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Volatility of Returns in Stock Market Investments: A Study of BRICS Nations

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ABSTRACT

Fluctuations in returns from investment in stocks make these risky. This factor should be kept in mind in stock investment decisions, which determines the relevance of this research. Through the study, the volatility in the stock returns of BRICS nations is analysed for inferring on the riskiness associated with investing in the respective nations, which is the **aim** of the research. For this study, the daily returns of five indexes representing each of the nation namely Ibovespa (Brazil), Moex (Russia), Nifty 50 (India), Hang Seng Index (HSI, China), and FTSE/JSE All Share Index (JALSH, South Africa) for a period of 14 years are collected and analysed. Both unconditional and conditional volatility in returns is analysed for each of the nations for imparting clearer and more comprehensive picture of the volatility in returns. Such an in-depth and long period analysis of volatility of the returns of the emerging BRICS economies is a **novelty** of the research that determined that no volatility model can be said as perfect for all economies for all time. The GARCH (1, 1) model was used to study for the returns of all the five indexes. The **results** of the study point out that the daily returns of all these indexes are heteroscedastic, implying presence of varying variance. Accordingly, the study **concludes** that the BRICS nations' index returns are more volatile and riskier, and authors are **recommended** to invest in those indexes with lesser conditional volatility.

Keywords: BRICS; risk; stock return; volatility forecasting; volatility of stock

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INTRODUCTION

Investment in stock market is one of the decisions that one takes with at most diligence. It is because of the inherent nature of risk in investing in equity. Among the investment avenues, equity investment can be considered as the riskiest as there is higher uncertainty in its returns. The return expected from equity and the actual return may vary, since the future is uncertain. If the actual return is same as the expected return, then the investor is satisfied. In other case, if the actual return is greater than what is expected, then the investor is overwhelmed with gain. However, if the actual return is less than the expected return, the investor faces loss. Thus, the uncertainty that the actual return can be less than the expected return is called the risk in investment.

One significant factor that contributes to this risk is the volatility in the returns. Volatility is usually termed as the degree of variation in the stock prices. The volatility may be positive/negative, normal/abnormal or conditional/unconditional. When volatility leads to rise in returns, then it is positive volatility. On the other hand, if volatility leads to fall in returns, it is negative volatility. Abnormal volatility happens as a consequence of any abnormal events that can affect the stock market.

Unconditional volatility refers to the fluctuations in the returns that are not dependent or conditional upon any other factors and it can be measured through the standard deviation and variance. Conditional volatility means that the variance of the returns is conditional to its past residuals or its own past variance. In that case, the variance calculated assuming unconditional volatility would not suffice to measure the actual volatility. This conditional variance is what the investors are more concerned about. Hence, it is the aspect of conditional variance that should be addressed and studied.

SIGNIFICANCE OF THE RESEARCH

In the present research an attempt is made to analyse the volatility patterns of the returns on investments in stock markets in the BRICS nations. The BRICS are the association of the five emerging economies of the Federative Republic of Brazil, the Russian Federation, the Republic of India, the People's

Republic of China and the Republic of South Africa. The first BRICS summit held in 2009 laid down the goals of the BRIC as "to promote dialogue and cooperation among our countries in an incremental, proactive, pragmatic, open and transparent way. The dialogue and cooperation of the BRIC countries is conducive not only to serving common interests of emerging market economies and developing countries, but also to build a harmonious world of lasting peace and common prosperity"[1]. The rationale for selecting BRICS nations is because of the fact that, they contribute considerably to the global economy. While considering Gross Domestic Product (GDP) in 2013, BRICS contributed about 27% of the global GDP.[2] The five BRICS nations together constitute a major part of the world population. It is 42% of the world population in 2013. Thus, deciding upon a stock investment in BRICS nations based on the risk involved in it, which in turn can be inferred through volatility analysis constitutes both the significance and scope of this research. The volatility analysis of stock returns involves the analysis of both conditional and unconditional variance of the daily returns of the selected stock indexes.

Stock indexes representing BRICS nations for a period of fourteen years were collected and used for analysis in this research. The indexes representing BRICS nations selected for the study include Ibovespa (Brazil), Moex (Russia), Nifty 50 (India), Hang Seng Index [HSI (China)], and FTSE/JSE All Share Index (JALSH, South Africa).

REVIEW OF LITERATURE

Various academicians all over the world have contributed to the literature related to volatility of returns. R.F. Officer studied the 1930s high volatility stressing on leverage effect along with the volatility of industrial production [1]. R. Merton introduced an inter-temporal Capital Asset Pricing Model (CAPM) giving due consideration to the volatility in the assets [2]. However, traditional volatility measures assumed constant variance and various econometric methods were developed based on it.

It was then that R.F. Engle introduced a new set of stochastic processes, namely Autoregressive Conditional Heteroscedasticity (ARCH) processes. These processes have an expected mean of zero, serially uncorrelated, but variances are non-constant and conditional upon the past. He also developed a regression model for measuring such processes [3]. The ARCH model of Engle assumed the variance to be conditional upon the past error squares only. T. Bollerslev introduced a more generalized ARCH model (GARCH) where the variance is conditional upon not only the past errors, but also its own past variances. The number of lags to be taken for errors and variance depends on the series to which the model is applied. However, pursuing to the principle of parsimony, GARCH (1, 1) model can fit almost all symmetrical distributions [4].

A symmetric ARCH model assumes that volatility is higher in a falling market than in rising market, which is mentioned as the leverage effect. But sometimes, responses can be viewed as in the work of R.F. Engle and V.K. Ng, where they provided a news impact curve in asymmetric response to good and bad news [5]. Engle (1990) had developed an Asymmetric GARCH (AGARCH) model [6].[1] The significant asymmetric models are Threshold ARCH (TARCH) developed by J-M. Zakoian and Exponential GARCH (EGARCH) model developed by D.B. Nelson [7, 8]. D.B. Nelson also developed GARCH-M and IGARCH. L. Glosten et al. developed the Threshold GARCH (TGARCH) model [9]. S. Taylor and G.W. Schwert developed Power GARCH (PGARCH) [10, 11]. All these models were developed in order to capture the volatility in all the varying possibilities.

Academicians and researchers have employed several of these models in their studies worldwide. G. Ogum analysed the volatility in the Kenyan and Nigerian market using EGARCH model [12]. E. Balaban and A. Bayar used both symmetric and asymmetric ARCH models to capture the volatility in fourteen countries [13]. J.Y. Uppal and I.U. Mangla made an effort to compare the Bombay Stock Exchange (BSE) and Karachi stock exchange (KSE) in terms of market volatility using GARCH-M [14]. P. Dennis et al. examined both implied volatility innovations and asymmetric volatility phenomenon for the S&P 100 index and 50 large U.S. firms [15].

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[1] History of BRICS. BRICS Information Portal. 2015. URL: https://infobrics.org/page/history-of-brics/ (accessed on 20.06.2020); Joint Statement of the BRIC Countries' Leaders (Yekaterinburg, Russia, June 16, 2009). BRICS Information Portal. 2015. URL: https://infobrics.org/document/3/ (accessed on 20.06.2020).

H. Guo and R. Savideas studied the idiosyncratic volatility in G7 countries [16], while D. Alberg, H. Shalit and R. Yosef estimated the volatility in Tel Aviv stock exchange [17]. C. Tudor studied the Romanian market volatility and found that EGARCH fitted well for the market [18]. S.M. Bartram et al. observed that the volatility of U.S. firms was higher mostly because of good volatility [19]. Y. Wang and C. Wu forecasted the energy market volatility using univariate and multivariate GARCH models [20]. C.M. Lim and S.K. Sek employed both symmetric and asymmetric GARCH to analyse the volatility of the Malaysian market [21].

The research thesis of K.B. Nalina was an exploratory to analyse the Indian stock market volatility [22] using the methodology suggested by J.Y. Campbell et al. [23]. Q. Zhang and S. Jeffry studied the volatility spill over between Mainland China and Hong Kong stock market [24]. M. Tamilselvan and S.M. Vali forecasted volatility [25] while P. Sharma and Vipul forecasted the stock market volatility based on international evidence using realized GARCH models [26].

A. Moriera and T. Muir claim that the volatility-managed portfolios increases Sharpe ratio, and provide many gains to the investors [27]. Equity volatility has been analysed with various possibilities by several authors like D. Carvahlo [28]. H.N.D. Seoane found a positive correlation between the sovereign income and the volatility after studying several European economies during debt crisis [29]. In the latest study of T. Bollerslev et al., a new factor-based estimator for high dimensional and multivariate volatility is introduced [30]. In a study of R. Selmi et al., it was noted that globalisation and trade openness amplify the international transmission of the volatility [31].

There were several attempts to capture the volatility in the BRICS nations by the academicians including that of N. Kishor and R.P. Singh [32] and C.B. Hunzinger et al. [33]. An investigation into the relation between the BRICS stock market and commodity futures market was made by S.H. Kang et al. using the Fractionally Integrated Asymmetric Power ARCH (FIAPARCH) model [34]. A wavelet analysis of mean and volatility spill overs between the oil and the BRICS stock market was conducted by H. Boubaker and S.A. Raza [35].

Thus, volatility has been studied and predicted to arrive at various investment decisions and to arrive at conclusions on economies. Various volatility models were fitted by the academicians all over the world to determine the most apt one for volatility analysis. However, there is no single model that can be said as apt for all stock markets or all economies. It depends on the market on which the study is being conducted. This fact itself points out the need for studying the volatility of the various economies to contribute to the investors and the literature alike. Hence, the present study intends to analyse the volatility patterns of BRICS, an emerging nations' association and to fit an appropriate volatility model for those nations under the current scenario.

STATEMENT OF THE PROBLEM

Volatility, especially conditional volatility poses a significant problem for investors in taking investment decisions. Predicting returns from investment can be done using varying models, but how far the predictions will stand in future depends on the volatility in the returns. Even if, volatility is predicted, how long it will persist depends on the volatility persistence of the returns. Thus, it is imperative to study the volatility of stock returns and especially that of the emerging economies association like BRICS. In this backdrop, the present study has been undertaken.

OBJECTIVE OF THE STUDY

The objective of the present study is to empirically analyse the volatility features of the daily returns of investments in stock markets of the BRICS nations.

METHODOLOGY

The study was conducted with secondary data collected from the selected stock market indexes representing BRICS nations. The selected indexes for the study include indexes representing BRICS nations: Ibovespa, Moex, Nifty 50, HIS, and JALSH index respectively. The data used for analysis cover the daily price index of the selected stock indexes which were collected from the official websites of the respective stock exchanges. The data were collected for a period of fourteen years with 3441 observations.

EMPIRICAL TESTS

The data analysis was made on the basis of daily returns of the BRICS indexes. Daily returns were calculated using the following formula:

$$Return = \frac{P_1 - P_0}{P_0},$$

where P_1 is the current price and P_0 is the previous or past price. Since daily returns are to be calculated, the price of the latest day is taken as P_1 and its immediately previous price is taken as P_0.

Jarque-Bera (JB) normality test was applied to analyse the normality in the returns. The JB test statistic is worked out by using the following formula:

$$\text{Jarque-Bera test statistic} = n\left[\frac{S^2}{6} + \frac{(K-3)^2}{24}\right],$$

where n is size of the sample, S is the skewness value and K is the Kurtosis value. The null hypothesis (H_0) of the JB test statistic is that the distribution is normal.

Augmented Dickey Fuller (ADF) Unit root test was also done for the returns of all indexes to ensure stationarity in returns. The null hypothesis (H_0) of ADF test is that there is a unit root (i.e. the series is non-stationary).

Both unconditional and conditional volatility analyses were done for the BRICS indexes. The unconditional volatility was measured through standard deviation and variance of the returns. The variance is calculated using the following formula:

$$\sigma^2 = \frac{\Sigma\,(X - \overline{X})^2}{N},$$

where σ^2 is variance, X represents the stock return, $\overline{X}$ is the mean of the stock returns and N is the number of observations. It will be constant for all observations. Hence may be called homoscedastic. The variance is said to be unconditional as it is purely independent and are uncorrelated with any of the explanatory variables or its own past values. The variances of the BRICS indexes were computed and compared to state the homoscedasticity of these nations in the research.

Conditional variance is at variance which is conditional upon its own past variances or conditional upon any of the explanatory variables. Conditional variance occurs when there is heteroscedasticity in the returns. So, heteroscedasticity test (Breusch-Pagan-Godfrey Test) is carried out by obtaining residual squares from the regression of the daily returns with its own lagged returns. ARCH model was applied to measure the conditional variance in the returns. ARCH method implies the use of squared residuals obtained out of the ARCH equation which is given as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2,$$

where σ_t^2 is the conditional variance, α_0 is the constant, α_1 is the ARCH coefficient and e_{t-1}^2 is the first lag of the squared residuals. The null hypothesis of the test is that there is no heteroscedasticity.

For those indexes that were found ARCH effect were put to misspecification test. Misspecification in model refers to the situation of bias in the model out of either omission of significant independent variables or adding insignificant variables into the model. The heteroscedasticity found in a series may be due to the misspecification in some cases and that heteroscedasticity cannot be considered as true conditional variance. Thus, the misspecification test is done on the residuals, that are put to Correlogram Q-Statistic test for testing whether the series is white noise or not. White noise refers to the stationary series with a zero mean, constant variance and insignificant autocorrelation. If the series is white noise, then the heteroscedasticity is pure and not out of misspecification in the model.

If there is ARCH effect, it is possible that there could be Generalized ARCH (GARCH) effected. While ARCH measures the variance conditional upon its past errors, GARCH measures the variance that is conditional upon both past errors and its own past variance. Therefore, GARCH model was applied to the returns of the indexes to measure the conditional variance. It was T. Bollerslev [4] who developed the GARCH model as an extension of the ARCH model. The GARCH (1, 1) model that is fitted to the index returns is shown below:

$$\sigma_t^2 = \alpha_0 + \alpha_1 e_{t-1}^2 + \beta_1 \sigma_{t-1}^2,$$

where σ_t^2 is the conditional variance, α_0 is the constant, α_1 is the ARCH coefficient, e_{t-1}^2 is the one lag squared residuals, β is the GARCH coefficient (γ_1 can also be used) and σ_{t-1}^2 is the lag of variance (past variance).

Table 1

Descriptive Statistics of Daily Index Returns for 14 Years

Descriptive Statistics	Ibovespa	Moex	Nifty 50	HIS	JALSH
Mean	0.00035	0.00037	0.000366	0.00022	0.000296
Median	0.0006	0.0004	0.0006	0.0006	0.0006
Standard Deviation	0.0180	0.0194	0.0144	0.0151	0.0125
Kurtosis	9.3150	28.5965	13.2224	9.3446	5.7013
Skewness	−0.1590	0.5885	−0.0256	0.2344	−0.2881
Range	0.2943	0.4735	0.3072	0.2704	0.1725
Minimum	−0.1478	−0.1866	−0.1298	−0.1270	−0.0972
Maximum	0.1465	0.2869	0.1774	0.1434	0.0753
Jarque-bera	12 454.18	119 377.50	25 184.2	12 510.2	4768.16
Probability	0.00	0.00	0.00	0.00	0.00

Source: Calculated based on the stock price data from 1/4/2006 to 31/3/2020 collected from the official website of the stock exchanges.

From the GARCH (1, 1) model fitted for the indexes, the coefficients were analysed to measure the volatility persistence. Volatility persistence is duration that the variances take to revert to the mean. Symmetric GARCH model restricts the sum of the ARCH (α_1) and GARCH (β_1) coefficients to be less than one. If the sum of the ARCH and GARCH coefficients are greater than 0.5, then there is high volatility persistence. That means it will take more time to mean reversion. On the contrary, if the sum is lower than 0.5, then the mean reversion will be faster showing low volatility persistence. Low volatility persistence is preferred to high volatility persistence as far as the investors are concerned. The Statistical Packages used for processing the data were EViews 9 and SPSS 23.

DATA ANALYSIS AND DISCUSSION

The empirical analysis of the volatility of the returns of the selected indexes are done in three phases. The first phase constitutes the analysis of summary statistics, the second phase is the analysis of unconditional variance in the returns and the analysis of conditional variance in the returns is made in the third phase.

ANALYSIS OF SUMMARY STATISTICS

The empirical study of the daily stock market returns of BRICS nations were calculated on the indexes representing each nation namely Ibovespa (Brazil), Moex (Russia), Nifty 50 (India), HSI (China) and JALSH (South Africa). The summary statistics of the daily returns of the five indexes are given in *Table 1*.

As shown in *Table 1*, Moex has the highest mean daily return with 0.00037 while HSI has the lowest (0.00022). Similarly, the standard deviation is also high for the Moex index (0.0194) while JALSH has the lowest dispersion (0.0125). The minimum and maximum return marked in the whole return series for each of the indexes are also shown in the *Table*, from which the range within the returns are lying can be inferred. In that case, it can be noted that Moex has the widest range of 0.4735 and JALSH has the least range (0.1725). This confirms their respective measure of dispersion shown by the standard deviation.

When analysing the Kurtosis, it can be seen that the daily return distribution of all indices is leptokurtic with Kurtosis greater than 3 (*Table 1*). Also, from the *Table 1*, it can be observed that all the indexes have the presence of asymmetry. Thus, it can be rightly concluded that the daily return distributions of the selected indexes are not normal. Moreover, the JB Statistic and its probability confirm that the series are non-normal. Normality is usually expected from data in order to make sure that the conclusions drawn based on such data are valid and can be generalised. However, in case of time series data, especially stock return data, normality need not

Table 2

Augmented Dickey Fuller Unit Root Test of the Indices for 14 Years

Stock Market Indexes	Augmented Dickey-Fuller test statistic		
	Constant	Constant, Linear Trend	None
Ibovespa: t-statistic	–62.21	–62.20	–62.19
Prob.	0.00	0.00	0.00
Moex: t-statistic	–59.01	–58.99	–58.99
Prob.	0.00	0.00	0.00
Nifty 50: t-statistic	–56.56	–56.57	–56.54
Prob.	0.00	0.00	0.00
HSI: t-statistic	–59.88	–56.57	–56.54
Prob.	0.00	0.00	0.00
JALSH: t-statistic	–58.81	–58.82	–58.78
Prob.	0.00	0.00	0.00

Source: Calculated based on the stock price data collected from the official website of the stock exchanges.

be ensured. Thus, it is quite usual that the returns of the selected indices are not normal.

Table 2 shows the ADF Unit root test results of the daily returns of the indexes under three cases, wherein the first case assumes a constant, the second case assumes a constant with linear trend and the third case with none of these.

From the statistical results presented in *Table 2*, it is seen that the probability is near to zero. The null hypothesis of the ADF Unit root test is that there is a unit root, meaning the series is non-stationary. Since all the probabilities are less than 0.05, the null hypothesis is rejected and thus, the series are stationary. A series is stationary if its mean and variance are constant over time and the value of the covariance between the two time periods depends only on the distance or gap or lag between the two time periods and not the actual time at which the covariance is computed [36]. For a stationary series, the parameters will not change despite changes in time. This validates the generalisation of the inferences drawn based on the stationary series. Here, in case of all the indices representing BRICS nations, the returns are found stationary.

UNCONDITIONAL VARIANCE ANALYSIS

The foremost step in the volatility analysis constitutes the unconditional variance analysis. It is the overall and simple testing of the return series for volatility using standard deviation and variance.

The daily returns of the indexes are regressed with its own previous lag (one) for finding the unconditional variance. Then the residuals are plotted in order to view how far the returns are scattered and dispersed. The *Fig. 1* shows the residual plot of the daily returns regressed with its one lag of all the indices. From the *Fig. 1*, the overall picture of the volatility in the returns of indexes is drawn. The residuals of all the indices are highly fluctuating and deviating from their means. Moreover, it seems that there is volatility clustering in its returns. Volatility clustering, as defined by B.B. Mandelbrot is that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes" [37]. Such kind of clustering can be viewed in the residual plot of the indices.

Volatility analysis of BRICS nations can be primarily done through unconditional variance analysis. *Table 3* shows the unconditional variance of the residuals/errors of the daily returns of the indexes, assuming the volatility is unconditional.

As shown in the *Table 3*, the residuals of the Moex index have the highest variance of 0.00038. It means that the Moex index returns are more volatile. Similarly, JALSH index returns are less volatile with a variance

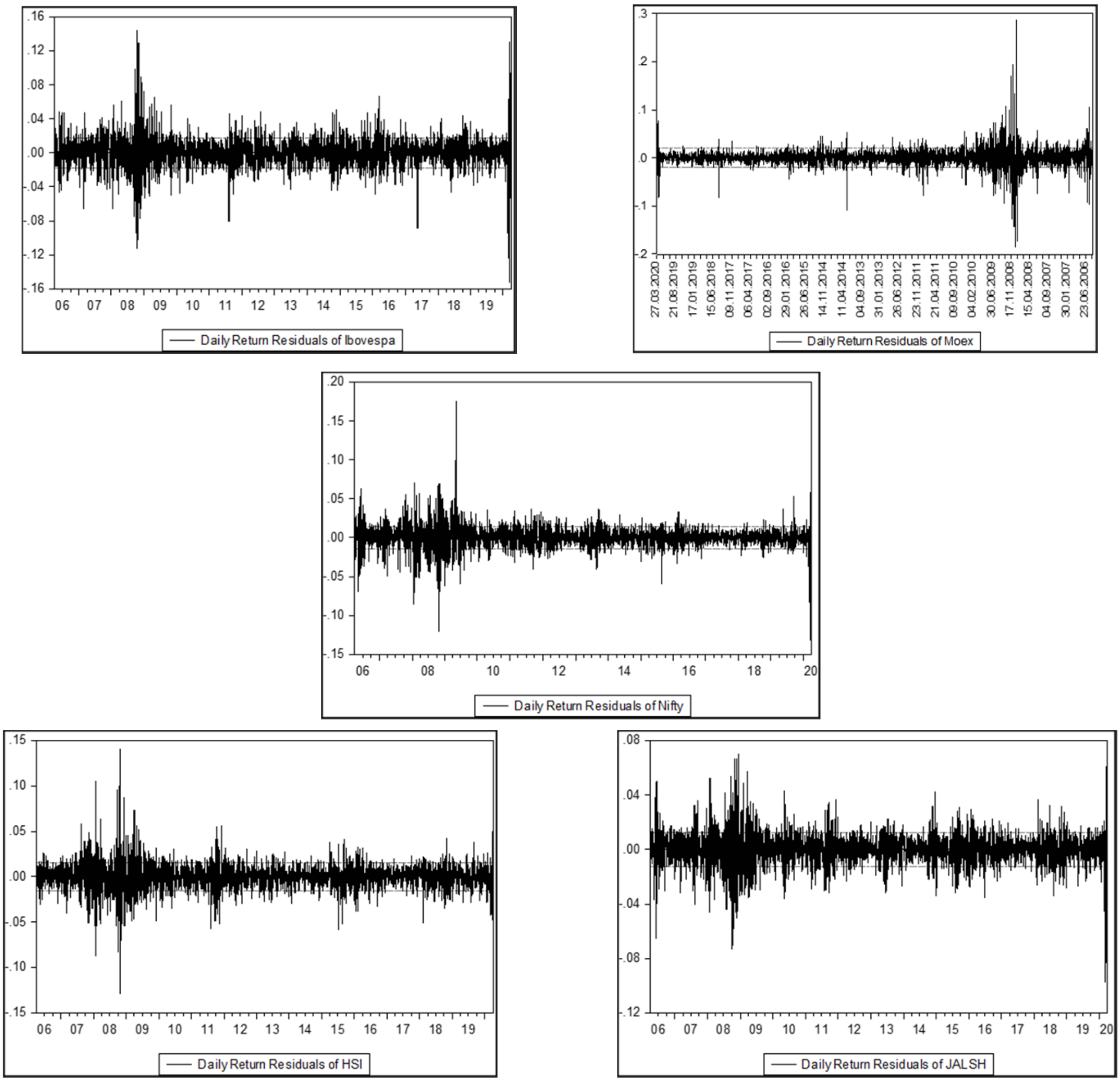

Fig. **Daily Return Residual Plot of the Indices for 14 Years**

Source: Plot generated using daily returns in EViews software.

of 0.00016. Ibovespa has a low variance compared to Moex, and greater than Nifty 50 and HSI. HSI is less volatile than Moex (0.00038) with a variance of 0.00023, but more volatile than Nifty 50.

CONDITIONAL VARIANCE ANALYSIS

The residual plot as shown in the *Figure* pointed out the volatility clustering in the returns of certain indexes. In that case, it is necessary to analyse the conditional variance of returns. Thus, heteroscedasticity needs to be tested for the returns of all indexes. Heteroscedasticity means different (hetero) dispersion (scedasticity). It implies the varying variance. Thus, there is a need to test the ARCH effect in the returns of the index to capture the whole volatility in the returns. If there is no ARCH effect, it means that there is no conditional variance and hence the unconditional variance is strong enough to measure the volatility in returns.

The ARCH variance is calculated by considering the first lag of the squared residuals obtained out of regression of the returns with its own lag. The *Table 4* shows the result of the ARCH test conducted on the daily returns of the selected indexes.

From the *Table 4*, it can be seen that the ARCH coefficient of Ibovespa is 0.3594. The t-statistic value is 22.61 and as the probability to get that value is 0.00, the null hypothesis that there is no heteroscedasticity is rejected and thus, the test is significant. It means that there exists conditional volatility in the returns of the index. It adds to the complexity in assessing the risk of the index and further, it contributes to the riskiness of investing in the Brazilian market. Similarly, in case of Moex, Nifty 50, HSI and JALSH also, the null hypothesis is rejected and there is heteroscedasticity in returns.

As shown in *Table 4*, all the five indices have significant heteroscedasticity. That is, the market is highly volatile and thus risky to invest. Only the magnitude of it varies between the indices. However, in order to ensure that the heteroscedasticity is not due to misspecification, the residuals of ARCH equation are put to the white noise test. Thus, Autocorrelation Test and the Q-Statistic along with its Chi-square probability are employed to the residuals to test whether they fit into white noise. The *Table 5* shows the result of the misspecification test done on the residuals of the ARCH regression.

The results of the residuals subjected to misspecification, as in *Table 5*, clearly point out that the residuals are purely white noise in all the cases. Thus, the heteroscedasticity found in the daily returns of the indices is pure and not out of any misspecification in the model.

Similarly, the conditional variance itself should also depend on its own, previous or past conditional variance (GARCH effect). Therefore, that variance should be integrated with the ARCH variance. Thus, GARCH (1, 1) model is applied here to find the gross conditional variance that arises due to the ARCH and GARCH effects, for the five indexes. The *Table 6* shows the result of GARCH (1, 1) model fitted to the indexes.

The *Table 6* shows the GARCH (1, 1) model fitted. A significant inference that can be made from the model is regarding the volatility persistence. If the sum of ARCH (α_1) and GARCH (β_1) coefficients is greater than 0.5, then there is greater volatility persistence. From the *Table 6*, it can be seen that the sum of the coefficients of Ibovespa is 0.9757, which is less than 1 but close to 1. It means that there is high volatility persistence. For Moex, the sum is 0.9975, which is nearly 1, for Nifty 50, the

Table 3

Unconditional Variance of the Daily Returns of the Indices for 14 Years

Stock Market Indexes	Variance
Ibovespa	0.00032
Moex	0.00038
Nifty 50	0.00021
HIS	0.00023
JALSH	0.00016

Source: Calculated based on the stock price data collected from the official website of the stock exchanges.

Table 4

ARCH Test of the Daily Returns for 14 Years

Sl. No.	Stock Market Indexes	α_1			
		Coefficient	t-Statistic	Probability	Significant/ Insignificant
1	Ibovespa	0.36	22.61	0.00	Sig.
2	Moex	0.16	6.88	0.00	Sig.
3	Nifty 50	0.14	8.48	0.00	Sig.
4	HSI	0.36	23.02	0.00	Sig.
5	JSE	0.21	12.89	0.00	Sig.

Source: Calculated based on the stock price data collected from the official website of the stock exchanges.
Note: α_1 is the ARCH coefficient. P value is the probability value of the t-statistic.

Table 5

Misspecification Test on the Residuals of ARCH Equation of the Indices for 14 Years

Sl. No.	Stock Market Indexes	Autocorrelation	Q-Statistic	Probability	White Noise (WN)/ Non random (NR)
1	Ibovespa	−0.008	0.218	0.640	WN
2	Moex	−0.014	0.674	0.411	WN
3	Nifty 50	−0.026	2.423	0.119	WN
4	HSI	0.001	0.003	0.954	WN
5	JALSH	0.011	0.407	0.523	WN

Source: Calculated based on the stock price data collected from the official website of the stock exchanges.

Table 6

GARCH (1, 1) Model Fitted for Indicesa for 14 Years

Index	Coefficient	Z-Statistic	Probability
Ibovespa: α_0	0.0000	6.0738	0.00
α_1	0.0852	11.4086	0.00
β_1	0.8905	90.1768	0.00
Moex: α_0	0.0000	5.0721	0.00
α_1	0.1192	15.4769	0.00
β_1	0.8783	130.8408	0.00
Nifty: α_0	0.0000	5.7627	0.00
α_1	0.1022	15.2566	0.00
β_1	0.8945	134.1795	0.00
HSI: α_0	0.0000	5.2843	0.00
α_1	0.0686	11.7288	0.00
β_1	0.9205	130.9760	0.00
JALSH: α_0	0.0000	5.0932	0.00
α_1	0.1017	11.4507	0.00
β_1	0.8849	87.0968	0.00

Source: Calculated based on the stock price data collected from the official website of the stock exchanges.
Note: α_0 is the Constant; α_1 is the ARCH Coefficient, and β_1 is the GARCH Coefficient.

sum is 0.9967, for HSI it is 0.9891 and for JALSH the sum is 0.9866, that is also high. Thus, Moex has the highest volatility persistence while Ibovespa has the lowest. In general, all the five indices have high volatility persistence. The fact intensifies the riskiness of the indices. Moreover, the GARCH (1, 1) model fitted for the daily returns of the indexes as per Maximum Likelihood Estimation (MLE) shows no asymmetry, as the sum of the ARCH and GARCH coefficients are less than 1.

Table 7 shows the total conditional variance of the indexes. It is the weighted sum of the past squared errors and the past variance obtained by applying the GARCH (1, 1) model. The aggregate conditional variance for the GARCH equations is calculated for each index and given in *Table 7*.

From the statistical results presented in *Table 7*, it can be seen that Moex has the highest total conditional variance and JALSH has the lowest conditional variance. It means that Moex is the most volatile and thus risky when compared to other indices, while JALSH is the least volatile. HSI is the second least volatile index with a total variance of 0.0645. Nifty 50 comes next with variance of 0.0816. Ibovespa (0.1224) has a variance less than Moex but greater than JALSH, HSI and Nifty 50.

After taking into consideration both conditional volatility and unconditional volatility of the daily return of indices representing BRICS nations, it can be inferred that Moex is having the highest volatility measuring 0.1681 (*Table 7*). At the same time, as per the analysis, JALSH has the lowest volatility.

Table 7

Total GARCH Variance of the Daily Returns of Indices for 14 Years

Stock Market Indexes	Total GARCH (Conditional) Variance
Ibovespa	0.1224
Moex	0.1681
Nifty 50	0.0816
HSI	0.0645
JALSH	0.0643

Source: Calculated based on the stock price data collected from the official website of the stock exchanges.

CONCLUSION

The daily returns of BRICS nations' indexes were analysed for studying the volatility patterns in it. The indexes selected representing the BRICS nations were Ibovespa, Moex, NIFTY 50, HIS, and JALSH. Upon unconditional variance analysis, among the indexes, the returns of Moex showed highest volatility while JALSH was the least volatile. Heteroscedasticity was detected for the returns of all the five indices. Therefore, conditional volatility analysis was called for. Accordingly, for each index, GARCH (1, 1) model was fitted after conducting misspecification test.

As per the GARCH (1, 1) model revelation, returns of Moex index has shown the highest volatility persistence level. The volatility persistence of the Ibovespa index was the lowest when compared with the others. However, all the five indexes had high persistence of volatility in their returns, implying they are very risky. When quantified the GARCH variance, returns of Moex index had the highest conditional variance. Thus, among the BRICS nations' indexes, it can be generalised that Moex is the most volatile while JALSH is less volatile. Thus, investment in the South African stock market can be said as less risky when compared to the other BRICS nations. It is a Russian stock market that is most risky among the other stock markets. When Indian stock market is considered, it can be said that it is among the less risky stocks along with South African, and China stock market. Brazilian stock market is less risky than Russian, but riskier than South African, China and Indian stock market.

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