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Quadrant categorization of spillover determinants of sovereign risk of BRICIT nations: a Bayesian approach

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Abstract

This study investigates the determinants that drive the volatility of the credit default swaps (CDS) of BRICIT (Brazil, Russia, India, China, Indonesia, and Turkey) nations as a proxy measure for sovereign risk. On the existence of cointegration, an unrestricted error correction model integrated with the autoregressive distributed lag (ARDL) model is applied to measure the short-run and long-run dynamics empirically. The study utilizes the Bayesian global vector autoregression methodology for cross-border spillover estimation. The study also suggests a strategy for policymakers for quadrant categorization to mitigate risk arising from cross-border spillover. The result of ARDL indicates that the global macroeconomic variables affect the BRICIT CDS more than domestic macroeconomic determinants, with Indian CDS being the most sensitive to Fed tapering. Notably, China's CDS is the most sensitive to shocks, with the CDS volatility primarily driven by China's geopolitical risk. Russian CDS is more sensitive to real effective exchange rates due to severe ruble depreciation than crude oil, despite Russia being a major oil exporter. The quadrant categorization indicates that the Indonesian stock market index is most interconnected with BRICIT CDS, while the Turkish long-term interest rates send the highest intensity spillover across BRICIT nations.

Keywords: Bayesian global vector autoregression (B-GVAR), BRICIT (Brazil, Russia, India, China, Indonesia and Turkey), Credit default swaps (CDS), Sovereign risk, Spillover

JEL Classification: C11, C15, C22, C58, F6, O1

Introduction

Since 2008, the most widely traded credit derivative instrument has been credit default swap (CDS).[1] CDS developed from a niche market to a highly liquid and active market and transfers credit risk, effectively hedging counterparty risk and speculating on other entities' credit risks. (Ballester et al. 2016; Koutmos 2019). CDS protection is given at a premium, called CDS spread, and an increase in CDS premium implies that the asset is more likely to default (Kim et al. 2015). In the first half of 2008, the unprecedented volumes of CDS contracts declined by 1%; however, the gross market value for CDS

[1] Credit Default Swap (CDS) is a financial product that acts as an insurance to debt. CDS buyer buys the protection for their debt from CDS seller against the default made by reference entity.

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contracts increased by 58%,[2] indicating investors' declining confidence in reference entities such as corporate or sovereign securities. Sovereign securities used to be considered safe securities; however, they are not considered risk-free after global crises, and many countries have encountered spillovers from crisis-originating countries. Recent examples of such crises are the 2008 Global Financial Crisis the European Sovereign Debt Crisis, and the Coronavirus pandemic. Sovereign credit risk (SCR) affects access to the global debt market and the risk premiums payable to obtain capital.

Emerging economies have recently attracted scholars' attention due to their high potential and increasing influence over the world economy. For example, Wang et al. (2020) found differences in CoVar values of sovereign CDS spreads from value at frisk figures for G7[3] and BRICS[4] nations to oil returns with heterogeneity in the spillover. Similarly, Bouri et al. (2017) studied emerging and frontier markets, while Kisla et al. (2018) focused on 20 emerging economies, including Brazil, China, Chile, Mexico, and Indonesia. Other studies concerning emerging markets include Pavlova et al. (2018) and Bouri et al. (2020). Recently, China has shown interest in expanding BRICS to inject development impetus into BRICS nations. The economic significance of BRICS nations has attracted many countries to join the bloc since its formation in 2001; however, the guidelines for eligible members are still pending. Turkey and Indonesia claim to be the potential candidates for such expansion as both are among the fastest growing economies in the world and have a bright future prospectus. Both countries are recognized as a part of MINT[5] countries that have the potential to provide maximum returns to investors and are members of the most economically powerful G20 nations. Turkey is among a few countries that showed positive growth performance in 2020, reaching the highest rate among G20 nations in 2021.[6] Conversely, Indonesia is one of the world's most populous countries and has emerged as a confident middle-income economy. China is Indonesia's biggest trading partner. Considering the relevance of these emerging economies globally, this study focuses on the most influential emerging economy of the BRIC (Brazil, Russia, India, and China) bloc, along with two more confident emerging economies and potential candidates for BRIC, i.e., Indonesia and Turkey (BRICIT).

Several pivotal factors influenced the decision to select BRICIT countries. First, as emerging markets characterized by rapid growth potential and distinct financial complexities, these nations hold substantial influence in the global economy. Analyzing fluctuations in their CDS volatility holds vital implications for investors and researchers. The prevalent sovereign risk within these markets (from political instability, weak institutional frameworks, and underdeveloped financial systems) emphasizes the need to grasp the underlying dynamics behind CDS fluctuations in these specific contexts. Furthermore, the diverse nature of the BRICIT group, comprising commodities-driven economies like Russia and Brazil and service-oriented ones like India and Indonesia, allows

[2] The CDS market has tendency to be more liquid than bond spreads and is preferable in terms of information dissemination. In contrast to bonds, the CDS market responds more quickly to changes in credit conditions (Zhang et al., 2022).

[3] The Group of Seven (G7) is an informal political and economic forum that includes the following countries: Canada, France, Germany, Italy, Japan, United Kingdom, and United States.

[4] *BRICS* is an acronym for five leading emerging economies of the globe: Brazil, Russia, India, China, and South Africa.

[5] MINT (Mexico, Indonesia, Nigeria, Turkey) is an acronym that refers to *a group of countries with the potential to realize rapid economic growth*.

[6] https://www.worldbank.org/en/country/turkey/overview

for a comprehensive examination of multiple factors affecting sovereign risk. These factors include commodity price shifts, political stability, inflation rates, and external debt dynamics. Moreover, compared to their developed counterparts, the heightened market volatility in BRICIT countries is influenced by geopolitical risks, policy uncertainties, fluctuating commodity prices, and currency instabilities. This situation requires a closer investigation into the determinants of CDS volatility. Given the limited research on emerging markets, especially concerning the use of CDS as a sovereign risk measure, focusing on the BRICIT countries presents a unique opportunity. This approach can provide invaluable insights into the intricacies of risk assessment within these dynamic economies.

Existing SCR literature and its CDS spillover patterns, exemplified by recent advancements in spillover capturing models (Liu and Huang 2024; Le et al. 2022; Srivastava et al. 2016; Debarsy et al. 2018) has focused on capturing interdependencies among CDS. Similarly, research on the cross-asset relationships of CDS (Huang and Liu 2023; Cheuathonghua et al. 2022; Feng et al. 2023; Bajaj et al. 2023; Sun et al. 2020) has revealed valuable insights derived from these linkages. The United States (US) is still a supreme economic power, and BRICIT is not immune to US influence, especially amid ongoing US-Russia adversarial relations and complex US-China commercial relations. Russia has already sent shockwaves throughout the world economy by invading Ukraine. Furthermore, China's geopolitical and geoeconomic orientation makes it a revolutionary power that threatens the US and global economic structure. Some of the consequences of these confrontations could spill over to other BRICIT nations, as the global sovereign risk of countries is interconnected (Bostanci and Yilmaz 2020). Indeed, most studies concentrated on developed countries initially since the crises mentioned above. Additionally, most research originated from two developed nations that influenced other countries, and emerging economies were only occasionally investigated.

Besides spillover risk originating from cross-border sovereigns, macroeconomic determinants can also influence sovereign CDS (Hilscher and Nosbush, 2010; Longstaff et al., 2011; Pavlova et al. 2018). However, the literature addressing macroeconomic determinants concerning sovereign risk remains limited, as highlighted by the works that focused on singular factors and their potential linkages (Kim et al. 2015; Apergis et al. 2016; Drago and Gallo 2016). Nevertheless, the cross-border influence of macroeconomic determinants is worth exploring, as policymakers are often constrained to analyze the complex network due to interconnectedness. Unlike other works, this study offers a comprehensive approach by integrating macroeconomic variables that potentially influence the CDS of BRICIT nations. In studying CDS volatility as a gauge for sovereign risk in the BRICIT nations, we prioritize domestic and global macroeconomic factors beyond the predefined variables. Adding more parameters to the research significantly complicates the process due to data availability issues, especially in emerging markets with limited transparency. Moreover, introducing new macroeconomic variables closely related to existing factors minimally contributes to understanding the response variable. Furthermore, the risk of overfitting arises, potentially introducing noise into the model rather than revealing fundamental relationships.

Nevertheless, the domestic and global economic and financial variables behind the spillover intensity are limited. Especially in the CDS context, there is a need to excavate

that spillover relationship from the investor's perspective and policymakers, as CDS is a direct reflection of sovereign risk. If a cross-country economic variable influences a CDS significantly, it is worth monitoring to safeguard the sovereign risk. The study assumes significance as it seeks to provide a comprehensive understanding of the determinants driving sovereign risk volatility. We incorporate economic indicators, including the Consumer Price Index (CPI), Real Effective Exchange Rate (REER), Stock Market Index (SMI), Long-term Interest Rate (LTR), and Geopolitical Uncertainty Index (GI), and global factors like crude oil (WTI), Federal Fund Rates (FFR), the Real Dollar Index (DI), and the Volatility Index (VIX). This study addresses the gap in the literature by capturing a holistic view of the multifaceted drivers of SCR.

Theoretically, SMI and REER are negatively linked to SCR; an increase in these variables indicates strong economic and sovereign health (Shahzad et al. 2017a, b). Inflation is a barometer of a country's growth; hence, we considered CPI to capture the impacts of inflation (Bajaj et al. 2023). Additionally, LTR is considered a proxy to account for the economy's fiscal condition. Recently, geopolitical uncertainty has become essential for the decision-making of sovereigns, investors, and stock market dynamics as the global geopolitical landscape has become highly volatile, particularly after the Russian invasion of Ukraine. These increasing complexities constitute a significant concern, and their examination is still nascent. Recently, Subramaniam (2022) examined the relationship between geopolitical uncertainty and bond yield. Similarly, this current study considered the GI to account for the political uncertainty of a country. As VIX measures global risk appetite, a rise in VIX significantly affects SCR (Hilscher and Nosbusch 2010; Shahzad et al. 2017a, b). Similarly, FFR and WTI have long-run impacts on CDS markets (Mensi et al. 2019; Bajaj et al. 2023). A change in the DI changes all the countries' foreign exchange rates. Strengthening the DI leads to the depreciation of other countries' currencies, adversely impacting the nation's SCR.

Before performing the interconnectedness study, we must determine country-specific and global variables' statistical and economic significance on BRICIT CDS. For the same, we opt for the autoregressive distributed lag model (ARDL) (Pesaran and Shin 1995), owing to our historical influence and the lagged response of domestic and global economic variables. Furthermore, bound testing is performed to capture the short and long-run dynamics simultaneously before integrating the error correction model (ECM). Subsequently, cross-country influence is captured via spillover estimation. Due to the data's periodicity and the curse of dimensionality, we adopt the Bayesian variant of the global autoregressive model (Cuaresma et al. 2016). The global vector autoregressive (GVAR) model's two-stage modeling divides the global system into smaller sub-systems and estimates each sub-system individually, which is restacked into a global system again. The Bayesian version of the vector autoregressive (VAR) model reduces the risk of overparameterization by imposing certain restrictions on VAR parameters and generating more accurate forecasts (Assaf et al. 2018). Hence, the VAR model is estimated for each country using the Bayesian stance, augmented with foreign variables to capture the influence of global factors. These country-specific models are restacked in the second stage based on the exogenous weight that yields a global representation of the model (i.e., B-GVAR). The B-GVAR model can succinctly analyze the interactions among countries vis-à-vis their economic and financial interrelationships, which is the motivation

behind choosing this methodology (Onipede et al. 2022). Based on B-GVAR modeling, we estimate generalized forecast error variance decomposition (Diebold and Yilmaz 2012). Apart from the absolute quantum of spillover, the count of CDS affects attributes of the propensity of virality. The proposed framework for this study differs from traditional approaches. One significant challenge we encountered was the reduction in data periodicity due to including macroeconomic variables; this situation affected the application of the VAR model for spillover analysis. The Bayesian approach allowed us to mitigate the impact of data insufficiency.

The results indicate that fluctuations in macroeconomic fundamentals have long-run repercussions for sovereign risk in BRICIT nations. India, China, and Russia are more exposed to global shocks than local ones, while Turkey is the least affected. One observation of the analysis is that China's CDS is most sensitive to domestic, cross-country, and global determinants, with its CDS volatility majorly guided by prevailing geopolitical uncertainty. Interestingly, Russia is a huge oil exporter, and the volatility in sovereign risk proxied by CDS is linked with the ruble's depreciation in 2014–2016, hampering investors' confidence in Russian government stability. Conversely, oil price fluctuations had no significant effect on the Russian CDS. India's sovereign risk is more vulnerable to tapering from the Federal Reserve (Fed) than any domestic macroeconomic variable. Fed tapering often causes cascading effects, leading to the fallout of the Indian rupee and interest rates on bonds (Kumar and Singh 2022a). For the BRICIT CDS, FED and VIX affect the global variables the most. This study's empirical evidence has relevant implications for CDS market participants. For instance, investors, speculators, and arbitrageurs may use the spillover information to improve their portfolio diversification, credit risk management, and asset allocation. Additionally, the results are helpful to policymakers who aim to minimize and stabilize the effects of crises on the economy (Shahzad et al. 2017a, b). Cross-border spillover analysis indicates that the Indonesian stock market is the most interconnected, representing a potential source of spillover. In contrast, the Turkish LTR sends the most substantial spillover transmission across BRICIT CDS. As governments are responsible for managing and strategizing the growth of their economy, they must consider many economic and geopolitical uncertainties and the possible repercussions for their country.

This comprehensive study can provide investors, policymakers, and researchers with crucial insights into the complex world of sovereign risk assessment in BRICIT, enabling informed decision-making and policy development. Our methodological framework enables a comprehensive analysis that considers long-term dynamics and short-term fluctuations, providing a sound understanding of the interplay between various domestic macroeconomic and global determinants. We identify specific influential variables, such as the impact of geopolitical uncertainty in China on Chinese sovereign risk and the influence of long-term interest rates on Russian CDS, providing novel insights. Moreover, the study's categorization of spillover effects into quadrants can help policymakers identify key determinants with high interconnectedness or intense spillover intensity, emphasizing the need for targeted risk management strategies in these nations. Additionally, the research's implications for policymakers are profound, offering a strategic framework for stabilizing the economy amid crises and managing potential geopolitical and economic uncertainties. By highlighting the crucial role of specific domestic and

global determinants in shaping sovereign risk volatility, this study provides policymakers with valuable insights that can inform their decision-making processes and aid in formulating effective macroeconomic policies. Our findings hold practical implications for market participants, empowering them to enhance portfolio diversification, refine credit risk management, and optimize asset allocation strategies across the BRICIT nations, contributing to a more resilient and robust financial landscape.

The rest of the paper is divided into six sections. Sect. "Literature review" briefly discusses the review of existing studies, Sect. "Methodological framework" describes the methodologies used, and Sect. "Data Description" explains the data. Sect. "Result discussion" discusses the result and its analysis, and Sect. "Conclusion" concludes the study.

Literature review

Studies on determinants of SCR have recently flourished due to the subject's relevance. Numerous studies have identified the role of macroeconomic factors that control the swings in sovereign risk. For example, Kocsis and Monostori (2016) outlined the relevance of local fundamentals, and Longstaff et al. (2011) linked a significant part of the sovereign risk to global factors. Hilsher and Nosbusch (2010) evaluated the effect of the volatility of fundamentals on sovereign CDS spreads, finding terms of trade to be economically and statistically significant in explaining CDS spreads. Additional research revealed that factors such as the 3-month London InterBank Offered Rate, FFR, political factors, VIX, treasury bill rates, GDP, government external debt, the MSCI Index, CPI, and stock markets are all determinants for sovereign risk (Lahiani et al. 2016; Pavlova et al. 2018; Sabhka et al. 2019; Chuffart and Hooper 2019). In contrast, other studies highlighted high interlinkages between the CDS markets and different financial markets (Wang and Moore 2012; Hammoudeh et al. 2013; Arouri et al. 2014; Sun et al. 2020; Wang et al. 2020; Ibhagui 2021).

Until recently, several research papers focused on the potential links and interconnectedness between sovereign markets and macroeconomic factors (Pavlova et al. 2018; Bouri et al. 2020; Bajaj et al. 2023). These studies used comprehensive methodological approaches, including correlation, regression, causality, and cointegration. Kisla et al. (2018) used spatial regression analysis to cite a few examples to assess the determinants and linkages between sovereign risk and macroeconomic factors. Chen et al. (2020) employed Granger causality and network structures to study the interconnections between European sovereign CDS markets. Along with causality, Bratis et al. (2020) used various other tools, including cointegration, to test the spillover effects of sovereign CDS and banks for core and peripheral European countries. Using fixed effect panel logistic regression, Fong et al. (2018) reported commodity prices as one of the critical risk factors of sovereign risk. Furthermore, Lahiani et al. (2016) found that crude oil did not impact the short-run dynamics regarding CDS in the banking and financial service sectors. Bouri et al. (2017) revealed significant volatility transmissions from commodity prices to sovereign CDS using the Lagrange multiplier. Cross quantilogram is another method Bouri et al. (2018) and Bouri et al. (2020) used to report the relation and asymmetric effect of sovereign risk and oil prices. Using the Markov regime-switching VAR framework, Guo et al. (2011) examined contagion effects between credit, energy, stock, and real estate markets. They determined oil prices and stock market shocks as the main

drivers behind credit markets during crises. Shahzad et al. (2017a, b) used the bootstrap rolling window approach and cross-quantilogram approach to document the directional predictability from oil to CDS spreads of GCC[7] countries and five other oil exporters; their results differed for all countries.

Pavlova et al. (2018) recently used Diebold and Yilmaz's (2012) connectedness index approach to analyze directional spillovers from oil volatility to ten oil-exporting countries. Singh et al. (2018) and Singh et al. (2019a, 2019b) applied a similar approach to understanding the system-wide connectedness between various markets, using network graphs to understand the complex interlinkages. Studying an entire system is complex, and including many countries and variables make the calculations huge and intricate. Furthermore, solving the entire system together can manipulate the results, as global factors are typical for all countries but act differently for different countries. The B-GVAR model can solve the issue by dividing the entire system into smaller sub-systems and solving the individual country model. The results are then stacked into one standard system. Its VAR reduces the risk of overparameterization by imposing certain restrictions on VAR parameters and generating more accurate forecasts (Assaf et al. 2018). This study relies on the B-GVAR model to estimate spillovers between SCR and macroeconomic factors. Based on B-GVAR, we estimate generalized impulse response functions and generalized forecast error variance decomposition (GFEVD); the interconnections are shown using network graphs. Additionally, we used ARDL (Pesaran and Shin 1995) with cointegration as a robustness check. A careful examination of the above literature highlights that research related to the interconnectedness of SCR and macroeconomic factors of BRICIT nations requires further examination, especially from the perspective of B-GVAR methodology.

To our knowledge, no literature has assessed the systemic spillovers between SCR and macroeconomic factors of BRICIT nations. We attempt to fill this gap by investigating the system-wide spillovers between macroeconomic factors and CDS spreads of BRICIT nations. The US economy influences the world economy through its fundamentals; therefore, this study considers the US economy to control global impacts.

Methodological framework

Autoregressive distributed lag cointegrating bounds model

The generalized ARDL (p, q) model of Pesaran and Shin (1995) can be mathematically illustrated as follows:

$$\mathrm{Y_t} = \mathbf{Y}_{0j} + \sum_{i=1}^{p} \delta_i Y_{t-i} + \sum_{i=0}^{q} \beta_i{}' X_{t-i} + \varepsilon_{it}$$

Here, $\mathrm{Y_t}$ is the logarithmic change of the CDS of the BRICIT nations, and "X" is a vector of the independent variables considered (CPI, REER, SMI, LTR, GI, WTI, FFR, DI, and VIX).

In the case of cointegration, the ECM can be specified as follows:

[7] The Gulf Cooperation Council (GCC) is a political and economic alliance of six Arab countries in the Middle East.

$$\Delta lnCDS_{\mathrm{t}} + a_0 + \sum_{i=1}^{p} \alpha_i \Delta lnCDS_{t-i} + \sum_{i=1}^{q1} \beta_{1i} \Delta cpi_{t-i}$$
$$+ \sum_{i=1}^{q2} \beta_{2i} \Delta lnreer_{t-i} + \sum_{i=1}^{q3} \beta_{3i} \Delta lnsmi_{t-i} + \sum_{i=1}^{q4} \beta_{4i} \Delta lnltr_{t-i}$$
$$+ \sum_{i=1}^{q5} \beta_{5i} \Delta gpr_{t-i} + \sum_{i=1}^{q6} \beta_{6i} \Delta lndol_{t-i} + \sum_{i=1}^{q7} \beta_{7i} \Delta lnfed_{t-i}$$
$$+ \sum_{i=1}^{q8} \beta_{8i} \Delta lnvix_{t-i} + \sum_{i=1}^{q9} \beta_{9i} \Delta lnoil_{t-i} + \lambda ECT_{t-1} + \varepsilon_t$$

Bayesian global vector autoregression (B-GVAR) model

The core of the B-GVAR involves VAR estimation, followed by stacking the estimated results with exogenous weights. Each VAR estimation includes country-specific variables treated as endogenous and foreign-specific variables treated as exogenous. The foreign-specific variable was computed as the weighted average of other nations' corresponding variables. Weight allocation can be based on average annual trade flow over time or capital flow across nations.

$$\text{Country} - \text{specific variable } (\mathrm{x_{it}}) \;=\; \ln\left(\mathrm{P_{t+1/}P_t}\right)$$

$$Foreign - specific\ variable\ (xit)* = \sum\nolimits_{(j=0)}^{N} (w_i j * x_i t)$$

Here, w_{ij} is the weight computed; (ij) reflects the share of country "j" in the net capital/trade flow of country "i." Table 1 shows the flow from country (i —> j).

Hence, the corresponding weight can be computed as follows:

$$\mathrm{W_{kj}} = \frac{d_{kj}}{\sum\limits_{j=1}^{N} d_{kj}, j \neq k}$$

The global VAR equation for the research is illustrated as follows.

The equation for BRICIT:

$$x_{it} = \sum\nolimits_{(i=1)}^{p} \alpha_i \Delta lnCDS_{(t-i)} + \sum_{i=1}^{p} \Psi_i x_{i,t-i} + \sum_{i=1}^{p} \Lambda_i x^*_{i,t-i} + \sum_{i=1}^{p} \Phi_i x^{**}_{i,t-i} + \varepsilon_{it} \qquad (1)$$

Table 1 Flow from country (i—> j)

$x_1 x_2 \ldots\ldots x_N$	**Total Flow**
$x_1 0 d_{12} \ldots\ldots$	$d_{1N} \sum_{j=1}^{N} d_{1j}, j \neq 1$
$x_2 d_{21} 0 \ldots\ldots$	$d_{2N} \sum_{j=1}^{N} d_{2j}, j \neq 2$
.....	
.....	
.....	
$x_N d_{N1} d_{N2} \ldots\ldots$	$0 \sum_{j=1}^{N} d_{Nj}, j \neq N$

where

$$x_i^{**} = \{\boldsymbol{\Delta} lndol**, \boldsymbol{\Delta} lnfed**, \boldsymbol{\Delta} lnvix**, \boldsymbol{\Delta}\mathbf{US.gpr}**, \boldsymbol{\Delta} lnoil**\}$$

x_i^* *are cross-country domestic variables termed as weakly exogenous* $= \sum_{i=1}^{N} W_i x_i$

$$x_i = \{\boldsymbol{\Delta lnCDS}, \boldsymbol{\Delta} cpi, \boldsymbol{\Delta} lnreer, \boldsymbol{\Delta} lnsmi, \boldsymbol{\Delta} lnltr, \boldsymbol{\Delta} gpr\}$$

The equation for the US model can be written as follows:

$$x_{it} = \sum_{i=1}^{p} \alpha_i \Delta lnCDS_{t-i} + \sum_{i=1}^{p} \Psi_i x_{i,t-i} + \sum_{i=1}^{p} \Lambda_i x_{i,t-i}^{*} + \sum_{i=1}^{p} \Phi_i x_{i,t-i}^{**} + \varepsilon_{it} \tag{2}$$

$$x_i = \{\boldsymbol{\Delta lnUS.CDS}, lndol, \boldsymbol{\Delta} lnfed, \boldsymbol{\Delta} lnvix, \boldsymbol{\Delta} US.gpr\}.$$

The equation for oil can be written as follows:

$$\boldsymbol{\Delta} lnoil_t = \sum_{i=1}^{p} \beta_i \Delta lnoil_{t-i} + \sum_{i=1}^{p} \delta_i \Delta lnCD_{t-i} + \mu_{\mathrm{it}} \tag{3}$$

where $\Delta lnCD = \sum_{i=1}^{N} \frac{1}{N} \Delta lnCDS_i$.

$\Delta lnCDS = \{\Delta lnBR, \Delta lnRU, \Delta lnIN, \Delta lnCH, \Delta lnID, \Delta lnTU\}$ is a vector for the sovereign CDS of BRICIT. Note that for the oil equation, equal weights have been assigned to each country CDS.

We then apply the stochastic search variable selection prior, which provides prior specification in the variance–covariance matrix. Mathematically, it can be deduced as follows:

$$\psi_{(ij)} | \delta_i j (1 - \delta_i j) \mathcal{N}(0, \tau_{0j}^2) + \delta_{ij} \mathcal{N}(0, \tau_{0j}^2) \tag{4}$$

The usage of binary variables (δ_{ij}) aids in the inclusion of a variable in each VAR estimation. The variance of the normal distribution for the prior is set to a large value to have an uninformative prior; the mean is set to zero. Depending on the binary value, the hierarchical prior setup can be deduced as follows:

$$\Psi_i | D_i \sim (0, R_i) \; and \; \Sigma_{\varepsilon i} \sim (S_i, \nu_i). \tag{5}$$

Here, $R_i = D_i D_i$ along with the Wishart prior chosen for $\Sigma_{\varepsilon i}$ and imposition of the Bernouli prior on $\delta_{ij} \sim Bernouli(q_{ij})$ following George et al. (2008).

Generalized forecast error variance decomposition

In the generalized forecast error variance decompositions (GFEVD) framework, the forecast error variance equations can be decomposed to see how much variance is caused by oneself for variable i and how much is contributed by the rest. Utilizing the concept, Diebold and Yilmaz (2012) derived a set of connectedness measures and deployed them to different levels of granularity from pairwise to system-wide "FROM," "TO," "NET," and "TOTAL" connectedness values.

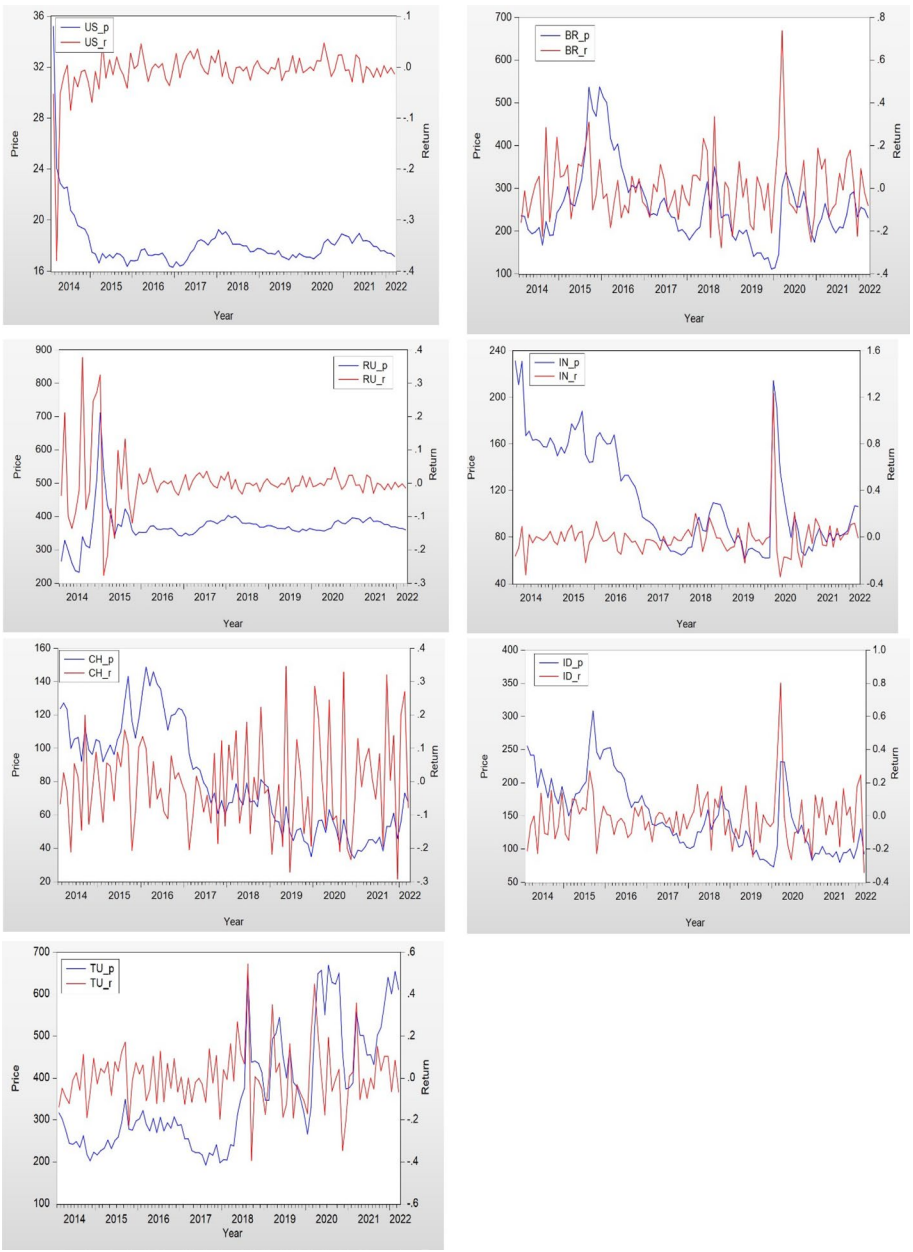

Fig. 1 Price/ Return Plot for CDS. Country codes: US = United States of America, BR = Brazil, RU = Russia, IN = India, CH = China, ID = Indonesia, and TU = Turkey

$$C_{FROM(i\leftarrow\blacksquare)}(H) = \frac{\sum_{j=1_{i\neq j}}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ij}^{g}(H)} \times 100 = \frac{\sum_{j=1_{i\neq j}}^{N} \tilde{\vartheta}_{ij}^{g}(H)}{N} \times 100 \tag{6}$$

$$C_{TO(\blacksquare\leftarrow i)}(H) = \frac{\sum_{j=1_{i\neq j}}^{N} \tilde{\vartheta}_{ji}^{g}(H)}{\sum_{i,j=1}^{N} \tilde{\vartheta}_{ji}^{g}(H)} \times 100 = \frac{\sum_{j=1_{i\neq j}}^{N} \tilde{\vartheta}_{ji}^{g}(H)}{N} \times 100 \tag{7}$$

$$C_{i(NET)}(H) = C_{\blacksquare \leftarrow i}(H) - C_{i \leftarrow \blacksquare}(H) \tag{8}$$

$$C_{TOTAL}(H) = \frac{\sum_{i,j=1_{i \neq j}}^{N} \widetilde{\vartheta}_{ij}^{g}(H)}{\sum_{i,j=1}^{N} \widetilde{\vartheta}_{ij}^{g}(H)} = \frac{\sum_{i,j=1_{i \neq j}}^{N} \widetilde{\vartheta}_{ij}^{g}(H)}{N} \tag{9}$$

Data description

For this study, the credit default swap(CDS) data is used as a proxy for SCR for BRICIT nations. The monthly data has been sourced from Bloomberg from January 2014 to March 2022. The reason for such a sample is the unavailability of CDS data for India before 2014. The domestic macroeconomic variables include CPI, REER, domestic SMI, LTR, and domestic geopolitical risk for that nation. The data were sourced from International Monetry Fund (IMF) and Federal Reserve Economic Data (FRED). We included the political risk index proposed by Caldara et al. (2022); the data were sourced from the Economic Policy Uncertainty data stream. Certain economic variables native to the US economy shape global macroeconomic fundamentals; hence, economic variables (FFR, DI, and VIX) were considered. The data was sourced from FRED. Figure 1 plots the price return plot for the CDS data, showing that compared to US CDS, the return series of BRICIT CDS has high volatility. The high uncertainty is indicative of prevailing economic uncertainty in these nations. Thus, further exploration of major economic indicators vis-à-vis CDS of BRICIT nations is required. The volatility in CDS is most pronounced in China. The volatility spikes closely correlate with the significant economic distress events associated with BRICIT CDS. For example, Russia's CDS volatility was more pronounced from 2014 to 2015, with an episode of sharp devaluation of the ruble and an excess crude supply. Since Russia is a huge crude exporter, the volatility in CDS could be attributed to oil price shocks and excessive devaluation in the ruble, deteriorating investor confidence in the Russian market. Furthermore, Turkey's volatility spike was comparatively higher during the 2018 presidential elections, with a falling lira. The sovereign uncertainty is reflected in the high volatility of the Turkish CDS return. For India and Indonesia, volatility in CDS was most prominent during the COVID-19 pandemic. An important observation is that China's CDS shows persistent high volatility in return throughout the period, indicating prevailing economic uncertainty. Compared to BRICIT nations, US CDS returns volatility is stable, with just one spike during 2014–2015, when shrinkage in advanced economies, mainly the US, was observed; however, post-2014, investors' perception of US sovereign risk was less skeptical.

In contrast, BRICIT nations can drive world growth with affirmative expansion and witness volatility in the sustenance of their domestic macroeconomic situations. A critical reason attributed to these emerging economies is political instability relative to developed markets, thus making investors' perceptions dicey. Moreover, the Fed's tapering exercise in balancing inflation and unemployment has led to an overnight fall in investors' sentiments. Thus, macroeconomic fundamentals have varied effects on BRICIT CDS. Appendix I depicts the transformation made to make the variables stationary before fitting the VAR model. Log transformation signifies the natural logarithm of the data, while log return signifies the monthly logarithmic change in the

Table 2 Descriptive statistics of CDS

	Mean	Std. Dev	Median	Min	Max	Range	Skewness	Kurtosis	Std. Error	ADF-Test
US_CDS	−0.0079	0.0443	−0.0046	−0.3789	0.0473	0.4262	−5.9847	47.4433	0.0045	−8.325
BR_CDS	−0.0019	0.1506	−0.0102	−0.2779	0.7381	1.016	1.3138	4.4781	0.0152	−5.645
RU_CDS	0.0027	0.0849	−0.0026	−0.2762	0.3773	0.6536	1.4645	7.1363	0.0086	−7
IN_CDS	−0.0096	0.1622	−0.0216	−0.3391	1.2335	1.5727	4.395	32.8498	0.0164	−6.381
CH_CDS	−0.0069	0.1405	−0.0181	−0.292	0.3462	0.6382	0.3631	−0.2987	0.0142	−7.469
ID_CDS	−0.0124	0.1522	−0.0117	−0.3408	0.8024	1.1432	1.556	6.8472	0.0154	−6.505
TU_CDS	0.0053	0.1466	−0.0026	−0.3925	0.5452	0.9377	0.6679	1.9854	0.0148	−6.095

US United States of America *BR* Brazil *RU* Russia *IN* India *CH* China *ID* Indonesia and *TU* Turkey

Table 3 Estimates from ARDL with Unrestricted ECM

	BR		RU		IN		CH		ID		TU	
variables	**Estimate**	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**	**Estimate**	**Pr(>|t|)**
(Intercept)	0.004	0.647	−0.002	0.845	0.004	0.718	−0.018	0.096	−0.009	0.381	0.001	0.913
L(CDS, 1)	−1.205	0***	−1.057	0***	−1.132	0***	−1.471	0***	−1.42	0***	−1.283	0***
L(cpi, 1)	−0.061	0.012*	−0.016	0.224	−0.02	0.353	0.08	0.007**	0.031	0.18	0.006	0.113
L(reer, 1)	−1.02	0.011*	−0.767	0.015*	−0.594	0.644	−0.392	0.733	−2.599	0.006**	−1.254	0***
L(smi, 1)	−0.581	0.075	0.409	0.125	−1.403	0.004**	−0.438	0.059	−1.098	0.031*	−0.642	0.009**
L(ltr, 1)	1.434	0***	0.873	0.001**	1.307	0.059	0.136	0.728	1.189	0.013*	1.104	0***
L(gpr, 1)	0.067	0.838	−0.032	0.243	0.169	0.424	0.193	0.004**	1.271	0.023*	−0.032	0.604
L(oil, 1)	−0.096	0.434	−0.13	0.299	−0.147	0.343	0.328	0.029*	−0.11	0.441	−0.087	0.422
L(fed, 1)	−0.111	0.011*	−0.014	0.712	−0.135	0.013*	−0.139	0.008**	−0.153	0.003**	−0.106	0.003**
L(vix, 1)	0.108	0.1	0.015	0.803	0.1	0.242	0.558	0***	0.332	0***	0.012	0.828
L(dol, 1)	1.128	0.33	−1.154	0.239	2.873	0.036*	3.639	0.005**	2.129	0.106	0.814	0.461
d(cpi)	−0.023	0.297	0.024	0.103	−0.002	0.876	0.046	0.024*	0.021	0.286	0	0.946
d(reer)	−0.358	0.173	−0.465	0.01*	0.634	0.421	−0.32	0.762	−0.843	0.152	−0.126	0.55
d(smi)	−0.484	0.023*	0.406	0.04*	−1.595	0***	−0.307	0.085	−0.86	0.011*	−0.495	0.001**
d(ltr)	1.043	0***	0.437	0.022*	0.799	0.074	0.064	0.815	0.595	0.052	0.967	0***
d(gpr)	0.032	0.869	−0.017	0.307	0.096	0.429	0.13	0.001**	0.632	0.056	−0.012	0.742
d(oil)	−0.125	0.151	−0.024	0.775	−0.323	0.005**	0.108	0.304	−0.067	0.515	−0.011	0.883
d(fed)	−0.064	0.09	0.033	0.329	−0.175	0.001**	−0.031	0.469	−0.089	0.044*	−0.068	0.029*
d(vix)	0.086	0.025*	0.017	0.635	−0.004	0.937	0.329	0***	0.194	0***	−0.008	0.812
d(dol)	0.644	0.52	−1.327	0.126	1.836	0.119	0.659	0.595	1.225	0.266	0.035	0.971
Adj.R-sq	0.8830		0.6868		0.8606		0.8580		0.8572		0.9232	
F-Test	30.5761		8.8847		25.0271		24.4902		24.3178		48.7237	
p-value	0.0000		0.0000		0.0000		0.0000		0.0000		0.0000	

*** = significance at—0.001, ** = significance at—0.01, * = significance at—0.05, and. = significance at—0.1

data series. Table 2 provides summary statistics for BRICIT CDS. Apart from Russia and Turkey, the average log return for the rest of the CDS is negative, though it remains near zero.

A negative average return of CDS implies investors' speculation of sovereign risk of a nation rising in the future. Thus, macroeconomic uncertainty and political instability are expected to intensify. Russian average returns show low dispersion across the mean, implying that investors' perception of rising uncertainty in Russia remains consistent without much deviation. From an investor's perspective, less volatility resonates with the risk-averse choice; however, from an economic perspective, prevalent economic and political uncertainty is alarming for the world order. Since Russia is a significant exporter of oil and gas, prevailing uncertainty could cause trade distortions. Hence, domestic macroeconomic fundamentals' short-term and long-term structural effects on the countries' sovereign risk require investigation. At the same time, secondary market investments have increased the cross-border flow of capital due to increasing market linkage among BRICIT countries due to bilateral trade. As a result, distress in one nation could transgress to others, inviting a comprehensive model for exploration.

Result discussion

Long and short-run dynamics from ARDL–ECM

Appendix I presents the bound test F-statistics to verify the existence of cointegration before fitting the unrestricted ECM on ARDL. For all the CDS, the F-test statistics exceed the upper bound for the different tolerance levels, signifying the presence of cointegration in the series. We then proceed with fitting the ECM model. Table 3 shows the estimates and the significance of long- and short-run dynamics estimated via ARDL with UECM. We restricted to lag one due to limited data points in our analysis from January 2014 to March 2022, with monthly periodicity. The adjusted R square for each equation is acceptable. The overall equation significance is validated by F-statistics, which exceeds F-critical at 5% tolerance for both the long and short-run estimates. Thus, the UECM model for each sovereign CDS is a good fit overall. The lag one value for each country's CDS significantly influences long-run CDS; thus, past series of CDS have the predictive ability for the new CDS return. Nonetheless, in the long run, asymmetry occurs for country-specific variables (CPI, REER, SMI, LTR, and domestic geopolitical risk) for BRICIT nations. Theoretically, the REER should impact the CDS; the same is observed for all the nations except India and China, where the exchange rate is floating and pegged, respectively, guaranteeing the reasonable stability of Chinese currency against other currencies (Feng et al. 2021). Due to the lack of a market-determined exchange rate, the long-run relationship between the REER of India and China is not significant for their sovereign CDS. It is complemented further by the significance pattern observed for the LTR on CDS. Notably, longer-maturity bonds are affected more by interest rate fluctuations. The logarithmic change in the LTR on 10-year government bonds influences the sovereign CDS of most BRICIT nations, with India and China being the exceptions. Hence, a similar trend is observed regarding long-term interest rates. This result aligns with Hammoudeh and Sari (2011), who found a significant influence of long-term

interest rates on country CDS. In fact, among country-specific variables, real effective exchange and long-term interest rates are the most significant influencers.

Regarding domestic and global variables, the impact of China's CDS is more pronounced than that of other countries. The long-term impact on China's CDS is more significant for the variables than the short-term. Interestingly, geopolitical risk is highly significant for China's short- and long-run CDS. As already observed in Fig. 1, China's CDS has high volatility, which has to be primarily attributed to geopolitical risk. Ambitious economic measures from China's government influenced every economic touch point, such as foreign direct investment inflow and low unemployment, projecting Chinese firms on the global stage. At the same time, interstate trade disputes in China increased due to a lack of transparency regarding the Chinese macroeconomy or geopolitical affairs, rendering the reported economic and financial figures unreliable. Perceived investors' sentiments of excessive unreliability result in high volatility in CDS returns. China has emerged as a global economic power with heavy reliance on a global supply chain network and centralized distribution setup. World logistics witnessed supply chain disruption during the COVID-19 pandemic, and persistent geopolitical risk levels devastated the world asset class (Singh and Roca 2022); hence, this study's findings are alarming for investors and policymakers who want to regulate their dependency on China. At the same time, volatile CDS reflects a lack of trust in the sovereign, which could further escalate to a fall in the foreign money flow. After China, Indonesia, and Turkey, CDS is more sensitive to macroeconomic variable fluctuations. The long-term effect is generally more pronounced than in short-run dynamics, and domestic macroeconomic policy changes require time to settle and reflect in CDS prices. Hence, the long-run relationship of country-specific variables is noticeable, though with certain asymmetries.

Regarding the global variables, asymmetry occurs for long- and short-run dynamics. In contrast, the long-term effect is more pronounced for the Fed rate, with Russia being the only exception. Nonetheless, the response to sudden Fed tapering is highly

Table 4 Bayesian global vector autoregression diagnostics

Bayesian Global Vector Autoregression		
Prior	**Stochastic Search Variable Selection Prior (SSVS)**	
Endogenous Lags	1	
Weakly Exogenous	1	
Posterior draws	30,000/10 = 3000	
Stable Posterior Draws	3000	
Cross-sectional Units	8	
Convergence Diagnostics		
Geweke Statistics	**155 out of 1848 variables, z-value exceed the 1.96 threshold (8.39%)**	
F-Test, first order serial autocorrelation of cross-unit residuals		
p-value	Number	%
> 0.1	28	66.67
0.05–0.1	8	19.05
0.01–0.05	1	2.38
< 0.01	5	11.90

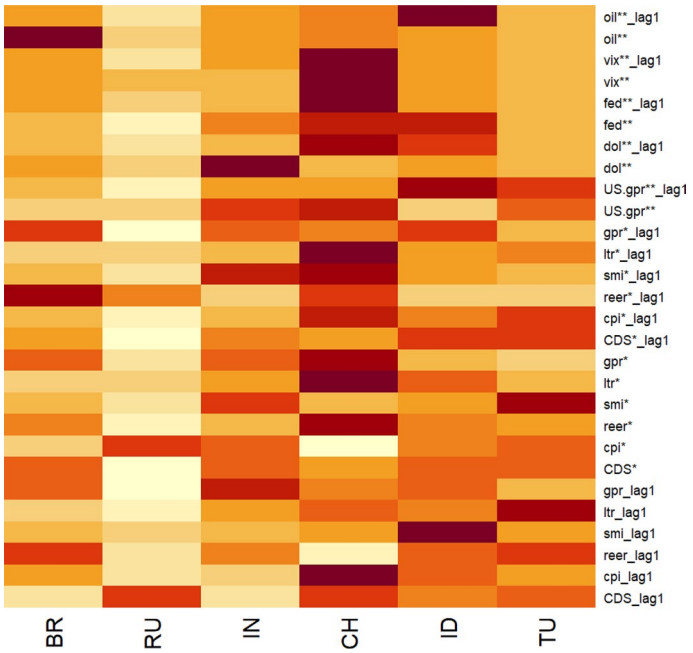

Fig. 2 Heatmap of Contribution in Bayesian VAR by Domestic and Global Variables

significant for India, implying the sensitivity of the Indian macroeconomy to Fed tapering. Apart from the Fed, the impact of DI and WTI on Indian CDS is highly significant in the short run. Notably, Indian financial indicators are sensitive to spillover risk from crude (Kumar and Singh 2022b). Interestingly, the shock in oil prices did not affect CDS in the short or long run for Russia. As Fig. 1 shows, 2014–2016 marks a high volatility period of Russian CDS. It could be attributed to oil price fluctuations, currency devaluation, or both. However, the findings indicate that only the exchange and long-term interest rates impact Russian CDS significantly. This finding implies that the loss of investors' trust in the Russian macroeconomy is primarily due to excessive currency devaluation. Notably, currency depreciation is often followed by equity market decline, which is more pronounced for developing nations (Patro et al. 2014). Significantly, for Russian CDS, the SMI impacts in the short run apart from the exchange and long-term interest rates. After the Fed, the effect is more pronounced for VIX, significantly impacting China, Indonesia, and Brazil. Notably, the sensitivity to the stock market is more prominent in the short run, where a rise in the SMI negatively influences the CDS for all nations. Theoretically, it can be explained as a shift in the lender's risk appetite, leading to a fall in demand for CDS as a hedge for a government bond. As a result, **a negative** relationship is justified from an economic sense (Norden and Weber 2009). Conversely, the same does not hold for Russia, where the SMI and CDS move in the same direction. This asymmetry is worth investigating to determine the economic underpinnings.

Notably, the ARDL ECM model lays the foundation for a long- and short-run relationship of domestic and global variables for BRICIT nations; however, due to globalization, the cross-border flow of capital has increased, inducing cross-country influence of an economic/financial indicator over others. Moreover, the domestic variables could also be associated with each other. Limited to the data observation and estimating

cross-country impact, we use the B-GVAR approach for cross-country association estimation. This approach aids in addressing the problem of dimensionality by avoiding pooling all the data together and applying the VAR-based approach. Instead, the VAR estimation occurs country-wise, and the VAR equations are stacked.

Cross-country association measure using Bayesian global vector autoregression

Table 4 illustrates the summary of the B-GVAR model. Notably, we restricted lag to one due to limited data. Additionally, WTI was taken as a global variable; thus, it is exogenous. Other foreign variables that may influence the sovereign CDS of BRICIT, such as FFR, VIX, DI, and US geopolitical risk, were included in the US model. The Gweke statistic shows that very few draws exceed the threshold, implying that most draws come from stationary distribution, reflecting convergence. The serial autocorrelation of residuals for low tolerance levels is also low. Notably, the F-test statistic reflects a reasonable likelihood of the estimated global model as the null hypothesis of zero autocorrelation is violated for high tolerance only. Hence, the B-GVAR diagnostics illustrate that the model is a good fit. Figure 2 displays the average contribution of each variable in the stacked B-GVAR equation. The variables in the stacked equation on the extreme right of the matrix Fig. 2 are segregated as endogenous for country-specific variables (no asterisk), weakly exogenous for cross-country-specific variables (*), and global variables (WTI, VIX, DI, FFR, US.gpr, and oil) (**). The observations indicate the existence of cross-border spillover from other nations' macroeconomic variables. China's CDS is most heavily related to cross-country and global variables compared to other BRICIT nations, highlighting the dominance of China in BRICIT as its sovereign risk is heavily related to the BRICIT nations. In contrast, Russia is least interconnected among the BRICIT as cross-country variables have little influence on Russian CDS. BRICIT economic variables influence Indonesia and Turkey more than Brazil and India (Table 3).

Implications for policymakers

As the output of the B-GVAR model confirms cross-border spillover, policymakers are often constrained by the quantum of cross-border macroeconomic determinants. At the same time, increasing market connectedness leads to heavy spillover linkage, which

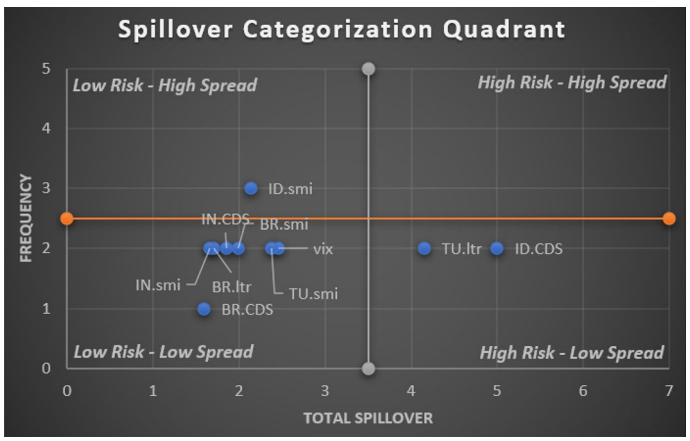

Fig. 3 Top 10 Spillover Transmitter Nodes to BRICIT CDS of 75% Quantile

could affect the country's sovereign risk. The more comprehensive the system is, the more challenging it becomes to identify the cross-border macroeconomic or worrisome financial variables. Apart from the absolute spillover quantum, identifying the number of national CDS exposed to high-intensity shocks is essential. Cross-border variables affect CDS more because they indicate solid market interconnections; thus, apart from prudential domestic macroeconomic policies, a close watch on the interconnected market has to be done. Proceeding with the past information on spillover linkage excavation, we can determine and scrutinize specific numbers of high-intensity spillover origination macroeconomic variables. To accomplish this, we segregate the high-intensity spillover over a certain threshold into quadrants. Notably, apart from the absolute quantum of spillover, virality also matters. The number of CDS affected by a macroeconomic variable is a good indication of a plausible spillover virality. Henceforth, quadrant construction plots absolute spillover regarding the count of CDS affected, termed frequency.

Post Bayesian VAR fitting, we apply GFEVD to decompose the shock for a variable as a summation of shock from itself and the rest. The shock decomposition for BRICIT CDS is then segregated to analyze the top spillover reception. The threshold cut-off is the 75% quantile, above which the top 10 spillovers are used. Figure 3 depicts the top 10 spillovers over the 75% quantile cut-off. Certain variables influence more than one CDS; thus, the spread is high. Puadrant division is used to plot "total spillover intensity" regarding "frequency," where frequency represents the number of CDS it affects. Notably, a policymaker can choose the cut-off quantile of spillover transmission and analyze the top transmitters along with their spread. Figure 3 shows the same with a 75% quantile cut-off, and the top 10 transmitters for the CDS market were subsequently analyzed. As observed, the Indonesian SMI sends shocks to BRICIT nations' CDS. This result implies that the Indonesian stock market shares more market interconnection with other BRICIT nations while remaining in the top 25 quantiles. Regarding the transmission intensity, the Turkish LTR and Indonesian SMI are too wary of sending the highest intensity transmission. The findings are a typical example of cross-border spillover significance, which should not be ignored.

Conclusion

The study investigates the determinants driving BRICIT nations' sovereign risk volatility. We apply the ARDL model with determinants segregated as domestic macroeconomic determinants (CPI, REER, SMI, LTR, and GI). The global determinants considered for the study include WTI, FFR, and VIX. Using the unrestricted ECM, we account for cointegration, long-term dynamics, and the short run. The results indicate that Chinese CDS is the most sensitive to domestic and global variables. Among country-specific variables, REER and LTR are the most significant influencers. Among the global variables, FFR is the most affected, with Indian CDS being the most sensitive to Fed tapering. In general, the long-term effects are more pronounced than the short-run impacts. Notably, geopolitical uncertainty in China is a significant cause of Chinese sovereign risk, causing massive volatility in CDS. Long-term interest rates linked with ruble devaluation primarily influence Russian CDS volatility. The findings statistically ascertain that domestic and global determinants impact the CDS volatility of BRICIT. Furthermore, to explore the cross-border influence of domestic determinants on CDS, we use the B-GVAR approach.

Our results highlight the existence of cross-border spillover from country-specific variables to BRICIT CDS. We categorized spillover into quadrants to assist policymakers in identifying domestic variables with high interconnectedness or spillover intensity. The top 1% spillover out of the 75% quantile cut-off indicates that the Indonesian SMI is more vulnerable to spillover virality owing to high interconnectedness with CDS. On the spillover intensity side, the Turkish LTR sends high-intensity spillover to BRICIT nations. Therefore, apart from managing their country-specific macroeconomic policies, policymakers should be wary of these two determinants. Policymakers can use the results to stabilize the effects of the crisis on the economy. As governments are responsible for managing and strategizing the growth of their economies, they must consider many economic and geopolitical uncertainties on the horizon and their possible repercussions for their country. This study can be extended by factoring in more variables that may bear an economic relationship with sovereign risk. This study's findings also have relevant implications for market participants who may use the spillover information to improve their portfolio diversification, credit risk management, and asset allocation across BRICT nations.

Appendix I: Variable Transformation to achieve stationarity

CDS	CPI	REER	SMI	LTR	GPR	OIL	FED	VIX	DOI
Log return	First difference	Log return	Log return	Log return	First difference	Log return	Log return	Log return	Log return

CDS Credit Default Swap *CPI* Consumer Price Index *REER* real effective exchange rate *SMI* stock market index *LTR* long term interest rate *GPR* geopolitical risk *DOI* real dollar index *FED* Fed rate VIX-VIX index *OIL* crude oil WTI.

Appendix II: Bound Test F-statistic

			I(0)	I(1)		
		10% critical	1.95	3.06		
		5% critical	2.22	3.39		
		1% critical	2.79	4.1		
	BR	RU	IN	CH	ID	TU
F-test	12.95	17.04	10.42	21.71	19.47	16.11

Abbreviations

CDS	Credit default swaps
BRICIT	BRICIT stands for Brazil, Russia, India, China, Indonesia, and Turkey
ARDL	Autoregressive distributed lag
B-GVAR	Bayesian global vector autoregression
VIX	Volatility index
GFC	Global financial crisis
ESDC	European sovereign debt crisis
SCR	Sovereign credit risk
MINT	An acronym that refers to *a group of countries like* Mexico, Indonesia, Nigeria, Turkey
CPI	Consumer price index
LTR	Long term interest rates

SMI	Stock market indices
REER	Real effective exchange rate
GI	Geopolitical uncertainty index
VIX	Volatility index
DI	Real dollar index
WTI	Crude oil
FFR	Federal funds rate
ECM	Error correction model

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Ethics approval and consent to participate
Not applicable

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