirical models have been developed to capture return and volatility spillovers across asset classes (Golitsis et al., 2022; Elsayed et al., 2022; Lin et al., 2021). Bouzgarrou et al. (2023) showed that market returns are more sensitive to economic and financial news than volatilities, with U.S. news strongly influencing global indices and Brazilian indices reacting more to domestic surprises. Assaf et al. (2023) emphasized the inconsistency of results across studies, attributing it to differences in events, contexts, and country-specific characteristics. Nevertheless, the literature broadly confirms that wars and geopolitical tensions negatively affect stock markets, though the magnitude varies across regions (Boubaker et al., 2022; Bouzguenda & Jarboui, 2025a). Developed countries tend to experience stronger adverse reactions than emerging countries, while higher-GDP economies appear more resilient (Assaf et al., 2023; Chalissery et al., 2024).

Finally, recent studies highlight the time-varying nature of spillovers. Zhang et al. (2024) demonstrated that countries' rankings as transmitters or receivers of shocks change over time, with spillovers intensifying during crises such as the COVID-19 pandemic. These findings underscore the importance of incorporating extreme scenarios into stress tests and regulatory frameworks. Similarly, McIver and Kang (2020) confirmed that spillovers between BRICS and U.S. equity markets evolve across crises, reinforcing the need for dynamic approaches to capture the complexity of global financial interconnectedness.

3. Methodology

To analyze the propagation mechanism of USA and BRICS stock indices returns across different quantiles, we employ the quantile connectedness approach (QVAR) proposed by Chatziantoniou et al. (2021). This framework allows us to calculate all connectedness metrics while capturing the system's dynamics across different market conditions. The choice of QVAR, combined with frequency-based analysis, is motivated by its ability to capture both short- and long-term market interactions and account for asymmetries in extreme market movements. Unlike standard VAR models, QVAR can examine connectedness across different quantiles, making it especially suitable for analyzing tail dependencies and shock propagation during crisis periods. The frequency decomposition further distinguishes short-term from long-term connectedness, providing deeper insights into evolving market relationships. These methodological choices are supported by prior literature and are particularly relevant given the high volatility and asymmetric distributions observed in our data.

We then proceed with the estimation of QVAR(p) as follows:

$$Y_t = \mu_t(q) + \Phi_1(q)Y_{t-1} + \Phi_2(q)Y_{t-2} + \cdots + \Phi_p(q)Y_{t-p} + \varepsilon_t(q) \tag{1}$$

where: Y_t and Y_{t-j}, i = 1, ..., p are N × 1 dimensional endogenous variable vectors, τ is between [0, 1] and represents the quantile of interest, p stands for the lag length of the QVAR model, μ(τ) is an N × 1 dimensional conditional mean vector, Φ_j (τ) is an N×N dimensional QVAR coefficient matrix, and u_t(τ) demonstrates the N × 1 dimensional error vector which has an N × N dimensional variance-covariance matrix, Σ(τ). To transform the QVAR(p) to its QVMA(∞) representation, we use Wold's theorem:

$$Y_t = \mu(q) + \sum_{j=1}^{p} \Phi_j(q)Y_{t-j} + \varepsilon_t(q) = \mu(q) + \sum_{i=0}^{\infty} \Omega_i(q)\varepsilon_{t-i} \tag{2}$$

Then, the generalized forecast error variance decomposition (GFEVD) (see Koop et al., 1996; Pesaran & Shin, 1998), a crucial concept of the connectedness approach, is introduced. The GFEVD allows us to forecast the impact of a shock in series *j* on variable *i*. It can be written as:

$$\phi_{ij}(H) = \frac{(\Sigma(q))_{jj}^{-1} \sum_{h=0}^{H-1}\left(\left(\Omega_h(q)\Sigma(q)\right)_{ij}\right)^2}{\sum_{h=0}^{H}\left(\Omega_h(q)\Sigma(q)\Omega_h'(q)\right)_{ii}} \tag{3}$$

where θ_{ij} (H) denotes the contribution of the *j*-th series to the variance of the forecast error of the *i*-th series at horizon H. As the rows of θ_{ij} (H) do not sum to 1, we need to normalize them to obtain ˜θij. Through the normalization, we get the following identities: PN *i*=1 θ_{ij} (H) = 1 and PN *j*=1 PN *i*=1 θ_{ij} (H) = N.

Next, we present successively the net pairwise connectedness, the total directional connectedness TO, the total directional connectedness FROM, and the net total directional connectedness, which are computed as follows:

$$NPDC_{ij}(H) = \tilde{\phi}_{ij}(H) - \tilde{\phi}_{ji}(H) \tag{4}$$

$$TO_i(H) = \sum_{i=1, i\neq j}^{N} \tilde{\phi}_{ji}(H) \tag{5}$$

$$FROM_i(\mathrm{H}) = \sum_{i=1, i\neq j}^{N} \tilde{\phi}_{ji}(H) \tag{6}$$

$$NET_i(H) = TO_i(\mathrm{H}) - FROM_i(\mathrm{H}) \quad (7)$$

The total connectedness index (TCI), which indicates the degree of network interconnectedness, can be designed by:

$$TCI(H) = N^{-1}\sum_{i=1}^{N} TO_i(H) = N^{-1}\sum_{i=1}^{N} FROM_i(H) \quad (8)$$

The TCI measures the average effect of a shock in one series on all others. The higher it is, the riskier the market.

Next, Chatziantoniou et al. (2021) explore the relationship between connectedness in the frequency domain. Considering the frequency response function, Ψ(e −iω) = P∞ h=0 e −iωhΨh, where i = √ −1 and ω denotes the frequency, to continue with the spectral density of xt at frequency ω, which can be defined as a Fourier transformation of the QVMA(∞):

$$S_x(\omega) = \sum_{h=-\infty}^{\infty} E(Y_t Y'_{t-h})\, e^{-i\omega h} = \Omega(e^{-i\omega h}) \sum_t \Omega'^{(e^{+i\omega h})} \quad (9)$$

They normalize the frequency GFEVD as follows:

$$\phi_{ij}(\omega) = \frac{(\Sigma(q))_{jj}^{-1}\left|\sum_{h=0}^{\infty}\left(\Omega(q)(e^{-iwh})\Sigma(q)\right)_{ij}\right|^2}{\sum_{h=0}^{\infty}\left(\Omega(e^{-iwh})\Sigma(q)\Omega(q)(e^{iwh})\right)_{ii}} \quad (10)$$

$$\tilde{\phi}_{ij}(\omega) = \frac{\phi_{ij}(\omega)}{\sum_{k=1}^{N}\phi_{ij}(\omega)} \quad (11)$$

where θij (ω) is the portion of the spectrum of the *i*-th variable at a fixed frequency ω that can be attributed to a shock in the *j*-th series. It can be assessed as a within-frequency indicator. To evaluate short-term and long-term connectedness rather than connectedness at a single frequency, they combined all frequencies within a specific range, d = (a, b): a, b ∈ (−π, π), a < b:

$$\tilde{\phi}_{ij}(d) = \int_a^b \tilde{\phi}_{ij}(\omega)\, d\omega \quad (12)$$

This would allow calculating connectedness measures as in Diebold and Yılmaz (2012, 2014), but in a fixed frequency range d (as for short or long term frequency):

$$NPDC_{ij}(d) = \tilde{\phi}_{ij}(d) - \tilde{\phi}_{ji}(d) \quad (13)$$

$$TO_i(d) = \sum_{i=1, i\neq j}^{N} \tilde{\phi}_{ji}(d) \quad (14)$$

$$FROM_i(d) = \sum_{i=1, i\neq j}^{N} \tilde{\phi}_{ij}(d) \quad (15)$$

$$NET_i(d) = TO_i(d) - FROM_i(d) \quad (16)$$

$$TCI(d) = N^{-1}\sum_{i=1}^{N} TO_i(d) = N^{-1}\sum_{i=1}^{N} FROM_i(d) \quad (17)$$

4. Data

The key motivation of this study is to examine the propagation mechanisms between stock indices of the USA and BRICS economies, using quantiles and frequencies.[1] Such a method allows analyzing different frequencies at a given quantile, or different quantile-connectedness measures at a given frequency. We collect closing prices from January 1st, 2016, to July 28, 2023, for the USA (SP500) and the BRICS stock indices (SSE, RTSI, BSE30, BVSP, and JTOPI). The selection of the indices studied (BSE30 for India, JTOPI for South Africa, BVSP for Brazil, SSE for China, RTSI for Russia, and S&P 500 for the United States) is based on their representativeness of the respective national markets, their widespread use in the academic literature on market connectedness (Syriopoulos et al., 2015; Jareño et al., 2023), and the availability of continuous and reliable time series over the study period. This selection ensures both the relevance and comparability of the results. All the datasets are retrieved from www.datastream.com. To calculate returns, we used the formula Rt=ln (Pt/Pt-1), where Pt denotes today's price.

1 The rate of occurrence or repetition of an event within a specified time frame.

Analyzing the relationship between the stock indices of the USA and BRICS offers a deep understanding of global economic interdependence. By exploring this relationship, stakeholders gain critical insights into global market integration, systemic risk assessment, and the crafting of resilient investment strategies, making it a fundamental endeavor for understanding the complexities of our interconnected world (Syriopoulos et al., 2015; Jareño et al., 2023).

Descriptive statistics of these return series are reported in Table 1. Among all indices, the BVSP index offers the highest average returns, while the RTSI exhibits the highest volatility. The same conclusion could be drawn for the pandemic period. However, during the war, the USA index shows the highest volatility, while the RTSI index offers the highest returns. On the other hand, we test for asymmetry in the distribution, whether it is left-skewed (if values are negative) or right-skewed (if values are positive), using the Skewness statistic. The results indicate that all assets exhibit left-skewed distributions. Furthermore, we analyze the Kurtosis statistic to determine whether the data follow a normal distribution or exhibit a heavy-tailed distribution, indicating an increased probability of extreme values, especially for RTSI. Such information allows making appropriate decisions based on the results of the heavy-tailed kurtosis test. The statistical values show that they are high for all studied assets. However, in general, all assets exhibit asymmetric distributions, as indicated by the Jarque-Bera statistic.

Table 1. Descriptive statistics of U.S. (S&P 500) and BRICS stock indices

		Before COVID			
Variable	Obs	Mean	Std. dev.	Min	Max
SP500	1,073	.0003641	.0085356	-.0451682	.0484032
SSE	1,073	-.0000782	.0113843	-.0799438	.0612992
RTSI	1,073	.000482	.0138679	-.1215325	.0896393
BSE30	1,073	.0003568	.0078956	-.0371215	.0518589
BVSP	1,073	.0007906	.0135903	-.0921068	.0638867
JTOPI	1,073	.0000472	.0099841	-.0464712	.0389774
		During COVID			
SP500	1,989	.0003994	.0116998	-.1276521	.0896832
SSE	1,989	-.0000286	.0106819	-.0799438	.0612992
RTSI	1,989	.0001591	.0213734	-.4829211	.2320443
BSE30	1,989	.0004895	.0105586	-.1410174	.0674683
BVSP	1,989	.0005231	.0157121	-.1599383	.1302282
JTOPI	1,989	.0002213	.0119324	-.1045042	.079071
		During War			
SP500	405	.0000913	.012611	-.0441991	.0539525
SSE	405	-.0002357	.0096097	-.0526801	.0342441
RTSI	405	.0008047	.0238332	-.0977277	.2320443
BSE30	405	.0005392	.0084367	-.0278262	.0335798
BVSP	405	.0001537	.0123357	-.0340746	.0539339
JTOPI	405	.000065	.0123721	-.0388194	.0534214

Note: SP500 = Standard & Poor's 500 Index (U.S.); SSE = Shanghai Stock Exchange Composite Index (China); RTSI = Russian Trading System Index (Russia); BSE30 = Bombay Stock Exchange 30 Index (India); BVSP = Bovespa Index (Brazil); JTOPI = Johannesburg Top 40 Index (South Africa). The table reports descriptive statistics for daily stock index returns before COVID-19 (January 2016–December 2019), during COVID-19 (January 2020–February 2022), and during the Russia–Ukraine war (February 2022–December 2022). Mean and standard deviation are expressed in daily return units. Min and Max indicate the minimum and maximum values observed in each period, respectively.

The mean values do not accurately reflect the actual state of affairs. To address this limitation, we charted the daily stock returns to derive more insightful insights. Notably, we observed significant volatility spikes across nearly all indices, particularly during the pandemic and the war. The pandemic saw particularly sharp peaks, but the elevated levels of volatility persisted during the war. Of particular interest, the Chinese index SSE exhibited consistent volatility throughout the entire period. Additionally, during the war, the RTSI experienced an exceptional surge in volatility, followed by a brief period of no returns.

Table 2. Asymmetry measures and correlation statistics of U.S. and BRICS stock indices

	SP500	SSE	RTSI	BSE.30	BVSP	JTOPI
Skewness	-0.864***	-0.726***	-5.746***	-1.689***	-1.195***	-0.543***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ex. Kurtosis	16.875***	7.179***	140.782***	23.960***	17.199***	7.325***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JB	23846.316***	4446.084***	1653488.496***	48524.346***	24987.547***	4544.699***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
ERS	-20.160***	-20.401***	-17.482***	-17.978***	-16.619***	-19.837***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Q(20)	218.290***	32.891***	40.094***	57.590***	79.160***	26.187***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Q2(20)	2282.361***	216.419***	116.825***	1016.600***	2237.693***	1527.528***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
kendall	SP500	SSE	RTSI	BSE.30	BVSP	JTOPI
SP500	1.000***	0.071***	0.172***	0.127***	0.241***	0.205***
SSE	0.071***	1.000***	0.105***	0.141***	0.056***	0.186***
RTSI	0.172***	0.105***	1.000***	0.176***	0.178***	0.251***
BSE.30	0.127***	0.141***	0.176***	1.000***	0.114***	0.252***
JTOPI	0.205***	0.186***	0.251***	0.252***	0.169***	1.000***

Note: SP500 = Standard & Poor's 500 Index (U.S.); SSE = Shanghai Stock Exchange Composite Index (China); RTSI = Russian Trading System Index (Russia); BSE.30 = Bombay Stock Exchange 30 Index (India); BVSP = Bovespa Index (Brazil); JTOPI = Johannesburg Top 40 Index (South Africa). Skewness and excess kurtosis tests for distributional properties. JB = Jarque–Bera test for normality. ERS = Elliott–Rothenberg–Stock unit root test. Q(20) = Ljung–Box test for autocorrelation up to lag 20.$Q^2(20)$ = Ljung–Box test for ARCH effects. Kendall's Tau measures rank correlation.*** denotes significance at the 1% level.

5. Empirical results

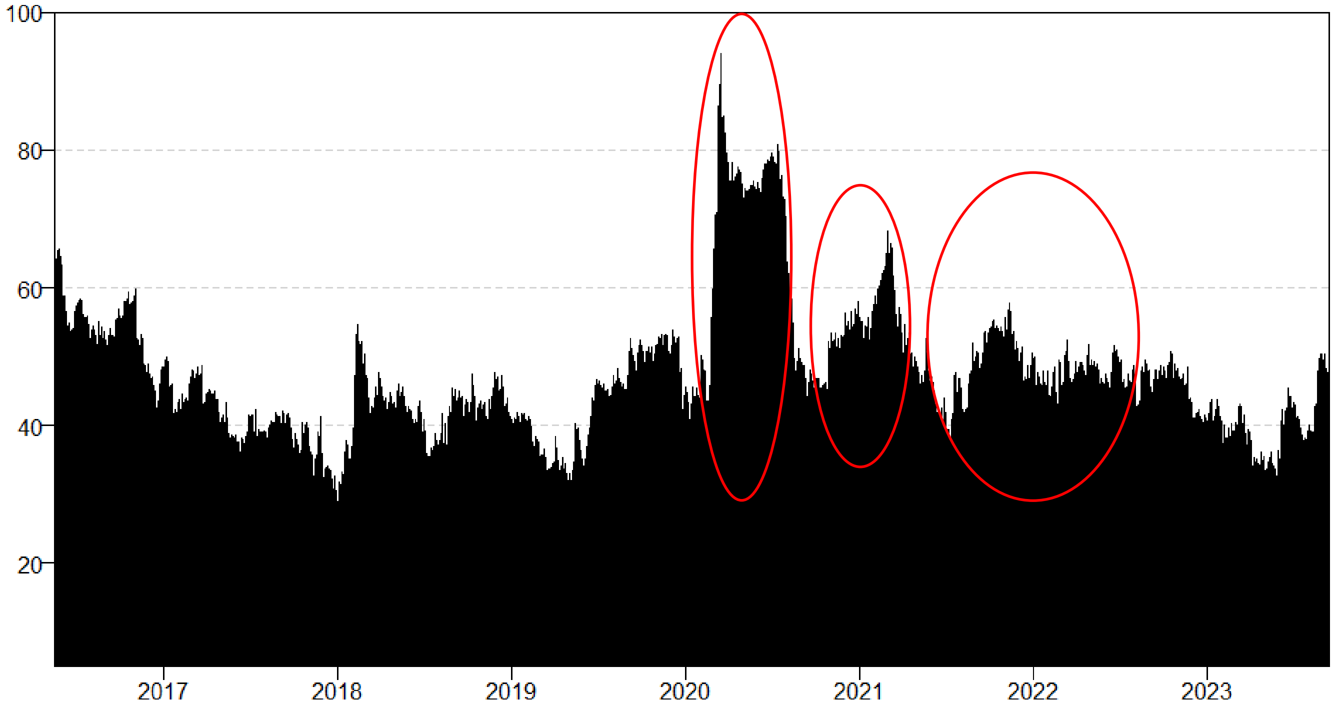
Next, we examine the study's results and discuss pertinent topics arising from it. We mainly focus on dynamic results based on quantiles and frequencies derived from empirical data, drawing on the work of Diebold and Yılmaz (2012, 2014) and Chatziantoniou et al. (2021). Thus, the novel method allows for assessing the connectedness by various quantiles and frequencies. Consequently, it provides a deeper understanding of the time-domain connectedness approach and a richer analysis of tail dependencies. Therefore, we can analyze whether short- and long-term connectedness varies across quantiles (Bouri et al., 2021; Yousaf & Yarovaya, 2022).

5.1. Dynamic connectedness measures in median quantile (Q=0.5):

The results in Figure 2 show that the TCI fluctuates on average between 30% and 60%, reaching a peak of 90% during COVID-19 (Q2 and Q3 in 2020), rising to 50-70% at the beginning of 2021 (corona waves), then declining to around 30%. During the war, it remained stable at 50% until the end of 2023. These findings suggest that large shocks can significantly disrupt the network of interconnections, as mutual interconnections among the studied assets amplify the transmission of risk spillovers across the USA and BRICS financial markets.

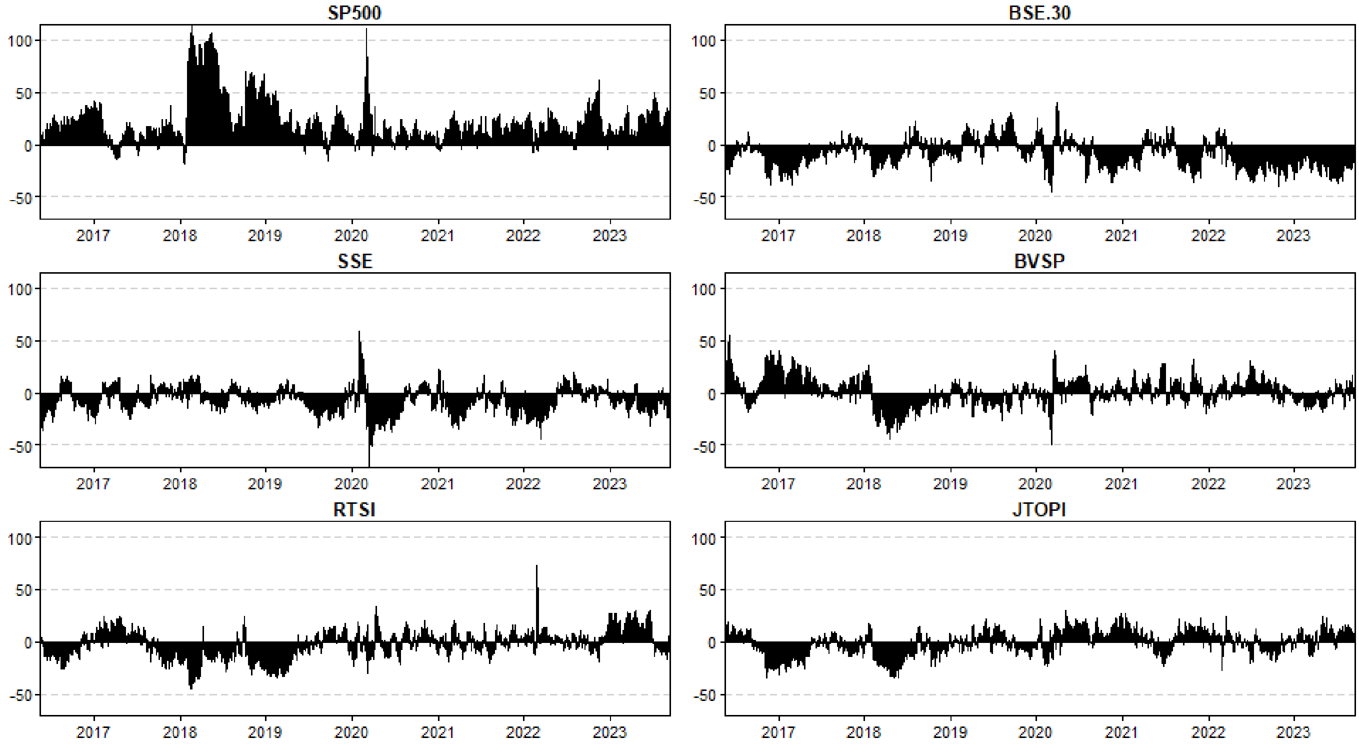
Considering the net-connectedness status in Figure 3 and following Aharon et al. (2023), we observe that all assets display different statuses as net transmitters or receivers across periods, except the S&P 500, which maintains a stagnant net-transmitting role. This stable behavior of the S&P 500 can be attributed to its dominant position and high liquidity in global financial markets, which make it less sensitive to short-term shocks than other BRICS indices (Boubaker et al., 2022). During COVID-19, SSE acted as a net receiver of shocks, while BSE and BVSP were net transmitters. During the war, BSE became a net receiver, whereas BVSP remained a net transmitter. The remaining indices demonstrate heterogeneous statuses, alternating between receiving and transmitting roles over time. These role fluctuations provide important insights for portfolio managers and risk managers, indicating that the system is susceptible to short-term shocks. They highlight the need to monitor both short- and long-term dynamics, enabling managers to adjust positions and implement effective hedging strategies, as assets may temporarily become net transmitters or receivers of shocks. Overall, this underscores the importance of dynamic and flexible investment strategies that account for time-varying interconnections among markets.

Figure 2. Dynamic Total Connectedness at the Median Quantile (Q = 0.5) for U.S. and BRICS Stock Indices, 2017- 2023



Note: Figure 2 shows the dynamic total connectedness index at Q = 0.5 for the U.S. (S&P 500) and BRICS stock indices (SSE, RTSI, BSE30, BVSP, JTOPI). Higher values indicate more substantial spillovers. Peaks correspond to major crises such as COVID-19 (2020), the Russia-Ukraine war (2022), and the 2023 banking turmoil.

Figure 3. Dynamic net total connectedness at the median quantile (Q = 0.5) among U.S. and BRICS stock indices



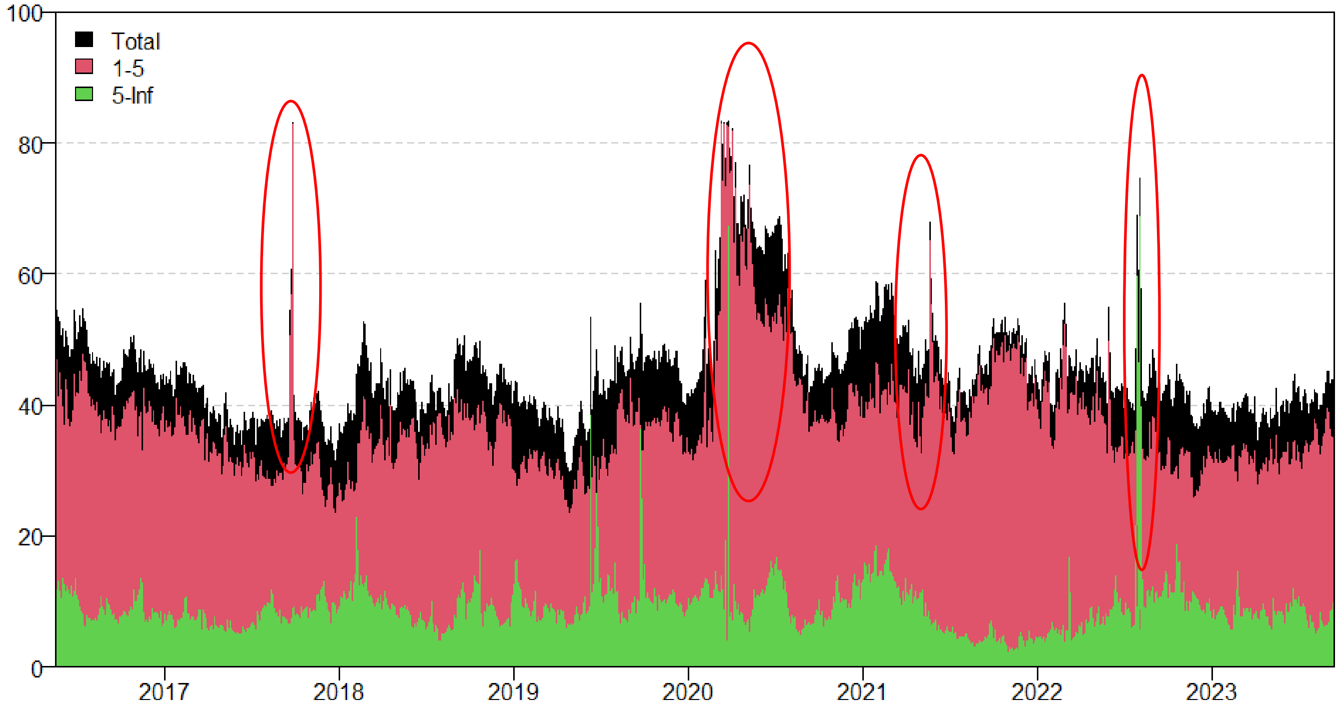
Note: Figure 3 shows the dynamic net total connectedness index among U.S. (S&P 500) and BRICS stock indices (SSE, RTSI, BSE30, BVSP, JTOPI). Positive values indicate net transmitters of shocks, negative values indicate net receivers. Sample period: 2017–2023.

5.2. Connectedness measures in median quantile (By virtue of frequency):

In Figure 4, we analyze the median short-term, long-term, and total dynamic connectedness, as a single analysis of the total TCI could mask the origins of the movements. We point out that the black-shaded areas represent total connectedness, while both the red- and green-shaded areas indicate short- and long-run connectedness. This is especially important when looking at both crises: COVID-19 and the war between Russia and Ukraine. The analysis shows that the increase in the total TCI is mainly driven by short-term dynamics, not by long-term dynamics. We find that the standard VAR overestimated the effects of the COVID-19 pandemic and the war, as the peaks of long-term TCI are subsequently corrected. When short-term connectedness surpasses long-term connectedness, it means a robust, immediate interconnection among the studied assets. This suggests that changes in one variable can quickly affect or be affected by others in the short run, indicating a highly sensitive system to short-term fluctuations and thus short-term connectedness. This suggests that investors react rapidly to market dynamics, focusing on short-term gains or losses. This dynamic highlights the need for attentive monitoring of short-term market trends, for controlling trading strategies and risk assessments, and for contextual interpretation of whether this connectivity is beneficial.

Besides, the long-term TCI remained relatively constant at lower values than the short-term TCI, with temporary peaks that affect the total TCI. Therefore, short-term and long-term dynamics should be examined separately. This is of significant importance to investors and risk managers, as a notable shift in the overall long-term TCI typically indicates a profound alteration in the market framework (refer to Chatziantoniou et al., 2021). Emphasizing the need to break down the comprehensive TCI into short- and long-term components is essential for a better understanding of its dynamics.

Figure 4. Dynamic total connectedness of U.S. and BRICS stock indices across different quantiles



Note: Results are based on a QVAR model with a 100 rolling window size, a lag length of order one (BIC), and a 100-step-ahead generalized forecast error variance decomposition. The black area represents the time-dependent connectedness values, while the green and red areas show the long- and short-term results.

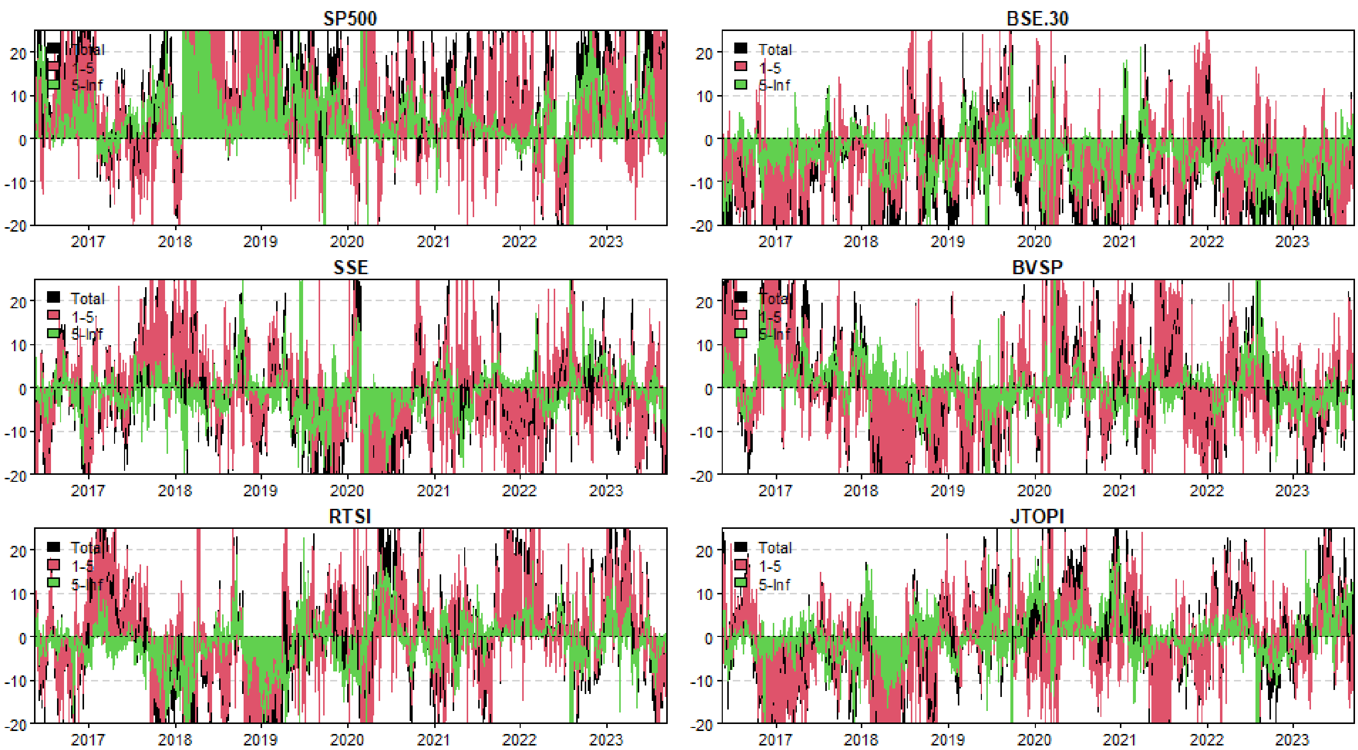
We next present the results for the net transmission power of each series in Figure 5, where negative (positive) values indicate net receivers (transmitters) of shocks.[2] The spillover pattern appears to be time-varying across frequencies since short- and long-term dynamics are not constant. Specifically, we found that both short- and long-term dynamics are responsible for each of the studied series being either a net transmitter or a net receiver of shocks. In contrast, the long-term net transmission mechanism provides a clear picture of SP500 shock spillover during 2018 and 2019. In the case of the SP500 Index, we observe that throughout the period of time, the short-term dynamics point to the fact that it is a net receiver of shocks, just temporarily and always caused by both short and long-term dynamics, the series becomes a net transmitter of shocks (Neto, 2025). Overall, for the USA and BRICS indices, short-term dynamics either strengthen or weaken the net transmission or reception power of the series, with a greater effect than long-term dynamics, and these dynamics are not constant over time. Several factors can explain why short-term dynamics have a more substantial impact than long-term dynamics. First, financial markets are susceptible to sudden economic and geopolitical events, such as COVID-19 or the Russia–Ukraine war, which can cause rapid, significant short-term fluctuations. Second, investors often react immediately to news and market variations, reinforcing short-term interactions among indices and intensifying shock transmission. Finally, peaks of total connectedness (TCI) are mainly driven by short-term dynamics, indicating that indices respond more strongly to immediate events than to long-term structural changes. To conclude, when short-term frequency consistently exceeds long-term frequency, it suggests a system characterized by frequent, dynamic interactions or

[2] Moreover, the total net connectedness is represented by black-shaded area results, while both red- and green-shaded findings point to both short- and long-run connectedness.

events in the short term relative to prolonged periods. This high short-term frequency is associated with elevated total net connectedness, indicating a substantial degree of interactivity and rapid changes within the system, mainly influenced by short-term events. This information is of significant interest to financial advisors and investors, as the short- and long-term characteristics of being a transmitter or receiver are changing over time. This highlights the need for investment strategies to adapt accordingly. Portfolio managers should actively monitor short-term fluctuations, adjust positions rapidly, and implement dynamic hedging strategies to manage risk effectively. Investment strategies must be flexible and responsive to both short- and long-term dynamics to maintain portfolio stability and capitalize on market opportunities.

Such a system is notably sensitive to immediate shifts or disturbances. Consequently, decision-making and analytical approaches should emphasize short-term trends and responses, recognizing their heightened frequency and potential to exert substantial impacts. Thus, such evidence on the network's influence on the series helps inform investment strategies to manage risk. We join the results of Dakhlaoui and Aloui (2016), Lan et al. (2023), and Zhang et al. (2024).

Figure 5. Dynamic net total connectedness of U.S. and BRICS stock indices across different quantiles

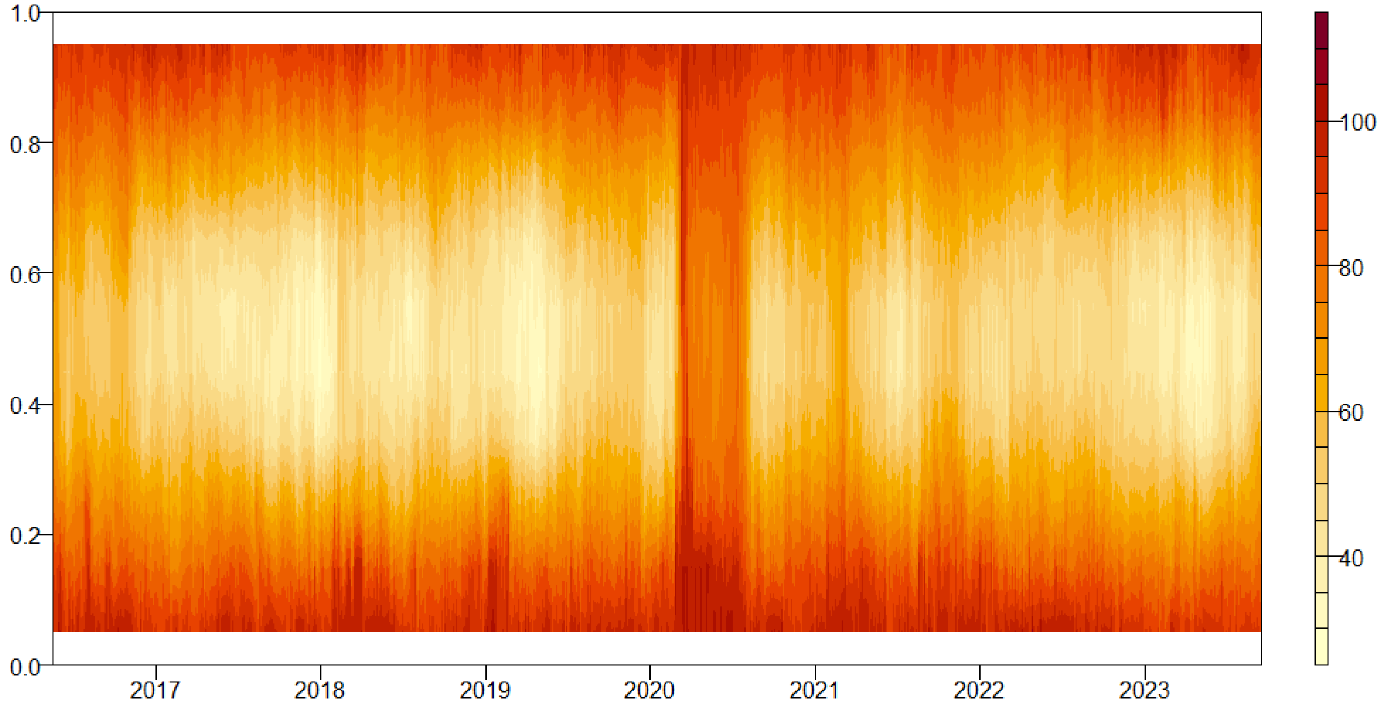


Note: The figure shows the net total connectedness index across quantiles (Q = 0.1, 0.5, 0.9) for U.S. (S&P 500) and BRICS indices (SSE, RTSI, BSE30, BVSP, JTOPI), 2017–2023.

5.3. Connectedness measures in different quantiles (By virtue of quantiles):

Next, we focus on risk spillover arising from quantiles. The results reported in Figure 6 demonstrate the total dynamic connectedness. Warmer shades on the plot indicate higher levels of connectedness. We find that connectedness is extreme both for highly negative returns (below the 20% quantile) and for highly positive changes (above the 80% quantile). We can conclude thus that the impact appears to be symmetric. Thus, our findings improve the robustness of previous findings. Moreover, the 50% quantile indicates the average connectedness over the entire period. It shows significant values at specific intervals (the end of 2017, Q1 of 2018, the second half of 2019, Q2 and Q3 of 2020, Q1 and Q4 of 2021, the beginning of 2022, and from the second half of 2022 to the beginning of 2023). This shows a somewhat cyclical pattern of connectedness over time, stemming from the fact that connectedness is extremely event-dependent (Oral & Özkan, 2024; Zhang et al., 2025).

Figure 6. Dynamic Total Connectedness of BRICS and U.S. Stock Markets Across Quantiles



Note: The figure shows the total connectedness index across quantiles for U.S. (S&P 500) and BRICS stock markets (SSE, RTSI, BSE30, BVSP, JTOPI), 2017–2023.

Next, we analyze net directional results across quantiles. These outcomes are taken in figures 7-8-9-10-11-12. Warmer shades on these plots indicate a net-transmitting asset, and cooler shades indicate a net-absorbing asset. According to the results, we notice that SP500 and BVSP are generally net transmitters of shocks to the network. Noteworthy episodes include the Q2 and Q3 of 2018, the beginning of 2019, and the coronavirus spread in Q2 of 2020 for the SP500. The BVSP net transmitter is very low compared to the USA index (Das and Roy, 2023), with a shifting role from net transmitter during 2017 and from the CORONA spread to the end of 2023, and a net receiver from 2018 and the first half of 2019 in the mean quantile. According to the results of Das and Roy (2023), the South African index is marked by a net reception of shocks at the end of 2016 and the beginning of 2018, and is elsewhere a net transmitter of volatility to the system.

Furthermore, the BSE index shows an alternating pattern of net transmission and reception of chocks, with a clear receiving role during the war. On the other hand, while SSE is almost a permanent receiver of volatility, the Brazilian index changes status over time and across quantiles, but it clearly shows a net receiver of shocks during 2018 and the beginning of 2019.

Figure 7. Net Dynamic Connectedness Across Quantiles – U.S. (S&P 500)

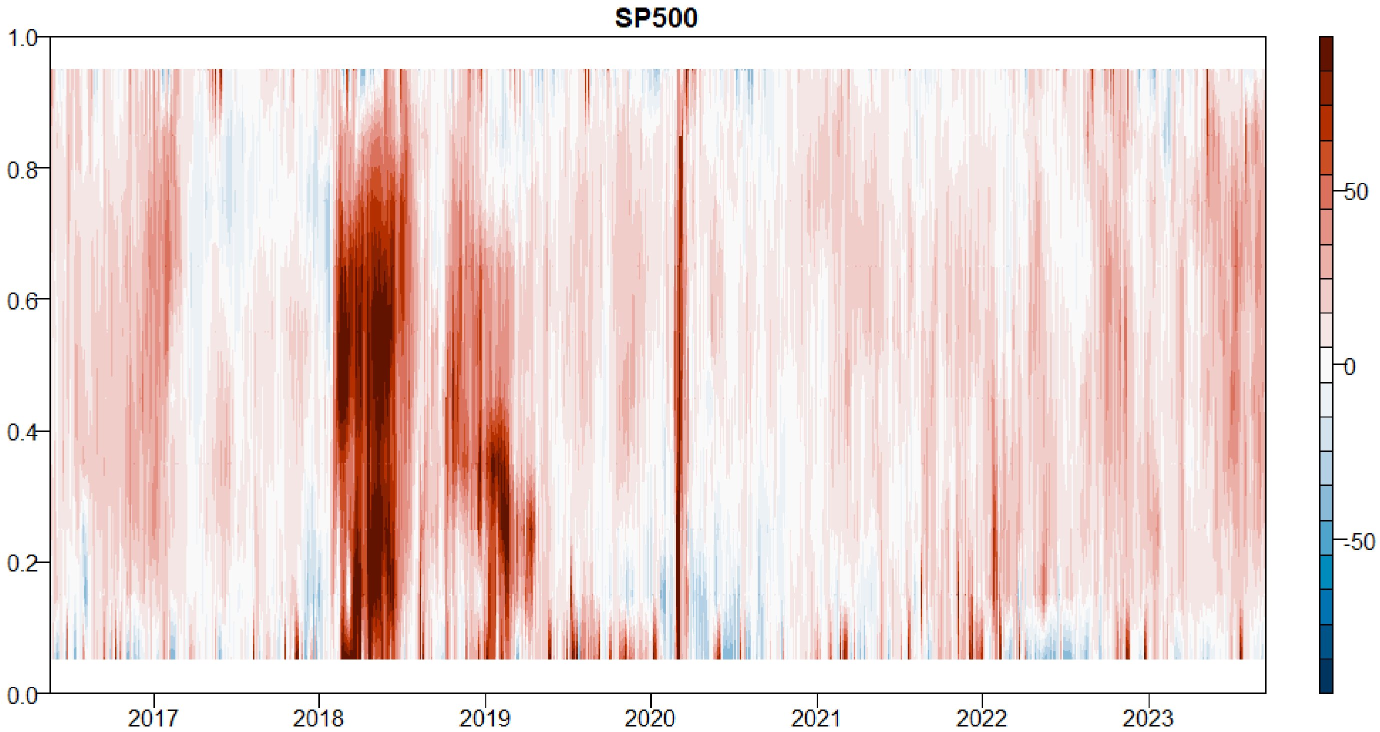


Figure 8. Net Dynamic Connectedness Across Quantiles – Russia (RTSI Index)

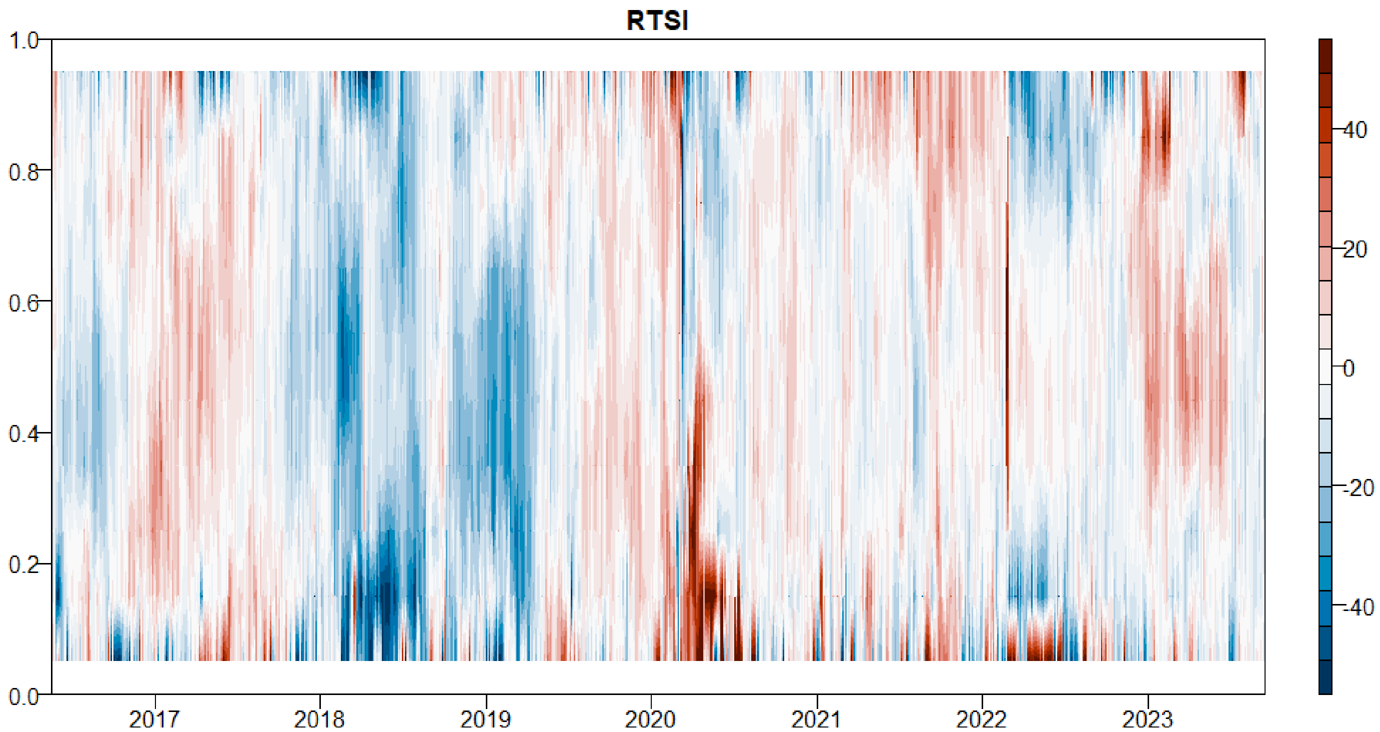


Figure 9. Net Dynamic Connectedness Across Quantiles – China (SSE Composite)

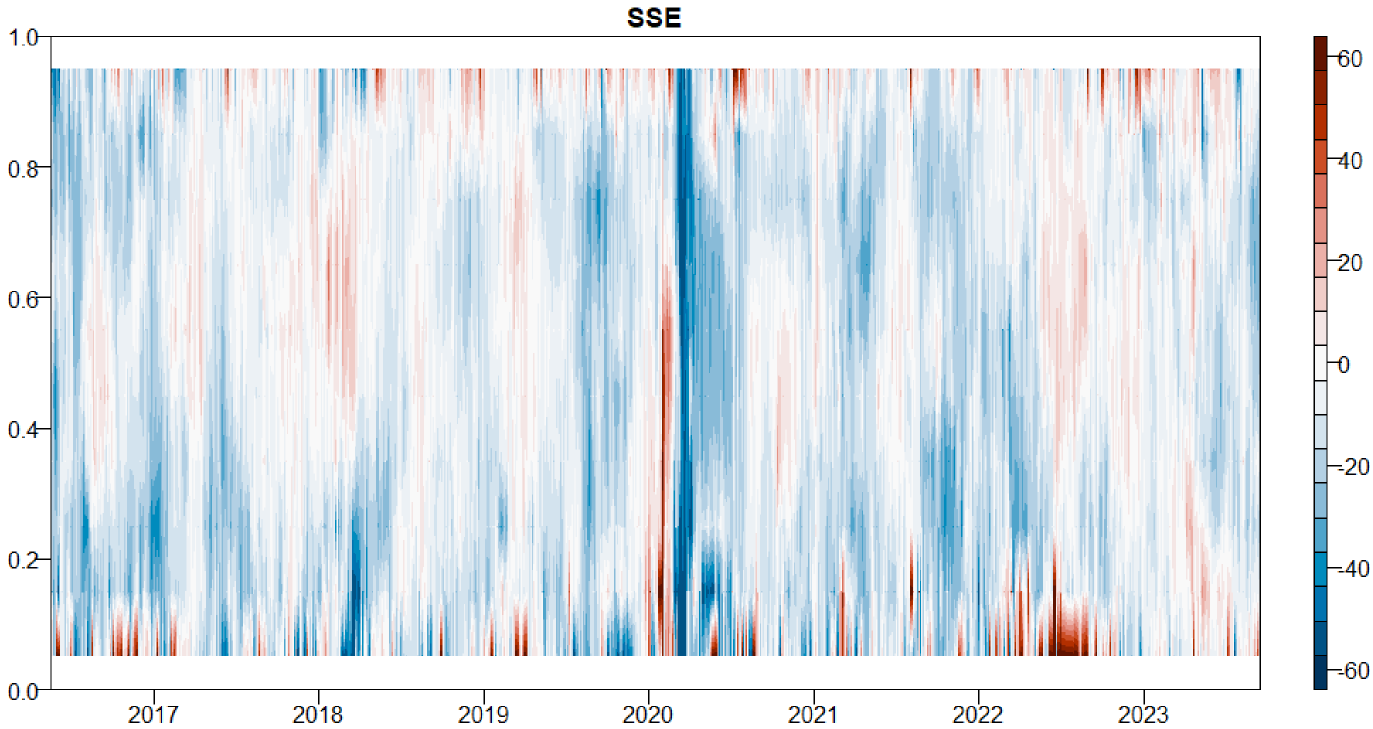


Figure 10. Net Dynamic Connectedness Across Quantiles – India (BSE 30 Index)

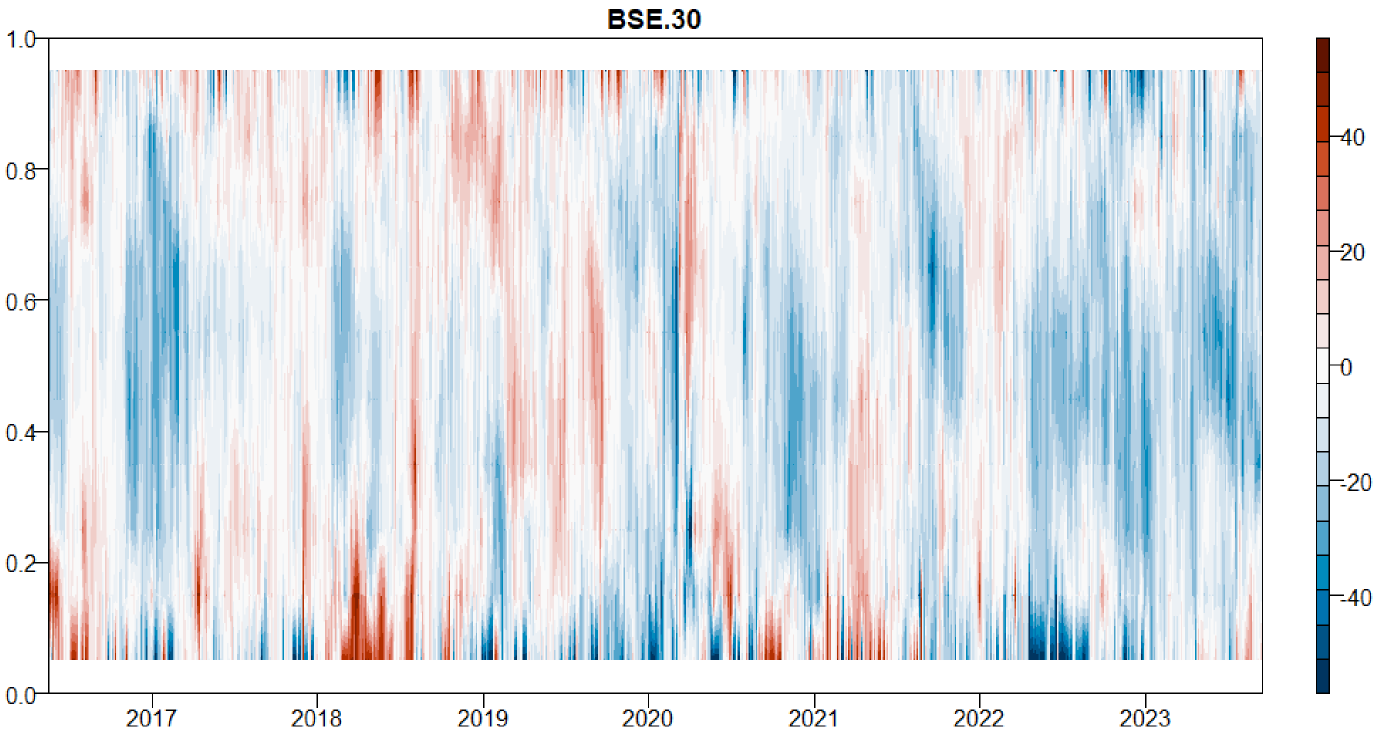


Figure 11. Net Dynamic Connectedness Across Quantiles – Brazil (BVSP Index)

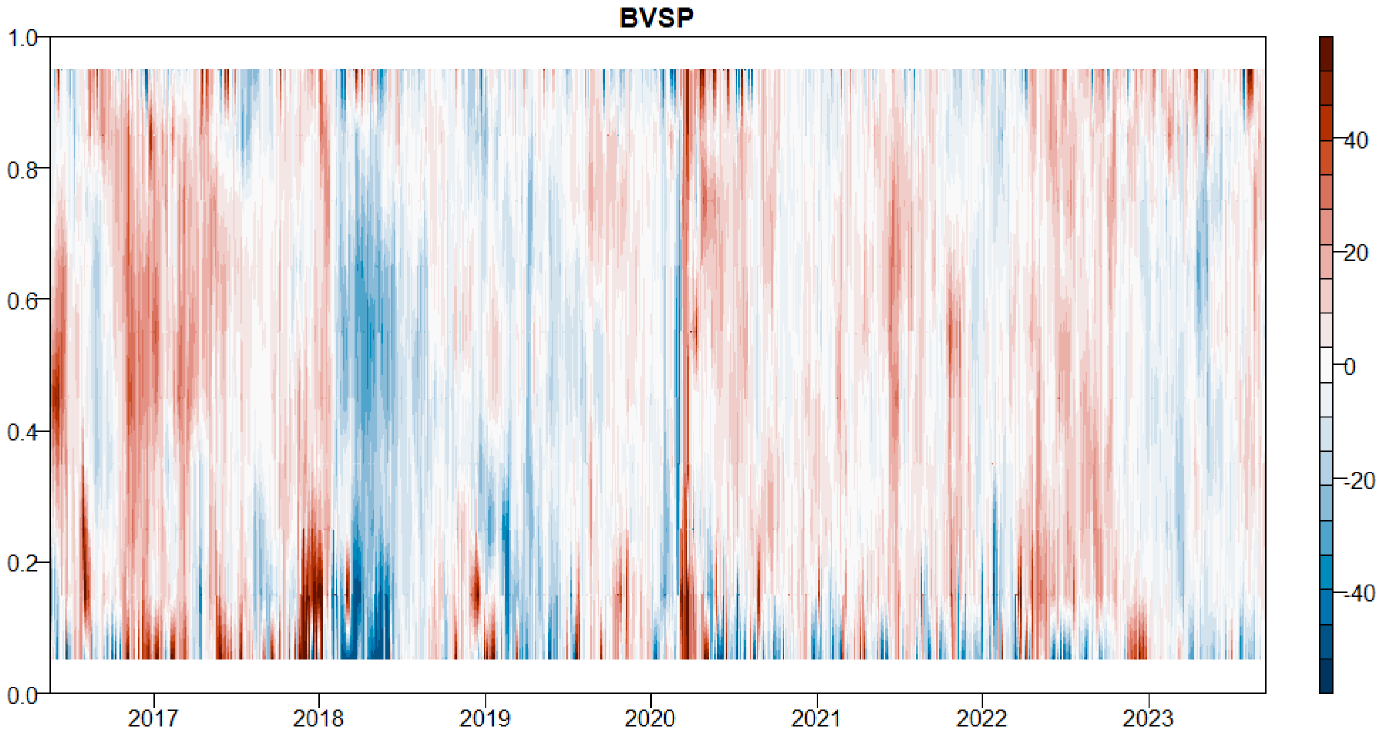
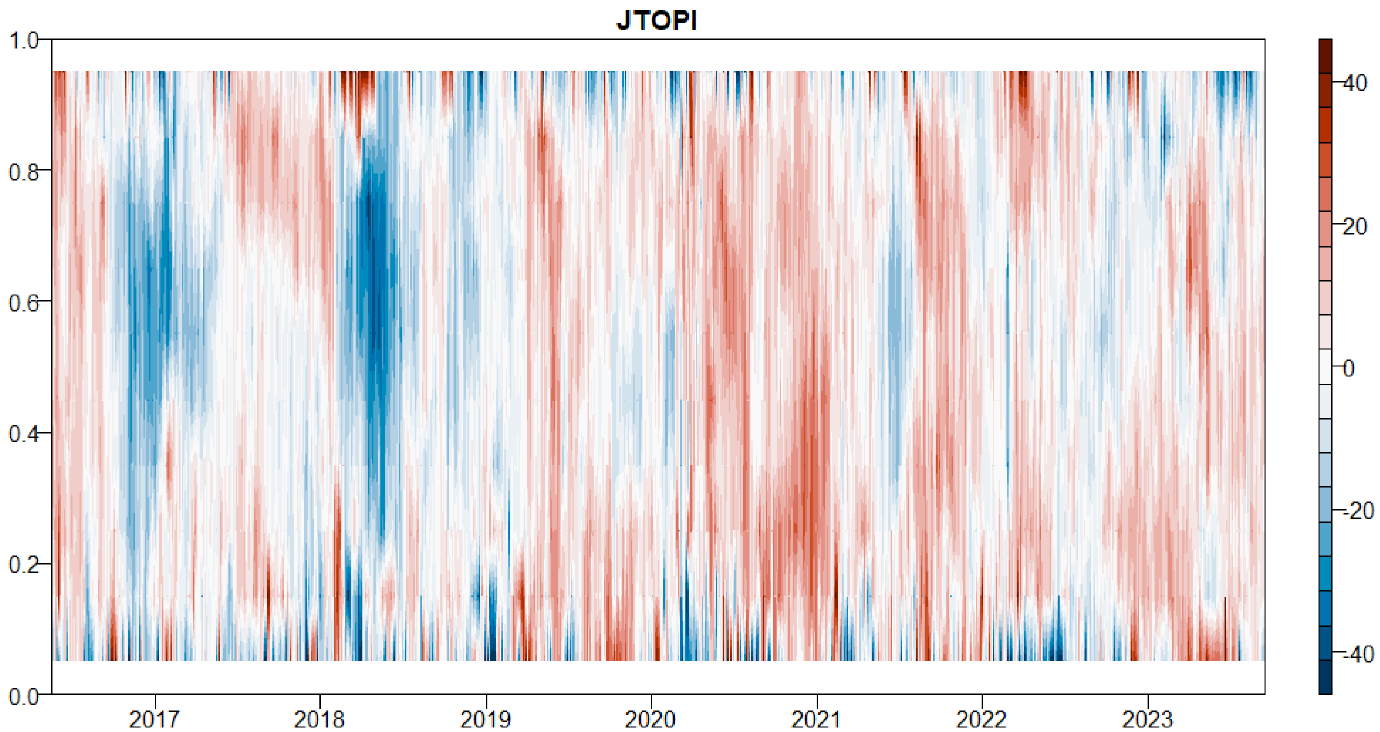


Figure 12. Net Dynamic Connectedness Across Quantiles – South Africa (JTOPI Index)



Note: These figures show the dynamic net connectedness indices for the U.S. (S&P 500) and BRICS stock markets from 2017 to 2023. Positive values indicate net shock transmitters (red), while negative values indicate net receivers (blue).

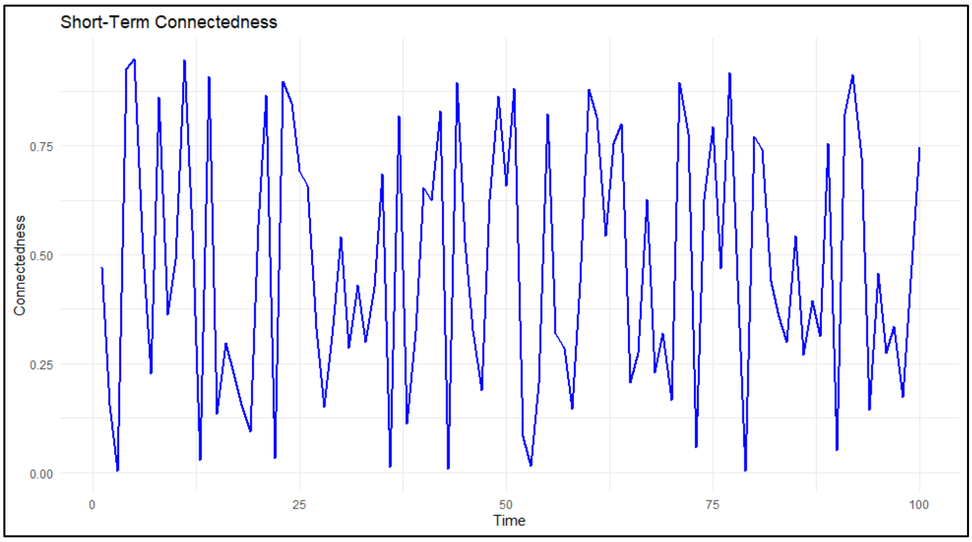
5.4. Connectedness measures in short and long frequency (By virtue of quantiles):

Considering the long-term Quantile Vector Autoregressive (QVAR) curve, which represents estimated conditional quantiles at different levels (see figures 13 and 14), discloses how the system behaves across quantiles in an extended timeframe. This curve provides insights into the distribution of the variable and its tail behavior, with higher quantiles indicating extreme outcomes and lower quantiles representing more typical outcomes. Shapes, sudden changes, or critical quantiles in the curve provide valuable insights into the system's behavior and potential areas for further study. Linking this long-term curve with its short-term counterpart can elucidate differences in behavior at corresponding quantile levels (see Figure 15). Considering the system's behavior across distinct quantiles is important for making informed decisions, particularly in risk assessment and strategic design, where long-term dynamics are critical for comprehensive analysis.

We find that, in both short- and long-term frequency, connectedness is generally high in the upper and lower quantiles, with higher values for short-term frequency. We can also conclude that the two frequencies are symmetric for highly negative returns (below the 20% quantile) and highly positive changes (above the 80% quantile). When examining the frequency dynamics across quantiles, a notable observation is that during particular periods, marked by green circles, the behavior of short-term and long-term dynamics appears to be opposite. This implies that at these specific quantile levels, short-term events tend to rise when long-term events decrease, and vice versa.

This inverse relationship between short-term and long-term dynamics at particular quantiles has several implications. Initially, it signifies a complex interplay between immediate fluctuations and broader system trends. Then, understanding these inverse movements can help anticipate shifts in the system: when short-term events escalate, long-term occurrences may be in decline, and vice versa. This intuition is valuable for decision-making and resource-allocation strategies, enabling a more nuanced and proactive approach to effectively handle system dynamics (Chalissery et al., 2024; Agarwal et al., 2024; Zhang et al., 2025).

Figure 13. Short-Term Total Connectedness Across BRICS and U.S. Stock Markets



Note: The figure shows the short-term total connectedness index for the U.S. (S&P 500) and BRICS stock markets (SSE, RTSI, BSE30, BVSP, JTOPI) during 2017–2023. Higher values indicate more substantial short-term spillovers among markets.

Figure 14. Long-Term Total Connectedness Across BRICS and U.S. Stock Markets

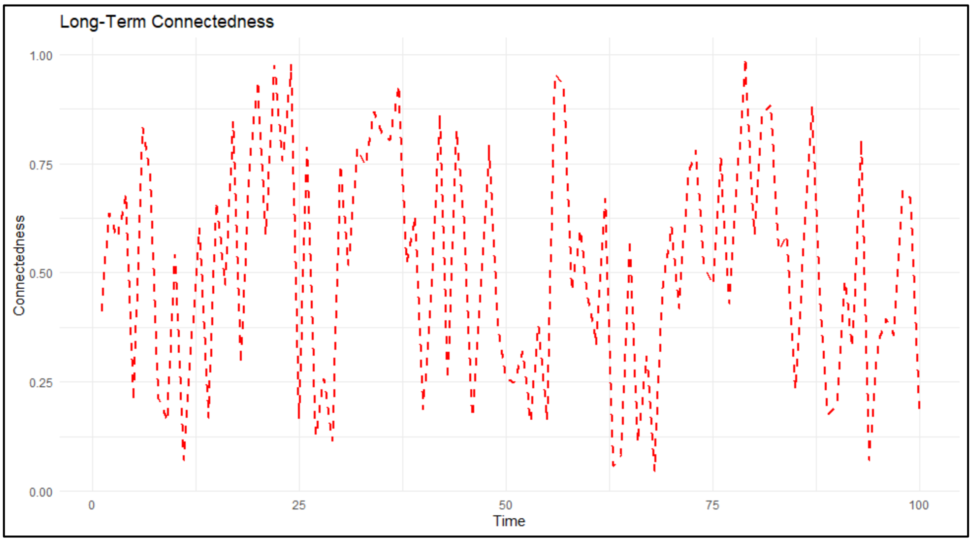
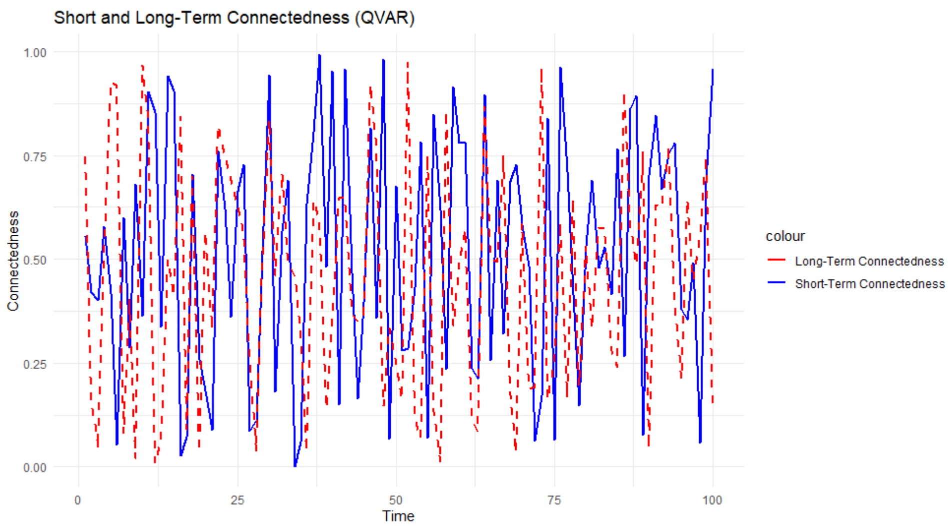


Figure 15. Short- and Long-Term Connectedness of BRICS and U.S. Stock Markets Using QVAR



Note: Figure 14 shows the long-term total connectedness index, while Figure 15 compares short-term (blue solid line) and long-term (red dashed line) connectedness indices estimated from a QVAR model. Both figures cover the U.S. (S&P 500) and BRICS stock markets over 2017–2023. Higher values indicate more substantial spillovers, with short-term connectedness capturing immediate effects and long-term connectedness reflecting more persistent interdependence across markets.

6. Conclusion

This study examined the dynamic return–risk connectedness between BRICS and U.S. markets across different quantiles and frequencies, with particular attention to the impact of major crises, including the COVID-19 pandemic, the Russia-Ukraine war, and the 2023 banking turmoil. The findings demonstrate that short-term dynamics dominate in shaping total connectedness, with indices alternating between being net transmitters and receivers of shocks depending on market conditions. The inverse relationship between short- and long-term dynamics at specific quantiles further underscores the system's sensitivity to immediate disturbances and highlights the importance of monitoring short-term market behavior (Diebold & Yilmaz, 2014; Chatziantoniou et al., 2021).

From a practical perspective, these results provide valuable insights for international investors, portfolio managers, and policymakers. They confirm the need to adapt investment strategies to account for heightened short-term volatility and shifting interdependencies, in line with previous evidence on the role of spillover analysis in asset allocation (Aloui et al., 2011; Mensi et al., 2017b; Jareño et al., 2023). Policymakers can also benefit from these insights, as understanding cross-market spillovers is essential for designing measures that enhance financial stability during episodes of global turbulence (Bekaert & Harvey, 2017; Chalissery et al., 2024; Neto, 2025). From a theoretical standpoint, the study contributes to the literature on market connectedness by employing a quantile and frequency-based framework that enriches traditional methodologies (Diebold and Yilmaz, 2012, 2014) and complements recent works such as Lan et al. (2023) and Zhang et al. (2024).

Nevertheless, some limitations remain. The analysis is restricted to BRICS and U.S. stock indices, excluding other emerging or developed markets and alternative asset classes such as bonds, commodities, or cryptocurrencies, which may also exhibit significant spillover effects (Salem & Jeribi, 2025). While the quantile connectedness approach provides robust insights, future research could integrate nonlinear models or machine learning methods to capture complex dynamics better (Shi, 2021). Expanding the scope to sectoral or green/blue indices (Bouzguenda & Jarboui, 2025b) and examining the role of institutional and macroeconomic fundamentals would further enrich the analysis. Moreover, given the growing importance of geopolitical and climate-related risks, investigating their influence on the persistence of spillovers would provide deeper insights into the resilience and vulnerabilities of global financial systems.

Overall, the results highlight the importance of considering both short and long-term dynamics in assessing inter-market linkages. By offering a more comprehensive understanding of risk transmission mechanisms, this study supports informed decision-making in investment and policy contexts. It contributes to ongoing debates on financial stability in an increasingly interconnected world.

Author Contributions: Conceptualization, M.B. and A.J.; methodology, M.B.; software, M.B.; validation, A.J.; formal analysis, A.J.; investigation, M.B.; writing original draft preparation, M.B.; visualization, M.B.; supervision, A.J.; project administration, A.J. All authors have read and agreed to the published version of the manuscript

Funding: The authors received no financial support for the research and authorship of this article.

Data Availability Statement: Data will be made available on request.

Conflicts of Interest: The authors have no conflicts of interest to declare that are relevant to the content of this article.

AI Use Statement: The author confirms that no AI-based tools were used in the preparation of this manuscript.

References

Agarwal, A., Dhankhar, N., & Mehla, S. (2024). Interconnectedness and Spillover Effects amongst the Stock Markets of the US, China, Germany, Japan, and India using the DCC-GARCH Model and the Diebold-Yilmaz Method. *Colombo Business Journal*, *15*(2). https://doi.org/10.4038/cbj.v15i2.197

Aharon, D. Y., Ali, S., & Naved, M. (2023). Too big to fail: The aftermath of Silicon Valley Bank (SVB) collapse and its impact on financial markets. *Research in International Business and Finance*, *66*, 102036. https://doi.org/10.1016/j.ribaf.2023.102036

Aloui, R., Aïssa, M. S. B., & Nguyen, D. K. (2011). Global financial crisis, extreme interdependences, and contagion effects: The role of economic structure?. *Journal of Banking & Finance*, *35*(1), 130–141.

Arin, K. P., Ciferri, D., & Spagnolo, N. (2008). The price of terror: The effects of terrorism on stock market returns and volatility. *Economics Letters*, *101*(3), 164–167. https://doi.org/10.1016/j.econlet.2008.07.007

Assaf, R., Gupta, D., & Kumar, R. (2023). The price of war: Effect of the Russia-Ukraine war on the global financial market. *The Journal of Economic Asymmetries*, *28*, e00328. https://doi.org/10.1016/j.jeca.2023.e00328

Bekaert, G., Harvey, C. R., Lundblad, C. T., & Siegel, S. (2017). Economic and Financial Integration in Europe1. *Capital Markets Union and Beyond*, 69. https://doi.org/10.7551/mitpress/11080.003.0006

Beraich, M., Amzile, K., Laamire, J., Zirari, O., & Fadali, M. A. (2022). Volatility spillover effects of the US, European, and Chinese financial markets in the context of the Russia–Ukraine conflict. *International Journal of Financial Studies*, *10*(4), 95. https://doi.org/10.3390/ijfs10040095

Bhuyan, R., Robbani, M. G., Talukdar, B., & Jain, A. (2016). Information transmission and dynamics of stock price movements: An empirical analysis of BRICS and US stock markets. *International Review of Economics & Finance*, *46*, 180–195. https://doi.org/10.1016/j.iref.2016.09.004

Boubaker, S., Goodell, J. W., Pandey, D. K., & Kumari, V. (2022). Heterogeneous impacts of wars on global equity markets: Evidence from the invasion of Ukraine. *Finance Research Letters*, *48*, 102934. https://doi.org/10.1016/j.frl.2022.102934

Boungou, W., & Yatié, A. (2022). The impact of the Ukraine–Russia war on world stock market returns. *Economics Letters*, *215*, 110516. https://doi.org/10.1016/j.econlet.2022.110516

Bouri, E., Lei, X., Jalkh, N., Xu, Y., & Zhang, H. (2021). Spillovers in higher moments and jumps across the US stock and strategic commodity markets. *Resources Policy*, *72*, 102060. https://doi.org/10.1016/j.resourpol.2021.102060

Bouzgarrou, H., Ftiti, Z., Louhichi, W., & Yousfi, M. (2023). What can we learn about the market reaction to macroeconomic surprise? Evidence from the COVID-19 crisis. *Research in International Business and Finance*, *64*, 101876. https://doi.org/10.1016/j.ribaf.2023.101876

Bouzguenda, M., & Jarboui, A. (2025). Quantile connectivity between cryptocurrency, commodities, gold, and BRICS index: what is the best investment strategy?. *Eurasian Economic Review*, *15*(1), 125–161. https://doi.org/10.1007/s40822-024-00290-y

Bouzguenda, M., & Jarboui, A. (2025). Unravelling Interconnectedness and Dynamic Behaviour in Financial Networks: Insights from Asset Analysis. *Global Business Review*, 09721509251337189. https://doi.org/10.1177/09721509251337189

Bretas, V. P. G., & Alon, I. (2020). The impact of COVID-19 on franchising in emerging markets: An example from Brazil. *Global Business and Organizational Excellence*, *39*(6), 6–16. https://doi.org/10.1002/joe.22053

Chalissery, N., Nishad, T. M., Naushad, J. A., Tabash, M. I., & Al-Absy, M. S. M. (2024). Beneath the Surface: Disentangling the Dynamic Network of the US and BRIC Stock Markets' Interrelations Amidst Turmoil. *Risks*, *12*(12), 202. https://doi.org/10.3390/risks12120202

Chatziantoniou, I., Gabauer, D., & Stenfors, A. (2021). Interest rate swaps and the transmission mechanism of monetary policy: A quantile connectedness approach. *Economics Letters*, *204*, 109891. https://doi.org/10.1016/j.econlet.2021.109891

Chen, A. H., & Siems, T. F. (2007). The effects of terrorism on global capital markets. In *The Economic Analysis of Terrorism* (pp. 99–122). Routledge. https://doi.org/10.4324/9780203016633-19

Dakhlaoui, I., & Aloui, C. (2016). The interactive relationship between the US economic policy uncertainty and BRIC stock markets. *International Economics*, *146*, 141–157.

Das, S., & Roy, S. S. (2023). Following the leaders? A study of co-movement and volatility spillover in BRICS currencies. *Economic Systems*, *47*(2), 100980. https://doi.org/10.1016/j.ecosys.2022.100980

Diamond, D. W., & Dybvig, P. H. (1983). Bank runs, deposit insurance, and liquidity. *Journal of Political Economy*, *91*(3), 401-419.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting*, *28*(1), 57-66.

Diebold, F. X., & Yılmaz, K. (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics*, *182*(1), 119-134. https://doi.org/10.1016/j.jeconom.2014.04.012

Dimitriou, C. J., Ewoldt, R. H., & McKinley, G. H. (2013). Describing and prescribing the constitutive response of yield stress fluids using large amplitude oscillatory shear stress (LAOStress). *Journal of Rheology*, *57*(1), 27–70. https://doi.org/10.1122/1.4754023

Elsayed, A. H., Naifar, N., Nasreen, S., & Tiwari, A. K. (2022). Dependence structure and dynamic connectedness between green bonds and financial markets: Fresh insights from time-frequency analysis before and during the COVID-19 pandemic. *Energy Economics*, *107*, 105842. https://doi.org/10.1016/j.eneco.2022.105842

Golitsis, P., Gkasis, P., & Bellos, S. K. (2022). Dynamic spillovers and linkages between gold, crude oil, the S&P 500, and other economic and financial variables. Evidence from the USA. *The North American Journal of Economics and Finance*, *63*, 101785. https://doi.org/10.1016/j.najef.2022.101785

Goodell, J. W. (2020). COVID-19 and finance: Agendas for future research. *Finance research letters*, *35*, 101512. https://doi.org/10.1016/j.frl.2020.101512

Hevia, C., & Neumeyer, P. A. (2020). A perfect storm: COVID-19 in emerging economies. *COVID-19 in developing economies*, *1*(1), 25–37. https://doi.org/10.4000/poldev.3457

Jareño, F., Escribano, A., & Umar, Z. (2023). The impact of the COVID-19 Outbreak on the connectedness of the BRICS's term structure. *Humanities and Social Sciences Communications*, *10*(1), 1–12. https://doi.org/10.1057/s41599-022-01500-1

Jeribi, A., Jena, S. K., & Lahiani, A. (2021). Are cryptocurrencies a backstop for the stock market in a COVID-19-led financial crisis? Evidence from the NARDL approach. *International Journal of Financial Studies*, *9*(3), 33.

Karkowska, R., & Urjasz, S. (2023). How does the Russian-Ukrainian war change connectedness and hedging opportunities? Comparison between dirty and clean energy markets versus global stock indices. *Journal of International Financial Markets, Institutions and Money*, *85*, 101768. https://doi.org/10.1016/j.intfin.2023.101768

Kenourgios, D., Samitas, A., & Paltalidis, N. (2011). Financial crises and stock market contagion in a multivariate time-varying asymmetric framework. *Journal of International Financial Markets, Institutions and Money*, *21*(1), 92–106. https://doi.org/10.1016/j.intfin.2010.08.005

Kumari, N., & Choi, S. H. (2022). Tumor-associated macrophages in cancer: recent advancements in cancer nanoimmunotherapies. *Journal of Experimental & Clinical Cancer Research*, *41*(1), 68.

Lan, T., Shao, L., Zhang, H., & Yuan, C. (2023). The impact of the pandemic on the dynamic volatility spillover network of international stock markets. *Empirical Economics*, 1–30.

Lin, Z. C., Wong, I. A., Kou, I. E., & Zhen, X. C. (2021). Inducing well-being through staycation programs in the midst of the COVID-19 crisis. *Tourism Management Perspectives*, *40*, 100907.

Lyócsa, Š., Halousková, M., & Haugom, E. (2023). The US banking crisis in 2023: Intraday attention and price variation of banks at risk. *Finance Research Letters*, *57*, 104209. https://doi.org/10.1016/j.frl.2023.104209

Mensi, W., Hammoudeh, S., Al-Jarrah, I. M. W., Sensoy, A., & Kang, S. H. (2017). Dynamic risk spillovers between gold, oil prices, and conventional, sustainability, and Islamic equity aggregates and sectors with portfolio implications. *Energy Economics*, *67*, 454–475. https://doi.org/10.1016/j.eneco.2017.08.031

Mensi, W., Hammoudeh, S., Nguyen, D. K., & Kang, S. H. (2016). Global financial crisis and spillover effects among the US and BRICS stock markets. *International Review of Economics & Finance*, *42*, 257–276. https://doi.org/10.1016/j.iref.2015.11.005

Mensi, W., Hammoudeh, S., Shahzad, S. J. H., & Shahbaz, M. (2017). Modeling systemic risk and dependence structure between oil and stock markets using a variational mode decomposition-based copula method. *Journal of Banking & Finance*, *75*, 258–279. https://doi.org/10.1016/j.jbankfin.2016.11.017

Mizumoto, K., Kagaya, K., & Chowell, G. (2020). Effect of a wet market on coronavirus disease (COVID-19) transmission dynamics in China, 2019–2020. *International journal of infectious diseases*, *97*, 96–101. https://doi.org/10.1016/j.ijid.2020.05.091

Naveed, M., Ali, S., Gubareva, M., & Omri, A. (2024). When giants fall: Tracing the ripple effects of Silicon Valley Bank (SVB) collapse on global financial markets. *Research in International Business and Finance*, *67*, 102160. https://doi.org/10.1016/j.ribaf.2023.102160

Neto, D. (2025). Wall Street sneezes and global finance catches a cold: How does geopolitical risk contribute? A tale of tail. *Finance Research Letters*, *73*, 106662. https://doi.org/10.1016/j.frl.2024.106662

Oral, F., & Özkan, İ. (2024). Measuring Connectedness and Network Analysis in Stock Markets for Developed and Developing Countries. *Uluslararası İktisadi ve İdari İncelemeler Dergisi*, (44), 189-206. https://doi.org/10.18092/ulikidince.1452554

Pandey, D. K., Lucey, B. M., & Kumar, S. (2023). Border disputes, conflicts, war, and financial markets research: A systematic review. *Research in International Business and Finance*, 101972.

Salem, S. B., & Jeribi, A. (2025). The nexus of blue economy, green finance, and energy commodities: A quantile VAR approach. *Modern Finance*, *3*(2), 96–119. https://doi.org/10.61351/mf.v3i2.272

Shi, K. (2021). Spillovers of stock markets among the BRICS: new evidence in time and frequency domains before the outbreak of the COVID-19 pandemic. *Journal of Risk and Financial Management*, *14*(3), 112. https://doi.org/10.3390/jrfm14030112

Spierdijk, L., & Umar, Z. (2014). Stocks for the long run? Evidence from emerging markets. *Journal of International Money and Finance*, *47*, 217–238. https://doi.org/10.1016/j.jimonfin.2014.06.003

Syriopoulos, T., Makram, B., & Boubaker, A. (2015). Stock market volatility spillovers and portfolio hedging: BRICS and the financial crisis. *International Review of Financial Analysis*, *39*, 7–18. https://doi.org/10.1016/j.irfa.2015.01.015

Wiseman, P., & McHugh, D. (2022). Economic dangers from Russia's invasion ripple across the Globe. *AP NEWS*, *2*.

World Bank. (2023). Africa's Pulse, No. 27, April 2023: Leveraging Resource Wealth During the Low Carbon Transition.

Yousaf Imran, Larisa Yarovaya (2022). Herding behavior in the conventional cryptocurrency market, non-fungible tokens, and DeFi assets., Finance Research Letters, Volume 50, 103299, ISSN 1544-6123. https://doi.org/10.1016/j.frl.2022.103299

Yousaf, I., & Goodell, J. W. (2023). Responses of US equity market sectors to the Silicon Valley Bank implosion. *Finance Research Letters*, *55*, 103934. https://doi.org/10.1016/j.frl.2023.103934

Zaremba, A., Umar, Z., & Mikutowski, M. (2019). Inflation hedging with commodities: A wavelet analysis of seven centuries' worth of data. *Economics Letters*, *181*, 90-94. https://doi.org/10.1016/j.econlet.2019.05.002

Zhang, B., Li, X., & Yu, H. (2013). Has the recent financial crisis permanently changed the correlations between BRICS and developed stock markets? *The North American Journal of Economics and Finance*, *26*, 725–738. https://doi.org/10.1016/j.najef.2013.05.003

Zhang, Y., Zhou, L., Liu, Z., & Wu, B. (2025). Spillover of fear among the US and BRICS equity markets during the COVID-19 crisis and the Russo-Ukrainian conflict. *The North American Journal of Economics and Finance*, *75*, 102308. https://doi.org/10.1016/j.najef.2024.102308

Zhang, Y., Zhou, L., Wu, B., & Liu, F. (2024). Tail risk transmission from the United States to emerging stock Markets: Empirical evidence from multivariate quantile analysis. *The North American Journal of Economics and Finance*, *73*, 102164. https://doi.org/10.1016/j.najef.2024.102164