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DCC GARCH Evaluation of Volatility Spillovers in Sovereign Bond Markets for Portfolio Optimisation

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Abstract

The main purpose of this paper is to examine the bond market volatility connectedness between BRICS (Brazil, Russia, India, China and South Africa) and five advanced market i.e. US, France, Italy, Germany and Japan, covering the period 2007-2023 (daily data), including covid-19 Pandemic. We find the persistence of volatility among the variable during crises. However, none of the bond indices of the developed market show a high magnitude of spillover to BRICS, denoting low integration between these countries during these crises. Russia and South Africa are the strongest transmitters of shocks to all other variables in BRICS. Overall it is being observed that the sovereign yield of India, China, and Brazil does not fluctuate much with U.S. and European markets during the crises, making them the most attractive market for risk minimisation and hedging. Therefore, this study suggests that in bond market BRICS have heterogeneous asset structure and can be looked for better bond's portfolio management.

Keywords: Garch. Volatility. Portfolio. Bond markets.

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1 Introduction

Interconnectedness in the financial markets across countries has increased tremendously during the last decade (Gubareva, 2021), and the global financial system is becoming more complex. Despite several enduring advantages like access to financial resources, market efficiencies, cost optimisation, etc., a host of disadvantages have crept in, threatening the global financial system, as is evident from the several instances of crisis in recent times. The spread of volatility across markets and related distortion of market structures frequently lead to contagion effects and challenge portfolio risk management in a global context. risk administration. The global spread of volatility jumps, particularly in the emerging markets, is an area of concern and debate among researchers, analysts, and policymakers (Christiansen, 2007). Apart from the stock markets, the bond markets have also caught attention in recent times, especially in the wake of the pandemic-related crisis. The financial recovery in the emerging bond market has lagged that of the advanced bond market, making emerging market bonds an attractive avenue for investment as they offer a higher yield compared to the developed bond market. They provide a nearly 4% higher annual

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return than sovereign bonds in advanced economies. Thus, emerging markets are viewed as a remunerative segment of the global economy. However, investors need to be acquainted with nominal ”tail risks” (i.e., the chances of significant losses occurring due to infrequent events). High market volatility is initially episodic for risk transmission and then becomes epidemic (Islam & Volkov, 2022).

Interdependence and contagions carry significant implications for international financial investors. They need to continuously monitor the correlations and dependencies and incorporate the impact of market microstructures on a dynamic basis. Considering this backdrop, the current study examines the volatility spillover effects of the bond markets in developed markets on a group of selected emerging economies constituted as the BRICS (Brazil, Russia, India, China, and South Africa). To assess the degree of interconnectedness during the economic and financial turmoil, we look for significant spillovers between sovereign bond markets in advanced and emerging economies. We gauge the effect of bond yield and volatility spillover using DCC-GARCH. The study uses the BEKK-GARCH model to examine the direction and degree of interconnectedness between the markets considered during the economic crisis. Our examination of bond yield spillover spillovers comprises large sample sets compared to the previous studies that have considered few markets in developed and developing countries. Our main motivation for selecting five major developed markets and five fastest-growing emerging markets is to develop an understanding of the relationship between developed and developing bond markets. The study covers four important periods of financial crises, i.e., the GFC, European debt crises, Brexit uncertainty, and the most recent COVID-19 pandemic crises. The study attempts to segregate the safe and risky countries for portfolio investment in terms of the nature and impact of sovereign bond spreads. The countries in which government bond yields remained low are considered safe, and on the contrary, the countries that have witnessed an upsurge in their sovereign bond yields are considered riskier (Xu et al., 2024). The results of our study carry significant implications for domestic and global fund managers and individual investors. It is estimated that the sovereign bond markets of the BRICS countries account for more than half of all outstanding local currency-guaranteed bonds.

2 Review of Literature

The incorporation of the financial markets gives rise to the rapid flow of information from one market to another, resulting in a quick transmission of volatility between the financial markets. Therefore, analysis of cross-border spillovers is extremely important for risk diversification. Volatility spillovers arise through financial connectedness and financial turmoil. Investors need to ascertain the volatility spillover to develop hedging tools to minimise the risk exposure. Furthermore, a profound understanding of Intermarket volatility spillover helps financial market policymakers work out suitable policies to reduce the risk of systematic instability.

The contagion among different financial markets has been a subject of much interest for researchers. The exploration of the spillover effect from developed countries' bond markets to emerging market economies using decomposition on high-frequency daily data of eight Asian emerging economies and five advanced economies shows that bond yields in Asian economies respond significantly to the variations in developed economies. Also, the spillover effects magnify unconventional monetary policy announcements as observed from May 2003 to September 2016. Ahmad, Mishra, and Daly's (2018) examine the sovereign bond connectedness between BRICS nations and major regional and global sovereign bond markets (US, EMU, and Japan). Their results of the directional connectedness method proposed by Diebold and Yilmaz's (2012) and network analysis show that South Africa and Russia are the primary sources of spillover to other countries in BRICS. The high observed integration between the United States and Japan is a significant source of spillover to the BRICS. The study also identifies a large set of financial and macroeconomic variables and finds that current account deficit, government debt, and interest rates hurt return and volatility spillover, while macroeconomic variables have a positive impact. According to the Global Economic Prospect, 2016 report and World Bank policy research note of 2015, a prolonged slowdown in some major emerging economies—the BRICS (Brazil, the Russian Federation, India, China, and South Africa) since 2010 has shown significant spillover to the other world economies through the channel of trade and finance. Some recent studies show China's financial market is highly influenced by the G7 countries and has a growing impact during periods of economic turmoil (Kirkulak Uludag & Khurshid, 2019).

Several studies have been conducted on contagion in the European government market during the global financial crisis and the eurozone sovereign debt crisis.Abad's (2013) examine the connectedness between the members of the European Monetary Union (EMU) by using the extreme negative and positive returns on a single day among various European countries to measure contagion. Empirical results reveal significant contagion between the old European Monetary Union (EMU) members and the new members during global financial and sovereign debt crises. By applying the measure developed by Diebold and Yilmaz's (2012) , the Vector Autoregressive (VAR) variance decomposition method, FernandezRodriguez2015<empty citation> confirm the volatility spillovers between the sovereign bond markets of euro area countries (central and peripheral). Divided into pre-crisis and crisis periods, they discover significant volatility transmission in the pre-crisis period, while the crisis period shows a decline in bond yield volatility spillover. Their study examines the dynamic integration of European government bond markets using multivariate econometric models and finds that global dynamics have a significant influence on the determination of yield differentials between euro government bonds. The bond markets in BRICS are connected, and financial shocks hailing from any BRICS country create a spillover effect for other BRICS countries (Xu et al., 2024). The grouping is becoming a focal point for a sychronised response to such regional shocks. Most of the existing literature focuses on cross-border connectedness among equity markets Umar et al.'s (2024) or other asset markets by Christiansen's (2007) and Mongkonkiattichai and Pattarathammas's (2010) analyse the financial contagion in the Indian commodity derivatives market to bond, foreign exchange, gold, and stock markets by applying the DCCMGARCH method for 2006–16. Their results confirm that commodities and stocks are the net transmitters of volatility, whereas bonds, gold, and foreign exchange are the net receivers of volatility.

Yurastika and Wibowo's (2021) examination of the spillover and asymmetric volatility between equity and green bond markets by using BEKK-GARCH and DCC-GARCH shows the presence of asymmetric volatility and the sensitivity to positive shocks in the green bond market and equity market. The study also finds that both markets do not respond significantly to adverse shocks. Bora and Basistha's (2021) have analysed the correlation between stock market return and bond yield in Central European countries during the European financial crisis by applying AG-DCC and GARCH specifications. The correlation has increased significantly in some countries (the United Kingdom, Germany, France, Spain, Portugal, Italy, the Czech Republic, Poland, and Hungary), while it has decreased in others (Spain, Portugal, Italy). Finally, in some countries, it remained the same as before the crisis (Czech Republic, Poland, Hungary). Gubareva's (2021) investigated time-varying volatility spillovers between stock markets of the countries most affected during the COVID-19 Pandemic and observed an unprecedented increase in dynamic spillovers in the period considered. The direction of Economic policy uncertainty (EPU) affects the net connectedness the information spillovers from one market to another may be positive or negative depending upon their economic condition. Based on the above literature current study evaluates the financial integration through the return and volatility spillover of the Bond market of advanced (US, France, Italy, Germany, Japan) countries for an association of developing countries coined as BRICS (Brazil, Russia, India, China, and South Africa). The primary purpose of this study is to analyse the dynamic correlation and volatility spillover effect using the DCC-GARCH and asymmetric GARCH BEKK model. In addition, the model investigates whether the degree of financial interconnectedness increases during economic and financial turmoil such as GFC, European debt crises, Brexit uncertainty, and the COVID-19 pandemic crises. Overall this study has important implications for cross-market portfolio allocation.

The paper's main contribution is that while the existing research examines the spillover between equity markets of mainly one or two developed countries and a few developing countries, the current study examines the bond yield spillover between five major developed markets and five. Second, this is the first study to analyse sovereign bond yield and volatility spillover during the four financial crises, i.e., GFC, European debt crises, Brexit uncertainty, and the most recent covid 19 pandemic crises. Precisely whether these financial crises imply to differentiate between safe and risky countries in terms of increase or decrease in sovereign spread. The countries in which government bond yields remained low are considered safe, and on the contrary, the countries that have witnessed an upsurge in their sovereign bond yield are considered riskier (nath Mukherjee, 2019).

3 Data Description and Methodology

We investigate the dynamic correlation and spillovers in the sovereign bond market between developed and developing countries during major economic crises. The period of the study from 9/5/2007 to 31/12/2023 covers the four major financial crises, i.e., the GFC, European debt crises, Brexit uncertainty, and the most recent COVID-19 pandemic crises, comprising 3746 observations. We use daily data of 10-year government bond yields for the U.S., Italy, France, Germany, and Japan for advanced economies and Brazil, Russia, India, China, and South Africa (BRICS) for emerging economies.

The developed countries selected for the study exhibit a relatively higher sovereign bond market capitalisation compared to the other advanced economies and this could potentially impact other bond markets. To address the non-sync issues arising from the difference in the market opening times of the different countries with varying time zones and nonsynchronous holidays, we estimate our model by dropping out the domestic returns where any foreign market is closed for trading and including the days when all the markets are open for trading. For minimum skewness and time consistency, we first generate the log-returns

$$r_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right)$$

of each bond market. Based on the ADF test we use the first differencing for dealing with non-stationarity in the variables.

Engle and Sheppard's (2001) have proposed the DCC-GARCH model that assumes that the coefficient of correlation varies over time. Cappiello, Engle, and Sheppard's (2006)further developed ADCC-GARCH to examine the asymmetry outcomes of shocks on the return volatility of an asset. Our study is in line with many researches which have explored the dynamic correlation between stocks and bonds with the ADCC model. Another such study analyses the dynamic correlation between bank stocks, contingent convertible bonds, and debts by employing the DCC-GARCH. DCC GARCH belongs to the group of models of conditional variances and correlations. The model preposition in this group is that the covariance matrix, Ht, could be decomposed into conditional standard deviations, Dt, and a correlation matrix, Rt. Both Dt and Rt are intended to be dynamic in the DCC-GARCH model. Hence, in the present study, we analyse the time-varying conditional correlation between advanced and emerging bond markets by using the DCC-GARCH model. The mean equation proposed by Engle and Sheppard's (2001) is as follows:

$$r_t = v_t + \lambda_1 r_{t-1} - 1 + \epsilon_t \tag{1}$$

where r_t denotes the bond return of the USA, France, Italy, Germany, Japan, Brazil, Russia, India, China, and South Africa over t-period. Therefore, r_t is a 10×1 vector of variable returns. ϵ_t represents $(\epsilon_{1t}, \epsilon_{2t}, \epsilon_{3t}, \ldots, \epsilon_{nt})$ where $\epsilon_t|\Phi_{t-1} \sim N(0, h_t)$. On the information set Φ_{t-1}, v_t is a constant conditioned mean vector, h_t is the conditional variance and covariance matrix, and λ_1 is the autoregressive coefficient of r_t at lag 1.

To determine the parameters of the DCC-GARCH, a two-stage estimation process is designed. In the first stage, GARCH coefficients are determined, and correlations are obtained in the final stage. H_t can be further expressed as:

$$h_t = d_t r_t d_t, \tag{2}$$

where $h_t = \text{diag}(h_{1t}, h_{2t}, \ldots, h_{nt})$ is an $n \times n$ matrix of conditional variances, r_t is the $n \times n$ conditional correlation matrix, and $d_t = \text{diag}(c_{it}^{1/2})$ is an $n \times n$ diagonal matrix of conditional standard deviations. c_{it} follows the GARCH(1,1) specification on conditional volatility:

$$c_{it} = \nu + \alpha_i \epsilon_{i,t-1}^2 + \beta_i c_{i,t-1}. \tag{3}$$

For DCC-GARCH-GJR and ADCC-GARCH, the univariate GARCH(1,1) in GJR is:

$$c_{it} = \nu + \alpha_i \epsilon_{i,t-1}^2 + \beta_i c_{i,t-1} + \delta_i \left(\min(\epsilon_{i,t-1}, 0)\right)^2. \tag{4}$$

The determinant for correlation is specified as:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}}. \tag{5}$$

r_t can be further expressed in terms of $P_t = q_{ij,t}$ as:

$$r_t = (\text{diag}(P_t))^{-1/2} P_t (\text{diag}(P_t))^{-1/2}. \tag{6}$$

Cappiello, Engle, and Sheppard (2006) originated ADCC as:

$$P_t = p + A^* \left(\epsilon_{t-1}\epsilon_{t-1}^T - p\right) + B^* \left(P_{t-1} - p\right) + C^* \left(u_{t-1}u_{t-1}^T - U\right), \tag{7}$$

where A, B, and C are positive Hermitian square matrices of the same dimension, $*$ is the element-wise product, $u_t = \min(\epsilon_t, 0)$, and:

$$U = \mathbb{E}[u_t u_t^T] = \frac{1}{T}\sum_{t=1}^{T} u_t u_t^T. \tag{8}$$

The models can be tested by applying the log-likelihood function. Let q denote the coefficient in d_t and p denote the coefficient in r_t. The log-likelihood function is given by:

$$L(q, p) = L_v(q) + L_c(p), \tag{9}$$

where:

$$L_v(q) = -\frac{1}{2}\sum \left(\log(2\pi) + 2\ln|d_t| + r_t d_t^{-2} r_t\right),$$
$$L_c(p) = -\frac{1}{2}\sum \left(-\epsilon_t^T \epsilon_t + \ln|r_t| + \epsilon_t^T r_t^{-1} \epsilon_t\right).$$

The purpose is to maximize the log-likelihood function. The study uses the BEKK-GARCH model to examine the interconnectedness between markets during the economic crisis. For a bivariate GARCH model, the BEKK model is as follows:

$$H_t = C^T C + B^T H_{t-1} B + A^T \epsilon\epsilon^T A, \tag{10}$$

where H_t is the conditional covariance matrix, A and B are $n \times n$ parameter matrices, and C is a lower triangular matrix.

4 Empirical Results

4.1 Descriptive Statistics

Table 1 describes the time series of ten economies' bond markets 'advanced and emerging economies. The table shows the summary of the daily closing return of the government bond of each market. The average returns of all the developed markets considered are negative except Germany. All the emerging markets have 0 average returns except Brazil and India. The volatility of the Japanese bond market is highest in all sovereign bond markets, followed by France and Germany. All the series are either positively or negatively skewed and leptokurtic, showing the disappearance of Gaussian distribution. Additionally, the J.B. statistic also asserts the same. The ADF test is probed for a testing unit root in all the return series. The results exhibit stationarity in all log return series and integration order of I(0).

Table 1. Characteristics of Distributions of the Series

Stat	USA	Italy	Frc	Ger	Japan	Brazil	Russia	India	China	S.A.
Mean	-0.0004	-0.0005	-0.005	0.0016	-0.0012	-0.0001	0	-0.0001	0	0
Max.	0.3678	0.381	2.7932	2.6391	3.434	0.2406	0.4597	0.1224	0.1193	0.1133
Min.	-0.431	-0.2374	-3.6636	-2.871	-3.2771	-0.1143	-0.2676	-0.059	-0.169	-0.056
Stdev	0.0282	0.0271	0.205	0.1593	0.2532	0.0171	0.0224	0.0078	0.0153	0.0094
Skew.	-0.787	0.8563	-2.5173	0.446	0.8447	1.3037	3.0343	1.218	-0.4522	1.1976
Kurt.	41.107	21.2362	93.2168	80.2611	49.4656	23.4608	75.889	27.028	13.8323	15.596
Sig	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*
ADF	-16.769	-14.933	-18.402	-18.018	-17.983	-15.27	-17.18	-14.579	-14.711	-14.509
LB(12)	198.21	138.46	133.47	272.64	373.39	394.86	223.21	37.482	474.66	32.515
sig	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*

Source: Own estimation

4.2 DCC-GARCH Model

Results Univariate GARCH estimation attained by DCC-GARCH for ten bond market indices i. e. U.S., Italy, France, Germany, Japan, Brazil, Russia, India, China, and South Africa are presented in 1. The results of DCC terms A and B are significant for every series considered. Considering that each daily bond return series A and B are positive and have a summation of less than unity (i.e., a + b < 1), time-varying co-movements are assured. Parameters a and b show the overall persistence of a series and depict the persistence of shocks and volatility of a series. Statistically significant joint parameters A and B of all ten series also exhibit conditional correlation's substantial time-varying persistence. The summation of coefficients A and B is 0.9913, which satisfies the non-negativity criteria for the DCC model to remain valid. The significant value of A shows short-run persistence while the significant value of B shows long-run persistence.

The GARCH term and ARCH term coefficient are positive and significant, suggesting that the conditional volatility of all the series is affected by yesterday's squared residuals and yesterday's variance (see table 2 and 3). The results of DCC-GARCH-GJR. After a negative shock, there are expectations of a more significant surge in volatility; this is known as the leverage effect and can be captured by the GARCH-GJR model. In panel (B), G term displays the result of asymmetry in the volatility of the return of variables. The conditional volatility of four return series, namely France, Germany, Japan, and Russia, shows a significant asymmetry effect, representing that the bond returns of these countries respond separately to positive and negative shocks. None of the other return series shows a significant positive symmetry effect. Except for Brazil and China, all the ARCH and GARCH parameters are positive and significant; their sum is less than one, highlighting the short-run and long-run persistence in conditional volatility. A comparison is made between ADCC-GARCH and DCC-GARCH-GJR to see whether ADCC can ascertain the asymmetric characteristics of joint conditional correlation among the variables. However, parameter C, which indicates DCC asymmetry, is insignificant. We dropped that alternative. Further on, we shall determine which model performs better in capturing conditional volatility. DCC-GARCH-GJR has a higher AIC and H.Q., and GJR-GARCH has the highest log-likelihood of the two models. This indicates a better fit of DCC-GARCH-GJR than of the three models considered in the study.

Criteria for Model Selection is represented in Table 4. To better understand the dynamic correlation between the variables, we plotted correlation parameters A and B for different pairs of variables for the period considered in the study. Figures 1 to 4 show a conditional correlation between bond return indices of sample countries. All the pairs are exhibiting variations in their correlations. Global financial crises (2007-2008), Russian financial crises (2008-2009), European Debt Crises (2011-2012), Chinese stock market crash (2015), Brazilian economic crisis (2016), Brexit Uncertainties (2017), and the recent COVID-19 pandemic (2019) were all significant financial turmoil.All these incidents had a substantial impact on the movement of bond returns. Fig 1 shows the dynamic correlation between the bond returns of the U.S. and BRICS nations. The highest conditional correlation is found between the U.S. and Brazil, while the U.S. and India exhibit the lowest correlation. These findings are in sync with Ahmad, Mishra, and Daly's (2018), who show financial connectedness between BRICS and global bond indices. Plots in Fig 1 show that fluctuations in correlation are heterogeneous across countries. There is an increase in correlation between US-Brazil, US-Russia, and US-SA during 2007-08, the period of the GFC, and it reached its highest in 2013, the period of the taper tantrum. The Federal Reserve executed the policy of quantitative easing in reaction to the recession of 2008 that caused a surge in U.S. Treasury yields known as taper tantrums. The correlation between US-India and US-China did not increase significantly as the recession was not felt equally across countries, particularly India and China, whose bond market grew substantially during this period. In 2011-12, the global financial crisis intensified with the European Debt Crisis. We can see that all pairs have increased in correlation during this period, as most BRICS countries have heavily invested in Eurobonds. The central banks of China and India held nearly 25% and 20% of Eurozone bonds, respectively, over this period. Any effect of Brexit is not evident in the correlation between the pairs, as there is no significant increase or decrease in correlation during this period. The impact of the COVID-19 pandemic can be seen in correlation analysis. Conditional correlation The U.S. and

Table 2. DCC-GARCH Estimation Results

Country	Return Equation		Variance Equation			+
	µ					
US	-0.000278	0.686864	0.000004	0.075026	0.919819	0.994845
	(0.273869)	(0.000182)	(0.208434)	(0.000041)	(0.0000)*	
ITL	-0.000492	0.727863	0.000002	0.075904	0.923096	0.999
	-0.039494	(0.0000)*	-0.302362	(0.0000)*	(0.0000)*	
FRA	-0.000458	0.881176	0.000005	0.106864	0.892136	0.999
	(0.097976)	(0.0000)	0.177177	0	0	
GER	-0.000728	-0.651201	0.000006	0.104493	0.894507	0.999
	(0.062724)	(0.000036)	(0.066258)	(0.0000)	(0.0000)	
JPN	-0.001044	-0.510428	0.000015	0.144415	0.854585	0.999
	(0.008818)	(0.022026)	0.038036	0	0	
BRZ	0.000534	-0.230708	0	0.058034	0.906279	0.964313
	(0.0000)	(0.896139)	(0.958435)	(0.0000)	(0.0000)	
RUS	-0.000163	-0.379411	0.000003	0.1383	0.8607	0.999
	(0.545358)	(0.004382)	(0.527629)	(0.001522)	(0.00000)	
IND	-0.000127	-0.530828	0	0.055194	0.943701	0.998895
	(0.112804)	(0.000154)	(0.838516)	(0.017325)	(0.0000)	
CHN	-0.000157	-0.402126	0.000002	0.108485	0.890514	0.998999
	(0.210578)	(0.0000)	(0.448083)	(0.001224)	(0.00000)	
SA	-0.000049	-0.667641	0.000008	0.112866	0.793998	0.906864
	(0.803236)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	

Multivariate DCC Equation

Coefficients	t-value	p-value	
A	0.012415	[9.379735]	(0.0000)*
B	0.978974	[301.441263]	(0.0000)*

Source: Own estimation

Table 3. DCC-GARCH-GJR Estimation Results

Country	Return Equation			Variance Equation		
	μ	λ	ϕ	α	β	δ
RUS	-0.0005	0.7423	0.0000	0.0318	0.9375	0.0564
ITL	-0.0006	0.6658	0.0000	0.0842	0.9200	-0.0104
FRA	-0.0005	0.3391	0.0000	0.0682	0.9143	0.0067
GER	-0.0011	-0.8016	0.0000	0.1092	0.8672	0.0191
JPN	-0.0007	-0.4942	0.0000	0.0750	0.8923	0.0045
BRZ	-0.0004	0.4925	0.0000	0.2664	0.6806	0.0584
RUS	-0.0007	-0.2113	0.0000	0.0565	0.9405	0.0544
IND	-0.0017	-0.3790	0.0000	0.0999	0.9097	0.0012
CHN	-0.0005	-0.3724	0.0000	0.0458	0.7147	-0.0933
SA	-0.3347	0.0000	0.0000	0.3159	0.0000	0.4352
Multivariate DCC Equation						
Coefficients			A: 0.1122	B: 0.8742		
t-value			8.7300	58.449		
p-value			0.0000*	0.0000*		

Source: Own estimation

Table 4. Criteria for Model Selection

Model	Akaike	Hannan-Quinn	Log-Likelihood
DCC-GARCH-GJR	-	-52.2	102051
	52.264		
DCC-GARCH	-	-52.352	97972.98
	52.413		

Source: Own estimation

BRICS reveal unsynchronized patterns across the pairs of countries. There is a sudden variation in the magnitude of correlation during the end of 2019 and the beginning of 2020, manifesting the impact of COVID-19 on government bond yields. The correlation dips immediately afterwards, indicating the effect of unconventional monetary policy measures taken by various nations in the wake of the pandemic. Fig 2, 3, 4 plot the dynamic correlation between Italy and BRICS, France and BRICS, and Germany and BRICS. All three European bond markets reveal similar shapes regarding their dynamic conditional correlation with the BRICS sovereign bond markets. South Africa shows the highest correlation with European countries, followed by Brazil and Russia, while India and China display the lowest correlation with the European Bond Market. It is noteworthy that Italy has a higher time-varying correlation with the BRICS market among all the developed markets. There is continuous high volatility in the dynamic correlation between European and BRICS countries for the post-2008 period and it reached its highest in 2013, clearly indicating the effect of the GFC and European sovereign debt crises on BRICS bond markets. After 2013, the dynamic conditional correlation between the European bond markets and BRICS stabilised, and that abruptly increased during 2016-17. The probable cause of this upsurge could be attributed to Brexit uncertainties. A notable increase in positive and negative correlations is observed by focusing on the COVID-19 pandemic period. The European bond market was more connected to the BRICS bond market during the COVID-19 outbreak. Japan displays the lowest conditional correlation with the BRICS market. This finding is consistent with Ahmad, Mishra, and Daly's (2018) and Mensi et al.'s (2021). Due to Japan's resilient financial system, the bond market is least fluctuating in correlation with BRICS. However, a post-2015 sudden spike in the time-varying correlation can be observed between Japan and BRICS, specifically Brazil, India, and South Africa. This duration could be linked with the Bank of Japan's sudden decision to approve a negative interest rate policy, which has rippled out across global government bond markets. The manoeuvre took place just 11 days after the Bank of Japan's sudden decision to track the footprints of Denmark, Switzerland, Sweden, and the Eurozone by following negative interest rates. The move raised a new concern regarding the aftermath of ultra-loose monetary policy adopted by central banks.

Table 5 and 6 represents the results of volatility spillover during the GFC. The rows signify market j and the columns signify market i. Accordingly, transmission falls out from market i to j. The ARCH parameters measure the effect of previous innovation. Among ten markets, past squared errors of U.S. bond returns negatively influenced the future bond volatility of France, Germany, Japan, Russia, and South Africa during the global financial crisis. The statistically insignificant ARCH coefficient of the U.S. with Brazil, India, and China confirms the resilience of the bond markets in these countries, despite all the instability generated by the U.S. bond markets during the GFC. On the contrary, the statistically significant parameters of France, Germany, Japan, Brazil, India, and South Africa show the persistent volatility in these countries' bond markets. Germany's statistically significant ARCH parameter with all five BRICS countries shows that an increase in the German bond return covariance influences the next-day bond return variance of BRICS countries. The ARCH coefficients of Italy are positive and statistically significant only with South Africa among all the BRICS countries, denoting the low persistence of volatility between Italy and BRICS countries. Most of the ARCH coefficients for Japan are positive and statistically significant, with BRICS showing the influence of Japanese bond market volatility on other sample countries. As Japan is a regional factor for BRICS and also has the second-largest government bond market in the Asia Pacific after China, it influences the volatility of BRICS bonds. Among the BRICS, almost all the ARCH coefficients of India and China are positive and significant with other variables, showing the effect of previous innovation in the bond markets of India and China is significantly affecting the next period bond variance of other sam-

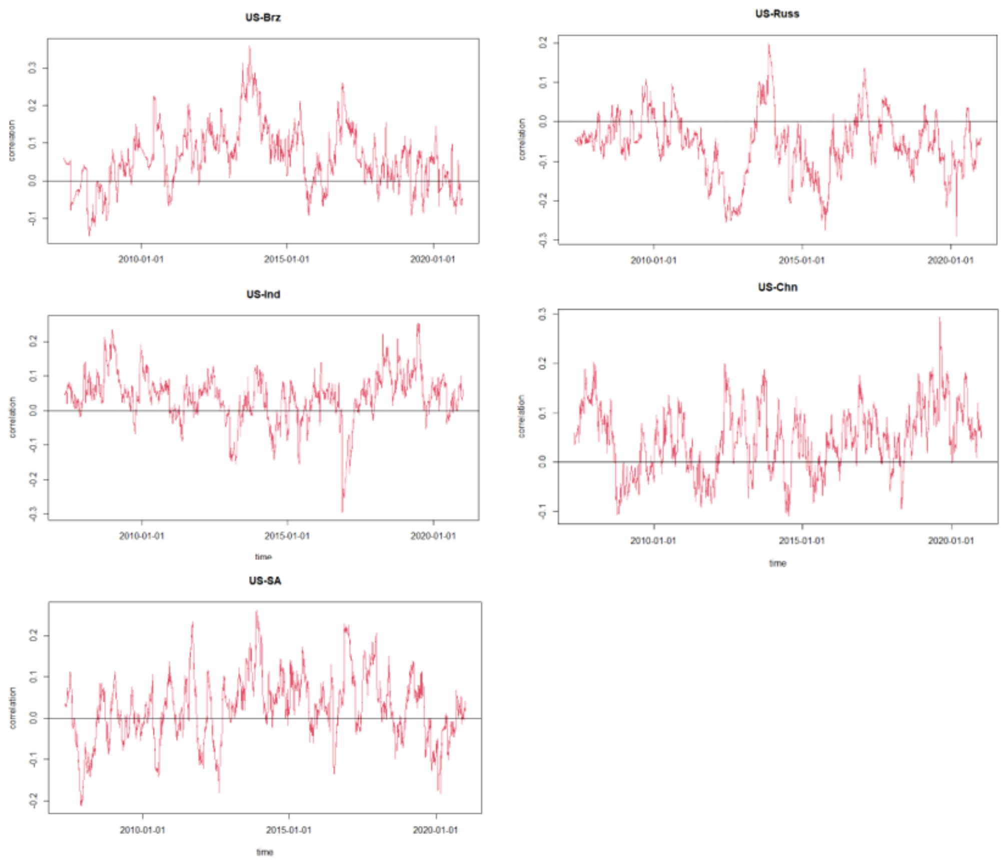

Figure 1. Conditional correlation between US and BRICS nations

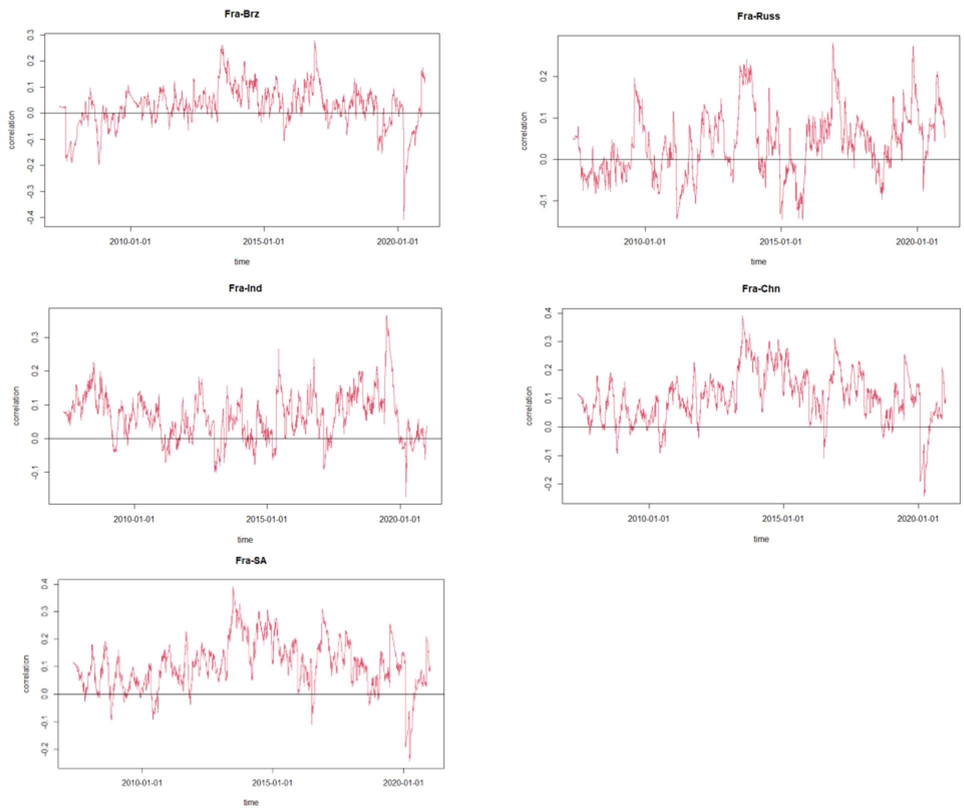

Figure 2. Conditional correlation between France and BRICS nations

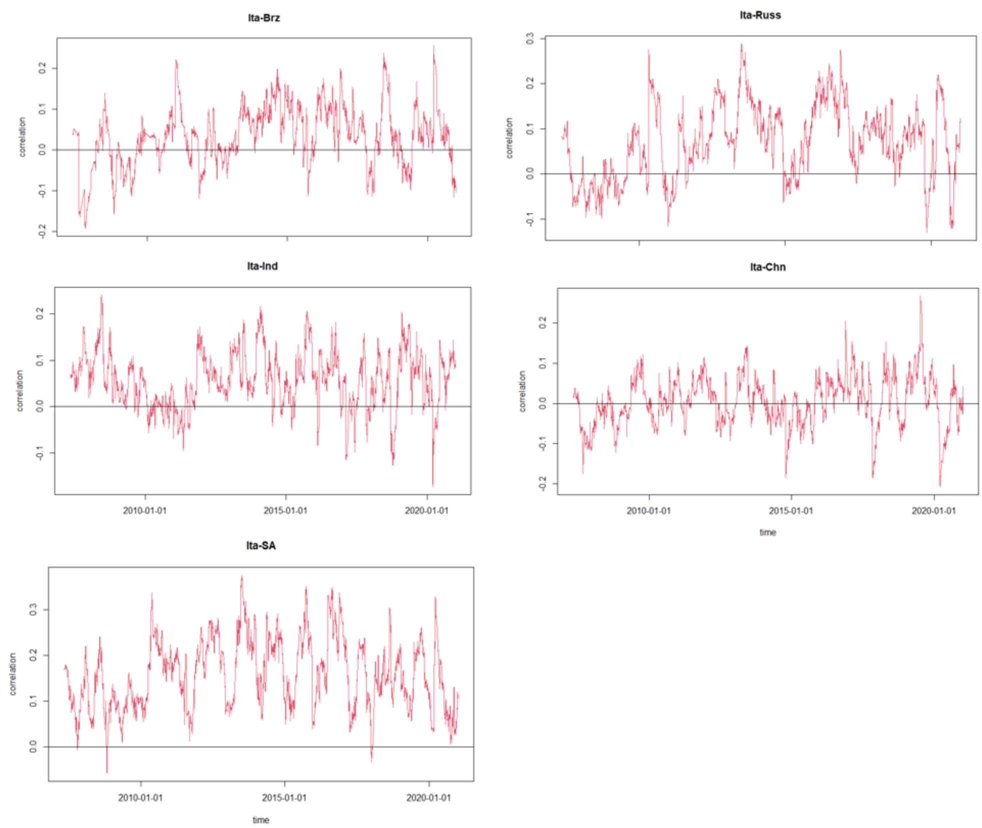

Figure 3. Conditional correlation between Italy and BRICS nations

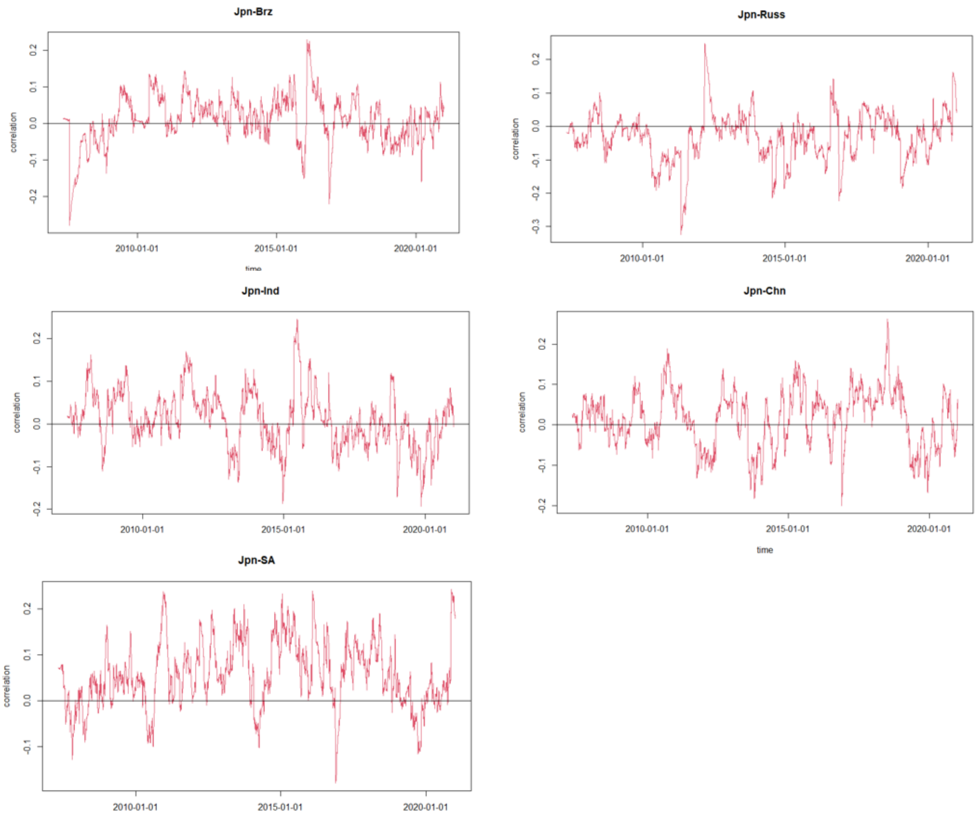

Figure 4. Conditional correlation between Japan and BRICS nations

Table 5. Global Financial Crises: ARCH Term

Country	US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA
US	-0.03298	-0.11321	-0.21268	-0.03526	-0.32798	-0.03686	-0.53555	-0.06845	0.102655	-0.10292
	0.650851	2.29E-06	0	0.137037	0	0.602566	4.99E-05	0.13145	0.099075	0.000145
FRA	-0.30372	0.035457	-0.25454	0.071272	-0.36743	0.908836	0.938708	0.407173	0.277979	0.779921
	0.121536	0.571623	0.000243	0.295051	0.000903	0.00029	0.017927	0.000116	0.214822	0
GER	0.4427	-0.03564	0.09323	-0.03064	0.339566	-0.33865	1.508377	0.237283	-0.791	-0.67452
	0.03011	0.626712	0.188566	0.646389	0.000487	0.069465	1.24E-05	0.013912	7.78E-06	0
ITL	0.108759	0.152103	0.262246	-0.1081	0.034229	0.082966	-2.22737	-0.41102	0.231896	0.189266
	0.568735	0.006759	5.72E-06	0.083524	0.75761	0.699983	3.00E-08	7.65E-05	0.226952	0.014072
JPN	0.445298	0.259292	0.249636	0.23084	0.306769	-0.31251	0.018387	0.18727	0.260039	-0.07768
	0.000745	2.70E-06	1.25E-05	6.20E-07	1.86E-05	0.016106	0.93388	0.008389	0.029828	0.095254
BRZ	0.119506	0.039614	-0.03016	-0.06273	0.042402	-0.05987	0.222951	-0.10749	-0.07402	0.078019
	0.053773	0.08335	0.267264	0.00855	0.25138	0.363729	0.078004	0.00869	0.224315	0.005379
RUS	0.151645	0.005438	-0.02983	0.019839	0.034879	0.053041	0.377422	0.09281	-0.11437	0.028536
	2.49E-05	0.762604	0.156875	0.209794	0.053874	0.105233	0	4.47E-06	0.000313	0.025474
IND	0.44489	0.102834	0.161436	0.034642	-0.16346	-0.05355	-0.48667	0.091967	0.030808	-0.12195
	5.14E-06	0.006239	0.000581	0.339005	8.08E-05	0.55222	0.004792	0.096809	0.726306	0.001552
CHN	-0.06636	-0.08859	-0.10301	-0.07121	-0.26399	0.134185	-0.99095	0.148502	0.633306	0.024553
	0.371825	0.000204	0.000213	0.000885	0	0.056264	0	2.48E-05	0	0.36087
SA	-0.04177	0.058614	-0.02977	0.029973	0.147054	-0.5526	0.692254	-0.07264	0.806607	0.618877
	0.701742	0.075709	0.406326	0.40205	0.014991	8.60E-07	0.00376	0.25286	0	0

Table 6. Global Financial Crises: GARCH Term

Country	US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA
US	0.47388	-0.1009	-0.06221	-0.13032	0.052325	-0.00199	0.221781	0.23799	0.356262	-0.07224
	0	2.18E-06	0.01165	0	0.151222	0.974021	0.030233	0	0	0.000765
FRA	-1.43862	0.536394	0.055622	-0.18104	-0.73781	-0.33379	-2.48113	0.078505	0.033792	0.112016
	0	0	0.450467	0.019118	0	0.046797	0	0.425515	0.865266	0.091057
GER	0.854603	0.30241	0.853825	0.364797	0.650668	0.087233	1.887297	-0.12795	-0.20189	-0.03361
	2.21E-05	0.002986	0	5.24E-06	0	0.678167	0	0.215858	0.220817	0.550384
ITL	0.472286	-0.23947	-0.23099	0.557655	-0.47209	-0.22191	0.77461	-0.45847	-0.05119	-0.03894
	0.005108	0.001172	6.46E-05	0	1.00E-08	0.267665	0.001851	2.30E-07	0.750534	0.465248
JPN	-0.37551	0.03651	-0.07862	0.069136	0.376318	0.610728	0.52613	0.09141	0.052997	-0.16922
	0.006933	0.532166	0.141869	0.091025	0	1.00E-08	0.019638	0.166554	0.618065	0.000121
BRZ	-0.00571	-0.00681	0.03714	0.044972	-0.05091	0.669177	-0.57552	0.001079	0.267491	0.061099
	0.929626	0.798534	0.095708	0.063053	0.091118	0	5.00E-08	0.975645	3.00E-08	0.005445
RUS	0.004626	-0.04301	-0.01625	-0.0659	-0.11719	0.101102	0.435386	-0.04028	-0.14921	0.025995
	0.874752	2.15E-05	0.098393	1.00E-08	0	6.83E-05	0	0.011862	1.00E-08	0.012959
IND	-0.47312	-0.05457	-0.06901	0.09418	-0.06142	-0.4136	-0.01716	0.491519	-0.38276	0.066817
	9.40E-07	0.084392	0.034255	0.006253	0.257243	2.77E-06	0.923271	0	0.00014	0.054968
CHN	-0.37753	-0.14099	-0.15426	-0.12129	-0.09797	0.019746	0.789089	-0.09623	0.49545	-0.09468
	0	0	0	0	0.000241	0.706224	0	0.002078	0	3.50E-07
SA	-0.04177	0.058614	-0.02977	0.029973	0.147054	-0.5526	0.692254	-0.07264	0.806607	0.618877
	0.701742	0.075709	0.406326	0.40205	0.014991	8.60E-07	0.00376	0.25286	0	0

Table 7. Diagnostics of Selected GARCH Model

Metric	US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA
LB (12)	39.47566	84.07761	51.42549	69.92840	97.05099	68.61024	54.00734	37.74741	22.19627	36.59965
P-Value	0.4937	0.0001	0.1064	0.0024	0.0000	0.0032	0.0686	0.5721	0.3299	0.6241
ML	34.51949	49.66273	38.69752	99.12375	36.68985	43.46315	37.04645	48.18896	53.07077	60.41889
P-Value	-0.7149	0.1407	0.5289	0.0000	0.6201	0.3261	0.6040	0.1754	0.0808	0.0201

ple countries. Among all the combinations, the most substantial ARCH effect (0.938708) was detected between France and Russia, which shows that the previous information from France is effecting the Russian bond market. The weakest ARCH effect (0.018387) is found between Japan and Russia. Thus, information shared between these markets is not affecting their future variances. The GARCH coefficient measures the presence of volatility clustering. For example, periods of high volatility tend to be followed by periods of high volatility within a prolonged period. Most of the GARCH coefficients are significant in the above table, showing the volatile persistence among variables. Unlike the ARCH coefficient, the diagonal GARCH coefficient is stronger than the off-diagonal coefficient, indicating that the lagged variance of the own market return affects the future return variance more than the lagged variance of other markets. Except for Brazil, all the coefficients of the U.S. are significant with emerging markets like Russia, India, China, and South Africa, indicating the persistence of volatility between these countries during global financial crises. The coefficient of France is significant only with Brazil and Russia in all developing economies (BRICS), denoting the most negligible impact of the volatility of one country on another. The GARCH coefficients of Germany and Italy do not show any significant effect on the bond market volatility of BRICS during the GFC. The lag variance of the Japanese bond market significantly impacted the future bond market volatility of Brazil, Russia, and South Africa during the GFC. Similar to the ARCH parameter, the GARCH coefficient shows the significant impact of India and China on other sample countries. Most minor volatility transmissions occur from Brazil and South Africa to other countries. The highest GARCH coefficient (1.887297) is found between Germany and Russia, indicating bond market connectedness between these countries during the GFC. The lowest and the second-lowest GARCH coefficients (-0.00199 and -0.00571) are detected between the U.S. and Brazil, Brazil, and the U.S., denoting that the volatility in these markets does not have any significant impact on each other. Table 7 represents the diagnostic results of the BEKK GARCH model. The Ljung Box test statistics for 12 lags for most of the variables suggest the absence of autocorrelation among the variables, and the result of square residual denotes that all the variables are free from serial correlation problems.

Table 8 represents the volatility spillover among variables during the European Debt Crisis.The ARCH coefficients of the U.S. are negative but significant for every other country except France, showing the impact of previous innovation in the U.S. affecting the future market volatility of these countries negatively during European debt crises. The ARCH parameters of France are significant for developing countries like Russia, India, and China, indicating the impact of past innovation in France on the future bond market volatility of these countries. Statistically significant ARCH parameters of Germany with Japan, Russia, and India show that an increase in the German bond return covariance influences the next-day bond return variance of these countries. The ARCH coefficient of Italy is statistically insignificant compared with every other sample country, showing the low bond market connectedness of these countries with Italy. The ARCH coefficient of Japan is significant only with Russia among BRICS, indicating that the shocks in the Japanese bond market are not affecting the emerging economies during the European Debt Crisis. The ARCH parameter of Brazil is significant only with Russia and China among BRICS countries, showing the least impact of Brazil on the volatility of other markets. The ARCH parameters for Russia are statistically insignificant with every other variable, indicating no shock spillover from Russia. The ARCH parameters of India are significant only with Brazil and China, among BRICS countries, showing the persistence of volatility spillover between these countries. Past innovation in the Chinese bond market significantly impacts the future bond market return variance of Russia and China among BRICS countries. Shocks in the Russian bond market significantly affected India and South Africa's bond market returns. The

Table 8. European Debt Crises

Metric	US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA
US	-0.16303	-0.02591	-0.31948	-0.14802	-0.22236	0.075224	-0.10712	-0.06567	-0.09314	-0.07899
	0.014713	0.652577	1.42E-06	0.006355	1E-08	0.012174	0.001005	0.000808	0.002386	0.003497
FRA	-0.35062	0.085369	0.019278	0.074662	0.130828	0.032377	0.102267	-0.0542	0.090858	-0.00968
	2.49E-06	0.170803	0.779568	0.312034	0.00092	0.218801	0.00102	0.001679	0.004758	0.71228
GER	-0.09562	-0.03147	0.281102	0.055517	0.104191	0.006909	0.12773	0.048718	-0.01572	-0.02139
	0.086822	0.503274	7.8E-07	0.216197	0.002109	0.790337	1.3E-07	0.001425	0.553851	0.277599
ITL	-0.15027	0.103229	-0.01069	0.224248	-0.10282	-0.15856	0.018852	0.022961	-0.06268	-4.7E-05
	0.071173	0.115631	0.895844	0.00049	0.041234	5.3E-07	0.624855	0.289119	0.080444	0.998542
JPN	-1.14405	-0.20122	-1.69006	0.107831	-0.53847	-0.06785	0.450811	0.045242	0.038716	0.022783
	0	0.08044	0	0.270406	0	0.177017	0	0.156871	0.486841	0.596906
BRZ	0.471372	-0.07803	0.104065	0.256212	0.18074	0.159149	-0.23653	-0.00458	-0.40822	-0.06526
	0.002238	0.500424	0.441485	0.015048	0.031547	0.002941	0.001309	0.891174	1E-08	0.189175
RUS	-0.16829	0.06263	-0.03934	-0.00454	0.081217	-0.05125	1.063382	-0.03422	-0.04067	0.045594
	0	0.298884	0.585023	0.931438	0.043858	0.068401	0	0.063256	0.22923	0.109833
IND	-0.35362	0.465319	-0.55481	0.524143	0.231416	0.173687	0.096841	0.082022	-0.54294	0.094952
	0.180322	0.013686	0.015156	0.005935	0.099039	0.035717	0.407175	0.140796	2E-07	0.205456
CHN	-0.38837	-0.10145	-0.22749	-0.19995	-0.25169	-0.03772	0.253125	0.040753	0.411903	0.121157
	0.009569	0.337732	0.073379	0.053676	0.001025	0.479064	0.000112	0.267466	0	0.005711
SA	-0.40328	-0.48786	-0.78249	-0.15648	-0.45898	0.087648	0.070357	-0.34244	0.033454	0.641564
	0.012094	0.003783	5.43E-06	0.33171	2.54E-05	0.162582	0.379851	0	0.678735	0

Table 9. Diagnostics of Selected GARCH Model

Metric	US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA
LB(12)	61.50709	48.24671	47.45015	38.60287	63.11066	34.58227	48.4471	39.43403	87.39896	49.24404
	0.016	0.1739	0.195	0.5332	0.0114	0.7122	0.1689	0.4956	0	0.15
ML	42.79676	55.03356	37.37555	57.43304	35.88975	59.47438	42.15322	53.12191	40.31375	42.02557
	0.352	0.0571	0.589	0.0364	0.6558	0.0243	0.378	0.0801	0.4564	0.3832

most significant ARCH coefficient (0.524143) is found between India and Italy, indicating the financial connectedness. The lowest is detected between Brazil and India (-0.00458), showing that past innovation in these markets does not affect their future bond return variance. Most of the GARCH coefficient is statistically significant, showing the volatile persistence among the variables. All the diagonal parameters are positive and statistically significant, indicating the volatility in all the sample countries is driven by their past fluctuations. In off-diagonal parameters, most of the coefficients of the U.S. and Japan are significant with BRICS countries, indicating the persistence of volatility in their bond markets. GARCH terms for France, Germany, and Italy are significant only with respect to Russia and South Africa among BRICS bond markets, implying the low persistence of volatility spillover between these markets. Most of the coefficients of China and India are significant for the BRICS market except Russia and South Africa, showing the low level of connectedness in their bond markets. Only India receives significant volatility transmission from South Africa, implying South Africa's quiet presence in the BRICS bond market during the European Debt Crisis.The most robust GARCH coefficient (0.802009) is found between India and Italy, indicating solid financial connectedness. The lowest is detected between France and India (-0.006242), showing that past innovation in these markets does not affect their future bond return variance. Table 9 represents the diagnostic results of the BEKK GARCH model. The Ljung Box test statistics for 12 lags for most of the variables suggest the absence of autocorrelation among the variables, and the result of square residual denotes that all the variables are free from serial correlation problems.

In the table 10 represents the estimated parameters of time-varying spillover during the Brexit referendum, from June 23, 2016, to April 13, 2018 (Guedes et al., 2019). Most of the diagonal ARCH parameters are significant, implying that the bond return of these countries is driven by past market innovation. Off diagonal ARCH coefficients of developed countries with BRICS, the United States coefficients are significant with Russia and India, France coefficients are significant with India and South Africa, and Japan coefficients are significant with only Brazil.In contrast, Italy's coefficients with India and South Africa are significant, implying that there is a spillover between developed and BRICS bond markets. The bond market of Germany does not show any significant impact on BRICS. Overall, none of the advanced market bond indices show a significant amount of spillover from the BRICS. Among the BRICS markets, most of the ARCH coefficients are significant, with BRICS implying that the volatility of BRICS bond markets responds to the shocks of BRICS bond markets. The most potent ARCH effect (0.729306) was detected between Russia and Brazil, indicating strong volatility persistence. Conversely, the weakest ARCH effect (-0.00022) was found between Germany and South Africa, showing that the previous standard information has the most negligible impact on their future return volatility. All the diagonal GARCH terms are significant, exhibiting that the volatility in all the sample countries is driven by their past fluctuations. Among the oblique parameters between advanced and BRICS markets, most of the coefficients of the U.S. are significant with Brazil and India, France with Russia, India, and South Africa, Germany with Brazil, Italy, Russia, and South Africa, while Japan with Brazil only, indicating the low persistence of volatility in their bond market.

All of the BRICS indices exhibit significant spillover with the BRICS bond market individually, denoting that the lagged variance of the BRICS market's return affects the future conflict of their recovery. Among all the sample countries, the U.S., in advanced and India, in emerging markets, show the highest connectedness with all other BRICS markets. The highest GARCH term (0.729306) is detected between Russia and Brazil, indicating the high connectedness between their bond markets. The lowest GARCH coefficients (0.000175) are seen between Germany and India, indicating that the volatility of these markets does not significantly impact each other. The

Table 10. Diagnostics of Selected GARCH Model

Metric	US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA
LB(12)	61.50709	48.24671	47.45015	38.60287	63.11066	34.58227	48.4471	39.43403	87.39896	49.24404
	0.016	0.1739	0.195	0.5332	0.0114	0.7122	0.1689	0.4956	0	0.15
ML	42.79676	55.03356	37.37555	57.43304	35.88975	59.47438	42.15322	53.12191	40.31375	42.02557
	0.352	0.0571	0.589	0.0364	0.6558	0.0243	0.378	0.0801	0.4564	0.3832

Table 11. BREXIT Uncertainties

Metric	US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA
US	0.053371	0.238983	-0.45226	0.283461	-2.58253	-0.01202	-0.05625	-0.05744	-0.01497	-0.02192
	0.296654	0.042789	0.046236	8.06E-05	7.54E-05	0.682478	0.01317	0.010053	0.446942	0.337951
FRA	0.296654	0.042789	0.046236	8.06E-05	7.54E-05	0.682478	0.01317	0.010053	0.446942	0.337951
	0.000411	0.012611	0.00745	0.024738	0.000165	0.789077	0.317165	0.000201	0.216083	0.007429
GER	0.001118	0.038403	0.548813	-0.00073	0.039959	0.002023	0.000348	-0.00031	0.00113	-0.00022
	0.61236	7.95E-06	0	0.848279	0.21607	0.087475	0.74313	0.700838	0.177411	0.832259
ITL	-0.04692	0.282493	0.059813	0.313337	0.835633	-0.00235	0.014103	-0.09097	0.020876	0.03707
	0.15089	0.017459	0.796959	7.4E-07	0.060815	0.910718	0.384324	1E-08	0.16336	0.057754
JPN	0.001183	-0.00822	-0.01738	-0.00819	0.755067	-0.00468	-0.00065	-2.9E-05	0.000594	-0.00219
	0.711244	0.281054	0.201461	0.051269	0	0.010032	0.617077	0.980149	0.610211	0.123167

Table 12. Diagnostics of Selected GARCH Model

Metric	US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA
LB(12)	51.98245	46.88625	52.1516	67.10588	66.71218	75.78815	43.07753	45.26385	82.18293	56.85195
	0.0971	0.2109	0.0944	0.0046	0.0051	0.0005	0.341	0.2616	0.0001	0.0407
ML	61.80356	124.4353	47.14488	73.35937	22.46534	5.951753	50.19977	30.009	41.21018	21.87581
	0.015	0	0.2035	0.001	0.9886	1	0.1295	0.875	0.4175	0.9912

flow of spillover from developed to BRICS markets is characterised by heterogeneous structures. However, during BREXIT uncertainties, the low transmission of volatility between advanced to BRICS bond markets may present diversification benefits for global investors during financial turmoil. Table 11 represents the diagnostic results of the BEKK GARCH model. The Ljung Box test statistics for 12 lags for most of the variables suggest the absence of autocorrelation among the variables, and the result of square residual denotes that all the variables are free from serial correlation problems (see table 13).

Table 13 depicts the results of dynamic spillover between developed and developing bond markets during the global pandemic, from January 30, 2020, to December 31, 2020. All the diagonal ARCH terms are positive and significant, denoting that their past market innovations significantly influenced the bond return of all the sample countries. Among five developed markets, the U.S. has a significant ARCH coefficient with Russia, China, and South Africa in BRICS, implying that the bond return of these countries is driven by past market innovation in the U.S. bond market. Significant ARCH parameters of France and Germany with Brazil, Russia, and SA show the bond market connectedness between these markets. The ARCH term of Italy is significant along with Brazil, China, and SA. Significant ARCH terms between Japan and Brazil, India, China, and South Africa demonstrate the significant level of volatility spillover from Japan to BRICS countries during the Pandemic (see table 14). The significant ARCH terms of Brazil and Russia with every other BRICS market denoting the past squared error of Brazil and Russia increase the future bond return variance compared to other markets.

Furthermore, the significant ARCH terms of Brazil and Russia with every other BRICS market denoting the past squared error of Brazil and Russia increase the past innovation in India does not significantly influence other markets in BRICS. The ARCH term of China is significant only, with India indicating the least effect of the Chinese bond market on other bond markets during the pandemic. The ARCH parameters of S.A. are significant for Brazil and India only. The strongest ARCH effect (0.646046) was detected between Brazil and Germany, indicating strong volatility persistence. The weakest ARCH effect (-0.00127) was found between France and India, showing that the previous common information has the least impact on their future return volatility. All the diagonal GARCH coefficients are positive and significant, denoting the volatility of all markets considered is driven by their past fluctuations. The GARCH term of the U.S. is significant with Brazil, Russia, India, and S.A., showing the persistence of volatility between the U.S. and these countries. Among developing markets, France's coefficient is significant only with India, establishing a weak connection between France and emerging markets. The GARCH terms of Germany and Italy are significant in most of the BRICS markets, indicating the volatility spillover between these markets during the pandemic. Japan's coefficients are significant, with Brazil, Russia, and South Africa among emerging markets. coefficient of Brazil is significant for each of the BRICS markets except China, showing the lower level of connectedness between Brazil and China during the pandemic. India has a significant GARCH term with each BRICS market, implying strong volatility persistence between these markets. Significant GARCH parameters between China and Brazil, India, and South Africa indicate high volatility persistence between these markets. The GARCH term of S.A. is significant with Russia, India, China, and S.A. The highest GARCH coefficient (0.891807) is found between S.A. and Japan, indicating bond market connectedness between these countries during the pandemic. The lowest (-0.00127) GARCH coefficient is detected between France and India, denoting that the volatility in these markets does not significantly impact each other. Table 15 represents the diagnostic results of the BEKK GARCH model. The Ljung Box test statistics for 12 lags for most of the variables suggest the absence of autocorrelation among the variables, and the result of square residual denotes that all the variables are free from serial correlation problems.

Table 13. Global Pandemic

US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA	
US	-0.12152	0.283187	0.289745	0.172574	-0.52715	-0.00538	0.05835	-0.00468	-0.01796	0.038144
	0.036695	0.031439	0.000134	0.000308	0.212262	0.792562	0.000116	0.517274	0.031208	0.0005
FRA	-0.000097	0.940175	-0.00168	0.01264	0.033695	0.00594	0.00301	0.002057	0.000388	0.002864
	0.988081	0	0.846657	0.019706	0.547646	0.04639	0.023287	0.015919	0.753065	0.029313
GER	-0.30854	-0.04253	0.742195	-0.03221	-1.1223	-0.08176	0.03973	-0.00024	-0.0109	-0.03093
	1.30E-07	0.76298	0	0.470387	0.019248	0.000239	0.004593	0.970156	0.222447	0.002169
ITL	0.17132	-0.02287	-0.46005	0.373212	1.703702	-0.09259	0.01541	-0.01571	0.043689	0.086824
	0.031232	0.896779	3.41E-06	2.40E-07	0.011402	0.012717	0.393802	0.108712	0.001389	0.00000012
JPN	-0.03306	0.052954	0.039574	0.004239	-0.46242	0.007784	0.000169	0.002393	-0.00627	0.008684
	0.000104	0.014038	0.000362	0.47878	3.00E-08	0.021673	0.916936	0.012434	2.84E-05	5.50E-07
BRZ	-0.46375	0.668246	0.646046	-0.1851	1.325272	0.240742	0.045602	-0.06301	-0.04873	-0.06514
	6.65E-05	0.051825	0.0002	0.053047	0.19319	1.11E-05	0.089621	3.02E-05	0.012369	0.003743
RUS	-0.31456	0.191079	-0.03935	-0.60767	0.405363	0.419627	0.785273	0.170721	-0.1483	-0.00642
	0.219751	0.774042	0.895177	0.015506	0.865559	0.001116	0	1.93E-05	0.002256	0.903016
IND	-0.13401	0.068649	-0.44503	-0.22207	1.27941	0.234444	0.005819	0.140526	0.011505	-0.10757
	0.682652	0.951102	0.328172	0.431886	0.721506	0.177167	0.94549	0.004667	0.854036	0.104016
CHN	0.494269	-3.93331	-0.9921	-0.05094	0.294658	-0.14023	-0.10749	-0.0911	0.175434	-0.01516
	0.074712	2.99E-05	0.011354	0.84134	0.924785	0.311711	0.181685	0.019516	0.001664	0.801478
SA	-0.70147	-0.09049	0.759121	-1.01869	0.891807	0.283939	-0.02037	-0.11565	0.006803	0.230453
	0.003503	0.899597	0.021817	1.06E-05	0.706853	0.010715	0.736142	0.000134	0.863554	4.79E-06

Table 14. GARCH Term

US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA	
US	0.682446	-0.02839	-0.02538	-0.03549	-5.06905	-0.16303	-0.03043	-0.02356	0.006985	-0.03186
	0	0.766999	0.619841	0.426633	0	0	0.016138	8.61E-06	0.459635	0.000963
FRA	-0.00774	0.755266	-0.01033	-0.00994	-0.0923	-0.00326	0.000237	-0.00127	-1.70E-05	0.000499
	0.018037	0	0.01394	0.001035	0.099866	0.092454	0.806085	0.003569	0.975392	0.494176
GER	-0.11692	-0.01622	0.737832	-0.00878	-2.94222	-0.04509	-0.06753	-0.01549	-0.00595	-0.02613
	0.001946	0.831562	0	0.76928	1.00E-08	0.049898	0	0.003704	0.291816	0.000101
ITL	0.061253	0.175597	0.072044	0.631518	1.161832	0.10199	-0.08217	0.001654	-0.06111	-0.02682
	0.409816	0.174942	0.313526	0	0.137246	0.003418	1.00E-08	0.810605	0	0.050911
JPN	-0.0487	-0.0036	0.014654	0.028485	-0.07711	-0.01604	0.00732	-0.00168	0.001568	-0.00824
	2.25E-06	0.865944	0.247523	9.37E-05	0.386248	0.000154	1.61E-05	0.178782	0.312878	2.00E-07
BRZ	-0.34664	-1.46882	-0.90693	0.017887	-9.31249	0.25934	-0.09357	-0.13376	0.026291	-0.11111
	0.030451	4.70E-07	3.70E-07	0.90363	0	2.82E-05	0.00562	0	0.382522	8.14E-05
RUS	1.106457	2.045011	1.258379	0.621068	7.214463	0.216514	0.632148	0.031384	-0.00722	0.076154
	1.26E-06	2.00E-08	0	0.000781	0.000745	0.030924	0	0.271033	0.838562	0.063185
IND	-1.03017	-1.25896	-0.90024	-0.87816	-6.04555	-0.89831	-0.29674	0.689825	0.136183	-0.36147
	0.000584	0.026555	0.006676	0.004734	0.205151	1.70E-07	0.000559	0	0.014966	2.50E-07
CHN	-0.09528	0.909504	0.818837	0.321078	12.99439	0.979772	-0.0991	0.145498	0.643744	-0.15895
	0.775949	0.122444	0.013877	0.20712	0.003501	2.00E-08	0.093797	0.000359	0	0.007999
SA	-0.50802	-1.86522	-0.67151	1.054486	12.46062	-0.01422	0.12088	0.108929	0.104262	0.659693
	0.095049	0.000501	0.020054	3.20E-06	0.001452	0.932278	0.04223	0.00244	0.005878	0

Table 15. Diagnostics of Selected GARCH Model

US	FRA	GER	ITL	JPN	BRZ	RUS	IND	CHN	SA	
LB(12)	54.42905	44.0341	53.81068	34.59386	53.56752	34.16799	51.06885	50.49992	71.79944	17.1166
P-Value	0.0637	0.3048	0.071	0.7118	0.0741	0.7295	0.1128	0.1235	0.0015	0.6454
ML	52.13237	5.466581	31.59434	66.12928	65.91272	31.09146	12.56717	25.14482	16.75489	18.0089
P-Value	0.0947	1	0.8262	0.0058	0.0061	0.8426	1	0.9678	0.9996	0.5868

5 Discussion and Conclusion

In the literature, we note that most of the studies examined bond-yield market spillovers between developed countries, mainly the U.S. and European countries, because of their fully developed bond markets. The current study takes a different viewpoint and examines the volatility spillover of the developed bond market for a group of selected emerging economies constituted as BRICS (Brazil, Russia, India, China, and South Africa) and studies whether the degree of interconnectedness in bond markets increased during the economic and financial turmoil such as the GFC, European debt crises, Brexit uncertainty, and COVID-19 pandemic crises. The study uses DCC-GARCH to gauge the effect of bond yield and volatility spillover. The study uses the BEKK-GARCH model to examine the direction and degree of interconnectedness between the markets considered during the economic crisis. The results of DCC GARCH show the persistence of volatility among variables for the period covered. The results show the increase in conditional correlation between developed and BRICS countries during crises. The highest conditional correlation is detected between the U.S. and BRICS, whereas the correlation between Japan and the BRICS bond market is the lowest. The conditional correlation between the European bond market and BRICS is moderate. The volatility spillover estimated through BEKK-GARCH shows a significant spillover coefficient between the U.S. and BRICS bond markets, except for Brazil. Volatility transmission from the European market to the BRICS bond market was insignificant, while the Japanese bond market showed significant transmission to the BRICS market during the GFC.

Volatility spillovers during the European debt crisis and the Brexit period depict similar results. Overall, none of the bond indices of the developed market show a high magnitude of spillover to BRICS, denoting low integration between these countries during these crises. During the global pandemic, the U.S., Italy, Germany, and Japan exhibited active transmission of shocks to the BRICS bond market. The U.S. is the primary catalyst of risk triggering during a pandemic, whereas European countries and Japan also show significant volatility spillover to the BRICS bond market. As per the GARCH result, the U.S., followed by Japan, exhibits an effective transfer of volatility spillover to others. Russia and South Africa are the strongest transmitters of shocks to all other variables in BRICS. Overall, it has been observed that the sovereign yields of India, China, and Brazil do not fluctuate significantly with those of the United States and Europe during crises, making them the most appealing markets for risk minimization and hedging. It is also one of the significant findings of the study. Therefore, we conclude that where the catalyst of crises is the U.S., like the GFC and the Global Pandemic, volatility transmission is substantial to the BRICS market. As the origin of crises in European countries like BREXIT and EDC, the contagion between advanced and BRICS markets tends to be insignificant. These findings are significant for policymakers and investors engaged in U.S. and BRICS bond markets. The study may also be helpful to trace the potential cause of the risk trigger and help formulate diversification strategies to safeguard the markets. From the asset allocation perspective, Brazil, India, and China seem to be the most attractive markets for decoupling processes as these markets are less integrated with other advanced bond markets. This study can be further lengthened to include an analysis of the micro-level debt investment flowing essentially from the USA, EMU, and Japan to BRICS countries.

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