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Sovereign Credit Default Swap Market Volatility in BRICS Countries Before and During the COVID-19 Pandemic

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Abstract: SCDS (Sovereign Credit Default Swaps) are becoming more widely used as a country risk indicator after 2008 and stand out for providing real-time information rather than periodic reporting. The COVID-19 pandemic has led to economic disruptions and a decline in international trade. Understanding how the Pandemic affects SCDS return volatility in emerging economies like BRICS forms the motivation for our research. With this study, we aim to determine the impact of the COVID-19 Pandemic on SCDS return volatility in Brazil, Russia, India, China and South Africa, known as the BRICS countries. We used the Exponential Generalized Autoregressive Conditional Heteroskedasticity (EGARCH) model to analyze the data, which consisted of the daily closing price data for SCDS. The date of the first COVID-19 case in each country has been taken as the beginning of the COVID-19 Pandemic in each country. The results of the estimated GARCH models show that the volatility processes of the SCDS return series differ between periods. EGARCH model results indicate that shocks created by news in these countries during the Pandemic have a small and persistent effect on Brazil and Russia's SCDS return volatility, while they have a large and enduring effect on China and South Africa's SCDS return volatility. The findings will guide policymakers and portfolio managers in determining risk management models.

Keywords: SCDS; EGARCH; Volatility; BRICS; COVID-19.

JEL classification: E5; H81.

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1. INTRODUCTION

A credit default swap (CDS) is a credit derivative that can be used to insure against a corporate or government bond issuer's credit risk. SCDS is a type of CDS that can be used to protect investors against sovereign debt losses caused by credit events such as default or debt restructuring. The CDS market is still in its early stages but has already become an important component of the global credit market. CDS were introduced in the 1990s and became popular in the early 2000s, with the total value of outstanding CDS reaching $61.2 trillion by 2007 (Bank for International Settlements, 2022). CDS and Credit Derivatives started in 1996 after many financial institutions viewed them as useful tools for risk management. The 1997 Asian crises, the 1998 Russian bond default and the International Swaps and Derivatives Association (ISDA) regulations accelerated the emergence of credit derivatives (Ranciere, 2002). On a regional basis, Latin American countries account for approximately 50-60% of the Credit derivatives market, Eastern European countries 23-30% of the Credit derivatives market, and other countries 10-20% of the Credit derivatives market and the most liquid markets are; Argentina, Brazil, Mexico, Russia, Turkey, and South Africa (Ranciere, 2002). CDSs are issued in USD and other powerful currencies, such as the Euro (Brigo *et al.*, 2019).

S&P Global, a leading financial data and analytics provider, is well-known for its credit risk analysis expertise. They provide the iTraxx SovX indices, a family of sovereign CDS indices covering global markets, including the BRICS. The sovereign CDS indices were created to track the market's perception of credit risk via CDS contract pricing. The first iTraxx SovX indices were introduced in 2007. The iTraxx SovX Western Europe was the first index launched, followed by the iTraxx SovX CEEMEA (Central and Eastern Europe, Middle East and Africa) and the iTraxx SovX Asia ex-Japan (S&P Down Jones Indices, 2023).

CDS were widely used to mitigate the risks associated with mortgage-backed securities and fixed-income products, contributing to the 2008 financial crisis and the European sovereign debt crisis (Bhatnagar *et al.*, 2023). Before the global financial crisis, more money was invested in CDSs than in other financial instruments, such as stocks, with a market capitalization of $60.4 trillion in 2007 (The World Bank Data, 2022).

The price of sovereign CDS has traditionally been used to assess the risk of a sovereign credit event. If the price of a sovereign CDS rises, the market perceives a higher risk of default, while a price decrease indicates a lower risk. Furthermore, the academic and practitioner literature on CDS is growing, with researchers looking into the role of counterparty credit risk in determining par CDS spreads, how quickly new information is reflected in CDS pricing in comparison to other markets, a measure of investor perception of the country's credit risk, and much more (Amstad *et al.*, 2016; Fontana and Scheicher, 2016; Cevik and Öztürkkal, 2020; Bomfim, 2022).

CDS are among the most contentious derivative instruments as a result of their roles in the 2008 financial crisis and subsequent debt crises in Europe. CDS proponents believe that the CDS market enables bond market lenders to reduce credit concentrations and meet regulatory goals while maintaining customer relationships (Amstad *et al.*, 2016; Cevik and Öztürkkal, 2020). On the other hand, opponents frequently see the contracts as speculative and potentially destabilizing, citing their differences from standard insurance policies covering property (Tevfik Kartal, 2020; Bhatnagar *et al.*, 2022).

Due to the CDS market regulation and relative financial market stability until 2019, investors' interest in this market has generally decreased. However, although SCDS account for a small portion of the sovereign debt market, their significance has grown rapidly since 2008, particularly in advanced economies (International Monetary Fund, 2013). The proportion of SCDS increased in the years following the global financial crisis, from less than 4% of notional amounts outstanding in the global CDS market in 2007 to around 14% in 2020 (Bomfim, 2022). CDS contracts issued on emerging-market government debt continue to dominate the SCDS market. Contracts referencing the sovereign debt of key emerging-market countries are frequently cited as among the most frequently negotiated in the global CDS market's sovereign sector (Bomfim, 2022).

The CDS market rose to $8.8 trillion in the first six months of 2020 and remained there until 2022 (Bank for International Settlements, 2022). This increase can be attributed partly to the uncertainty caused by COVID-19 when market participants used CDSs to adjust their risk exposures and infer changing market views on credit risk (Bank for International Settlements, 2022). Due to COVID-19, debt became more expensive because of capital outflows from emerging markets, an increase in the spreads on their SCDSs, and a decline in the value of their currencies (Daehler *et al.*, 2021).

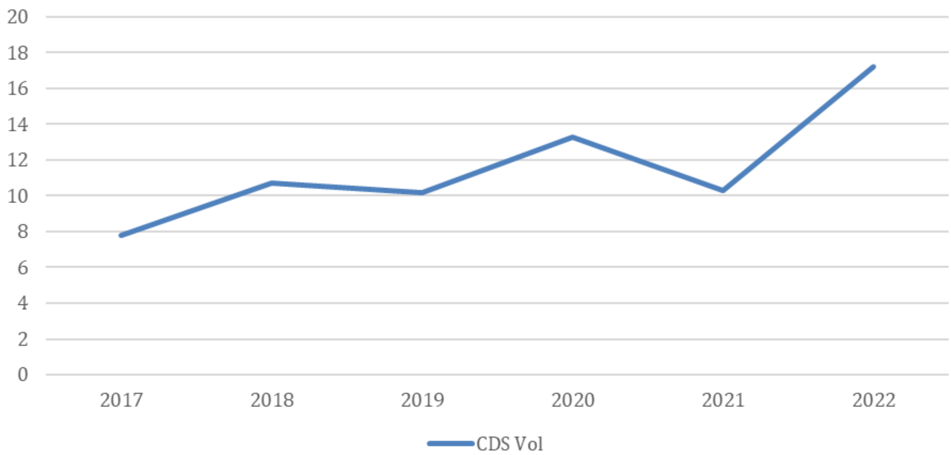

Figure no. 1 – CDS Volume (trillions of USD)
Source: adapted from Barnes (2022)

In Figure no. 1, we can note how the trading volume of CDS increased during the Pandemic period in 2020 and decreased the following year. We witnessed a sharp rise in 2022, maybe due to Russia's invasion of Ukraine and the rising regional and global geopolitical risks.

Although the United States, China, Japan, and Germany continue to be the world's largest economies in terms of nominal GDP, some rankings have shifted as a result of the Pandemic. India, the world's fifth-largest economy in 2019, slipped to sixth place behind the U.K. in 2020 (The World Bank Data, 2022). India was subjected to strict lockdowns during the COVID-19 pandemic as the country struggled to contain the coronavirus, and it took three years to return to fifth place in 2022. Brazil's economy fell from ninth to twelfth in 2020, making it the only country to fall out of the top ten and remain there in 2022 (The World Bank Data, 2022). South Korea entered the top ten since it was one of the earliest countries outside China to report cases of COVID-19 in early 2020 (The World Bank Data, 2022). This lends credence to our study's motivation to investigate SCDS return volatility as a risk indicator in emerging economies such as the BRICS.

During 2020, the economic disruptions brought about by COVID-19 resulted in a decline in international trade. However, because global demand resumed, international trade rebounded in 2021 and increased further during 2022 (UNCTAD, 2023). As we see in Table no. 1, the exports in 2020 of almost all BRICS countries fell. On the other hand, China increased its exports by 3.84%, and other BRICS countries' exports fell by 11.86% (South Africa). Thus, we can conclude that the Pandemic negatively affected the BRICS countries, causing the rise of credit default problems in these countries.

Table no. 1 – Export yearly change by Country %

Country	*2017*	*2018*	*2019*	*2020*	*2021*
Brazil	4.91	4.05	-2.56	-1.84	5.79
Russia	5.01	5.55	0.73	-4.10	3.50
India	4.56	11.93	-3.39	-9.24	24.32
China	10.23	9.53	-1.02	3.84	30.19
South Africa	-0.27	2.74	-3.45	-11.86	9.99

Source: The World Bank Data (2022)

We can see the GDP Growth of the BRICS countries between 2019 and 2022. According to IMF data (International Monetary Fund, 2022), except for China, all of the BRICS countries' GDP fell (3.6% in Russia, 4.5% in Brazil, 7.5% in South Africa and 8.0% in India). However, the growth rate in China fell to 2.3% from 6.0% during the COVID-19 pandemic in 2020. Therefore, we can say that the COVID-19 pandemic had an adverse effect on all BRICS countries.

Table no. 2 – Real GDP Growth %

Country	*Estimate*		*Projections*	
	2019	*2020*	*2021*	*2022*
Brazil	1.4	–4.5	3.6	2.6
Russia	1.3	–3.6	3.0	3.9
India	4.2	–8.0	11.5	6.8
China	6.0	2.3	8.1	5.6
South Africa	0.2	–7.5	2.8	1.4

Source: IMF (2022)

These effects can be caused by problems in the supply chain, etc., because of the pandemic restrictions. There are many avenues: supply chains may be affected, the failure to receive necessary inputs from other countries, the closure of export markets, transportation challenges, currency fluctuations, the financial state of a country before the Pandemic and the political status of a country.

There is no official definition of an emerging market, but the IMF defines one based on systemic presence, market access, and income level. The IMF defined 20 emerging market countries in 2020, accounting for 34% of global nominal GDP in U.S. dollars and 46% in purchasing-power-parity terms (Duttagupta and Pazarbasiogly, 2021). Brazil, Russia, India, China, and South Africa (BRICS) have long been among the world's fastest-growing emerging market economies, owing to low labour costs, favourable demographics, and abundant natural resources during a global commodities boom (Duttagupta and Pazarbasiogly, 2021). BRICS is a club of emerging powers attempting to increase political and economic integration in response to new global challenges. In this study, we do not examine BRICS as an institution but rather each country's potential, as Brazil, Russia, India, China, and South Africa account for around 25% of the global GDP, 40% of the world's population, and 12% of global trade in 2021 (The World Bank Data, 2022).

With this study, we aimed to determine the impact of the COVID-19 Pandemic on SCDS return volatility in Brazil, Russia, India, China and South Africa, namely because, as noted above, Emerging countries are more vulnerable to some risks than developed markets. We look at the volatility of sovereign CDS as an indicator of the country's economic stability/instability and ranking. The more volatile the BRICS countries' CDS prices are, the less stable their economies are and the lower their ranking.

In the literature, very few studies examine the impact of the Covid-19 pandemic on SCDS prices. This study distinguishes itself from the existing literature by revealing the effect of the Pandemic on SCDS return volatility and the persistence of volatility. The study predicts the impact of the Pandemic on SCDS return volatility using EGARCH models. As one of the first studies conducted on the volatility of BRICS SCDS returns, this study uniquely contributes to the literature.

Our findings contribute to SCSD perception as a market sentiment indicator towards specific reference entities and credit risk in general. Moreover, COVID-19 has recently triggered another crisis; thus, this study complements the literature on CDS in the context of COVID-19 with meaningful empirical relationships that SCSD return volatility has with a country's economic stability.

Our findings indicate that the shocks caused by news in countries have varying effects on SCDS return volatility both before and during the pandemic period. However, it is observed that the persistence of SCDS return volatility is longer during the Pandemic than in the pre-pandemic period across all countries. In addition, the increases in volatility in SCDS returns and the long duration of volatility can be interpreted as increased risks for countries during the pandemic period.

Understanding the effect of a pandemic on the volatility of sovereign credit default swaps is important for policymakers since this can help determine models for managing a country's expected credit risk exposure. Furthermore, because SCDS return volatility can be used as a reliable indicator of investors' views on credit risk exposure, this study has practical implications for investors interested in emerging markets.

2. LITERATURE REVIEW

So far, researchers and practitioners have focused on the primary applications of credit default swaps from the perspective of those who participate in the credit derivatives market (Wigan, 2009; Grima *et al.*, 2020; Srivastava and Dashottar, 2020; Wu *et al.*, 2020). Less obvious but potentially very significant is the growing use of pricing data from credit default swaps by market participants and non-participants alike as indicators of market sentiment toward specific reference entities and credit risk in general. In the literature, the number of studies examining the impact of the Covid-19 pandemic on SCDS is limited. However, a substantial body of literature investigates the relationship between CDS prices and different financial instruments.

A study by Cevik and Öztürkkal (2020) shows the impact of infectious diseases on the evolution of sovereign CDS spreads. After controlling for macroeconomic and institutional factors, they found that infectious-disease outbreaks have no discernible effect on CDS spread. However, their granular analysis using high-frequency (daily) data indicated that the COVID-19 Pandemic significantly impacted market-implied sovereign default risk. This adverse effect was more pronounced in advanced economies.

This analysis shows that more stringent domestic containment measures help lower sovereign CDS spreads. The macro-fiscal cost of efforts to curb the spread of the disease could undermine creditworthiness, eventually pushing the cost of borrowing higher and decreasing economic stability (Cevik and Öztürkkal, 2020). Cevik and Öztürkkal (2020) support the findings of Apergis *et al.* (2022), who research global and local COVID-19 indicators and examine how the Pandemic measured by these indicators affects U.S. corporate CDS spreads. The results provide strong evidence for the significant impact of the severity of the Pandemic on U.S. corporate CDS spreads. COVID-19 has driven up CDS prices, and the magnitude and significance of this increase have been heterogeneous across sectors. Specifically, banking, travel, leisure, transportation, airlines, and restaurants were the worst affected sectors, while media, technology, telecommunications, pharmaceutical, information, and data technology firms were not affected by the Pandemic. Hasan *et al.* (2023) have found similar results in their study. Hasan *et al.* (2023) investigated the response of global corporate CDS spreads to the COVID-19 pandemic for 655 companies operating in different industries in 27 countries. The study demonstrates an increase in corporate CDS spreads due to the Pandemic, which is more pronounced for larger companies with higher leverage and closer to the default threshold.

Fender *et al.* (2012) analyzed the CDS premiums of emerging countries using a GARCH(1,1) model. The models were estimated for two separate periods to observe the impact of the global financial crisis. The findings indicate that global and regional risks have a more significant influence on the CDS premiums of emerging countries than their own dynamics, and during the crisis period, the impact of external factors on CDS premiums is more crucial.

According to Amstad *et al.* (2016), global investors differentiate between economies by focusing on sovereign risk, as reflected in monthly returns on CDSs. By dividing their sample into two periods and extracting risk factors from CDS returns, they found an "old normal" in which a single global risk factor drove half of the variation in returns and a new normal in which that risk factor became even more dominant. They noted that tests for breaks in the time series of these returns suggested a new norm and highlighted that the way countries loaded on this factor did not depend on economic fundamentals in both the old and new normal.

Raimbourg and Salvadè (2021) analyzed the evolution of CDS spread and CDS volatility around European sovereign rating announcements over the period 2008 to 2013. They show that the effect of the announcement differs depending on the issuer's credit quality (Investment Grade versus Speculative). An investment grade country's downgrading and negative credit watch stabilize the market as volatility decreases right after its release. By contrast, the announcements regarding speculative grade countries trigger an increase in both CDS spread and volatility. In doing this, they also show that these announcements not only affect the CDS of the country but spill over to the German CDS.

A study providing a thorough investigation of the lead-lag connection between stock indices and sovereign credit default swap (CDS) returns for 14 European countries and the U.S. over the period 2004–2016 was carried out by Ballester and González-Urteaga (2020). They used a rolling VAR framework to analyze the connection process over time, covering both crisis and non-crisis periods. Examine the connection between stock market volatility and CDS returns. They found that a connection between the credit and equity markets exists and that it is a time variable that seems related to financial crises. Furthermore, the authors observed that stock market returns anticipate sovereign CDS returns, and sovereign CDSs anticipate equity return conditional volatility, completing a market connectedness circle. They further noted that the contribution percentages in terms of returns are more intense in the U.S. than in Europe. The opposite result is found with respect to volatilities, highlighting the greater impact in Eurozone countries compared to non-Eurozone countries.

Vurur and Özen (2020) examined the effect of the COVID-19 Pandemic on the relationship between CDS premiums and the main stock market indices of England, Germany, France, Italy, and Spain. The study's findings showed that the relationship between CDS premiums and stock market indices increased significantly after the Pandemic.

A comparison of the market pricing of the euro area government bonds and the corresponding CDSs was carried out by Fontana and Scheicher (2016). They specifically analyzed the "basis", defined as the difference between the premium on the CDS and the credit spread on the underlying bond, using weekly data for a period that contained several episodes of sovereign market distress. Their observations show a complex relationship between the derivatives market and the underlying cash market characterized by sizable deviations from the no-arbitrage relationship. They highlight that short-selling frictions explain the persistence of positive basis deviations. In contrast, funding frictions explain the persistence of negative basis deviations. These are observed in countries with weak public finances.

Tevfik Kartal (2020) examines how the sovereign CDS spreads of Turkey behaved during the COVID-19 pandemic times by considering that CDS spreads reflect countries' riskiness, vulnerability, financial stability, and macroeconomic stability. Most emerging countries' CDS spreads have increased with the emergence of the COVID-19 Pandemic. This study focuses on two periods, 'before COVID-19' and 'COVID-19 pandemic times', applying the Multivariate Adaptive Regression Splines (MARS) method to daily data of six independent variables and six COVID-19 situations. His findings reveal that (i) influential factors on Turkey's CDS spreads are the BIST100 index, VIX index, MSCI Turkey index, and USD/TL foreign exchange rates for the period which is before the COVID-19 pandemic times; (ii) MSCI emerging market index, number of new deaths from COVID-19, USD/TL foreign exchange rates, the weighted average cost of funds, number of new cases from COVID-19, and VIX index effect on Turkey's CDS spreads during the COVID-19 pandemic times, respectively; (iii) on the other hand, number of cumulative cases, number of cumulative deaths, and measures do not affect Turkey's CDS spreads in any period. Taking precautions to decrease the negative effects on Turkey's CDS spreads while considering the importance of the number of deaths from the COVID-19 Pandemic is very important. Hence, he suggests Turkey could stimulate foreign portfolio investment inflows by decreasing CDS spreads.

Kandemir *et al.* (2022) research also demonstrated the predictive power of CSD premiums as risk indicators. They examined the interaction between the changes in Turkey's CDS premiums and the BIST 100 index, exchange rates, and bond rates. The interaction between the CDS and BIST 100 index, exchange rates, and bond interest rates were analyzed via cDCC-EGARCH and causality in variance. As a result of the analysis, it can be seen that the effect of shocks created by increases for CDS, USD/TL, EU/TL, and bond interest series is more and more significant than shocks created by decreases. According to the variance causality analysis results, a unidirectional causality relationship was found between exchange rates and interest rates on CDS premiums. A causality relationship was determined from CDS premiums to the BIST 100 index. It is possible to predict the volatility in CDS premiums from the first lag by monitoring exchange rates and bond rate volatility.

An investigation, using the Toda Yamamoto causality test on daily closing data, of the relationship between the VIX index and the BRICS countries' stock market, carried out by Gürsoy (2020), demonstrated that the VIX index is in bilateral causality with the Russian (RTSI) and South African (INVSAF40) stock markets as of the dates of 02.24.2011 and 06.01.2020. On the other hand, it is determined that the price movements in the VIX index have a unilateral causality relationship with the India (BSESN) and China (SSEC) indices. However, it has been seen that the VIX index does not have a unilateral or bilateral causal relationship with the Brazilian (BOVESPA) stock market. These findings corroborate our previous findings on the leverage effect within BRICS countries. The variation in the significance of SCDS as risk indicators depending on domestic factors explains the study's different results for different countries. This is consistent with Kocsis and Monostori (2016) findings, who used a dynamic hierarchical factor model to aggregate information on fundamental economic indicators to investigate the determinants of sovereign CDS spreads on a sample of Eastern European data. SCDS spreads were regressed on forecasts of factors. They found that domestic fundamentals explain more of SCDS spread variance than global factors, largely due to their ability to explain differences in sovereign risk across countries. The effects on SCDS spreads are time-varying, and in terms of economic significance, the factor of institutional-political strength stands out.

An investigation on volatility transmission from commodities to sovereign CDS spreads of emerging and frontier markets carried out by Bouri *et al.* (2017), using daily data for seventeen emerging and six frontier countries, highlights significant volatility spillover from commodity markets to sovereign CDS spreads of emerging and frontier markets. They found that this effect is strong for most countries and that the results differ by country and over time.

Pu and Zhang (2012) examined the global impact of the 2010 German short sale ban on sovereign credit default swap (CDS) spreads, volatility, and liquidity across 54 countries. They found that CDS spreads continued rising after the ban in the debt crisis region, which suggests that the short-selling ban cannot suppress soaring borrowing costs in these countries and that the ban helps stabilize the CDS market by reducing CDS volatility. They further noted that the reduction in CDS volatility is greater in the eurozone than in the non-eurozone.

3. SAMPLE

We used a dummy variable to measure the impact of the COVID-19 Pandemic on SCDS return volatility. In addition, we compared SCDS return volatilities in terms of the pre-pandemic and pandemic periods using the 5-year CSD price data of the five BRICS countries, divided into two buckets: "before the COVID-19 pandemic outbreak period" and "during the COVID-19 pandemic outbreak period". The dataset used in this study consisted of daily closing price data from January 2, 2018, to February 28, 2022, for BRGV5YUSAC (Brazil), RUGV5YUSAC (Russia), INGV5YUSAC (India), CNGV5YUSAC (China), and ZAGV5YUSAC (South Africa) CDS. This data was collected from the Thomson Reuters Eikon System and the Bloomberg database.

We focused on the 5-year SCDS contracts in this study rather than other maturities because they are the most commonly traded contracts. During the sample period, each 5-year contract traded at least once daily in each chosen country.

A dummy variable was included to measure the impact of the COVID-19 Pandemic on SCDS return volatility. The dummy variable COVID-19 assumes a value of 0 for the pre-pandemic period and 1 for the pandemic period. The date of the first COVID-19 case in each country has been accepted as the beginning of the COVID-19 Pandemic. The first case dates in the countries were determined from the Worldometers database. The first case dates were 26.02.2020 for Brazil, 31.01.2020 for Russia, 30.01.2020 for India, 31.12.2019 for China and 05.03.2020 for South Africa. As seen in Table no. 3, the study was evaluated considering three periods.

Table no. 3 – Data Periods

Country	***Term***	***Date***	***Observations***
Brazil	All Term	02.01.2018-28.02.2022	1051
	Pre-Pandemic	02.01.2018-25.02.2020	541
	Pandemic	26.02.2020-28.02.2022	510
Russa	All Term	02.01.2018-23.02.2022	1048
	Pre-Pandemic	02.01.2018-30.01.2020	524
	Pandemic	31.01.2020-23.02.2022	524
India	All Term	02.01.2018-28.02.2022	728
	Pre-Pandemic	02.01.2018-29.01.2020	422
	Pandemic	30.01.2020-28.02.2022	306
China	All Term	02.01.2018-28.02.2022	1050
	Pre-Pandemic	02.01.2018-28.02.2020	503
	Pandemic	02.01.2020-28.02.2022	547
South Africa	All Term	02.01.2018-28.02.2022	1054
	Pre-Pandemic	02.01.2018-04.03.2020	547
	Pandemic	05.03.2020-28.02.2022	507

While the World Health Organization (WHO) announced the Pandemic on 11 March 2020, we preferred to use the data when the first COVID-19 case was announced in each country. This is because we believe that local markets have been affected mostly by local factors, and we also believe that a country that has not seen a COVID-19 case could have some advantages over a country that has had COVID-19 cases. Additionally, since there was a large amount of missing data in the Indian data, it was not included in the analysis.

In addition, in the study, SCDS return volatilities were compared in terms of pre-pandemic and pandemic periods, which were created considering these dates.

SCDS returns are calculated using the formula:

$$R_t = \ln (P_t/P_{t-1}) \tag{1}$$

The CDS return series of the countries are shown in Figure no. 2.

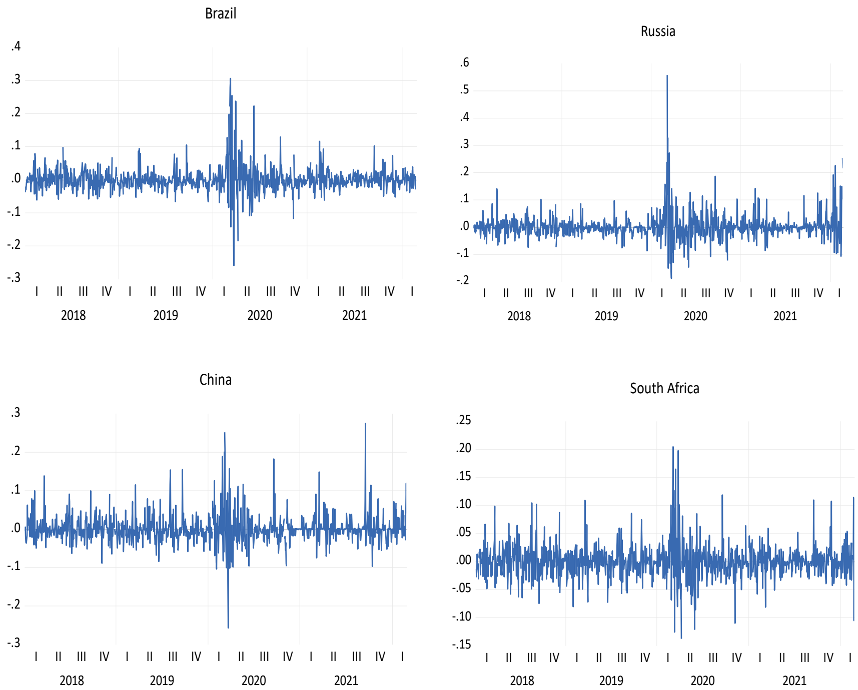

Figure no. 2 – CDS Return of BRICS Countries
Source: authors' compilation

The figures show that at the beginning of the Pandemic, the fluctuations in the SCDS returns of the countries were more intense. The Figures of India do not provide the full data set information since some time intervals are missing. In Table no. 4, descriptive statistics of countries' SCDS returns are provided for the whole period, consisting of a combination of the pre-pandemic and pandemic periods. Data availability for each country's CDS prices vary due to several reasons, such as holidays, market closures, or incomplete data reporting.

Table no. 4 – Descriptive Statistics

SCDS Return Series	Term	Mean	Std.Dev.	Skewness	Kurtosis	Jarque-Bera	Observations
Brazil	All Term	0.000984	0.037539	1.859236	20.91727	14663.89***	1051
	Pre-Pandemic	-0.000428	0.025418	0.654115	4.730601	106.0911***	541
	Pandemic	0.002482	0.047086	1.767547	16.80276	4314.025***	510
Russia	All Term	0.002151	0.045636	3.029882	30.87537	35534.06***	1048
	Pre-Pandemic	-0.000135	0.025694	0.883710	7.139504	442.3273***	524
	Pandemic	0.005104	0.059090	2.601185	21.23273	7849.024***	524
China	All Term	0.000930	0.037415	1.341697	13.46091	5102.621***	1050
	Pre-Pandemic	-0.000442	0.030378	1.241562	7.224680	504.2902***	504
	Pandemic	0.002198	0.042888	1.263961	13.23647	2529.247***	546
South Africa	All Term	0.000783	0.030207	0.976425	9.990274	2313.423***	1054
	Pre-Pandemic	0.000788	0.026333	0.500844	5.107839	124.1318***	547
	Pandemic	0.000778	0.033921	1.183007	11.08618	1499.543***	507

Note: *** indicates statistical significance at the 1 percent level.
Source: Prepared by the Authors

When we examine the standard deviations of the SCDS return series, the standard deviations of Brazil, Russia, China and South Africa have increased in the pandemic period compared to the pre-pandemic period. This result shows that SCDS returns have more volatility during the pandemic period. It is seen that only the standard deviation of the India SCDS return series decreased during the pandemic period. It can be said that this is because there is a lot of missing data in the India data set.

According to the Jarque-Bera test statistics, the countries' SCDS return series do not exhibit a normal distribution. The stationarities of the series were investigated with the Augmented Dickey-Fuller (ADF) unit root test developed by Dickey and Fuller (1979), and the results are given in Table no. 5. According to the ADF unit root test results, it was determined that the series were stationary at the level.

Table no. 5 – Unit Root Test

SCDS Return Series	Term	ADF Test Statistic	Critical Values %1	%5	%10	Stability Level
Brazil	All Term	-18.87267***	-3.436366	-2.864084	-2.568176	I(0)
	Pre-Pandemic	-20.65689***	-3.442231	-2.866673	-2.569564	I(0)
	Pandemic	-19.93250***	-3.442970	-2.866999	-2.569739	I(0)
	All Term	-6.521523***	-3.436493	-2.864140	-2.568206	I(0)
Russia	Pre-Pandemic	-20.74927***	-3.442625	-2.866847	-2.569657	I(0)
	Pandemic	-4.884846***	-3.443072	-2.867044	-2.569763	I(0)
	All Term	-8.888055***	-3.439192	-2.865332	-2.568846	I(0)
China	Pre-Pandemic	-11.34313***	-3.443175	-2.867089	-2.569787	I(0)
	Pandemic	-5.696384***	-3.442413	-2.866753	-2.569607	I(0)
	All Term	-7.406008***	-3.436425	-2.864111	-2.568190	I(0)
South Africa	Pre-Pandemic	-22.71878***	-3.442098	-2.866614	-2.569533	I(0)
	Pandemic	-6.627301***	-3.443388	-2.867183	-2.569837	I(0)

Note: ** and *** indicate statistical significance at the 5 and 1 percent levels, respectively.
Source: Authors computed

4. METHODOLOGY

The study modelled the volatility of SCDS return values in BRICS countries with the GARCH model. To be able to model the volatility of time series data, it is necessary to initially investigate whether there is an ARCH effect (volatility) in the series. The ARCH LM test will determine the presence of volatility in the series. The ARCH-LM test is tested by estimating the autoregressive moving average (ARMA) model. Once it is established that there is an ARCH effect in the series, general autoregressive conditional heteroskedasticity (GARCH) models will be employed to model the volatility.

4.1 ARMA Model

The autoregressive moving average (ARMA) model, proposed by Box and Jenkins (1976) and widely known as the Box-Jenkins method (Gujarati, 2003), is employed for forecasting univariate time series data. The autoregressive moving average model is a forward-looking prediction model for fixed (discrete or interrupted) and stationary time series consisting of observation values obtained at equal time intervals. These models are developed based on the assumption that events over time are stochastic in nature and that the time series related to these events constitutes a stochastic process (Enders, 2015). Autoregressive moving average (ARMA) models combine autoregressive (A.R.) and moving average (M.A.) models. The observation value at any given time period of a time series is expressed as a linear combination of a specific number of preceding observation values and the error term. The ARMA model includes a component with p terms from the A.R. model and q terms from the M.A. model, written as ARMA(p,q). The ARMA(p,q) model is expressed as follows (Gujarati, 2003; Brooks, 2008):

$$y_t=\varphi_0+\varphi_1 y_{t-1}+\varphi_2 y_{t-2}+\cdots+\varphi_p y_{t-p}+u_t-\theta_1 u_{t-1}-\cdots-\theta_q u_{t-q} \quad (2)$$

here, p and q indicate the degree of the model. and φ and θ refer to the model's parameters.

4.2 GARCH Model

The Autoregressive Conditional Heteroskedasticity (ARCH) model developed by Engle (1982) allows for a better understanding of the dynamic properties of financial time series and for predicting heteroskedasticity over time. Later, Bollerslev (1986) developed the GARCH (Generalized ARCH) model based on the weighting of past error squares. The GARCH (p,q) model is the model in which variance is explained depending on past variances of past volatility and dependent variables. The GARCH (p,q) model is as follows (Enders, 2015).

$$h_t= \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i} \quad (3)$$

GARCH models contain some restrictions on α_i parameters. In these models q>0, p≥0, $\alpha_0>0$, $\alpha_i\geq 0$ (i=1,2,3,….,q) and $\beta_i\geq 0$ (i=1,2,3,…,p) conditions should be met. In addition, in addition to these constraints, $\alpha_i + \beta_i < 1$ should be. Providing this constraint indicates that the process has a static structure. $\alpha_i + \beta_i \geq 1$ does not statistically estimate volatility (Engle, 2002).

In equation (3), α_i and β_i are the coefficients of ARCH and GARCH terms, respectively. Large values of the ARCH and GARCH parameters influence conditional volatility differently. A high ARCH parameter implies that the effects of a shock are more pronounced in the subsequent period. In contrast, a high GARCH parameter indicates that the effects of a shock persist for a long time (Enders, 2004, p. 134). Therefore, the large ARCH value will increase volatility in the short term, and the large GARCH value will increase volatility in the long term (Nazlioglu *et al.*, 2013).

4.2.1 EGARCH Model

The models known as ARCH/GARCH suffer from a significant limitation, as they assume that positive and negative shocks in financial markets have the same effect on the volatility of financial assets. Furthermore, these models only focus on the magnitude of volatility, neglecting the sign of volatility. However, it is frequently observed in financial markets that negative news (negative shocks) tends to impact volatility more than positive news of the same magnitude (positive shocks). This phenomenon, expressed as the leverage effect, cannot be detected by ARCH/GARCH models. Therefore, to address this limitation and provide a more suitable analysis of asymmetry in the volatility of time series data, the Exponential-GARCH

(Exponential Generalized Autoregressive Conditional Heteroskedasticity) model was developed by Nelson (1991). One of the most important features of this model is its ability to model asymmetric effects by eliminating the non-negativity constraint introduced in GARCH models, primarily due to the logarithmic nature of the conditional variance. Nelson (1991) proposed the EGARCH model, which allows for a more nuanced understanding of the asymmetric impact on time series volatility. The model is expressed as follows:

$$\log(h_t) = \omega + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{i=1}^{q} \alpha_i \frac{|u_{t-i}|}{\sqrt{h_{t-i}}} + \sum_{i=1}^{q} \gamma_i \frac{u_{t-i}}{\sqrt{h_{t-i}}} \tag{4}$$

In the model, h_t shows the conditional variance, h_{t-j} shows the values of the conditional variance going back to the j periods, u_{t-j} shows the values of the error terms going back to the i periods. ω, β_j, α_i, and γ_i are EGARCH model parameters. α_i, γ_i, and β_j measure innovation, asymmetry, and persistence, respectively. The presence of asymmetric volatility in the EGARCH model depends on the statistically significant γi parameter. The γ_i parameter shows both the leverage effect and the asymmetry of the series. In the model, if $\gamma_i = 0$, it means that a positive shock and a negative shock have the same effect on volatility. If $\gamma_i \neq 0$, it indicates the presence of an asymmetric effect in the series. If $-1 < \gamma_i < 0$, a negative shock increases volatility more than a positive shock (Brooks, 2008).

4.2.2 EGARCH Model with Regressors

This EGARCH model with additional regressors is used in this article to estimate the impact of the COVID-19 Pandemic on SCDS return volatilities. The EGARCH model has been extended by including a dummy variable for the COVID-19 period.

$$\log(h_t) = \omega + \sum_{j=1}^{p} \beta_j \log(h_{t-j}) + \sum_{i=1}^{q} \alpha_i \frac{|u_{t-i}|}{\sqrt{h_{t-i}}} + \sum_{i=1}^{q} \gamma_i \frac{u_{t-i}}{\sqrt{h_{t-i}}} + \delta_1 COVID_t \tag{5}$$

In the equation, if the coefficient δ_1 is negative and significant, it indicates a relationship between COVID-19 and the decrease in SCDS return volatility. If the coefficient δ_1 is positive and significant, it will indicate a relationship between the increase in COVID-19 and SCDS return volatility.

5. ANALYSIS AND RESULTS

It is necessary to determine whether the SCDS return series is heteroskedastic to model its volatility. First, the Autoregressive Moving Average (ARMA) model structure, which is the series' linear stationary stochastic model, must be determined. Table no. 2 shows the most appropriate ARMA models for the series based on Akaike Information Criteria (AIC), Schwartz Information Criteria (SCI), and Log Likelihood ratio. Second, autocorrelation and ARCH LM tests were run to determine the heteroscedasticity status of the series, and the results are shown in Table no. 6.

Table no. 6 – ARMA Models of Developing Countries

SCDS Return Series	Term	AIC	SIC	LogL	$Q^2(10)$	ARCH LM(10)
Brazil	All Term ARMA(2,4)	-3.785319	-3.747584	1997.185	1539.3***	60.10038***
	Pre-Pandemic ARMA(2,1)	-4.513272	-4.473592	1225.840	45.718***	3.962663***
	Pandemic ARMA(2,4)	-3.289661	-3.223239	846.8637	727.07***	33.15081***
Russia	All Term ARMA(1,2)	-3.383787	-3.360148	1778.104	330.77***	21.35982***
	Pre-Pandemic ARMA(1,0)	-4.484607	-4.460209	1177.967	39.359***	3.874172***
	Pandemic ARMA(3,4)	-2.895434	-2.822241	767.6038	127.41***	7.390298***
China	All Term ARMA(3,2)	-3.762597	-3.729553	1982.363	309.90***	19.48894***
	Pre-Pandemic ARMA(3,3)	-4.165746	-4.098721	1057.768	10.659**	2.149714**
	Pandemic ARMA(4,3)	-3.499405	-3.428483	964.3377	183.93***	11.83709***
South Africa	All Term ARMA(3,1)	-4.166806	-4.138569	2201.907	470.73***	25.48141***
	Pre-Pandemic ARMA(1,0)	-4.427541	-4.403933	1213.932	19.684**	1.851277**
	Pandemic ARMA(0,0)	-3.927571	-3.919230	996.6392	275.98***	13.39672***

Note: ** and *** indicate statistical significance at the 5 and 1 percent levels, respectively.

Source: Authors computed

Ljung-Box Q^2 statistics and ARCH LM test results were evaluated up to the 10th lag. It was observed that there was no heteroscedasticity in India's all-term, pre-pandemic and pandemic periods. This can be attributed to the deficiencies in India's SCDS return data (Zaidi and Rupeika-Apoga, 2021). As a result, developing a reliable model for India is impossible. The fact that the Q^2 and ARCH LM values of other countries' SCDS return series are statistically significant at the 1% significance level indicates heteroscedasticity, and the series' volatility can be estimated.

The EGARCH model was used to estimate the countries' SCDS return series volatility. EGARCH models were applied to the residual series obtained from ARMA models. For the most suitable estimation of the EGARCH model, it is essential for its parameters to be statistically significant. Among the estimated models, the one with lower values for the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) and a higher likelihood ratio (L.R.) is selected as the most appropriate model. The suitable EGARCH model results for the countries' SCDS return series are presented in Table no. 7.

In the EGARCH models, the coefficient of the constant term and the ARCH and GARCH parameters are statistically significant for all return series. Large values of the ARCH and GARCH parameters influence conditional volatility in different ways. A high ARCH parameter implies that the effects of a shock are more pronounced in the subsequent period. In contrast, a high GARCH parameter implies that the effects of a shock are more persistent (Enders, 2004, p. 134). Therefore, the large ARCH value will increase volatility in the short term, and the large GARCH value will increase volatility in the long term. Within the scope of GARCH models, in addition to calculating the persistence of shocks, the half-life of shocks can also be computed. In this context, the formula ln (0.5)/ln (βj) has been used to calculate the half-life of shocks (Özdemir *et al.*, 2021). The leverage parameter (γ) measures whether the impact of positive and negative shocks on return volatilities is asymmetric.

Table no. 7 – EGARCH Models

	Brazil EGARCH(3,3)	**Russia EGARCH(3,1)**	**China EGARCH(3,1)**	**South Africa EGARCH(3,3)**
$\boldsymbol{\omega}$	-1.897570	-0.597149	-1.257527	-0.440998
	(0.0000)	(0.0000)	(0.0000)	(0.0078)
$\boldsymbol{\alpha_1}$	0.263111	0.258059	0.371192	0.189855
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
$\boldsymbol{\alpha_2}$	0.388039	-	-	0.131642
	(0.0000)			(0.0339)
$\boldsymbol{\alpha_3}$	0.229753	-	-	-0.206368
	(0.0000)			(0.0000)
λ	0.021147	0.084319	0.162010	0.078127
	(0.0000)	(0.0000)	(0.0000)	(0.0016)
$\boldsymbol{\beta_1}$	-0.349532	1.124184	0.148316	0.734336
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
$\boldsymbol{\beta_2}$	0.227041	-0.805298	0.341326	0.609981
	(0.0000)	(0.0000)	(0.0000)	(0.0095)
$\boldsymbol{\beta_3}$	0.950525	0.617625	0.363111	-0.393880
	(0.0000)	(0.0000)	(0.0000)	(0.0109)
$\boldsymbol{\alpha_i}$	0.880903	0.258059	0.371192	0.115129
$\boldsymbol{\beta_j}$	0.828034	0.936511	0.852753	0.950437
Half-life	3.67	10.56	4.35	13.63
		Diagnostic Statistic		
AIC	-4.320801	-3.951058	-4.019506	-4.395725
SIC	-4.283065	-3.922692	-3.991183	-4.358075
LogL	2278.581	2076.354	2116.241	2324.547
Q^2(10)	2.1374	3.6218	2.2458	2.3799
	(0.995)	(0.963)	(0.994)	(0.993)
ARCH	0.195969	0.363257	0.231451	0.241267
LM(10)	(0.9966)	(0.9621)	(0.9932)	(0.9920)

Note: Q2 and ARCH LM tests were examined until the 10th lag. The ( ) values indicate the probability values.
Source: Authors computed

The leverage parameter is positive and significant for countries' CDS return volatilities. The positivity of the parameter implies that positive shocks have a greater impact on CDS return volatilities as compared to negative shocks. A high ARCH parameter suggests that the effects of a shock are more pronounced in the subsequent period. Shocks in country markets most significantly affect Brazil's CDS return volatility. A high GARCH parameter implies that the effects of a shock are more persistent. The CDS return volatilities of Russia and South Africa tend to be more persistent. To determine how long CDS return volatility lasts on a daily basis, the half-life (H.L.) has been calculated. In this context, the persistence of a shock on Brazil's CDS return is approximately 3.67 days, 10.58 days for Russia, 4.35 days for China, and 13.63 days for South Africa.

The EGARCH model has been extended by including a dummy variable for the COVID-19 period to determine the effect of the COVID-19 Pandemic on the volatility of the SCDS return series. Table no. 8 presents the results of the EGARCH models, which adds the coronavirus variable to the conditional variance equation.

The COVID-19 Pandemic positively and significantly affects CDS return volatilities in Brazil and Russia. The Pandemic increases the CDS return volatility by approximately 10% in Brazil and around 9% in Russia.

Table no. 8 – EGARCH Models with COVID-19 Variables

	Brazil EGARCH(3,3)	**Russia EGARCH(3,1)**	**China EGARCH(3,1)**	**South Africa EGARCH(3,3)**
$\boldsymbol{\omega}$	-2.404374	-0.865598	-1.270058	-0.489806
	(0.0000)	(0.0000)	(0.0000)	(0.0042)
$\boldsymbol{\alpha_1}$	0.356192	0.294465	0.373859	0.191399
	(0.0000)	(0.0000)	(0.0000)	(0.0001)
$\boldsymbol{\alpha_2}$	0.383510	-	-	0.125342
	(0.0000)			(0.0415)
$\boldsymbol{\alpha_3}$	0.179750	-	-	-0.192718
	(0.0000)			(0.0002)
λ	-0.035805	0.070973	0.157030	0.087671
	(0.0042)	(0.0001)	(0.0000)	(0.0010)
$\boldsymbol{\beta_1}$	-0.274234	1.133660	0.133292	0.709619
	(0.0000)	(0.0000)	(0.0667)	(0.0001)
$\boldsymbol{\beta_2}$	0.182396	-0.794217	0.341313	0.622528
	(0.0000)	(0.0000)	(0.0000)	(0.0063)
$\boldsymbol{\beta_3}$	0.854654	0.568371	0.377833	-0.386791
	(0.0000)	(0.0000)	(0.0000)	(0.0105)
$\boldsymbol{\delta}$**(COVID)**	0.096404	0.088293	0.015890	0.011125
	(0.0087)	(0.0000)	(0.2082)	(0.1284)
$\boldsymbol{\alpha_i}$	0.919452	0.294465	0.373859	0.124023
$\boldsymbol{\beta_j}$	0.762816	0.90781	0.852438	0.945356
Half-life	2.56	7.16	4.34	12,33
		Diagnostic Statistic		
AIC	-4.293511	-3.972371	-4.018012	-4.395262
SIC	-4.251058	-3.939277	-3.984968	-4.352906
LogL	2265.240	2088.523	2116.456	2325.303
$\mathbf{Q^2(10)}$	2.6515	3.8688	2.2237	2.4479
	(0.988)	(0.953)	(0.994)	(0.992)
ARCH	0.244805	0.392814	0.228914	0.248220
LM(10)	(0.9915)	(0.9502)	(0.9935)	(0.9910)

Note: Q^2 and ARCH LM tests were examined until the 10th lag. The ( ) values indicate the probability values.

Source: Authors computed

According to the results of Table no. 8, the effect of the COVID-19 Pandemic on the SCDS return volatility could not be measured well by adding the dummy variable. For this reason, the analysis period was divided into two periods, the pre-pandemic period and the pandemic period, taking into account the dates of the COVID-19 cases in the countries. In these two periods, countries' SCDS return volatilities were measured with the EGARCH model. Model results are given in Table no. 9 in comparison. In the EGARCH model, the volatility processes of the return series differ between periods.

Leverage parameters are positive and significant for both the Pandemic and other periods. This result indicates that during the pandemic period and the other periods, positive shocks have a greater impact on SCDS return volatilities compared to negative shocks. In China and South Africa, the impact of ARCH on SCDS returns during the Pandemic was smaller than in the pre-pandemic period. In addition, the GARCH coefficient in the pandemic period is quite high compared to the other period. These results show that the effects of the shocks experienced during the pandemic period on the SCDS returns are small and permanent for a long time. In Russia and China, the impact of ARCH on SCDS returns during the Pandemic was bigger than in the pre-pandemic period. However, the GARCH coefficient was similarly high in both the pandemic and other periods. These results show that the effects of the shocks experienced during the Pandemic on the SCDS returns are big and permanent for a long time. According to the half-life, the impact of shocks on volatility persists for a longer duration during the pandemic period. In other words, it has been determined that the effect of shocks created by news in countries on SCDS return volatility continued for an extended period during the pandemic period.

Table no. 9 – EGARCH Models for Pre-Pandemic and Pandemic Period

	Brazil		**Russia**		**China**		**South Africa**	
	Pre-Pandemic EGARCH(1,1)	Pandemic EGARCH(3,1)	Pre-Pandemic EGARCH(3,3)	Pandemic EGARCH(3,1)	Pre-Pandemic EGARCH(3,2)	Pandemic EGARCH(2,1)	Pre-Pandemic EGARCH(1,2)	Pandemic EGARCH(3,2)
$\boldsymbol{\omega}$	-2.582088	-0.256976	-5.280150	-0.564948	-0.839084	-0.988193	-0.914638	-1.011655
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0259)	(0.0000)	(0.0001)	(0.0000)
$\boldsymbol{\alpha_1}$	0.292068	0.151124	0.268011	0.258834	0.034698	0.408706	0.258341	0.166836
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0217)	(0.0000)	(0.0038)	(0.0000)
$\boldsymbol{\alpha_2}$	-	-	0.124174		-0.031285	-	-0.244968	0.177192
			(0.0027)		(0.0380)		(0.0054)	(0.0000)
$\boldsymbol{\alpha_3}$	-	-	0.228039		-	-	-	-
			(0.0016)					
λ	0.103154	0.036674	0.099555	0.135917	0.048129	0.180484	0.158666	0.031251
	(0.0168)	(0.0069)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0004)
$\boldsymbol{\beta_1}$	0.681540	1.834041	0.750824	1.194681	1.970944	0.445454	0.876843	-0.948237
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\boldsymbol{\beta_2}$	-	-1.699044	-0.971325	-0.912803	-1.937506	0.448759	-	0.877396
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		(0.0000)
$\boldsymbol{\beta_3}$	-	0.844698	0.568898	0.655994	0.849531	-	-	0.970835
		(0.0000)	(0.0000)	(0.0000)	(0.0000)			(0.0000)
$\boldsymbol{\alpha_i}$	0.292068	0.151124	0.620224	0.258834	0.003413	0.408706	0.013373	0.344028
$\boldsymbol{\beta_j}$	0.681540	0.97970	0.348397	0.937872	0.882969	0,894213	0.876843	0.899994
Half-life	1,80	33.78	0.65	10.80	5.56	6.19	5.27	6.57
				Diagnostic Statistic				
AIC	-4.589881	-4.147772	-4.573737	-3.458736	-4.285161	-3.960813	-4.510287	-4.462879
SIC	-4.558136	-4.097955	-4.508676	-3.409940	-4.226514	-3.921412	-4.470941	-4.404498
LogL	1245.563	1063.682	1206.319	912.1887	1086.860	1086.302	1238.564	1138.340
Q^2(10)	5.0293	1.4332	3.7149	2.9142	5.3705	1.7627	2.4885	5.2586
	(0.899)	(0.999)	(0.959)	(0.983)	(0.865)	(0.998)	(0.991)	(0.873)
ARCH	0.499336	0.136498	0.369722	0.247372	0.617730	0.180152	0.256937	0.580627
LM(10)	(0.8907)	(0.9993)	(0.9594)	(0.9906)	(0.7992)	(0.9976)	(0.9896)	(0.8302)

Note: Q^2 and ARCH LM tests were examined until the 10th lag. The ( ) values indicate the probability values.

Source: Authors computed

Tables no. 7, no. 8 and no. 9 also include diagnostic test statistics for GARCH models. As a result of the predicted GARCH models, the ARCH-LM test was repeated to determine whether the ARCH effect in the residual series had been lost. The statistical values of the ARCH-LM test calculated up to the 10^{th} lag were statistically insignificant, and the conditional variance effect in the series disappeared. No autocorrelation issues were found in the model series when autocorrelation was examined using the Ljung-Box Q^2 test until the 10^{th} lag.

6. DISCUSSION

In this study, we investigated the role of SCDS return volatility as a risk indicator and whether it can be used as an early warning indicator of risk. COVID-19 is a natural event that disrupts the economic system's functioning and significantly negatively impacts assets, production factors, output, employment, or consumption, among other things (Grima *et al.*, 2021). During hazards such as a pandemic, emerging and developing economies suffer the most because their governments' access to international capital markets is limited, and their ability to respond to external shocks is limited (Daehler *et al.*, 2021).

During COVID-19, many countries' exposure to credit risk increased significantly, particularly in emerging markets, raising interest in reallocating credit risk and liquidity during times of stress (Grima *et al.*, 2021). SCDS has been identified as a solution for this, reviving interest in the market (Bomfim, 2022). On the other hand, because of the prospect of prolonged lockdowns and a slower GDP growth recovery, epidemiological deterioration can reduce confidence in sovereign credit markets (Daehler *et al.*, 2021).

As a result, we take a similar stance to Amstad *et al.* (2016) in this paper. They see the volatility of SCDS as an indication of the stability and ranking of the country's economy. They examined SCDS returns for 18 emerging markets and 10 advanced countries from January 2004 to December 2014, using monthly data from January 2004 to December 2014. The authors discovered that while global risk factors change whether SCDS spreads rise or fall over time, the extent to which these spreads rise or fall varies by country. Amstad *et al.* (2016) found that SCDS returns after the 2008 financial crisis moved over time largely to reflect the movements of a single global risk factor, with variation across sovereigns reflecting the designation of "emerging market" for the most part.SCDS are considered an important risk indicator in financial markets. Both investors and policymakers benefit heavily from SCDSs in their decision-making processes (Amstad *et al.*, 2016; Bomfim, 2022). An increasing SCDS premium indicates negative volatility and increased risks in financial markets (Fontana and Scheicher, 2016). As a result, estimating the volatility of a country's SCDS returns is critical.

In the study, the change in the SCDS return volatility of the BRICS countries was examined by adding the dummy variable created by first considering the COVID-19 case dates in the model and the volatility of the SCDS return values. The estimation was carried out before and during the COVID-19 Pandemic, and the persistence of the volatility between the periods was compared. The SCDS return volatility of countries was estimated using EGARCH models.

When the COVID-19 variable was added to the EGARCH model, it was seen that the COVID-19 pandemic only had a statistically significant and positive effect on Russia's and Brazil's SCDS return volatility. Considering the COVID-19 pandemic, it was observed that shocks arising from news increased the volatility of Brazil's SCDS returns. However, it was determined that the persistence period of volatility in returns was short, lasting only 2.5 days before disappearing. In Russia's case, the shocks' impact on SCDS return volatility was less pronounced, but the persistence period of volatility lasted for 7 days before dissipating.

The data period was divided into the pre-pandemic and pandemic periods, and SCDS return volatility processes were compared. In the GARCH models of the Brazilian SCDS returns, the coefficient of the ARCH effect decreased from 0.292 to 0.151, while the GARCH coefficient increased from 0.681 to 0.979. These results show that the effect of the news on Brazilian SCDS yield volatility decreased, but the duration of its effect on volatility increased during the pandemic period.

In the GARCH models of the Russia SCDS return, the coefficient of the ARCH effect decreased from 0.620 to 0.258, while the GARCH coefficient increased from 0.348 to 0.937. These results show that the effect of the news on Brazilian SCDS yield volatility decreased, but the duration of its effect on volatility increased during the pandemic period.

In the GARCH models of Chinese SCDS returns, while the coefficient of the ARCH effect increased from 0.003 to 0.408, there was a very slight increase in the GARCH coefficient from 0.882 to 0.894. In the GARCH models of South African SCDS returns, the coefficient of the ARCH effect increased from 0.013 to 0.344, while the GARCH coefficient showed a very slight increase from 0.876 to 0.899. These results indicate that news increased the volatility of Chinese and South African SCDS returns and extended the impact duration during the pandemic period.

Half-life measure is higher during the pandemic period. This indicates that the impact of news on SCDS return volatilities lasts longer. For Brazil, the persistence of a shock on CDS returns has increased from approximately 1.8 days to 33.7 days. For Russia, it has increased from 0.65 days to 10.8 days. In the case of China, it has changed from 5.56 days to 6.19 days, and for South Africa, it has increased from 5.27 days to 6.57 days.

This study's findings are consistent with Tevfik Kartal (2020), Apergis *et al.* (2022), and Hasan *et al.* (2023) studies. Tevfik Kartal (2020) examines how the sovereign CDS spreads of Turkey behaved during the COVID-19 pandemic times by considering that CDS spreads reflect countries' riskiness, vulnerability, financial stability, and macroeconomic stability. Most emerging countries' CDS spreads have increased with the emergence of the COVID-19 Pandemic.

Apergis *et al.* (2022), global and local COVID-19 indicators, examine how the Pandemic measured by these indicators affects U.S. corporate CDS spreads. The results provide strong evidence that the Pandemic has increased CDS prices. Hasan *et al.* (2023) investigated the response of global corporate CDS spreads to the COVID-19 pandemic for 655 companies operating in different industries in 27 countries. The study has demonstrated increased corporate CDS spreads due to the Pandemic.

7. CONCLUDING REMARKS

Although we did our best to capture as much data as possible, our study has some limitations Since some countries, especially BRIC countries, do not provide information on a timely basis, and often, the reliability of the information might be questionable. First, our findings do not fully cover the BRICS due to data issues in India. Second, the inclusion of other countries in the discussion and future research on the use of SCDS as a risk indicator would improve opportunities for international comparison and benchmarking. Third, COVID-19 capturing the COVID-19 recovery period and risk indicator behaviour would be interesting. Fourth, the authors define the COVID-19 Pandemic as the first date that COVID-

19 cases were publicly reported in a country. However, it is important to acknowledge the potential limitations and uncertainties associated with these sources of information, especially in countries where there may be data transparency or reliability issues. Traders are not going to wait until a country makes a formal announcement. Traders will form their own assessment of the scale of a pandemic in a country and the economic consequences for the country.

However, our research answers how international investors differentiate between different economies when entering or exiting emerging markets. Our research shows that SCDS-based indexes make it easier for investors and market observers to obtain exposure to or simply track a specific credit market sector. Furthermore, they aid in comprehending how global investor behaviour changes during crises such as the 2008 global financial crisis or the COVID-19 Pandemic. According to the literature review, prices in the credit default swap market tend to incorporate information faster than prices in the corporate bond market because it is sometimes easier to enter into swap positions than to buy or sell certain corporate bonds and loans. Although whether the information is reflected first in credit derivatives or cash markets remains an empirical question Bomfim (2022), investors and regulators have begun to pay closer attention to credit default swap signals.

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References

Amstad, M., Remolona, E., & Shek, J. (2016). How Do Global Investors Differentiate between Sovereign Risks? The New Normal Versus the Old. *Monetary and Economic Department, BIS Working Papers*. Retrieved from https://econpapers.repec.org/paper/bisbiswps/541.htm

Apergis, N., Danuletiu, D., & Xu, B. (2022). CDS Spreads and the COVID-19 Pandemic. *Journal of International Financial Markets, Institutions and Money*, *76*(January), 1-32. http://dx.doi.org/10.1016/j.intfin.2021.101433

Ballester, L., & González-Urteaga, A. (2020). Is There a Connection between Sovereign CDS Spreads and the Stock Market? Evidence for European and U.S. Returns and Volatilities. *Mathematics, 8*(10), 1-34. http://dx.doi.org/10.3390/math8101667

Bank for International Settlements. (2022). Credit Default Swaps. Retrieved 12 November 2022, from BIS https://stats.bis.org/statx/srs/table/d10.1?p=20072&c=

Barnes, C. (2022). CDS Volumes Now $6.6Trn Higher than Last Year. Retrieved from https://www.clarusft.com/cds-volumes-now-6-6trn-higher-than-last-year/

Bhatnagar, M., Özen, E., Taneja, S., Grima, S., & Rupeika-Apoga, R. (2022). The Dynamic Connectedness between Risk and Return in the Fintech Market of India: Evidence Using the GARCH-M Approach. *Risks, 10*(11), 1-16. http://dx.doi.org/10.3390/risks10110209

Bhatnagar, M., Taneja, S., & Rupeika-Apoga, R. (2023). Demystifying the Effect of the News (Shocks) on Crypto Market Volatility. *Journal of Risk and Financial Management, 16*(2), 1-16. http://dx.doi.org/10.3390/jrfm16020136

Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327. http://dx.doi.org/10.1016/0304-4076(86)90063-1

Bomfim, A. N. (2022). Credit Default Swaps. *Finance and Economics Discussion Series,* (2022-023). Retrieved from https://ideas.repec.org/p/fip/fedgfe/2022-23.html http://dx.doi.org/10.17016/FEDS.2022.023

Bouri, E., de Boyrie, M. E., & Pavlova, I. (2017). Volatility Transmission from Commodity Markets to Sovereign CDS Spreads in Emerging and Frontier Countries. *International Review of Financial Analysis, 49*(January), 155-165. http://dx.doi.org/10.1016/j.irfa.2016.11.001

Box, G. E. P., & Jenkins, G. M. (1976). *Time Series Analysis: Forecasting and Control* (2nd ed.). San Francisco: Holden-Day.

Brigo, D., Pede, N., & Petrelli, A. (2019). Multi-Curency Credit Default Swaps. *International Journal of Theoretical and Applied Finance, 22*(4), 1-35. http://dx.doi.org/10.1142/S0219024919500183

Brooks, C. (2008). *Introductory Econometrics for Finance* (2nd ed.): Cambridge University Press. http://dx.doi.org/10.1017/CBO9780511841644

Cevik, S., & Öztürkkal, B. (2020). Contagion of Fear: Is the Impact of COVID-19 on Sovereign Risk Really Indiscriminate? *IMF Working Paper, 20*(263), 1-21. http://dx.doi.org/10.5089/9781513561578.001

Daehler, T. B., Aizenman, J., & Jinjarak, Y. (2021). Emerging Markets Sovereign CDS Spreads During COVID-19: Economics Versus Epidemiology *27903*, 1-37. Retrieved from

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. *Journal of the American Statistical Association, 74*(366), 427-431. http://dx.doi.org/10.2307/2286348

Duttagupta, R., & Pazarbasiogly, C. (2021). Miles to Go: The Future of Emerging Markets. Retrieved from

Enders, W. (2004). *Applied Econometric Time Series* (2nd ed.). Hoboken: John Wiley & Sons, Inc.

Enders, W. (2015). *Applied Econometric Time Series* (4th ed.): Hoboken: John Wiley & Sons, Inc.

Engle, R. F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica, 50*(4), 987-1007. http://dx.doi.org/10.2307/1912773

Engle, R. F. (2002). Dynamic Conditional Correlation: A Simple Class of Multivariate Generalized Autoregressive Conditional Heteroskedasticity Models. *Journal of Business & Economic Statistics, 20*(3), 339-350. http://dx.doi.org/10.1198/073500102288618487

Fender, I., Hayo, B., & Neuenkirch, M. (2012). Daily Pricing of Emerging Market Sovereign CDS Before and During the Global Financial Crisis. *Journal of Banking & Finance, 36*(10), 2786-2794. http://dx.doi.org/10.1016/j.jbankfin.2012.06.017

Fontana, A., & Scheicher, M. (2016). An Analysis of Euro Area Sovereign CDS and Their Relation with Government Bonds. *Journal of Banking & Finance, 62*(January), 126-140. http://dx.doi.org/10.1016/j.jbankfin.2015.10.010

Grima, S., Kizilkaya, M., Rupeika-Apoga, R., Romānova, I., Dalli Gonzi, R., & Jakovljevic, M. (2020). A Country Pandemic Risk Exposure Measurement Model. *Risk Management and Healthcare Policy, 13*(October), 2067-2077. http://dx.doi.org/10.2147/RMHP.S270553

Grima, S., Rupeika-Apoga, R., Kizilkaya, M., Romānova, I., Dalli Gonzi, R., & Jakovljevic, M. (2021). A Proactive Approach to Identify the Exposure Risk to COVID-19: Validation of the Pandemic Risk Exposure Measurement (PREM) Model Using Real-World Data. *Risk Management and Healthcare Policy, 14*(November), 4775-4787. http://dx.doi.org/10.2147/RMHP.S341500

Gujarati, D. N. (2003). *Basic Econometrics* (4th ed.). New York: McGraw-HiII/lrwin.

Gürsoy, S. (2020). Investigating The Relationship Between VIX Index and BRICS Countries Stock Markets: An Econometric Application. *Mehmet Akif Ersoy Üniversitesi Uygulamalı Bilimler Dergisi, 4*(2), 397-413. http://dx.doi.org/10.31200/makuubd.735380

Hasan, I., Marra, M., To, T. Y., Wu, E., & Zhang, G. (2023). COVID-19 Pandemic and Global Corporate CDS Spreads. *Journal of Banking & Finance, 147*(February), 1-14. http://dx.doi.org/10.1016/j.jbankfin.2022.106618

International Monetary Fund. (2013). *Global Financial Stability Report (GFSR)*. Retrieved from Washington:

International Monetary Fund. (2022). *World Economic Outlook: War Sets Back The Global Recovery*. Retrieved from Washington, DC:

Kandemir, T., Vurur, N. S., & Gökgöz, H. (2022). Investigation of the Interaction between Turkey's CDS Premiums, BIST 100, Exchange Rates and Bond Rates Via cDCC-EGARCH and Causality Analysis in Variance. *KMU Journal of Social and Economic Research, 24*(42), 510-526.

Kocsis, Z., & Monostori, Z. (2016). The Role of Country-Specific Fundamentals in Sovereign CDS Spreads Eastern European Experiences. *Emerging Markets Review, 27*(June), 140-168. http://dx.doi.org/10.1016/j.ememar.2016.05.003

Nazlioglu, S., Erdem, C., & Soytas, U. (2013). Volatility Spillover between Oil and Agricultural Commodity Markets. *Energy Economics, 36*(March), 658-665. http://dx.doi.org/10.1016/j.eneco.2012.11.009

Nelson, D. B. (1991). Conditional Heteroskedasticity in Asset Returns: A New Approach. *Econometrica, 59*(2), 347-370. http://dx.doi.org/10.2307/2938260

Özdemir, L., Ozen, E., Grima, S., & Romānova, I. (2021). Determining the Return Volatility of Major Stock Markets Before and During the COVID-19 Pandemic by Applying the EGARCH Model. *Scientific Annals of Economics and Business, 68*(4), 405-419. http://dx.doi.org/10.47743/saeb-2021-0022

Pu, X., & Zhang, J. (2012). Sovereign CDS Spreads, Volatility, and Liquidity: Evidence from 2010 German Short Sale Ban. *Financial Review, 47*(1), 171-197. http://dx.doi.org/10.1111/j.1540-6288.2011.00325.x

Raimbourg, P., & Salvadè, F. (2021). Rating Announcements, CDS Spread and Volatility During the European Sovereign Crisis. *Finance Research Letters, 40*(May), 101663. http://dx.doi.org/10.1016/j.frl.2020.101663

Ranciere, R. G. (2002). *Credit Derivatives in Emerging Markets*. Retrieved from https://repositori.upf.edu/bitstream/handle/10230/1080/856.pdf?sequence=1

S&P Down Jones Indices. (2023). Credit Default Swap (CDS) Indices. Retrieved from https://www.spglobal.com/spdji/en/indices/products/cds-indices.html

Srivastava, V., & Dashottar, S. (2020). Default Probability Assessment for Project Finance Bank Loans and Basel Regulations: Searching for a New Paradigm. *The Journal of Structured Finance, 25*(4), 41-53. http://dx.doi.org/10.3905/jsf.2019.1.088

Tevfik Kartal, M. (2020). The Behaviour of Sovereign Credit Default Swaps (CDS) Spread: Evidence from Turkey with the Effect of Covid-19 Pandemic. *Quantitative Finance and Economics, 4*(3), 489-502. http://dx.doi.org/10.3934/QFE.2020022

The World Bank Data. (2022). Statistics. from The World Bank Data https://data.worldbank.org/

UNCTAD. (2023). *Key Statistics and Trends in International Trade 2022*. Paper presented at the United Nations Conference on Trade and Development. https://unctad.org/system/files/official-document/ditctab2023d1_en.pdf

Vurur, N. S., & Özen, E. (2020). Effects of the COVID-19 Epidemic on the Relationship between CDS Premiums and Stock Market Indices: An Application for Major European Indices. *Journal of Research in Economics, Politics & Finance, 5*(Special Issue), 97-114.

Wigan, D. (2009). Financialization and Derivatives: Constructing an Artifice of Indifference. *Competition & Change, 13*(2), 157-172. http://dx.doi.org/10.1179/102452909X417033

Wu, W., Xu, D., Zhao, Y., & Liu, X. (2020). Do Consumer Internet Behaviours Provide Incremental Information to Predict Credit Default Risk? *Economic and Political Studies, 8*(4), 482-499. http://dx.doi.org/10.1080/20954816.2020.1759765

Zaidi, S. H., & Rupeika-Apoga, R. (2021). Liquidity Synchronization, Its Determinants and Outcomes under Economic Growth Volatility: Evidence from Emerging Asian Economies. *Risks, 9*(2), 1-20. http://dx.doi.org/10.3390/risks9020043