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Long-term volatility forecasting of Brazilian stock index behavior using suitable GARCH family models

Santosh Kumar[1], Bharat Kumar Meher[2], Ramona Birau[3], Mircea Laurentiu Simion[4], Florescu Ion[5], Abhishek Anand[6], Sunil Kumar[7]

Abstract:
GARCH (Generalize Autoregressive Conditional Heteroscedasticity) family models, notably the GARCH (1,1), GJR-GARCH,EGARCH, M GARCH, and TGARCH models,(Chang, McAleer, & Tansuchat, 2012) are used in this study to empirically test volatility clusters of the IBOVESPA index using data from 20 May 1993 to 17 March 2023. A further perspective on asymmetric volatility clustering and leptokurtosis patterns is offered by the empirical analysis, which is based on daily observations from the Brazil stock market (7380). The study examines the existence of asymmetries in the patterns that transmit volatility, the movement of shocks with higher positive and negative magnitudes, and the suitability of the model. In addition, the purpose of this study is to evaluate the accuracy of volatility forecasts using both univariate and multivariate models that of Normal, Student-t, and Generalized Error Distribution constructs in predicting stock volatility over a period of more than 30 years, from May 1993 to March 2023 in the Brazilian stock markets. The results supported the existence of the leverage effect during the sampling period. Furthermore, the empirical results revealed that the sample returns of the chosen stock market had a significant level of volatility. By adding new factual data on the long-term performance of the Brazilian stock market, particularly in light of exaggerated events, this study adds to the body of literature already in existence. By adding new empirical data on the long-term behavior of the Brazilian stock market, particularly in light of extraordinary occurrences, this study adds to the body of literature already in existence.
Keywords: *Volatility, Forecasting, MGARCH model, EGARCH model, GJR-GARCH model, emerging stock market.*
JEL Classification: C5, C55, C58 G15, G17

[1] Department of Commerce, Darshan Sah College, Katihar (Under Purnea University, Purnia), India – 854105, Email: krsant1994@gmail.com.
[2] PG Department of Commerce, Purnea University, Purnia, Bihar, India – 854301, Email: bharatraja008@gmail.com.
[3] Faculty of Economic Science, University Constantin Brancusi, Tg-Jiu, Romania, Email: ramona.f.birau@gmail.com.
[4] University of Craiova, Doctoral School of Economic Sciences, Craiova, Romania, Email: simionmircealaurentiu@gmail.com.
[5] University of Craiova, Doctoral School of Economic Sciences, Craiova, Romania, Email: ionut.florescu2021@yahoo.com.
[6] PG Department of Economics, Purnea University, Purnia, Bihar, India – 854301, Email: abhi2eco@gmail.com.
[7] Department of Economics, Purnea College, Purnia, Bihar, India – 854301, Email: sunil197779@gmail.com.

1. Introduction

Major corporations in the Brazilian capital market are listed in IBOVESPA, which serves as the primary performance indicator for equities traded in B3. It was established in 1968, and for the past 50 years, it has served as a standard for investors all around the world. Volatility clustering, leptokurtosis, and asymmetric volatility are the three most prevalent time series analytic phenomena. (Okorie & Lin, 2020). For the estimate and forecasting of volatility, these kinds of time series features have sparked the creation of different models with varying degrees of variance(Raja Ram, 2020). Stock market volatility refers to ups and downs based on investment inflows and outflows (Gunay, 2020).The ability to draw in investors, whether good or negative, has been highly successful. It is a crucial element that results from the bulls and bears in the stock market and a significant return generator (Choudhary, 2020). It has been very successful to attract investors, whether positive or negative. It is a substantial return generator and a fundamental component that arises from the bulls and bears in the stock market (Pavlyshenko, 2020). Financial econometrics' recent acceleration of development has made it possible to predict volatility, which has drawn even more investors and decision-makers. However, emerging market volatility is still largely researched, particularly in the context of catastrophic events like the global financial crisis. Consequently, stylized features including volatility clustering, leverage impact, leptokurtosis, skewness, and heteroscedasticity were used to describe the dynamic behavior of emerging stock markets. In contrast to the situation where volatility is produced by an increase in stock returns, in general, a fall in stock returns leads an increase in volatility to be larger. Long periods of high market volatility following a period of high market volatility, and long periods of low market volatility following a period of low market volatility, are examples of volatility clustering (Pindyck, 2004). The volatility asymmetry of a company is greater when it is predicted by a negative return rather than a positive return of the same size (Hailemariam & Smyth, 2019).

The Risk Premium Effect (Peter et al., 2012) and Leverage Effect are the primary reasons of this phenomenon. Hawaldar et al. (2020) proposed the leverage effect theory, which contends that there is a general tendency for increases in return volatility to be negatively correlated with changes in stock return and that variability is often higher during market dips (bad news) than during market advances (good news). As shown by later research such as Kilian (2008) and Narayan et al. (2014), the leverage effect is insufficient to explain this phenomenon. Even if the distributions of the underlying market shocks are conditionally normal, the volatility feedback can still explain these return characteristics. The conditional variance is likely to respond to good and bad news asymmetrically when there is an asymmetric influence in time series data. Most of the time, the GARCH and ARCH models can be used to estimate and forecast the variance of time series data, but they frequently miss out on important facets of the asymmetric behavior of financial data. Many researchers have looked at how conditional volatility reacts differently to positive and negative news and events across different asset classes. While this effect of merging key financial assets in the Indian financial market has not been studied, it is likely to have significant implications for a country like Brazil.

Another important issue is focused on efficient market theory and its implications on stock market behaviour (Birau, 2011, Spulbar et al., 2022,).

In the past, Brazilian studies have mostly concentrated on customising conditional variance models for the Brazilian stock market. In addition, most previous research has either used univariate GARCH models or evaluated the asymmetric effect on the volatility of a single financial instrument (Peter et al., 2012). The most interesting and previously unexplored aspect is the use of multiple univariate GARCH models to measure the asymmetry in the volatility of different financial assets. By utilizing numerous GARCH models and various financial assets, this work will contribute to the body of literature. A summary of all the papers in this area will be useful for the research community. Also, it will assist local and foreign investors in building their portfolios, lowering investment risk by avoiding putting all of their eggs in one basket. The use of such long-term period as there would be adequate data points and the leverage effect if exist in the data might have played a significantly more significant role in explaining volatility asymmetry.

2. Review of Literature

Multiple models with varying degrees of accuracy have been developed in recent years for estimating and forecasting important properties of time series data. There have been many tests of Models of Generalized Autoregressive Conditional Heterogeneity, both in terms of univariate accuracy and asymmetric volatility (Bollerslev, 1986). The primary focus of this research is to learn more about the stock market's volatility, and to do so, we review related studies. The autoregressive conditional heteroscedasticity model (Harvey & Sucarrat, 2014)and its generalized version focus on capturing efficiently volatility clustering. Many researcher (Almeida & Hotta, 2014, Glosten et al., 1993, Badarla et al., 2022, Trivedi et al., 2022) used financial econometrics i.e. GARCH model to detect the volatility based on presence of skewness and asymmetry of financial time series data.

The authors (Thakolsria et al., 2015, Ormos & Timotity, 2016, Agboluaje et al., 2016) applied the test for the leverage and volatility feedback effects in emerging stock markets, based on modelling two of the GJR-GARCH and PGARCH parametric asymmetric volatility models using the daily high frequency data from the Stock Exchange of Thailand. Also, a study used the daily share indices of Kenya, Germany, the United States, China, and South Africa to estimate asymmetric GARCH models with endogenous break dummies under two unique hypotheses. The findings revealed that while asymmetric effects were absent from Kenyan and Nigerian market returns, they were present in other stock returns (Uyaebo et al., 2015). Similarly, a study examined the intraday price volatility procedure in a few Australian wholesale power markets using GARCH model, Normal APARCH, Student APARCH, Risk Metrics, and Skewed Student APARCH models (Higgs & Worthington, 2005, Hawaldar et al., 2022).

Few papers on volatility with high-frequency data, where a paper attempts to demonstrate that the relationship between volatility and price processes can be assessed more precisely and correctly using high frequency data along with the ability of definite stochastic volatility models to analyze the pattern observed in high frequency data (Litvinova, 2003, Khanthavit, 2020, Okorie & Lin, 2020, Ashraf, 2020, Meher et al., 2020). By including knowledge of latent volatility processes that take place when markets are closed and no transactions take place, some papers have proposed a way to improve volatility modelling (Matei et al., 2019, Liu et al., 2020, Onali, 2020). Also, a study used the GARCH model to examine the trends in natural gas and crude oil price volatility in the US since 1990 (Pindyck, 2004, Chang et al., 2012). Also, a study used intraday data from the Gold 5 minutes to compare realized GARCH models with several conventional GARCH models (Hawaldar et al., 2020, Abounoori & Zabol, 2020, Manera et al., 2013, Mukherjee & Goswami, 2017).

Recent researches on the epidemic haven't yet provided any insight into how to use modelling asymmetric price volatility using high-frequency data the Brazilian stock market using the IBOVESPA index. This research gap is a highly viable one since employing minute-level data to get a closer look at how the pandemic will affect the price volatility of individual stocks, asymmetric volatility models could be useful.

3. Research Methodology

The study uses secondary data with a high frequency and is empirical in character. This paper's primary goal is to examine the method for estimating the influence of long-term volatility on the Brazilian stock market using the IBOVESPA index. We use GARCH (Generalized Autoregressive Conditional Heteroscedasticity) models (Bollerslev, 1986). Two well-known asymmetric volatility models, EGARCH, TGARCH, and MGARCH models, have been applied. ADF (Augmented Dickey Fuller test) has been used to determine whether the data is stationary in nature in order to apply EGARCH, TGARCH, and MGARCH models. Log Daily Returns have been established to transform irregularly spaced data into regularly spaced data. For selection of the most appropriate volatility model for stock markets, numerous criteria have been used to examine the results of the models after that different model had been created using different distributions. In addition, the empirical results are significant at levels of 10%, 5%, and 1%, with the 5% significant level being taken into account for the following modelling process. E-Views 10 has been applied to the creation of models for certain stock indexes. Except for legal holidays and other occasions when stock markets don't conduct transactions, the financial time series comprises of daily closing prices for the sample stock index for the years starting on May 20, 1993, and ending on March 17, 2023. The sample data series also contains 7380 daily observations in total. The log-difference of the closing prices of the stock market's chosen index, namely the IBOVESPA index, is used to calculate the continuously-compounded daily returns as follows :

Conversion of Log:

$$y_t = In\_\left(\frac{p_t}{p_{t-1}}\right) = In(p_t) - In(p_{t-1})$$

ADF Process:

$$(1-L)\,yt = \beta 0 + (\alpha - 1)\,yt - 1 + \varepsilon_i$$

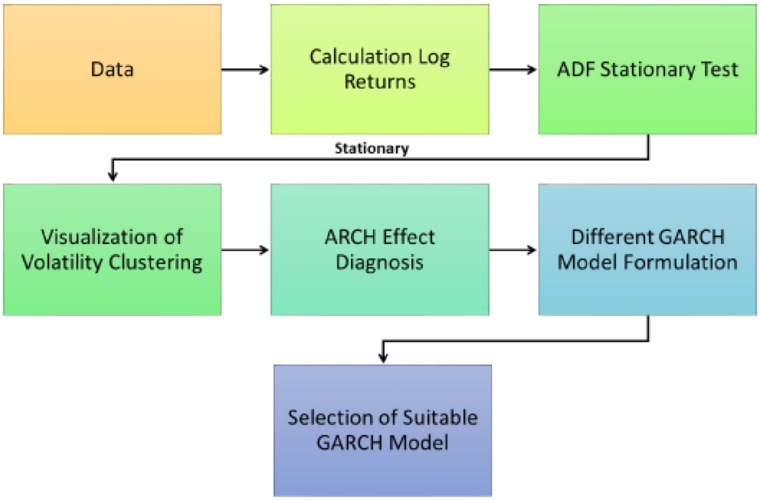
GARCH Models

The variance in a GARCH model (general)is written as:

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-j}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-1}^2$$

Where σ_t^2 is the return residual, εt is the conditional variance, and α_0 , α_i and β_j are the parameters to be calculatedTo make the model reliable, the α_0 , α_i and β_j must all have nonnegative values, and α_i + β_j are expected to be less than 1. This is an essential prerequisite for the positive variance. In the financial data series, higher values of the α_i coefficient show a greater volatility response to market shocks, whereas larger coefficients of the β_j coefficient show the presence of market shocks.

Figure 1. Analysis Process Flow Chart.



4. Empirical Results and Discussion

The property of summary of statistics provides 0.0011 mean with 0.02 degree of SD. The risk factor is increased by the excess kurtosis and positive skewness in the case of IBOVESPA index. The presence of leptokurtic influence on the series returns is shown by the aberrant pattern of kurtosis.

Table No. 1 - Descriptive Statistics

Mean	**Median**	**Maximum**	**Minimum**
0.001102	0.001150	0.288325	-0.172082
Standard deviation (SD)	**Coefficient of variance**	**Skewness**	**Kurtosis**
0.021917	19.88	0.356035	14.33944
Observations	7381		

Source: Authors' Own Computation

In the financial series of the IBOVESPA index, the standard deviations degree shows 0.0219 relative risks. It is quite notable that the kurtosis indicates a substantially higher degree than the normal level while the skewness represents non-negative returns that are barely on the boundary of the 0.3560 level. The good news for investors and proof of good returns throughout the course of the seven-year study were indicated by this. Nonetheless, the IBOVESPA index contains a significant number of normal volatility rates and quantifiable anomalous scales.Series returns provide a definite and obvious indicator of the market decline caused by the global financial crisis (see fig1). The post-financial crisis scale and the positive returns ratios should be the attention of investors, academics, and researchers. It unequivocally demonstrates how seriously investors take long-term investing. To be sure, the IBOVESPA index contains a lengthy list of typical volatility rates and quantifiable abnormal scales.

Figure 2. Movement Pattern of IBOVESPA Index of Brazil

Source: Authors own computation using EVIEWS 10

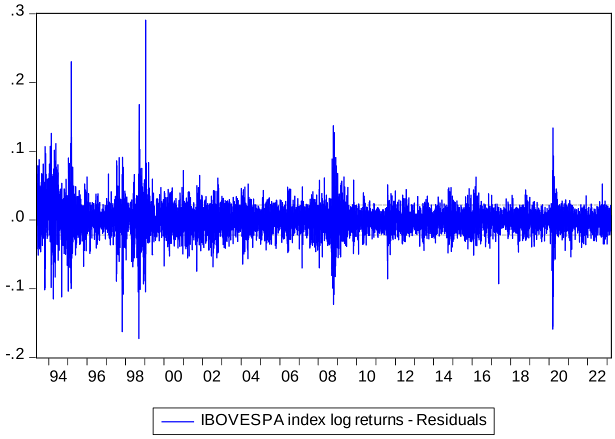
Log returns for financial data series, such as the Brazil IBOVESPA index, have been determined for the three asymmetric GARCH Models, EGARCH, TGARCH, and MGARCH. The sample data for the IBOVESPA index closing price have become immobile as a result. The sample data of the Brazil stock price were again tested for stationarity using the unit root test, or the Augmented Dickey Fuller Test, which includes the test equations Intercept, Trend, and Intercept and None. It was discovered that the sample data are stationary because the probability values are significant at levels of 10%, 5%, and 1%. (Table 2).

Table No. 2 : Outcomes of ADF test of Statistic

Null Hypothesis: Unit root exists in the IBOVESPA index Log returns.			
Exogenous: Constant			
Lag Length: 9 (Automatic - based on SIC, max lag=35)			
		t-Statistic	Prob.*
ADF test statistic		-23.25096	0.0000
Critical values of test:	1% level	-3.431060	
	5% level	-2.861738	
	10% level	-2.566917	

Source: Authors' own Computations using Eviews10

The following sections are built on evaluating the relevant hypotheses needed to create the EGARCH, T GARCH, and MGARCH models. Figure 3 shows graphs with the log returns of the IBOVESPA index displayed to show the presence of volatility clustering.Figure no. 3. Movement style of the Stationary Series for IBOVESPA indices for the sample timeframe from 5/20/1993 to 3/17/2023.



Source: Authors' own Computations using Eviews10

The property of figure 3 indicates there are different clusters in this diagram because we can see that in Line graphs figure 3, sometimes volatility is high and sometimes volatility is less.

After examining the log return graphs of a few selected financial data series in Figure 3, it is clear that the data exhibits volatility clustering, whereby large variations in log returns were followed by equally large differences in log returns, and vice versa. Moreover, it can be seen that among the most recent sample years, throughout the COVID-19 pandemic period. The returns of the stocks in the Brazil IBOVESPA index were highly variable. These significant changes during 2020 are a blatant sign that the pandemic is having a leveraging impact on market values, stock price volatility simulations using an asymmetric GARCH model would be appropriate. In addition to verifying the presence of volatility clustering, the ARCH effect must also be present in the data of the chosen financial index in order to apply GARCH models. Table 3 lists the ARCH effect findings for the six companies.

Table No. 3: Outcomes of ARCH Effect testing

Heteroscedasticity Test: ARCH				
F-statistic	461.7871	Prob. F(2,7376)		0.0000
Obs*R^2	821.1330	Prob. χ^2		0.0000
Component	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000277	2.05E-05	13.50253	0.0000
RESID^2(-1)	0.190118	0.011328	16.78230	0.0000
RESID^2(-2)	0.231015	0.011325	20.39932	0.0000

Source: Author's own computations using EViews 10

The results of the heteroscedasticity test of stock returns for the Brazil IBOVESPA index are shown in Table 3, which would indicate the presence of the ARCH effect in the stock price data. In the table 2 the dependent variable is $residual^2$and we are analyzing whether the$residual^2$of any day can be predicted by RESID^2(-1) or previous lag and 2 lag with significant value. Lagrange Multiplier (LM) data, which are presented as Observed R Squared, can be used to check for the ARCH effect. The observed R squared value is 821.13, and even at a 1% threshold of significance, the probability values associated with this value are significant. Also, the significance value of the F statistics is less than 0.05, making it likewise significant. After determining whether ARCH effects exist, the three asymmetric GARCH models—EGARCH, TGARCH, and MGARCH—have been developed using three distinct error distribution constructs—Normal Distribution Error Construct, Student t's Distribution Error Construct, and Generalized Error Distribution Construct. The leverage effect, which is created by the negative correlation between returns and volatility, is not captured by the conventional GARCH model since it is asymmetric in nature. The EGARCH, TGARCH, and TGARCH models' unique selling point is their ability to capture the leverage effect of shocks like policy, information, news, occurrences, and market events.

"The log of the variance distinguishes the EGARCH model from the GARCH variance structure" (Dhamija & Bhalla, 2010). Also, "the advantage of employing EGARCH is that it works with the log of the variance, which ensures the positivity of the parameters" (Hassan, 2012).

The following formula is for EGARCH model.

$$\log\left(\sigma_t^2\right) = \omega + \sum_{j-i}^{p} \beta i \log\left(\sigma_{t-i}^2\right) + \sum_{j-1}^{q} \alpha i \left\langle \frac{\varepsilon i - t}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| - yi \frac{\varepsilon i - t}{\sigma i - t} \right\rangle$$

where

log (σ_t^2) *= log of variance or log returns* ω *= Constant*

βi *= Effects of ARCH* αi *= Asymmetric effects*

yi *= Effects OF GARCH*

"The threshold GARCH (TGARCH) is similar to the GJR model, different only because of the standard deviation, instead of the variance, in the specification" (Ali, 2013). For the TGARCH(1,1) model, use the following formula. This model also addresses the conditional standard deviation. TGARCH was described thusly:

$$\sigma_t = \omega + \alpha\sigma_{t-1}\left[\varepsilon_t - c\varepsilon_t\right] + \beta\alpha_{t-1}$$

$$\sigma_t = \omega + \alpha\iota\left[\varepsilon_{t=1} \geq 0\right]\varepsilon_{t=1} + \gamma\iota\left[\varepsilon_{t=1} < 0\right]\varepsilon_{t=1}\beta\alpha_{t-1}$$

If $\gamma > 0$, there is an asymmetry, showing that news with positive and negative signals has differing effects on conditional volatility. The asymmetry is evident because the impulse of the unfavorable shocks ($\alpha + \gamma$) is higher than the impulse of the positive shocks (α).

The GARCH-M model

The GARCH model neglects the process underlying volatility feedback.It captures the "GARCH-in-mean" model, also known as the GARACH-M model, proposed by (Engle, 1986)

$$y_t = c + \xi h_t + u_{t.}$$

Or consider using the standard deviation of the series to represent risk rather than variance. That is:

$$y_t = c + \xi \sqrt{h_t} + u_t.$$

Here, the standard deviation of the series is used to measure the risk of asset return with GARCH-M. That is:

$$y_t = \varphi + \sum_{k=1}^{p} \theta_k h_{t-k} + \sum_{i=1}^{q} b_i u_{t-i}^2$$

It is necessary to analyze the outcomes of the developed models with the three distinct distributions in order to select an optimal model. "The standard way to choose a model is to make sure that the ARCH and GARCH coefficients are statistically significant and that the framed model doesn't have heteroscedasticity or autocorrelation. Models that score higher on Log Likelihood statistics, R squared, and adjusted R squared are preferred, while those that score lower on the AIC (Akaike Information Criterion) and the SIC (Schwarz Information Criterion) are preferred." (Meher et al., 2020).

Implementation of EGARCH, TGARCH and MGARCH Models for Brazil IBOVESPA index

The Ibovespa Index, often known as Bovespa, consists of almost 70 equities traded on the Sao Paulo Stocks, Mercantile & Futures Exchange and serves as a leading indicator of the average observed behavior of the Brazilian stock market. Its hypothetical portfolio, which is updated every four months, is made up of stocks that.

Table No. 4: Decision Table of EGARCH (1, 1), TGARCH (1, 1), or MGARCH (1, 1) Model for the Brazil IBOVESPA Index

	EGARCH			TGARCH			MGARCH		
Statistics	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution	Normal Distribution	Student t's Distribution	Generalised Error Distribution
Significant Coefficients	☑ (Yes)	☑	☑	☑	☑	☑	☑	☑	☑
Significant ARCH effects	☑	☑	☑	☑	☑	☑	☑	☑	☑
Significant GARCH effects	☑	☑	☑	☑	☑	☑	☑	☑	☑
Log Likelihood	19321.60	19379.63	19355.62	19259.80	19359.89	19336.36	19271.04	19370.47	19348.01
R squared	0.015249	-0.000062	-0.000142	0.000400	0.000118	0.000288	0.004489	0.004907	0.004559
Adjusted R^2	0.014982	-0.000333	-0.000413	0.000129	-0.000153	0.000017	0.004084	0.004502	0.004154
Akaike info criterion	-5.234309	-5.249764	-5.243258	-5.217831	-5.244686	-5.238309	-5.220878	-5.247281	-5.241195
Schwartz criterion	-5.227759	-5.242277	-5.235772	-5.215901	-5.242435	-5.236057	-5.218627	-5.239794	-5.233708
Heteroscedasticity	No	No	No	No	No	No	No	No	No
Autocorrelation	No	No	No	No	No	No	No	No	No

The aforementioned table 4 shows that the coefficients, ARCH Effect, and GARCH are all statistically significant in all three EGARCH (1,1), three TGARCH (1,1), and three MGARCH (1,1) models with a normal distribution error construct, a Student t's distribution error construct, and a Generalized error distribution construct, respectively. After constructing the aforementioned models, it was determined that none of the nine models had heteroscedasticity (as determined by the ARCH LM Test) or autocorrelation (as determined by the correlogram of residuals and squared residuals).EGARCH with Student t's Distribution has the lowest AIC (-5.249) and SIC (-5.242) when compared to the other eight models when the AIC and SIC of all the aforementioned six models are compared. Aside from having the highest R and Adjusted R squared values in comparison to the other eight models, this model also has the highest Log Likelihood (19379.63). As a result, this model is thought to be the best one.The table below lists the outcomes of the chosen EGARCH (1,1) Model for the Brazil IBOVESPA index.

Table No. 5. Results of EGARCH (1,1) with Student's t distribution Error Construct
Source: Author's own computations using EViews 10

Measured variable: Brazil IBOVESPA index log returns				
Method: ML ARCH - Student's t distribution				
Sample (adjusted): 5/21/1993 3/17/2023				
Total observations: 7380				
MA Backcast: 5/20/1993				
Presample variance: backcast (parameter = 0.7)				
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6) *RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))				
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000773	0.000176	4.379596	0.0000
AR(1)	-0.500642	0.414567	-1.207628	0.2272
MA(1)	0.518206	0.409247	1.266244	0.2054
Variance Equation				
C(p)	-0.259128	0.025876	-10.01417	0.0000
C(q)	0.181782	0.012000	15.14801	0.0000
C(r)	-0.050855	0.006037	-8.423949	0.0000
C(s)	0.985360	0.002547	386.8239	0.0000
T-DIST. DOF	9.519221	0.822159	11.57831	0.0000
R^2	-0.000062	Mean		0.001093
Adjusted R^2	-0.000333	S.D.		0.021905
S.E. of regression	0.021909	Akaike info criterion		-5.249764
Sum^2 resid	3.540920	Schwarz criterion		-5.242277
Log likelihood	19379.63	Hannan-Quinn criter.		-5.247191
Durbin-Watson stat	1.975956			
Inverted AR Roots	-.50			
Inverted MA Roots	-.52			

The IBOVESPA index for Brazil is represented in the following table as the output of the EGARCH (1,1) model using Student t's Distribution Construct. The outcomes come in two sections. The variance equation is represented in the lower area, while the main equation is shown in the upper portion. The constant (C) in the primary equation is significant because their probabilities are less than 0.05.
Conditional log variance or log returns equation is as follow:

$$\log\left(\sigma_t^2\right) = \omega + \sum_{j-i}^{p} \beta i \log\left(\sigma_{t-i}^2\right) + \sum_{j-1}^{q} \alpha i \left\langle \frac{\varepsilon i - t}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| - yi \frac{\varepsilon i - t}{\sigma i - t} \right\rangle$$

In the table 5() C(p) = ω (Constant), C(q)= βi = ARCH Effects, C(r) αi = Asymmetric effects and C(s) yi = GARCH effects

As their probability values are all less than 0.05, every coefficient in the variance equation is considered significant. In addition, the model has the lowest AIC (-5.249) and SIC (-5.242) among comparable models. Comparing Log Likelihood to the other pertinent models, the value is greater at 19379.63. Focus should be placed on the fact that the co-efficient of the asymmetric term () is negative, or -0.050855, and statistically significant. This suggests that there is a leverage effect on the company's stock price volatility, and it also suggests that negative news has a greater impact on this volatility. As a result, the variance equation can be illustrated as follows.

$$\log\left(\sigma_t^2\right) = -0.259128 + \sum_{j-i}^{p} 0.181782 \log\left(\sigma_{t-i}^2\right) + \sum_{j-1}^{q} -0.050855 \left\langle \frac{\varepsilon i - t}{\sigma_{i-t}} \left| \frac{-\sqrt{2}}{n} \right| - 0.985360 \frac{\varepsilon i - t}{\sigma i - t} \right\rangle$$

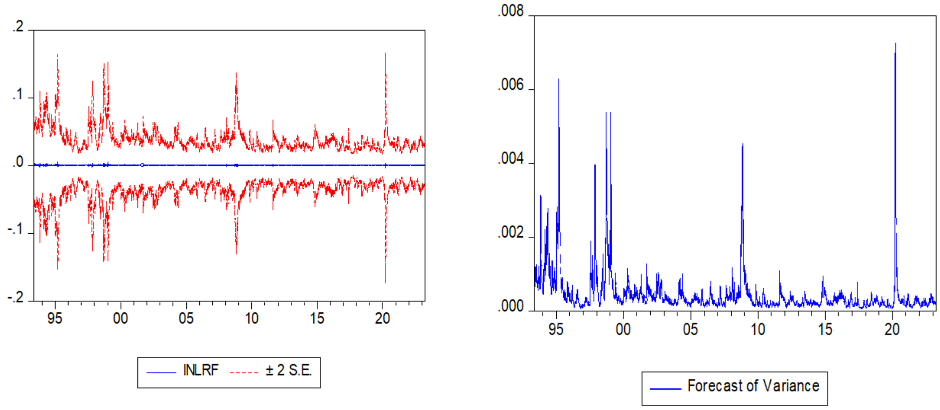
5. Evaluation of Prediction using the Selected Model

Models are used to forecast volatility in five steps after they have been estimated (Alper, Fendoglu, & Saltoglu, 2009). When predicting volatility using GARCH-type models, the conditional variance of the returns for each time period, based on past values, is equivalent to the conditional variance of the residuals for the same period, given its prior values. It is possible to track volatility and identify patterns by using forecasting in conjunction with GARCH model estimations. For all five countries, forecasts are taken out for the entire out-of-sample time. The conditional variance equation, as previously mentioned,

$$h_t = \alpha_0 + \alpha_1 u_{t-1}^2 + \beta h_{t-1}$$

Forecasting Volatility for Brazil IBOVESPA index of the for the total sample days Data i.e. 20th May, 1993& 17th March, 2023by applying the approach given above. The following graphs are intended to help you comprehend the anticipated asymmetric stock price volatility of Brazil IBOVESPA index during the sample periods in figure 3.

Figure 3 Forecasting volatility:



For the dates 20 May 1993 and 17 March 2020, the Brazil IBOVESPA index line graphs display expected returns and expected variation. The results of the furcating table show that the return on assets is stable, and the first predicted return graph shows that the stock price returns of the Brazil IBOVESPA index were consistent over the sample periods of time.

6. Conclusion

The study's primary goal is to assess the precision of the GARCH, GARCH-in-Mean, EGARCH, and TGARCH models and to determine whether an asymmetric influence exists in the conditional volatility of the Brazil IBOVESPA index using the Normal, Student-t density functions, and Generalized Error Distribution. The study finds that EGARCH models with student t's distribution, the lowest Schwarz criterion, and the highest Log likelihood replicate the asymmetrical behaviorof the Brazil IBOVESPA index's volatility stock return. On the standard density and EGARCH (Exponential GARCH) model depicted in figure (5), the prior empirical findings offer a useful comparative framework.This denotes a high magnitude measurement of aberrant volatility and density in the case of return series. In order to assess the suitability and importance of empirical findings, the value of BIC was taken into account. The variance equation fit precisely at the degree of 1%, signifying the highest significance, however, at the 10% level of significance, the statistical property for the conditional mean equation is significant. In light of the fact that the EGARCH model can be used to estimate the volatility spillovers in the event that Brazil's IBOVESPA index returns, the value of log probability is taken into consideration to be -19379.In addition, the EGARCH model yields substantial results, indicating the existence of leverage effects (asymmetry) in particular financial series. In addition, it suggests that negative shocks (volatility) will recur over a longer time frame. Additional information about volatility patterns, similar responses to external shocks, investor risk aversion, effects of the influx of new information onto the market, financial integration, risk management, and the detrimental effects of the global financial crisis can be found in empirical analysis. The study's selection of a single stock market, in this case, the Brazilian stock market, is a major limitation. We shall take into account a comparative empirical analysis between the nations of the G-20 for next research investigations. In addition, we will broaden the scope of the investigation by including hybrid methods, and the period of time we focus on will be longer.

Authors' Contributions:

The authors contributed equally to this work.

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