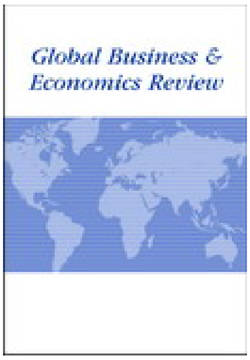

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Modelling stock market volatility using asymmetric GARCH models: evidence from BRICS stock markets

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Modelling stock market volatility using asymmetric GARCH models: evidence from BRICS stock markets

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Abstract: This study aims to examine the evidence of the behaviour of asymmetric volatility in the BRICS stock markets, and the analysis is based on daily data from January 2004 to December 2018. Two models from the generalised autoregressive conditional heteroskedasticity (GARCH) family have been used to capture the leverage effect. Results based on both models provide strong evidence of presence of asymmetric volatility in the BRICS stock market. The results also reveal that there is evidence of the presence of strong volatility persistence in case of BRICS countries except in case of China. The study argues that higher volatility corresponds to a higher probability of a declining market, while lower volatility corresponds to a higher probability of a rising market. Investors can use this data on long-term stock market volatility to align their portfolios with the associated expected returns.

Keywords: BRICS; EGARCH; GJR-GARCH; leverage effect; asymmetric volatility.

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1 Introduction

Emerging economies have gained a lot of attention from researchers during the last few decades since their economic growth of these countries exceeds that of industrialised countries (Lehkonen and Heimonen, 2014; Cao and Shi, 2021). BRICS countries have become the centre of attraction among researchers after the coining of the term by O'Neill (2002). It comprises Brazil, Russia, India, China, and South Africa. South Africa joined the acronym in 2008. BRICS countries are continuously developing and by the end of 2050, they will outperform most of the countries of the world. The rationale behind this forecast is all the countries in the BRICS stock market liberalised in the same period and their policies are focused on growth (Khatun and Bist, 2019). Investment portfolios in these countries are going to see a high rise as the economies are expected to see higher growth (Wilson and Purushothaman, 2003; Ruzima and Boachie, 2018). It is expected that they will outperform the G7 economies by 2050 and that China and India would become the first and third-largest economies followed by Brazil, Russia, and South Africa by then. The changes in the BRICS stock market have been an area of interest for international investors (Kalu et al., 2020).

The economies of the Brazil, Russia, India and China (BRIC) nations have distinct positioning in terms of sector strength and economic determinants, and their markets have low correlation coefficients (Mostafa and Stavroyiannis, 2016). Trade between BRIC countries has increased dramatically during the last ten years, contributing to more countercyclical growth (Grabel, 2019). China is the biggest user of base metals, and Brazil is the largest producer of iron ore (Jégourel, 2021). India is the fourth-largest oil importer in the world (Locke, 2019), and Russia is the third-largest exporter of natural gas (Kanat et al., 2022). Brazil and Russia provide the natural resources required by India's and China's industrial demand and urbanisation, presenting a favourable supply-and-demand equilibrium. Because of how stable these markets are, many investors believe they will eventually displace the G7 as the world's superpowers. Recent significant capital inflows into BRIC nations have made them a popular choice for investors looking for global diversification (Mishra et al., 2022). In order to gauge the stock markets' long-term contribution to the global economy, their effectiveness must be evaluated. Furthermore, given the complexity and competitiveness of the emerging BRICS stock market, a thorough understanding of return and volatility dynamics is crucial (Tripathy, 2017).

The stock market analysis or prediction or capturing the volatility has been pivotal in the financial market (Aziz and Hussain, 2021). Understanding the dynamics of volatility is essential in portfolio optimisation, risk management, and hedging (Jeribi et al., 2022; Ezzat, 2012). Conditional heteroscedasticity is defined as the volatility of a stock, which describes the conditional standard deviations of the underlying asset returns (Guesmi et al., 2019). The volatility of the stock market changes over a period of time and they exhibit a clustering effect. The asymmetric effect on the volatility has been captured by many researchers in the univariate and multivariate models in the case of emerging markets and trading blocs (Bhowmik and Wang, 2020). There has been meagerness in capturing the asymmetric volatility in the case of the BRICS stock markets.

The fluctuation or the changes in the markets are always been the area of interest among researchers. The characteristics displayed by financial time series in general and stock prices, in particular, are volatility clustering, i.e., large changes tend to be followed by large changes and small changes tend to be followed by small changes (Brooks, 2008). The second characteristic exhibited by the financial time series is they show the leptokurtosis effect meaning that the distribution of their returns is fat-tailed (Brooks, 2008; Patra, 2021). The third characteristic displayed by the financial time series is they show leverage effect, which refers to changes in stock prices that are negatively correlated with changes in volatility. This characteristic was first experienced by Black (1976) where volatility increased more after negative shocks than after positive shocks of the same magnitude.

Asymmetric volatility is defined as the negative correlation between stock returns and volatility since the drop in the value of a stock price increases the financial leverage, which increases the risk in the stock and in turn enhances the volatility (Awartani and Corradi, 2005). The limitation of the basic GARCH model propounded by Bollerslev (1986) is they are not able to capture the sign of the conditional volatility, whereas they capture the conditional volatility or volatility clustering effect in the markets. The basic GARCH models are not able to capture whether it is the bad news or the good news that is affecting the markets (Valadkhani et al., 2005; Palomba, 2008). The limitation of the basic GARCH model has been captured by the recent class of models such as EGARCH (Nelson, 1991), TGARCH or GJR-GARCH (Glosten et al., 1993).

The leverage effect in the stock market was the first encounter by Black (1976). It is the phenomenon when there is a negative correlation between stock prices and changes in volatility. The conventional ARCH test by Engle (1982) and the GARCH test (generalised ARCH) by Bollerslev (1986) capture volatility clustering and leptokurtosis effect in the stock prices. But they only capture the symmetric effect in the distribution but fail to capture the leverage effect in the markets.

In this paper, we examine the asymmetric volatility in the BRICS stock market with E-GARCH and GJR-GARCH models. The EGARCH model displays the principal features: they impose restrictions on the parameters to be estimated to a positive value so that they can capture a positive effect on the conditional variance. They remove the limitation of the traditional model of the absence of an asymmetric term in the GARCH model (Maghyereh et al., 2005). The EGARCH model use log-conditional variance, which incorporates the leverage effect in the exponential form and not quadratic (Ekong and Onye, 2017). More precisely, this study addresses the unanswered questions about the symmetric and asymmetric behaviour of the BRICS stock market. The motivation for this paper stems from the fact of looking into how the volatility of the emerging stock market BRICS reacts to good and bad news.

This study contributes to the existing literature by capturing the asymmetric volatility with two different models, i.e., E-GARCH and GJR-GARCH models. It explains the volatility modelling using recent daily returns and uses the leverage term of the EGARCH model to capture the asymmetry in volatility clustering. Very limited studies have investigated the asymmetric volatility in the BRICS stock market using the univariate GARCH model and so far no study has compared the results of the two models, to look at which model is better to capture the asymmetry in the volatility clustering.

2 Literature review

There have been a plethora of studies analysing the behaviour of the stock market of the world in general and emerging market in specific. But, there is scantiness in the studies, which have looked at the asymmetric behaviour of the BRICS stock market. The entire review of literature on these studies has been divided into two heads: the first head, talks about the studies focusing on the asymmetric behaviour of the stock market and secondly, it talks about the studies done on the BRICS stock markets.

2.1 Asymmetric behaviour of the stock market

Liu et al. (2022) aimed to investigate a useful method for predicting stock volatility by choosing dynamic VIX thresholds. The study investigated the VIX's predictability and its S&P 500 above-threshold values. The findings show that using VIX criteria can greatly increase forecast accuracy. The above-threshold VIX has a stronger forecasting performance during expansions, according to the out-of-sample R^2 data. Ballinari et al. (2022) looked into how stock market information processing is related to retail and institutional investor attention. Results with a focus on 360 US stocks in the S&P 500 universe reveal that increased retail investor attention around news releases raises the post-announcement stock return volatility, whereas institutional investor attention has a small but unfavourable impact on volatility on days after news releases on average over the cross-section of companies. Ghani et al. (2022) analysed, using the GARCH-MIDAS (mixed data sampling) model, the effects of the economic policy uncertainty index (EPU) and macroeconomic variables on the volatility of the Pakistan stock market. Results revealed that the index of economic policy uncertainty has the ability to predict the volatility of the Pakistani stock market. Furthermore, with a higher out-of-sample R-square value than any other variable, oil prices are the most effective predictor of volatility. Chen et al. (2022) used the S&P 500 index and WTI oil prices for the period of January 1990 to December 2021 to examine the added benefit of stock market volatility over oil volatility. The nonlinear threshold effect of stock market shock on oil market volatility is captured by the threshold autoregressive regression (TAR) model. According to empirical study, both in-sample and out-of-sample results emphasise the superiority and efficacy of the nonlinear threshold regression model's predictions, pointing to the significant importance of stock volatility's strong threshold effects for predicting oil volatility.

Ezzat (2012) modelled volatility during the period of the financial crisis. The findings of the study display higher volatility during the financial crisis. The leverage effect was found during the period of the revolution. Whereas Kumar and Sahu (2018) estimated the clustering volatility in the Indian stock markets by using the ARCH class family model. The impact of the regime shifts on the asymmetry and persistence of volatility was captured by Kumar and Maheswaran (2012) from the vantage point of modelling volatility in general and in assessing the forecasting ability of the GARCH class of models in the context of the Indian stock market by comparing the performance of Inclan and Tiao's (IT) (1994) and Sansó et al.'s (AIT) (2004) iterated cumulative sums of squares (ICSS) algorithms by conditional and unconditional variance. In addition, Ekong and Onye (2017) estimated the symmetric and asymmetric effects of the GARCH class of models. There was a presence of leverage effect in stock returns volatility in Nigeria using daily all-share stock data and there was a decline in persistence parameter after incorporating trading volume. In another work, Abdalla and Winker (2012) captured both symmetric and asymmetric volatility using GARCH models in Khartoum Stock Exchange (KSE) (from Sudan) and Cairo and Alexandria Stock Exchange (CASE) (from Egypt) stock markets. The result of the study show evidence of the presence of asymmetry in the stock returns of the market hence, there is a presence of leverage effects. The asymmetric volatility, day-of-the-week effect, and leverage effect are tested using GJR GARCH and APARCH models in the Tel Aviv Stock Exchange (TASE) indices and the results of the study show presence of asymmetric volatility with fat-tailed densities improve overall estimation for measuring conditional variance (Alberg et al., 2008). In the same line, Oberholzer and Venter (2015) analysed the volatility changes during the crisis period using the asymmetric GARCH models. The results of the study state during the financial crisis the GJR-GARCH was the best fitting model for all indices except for the JSE/FTSE fledgling index (J204) where EGARCH was the best fitting model.

Salisu et al. (2022) employed the generalised autoregressive conditional heteroskedasticity-mixed data sampling (GARCH-MIDAS) method to examine the forecasting performance of two comparatively understudied indicators of financial conditions. The findings found that using the two financial indicators (individually and collectively) does actually enhance the accuracy of stock market volatility models' long- and short-term forecasts. Wu et al. (2022) used a panel data assessment technique to investigate the impact of allowing SSE 50ETF index options trading on stock market volatility. The main conclusions hold up well under other econometric models, such as principal component analysis, GARCH-family model, and LASSO regression. According to the study's findings, the introduction of SSE index options gives investors better tools for risk management and enhances price discovery in the stock market. Liu and Guo (2022) examined the accuracy of model shrinkage techniques with conventional individual AR-type and combination forecasting models in predicting volatility of the US stock market. The results demonstrated that the Lasso shrinkage method performs much better in both the individual models as well as the combination methods for out-of-sample forecasting. Kuranchie-Pong and Forson (2021) examined Ghana Stock Exchange (GSE) for overconfidence bias and volatility both the pre-COVID-19 pandemic and COVID-19 pandemic periods. The study uses GARCH (1, 1) and GJR-GARCH (1, 1) models to determine if overconfidence bias contributed to volatility during the pre-COVID-19 pandemic and COVID-19 pandemic periods as well as pairwise Granger causality to test for the presence of overconfidence bias on the Ghana stock market. Findings: the study discovers a unidirectional Granger causation during the COVID-19 pandemic era connecting weekly market returns to weekly trade volume. These findings suggest that during the COVID-19 epidemic era, an overconfidence bias existed in the Ghana stock market.

2.2 Studies on the BRICS stock markets

The dependence structure among the BRICS stock market and global factors was analysed by Mensi et al. (2014), and the result of the study shows that US economic policy uncertainty was not having any significant impact on the BRICS stock markets. Where, Hammoudeh et al. (2013) examine the symmetric relationship between the BRICS indices and ICGR's by taking economic, financial, and political and West Texas intermediate oil prices into consideration. In this line, Hoti and McAleer (2005a, 2005b) used a four-country risk rating making an addition of the composite risk for various countries studied and they found significant risk factors. Ono (2011) and Lin et al. (2007) tried to look for the impact of the macroeconomic variables on the stock markets. The studies discussed above focus on the global financial crisis in general, it tries to answer the questions like impact of GFC and changes in the behaviour of the stock market after the happening of the BRICS stock market, changes in the pattern of the co-movement among the markets. In addition, the behaviour of the stock and bonds markets of BRIC markets are captured by Bianconi et al. (2013) while the study found that in the long-run BRIC bond and stock markets deviate among themselves from US financial stress measures. The dynamic conditional correlation among them increased after the global financial crisis.

The existence of contagion among the US and Indian stock markets was proved by the DCC-GARCH model in a bivariate case, the correlation among the markets increased during the crisis period as compared to the pre-crisis period (Chittedi, 2015). Whereas, Gahlot and Datta (2012) examined the impact of futures trading on the volatility and efficiency of the stock market and the day of the week effect in the BRIC stock market. The result of the study indicates that future trading led to a reduction in the volatility of the Indian stock market. There is some evidence of the presence of the day-of-the-week effect in the Indian stock market. While Boubaker and Raza (2017) investigate the spillover effect of volatility and shocks between oil prices and the BRICS stock markets. It was found that oil price and stock market prices are directly affected by their news and volatility and indirectly spillover effect was decomposed into many sub-spillovers on different time scales according to heterogeneous investors and market participants. Whereas, Adu et al. (2015) studies the pattern of the stock returns distribution of the emerging market economies and they exhibit patterns that are distinctively different from developed countries: returns are noted to be highly volatile and auto correlated and long-horizon returns are predictable. This study questions the rationale behind this supposition and proceeds to test more formally for normality using the multivariate joint test for skewness and kurtosis. The results of the study exhibit the following results that the distribution of stock returns for the BRICS exhibits peachiness with fatter and longer tails and this is invariant to both the unit of measurement and the time horizons of returns. Volatility clustering is prevalent in all markets and these decays exponentially for all but Brazil. The relationship between risk and return is found to be significant and risk premiums are prevalent in the sample of the study.

Aggarwal and Tiwary (2022) studied how deregulation affected the transfer of volatility between Indian stock markets and worldwide oil prices. The results demonstrate that despite oil price deregulation, the long-term spillover of oil prices on stock markets also persists as a result of ongoing interventions in the form of taxation adjustments and price freezes during elections. Yi et al. (2022) used the heterogeneous autoregressive (HAR) model and other extended models to predict the realised volatility (RV) of the Chinese stock market. According to the findings, the aggregate volatility data from the G7 stock markets strongly predicts the volatility of the Chinese stock market. In the context of COVID-19 in India, Naik et al. (2021) investigated the investing activities of institutional investors and the effect of their trading approaches on market volatility. It specifically aims to provide a thorough study of local and overseas mutual fund managers' (MFs) investing in equities and debt instruments. It was discovered that the development of COVID-19 had no impact on stock market volatility during the research period. Specifically, the results show that the FPI's total trading operations in debt instruments and its net sales of shares have a beneficial influence on market volatility. Further research demonstrates that while the MF's trading strategy has no effect on market volatility, the FPI's momentum buys and contrarian sales do. Ferreira et al. (2021) examined how investor emotions affected the Brazilian stock market's volatility. In particular, it sought to determine if asymmetric sentimental behaviour may be seen in emerging markets while taking into account enterprises with challenging features. The findings show that mood has a negative and substantial link with market volatility in Brazil as well as evidence of an asymmetrical behaviour, with pessimistic times statistically showing a greater tendency. The explanatory sentiment capacity is sensitive to the features of the firms, according to further analyses.

Li et al. (2021) described an empirical link between COVID-19 fear and stock market volatility. Studying COVID-19 fear with stock market volatility is crucial for planning adequate portfolio diversification in international financial markets. The study used AR (1)–GARCH (1, 1) to measure stock market volatility associated with the COVID-19 pandemic. Our findings suggest that COVID-19 fear is the ultimate cause driving public attention and stock market volatility. The results demonstrate that stock market performance and GDP growth decreased significantly through average increases during the pandemic. Further, with a 1% increase in COVID-19 cases, the stock return and GDP decreased by 0.8%, 0.56%, respectively. Gao et al. (2021) compared the effects of COVID-19 on stock market volatility between the USA and China using an unique wavelet-based quantile-on-quantile approach. This study's findings show the variations in financial market reaction to various epidemic management strategies. A loose monetary policy may be an effective way to stabilise the market given that COVID-19 is not being adequately regulated. Kusumahadi and Permana (2021) sought to investigate how COVID-19 affected stock return volatility over 15 different nations. The study concludes that changes in exchange rates have significantly impacted stock returns in the majority of nations using daily data from January 2019 to June 2020. The study also noted structural alterations during the observation period; these alterations take place earlier in the time frame as well as after the initial COVID-19 instance. With the exception of the UK, the study found evidence that the development of COVID-19 had an impact on stock return volatility. This evidence comes from threshold generalised autoregressive conditional heteroskedasticity regressions. Additionally, we discover that the presence of COVID-19 in a nation has a favourable impact on return volatility. Wang et al. (2021) proposed a two-phase flow model under the premise that stock and capital flows control stock price and return volatility. Computer models indicate that collective and monodirectional capital or stock movements have varied effects on stock return volatilities. Magnani et al. (2021) sought to analyse the connection between monetary and fiscal credibility and the volatility of the Ibovespa index of the Brazilian stock market. The findings show that macroeconomic indicators are more predictable and stable and those economic agents have higher trust in the Brazilian stock market the more credible the target set by the Brazilian Central Bank is. Engelhardt et al. (2021) if trust influences stock market volatility globally during the COVID-19 epidemic has been explored. Using a sample of 47 national stock markets, we discover that high-trust nations had much-reduced stock market volatility (in reaction to COVID-19 case announcements). Trust in both the governments of the nations and in one's fellow people is crucial. Wu et al. (2021) expanded the realised EGARCH-MIDAS (REGARCH-MIDAS) model to include implied volatility (IV), which is generated from option pricing. We are now able to investigate the additional information content of IV for volatility predictions. IV includes useful information for predicting volatility, according to an empirical study using the S&P 500 index. Compared to the EGARCH, REGARCH, REGARCH-MIDAS, EGARCH-IV, and REGARCH-IV models, our suggested model anticipates out-of-sample volatility with more accuracy.

The review of the earlier studies states that few studies focus on the asymmetric volatility and leverage effect of the BRICS stock markets in the period of the study. Earlier studies have examined the asymmetric volatility in the emerging market of the world, but the BRICS stock market has not been captured in this context. So, this study tries to examine the leverage effect in the BRICS stock market using the asymmetric GARCH model.

3 Data description and preliminary analysis

The dataset considered in this empirical study consists of daily closing prices of stock indices of each of the BRICS stock markets, which are collected from Bloomberg Database. For each of the countries there respective indices are taken into consideration: BOVESPA (Brazil), MICEX (Russia), SENSEX (India), SHCOMP (China) and JALSH (South Africa). The returns for each indices are calculated by taking the natural logarithm of the current day closing prices with the previous day closing price. The return of the daily closing prices is calculated to make stock prices unit free.

The stock market closing price returns (r_t) are computed as follows:

$$r_t = 100 * \ln\left[\frac{P_t}{(P_t - 1)}\right] \tag{1}$$

where P_t is the closing stock price index for the stock market at time t. r_t is the stock market return. The time period of the study stretch from 1st January 2004 to 31st December 2018. Only common trading days are considered excluding all the holidays, weekends and other non-trading days from the sample (Wang and Firth, 2004).

3.1 Descriptive statistics

The summary statistics of daily closing returns of our five indices are reported in Table 1. The returns are heavy tailed with kurtosis more significant than a normal distribution. Where, Jarque-Berra test confirms the leptokurtosis behaviour of our digital currencies.

Table 1 provides the descriptive statistics of the daily return of all the indices under the study. The median daily return for Micex is highest of all the indices. The mean daily return of Sensex is highest of all the indices. Sensex seems to be more volatile among all the other indices. Higher daily standard deviation for all the indices points towards a higher risk in the Indian stock market compared to the other indices in the study. Jarque-Bera statistics confirm the significant non-normality in the daily return of all the indices. The significant and negative skweness and excess kurtosis is displayed by all the indices. Hence, displaying highly leptokurtic relative to a normal distribution. The ARCH-LM test provides evidence in support of the presence of conditional heteroskedasticity in both level and return series, so the data is good to go for further volatility modelling.

Figure 1 presents the daily closing prices for the five indices. The price series of the all the five countries are plotted on the figure 1 representing the data at level is not mean reverting. Hence, the data are not stationary.

Table 1 Statistical properties of daily return basic descriptive statistics

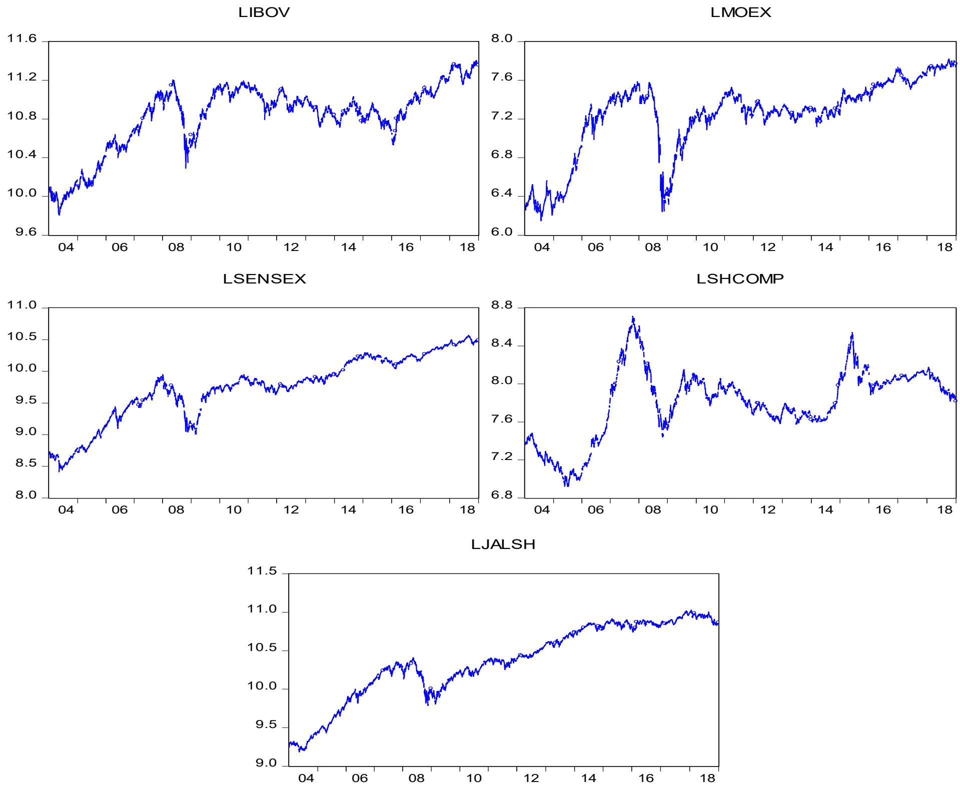
		BOVESPA	*MICEX*	*SENSEX*	*SHCOMP*	*JALSH*
Level data	Mean	10.83	7.23	9.74	7.81	10.36
	Median	10.91	7.31	9.80	7.87	10.37
	SD	0.344	0.39	0.51	0.36	0.48
	Skewness	–1.02	1.13	–0.69	–0.41	0.65
	Kurtosis	3.43	3.44	2.81	2.93	2.58
	JB	677.63	821.85	307.49	106.26	295.13
		(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*
	Observations	3,738	3,738	3,738	3,738	3,738
Differenced data	Mean	0.034	0.04	0.05	0.01	0.04
	Median	0	0.07	0.02	0	0.042
	SD	1.72	1.98	1.42	1.62	1.18
	Skewness	–0.011	0.21	–0.02	–0.47	0.189
	Kurtosis	8.92	24.19	14.02	8.27	6.95
	JB	5,461.08	69,966.74	18,893.07	4,463.46	2,456.56
		(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*
	Observations	3,737	3,737	3,737	3,737	3,737
Panel B: conditional hetroscedasity						
ARCH LM test		90.093	57.808	169.568	84.116	176.360
		(0.00)*	(0.00)*	(0.00)*	(0.00)*	(0.00)*

Notes: JB statistic is the Jarque-Bera test for normality. SD stands for standard deviation. The value in the parenthesis is the P-value. * shows the level of significance at 1% and better.

Source: Author's calculation

Figure 1 presents the daily returns for the five indices. The attribute of volatility clustering is shown by daily return, as they oscillate around zero. In 2007–2009 higher volatility is demonstrated by all returns. Figure 1 plots the daily returns for stock markets. The lower panel showed that during the period of investigation, all of the BRICS stock markets have related trends. Unit mid-2008, all the stock markets increased continuously, interestingly. Due to the global financial crisis in late 2008 and 2009, stock markets experienced a sharp fall. Afterward, followed by a downward phase, these markets experienced an upward trend.

Figure 1 Daily closing prices of five stock indices (see online version for colours)



3.2 *Testing for stationary*

The conventional unit root test is reported in Table 2 and the results of the stationarity test of stock indices series – the tests conducted with intercept, with both intercept and trend, and without intercept. The Phillips and Perron (PP) (1988) augmented Dickey and Fuller (ADF) (1979, 1981), and Kwiatkowski et al. (KPSS) (1992) tests are the three alternatively tests employed. At the 5% level of significance, the ADF and PP test displayed that all the series of stock indices are non-stationary at level, and at the first difference they are stationary. Hence, the series integrated order one I (1). Finally, to provide robust results, the KPSS test for the null of level or trend stationery against the alternative of non-stationary is also applied. However, the KPSS test indicates that series are I (1) when the first difference of each stock price index is taken.

Table 2 Unit root tests

		BOVESPA	*MICEX*	*SENSEX*	*SHCOMP*	*JALSH*
Level data	ADFc	0.31	0.23	0.54	0.46	0.22
	ADFτ	0.39	0.28	0.32	0.84	0.41
	PPc	0.36	0.25	0.57	0.41	0.17
	PPτ	0.49	0.34	0.40	0.79	0.54
	KPSSc	4.03	4.28	6.74	2.26	7.12
	KPSSτ	1.048	0.39	0.55	0.52	0.60
Differenced data	ADFc	0.0001*	0.00*	0.0001*	0.0001*	0.00*
	PPc	0.00*	0.0001*	0.0001*	0.0001*	0.0001*
	KPSSc	0.09**	0.09**	0.08**	0.13**	0.30**

Notes: * and ** indicates significance at 1% and 5% respectively, ADFc and ADFτ are the standards augmented Dickey-Fuller (ADF) test statistics and Phillips-Perron (PP) test statistics when the relevant auxiliary regression contains a constant and a constant and trend, respectively.

Source: Kwiatkowski et al. (1992)

4 Econometric framework and methodology

4.1 Unit root test

The series is said to be stationary if the mean and variance of that series and auto-covariance of the series remain constant over time. If a series is following a random walk process, it must be stationary. The series which are observing these properties is called a stationary time series. The series that is stationary at the level is integrated of order zero [I (0)]. The unit root test check for the series is stationary or not. A combination of the augmented Dickey-Fuller (ADF) and Dickey and Fuller (1979) unit root test is used to check the order of integration among the markets. It also employed the Phillips-Perron (PP) stationarity test and the alternative Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test. Three tests have been used to check the consistency of the result.

4.2 E-GARCH model

The basic limitation of the GARCH models is that they take only a symmetric element of the volatility into consideration despite the effect of positive and negative shocks. The conventional GARCH models propounded by Bollerslev (1986) take conditional variance as a function of the magnitude of the lagged residuals and do not take their sign since squaring the lagged error, a sign is lost. Whereas, it has been stated that a negative shock to the stock prices is likely to increase volatility more than the intensity of the positive shock (Brooks, 2008).

The exponential GARCH or the E-GARCH model was propounded by Nelson (1991). The conditional variance equation is defined as:

$$\ln\left(\sigma_t^2\right) = \omega + \beta \ln\left(\sigma_{t-1}^2\right) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}}\right] \tag{2}$$

The model stated above captures the asymmetric response of time-varying variance to shocks and at the same time ensures that the variance is always positive. Whereas, in equation (2) γ is the leverage or the asymmetric response parameters. In most of the cases γ is expected to be positive so that a negative shock increases the future volatility or uncertainty while a positive shock eases the effect on future uncertainty. In financial time series analysis, a negative shock mostly implies bad news, leading to more uncertain future (Wang, 2003).

4.3 GJR-GARCH model

It is the simple extension of the basic GARCH model with an additional term that take in to account for asymmetries in the volatility of financial time series, pounded by Glosten et al. (1993). The GJR-GARCH model is also known as TGARCH model or threshold GARCH The conditional variance is defined as

$$\sigma_t^2 = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma u_{t-1}^2 I_{t-1} \tag{3}$$

where

$$\begin{aligned} I_{t-1} &= 1 \text{ if } u_{t-1} < 0 \\ &= 0 \text{ otherwise.} \end{aligned}$$

To capture leverage effect, $\gamma > 0$. The condition for the non-negativity will be $\alpha_0 > 0$, $\alpha_1 > 0$, $\beta \geq 0$, and $\alpha_1 + \gamma \geq 0$. GJR showed how the effect of bad and good news to have different effect on the volatility. If $u_{t-1} = 0$ it is a threshold, that shocks greater than the threshold value it would have a different effect than the shock below the threshold. Whereas I_{t-1} is a dummy variable that is equal to one if $u_{t-1} < 0$ and is equal to zero if $u_{t-1} \geq 0$.

The positive value of u_{t-1} are associated with a zero value of I_{t-1}. So, if $u_{t-1} \geq 0$, the effect of an u_{t-1} shock on σ_{t-1}^2 is a $\alpha_1 u_{t-1}^2$. Whereas, when $u_{t-1} < 0$, $I_{t-1} = 1$, and the effect of an u_{t-1} shock on σ_t^2 is $(\alpha_1 + \gamma)\, u_{t-1}^2$. If $\gamma > 0$, negative shocks will have larger effect on volatility than positive shocks.

The term γI_{t-1} allows for good news when $u_{t-1} > 0$ and bad news $u_{t-1} < 0$, to impact the conditional variance differently. Where, α_1 represent the impact of good news and $(\alpha_1 + \gamma_1)$ represents the impact of bad news on conditional volatility. So, if $\gamma_1 > 0$ then the GJR-GARCH model can capture the asymmetric property of volatility.

The primary limitation of the basic GARCH model is that they enforce a symmetric response of volatility to positive and negative shocks. Whereas, it is every argued that a negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude.

5 Empirical results and discussion

This section reports the results and findings of the objectives of the study. Before moving into further modelling of the volatility it is the basic pre-condition that the data are displaying ARCH effect in them.

Table 3 E-GARCH (1, 1) results

Variable	*Brazil*	*Russia*	*India*	*China*	*South Africa*
			Panel A		
Mean					
μ	0.029	0.055	0.056	0.032	0.035
	(0.228)	(0.008)*	(0.000)*	(0.063)***	(0.017)**
Variance					
ω	–0.057	–0.136	–0.121	–0.080	–0.089
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
α	0.100	0.209	0.171	0.117	0.115
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
β	0.980	0.978	0.983	0.994	0.984
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
$\alpha+\beta$	1.080	1.187	1.153	1.112	1.099
γ	–0.058	–0.047	–0.069	0.005	–0.094
	(0.000)*	(0.000)*	(0.000)*	(0.128)	(0.000)*
			Panel B		
Log-likelihood	–6,934.253	–6,857.324	–5,831.338	–6,509.567	–5,319.583
SIC	3.714	3.681	3.132	3.495	2.858
JB-stat	1,109.794	6,366.370	2,455.500	1,521.964	166.009
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
Q (20)	18.802	5.769	53.321	37.883	23.421
	(0.535)	(0.999)	(0.000)*	(0.009)*	0.269
Qs (20)	13.459	5.862	47.783	30.706	26.085
	(0.857)	(0.999)	(0.000)*	(0.059)**	(0.163)
ARCH-LM (5)	0.897	0.807	0.650	4.429	1.112
	(0.482)	(0.544)	(0.662)	(0.001)*	(0.352)
ARCH-LM (10)	0.715	0.419	4.325	2.503	1.710
	(0.711)	(0.938)	(0.000)*	(0.005)*	(0.073)***

Notes: The value in the parenthesis is the p-value. JB stands for Jarque-Bera test, SIC stands for Swartz Bayesian criterion, Q and Qs stands for Ljung Box and Ljung Box square statistics. *, ** and *** denotes rejection of the null hypothesis at 1%, 5% and 10% level respectively.

Source: Author's calculation

The result reported in Table 1 states that for all the five indices of the BRICS countries display that they show strong evidence of the presence of ARCH effect in the data. Hence, the series are good to go for volatility modelling.

5.1 E-GARCH (1, 1) results

To capture the impact of bad news on the stock and to see whether the impact is more pronounced than the good news. Table 3 displays the results of the EGARCH model capturing the leverage effect in the BRICS stock markets, i.e., the tendency of the volatility to decline when returns rise and to rise when the returns fall (Taylor, 1986).

The mean equation in Table 3 is μ is constant and in the variance equation, ω denotes the constant term, α denotes the ARCH term and the GARCH term is denoted by β, where γ denotes the asymmetry term. The coefficient of α and β captures the lagged conditional variance and the squared disturbance term have an impact on the conditional variance when they are significant. The previous period's news volatility has an effect on the current period's volatility. The volatility persistence is calculated in each market by $\alpha + \beta$, i.e., the ARCH and GARCH coefficients. The sum of the two estimated coefficients is larger than one for all the five indices, i.e., BOVESPA, MICEX, SENSEX, SHCOMP, and JALSH indices, suggesting shocks to conditional variance are highly persistent and tend to be explosive. They exhibit volatility clustering characteristics in all the five BRICS stock market, i.e., high returns tend to be followed by large changes and small changes in the return is followed by small changes.

The asymmetric (leverage) term captured by the parameter of γ is statistically significant for all the indices at a 1% level of significance except in the case of the Chinese stock market whereas, all the indices show negative signs except that of the Shanghai composite index. The negative shocks imply a higher next-period conditional variance than the positive shock of the same sign as is the case of the Chinese market.

Panel B of Table 3 reports the diagnostic test of the model. There is no ARCH effect left at lag 5 and at lag 10 for all the indices except in the case of the Chinese market. In Shcomp series reject the null of no ARCH effect at 1% level of significance. Whereas, the Ljung Box Box Q test for the null of serial correlation is not rejected at lag 5 at any level of significance, and at lag 10 they does not stand rejected at any level of significance for all the five series except in the case of India and China.

5.2 GJR-GARCH results

The results of the GJRGARCH model are presented in Table 4. The estimated TGARCH (1, 1) model coefficient of leverage effect is significant at 1% level of significance and positive for all the indices except for the Shanghai composite index, which means the asymmetry effect is present during the period of the study and the results of the TGARCH is consistent with the EGARCH model, i.e., bad news has more impact on the volatility of the Brazil, India, Russia and South Africa stock markets, than positive shocks of the same magnitude. China's market display opposite results but the coefficient are not significant at any level of significance.

The result of the GARCH is significant for all the five indices displaying previous day volatility is affecting today's volatility and the coefficient of the GARCH is higher than the ARCH term for all the five indices. The significant leverage term indicates that the positive and negative news doesn't have similar results for all the four markets. Hence, the result of four markets substantiates the previous results by Adu et al. (2015) of negative news having more impact on volatility than positive news.

Table 4 GJRGARCH (1, 1) results

Variable	*Brazil*	*Russia*	*India*	*China*	*South Africa*
			Panel A		
Mean					
μ	0.024	0.060	0.058	0.021	0.034
	0.317	(0.006)*	(0.000)*	0.271	0.213
Variance					
ω	0.065	0.064	0.024	0.008	0.018
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
α	0.015	0.068	0.037	0.055	0.007
	(0.011)**	(0.000)*	(0.000)*	(0.000)*	(0.237)
β	0.922	0.878	0.904	0.947	0.918
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
$\alpha+\beta$	0.922	0.946	0.904	1.001	0.925
γ	0.075	0.066	0.091	–0.004	0.117
	(0.000)*	(0.000)*	(0.000)*	0.338	(0.000)*
			Panel B		
Log-likelihood	–6,920.422	–6,840.936	–5,821.590	–6,510.776	–5,213.570
SIC	3.715	3.672	3.127	3.496	2.859
JB–stat	871.859	6,263.317	2,146.726	1,452.602	165.267
	(0.000)*	(0.000)*	(0.000)*	(0.000)*	(0.000)*
Q (20)	17.662	5.523	51.303	39.449	21.180
	(0.610)	(0.999)	(0.000)*	(0.006)*	(0.387)
Qs (20)	13.243	4.050	29.897	20.339	23.512
	(0.867)	(1.000)	(0.072)***	(0.437)	(0.264)
ARCH-LM (5)	1.091	0.416	0.874	2.139	1.743
	(0.363)	(0.838)	(0.498)	(0.058)***	(0.121)
ARCH-LM (10)	0.689	0.232	2.722	1.371	1.604
	(0.736)	(0.993)	(0.003)*	(0.187)	(0.099)

Notes: The value in the parenthesis is the p-value. JB stands for Jarque-Bera test, SIC stands for Swartz Bayesian criterion, Q and Qs stands for Ljung Box Q and Ljung Box Q square statistics. *, ** and *** denotes rejection of the null hypothesis at 1%, 5% and 10% level respectively.

Source: Author's calculation

The volatility persistence in the return of each series is calculated as $\alpha+\beta$ from Table 4. The parameter α denotes the ARCH term and β denotes the GARCH term. The volatility is said to be persistent if $\alpha+\beta$ is close to one, if it is less than unity it is less persistent and greater than one leading to explosive volatility (Adu et al., 2015). The result of the study found strong volatility persistence in the case of Brazil (0.922), Russia (0.946), India (0.904), and South Africa (0.925) whereas China (1.001) shows evidence of explosive volatility. Thus, the result of the study states that in the case of BRICS countries except in the case of China all other countries show strong evidence of long memory in their respective return series, and shocks to volatility do not tend to decay very quickly stating previous volatility do have a strong predictive power on the current volatility of the respective countries.

Panel B of Table 4 reports the diagnostic test of the model. There is no ARCH effect left at lag 5 and at lag 10 for all the indices except in the case of India (at lag 10) and China (at lag 5) market. In Shcomp series reject the null of no ARCH effect at 1% level of significance. Whereas the Ljung Box Box Q test for the null of serial correlation is not rejected at lag 5 at any level of significance, and at lag 10 they do not stand rejected at any level of significance for all the five series except in the case of India and China.

While, comparing which among the two model best capture the asymmetric volatility in the case of Brazil, Russia, China, and South Africa EGARCH model give the best predictability since the SIC criteria is giving a lower value in the EGARCH model. Whereas, in the case of India GJRGARCH or TGARCH model captures the best.

6 Summary and concluding remarks

The capturing of the volatility of the stock market has always remained pivotal among the researchers of the financial market. Black (1976) firstly mentioned the leverage effect in the volatility of the financial market, after a number of researchers have tried to capture the volatility in general and asymmetric volatility in particular among the stock market of the world to look at which model captures the best asymmetric volatility. The emerging and the developed market has been a lot captured by a number of researchers after the coining of the term BRICS by O'Neill (2002), these countries have gained an enormous amount of attention among the researches. But so far there are least researches that have captured asymmetric volatility among the BRICS stock market in the univariate framework from January 2004 to December 2018.

This study empirically modelled the asymmetric volatility of returns in the BRICS stock markets using daily data. The methodology used in the study to achieve the objective of the study is the EGARCH model by Nelson (1991) and the GJR-GARCH model by Glosten et al. (1993) to estimate the volatility of the BRICS stock market and to capture the leverage effect in the univariate framework. Results of both models provide strong evidence presence of asymmetric volatility in the BRICS stock market that bad news has more impact on the volatility of the market than good news except in the case of the Chinese stock market which displays a different result. There is evidence of the presence of strong volatility persistence in the case of BRICS countries except in the case of China. Where all other countries show strong evidence of long-memory in their respective return series, shocks to volatility do not tend to decay very quickly stating previous volatility does have a strong predictive power on the current volatility of the respective countries. China's stock market gives evidence of explosive volatility.

These findings have important implications for regulators and the investment community at large. The study argues that higher volatility corresponds to a higher probability of a declining market, while lower volatility corresponds to a higher probability of a rising market. Investors can use this data on long-term stock market volatility to align their portfolios with the associated expected returns. Among both of the model used in the study EGARCH model capture the leverage effect more effectively in comparison to the threshold GARCH model. So, further studies involved in the forecasting of the return and volatility can use the EGARCH model for further analysis.

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