Modelling Stock Market Volatility During the COVID-19 Pandemic: Evidence from BRICS Countries

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The objective of the research paper is to identify the stock market volatility pattern of BRICS countries during the outbreak of the COVID-19 pandemic. The study is based on the time series data, which consists of the daily closing price of the BRICS countries' index for a two-year (pandemic) period from 1st January 2020 to 31st December 2021. Both the symmetric and asymmetric models of Generalized Autoregressive Conditional Heteroscedasticity (GARCH) have been employed in the study to investigate whether volatility changes over the pandemic period. The result of the GARCH-M (1, 1) model evidenced the presence of a positive and insignificant risk premium. Based on the empirical work carried out using the market index of BRICS countries, it was found from EGARCH (1,1), and TGARCH (1,1) models that there exists a leverage effect in the countries, viz. Brazil, Russia, India, China and South Africa. Since the stock price during the pandemic period triggered the entire financial market, the investors, fund managers and portfolio managers should be more aware of the uncertainty and need to adjust their investments accordingly.

Key Words: BRICS countries, conditional volatility, GARCH models, leverage effect, market return
JEL Classification: C32, C53

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Introduction

The virus called corona, which originated in Wuhan City, China has a dangerous effect on the life of humans and caused, foremost, ruin in the global market. Since stock prices are highly sensitive to major events which occur worldwide, the outbreak of COVID-19 influenced and affected the stock return widely. The stock market and its investors always react to every economic and major event which happens worldwide (De Bondt and Thaler 1990). The stock market has both a positive and negative impact on economic events; for instance Taqi, Shamin, and Ajmal (2018), and Lodha, Kumawat, and Bapna (2018) explored the impact of demonetization on different sectors in the Indian capital market. So far, even natural catastrophes have registered significant influence on the global market. There have been many studies which made an attempt to explore the effect of natural calamities on the capital market (Kim 2011; Wang and Kutan 2013). Equally, the stock market also responded to epidemic diseases such as SARS and H7N9, which caused a negative impact on human health and the economy. For instance, Chen et al. (2009) investigated the impact on the stock market during the Severe Acute Respiratory Syndrome (SARS) outbreak. Gu et al. (2014) and Qui et al. (2018) pointed out that the social and economic impacts of H7N9 disease did not spread widely and were not as serious as in the case of SARS.

The economic effect has become worse in many countries during this current outbreak. BRICS is the emerging countries (Brazil, Russia, India, China and South Africa) that play a key role in promoting economic and regional development and thereby removing trade barriers. These countries have also faced problems in the course of the pandemic. During the outbreak of COVID-19, the stock price indexes of most of the countries were significantly diminished. Hence, to gain awareness of the impact of COVID-19 on the stock market, BRICS countries in particular are taken into consideration for the study.

The univariate GARCH model is the most popular method used to examine volatility and the extension of the GARCH-M model is the best one to identify the risk return relationship (Engle, Lilien, and Robins 1987). Further extension models, viz. EGARCH and TGARCH, will help to identify the asymmetric volatility and the existence of the leverage effect (Nelson 1991; Zakoian 1994). Hence, the present research paper focused on identifying the volatility fluctuations of BRICS countries during the COVID-19 pandemic period by incorporating different univariate GARCH family models. Therefore, based on the literature and background, the following objectives are framed:

1. To explore the volatility pattern of BRICS countries indices using a symmetric and asymmetric model.
2. To detect whether the daily return series show the leverage effect using asymmetric models.

The research paper is organized in such a way that it presents a deep background of the literature in the second section, followed by research methodology in the third section. The study elaborates on the result and interprets it in detail in the fourth section. Finally, the study is concluded in the fifth section.

Literature Review

Several studies have scrutinized the relationship between return and risk (volatility) using the GARCH models developed by Bollerslev (1986), since it is an exact prediction of volatility in the equity market. Among GARCH models, the GARCH-M model postulates the exact relationship between return and risk. For instance, Dean and Faff (2001), Karmakar (2007), Wang and Yang (2013), Banumathy and Azhagaiah (2015), and Singh and Tripathi (2016) used the GARCH-M model in their study and proved the positive relation which exists between return and conditional variance. Yakob and Delpachitra (2006) examined the relationship between risk and return of 10 countries in the Asia-Pacific region. The result of the study revealed that out of ten, only two countries showed an insignificant relationship with negative coefficients. Zakaria and Winker (2012) empirically tested the volatility of two major countries, Sudan (Khartoum Stock Exchange) and Egypt (Cairo and Alexandria Stock Exchange) over the period of five years. Using the symmetric model of GARCH-M, the study found a positive and statistically significant relationship exists for both the markets. Further, Tah (2013) investigated the stochastic behaviour of the Nairobi Stock Exchange of Kenya and Lusaka Stock Exchange of Zambia, and using the GARCH-M model it was found that there was no significant relation between conditional variance and expected return for Kenya whereas there exists a negative and significant relation for Zambia. Similarly there exists a negative and significant abnormal return in the Indonesia Stock Exchange during the pandemic period (Endri et al. 2021). On the other hand, many studies were undertaken to capture asymmetry in volatility clustering using the variations in GARCH models called EGARCH and TGARCH. The returns of the Egyptian stock market during the period 1998 to 2009 were used to study volatility and proved that EGARCH is the best fit model for measuring volatility clustering (Ahmed and Aal 2011).

The COVID-19 pandemic has been the most susceptible period, which not only affected human life but also exaggerated the economy worldwide; for instance, the exchange rate of the Japanese Yen became stronger during COVID-19 (Narayan, Devpura, and Wang 2020). Recently, in the Indian context, a study was made by Singh, Makhija, and Chacko (2021) which attempted to identify the effect of COVID-19 on investment and proved that the currencies volatility increased, and that the Indian S&P ESG 100 index's return and volatility does not depict any effect because of the COVID-19 crisis. Studies have been done by various researchers in examining the volatility of the stock market due to the COVID-19 virus. Ngu, Mahdi, and Szulczyk (2021) studied the impact of COVID-19 on the stock market volatility of Malaysia and Singapore with the help of the EGARCH model, using the daily closing indices between 1st July 2019 and 31st August 2020 and pointed out the existence of the leverage effect in both the markets. Mohammad, Shabbir, and Chavali (2020) proved that the Indian stock market had a positive average abnormal return during the lockdown period and a negative abnormal return during the pre-lockdown period, while the uncertainty of COVID-19 adversely affected the US stock market (Xu 2021). Bouri et al. (2021) argued that COVID-19 influenced the market very strongly for emerging stock market. The affected countries' (Belgium, China, France, Germany, Italy, the Netherlands, South Korea, Spain, Switzerland, the United Kingdom, and the United States) stock market indices showed a negative impact on their return because of the delayed market responses (Khatatbeh, Hani, and Abu-Alfou 2020). Naik and Reddy (2021) showed the evidence that the GARCH model is superior in forecasting volatility. Recently, few researchers examined the systemic risk spill over effects among global markets during the COVID-19 pandemic (e.g. Jiang, Fu, and Ruan 2019; Abuzayed et al. 2021; Choi 2022).

There are only a few studies which examined the stock market volatility among BRICS countries, for instance, Bouri et al. (2018), using the 'Bayesian Graphical Structural Vector Autoregressive (BGSVAR) model,' examined the volatility among BRICS countries concurrently with nine predictor variables (Canada, France, Germany, the Netherlands, Japan, Sweden, Switzerland, the UK and US), together with two commodity markets (Gold and Oil). The study found that the US is the major dominating predictor in BRICS, whereas the same is not present in Brazil and China, indicating that people are more conscious about the local market when compared to the US market. The risk spillovers between the BRICS stock markets and precious metal markets were examined by Jiang, Fu, and Ruan (2019) using the GARCH models and they pointed out that the volatility is long persisting and fluctuates greatly for a prolonged period.

Although there were many studies that concentrated on the pandemic impact among many developing and developed countries, there were no sufficient studies concentrating on the BRICS countries, especially during the pandemic period. Hence, the present study concentrated on exploring the volatility clustering of BRICS countries. The present study applied symmetric as well as asymmetric GARCH models to identify the facts of return.

Research Methodology

DATA SOURCE

The present paper customizes secondary data which were collected from official websites (www.yahoofinance.com; www.investing.com). The stock indices of Brazil (BOVESPA), Russia (IMOEX), India (Nifty 50), China (SSE Composite Index) and South Africa (SA Top 10) have been taken for the study. COVID-19 originated in Wuhan city at the end of 2019; it started spreading all over the world gradually and India was a victim in January 2020 (Andrews et al. 2020). Hence, to identity and examine the volatility clustering, especially during the pandemic period, the daily closing prices of the BRICS market index have been collected from 1st January 2020 to 31st December 2021.

RESEARCH METHODS

Pertinent econometric tools, viz. the normality test, unit root test, ARCH-LM test and GARCH family model were used and have been analysed using the Eviews 10 Econometrics package. The returns (r_t) of each BRICS country were calculated using the following formula:

$$r_t = \frac{P_t}{P_{t-1}} \times 100, \tag{1}$$

where r_t is logarithmic daily return on BRICS index for time t, P_t is closing price at time t, and P_{t-1} is corresponding price in the period at time $t-1$.

BASIC STATISTICAL TOOLS USED IN THE STUDY

First, the descriptive statistics have been calculated to know whether the returns are normally distributed for the study period:

H0 *Data are normally distributed (JB = 0).*

H1 *Data are not normally distributed (JB ≠ 0).*

Second, for checking whether the data are stationary or non-stationary, the unit root test called the Augmented Dickey-Fuller Test (ADF) has been employed (Dickey and Fuller 1979):

HO *Returns are non-stationary (there is a unit root).*

H1 *Returns are stationary (there is no unit root).*

Third, the Lagrange Multiplier (LM) test for Autoregressive Conditional Heteroscedasticity (ARCH) is used to test the presence of heteroscedasticity in the residual of the return series.

HO *There is no ARCH effect.*

H1 *There is an ARCH effect.*

TECHNIQUE USED FOR VOLATILITY MEASUREMENT

The study used symmetric and asymmetric Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models to identify the volatility clustering and leverage effects. Symmetric models, viz. GARCH (1, 1) and GARCH-M (1, 1) were employed for modelling conditional volatility and EGARCH (1, 1) and TGARCH (1, 1) were applied for modelling asymmetric volatility.

GENERALIZED AUTOREGRESSIVE CONDITIONAL HETEROSCEDASTIC (GARCH) MODEL

Bollerslev (1986) independently developed the GARCH model, which lets the conditional variance be dependent upon previous own lags. The simplest model specification of GARCH (1, 1) is as follows:

Mean equation: $r_t = \mu + \epsilon_t$,
Variance equation: $\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \alpha\epsilon_{t-1}^2$,

where $\omega > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$, and r_t is return of the asset at time t, μ is average return, ω is constant term, α is coefficient of the ARCH term, β is oefficient of the GARCH term, and ϵ_t is residual return.

GARCH-IN-MEAN (GARCH-M) MODEL

The extension of the GARCH model is the GARCH-M model that lets the conditional mean depend on its conditional variance. A simple GARCH-M (1, 1) model can be written as:

Mean equation: $r_t = \mu + \lambda\sigma_\tau t^2 + \epsilon_t$,
Variance equation: $\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2$.

The parameter λ in the mean equation is called the risk premium. A positive λ indicates that the return is positively related to its volatility.

EXPONENTIAL GARCH MODEL

This model is used to identify the presence of the leverage effect. The model was developed by Nelson (1991) and it is given by the following equation:

$$Ln(\sigma_t^2) = \omega + \beta_1 Ln(\sigma_{t-1}^2) + \alpha \left\{ \left| \frac{\epsilon_{t-1}}{\sigma_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma - \frac{\epsilon_{t-1}}{\sigma_{t-1}}. \tag{2}$$

THRESHOLD GARCH MODEL

The threshold GARCH was developed by Zakoian (1994) and the generalized specification for the conditional variance is given by:

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \gamma d_{t-1} \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \tag{3}$$

where d_{t-1} if $\epsilon_{t-1} > 0$ means 'bad news' and 0 if $\epsilon_{t-1} \geq 0$ means 'good news.' The leverage parameter γ, if significant and positive, denotes that negative shocks have a greater effect on σ_t^2 than positive shockwaves.

Results

Table 1 shows the descriptive statistics and the result of the ADF and ARCH LM test. The descriptive statistics for the original data of five market indexes during the pandemic period has been tabulated clearly. It is clear from the table that the raw dataset shows a vast difference in the mean and standard deviation value, which evidently exhibits a structural difference among BRICS countries. Figure 1 shows the daily time series

TABLE 1 Descriptive Statistics, ADF Test and ARCH LM Test of BRICS Countries

Item	Brazil	Russia	India	China	S. Africa
(a) Mean	107909.3	3318.204	13574.85	3331.205	55274.51
Standard deviation	14200.26	508.4722	2800.860	273.8620	6624.586
Skewness	−0.810510	0.054827	−0.067144	−0.810423	−0.518018
Kurtosis	3.1911	1.9362	1.8846	2.3602	2.6936
Jarque-Bera Statistics	56.5045*	24.2533*	26.7638*	64.3973*	24.7554*
(b) ADF Statistics	−27.6626*	−22.9366*	−22.6908*	−21.8792*	−22.9366*
MacKinnon one side critical values: 1% −3.4430; 5% −2.8670; 10% −2.5697					
(c) F Statistic	220.5273*	8.559979*	12.27954*	3.791872*	1.296248*
Obs*R-squared (TR2)	154.1049*	154.1049*	154.1049*	3.778518*	1.298050*

NOTES Row headings are as follows: (a) descriptive statistics, (b) ADF test, (c) ARCH LM test. * Significant at 1%. Computed results based on secondary data.

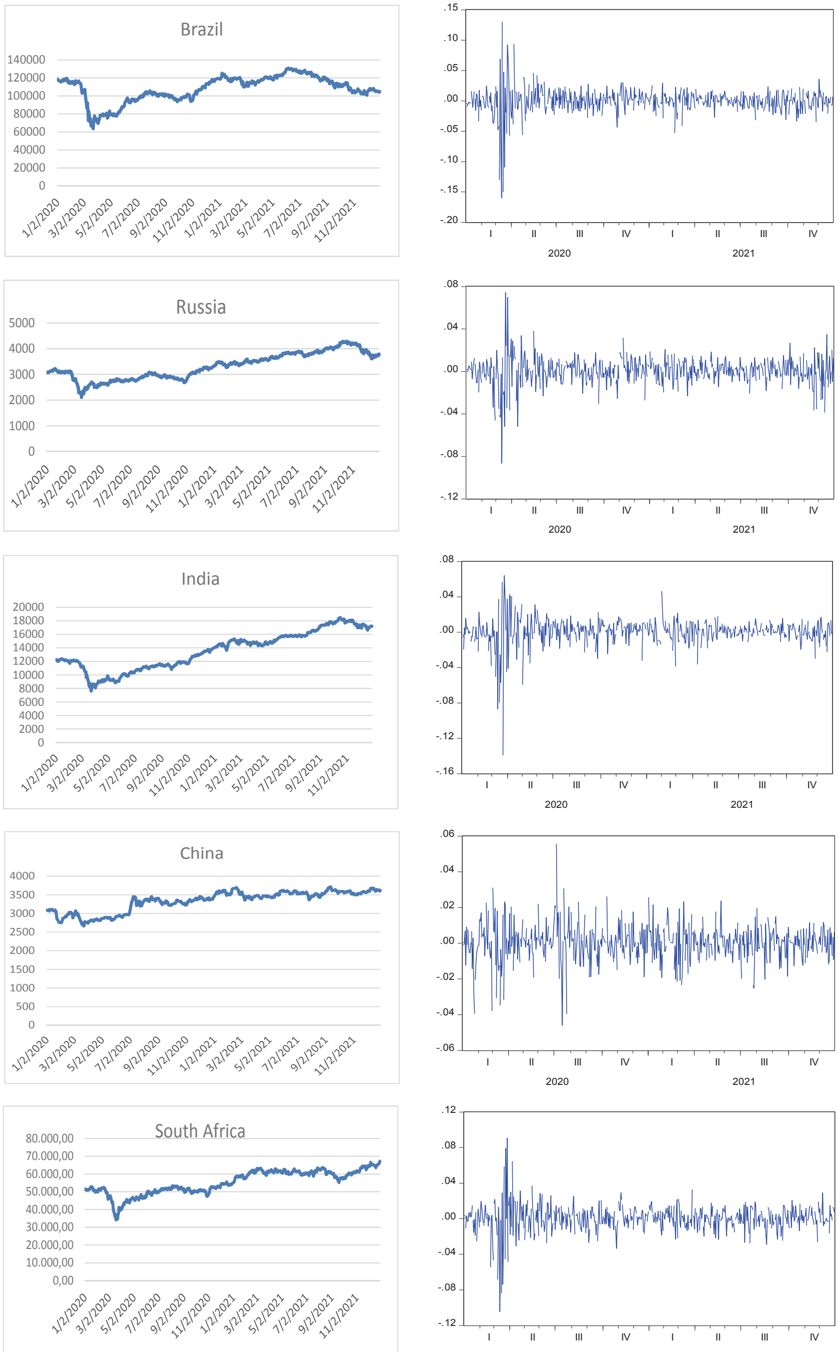

FIGURE 1 The Daily Prices (left) and the Returns (right) of BRICS Countries

data set (left) and the return series (right) of BRICS countries. It is inferred from the graphs on the right that there are bounces over the study period which denote that volatility is relatively high and low, exhibiting the volatility clustering covering the aforesaid period. All BRICS countries' stock indexes exhibit negative skewness (except Russia) and kurtosis greater than three (Brazil) indicates that the dataset has heavier tails, which does not accompany a normal distribution, i.e. there is a presence of large movements of share price over the sample period.

The value of the JB test rejects *H*o as the statistics are significant at 1%, denoting that during the period of COVID-19, the stock prices were not normally distributed. To test the stationarity, the Augmented Dickey Fuller test (ADF) is applied and the result shows that the returns are stationary at levels for all the countries. The p values of ADF statistics are less than 0.05, indicating that the time series data for the study period is stationary. Hence, the hypothesis *'Ho: Returns are non-stationary'* was rejected at level for the BRICS countries, as the ADF statistics are significant at the 1% level, indicating the series are stationary and exhibiting the presence of a unit root.

Before applying GARCH, it is essential to check the presence of the ARCH effect in the return series. Since the p value is less than 0.05 and test statistics are highly significant at 1% the null hypothesis *'Ho: There is no ARCH effect'* is rejected, confirming the presence of the ARCH effect in the residuals and hence the outcome permits for the estimation of GARCH extension models. The results depict the presence of volatility clustering in the return series.

Figure 1 shows the daily prices and the returns of BRICS countries.

Table 2 depicts the result of the GARCH (1, 1) model where α and β determine the short-run dynamics of the volatility. In the conditional variance equation, ARCH term (α) and GARCH term (β) are extremely significant at 1%. The sum of these coefficients (α and β) are also close to unity, indicating that the shock at time t will continue to future periods of BRICS countries, indicating that the volatility is persistent. However, it is proved that the variance equation is well specified and does not exhibit an additional ARCH effect for the entire study period by applying the ARCH-LM test on residuals.

Table 3 reports the result of the GARCH-M (1, 1) model, which is used to find the risk and return relationship among the stock index of BRICS countries. The constant (μ) in the mean equation is insignificant, which indicates that the returns are not up to the level for investment. The con-

TABLE 2 Results of GARCH (1, 1) Model

Coefficients	Brazil	Russia	India	China	S. Africa
(a) μ (constant)	0.2866	0.0294**	0.1586**	0.0104	0.3558
(b) ω (constant)	30.645*	0.0055**	0.0922*	0.0116*	3.3023**
α (ARCH effect)	0.1393*	0.0971*	0.0971*	0.1203*	0.0829*
β (GARCH effect)	0.7546*	0.8686*	0.8693*	0.7810*	0.8518*
$\alpha+\beta$	0.8939	0.9657	0.9664	0.9013	0.9347
Log likelihood	−2137.864	−196.9624	−921.9628	−151.3065	−1695.782
Akaike Info. Crit. (AIC)	8.4325	0.7911	3.6455	0.6114	6.6920
Schwarz Info. Crit. (SIC)	8.4658	0.8245	3.6788	0.6447	6.7253
(c) ARCH-LM test stat.	0.1297	0.7617	0.1039	0.1920	0.8875
Prob. Chi-square (1)	0.7182	0.3822	0.7467	0.6606	0.3456

NOTES Row headings are as follows: (a) mean, (b) variance, (c) test for heteroscedasticity. Computed results based on secondary data. * Significant at 1% level, ** significant at 5% level.

TABLE 3 Results of GARCH-M (1, 1) Model

Coefficients	Brazil	Russia	India	China	S. Africa
(a) μ (constant)	0.1517	−0.0043	0.0935	0.0043	−0.4330
λ (risk premium)	0.0005	0.0978	0.0329	0.0619	0.0184
(b) ω (constant)	30.6660*	0.1044	0.0982**	0.0116**	3.3361
α (ARCH effect)	0.1394*	0.1500	0.1024*	0.1206*	0.0839
β (GARCH effect)	0.7545*	0.6000*	0.8621*	0.7806*	0.8500
$\alpha+\beta$	0.8939	0.7500	0.9645	0.9012	0.9339
Log likelihood	−2137.855	−287.2466	−921.6941	−151.2896	−1694.869
Akaike Info. Crit. (AIC)	8.436437	1.1505	3.6484	0.6153	6.6923
Schwarz Info. Crit. (SIC)	8.478076	1.1922	3.6900	0.6569	6.7340
(c) ARCH-LM test stat.	0.112659	0.5063	0.2253	0.1829	0.7763
Prob. Chi-square (1)	0.7367	0.4761	0.6344	0.6683	0.3777

NOTES Row headings are as follows: (a) mean, (b) variance, (c) test for heteroscedasticity. Computed results based on secondary data. * Significant at 1% level, ** significant at 5% level.

ditional variance's coefficient (λ) in the mean equation is insignificant, which implies that returns are independent of the risk due to conditional variance in the return series. It shows that the estimated coefficient of risk premium (λ) in the mean equation is positive but insignificant for

TABLE 4 Result of EGARCH (1, 1) Model

Coefficients	Brazil	Russia	India	China	S. Africa
(a) μ (constant)	−0.1103	0.0200	0.1085	0.0074	0.1665
(b) ω (constant)	0.2650**	−0.2248*	1.0656*	−0.4680*	0.1483**
α (ARCH effect)	0.1747*	0.1516**	0.3191*	0.2582*	0.1053**
β (GARCH effect)	0.9280*	0.9466*	−0.3457**	0.8744*	0.9411*
γ (leverage effect)	−0.1326*	−0.0992*	0.2153*	−0.0243	−0.1474*
$\alpha + \beta$	1.1027	1.0982	0.0266	1.1326	1.0464
Log likelihood	−2133.955	−194.2449	−965.0866	−153.2841	−1691.511
Akaike Info. Crit. (AIC)	8.4210	0.7844	3.8192	0.6231	6.6791
Schwarz Info. Crit. (SIC)	8.4627	0.8260	3.8608	0.6648	6.7208
(c) ARCH-LM test stat.	0.4175	1.1681	4.2945	0.0737	0.7303
Prob. Chi-square (1)	0.5175	0.2794	0.1387	0.7856	0.3922

NOTES Row headings are as follows: (a) mean, (b) variance, (c) test for heteroscedasticity. Computed results based on secondary data. * Significant at 1% level, ** significant at 5% level.

the study period, indicating that higher risk, provided by the conditional variance, will not certainly lead to higher returns.

Finally, the ARCH-LM test statistics are employed to check whether the model fulfilled all the conditions of the model or not and the results prove that the p value of the ARCH-LM test is above the 5% level, so the hypothesis cannot be rejected, revealing that the LM test did not exhibit any additional ARCH in the residuals, which signifies that the variance equations are well specified.

EGARCH (1, 1) is employed for analysing the asymmetrical effect of volatility in BRICS countries and the results are reported in table 4. It reveals that the coefficient of the ARCH effect (α) and GARCH (β) are significant and positive, which indicates that volatility is present in BRICS countries. The ARCH coefficient α and coefficient of GARCH, β, are greater than one (except India), indicating that the conditional variance is volatile and unstable. The leverage coefficient γ is significantly positive at the 1% level for all countries except China, providing the presence of the leverage effect in the return during the study period. Since the coefficient of the leverage effect (γ) is significant, it reveals that there is a significant impact of the COVID-19 period on the volatility of BRICS countries.

Another model to test the asymmetric volatility in BRICS countries is

TABLE 5 Result of TGARCH Model

Coefficients	Brazil	Russia	India	China	S. Africa
(a) μ (constant)	−0.1964	0.0215	0.1215**	0.0094	0.0961
(b) ω (constant)	32.752*	0.0063**	0.1069*	0.0123**	2.4923*
α (ARCH effect)	−0.0063	−0.0012	−0.0249**	0.1135*	−0.0534*
β (GARCH effect)	0.7861*	0.8936*	0.8846*	0.7719*	0.9163*
γ (leverage effect)	0.1924*	0.1149*	0.1718*	0.0200	0.1671*
$\alpha + \beta$	0.7798	0.8942	0.8597	0.8854	0.8629
Log likelihood	−2132.091	−191.8238	−911.3339	−151.2518	−1684.186
Akaike Info. Crit. (AIC)	8.4137	0.7748	3.6076	0.6151	6.6503
Schwarz Info. Crit. (SIC)	8.4553	0.8165	3.6492	0.6568	6.6919
(c) ARCH-LM test stat.	0.0202	0.6282	0.0029	0.1074	0.377054
Prob. Chi-square (1)	0.8866	0.4274	0.9569	0.7426	0.5385

NOTES Row headings are as follows: (a) mean, (b) variance, (c) test for heteroscedasticity. Computed results based on secondary data. * Significant at 1% level, ** significant at 5% level.

TGARCH (1, 1) and the result is shown in table 5. It helps to study the presence of leverage effects in the returns of the BRICS indices during the pandemic period. In the TGARCH (1, 1) model, the coefficient γ (leverage effect) is known as the asymmetry or leverage parameter, which is positive and highly significant for Brazil, Russia, India and South Africa. It indicates that when compared to positive shocks, the negative shocks have a greater effect on the conditional variance. Hence it is proved from the TGARCH (1, 1) model that the negative shock is because of COVID-19, where the entire BRICS countries indexes have been affected. Moreover, the LM test statistic for the TGARCH (1, 1) model does not show any additional ARCH effects in the residual, which implies that the 'variance equation is well specified.'

Conclusion

The present study tested the volatility of the BRICS index using the symmetric and asymmetric GARCH models. Daily closing prices of the BRICS countries index from January 1, 2020 to December 31, 2022 have been used for the analysis. Symmetric models, GARCH (1, 1), GARCH-M (1, 1) and asymmetric models, EGARCH (1, 1), and TGARCH (1, 1) were employed in the study to identify the volatility pattern and leverage effect. From the symmetric models it was found that the risk premium is insignificant for all BRICS countries, indicating that the daily returns are not associated with risk due to past volatility. The result of the symmetric models supports the findings of Karmakar (2005), Banumathy and Azhagaiah (2015), and Zakaria and Winker (2012), whereas the result of GARCH-M (1, 1) is opposed to the findings of Karmakar (2007), which exhibits a significant risk premium. However, from the asymmetric models, viz. EGARCH (1, 1), and TGARCH (1, 1), the study found the 'presence of leverage effect in all four countries except China' (Karmakar 2007; Zakaria and Winker 2012). Overall, the study proves that the BRICS countries indexes were more volatile during the period of COVID-19, which does not considerably provide a better return.

The implications of the present study's findings will be fruitful for individual and institutional investors as it evidences the presence of risk during the sample period. The volatility bounces enormously during the aforesaid sample period which triggered the entire financial market, and it paves the way for the investors, fund managers and portfolio managers to be more aware about the risk and to adjust their investments accordingly.

The objective of the present study is to model the volatility pattern of the return structure in emerging BRICS countries. The research tried to examine the volatility clustering and its leverage effects using univariate GARCH models and their extension. Further research can be extended to concentrating on using the multivariate GARCH model, which uses not only variances but also covariances. Moreover, other emerging countries can also be taken as a sample for the accomplishing of better results worldwide.

References

Abuzayed, B., E. Bouri, N. Al-Fayoumi, and N. Jalkh. 2021. 'Systemic Risk Spillover Across Global and Country Stock Markets during the COVID-19 Pandemic.' *Economic Analysis and Policy* 71 (14): 180–97.

Ahmed, M., and A. E. Aal. 2011. 'Modelling and Forecasting Time Varying Stock Return Volatility in the Egyptian Stock Market.' *International Research Journal of Finance and Economics* 78:96–113.

Andrews, M. A., B. Areekal, K. R. Rajesh, J. Krishnan, R. Suryakala, B. Krishnan, C. P. Muraly, and P. V. Santhosh. 2020. 'First Confirmed Case of COVID-19 Infection in India: A Case Report.' *Indian Journal of Medical Research* 151 (5): 490–92.

Banumathy, K., and R. Azhagaiah. 2015. 'Modelling Stock Market Volatility: Evidence from India.' *Managing Global Transitions* 13 (1): 27–42.

Bollerslev, T. 1986. 'Generalized Autoregressive Conditional Heteroskedasticity.' *Journal of Econometrics* 31 (3): 307–27.

Bouri, E., R. Demirer, R. Gupta, and J. Nel. 2021. 'COVID-19 Pandemic and Investor Herding in International Stock Markets.' *Risks* 9 (9): 168.

Bouri, E., R. Gupta, S. Hosseini, and C. K. M. Lau. 2018. 'Does Global Fear Predict Fear in BRICS Stock Markets? Evidence from a Bayesian Graphical Structural VAR model.' *Emerging Markets Review* 34:124–42.

Chen, C. D., C. C. Chen, W. W. Tang, and B. Y. Huang. 2009. 'The Positive and Negative Impacts of the SARS Outbreak: A Case of the Taiwan Industries.' *The Journal of Developing Areas* 43 (1): 281–93.

Choi, Y.-S. 2022. 'Volatility Spillovers among Northeast Asia and the US: Evidence from the Global Financial Crisis and the COVID-19 Pandemic.' *Economic Analysis and Policy* 73 (33): 179–93.

Dean, W. G., and R. W. Faff. 2001. 'The Inter-Temporal Relationship between Market Return and Variance: An Australia Perspective.' *Accounting and Finance* 41 (3): 169–96.

De Bondt, W. F. M., and R. Thaler. 1990. 'Do Security Analysts Overreact?' *American Economic Review* 80 (2): 52–7.

Engle, R. F., D. Lilien, and R. P. Robins. 1987. 'Estimating Time Varying Risk Premia in the Term Structure: The Arch-M Model.' *Econometrica* 55 (2): 391–407.

Dickey, D. A., and W. A. Fuller. 1979. 'Distribution of the Estimators for Autogressive Time Series with a Unit Root.' *Journal of American Statistical Association* 74 (366): 427–31.

Endri, E., W. Aipama, A. Razak, L. Sari, and R. Septiano. 2021. 'Stock Price Volatility during COVID 19 Pandemic: The GARCH Model.' *Investment Management and Financial Innovations* 18 (4): 12–20.

Gu, S., J. Lu, M. Yu, X. Wei, and Y. Hu. 2014. 'Path Analysis and Evaluation about Health Communication for H7N9 Emergencies in Shanghai.' *Health Education and Health Promotion* 9 (1).

Jiang, Y., Y. Fu, and W. Ruan. 2019. 'Risk Spillovers and Portfolio Management between Precious Metal and BRICS Stock Markets.' *Physica A: Statistical Mechanics and its Applications* 534 (1): 120993.

Karmakar, M. 2005. 'Modelling Conditional Volatility of the Indian Stock Markets.' *Vikalpa* 30 (3): 21–37.

———. 2007. 'Asymmetric Volatility and Risk-Return Relationship in the Indian Stock Market.' *South Asia Economic Journal* 8 (1): 99–116.

Khatatbeh, I. N., M. B. Hani, and M. N. Abu-Alfoul. 2020. 'The Impact of COVID-19 Pandemic on Global Stock Markets.' *International Journal of Economics and Business Administration* 8 (4): 505–14.

Kim, C. K. 2011. 'The Effects of Natural Disasters on Long-Run Economic Growth.' *Michigan Journal of Business* 4 (1): 11–49.

Lodha, S., E. Kumawat, and C. Bapna. 2018. 'Impact of Demonetization Announcement on Indian Stock Market: An event study.' *Pacific Business Review International* 11 (6): 75–87.

Mohammad, A., A. Shabbir, and K. Chavali. 2020. 'Stock Market Response during COVID-19 Lockdown Period in India: An Event Study.' *Journal of Asian Finance, Economics and Business* 7 (7): 131–7.

Naik, M. S., and Y. V. Reddy. 2021. 'India VIX and Forecasting Ability of Symmetric and Asymmetric GARCH Models.' *Asian Economic and Financial Review* 11 (3): 252–62.

Narayan, P. K., N. Devpura, and H. Wang. 2020. 'Japanese Currency and Stock Market: What Happened during the COVID-19 Pandemic?' *Economic Analysis and Policy* 68:191–8.

Nelson, D. B. 1991. 'Conditional Heteroscedasticity in Asset Returns: A New Approach.' *Econometrica* 59 (2): 347–70.

Ngu, J. C., S. Z. Mahdi, and K. R. Szulczyk 2021. 'The Impact of COVID-19 Pandemic on Stock Market Return Volatility: Evidence from Malaysia and Singapore.' *Asian Economic and Financial Review* 11 (3): 191–204.

Qui, W., C. Chu, A. Mao, and J. Wu. 2018. 'The Impacts on Health, Society, and Economy of SARS and H7N9 Outbreaks in China: A Case Comparison Study.' *Journal of Environmental and Public Health* 2018 (7). https://doi.org/10.1155/2018/2710185.

Singh, N. P., P. Makhija, and E. Chacko. 2021. 'Sustainable Investment and the COVID-19 Effect: Volatility Analysis of ESG Index.' *International Journal of Sustainable Economy* 13 (4): 357–68.

Singh, S., and L. K. Tripathi. 2016. 'Modelling Stock Market Return Volatility: Evidence from India.' *Research Journal of Finance and Accounting* 7 (13): 93–101.

Tah, K. A. 2013. 'Relationship between Volatility and Expected Returns in two Emerging Markets.' *Business and Economics Journal* 84.***

Taqi, M., M. A. Shamin, and M. Ajmal. 2018. 'Demonetization and its Impact on Indian Capital Market.' *Pacific Business Review International* 11 (3): 51–8.

Wang, L., and A. Kutan. 2013. 'The Impact of Natural Disasters on Stock Markets: Evidence from Japan and the US.' *Comparative Economic Studies* 55 (4): 672–686.

Wang, J., and M. Yang. 2013. 'On the Risk Return Relationship.' *Journal of Empirical Finance* 21 (C): 132–41.

Xu, L. 2021. 'Stock Return and the COVID-19 Pandemic: Evidence from Canada and the US.' *Finance Research Letters* 38:101872.

Yakob, N. A., and S. Delpachitra. 2006. 'On the Risk-Return Relationship: An Application of GARCH (p, q)-M Model to Asia Pacific Region.' *International Journal of Science and Research* 2 (1): 33–40.

Zakaria, S. S. A., and P. Winker. 2012. 'Modelling Stock Market Volatility Using Univariate GARCH Models: Evidence from Sudan and Egypt.' *International Journal of Economics and Finance* 4 (8): 161–76.

Zakoian, J. M. 1994. 'Threshold Heteroscedasticity Models.' *Journal of Economic Dynamics and Control* 18 (5): 931–44.