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THE IMPACT OF COVID-19 ON THE VOLATILITY OF BRICS STOCK RETURNS

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ABSTRACT

This study analyzes for the first time the impact of the novel coronavirus known as COVID-19 on stock market volatility for the BRICS countries (Brazil, Russia, India, China, and South Africa) using the GJR-GARCH model. We find that during the coronavirus period, Brazil, India, and South Africa exhibit very high volatility, with negative returns exceeding those faced by these indices during the 2008 financial crisis. On the other hand, the Russian and Chinese indices are shown to have faced greater volatility during the 2008 crisis than they have so far exhibited due to coronavirus. Furthermore, the results of the GJR-GARCH models show that COVID-19 variable has a significant positive impact on stock market volatility for Brazil, India, China, and South Africa but an insignificant impact for Russia. Moreover, of these nations, Brazil has thus far been most heavily affected by the virus, followed by South Africa, China, and India.

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Contribution/ Originality: This study attempts to contribute a range of useful insight by analyzing for the first time the influence of the novel coronavirus on stock market volatility in BRICS countries to better understand the dynamics of BRICS stock markets in order to more efficiently support realistic asset pricing and volatility predictions.

1. INTRODUCTION

As of the 28th of Jan 2022, the coronavirus pandemic has caused more than 5.6m deaths, with known infections exceeding 369 million. Although the outbreak appears to be stabilizing in China, many other countries are still struggling to slow the spread of the disease and prevent healthcare systems from becoming overwhelmed. However, the human toll of the virus is only a single facet of the problem; a second major issue is the level of economic disruption being caused by the lockdown measures which have been required to contain the virus. Almost every major international institution and bank has cut its growth forecasts in response to the pandemic. With respect to the manufacturing sector, the virus has led to disruption of the supply chain, the closure of factories and offices, and significant travel restrictions. The services industry has experienced a substantial decline in consumer spending thanks to the mass closure of retail stores, restaurants, and travel services. Consumers, suppliers, and financial intermediaries—virtually every player on the global economic stage—have been negatively impacted by the virus, making a sustained and coordinated governmental response essential (Selmi & Bouoiyour, 2020; Yousef, 2020; Yousef. & Shehadeh, 2020). The actual response from around the world, however, has been uncoordinated and chaotic, leading to a sense of confusion which has increased the anxiety of the general population and caused a widespread loss of confidence in the ability of the authorities to manage the crisis effectively. Turbulence in financial markets, which are known for their extreme reactions to crisis, tend to further exacerbate the general feeling of panic. The world economy thus appears to be in a delicate position at present, and many experts fear that unless the disease is brought swiftly under control, the combination of the pandemic and the aging business cycle already underway will lead to a global recession.

In this context, the economies of the BRICS nations (Brazil, Russia, India, China, and South Africa), which have experienced rapid growth in recent decades and are becoming increasingly integrated with the world's most developed countries in terms of trade and investment, may find themselves in a unique position of vulnerability (Rasoulinezhad & Jabalameli, 2018). The decision to apply this research to the BRICS countries is based on their various roles and growing prominence within the global market. The five BRICS nations comprise some of the world's leading emerging economies. Together they include approximately 45% of the world's population, provide approximately 20% of total global output, and contain an estimated US$4.7 trillion in joint foreign reserves. All of this, along with their continuing rapid economic growth, gives them significant influence within the global economy. According to the World Bank Database, the combined GDP of these nations reached $19.7 trillion in 2019, which is significantly higher than the Eurozone's $13.34 trillion and not far behind the USA's $21.431 trillion. Furthermore, the rapid growth in international trade between these countries and the rest of the world is linked to high levels of foreign direct investment in the private sector (Mensi, Hammoudeh, Reboredo, & Nguyen, 2014; Ruzima & Boachie, 2018; Salisu & Gupta, 2021). However, the natural level of volatility in these important emerging markets will likely correspond to uncertainty in global equity markets through international trade channels (Balli, Uddin, Mudassar, & Yoon, 2017), and it is necessary to acknowledge that returns volatility is an important aspect of asset valuation, hedging, and portfolio optimization models. In other words, inaccurate volatility predictions may lead to mispricing of stocks, over- or under-hedged business risk, and poor budgeting decisions, all of which can have significant implications for profits and cash flow. For this reason, it is essential for investors, corporate decision makers, and policymakers to keep close tabs on and continuously model stock market volatility.

All of these characteristics make BRICS an ideal context for research of the kind conducted here. Despite increased scrutiny of these nations as interest in their economic future has grown, the relevant body of empirical research would benefit from additional data. This study thus attempts to fill certain gaps and hopes to contribute a range of useful insight. Specifically, we attempt to answer the following research question: What is the impact of the coronavirus on stock market volatility in the BRICS countries? This research aims to better understand the dynamics of BRICS stock markets and the impact of COVID-19 in order to more efficiently support realistic asset pricing and volatility predictions. The study uses data from the primary local market index in each BRICS country, i.e. the Sao Paulo SE Bovespa Index in Brazil, the MOEX Russia Index in Russia, the S&P BSE Sensex Index in India, the Shanghai SE Composite Index in China, and the FTSE/JSE SA Top 40 Companies Index in South Africa. The period of study is 2012-2020, with 2012 chosen as a starting point in order to avoid implications from previous financial crises (e.g. the Asian financial crisis, the 2008 financial crisis, and the European debt crisis of 2010-2011).

The results reveal that during the coronavirus period, Brazil, India, and South Africa exhibit very high levels of volatility, with negative returns during this period which exceed those faced by these indices during the 2008 crisis. In addition, the minimum returns values for these three countries occurred during the coronavirus period (March 2020). On the other hand, the Russian and Chinese indices are shown to have faced greater volatility during the 2008 crisis than they so far have due to coronavirus, with the minimum returns values for the MOEX Russia and the Shanghai SE Composite Index occurring outside the coronavirus period. In addition, the results of the GJR-GARCH models show that COVID-19 variable has a significant positive impact on stock market volatility for four BRICS countries (i.e. Brazil, India, China, and South Africa), but an insignificant impact for Russia. Moreover, the coefficients of this variable show that of these nations, Brazil has thus far been most severely affected by the virus, followed by

South Africa, China, and India. These findings indicate that the Russian economy has so far been impacted by coronavirus to a lesser degree than the other BRICS nations.

Our results thus demonstrate that with the exception of Russia, the BRICS stock markets have reacted to the pandemic with marked volatility. This is due to investors engaging in panic-selling amid fear that markets will remain turbulent thanks to the massive reduction in global economic activity that has corresponded to coronavirus lockdowns. The long-term influence of the virus on stock market volatility depends largely on the ultimate scope and duration of the outbreak and the corresponding responses by governments and central banks. If a vaccine or other effective treatment is not discovered swiftly, continued panic is likely to have a long-lasting impact on the global financial environment.

The focus of this study is on the five nations known as the BRICS countries, which are thought to represent the world's most significant emerging economies in terms of stock market development and economic growth. Since the study's implications extend to the domains of both market regulation and investment risk in the face of this type of pandemic, the findings of this research will be of interest to policymakers, finance professionals, and investors. Specifically, this study provides a resource for supporting the development of market policy related to potential future pandemics as well as giving investors and fund managers insight into how best to respond. Many believe that the coronavirus period under investigation in this research is likely to become the worst economic crisis since the Great Depression. In addition, given the sensitivity of stock volatility to various types of shock in these countries, another policy implication which derives from the findings of this study is the necessity to develop strategies for portfolio creation and diversification within the BRICS context. Furthermore, this study's findings may help guide investors and other market participants with respect to purchasing stock in emerging economies by helping them to anticipate the various types of shock leading to volatility.

The rest of this article is organized as follows: Section 2 presents some general data on coronavirus cases and growth in the BRICS countries; Section 3 provides a literature review; Section 4 presents the study's data collection procedures and methodology; Section 5 discusses the results of the data analysis; and Section 6 contains conclusions.

2. CORONAVIRUS AND STOCK INDICES IN BRICS COUNTRIES

Figure 1 presents the daily cumulative number of coronavirus cases for each BRICS country. Although the virus originated in China, its prevalence in many other countries has now far surpassed its transmission in the country of origin. By the first day of May 2020, the highest number of cases in a BRICS country corresponded to Russia, which had reported more than 100,000 infections. This was followed by Brazil with approximately 85,000 cases, China with 84,000 cases, India with 35,000 cases, and South Africa with 5,600 cases.

Figure 1 also presents the daily growth rate in the cumulative number of cases for each BRICS country. All five countries exhibit high levels of volatility in the growth rate of confirmed cases, but the precise periods of growth vary for each nation. For example, the average daily growth rate in China for January was 19%, but that had decreased to 0.07% by April. On the other hand, the average daily growth rates in Brazil and South Africa were highest in the month of March, at 27.19% and 29.96% respectively, but decreased to 9.5% and 4.65% in April. The trends in India and Russia were similar, with average March growth rates of 14.62% and 22.61% respectively, decreasing to 10.9% and 13.3% for April.

It can thus be seen that China is the only BRICS nation to have so far achieved a true stabilization with respect to new cases, with an average of 57 daily new cases in April compared to 2,400 per day in February. This may be due to China's use of rigorous methods to halt the spread of the virus, including a focus on early detection, strict quarantine, and prompt treatment. Although the Chinese city of Wuhan has been identified as the origin of the outbreak and China has been accused of early attempts to cover it up, the country has since sought to highlight its role in controlling the global spread of the virus. With its own epidemic abating, China has now begun to focus on controlling the potential re-introduction of the disease by people entering China from overseas, where the outbreak has yet to be brought under control.

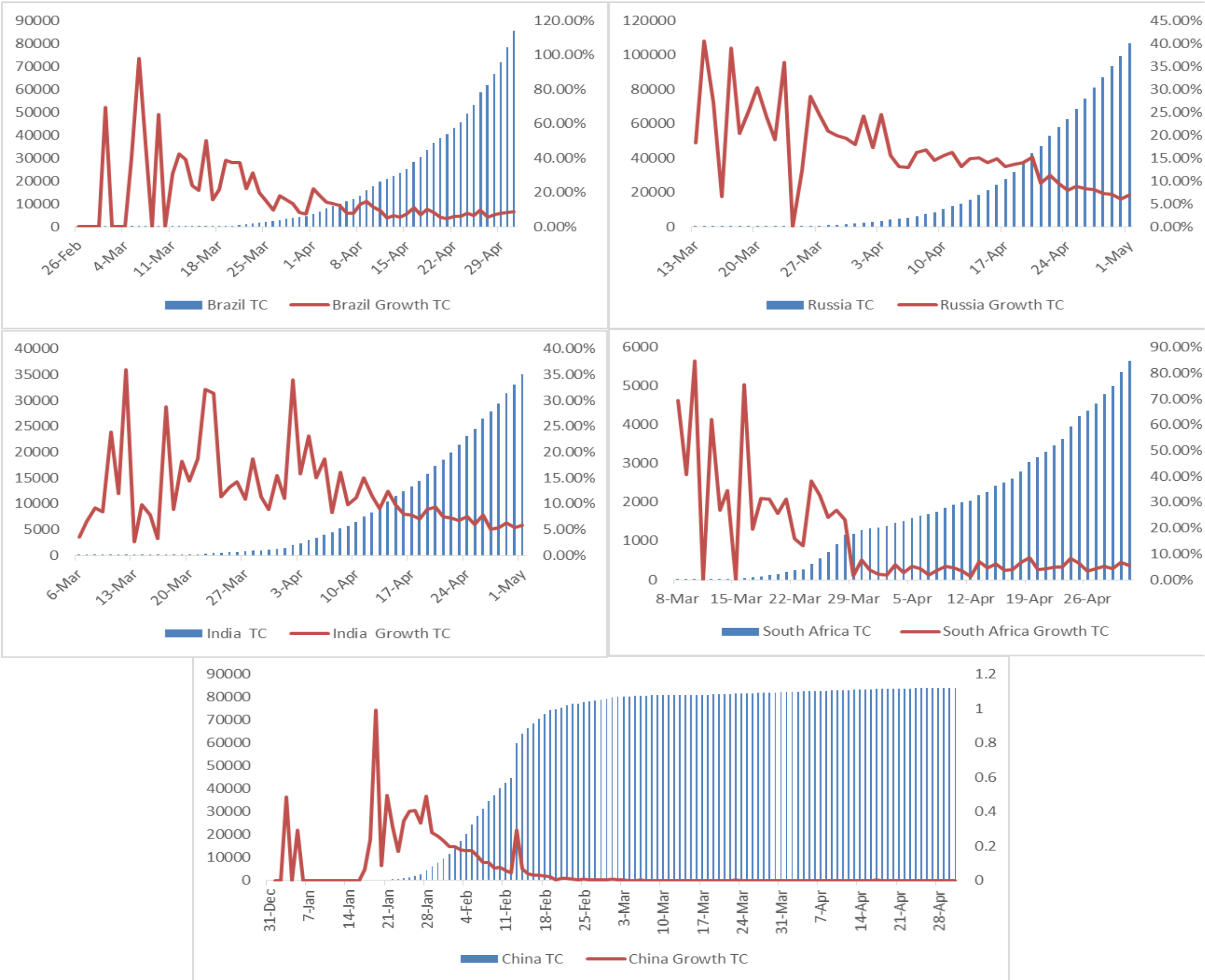

Figure 1. Daily cumulative COVID-19 cases and daily growth rate for each BRICS country.

Figure 2 presents the daily index returns, and Figure 3 presents the standard deviations of the daily index returns for each BRICS country index (i.e. Sao Paulo SE Bovespa Index, MOEX Russia Index, S&P BSE Sensex Index, Shanghai SE Composite Index, and FTSE/JSE SA Top 40 Companies Index). It can be seen that Brazil, India, and South Africa have experienced very high volatility during the coronavirus period (Jan-2020 to May-2020), with negative returns (in the downside of the returns charts) exceeding those faced by these indices during the 2008 crisis. Moreover, these countries reported very high standard deviation values during the coronavirus period. For example, for the period Jan-2006 to May-2020, the highest standard deviation for Brazil's index returns occurred on 9/10-Mar-2020, and on 12-Mar-2020, the index lost 16% of its value in one day. Furthermore, on the same day, the South African and Indian indices decreased by 10% and 9% respectively.

On the other hand, the 2008 financial crisis affected the Russian and Chinese indices more than the coronavirus period. Figure 3 reveals that these two countries experienced high volatility during the 2008 crisis, with the largest declines in daily market returns for both countries occurring on 19-Sep-2008 (-25% and -9% for Russia and China respectively). It thus seems that the severity of the impact of COVID-19 on the BRICS nations has not been universal. In this paper, GJR-GARCH model is used to analyze the impact of COVID-19 on stock market volatility for each BRICS country.

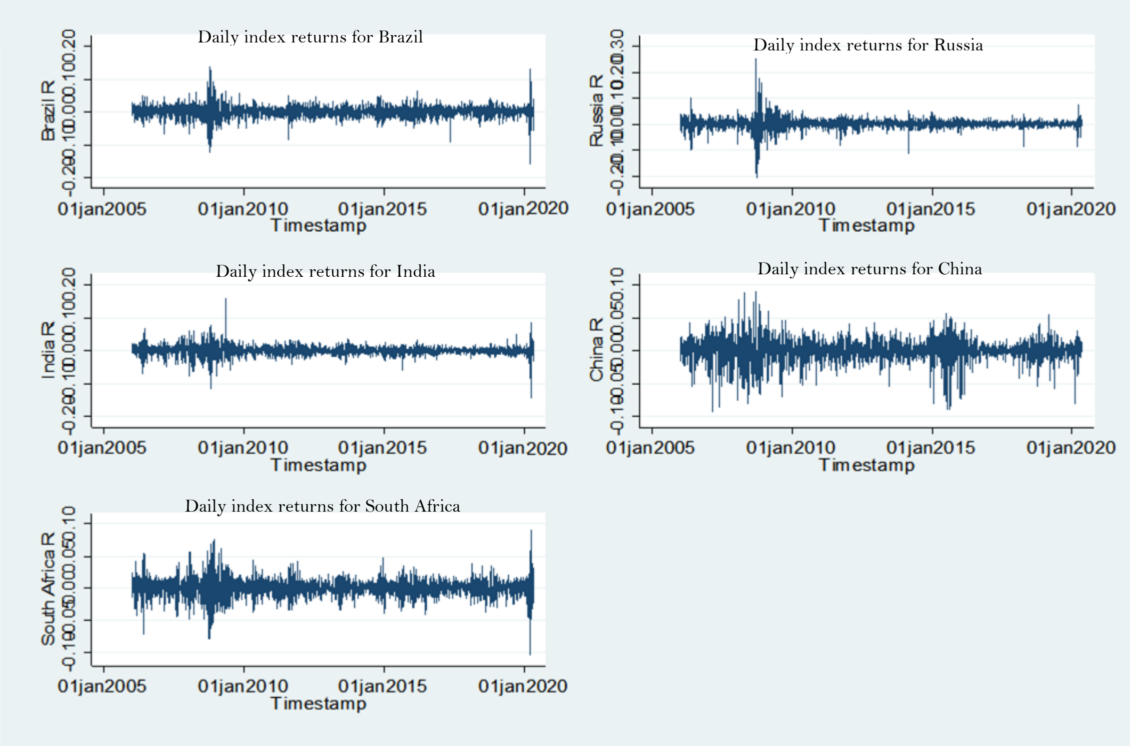

Figure 2. Daily index returns for each BRICS country index.

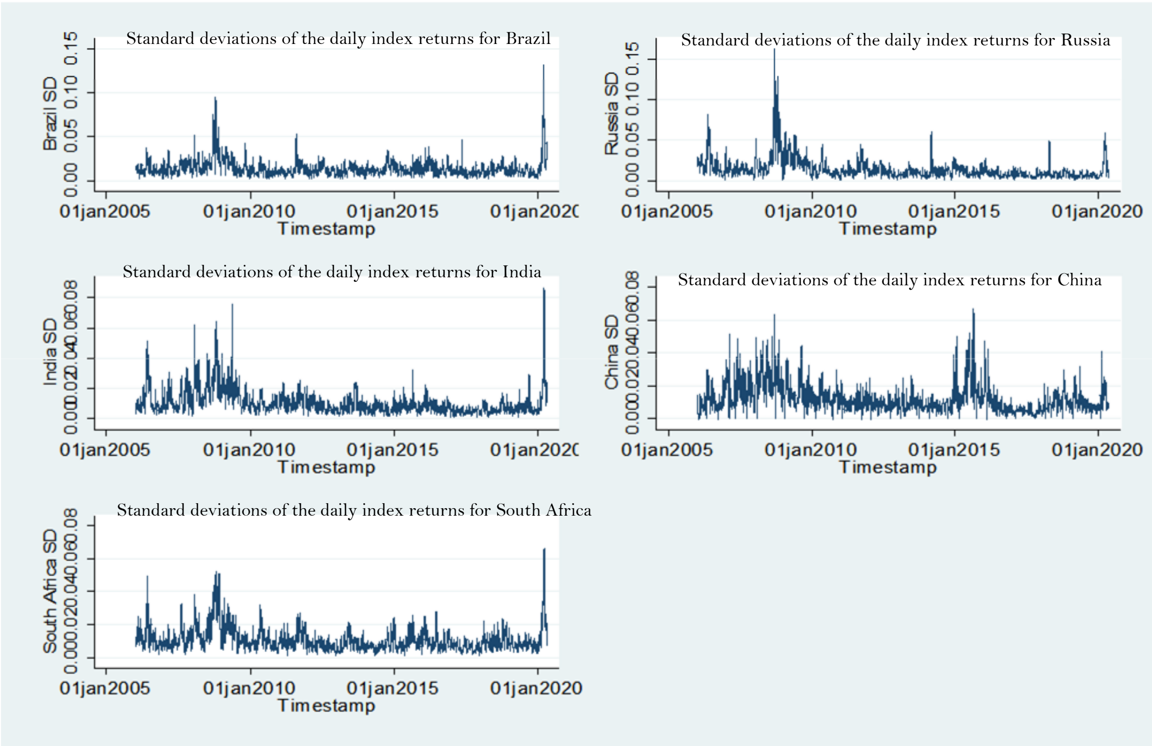

Figure 3. Standard deviations of the daily index returns for each BRICS country.

3. REVIEW OF LITERATURE

In economic terms, the concept of volatility relates to uncertainty and unpredictability and has significant implications for risk assessment. It is generally considered an indication of disruption to the market involving the unfair pricing of securities and other impacts. Increased volatility in stock market returns tends to frighten risk-averse investors and can have a significant negative knock-on effect on the economy as a whole; for this reason, stock market volatility is a popular area of research amongst economists.

Furthermore, over the last few decades, interest in market volatility has increased significantly (Nguyen & Nguyen, 2019; Siddiqui & Erum, 2016). It can be broadly defined as the analysis of variation in stock prices over time, and is often treated as a standard measurement of risk. The ARCH model was formulated in 1982 by Engle to assess conditional variance. However, the estimation work involved in this model often proved to be lengthy and difficult to interpret. In 1986, Bollerslev developed the GARCH model as an alternative to overcome the problems associated with the ARCH model, and in 2001, Engle undertook further enhancements and presented the GARCH(1,1) as the simplest and most robust model for assessing volatility. The GARCH family of models has been used extensively to study market volatility.

For example, Brooks (1998); Pagan and Schwert (1990) demonstrated that the GARCH models are appropriate for use with U.S. indices. Floros (2008) used GARCH and its variants to explain volatility and risk in Israeli and Egyptian markets using daily observations from the TAS-100 index (Israel) and the CMA General Index (Egypt). The researcher found that the CMA index experienced significant volatility. In India, Goudarzi and Ramanarayanan (2010) investigated the volatility of the BSE 500 index over a period of ten years using ARCH and GARCH models. The Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) were then used to determine the most appropriate model for explaining volatility clustering and mean reverting in the series, and this turned out to be the GARCH(1,1).

In addition, several GARCH extensions have been proposed, such as the EGARCH (Exponential GARCH) developed by Nelson (1991) and the Threshold GARCH (TGARCH) and GJR-GARCH developed by Glosten, Jagannathan, and Runkle (1993) and Zakoian (1994). These models have also been used substantially in economics research. Chiang and Doong (2001) used the TGARCH to measure the relationship between volatility and returns in seven Asian stock markets. Ng and McAleer (2004) applied the GARCH(1,1) and other models to the Nikkei 225 and S&P 500 Composite Index to estimate and forecast the volatility of daily returns. They found that the estimation ability of these models depended on the data used, although with respect to the Nikkei 225 index, the GARCH(1,1) appeared to perform best.

Liu and Hung (2010) analyzed the daily volatility of the S&P100 index series between 1997 and 2003 to find that the GJR-GARCH model achieved the most accurate estimates. Sakthivel, VeeraKumar, Raghuram, Govindarajan, and Anand (2014) used the GJR-GARCH model to study the impact of the global financial crisis on stock market volatility from 01-Mar-2005 to 30-Dec-2012. The period of study was divided into a pre-crisis period (01-Mar-2005 to 30-Jan-2008) and a post-crisis period (01-Feb-2008 to 30-Dec-2012), and a dummy variable was used to demonstrate the influence of the crisis on the volatility of returns. The study found that the volatility of mean returns increased during the post-crisis period compared to the pre-crisis period. Finally, a study by Angabini and Wasiuzzaman (2011) focused on volatility in the Malaysian stock market during the 2008 crisis and found that the most appropriate model for measuring conditional variance was the GJR-GARCH(1,1).

4. METHODOLOGY AND DATA COLLECTION

The data for this study were gathered from Thomson Reuters and included daily market close index values for the period 01-Jan-2012 to 01-May-2020. As noted above, we use the primary local market index in each of the BRICS countries: the Sao Paulo SE Bovespa Index in Brazil, the MOEX Russia Index in Russia, the S&P BSE Sensex Index in India, the Shanghai SE Composite Index in China, and the FTSE/JSE SA Top 40 Companies Index in South Africa. The year 2012 was chosen as a starting point in order to avoid implications from previous financial crises, such as the Asian crisis, the Russian and Brazilian crises, the 2008 crisis, and the European debt crisis of 2010-2011. Following Tanna and Yousef (2019), we use logarithmic returns (log-returns) to represent daily stock returns.

In order to develop the volatility series, a generalized ARCH (GARCH) (Bollerslev, 1986) technique is used. In recent literature on financial volatility, the GARCH method is the most commonly employed class of time series model (e.g. (Go & Lau, 2016; Nguyen & Nguyen, 2019; Siddiqui & Erum, 2016)). The appeal of this technique is that it captures both volatility clustering and unconditional return distributions with heavy tails, and the model involves a joint estimation of a mean and a conditional variance equation. Specifically, the GARCH (1,1) model is used in this study. It can be written as follows:

Conditional Mean Equation

$$y_t = \mu + \varepsilon_t \tag{1}$$

Conditional Variance Equation

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} \tag{2}$$

Equation 1 presents the conditional mean equation and equation 2 presents the conditional variance equation, where ω and μ are the constants, y_t and h_t are the conditional mean and conditional variance, and ε_t is the error term. α_1 and β_1 are the coefficients of the ARCH and GARCH terms respectively, where α_1 represents the response to shock and β_1 represents the time it takes for any change to die away. The short-run dynamics of the volatility time series are determined by the size of the parameters α_1 and β_1. If the sum of the coefficient is equal to one, then any shock will create a permanent change in all future values, and the shock to the conditional variance is thus considered 'persistent'.

The appeal of the GARCH models relates to their relative simplicity and ability to capture the persistence of volatility. However, the primary weakness of the method is that the conditional variance is unable to respond to an asymmetrical rise and fall in stock returns. A number of additional models have thus been introduced to deal with this issue, which are collectively known as the asymmetrical GARCH models. The GJR-GARCH provides the means to account for leverage effects of price change on conditional variance and is thus a strong option for capturing asymmetric phenomena. Specifically, the GJR-GARCH (1,1) model is used in this study to analyze the correlation between asymmetric volatility and returns. It can be specified as follows:

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma_i I_{t-1} \varepsilon_{t-1}^2 \tag{3}$$

$$I_{t-1} \begin{cases} 1 \; if \; \varepsilon_{t-1} \leq 0 \\ 0 \; otherwise \end{cases} \tag{4}$$

Equation 3 and 4 present the conditional variance and asymmetry parameter equations respectively. Gamma (γ_i) is known as the asymmetry or leverage parameter. In this model, good news ($\varepsilon_{t-1} > 0$) and bad news ($\varepsilon_{t-1} \leq 0$) have a differential impact on the conditional variance. The impact of good news is written as α_1, while the impact of bad news is specified as α_1+γ_i. Therefore, if γ_i is positive and significant, negative shocks have a greater effect on conditional variance (h_t) than positive shocks. Thus, if the model succeeds in modelling an asymmetric impact of past phenomena on current conditional variance, then the estimated coefficient of leverage effects (gamma) will be positive and significant.

In order to analyze the impact of the coronavirus on the volatility of market indices, a dummy variable has been included in the variance equation. The modified model representing the GJR-GARCH approach, therefore, can be written as follows:

Conditional Mean Equation

$$y_t = \mu + \varepsilon_t \tag{5}$$

Conditional Variance Equation

$$h_t = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 h_{t-1} + \gamma_i I_{t-1} \varepsilon_{t-1}^2 + \delta_1 COVID_{\,i} + \varphi_1 OIL_{\,i} \tag{6}$$

Equation 5 and 6 present the conditional mean equation and conditional variance equation respectively. The value of the dummy variable $COVID$ is thus 0 for the pre-coronavirus period (i.e. before Dec-2019) and 1 for the current coronavirus period (i.e. Jan-2020 to April-2020). This means that a significant negative coefficient for $COVID$ would indicate a correlation between coronavirus and a decrease in the volatility of BRICS markets, while a significant positive $COVID$ coefficient would imply a correlation between coronavirus and an increase in the volatility of these markets. In addition, we have also tested the impact of oil prices on stock market volatility (OIL). In this regard, we use daily data for the same time period and use Brent crude oil as a proxy for global oil price given that this type comprises 60% of global daily oil consumption (Maghyereh, 2006).

5. RESULTS AND DISCUSSION

Table 1 presents the results of the descriptive statistical analysis for each BRICS Index over the period 2012-2020, based on the previously discussed indices for each country.

Table 1. Descriptive statistical analysis for each BRICS index.

Country	Brazil	Russia	India	China	South Africa
Mean	0.014%	0.028%	0.034%	0.013%	0.021%
Minimum	-15.994%	-11.419%	-14.102%	-8.873%	-10.450%
Maximum	13.023%	7.435%	8.595%	5.604%	9.057%
Std. Dev.	1.587%	1.157%	1.034%	1.332%	1.098%
C.V.	114.110	41.904	30.095	105.600	52.716
Skewness	-0.980	-0.855	-1.399	-1.094	-0.551
kurtosis	14.968	10.668	25.076	7.8278	11.179
Jarque-Bera	20802***	10655***	58118***	6031***	11519***

Note: Asterisks indicate significance at 1% (***).

The results show that the average daily returns for all BRICS countries are positive, demonstrating that, overall, index prices have increased during the period 2012-2020. However, clear differences are present between the BRICS countries in the minimum and maximum values. The minimum returns values for Brazil, India, and South Africa occurred during the coronavirus period, with the Bovespa Index decreasing by 15.994% on 12-Mar-2020, the S&P BSE Sensex Index decreasing by 14.1% on 23-Mar-2020, and the FTSE/JSE SA Top 40 Companies Index decreasing by 10.45% on 12-Mar-2020. On the other hand, the Russian and Chinese indices were more heavily impacted by the 2008 financial crisis than by the coronavirus period; the minimum returns values for the value of both the MOEX Russia and the Shanghai SE Composite Index occurred outside the coronavirus period.

Moreover, the descriptive statistics reveal that the returns for all five BRICS indices are negatively skewed, with the returns exhibiting a long left tail, i.e. a long tail in the negative direction. Specifically, the kurtosis for all five indices is > 3, which indicates a non-normal, fat-tailed distribution, and the Jarque-Bera statistic confirms this departure from a normal distribution, rejecting the assumption of normality at a 1% level of significance. Hence, the null hypothesis of normal distribution is rejected.

Prior to econometric modelling, however, it is necessary to make the data series stationary, meaning that the mean and autocovariances of the series do not depend on time. We use the augmented Dickey-Fuller (ADF) test to assess the stationarity of the return series for the five BRICS markets. The null hypothesis predicts that the returns are nonstationary, i.e. they have a unit root. The results reported in Table 2 reveal that all five index returns were stationary in levels and at first differences, and the null hypothesis is thus rejected.

Table 2. Dickey-Fuller and ARCH effect tests.

Country	Dickey-Fuller tests Statistic				ARCH effect
	Level		First Difference		LM
	Coefficient	t-ratio	Coefficient	t-ratio	
Brazil	-0.963	-11.910***	-13.408	-15.470***	751.526***
Russia	-0.940	-16.729***	-12.987	-16.579***	157.050***
India	-0.970	-10.233***	-12.321	-15.510***	504.667***
China	-0.867	-9.274***	-12.747	-15.788***	268.837***
South Africa	-1.117	-11.989***	-12.729	-16.044***	683.155***

Note: Asterisks indicate significance at 1% (***).

The main focus of this study, however, is the volatility of the BRICS indices, and the Lagrange Multiplier test (ARCH-LM) proposed by Engle (1982) is thus used to test the residuals of the respective mean equations fitted for each index for ARCH effects. The assumption of heteroscedasticity is based on the observation that the magnitude of residuals appears to be related to the magnitude of recent residuals in many financial time series. The results presented in Table 2 reveal that the ARCH-LM test statistics are highly significant, meaning that an ARCH effect is indeed present in the data, and this allows the conclusion that the current volatility of BRICS indices is significantly impacted by past levels of volatility.

Next, the GJR-GARCH (1,1) technique is used to model the volatility of the return series in the BRICS indices. In order to test the impact of coronavirus on index volatility for each BRICS country, we add a dummy variable into the conditional variance equation which is equal to 1 for the COVID-19 period and 0 otherwise. The results are reported in Table 3.

The coefficient gamma is shown to be positive and significant for Russia and Brazil but insignificant for India, China, and South Africa, indicating the presence of leverage effects in Russia and Brazil only. In stock indices or individual securities, negative shocks usually lead to greater volatility (i.e. decrease in value) than positive events. This is because investors typically have stronger emotional reactions to bad news than to good news.

It can also be seen in Table 3 that the COVID-19 dummy variable has a significant positive impact on every BRICS index except Russia. Specifically, the GARCH model reveals that the COVID-19 coefficient is largest for Brazil (0.155), followed by South Africa (0.056), China (0.08), India (0.037), and finally Russia (0.014), whose value is statistically insignificant. Except for Russia, therefore, all BRICS countries demonstrate an increase in stock market volatility which correlates to COVID-19. The results in Table 3 reveal that oil prices have a significant positive impact on stock market volatility for Russia, India, and China but an insignificant impact for South Africa and Brazil. The insignificant influence of oil prices on South African and Brazilian stocks may indicate the resilience of these countries' stocks to oil price shocks. Interestingly, the oil price coefficient is largest for Russia (0.084), indicating that the changes in oil price will influence Russian stock market volatility more than COVID-19.

Table 3. GJR-GARCH (1,1) model for BRICS countries.

	Brazil		Russia		India		China		South Africa	
	coeff.	z	coeff.	z	coeff.	z	coeff.	z	coeff.	z
Conditional mean equation										
const	0.023	0.824	0.041	1.838*	0.039	2.311**	0.020	1.004	0.011	0.565
Conditional variance equation										
const	0.273	4.226***	-0.110	-5.323***	-0.025	-1.457	-0.050	-3.927***	0.032	1.272
CORONA	0.151	3.528***	0.024	1.585	0.039	2.155**	0.080	10.21***	0.056	3.361***
LogBrent	0.011	0.827	0.084	7.223***	0.027	2.808***	0.032	4.404***	-0.004	-0.355
alpha	0.063	5.631***	0.057	6.564***	0.034	0.1288	0.047	12.4***	0.032	0.062
gamma	0.405	4.455***	0.326	5.113***	0.993	0.1286	-0.044	-1.497	1.006	0.062
beta	0.869	52.5***	0.902	81.27***	0.902	84.81***	0.947	278.3***	0.909	88.04***
Llik:	-3789		-3227		-2743		-3330		-2953	
BIC:	7632		6509		5540		6715		5959	
AIC:	7592		6469		5501		6675		5920	
HQC:	7606		6483		5515		6689		5934	

Note: Asterisks indicate significance at 10% (*), 5% (**), and 1% (***). Z-statistics are based on robust standard errors and OPG estimators. Llik: log-likelihood, BIC: Bayesian information criterion, AIC: Akaike Information Criterion, HQC: Hannan-Quinn information criterion.

This suggests that high levels of oil shocks tend to increase stock market volatility in Russia and that drops in oil price have a much greater effect on the Russian economy than coronavirus and this could help explain the recent clash between Russia and Saudi Arabia over oil prices. On 6th March, Russia refused to reduce its oil supply as suggested by OPEC. On 8th March, Saudi Arabia responded by reducing its oil prices (by around $6-8 per barrel) for European and Asian customers and oil production increases. This stalemate is resulting in additional uncertainty for the Russian economy.

The key question raised by these findings is: why has the COVID-19 pandemic had such a powerful impact on stock market volatility? To begin with, the panic associated with the virus has a negative impact not only on public health, but also on trade and tourism, leading to local food shortages and having profound ramifications for the world economy. These effects are worsened by the severity of the pandemic and the apparent ease with which the virus is transmitted. Furthermore, as coronavirus continues to headline all news syndicates and with every country making daily announcements of new confirmed cases and deaths, society has become saturated with information about the pandemic. This means that the stock market impact of the situation is temporally concentrated, which leads to increased volatility. In addition, the interconnectedness of the modern global economy (e.g. in terms of cross-border commuting, ease of travel, low communication costs, low transport costs, and geographically expansive supply chains) creates a vast ripple effect which is exacerbated the wider it spreads. The shift in the structure of the economy to focus more on services involving face-to-face interaction also comes into play, given that the social distancing measures put in place to slow transmission of the disease have created an abrupt cessation in demand for such services. Finally, in terms of behavioural and policy reactions to the pandemic, lockdown measures have vastly reduced the flow of labour to businesses, leading to a sudden and colossal reduction in the output of goods and services.

The novel coronavirus known as COVID-19 is thus creating a massive increase in economic uncertainty and disruption which has increased volatility and lowered valuations in the BRICS countries. For the present, it remains impossible to pin down the precise nature of the impact of the virus on these economies, but it remains clear that the situation entails serious risks. The results of the analysis presented here clearly indicate that the continued spread of the pandemic is impacting BRICS stock indices, but the ultimate extent of the damage, both in BRICS countries and to the broader financial system, remains unclear. If volatility continues to increase and more businesses fail to meet their financial obligations, it will be essential to keep disruptions to the chain of payments to a minimum in order to avoid further excessive risk-averse conduct in the market.

6. CONCLUSION

This paper has analyzed for the first time the influence of the novel coronavirus known as COVID-19 on stock market volatility in BRICS countries. We use the following indices for each country: the Sao Paulo SE Bovespa Index in Brazil, the MOEX Russia Index in Russia, the S&P BSE Sensex Index in India, the Shanghai SE Composite Index in China, and the FTSE/JSE SA Top 40 Companies Index in South Africa.

We find that, during the coronavirus period, Brazil, India, and South Africa exhibited very high volatility, with all three countries experiencing negative returns exceeding those faced during the 2008 financial crisis. Furthermore, the minimum returns values for these three countries occurred during the coronavirus period (March 2020). Furthermore, the minimum returns values for MOEX Russia and the Shanghai SE Composite Index occurred outside the coronavirus period.

The results of the GJR-GARCH models show that coronavirus has a significant positive impact on stock market volatility for four of five BRICS countries (i.e. Brazil, India, China, and South Africa), but an insignificant impact for Russia. Moreover, the coefficient of the COVID-19 dummy variable is largest for Brazil, followed by South Africa, China, and India. This indicates that the coronavirus pandemic is not impacting Russia as severely as the other four BRICS countries.

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