

Sovereign Credit Risk Interdependencies and Shock Transmission Across Countries and Maturities in BRICS

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Abstract

This study examines the interconnectedness of sovereign credit risk across BRICS countries and different maturities, focusing on the transmission of shocks within the Credit Default Swap (CDS) market. Using the Time-Varying Parameter Vector Autoregression (TVP-VAR) methodology, we analyze daily sovereign CDS spreads for maturities of 6 months, 5 years, and 10 years from June 2018 to April 2022. The results reveal significant co-movements among BRICS CDS spreads, with distinct patterns across countries and maturities. Brazil and China emerge as key transmitters of shocks over medium and long terms, while South Africa shows rapid responses to short-term changes. Conversely, India and China act as net receivers of shocks, highlighting varying sensitivities across time horizons. This research provides fresh insights into the dynamic interplay of sovereign credit risk within BRICS, emphasizing both country-specific and maturity-related dimensions. The findings have practical implications for investors and policymakers, suggesting the need for enhanced economic policy coordination, including central bank collaboration and the creation of monitoring and research mechanisms to bolster economic resilience and mitigate systemic risks.

Keywords: BRICS, cross-country, cross-maturity, sovereign credit risk connectedness, TVP-VAR.

Introduction

In recent years, BRICS countries have experienced a high volume of external debts for both short and long maturities as shown in Table 1. This requires careful examination of the credit risk of these countries across various investment horizons. Indeed, analyzing the credit risk becomes crucial in understanding the dynamics of debt and potential investment implications. Furthermore, studying the interrelation of credit risk among the BRICS countries provides valuable insights into the interconnectedness of their financial systems. Additionally, investigating the relationship between credit maturities for each individual BRICS country and collectively for all BRICS countries can reveal patterns and trends that impact the overall credit environment. Credit risk connect CRC could help BRICS banks identify bad loans, and that leads to a decrease in Non-Performing Loans NPLs, which frees up capital for banks to lend new borrowers, stimulating economic activity.

This multifaceted analysis contributes to a comprehensive understanding of credit risk of BRICS countries and on which strategic decision-making is based for investors and policymakers.

Table 1. The evolution of short- and long-term external debt of the BRICS countries in billions of Dollars

| year | Brazil | | Russia | | India | | China | | South Africa | |
|------|------------|-----------|------------|-----------|------------|-----------|------------|-----------|--------------|-----------|
| | short-term | long-term | short-term | long-term | short-term | long-term | short-term | long-term | short-term | long-term |
| 2018 | 66.84 | 486.9 | 54.2 | 415.7 | 103.9 | 411.7 | 1218 | 732.9 | 47.86 | 129.8 |
| 2019 | 79.18 | 485.5 | 68.3 | 409.6 | 106.7 | 448.7 | 1205 | 899.1 | 44.49 | 143.7 |
| 2020 | 68.98 | 476.1 | 61.85 | 390.9 | 103.5 | 455.7 | 1236 | 1079 | 37.07 | 131.3 |
| 2021 | 78.75 | 473.9 | 76.95 | 369.9 | 114.6 | 474.1 | 1446 | 1205 | 36.29 | 122.2 |
| 2022 | 67.77 | 492.9 | 65.56 | 286.5 | 129.1 | 465.6 | 1265 | 1075 | 42.94 | 118.8 |

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Source: World Bank - January 2024

In this work, to study the international and maturity-related connectedness of credit risk in the BRICS market, the Credit Default Swap (CDS) spread is used as the measure of the risk. This choice is driven by the strong recommendation of practitioners and theorists that CDS is the most effective tool for evaluating a country's credit worthiness (Romanyuk, 2021). Indeed, CDS reflects information immediately and more precisely than data published by rating agencies and the probability of default revealed by this credit derivative is more real than that obtained from other market data (Jarrow et al, 1997; Zhu, 2006; Flannery et al., 2009; Dwyer et al., 2010; Jacobs et al., 2016; Rodríguez et al., 2019; Abid et al., 2020 and Abid and Abid, 2023). The CDS is a financial derivative that provide protection against the default risk of a country. It is essentially insurance contracts where the buyer of the CDS pays periodic premiums to the seller in exchange for a promise of compensation in the occurrence of a credit event. This definition makes CDS a valuable source of information for assessing credit risk. Therefore, the use of the CDS can be explained by the close relation between CDS quotation and credit risk, also price and quantity fluctuations of sovereign default insurance are explained by sovereign credit risk (Augustin et al., 2022).

By combining the connectedness approach and credit risk measurement, this paper proposes an appropriate analytical framework involves exploring the connectedness comprising various BRICS countries and diverse CDS maturities. This connectedness approach emphasizes not only the overall interaction across the system but also the specific interactions between countries and maturities. Thus, we delve into the time varying transmission mechanisms between CDS spreads in different countries and maturities. The objective of this paper is analyzing dynamic connectedness measures of sovereign credit risk in BRICS region in more depth and improving the interpretability of information concerning the cross-maturity and cross-country credit risk propagation mechanism. Our study utilizes CDS spreads for 6month, 5, and 10-year maturities, encompassing the BRICS countries from 2018 to 2022.

The remainder of the paper is organized as follows: Section 2 presents the literature review. Section 3 offers an overview of the data utilized in the study. Section 4 outlines the methodology employed, providing detailed insights. The results are presented in Section 4, followed by a concluding discussion and a summary of the managerial implications in Section 5.

Literature Review

The fixed income asset market exhibits a significant level of interconnectedness compared to other asset markets, characterized by its international and maturity-related dimensions. For instance, Ilmanen's influential work in 1995 showed a significant correlation between the expected yields of G7 country bonds with long-term maturities. Sutton (2000) confirmed the results of Ilmanen (1995) and proved also that this correlation is time-varying and tends to increase with the integration of international financial markets since the 1980s. In the same context, Johansson (2008) showed that connectivity increases during periods of high volatility and stress in the financial system and with the integration of bond markets in different geographic regions. The impact of stress in the financial system on connectivity is also proven by Gabauer et al. (2020) who showed that interconnectivity in the Asia-Pacific bond market varies over time and peaks during the financial crisis in 2007. Chatziantoniou and Gabauer (2021) studied pairwise country connectivity in a period of financial risk and found pairs whose connectivity is sensitive to risk. Recently, Chatziantoniou et al. (2022) investigated dynamic connectedness between green bond, green equity, sustainability investments and energy markets and they found a total connectedness dependent to economic event. The key takeaway from these studies is the necessity to consider a dynamic aspect when examining the interaction among financial variables, including bond yields. It emphasizes that stress periods can be pivotal in formulating conclusions that are pertinent to the markets being analyzed, which prompts us to study directly the credit risk connectivity on international and maturity dimensions.

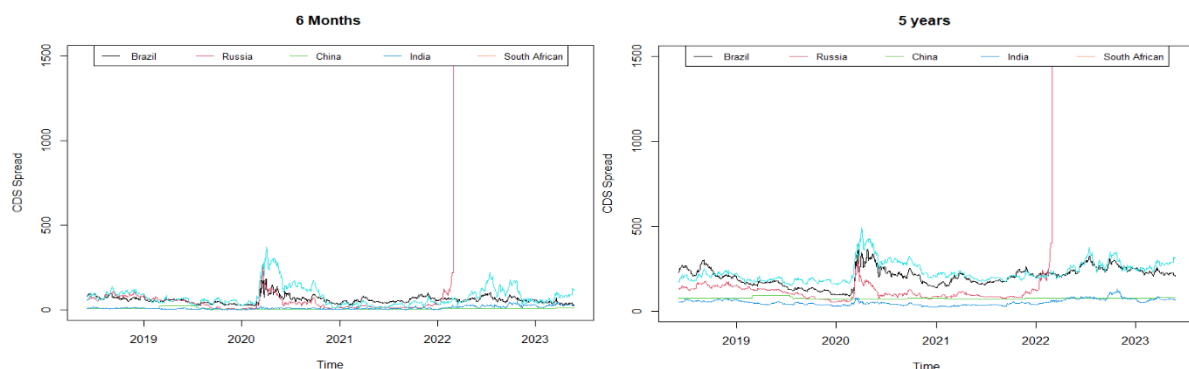
The works illustrated above studied the connectivity of bonds in terms of return and not in terms of credit risk despite the fact that the bond spread is a measure of credit risk. In our work we will focus on sovereign credit risk measured by the CDS spread. So, considering these previous works, we firmly advocate that to achieve a more comprehensive understanding of the influence of sovereign credit risk levels on financial

markets, it is imperative to recognize two parallel dimensions: cross-maturity interaction and cross-country interaction. Our approach differs from previous studies by considering not only the dynamic evolution of cross-country or cross-maturity spillovers, but in combination. Indeed, in previous works, the international and maturity-related dimensions have been treated as separate phenomena. For instance, Sutton (2000), Flavin et al (2002), Gracia-de Dandoain and Kremer (2017), Gabauer and Gupta (2018), Greenwood-Nimmo et al. (2021) and Chatziantoniou and Gabauer (2021) are only interested in the cross-country angle. Further researches have given importance to cross-maturity such as Gabauer et al. (2020) and Chatziantoniou et al. (2022). Our paper is, perhaps, most relatable to Stenfors et al. (2022), who study the international and maturity-related dimensions. In the maturity context author studied the short, median and long-term horizons and in the international context, the cross-currency is investigated. However, in our paper the cross-country angle is studied instead of the cross-currency to examine the dynamic interconnectivity of sovereign credit risk with taking into consideration also cross-maturity. We brighten the dynamic aspect of connectedness because over time, this spillover framework may vary, reflecting changes in the macroeconomic environment and global economic events, such as the COVID-19 pandemic and the Ukraine-Russia crisis of 2022.

However, many approaches rely on a rolling-window VAR method (Diebold and Yılmaz (2009, 2012, 2014; Baruník et al., 2017; Asl et al., 2021; Adekoya et al., 2022; Baruník and Křehlík, 2018; Chatziantoniou et al., 2021a; Demirer et al., 2018; Gabauer et al., 2020; (Antonakakis et al., 2019; Lastrapes and Wiesen, 2021; Chatziantoniou et al., 2021b, 2022; Greenwood-Nimmo et al., 2021) which has drawbacks like outlier sensitivity, loss of observations, parameter flattening, and arbitrary window size selection. To address these issues, Antonakakis et al. (2020) proposed a dynamic connectedness approach based on time-varying parameter vector autoregressions (TVP-VAR) with heteroscedastic variance-covariances. In this paper, the authors employ and extend the TVP-VAR methodology. They address the complexity of interpreting spillovers by using aggregated connectedness measures inspired by Gabauer and Gupta (2018) and introducing the concept of conditional connectedness. This combination allows for the extraction and interpretation of spillover patterns, adding value to the literature on connectedness measures.

Data

Our research focuses on analyzing CDS spreads and their relationship with maturity, particularly within the BRICS countries. Utilizing data extracted from Datastream, we collected daily prices of CDS spreads spanning three distinct maturities: 6-month (6M), 5-year (5Y), and 10-year (10Y) periods. The data covers a timeframe ranging from June 4, 2018, to April 1, 2022. The selection of these benchmark maturities, namely 6 months, 5 years, and 10 years, is deliberate and strategic. We believe that these timeframes offer a comprehensive representation of short-term, medium-term, and long-term market dynamics respectively, within the context of CDS spreads. This choice ensures that our analysis captures a broad spectrum of temporal influences on CDS spreads, enabling us to discern patterns and fluctuations across different maturity horizons with greater accuracy and reliability. Figure 1 displays the evolution of CDS dynamic for BRICS countries.



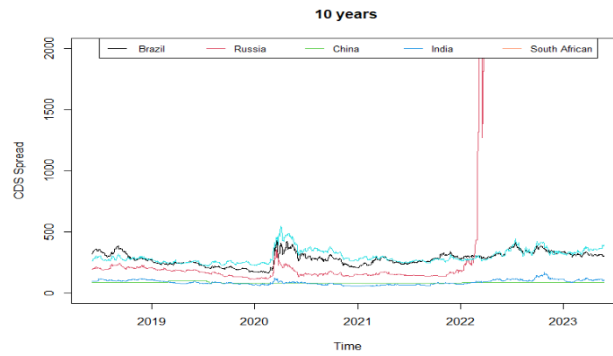


Figure 1. CDS spread evolution of 6 months, 5- and 10-year maturities for BRICS countries

Table 2 presents descriptive statistics of CDS spreads across three maturities for BRICS countries. On average, CDS spreads increase with maturity for most countries except Russia, where spreads decrease with longer maturities. This suggests a reduced insolvency risk for Russia in the long term compared to other countries. In Brazil, Russia, and China, variance of CDS spreads follows the same trend as the average spread, indicating lower dispersion for longer-maturity contracts in Russia, while Brazil and China show additional dispersion with longer maturities. However, for India and South Africa, variance remains constant across maturities, implying independence from maturity. This analysis suggests varying levels of risk and dispersion in CDS spreads across BRICS countries, with Russia showing a unique pattern of decreasing risk with longer maturities. The analysis of the data reveals several important findings. Firstly, all series, except for 10YB, show significant right skewness, indicating a distribution skewed towards higher values. Additionally, all series exhibit significant platykurtosis, suggesting thinner tails compared to a normal distribution. The Jarque and Bera (1980) normality test confirms that all series are significantly non-normally distributed at the 1% significance level. Furthermore, it's noteworthy that all CDS spreads are stationary according to the findings of Elliott et al. (1996). Additionally, the series display autocorrelation and demonstrate ARCH/GARCH errors, at least at the 10% significance level, as indicated by the tests conducted by Fisher and Gallagher (2012). These statistical insights strongly support our decision to model the interdependence of CDS spreads using a TVP-VAR model. This model accounts for heteroscedastic variance–covariances in the data, providing a robust framework for analysis.

Table 2. Data summary statistics

| | 6M B | 5YB | 10Y B | 6MR | 5YR | 10Y R | 6MI | 5YI | 10YI | 6MC | 5YC | 10Y C | 6MS A | 5YS A | 10Y SA |
|--------------|--------------------|--------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| Mean | 60.301 | 205.285 | 283.645 | 6812.899 | 3047.859 | 2321.947 | 8.871 | 79.076 | 87.572 | 12.935 | 53.936 | 90.490 | 78.471 | 232.429 | 301.585 |
| Variance | 447.15 | 2790.15 | 2891.62 | 15047.9 | 2779.1 | 1505.8 | 27.29 | 26.45 | 26.22 | 77.73 | 312.19 | 381.93 | 3266.59 | 3099.82 | 2990.95 |
| Skewness | 1.403** (0.000) | 0.037 (0.585) | 0.025 (0.713) | 1.494*** (0.000) | 1.290*** (0.000) | 1.315*** (0.000) | 2.092*** (0.000) | 2.108*** (0.000) | 2.111*** (0.000) | 1.356*** (0.000) | 0.951*** (0.000) | 0.546*** (0.000) | 1.880*** (0.000) | 1.309*** (0.000) | 1.221*** (0.000) |
| Ex. Kurtosis | 4.439** (0.000) | 0.247** (0.047) | 0.551*** (0.000) | 1.383*** (0.000) | 0.291** (0.015) | 0.183 (0.164) | 4.159*** (0.000) | 4.220*** (0.000) | 4.230*** (0.000) | 1.240*** (0.000) | 1.000 (0.000) | 0.069 (0.550) | 4.288*** (0.000) | 1.838*** (0.000) | 1.488*** (0.000) |

| | | | | | | | | | | | | | | | |
|-------------|--------------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|-----------------------------------|
| JB | 149 3.8* ** (0.0 00) | 3.59 2 (0.1 66) | 16.5 8*** (0.0 00) | 587.2 7*** (0.00 0) | 365. 04** * (0.00 0) | 376. 29** * (0.00 0) | 1884 .74* ** (0.00 0) | 1927 .49* ** (0.00 0) | 1934 .44* ** (0.00 0) | 481. 89** * (0.00 0) | 250. 15** * (0.00 0) | 64.8 7*** (0.00 0) | 1762 .13* ** (0.00 0) | 554. 29** * (0.00 0) | 442. 92** * (0.00 0) |
| ERS | - 3.33 9** * (0.0 01) | - 2.95 9*** (0.0 03) | - 2.58 7*** (0.0 10) | - 2.081 ** (0.03 8) | - 0.06 9 (0.94 5) | - 0.58 9 (0.55 6) | - 2.02 5** (0.04 3) | - 2.02 6** (0.04 3) | - 2.02 5** (0.04 3) | - 2.99 *** (0.00 3) | - 2.48 ** (0.01 3) | - 2.22 ** (0.02 6) | - 2.79 *** (0.00 5) | - 1.70 * (0.08 9) | - 2.07 ** (0.03 9) |
| Q(20)) | 834 3.9* ** (0.0 00) | 1137 1.6* ** (0.0 00) | 1149 5.7* ** (0.0 00) | 1163 1.9** * (0.00 0) | 1301 0.8* ** (0.00 0) | 1279 3.6* ** (0.00 0) | 1234 4.9* ** (0.00 0) | 1233 9.3* ** (0.00 0) | 1234 0.6* ** (0.00 0) | 1042 6.1* ** (0.00 0) | 1181 1.6* ** (0.00 0) | 1201 1.9* ** (0.00 0) | 1120 2.6* ** (0.00 0) | 1127 0*** (0.00 0) | 1132 9.5* ** (0.00 0) |
| Q2(20)) | 648 0.6* ** (0.0 00) | 1062 9.9* ** (0.0 00) | 1104 3.4* ** (0.0 00) | 5861. 3*** (0.00 0) | 1267 4.7* ** (0.00 0) | 1195 1.1* ** (0.00 0) | 1210 7.5* ** (0.00 0) | 1230 2.8* ** (0.00 0) | 1230 7.4* ** (0.00 0) | 9139 .01* ** (0.00 0) | 1125 2.1* ** (0.00 0) | 1162 6*** (0.00 0) | 1045 3.3* ** (0.00 0) | 1089 7.3* ** (0.00 0) | 1101 8.4* ** (0.00 0) |

Notes: The descriptive analysis for the three maturities (6 months 6M, 5 years 5Y, and 10 years 10Y) of each BRICS country is presented. The notation ***, **, * indicates significance at the 1%, 5%, and 10% levels, respectively. P-values are denoted in parentheses. Various statistical tests are conducted for skewness, kurtosis, Jarque-Bera normality test (JB), Elliott et al. unit-root test (ERS), and Fisher and Gallagher weighted Portmanteau tests ($Q(20)$ and $Q2(20)$).

Methodology

In this study, we utilize aggregated connectedness measures inspired by Gabauer and Gupta (2018). Additionally, we introduce the concept of the conditional connectedness approach. By combining these two frameworks, we aim to uncover and clarify spillover patterns, thereby enhancing the interpretability of our findings. This innovative concept adds significant value to the existing literature, which is focused on introducing, refining, and extending various connectedness measures

Time-varying parameter vector autoregressions

We commence by estimating a time-varying parameter vector autoregression (TVP-VAR) with a lag length of one, as recommended by the Bayesian Information Criterion (BIC). The mathematical formulation of the TVP-VAR model is represented as follows:

$$Z_t = B_t Z_{t-1} + \mu_t, \quad \mu_t \sim N(0, S_t) \quad (1)$$

$$\text{vec } B_t = \text{vec } B_{t-1} + v_t, \quad v_t \sim N(0, R_t) \quad (2)$$

Where Z_t , Z_{t-1} and μ_t are $k \times 1$ dimensional vectors, representing all IRS series at time t , $t - 1$, and the error term, respectively. B_t and S_t are $k \times k$ dimensional time-varying parameter and variance-covariance matrices, while $\text{vec } B_t$ and v_t are $k^2 \times 1$ dimensional vectors, and $\text{vec } B_t$ is a $k^2 \times k^2$ dimensional parameter variance-covariance matrix.

In simpler terms v_t induces variations in the VAR parameters over time, and it is assumed that the variance of v_t denoted as R_t also changes over time using a Kalman filter approach. Consequently, B_t illustrates the

time-varying relationship between Z_t and its lagged values Z_{t-1} , while the variance–covariances of the error term μ_t exhibit a heteroscedastic nature denoted by S_t . This is particularly relevant as financial market volatility fluctuates significantly over time and holds substantial importance for risk and portfolio management.

Connectedness approach

Subsequently, we calculate the H-step ahead (scaled) generalized forecast error variance decomposition (GFEVD) following the approach of Koop et al. (1996) and Pesaran and Shin (1998). The GFEVD is entirely invariant to the variable ordering, unlike the orthogonalized forecast error variance decomposition, as discussed by Diebold and Yilmaz (2009). It's essential to note that when using structural representations of shocks, a common practice in applied macroeconomics, these shocks should be based on some underlying economic theory. However, given the absence of a generally accepted theoretical model for IRS spillovers, we adopt the recommendation of Wiesen et al. (2018) and prefer the GFEVD analysis. As the GFEVD relies on vector moving average (VMA) coefficients, we need to transform the TVP-VAR into a TVP-VMA using the Wold representation theorem;

$$Z_t = \sum_{i=1}^p B_{i,t} Z_{t-i} + \mu_t = \sum_{j=0}^{\infty} A_{j,t} \mu_{t-j} \quad (3)$$

The (scaled) Generalized Forecast Error Variance Decomposition ($\widetilde{\varphi}$), denoted as $\widetilde{\varphi}_{ij,t}^g(H)$, normalizes the (unscaled) GFEVD ($\varphi_{ij,t}^g(H)$) to ensure that each row sums up to unity. Therefore, $\varphi_{ij,t}^g(H)$ represents the influence series j has on series i in terms of its forecast error variance share. This can also be interpreted as the pairwise directional connectedness from j to i . The computation is expressed as follows:

$$\varphi_{ij,t}^g(H) = \frac{S_{ii,t}^{-1} \sum_{t=1}^{H-1} (I'_i A_t S_t I_j)^2}{\sum_{j=1}^k \sum_{t=1}^{H-1} I'_i A_t S_t I_j} \quad , \quad \widetilde{\varphi}_{ij,t}^g(H) = \frac{\varphi_{ij,t}^g(H)}{\sum_{j=1}^k \varphi_{ij,t}^g(H)} \quad (4)$$

Given that $\varphi_{ij,t}^g(H)$ normalizes to ensure that each row sums up to unity, mathematically expressed as $\sum_{j=1}^k \varphi_{ij,t}^g(H) = 1$ and $\sum_{i,j=1}^k \widetilde{\varphi}_{ij,t}^g(H) = k$, and I_i corresponds to a zero vector with unity in the i th position.

The connectedness measures proposed by Diebold and Yilmaz (2012, 2014) are derived from the Generalized Forecast Error Variance Decomposition (GFEVD).

$$C_{i \rightarrow ., t} = \sum_{j=1, i \neq j}^k \widetilde{\varphi}_{ij,t}^g(H) \quad (5)$$

$$C_{i \leftarrow ., t} = \sum_{j=1, i \neq j}^k \widetilde{\varphi}_{ji,t}^g(H) \quad (6)$$

$$C_{it} = C_{i \rightarrow ., t} - C_{i \leftarrow ., t} \quad (7)$$

$$C_t = \frac{k}{k-1} \sum_{i=1}^k C_{i \rightarrow ., t} \equiv \frac{k}{k-1} \sum_{i=1}^k C_{i \leftarrow ., t} \quad (8)$$

$C_{i \rightarrow, t}$ represents the aggregated impact that a shock in series i has on all other series, defined as the total directional connectedness to others.

$C_{i \leftarrow, t}$ illustrates the aggregated influence that all other series have on series i , defined as the total directional connectedness from others.

C_{it} represents the net total directional connectedness, identifying whether series i is a net transmitter or receiver of shocks. If $C_{it} > 0$, series i is a net transmitter; if $C_{it} < 0$, series i is a net receiver.

The total connectedness index, C_t , calculates the average shock spillover from one series to all others.

Empirical Results

In this section, we present the key findings of the study and delve into their implications. Our primary goal is to illuminate various aspects of the issue, considering not only spillovers across CDS spreads but a maturity. This broader approach enhances our understanding of the strong interconnections within each group of CDS spreads or maturities.

Effects by virtue of maturity

We initiate our examination by assessing spillovers for each CDS spread individually across various maturities. The findings are presented in Table 3.

Table 3. Conditional country-specific connectedness table

| Brazil | | | | |
|--------|-------|-------|-------|-------------|
| | 6M | 5Y | 10Y | FROM |
| 6M | 38.89 | 31.33 | 29.79 | 61.11 |
| 5Y | 27.29 | 36.29 | 36.42 | 63.71 |
| 10Y | 25.65 | 35.88 | 38.47 | 61.53 |
| TO | 52.94 | 67.21 | 66.20 | 186.35 |
| NET | -8.17 | 3.50 | 4.68 | TCI = 62.12 |
| Russia | | | | |
| | 6M | 5Y | 10Y | FROM |
| 6M | 42.41 | 30.05 | 27.54 | 57.59 |
| 5Y | 34.38 | 33.84 | 31.78 | 66.16 |
| 10Y | 31.90 | 34.39 | 33.71 | 66.29 |
| TO | 66.28 | 64.44 | 59.32 | 190.04 |
| NET | 8.69 | -1.71 | -6.98 | TCI = 63.35 |
| India | | | | |
| | 6M | 5Y | 10Y | FROM |
| 6M | 33.56 | 33.26 | 33.18 | 66.44 |
| 5Y | 33.19 | 33.42 | 33.38 | 66.58 |
| 10Y | 33.14 | 33.43 | 33.43 | 66.57 |
| TO | 66.33 | 66.69 | 66.56 | 199.59 |
| NET | -0.11 | 0.11 | 0.00 | TCI = 66.53 |
| China | | | | |
| | 6M | 5Y | 10Y | FROM |
| 6M | 39.98 | 31.24 | 28.77 | 60.02 |
| 5Y | 29.99 | 35.72 | 34.29 | 64.28 |

| | | | | |
|--------------|-------|-------|-------|-------------|
| 10Y | 27.99 | 34.70 | 37.31 | 62.69 |
| TO | 57.98 | 65.95 | 63.06 | 186.99 |
| NET | -2.03 | 1.66 | 0.37 | TCI= 62.33 |
| South Africa | | | | |
| | 6M | 5Y | 10Y | FROM |
| 6M | 34.69 | 33.12 | 32.19 | 65.31 |
| 5Y | 32.77 | 34.00 | 33.23 | 66.00 |
| 10Y | 31.98 | 33.43 | 34.58 | 65.42 |
| TO | 64.75 | 66.55 | 65.42 | 196.72 |
| NET | -0.56 | 0.55 | 0.00 | TCI = 65.57 |

Notes: Results are based on a TVP-VAR(0.99,0.99) model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

To provide an overall perspective, the table presents the average Total Connectedness Index (TCI) value for each CDS spread, considering all maturities. This index serves to gauge whether, on average, there are high or low co-movements within the network or system of different maturities. It's crucial to note that the main diagonal of individual CDS spread in the table corresponds to idiosyncratic shocks. In contrast, off-diagonal elements depict interactions across different maturities, providing insights into the dynamics of the system.

The table 3 presents the conditional country-specific connectedness among the BRICS nations based on the TVP-VAR (0.99,0.99) model with a lag length of order 1 (BIC) and a 10-step-ahead forecast. For Brazil, the values depict the percentage of shocks transmitted from each maturity to others (FROM), the total transmitted shocks to other maturities (TO), and the net transmission (NET) of shocks. Notably, Brazil acts as a net receiver of shocks in the 6M maturity, with -8.17% net transmission, indicating that it receives more shocks than it transmits. However, in the 5Y and 10Y maturities, Brazil is a net transmitter of shocks, with values of 3.50% and 4.68% respectively. The TCI for Brazil is calculated to be 62.12%, suggesting a relatively high level of interconnectedness among the different maturities. Similarly, for Russia, India, China, and South Africa, the table provides a breakdown of shock transmission across different maturities. Each country exhibits variations in its net transmission of shocks across different maturities. Russia, for example, shows net transmission values of 8.69%, -1.71%, and -6.98% for the 6M, 5Y, and 10Y maturities respectively, with a TCI of 63.35%. India, China, and South Africa also demonstrate their unique patterns of shock transmission and interconnectedness across different maturities. Overall, the table offers insights into the transmission and reception of shocks within the CDS markets of BRICS countries, highlighting the interconnectedness and dynamics among different maturity horizons.

Before delving into potential implications, it is valuable to expand our analysis by adopting a more dynamic framework. The findings presented in Table.3 offer total average values for the entire sample period, providing a static overview that may overlook the evolving interaction across CDS spreads. In other words, a more detailed exploration of the relationships within this network requires a dynamic framework that captures the intertemporal evolution of spillovers and their connection to broader developments in real economic activity. The TVP-VAR method, as introduced in the previous section, facilitates this analysis. It enables us to better comprehend the underlying linkages by associating spillovers within the system with changes in real economic activity. Our analysis encompasses two types of results: static results, represented by average values over the entire sample period, typically conveyed in tables to offer a comprehensive overview; and dynamic results, presented through plots, which provide a more detailed and time-specific perspective. Dynamic results of TCI are presented in Figure 2. This figure enables to identify the evolution of connectedness magnitude over time, highlight major events impacting network connectedness, and reveal shifts in the net position of each variable across different periods. This dual approach ensures a comprehensive understanding of the issue at hand.

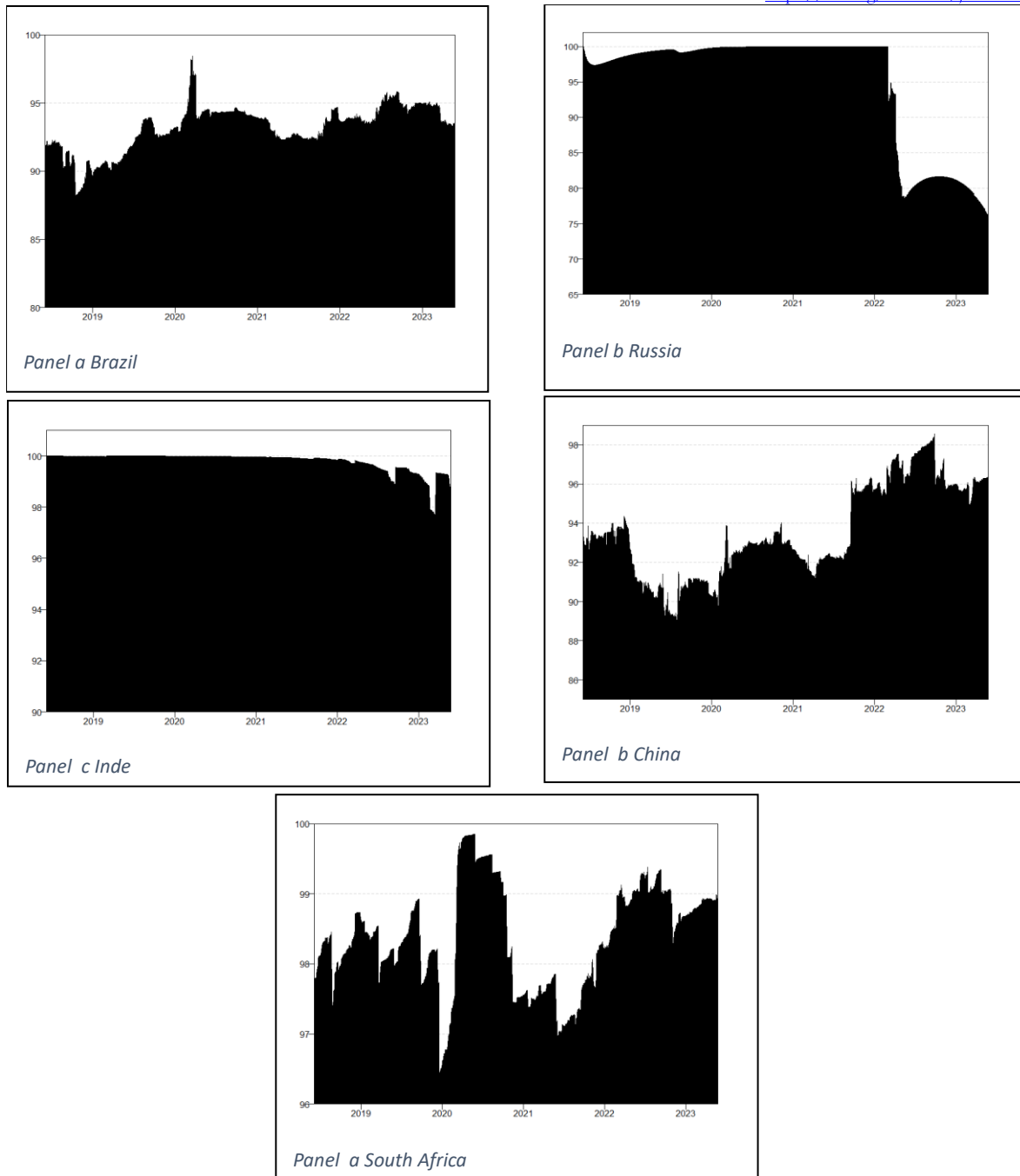


Figure 2. Country dynamic total connectedness

Notes: Results are based on a TVP-VAR (0.99,0.99) model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

In this context, we move forward by presenting the net connectedness results for each individual network of CDS spreads, as depicted in Figure 3. It's important to note that values above (below) zero signify that a specific maturity acts as a net transmitter (net recipient) of shocks within the system to all other maturities of the CDS spreads.

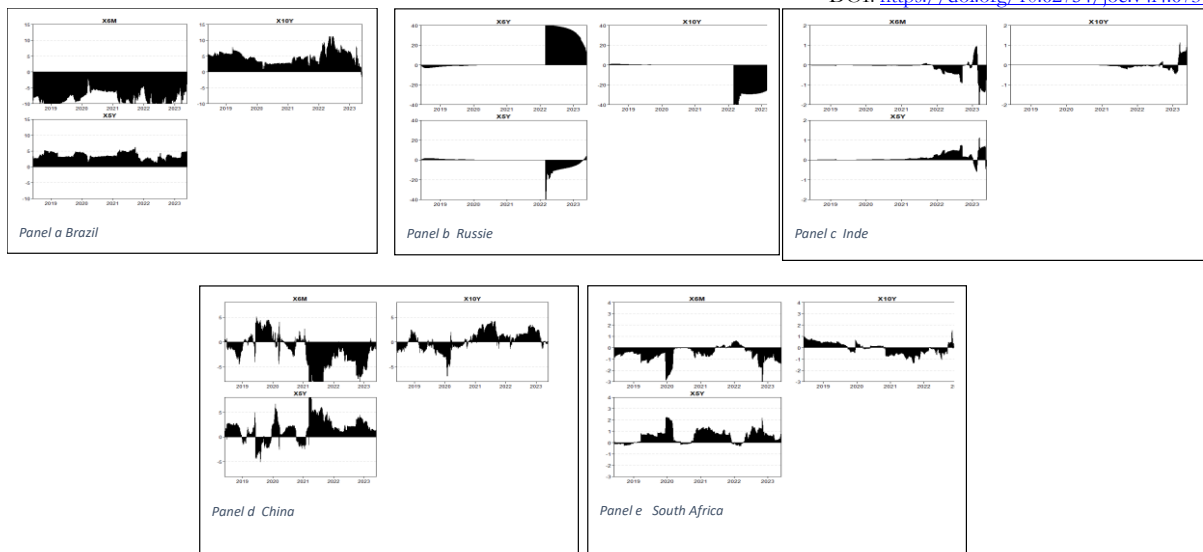


Figure 3. Country net total directional connectedness

Notes: Results are based on a TVP-VAR (0.99,0.99) model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

The Figure 3 shows that Brazil the 5Y and 10Y maturities appear to be the net transmitter of shocks throughout the period of analysis. In addition, we cannot identify any time intervals whereby the shorter term 6 months has had a non-trivial impact as a net transmitter. The same results are shown for Russia after the war before the beginning of 2022, so, after the war the direction of net connectivity was reversed with a very significant increase in the extent of connectivity which gradually deteriorates but still remains significant. The 5Y maturity and 6 months maturity still remain the net transmitter and net recipient respectively for South Africa and the longer term 10Y for this country it clearly does not have as prominent a role as a net transmitter as the 5Y maturity or a net recipient as the 6M maturity. For India and China, the direction of net connectivity is variable, we find a role of transmitter and receiver for the same maturity, but with a dominance of the transmitting role for the 5Y maturity and of the recipient role for the 6 months maturity. Overall, net connectedness findings suggest that the shorter term 6M receive sovereign credit risk feedback from the 5 years maturity which is the dominant net transmitter of risk and thus largely determines innovations within the specific systems with the exception of the case of Russia after the war. While the directional net connectedness of the 10Y maturity in general is variable; sometimes transmitter and sometimes recipient of sovereign credit risk.

Effects by virtue of country

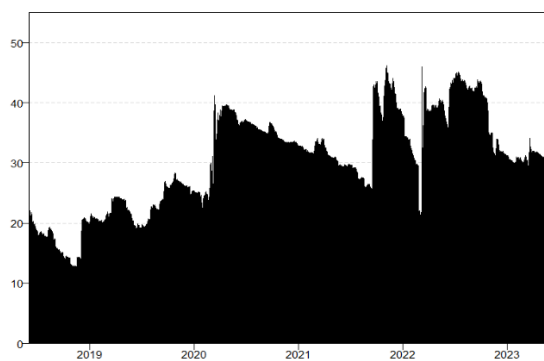
The examination of spillovers is focused on individual maturities, as presented in Panels A, B, and C, representing short, medium, and long-term CDS spreads, respectively. The results are summarized in Table 4. The TCI indices for short, medium, and long-term CDS are 24.09%, 63.58%, and 47.60%, respectively. These values indicate that the TCI is moderate for both short and long terms, while it is strong for the medium term. This suggests varying degrees of interdependence in CDS spreads across different maturity horizons (Alexander and Kaeck., 2008; Camba-Méndez., 2016). The primary transmitter varies based on the maturity of the analyzed periods. In the short term, Brazil (47.47%) and South Africa (38.39%) stand out as the most significant contributors, indicating a predominant influence on economic indicators over the next 6M. In the medium term, over a 5Y period, Brazil (77.03%) maintains its position as the main issuer, closely followed by India (71.13%), underscoring their substantial impact on overall economic performance. In the long term, over a 10Y period, Brazil (63.21%) remains at the forefront as the primary issuer, followed by South Africa (61.99%) and Russia (43.41%). The distinction of Brazil as a significant issuer of CDS spreads across the short, medium, and long term can be attributed to various key factors related to its economy and financial environment. As one of the largest emerging economies, Brazil holds

considerable influence in global financial markets. Factors such as economic performance, political and institutional dynamics, and exposure to economic risks contribute to investor perceptions. The results of TCI dynamics are presented in Figure 4.

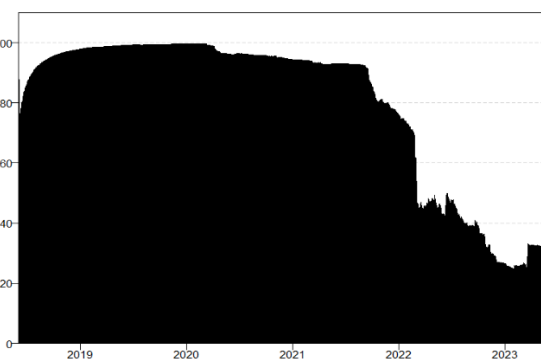
Table 4. Maturity-specific connectedness table

| | Brazil | Russia | India | China | SouthAfrica | FROM |
|-------------------|--------|--------|-------|--------|-------------|-------------|
| Panel A : 6M | | | | | | |
| Brazil | 70.55 | 1.78 | 1.74 | 5.25 | 20.69 | 29.45 |
| Rusia | 2.76 | 94.45 | 0.30 | 1.14 | 1.35 | 5.55 |
| India | 3.04 | 7.99 | 85.32 | 1.57 | 2.08 | 14.68 |
| China | 14.04 | 4.51 | 1.84 | 65.36 | 14.26 | 34.64 |
| SouthAfrica | 27.64 | 1.45 | 1.12 | 5.94 | 63.85 | 36.15 |
| TO | 47.47 | 15.72 | 5.00 | 13.89 | 38.39 | 120.47 |
| NET | 18.02 | 10.17 | -9.68 | -20.75 | 2.24 | TCI= 24.09 |
| Panel B : 5 Years | | | | | | |
| Brazil | 31.32 | 11.20 | 21.83 | 13.58 | 22.07 | 68.68 |
| Russia | 15.21 | 42.40 | 15.62 | 13.58 | 13.19 | 57.60 |
| India | 21.41 | 12.44 | 34.69 | 14.52 | 16.94 | 65.31 |
| China | 16.20 | 14.70 | 15.65 | 38.61 | 14.84 | 61.39 |
| SouthAfrica | 24.20 | 10.09 | 18.03 | 12.59 | 35.08 | 64.92 |
| TO | 77.03 | 48.43 | 71.13 | 54.27 | 67.05 | 317.90 |
| NET | 8.34 | -9.16 | 5.81 | -7.12 | 2.13 | TCI = 63.58 |
| Panel C :10 Years | | | | | | |
| Brazil | 43.21 | 11.49 | 6.82 | 12.15 | 26.34 | 56.79 |
| Russia | 10.45 | 58.51 | 8.70 | 12.81 | 9.52 | 41.49 |
| India | 8.39 | 8.67 | 69.69 | 5.63 | 7.62 | 30.31 |
| China | 17.46 | 13.29 | 5.95 | 44.78 | 18.52 | 55.22 |
| SouthAfrica | 26.92 | 9.96 | 6.84 | 10.48 | 45.80 | 54.20 |
| TO | 63.21 | 43.41 | 28.31 | 41.08 | 61.99 | 238.01 |
| NET | 6.42 | 1.92 | -1.99 | -14.14 | 7.79 | TCI = 47.60 |

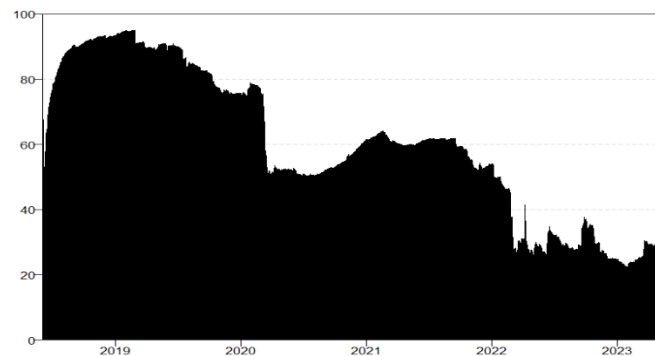
Notes: Results are based on a TVP-VAR(0.99,0.99) model with lag length of order 1 (BIC) and a 10-step-ahead forecast.



Panel (a) 6M



Panel (b) 5Y



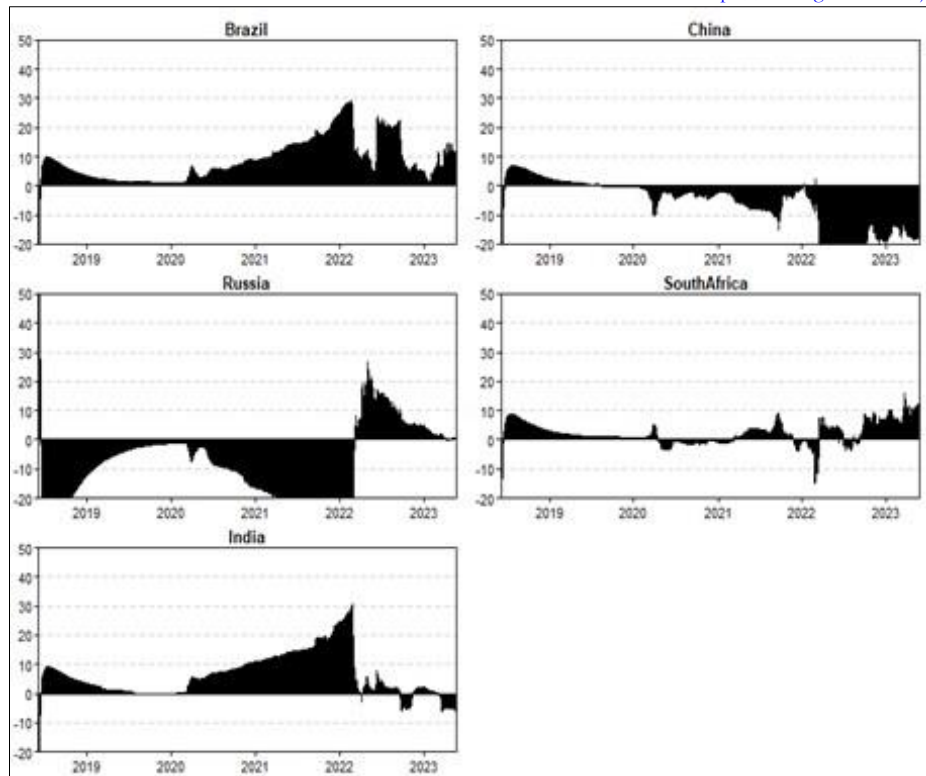
Panel (c) 10Y

Figure 4. Maturity dynamic total connectedness. Panel (a) Total Connectedness Index short term. Panel (b) Total Connectedness Index medium term. Panel (c) Total Connectedness Index long term.

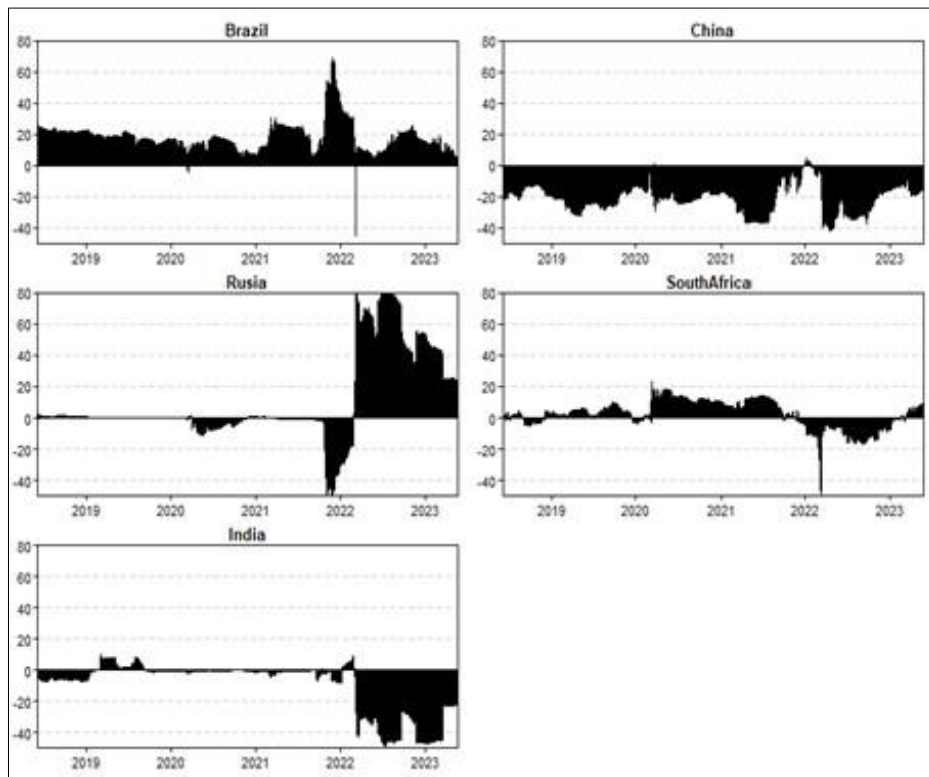
Notes: Results are based on a TVP-VAR(0.99,0.99) model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

The relative political stability and government policies, particularly fiscal and monetary measures, also play a crucial role. Market responsiveness to economic and financial events, coupled with the potential for greater volatility, further emphasizes Brazil's influential position as a CDS spreads issuer. The analysis of the "FROM" column indicates that the CDS of Brazil is notably impacted by shocks from CDS of other BRICS countries over medium and long terms, with percentages of 68.68% and 56.79%, respectively. Conversely, South Africa emerges as the primary short-term shock recipient, with a percentage of 36.15%. This observation highlights varying economic sensitivities across different time frames, with CDS of Brazil being more susceptible over extended periods and the CDS of South Africa showing prompt reactions to short-term fluctuations in the CDS of other BRICS nations.

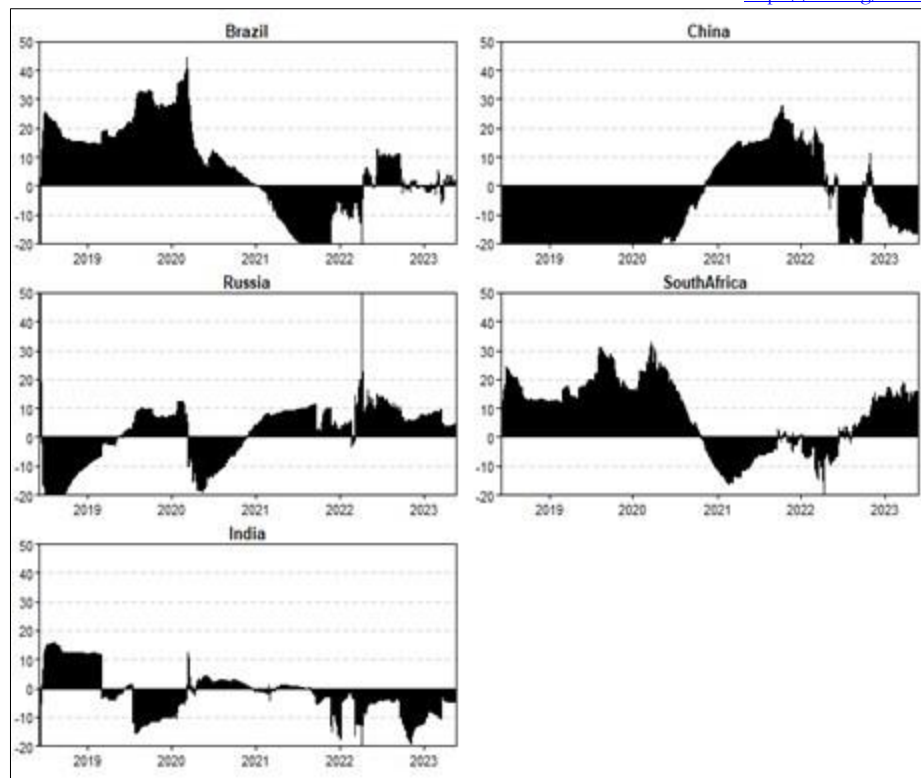
The analysis of the "TO" line indicates that Brazil's CDS is the main transmitter to all other countries in the short, medium, and long term. Conversely, India has the weakest transmission in both the short and long term, with percentages of 5% and 28.31% respectively. Additionally, Russia has the weakest transmission in the medium term, representing 48.43%. For the net line, India and China are net receivers in both the short and long terms, while only China is a net receiver of shocks in the medium term. As a result, the findings in Figure 5 illustrate the dynamic variations of net connectivity. Overall, in the short and medium term, all markets exhibit similar movements but with varying magnitudes. Brazil acts as a net transmitter of shocks in the short and medium term, while China serves as a net receiver of shocks. Before the declaration of the war between Ukraine and Russia in 2022, Russia was a net receiver of shocks and then became a net transmitter during the war, both in the short and medium term. In general, India acts as a net transmitter of shocks before the declaration of the war between Ukraine and Russia in 2022 and becomes a net receiver during the war, both in the short and medium term. Regarding South Africa, short-term net index variations shift quickly from being a transmitter to a receiver, while in the medium term, it acts as a net transmitter of shocks before the declaration of the war between Ukraine and Russia in 2022 and as a net receiver during the war between Ukraine and Russia in 2022. In the long term, Brazil and South Africa (China) act as net transmitters (receivers) of shocks from 2018 until mid-2021. Then, they become net receivers (transmitters) of shocks from mid-2021 until the end of 2022, and then transform into net transmitters (receivers) of shocks during the war between Ukraine and Russia in 2022. As for Russia (India), from 2018 until the end of 2019, it behaves as a net receiver (transmitter) of shocks. Once the war between Ukraine and Russia erupts, Russia (India) acts as a transmitter (net receiver) of shocks. The net index plays a crucial role in tracking market performance, making investment decisions, comparing returns, and evaluating economic health. It provides investors with a valuable reference framework for analyzing and understanding market movements and making informed investment decisions.



Panel (a) 6M



Panel (b) 5Y



Panel (c) 10Y

Figure 5. Maturity dynamic Net connectedness. panel a) Net Connectedness Index short term Panel b) Net Connectedness Index medium term Panel c) Net Connectedness Index long term Notes: Results are based on a TVP-VAR(0.99,0.99) model with lag length of order 1 (BIC) and a 10-step-ahead forecast.

Conclusion

Our paper delves into the dynamic transmission mechanisms among 6-month, 5-year, and 10-year CDS spreads across the BRICS countries from June 4, 2018, to April 1, 2022. By amalgamating the TVP-VAR algorithm by Koop and Korobilis (2014) with the dynamic connectedness approach proposed by Diebold and Yilmaz (2012, 2014). Our study provides valuable insights into the interconnectedness and transmission of shocks within the CDS markets of BRICS countries. The analysis underscores the importance of considering varying maturities in understanding market dynamics and systemic risks. Brazil's prominent role as a transmitter of shocks highlights its influence on regional creditworthiness, slower economic growth, financial market stress, and financial stability. The findings also reveal the differing sensitivities of BRICS countries to short-term fluctuations and long-term developments, emphasizing the need for robust risk management strategies and improving the financial regulations. The results indicate that policymakers need to pay attention to movements in different BRICS markets by assessing the degree of short-term, medium-term and long-term credit risk independence and hence its vulnerabilities with respect to credit risk contagion, in particular to evaluate the efficacy of their policy actions given the credit risk sensitivity of one country affecting the other. Furthermore, the provided results are also interesting for market participants investing in BRICS markets to consider regional and maturity influences, contagion mechanism in framing the diversification and hedging strategies in their portfolios.

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