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ORIGINAL PAPER

Longitudinal Volatility Analysis of OMX Tallinn Index in the case of the emerging stock market of Estonia using PARCH Model

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Abstract:
The purpose of the empirical research study is to analyze the volatility of OMX Tallinn Index in Estonia from 2002 to 2022 in three major period phases i.e. 2002-2008, 2009-2015 and 2016 to 2022. Moreover, it attempted to formulate PARCH Model for each phases of OMX Tallinn Index in Estonia from 2002 to 2022 that could grasp not only the volatility but also asymmetric volatility caused by various important events for each particular period. The total sample size is 6,032 i.e. 3 phases of 1826 observations each. The selected period covers a series of extreme events such as the global financial crisis, the COVID-19 pandemic, the war between Russia and Ukraine that began in 2021 and others. The empirical results are relevant and contribute to the existing literature.

Keywords: *PARCH model, asymmetric volatility, GARCH family models, Longitudinal Volatility Analysis; emerging stock market; leverage effect; COVID-19 pandemic; global financial crisis (GFC); extreme events*

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Introduction

High volatility is a conception of a symptom of market distortion whereby securities are not being valued fairly and the capital market is not operating as well as it should (Daly, 2008). Hence, if it is possible to predict the volatility, then more return could be generated by taking appropriate investment decisions. Measuring of volatility has various applications especially in trading, investment, and portfolio selection of stock and commodities market because it assists the investors in risk management, derivative pricing, hedging, and predicting price. Moreover, studying volatility enables to predict the direction of any market then any one can have a good intent what to expect from economy, hence volatility has operations beyond the stock and commodities market. There are various techniques that is used in measuring volatility like historical volatility, Bollinger bands which are considered as traditional methods and such methods are easily understood by layman investors as well. The modern methods include many algorithmic functions for the purpose of modelling volatility like ARCH, GARCH, EGARCH, TGARCH, PARCH etc. These volatility models are used to describe a changing, possibly volatile variance and to predict volatility of a time series data.

The ARCH (Autoregressive Conditional Heteroscedasticity) model proposes that the variance of residuals regressed on the squared error terms from the periods of past. The residual terms should be conditionally normally distributed and serially uncorrelated. One of the major limitations of this ARCH model is it "supposes that the variance or heteroscedastic of tomorrow's return is an equally weighted average of the residuals' squared from the last 22 days. The assumption of equal weights looksill-favoured, as one may think that the more recent events would be more significant and therefore should have more weights." (Engle, 2001). Hence an advancement has been done in ARCH model by Tim Bollerslevin 1986 and named it as GARCH. In contrary to ARCH Model, GARCH (Generalised Autoregressive Conditional Heteroscedasticity) has diminishing weights that now is decline to zero. It provides parsimonious models that are soft to estimate and, even in its simplest form, has proven astonishingly successful in forecasting conditional variances (Bollerslev, 1986). Moreover, "The latest volatility process of asset returns is material for a wide variety of operations, such as risk management and option pricing whereas generalized autoregressive conditional heteroscedasticity (GARCH) models are extensively used to model the dynamic features of volatility" (Peter, Huang, & Shek, 2012). Inverse correlation between the return and the shocks is a salient feature of the stock market (Ali, 2013) but it is not captured by simple GARCH, hence an advanced model proposed by Glosten, Jagannathan and Runkle (GJR) propound GJR-GARCH also known as Threshold GARCH (TGARCH) with differing effects of positive and negative shocks taking into account the leverage portent.(Glosten, Jagannathan, & Runkle, 1993)The leverage portent is caused by the fact that adverse returns have more influence on future volatility than do favourable returns (Almeida & Hotta, 2014). To capture the above leverage portent or effect, Exponential GARCH (EGARCH) model has been developed in which the "conditional distribution is heavy-tailed and skewed is proposed. The characteristics of the model, including autocorrelations, unconditional moments and the asymptotic distribution of the maximum likelihood estimator, are portrayed" (Harvey & Sucarrat, 2014).

This paper strives to study the effects of important events on OMX Tallinn Index in Estonia from 2002 to 2022 in three phases i.e. 2002-2008, 2009-2015 and 2016 to 2022 by using an advanced asymmetric volatility model i.e. PARCH Model. The reason for taking the Tallinn Index in Estonia because it is the main stock market index in Estonia. It reflects changes in the prices of shares listed in the Main and Investor lists of the Estonian Stock Exchange, and the Tallinn Stock Exchange. It uses the Paasche Index Formula. The value of the index was calibrated to 100 on 3 June 1996.The OMX Tallin All-Share Gross Index includes all the shares listed on Tallin Stock Exchange. The objective of the Index is to represent the overall state and changes in the level of the Estonian economy. The purpose is to mimic the population of stocks representing the index, without complying with liquidity and stability requirements. Since there is no filtering for liquidity the Indexes themselves may not be easy to replicate in a portfolio or benchmark against and the pricing of the constituents, and hence the index level, may lag due to infrequent trading in the underlying shares.

Review of Literature

This part highlights some of the important research works that have been done in the area of volatility and stock markets. Some studies on asymmetric volatility where a study on modelling the asymmetric or leverage effect in conditional variance of EGARCH (Exponential Generalized Autoregressive Conditional Heteroscedasticity) with (CWN) Combine White Noise model to derive suitable results using the quarterly data of U.K. Real Gross Domestic Product (GDP) from 1960-2014 and proved that CWN estimation is more efficient (Agboluaje, Ismail, & Yip, 2016). Similarly, a study based on modelling three parametric asymmetric volatility models namely EGARCH, GJR-GARCH and PGARCH by employing the daily high frequency data related to the Stock Exchange of Thailand from 4th January, 2005 to 27th December, 2013,to test the leverage and volatility feedback effects and also constitutes the subprime crisis period in US that may affect the volatility of market return in emerging stock markets (Thakolsria et al., 2015). Moreover, Trivedi et al. (2022) investigated the behavior of Russian stock market for a very long selected period of over 20 years based on GARCH models. Badarla et al. (2022) also investigated the behavior of certain selected stock markets from Switzerland, Austria, China and Hong Kong using GARCH models.

Furthermore, a study with an objective to reveal the distinction between this connection and similar ones specific to developed economies (Albu et al., 2015). A study estimated Asymmetric GARCH models with endogenous break dummy on two novel assumptions using all share index on daily basis of Kenya, Germany, United States, China and South Africa ranging from 14thFebruary, 2000 to 14th February, 2013.The results suggested the absence of asymmetric effect in Kenya and Nigeria stock returns, but existed in others (Uyaebo et al., 2015). A study depicts the impact of ESG on returns and volatility (Meher et al., 2020). Similarly, another research paper used GARCH, Normal APARCH, Student APARCH, Risk Metrics and Skewed Student APARCH to examine the intraday price volatility procedure in few Australian whole sale electricity markets i.e. Queensland, New South Wales, Victoria and South Australia of half-hourly electricity prices and demand volumes over the period 1 January 2002 to 1 June 2003 where skewed Student APARCH model produces the best results in first three markets and the Student APARCH model in the Victoria market (Higgs & Worthington, 2005). Few papers on volatility with high-frequency data, where a paper attempts to show that the relationship between volatility and price processes can be assessed more precisely and correctly using high frequency data along the ability of definite stochastic volatility models to analyze the pattern observed in high frequency data (Litvinova, 2003; Meher et al., 2020; Meher et al., 2021). A paper suggested a methodology to refine modelling volatility by inculcating information that exists on latent volatility processes when the markets are closed and no transactions occur with high-frequency data (Matei, Rovira , & Agell, 2019).A research applied E-GARCH approach to data from 2015 to 2018, to explore the influence of investor sentiment on the return rate of the Shanghai Composite Index.(Chen & Haga, 2021). Again, a paper investigates whether changes in firm's investor following can influence volatility in the French stock market. By defining a novel proxy of investor following, the paper contributes to the emerging literature of the impact of information technology on financial markets (Aouadi et al., 2014) a study on effect of COVID-19 on stock markets mentioned in the review of literature and an existing study is also there on effect of COVID-19 pandemic on the price volatility of Crude Oil and Natural Gas of MCX India using EGARCH (Meher et al., 2020)

Objectives of the Study

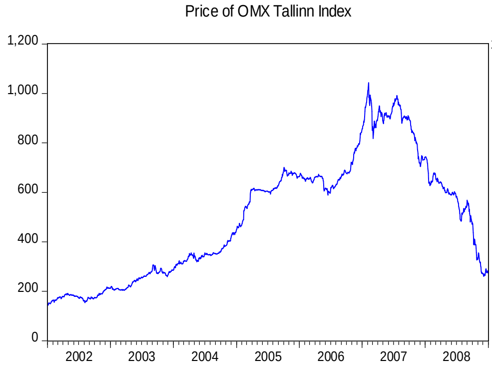
- To analyze the volatility of OMX Tallinn Index from Estonia stock market from 2002 to 2022 in three phases i.e. 2002-2008, 2009-2015 and 2016 to 2022.
- To formulate PARCH Model for each phases of OMX Tallinn Index in Estonia stock market from 2002 to 2022 that could grasp not only the volatility but also asymmetric volatility caused by various important events for each particular period.

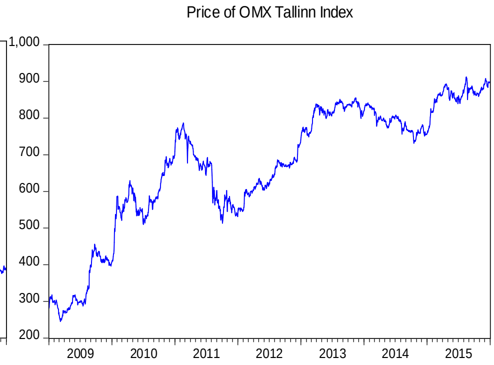
Research Methodology

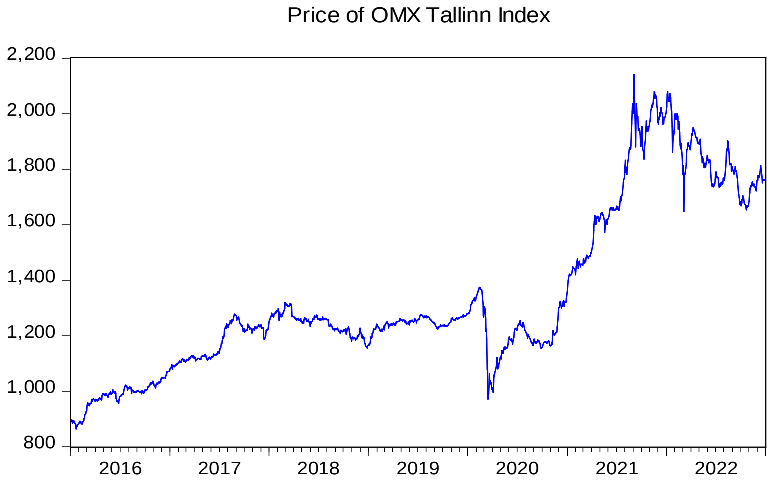
The study is Empirical in nature. The study is based on secondary data. The secondary data involves the daily closing prices of OMX Tallinn Index of 21 years i.e. from 1st January, 2002 to 31st December, 2022. These duration of 21 years is divided into 3 phases containing 7 years in each phase. The daily closing prices of OMX Tallinn Index of 21 years covers the sample period from 1st January, 2002 to 31st December, 2022. Wherever required, attempt has been made to make the unbalanced data into balanced data i.e. 5 days a week. The total sample size is 6,032 i.e. 3phases of 1826 observations each (Hwang & Pereira , 2004). For the application of PARCH, Log Returns have been calculated to make the data stationary and Augmented Dickey Fuller Test (ADF) has been employed to check the whether the data is stationarity in nature. PARCH models have been trailed and tested on the basis of various statistical parameters to find a suitable PARCH model for each phase of the Index. For the purpose of formulating models and forecasting volatility of all the three phases of 21 years of OMX Tallin Index, E-Views 10 has been used.

Analysis, Results and Discussion

The PARCH model Taylor (1986) and Schwert (1989) proposed a standard deviation GARCH model. Compared with Bollerslev's GARCH model, this model is used to fit the standard deviation to reduce the impact of large shocks on the conditional variance. Ding et al. (1993) further generalised the standard deviation GARCH model, naming it the power autoregressive conditional heteroscedasticity model (PARCH), with the following variance equation:

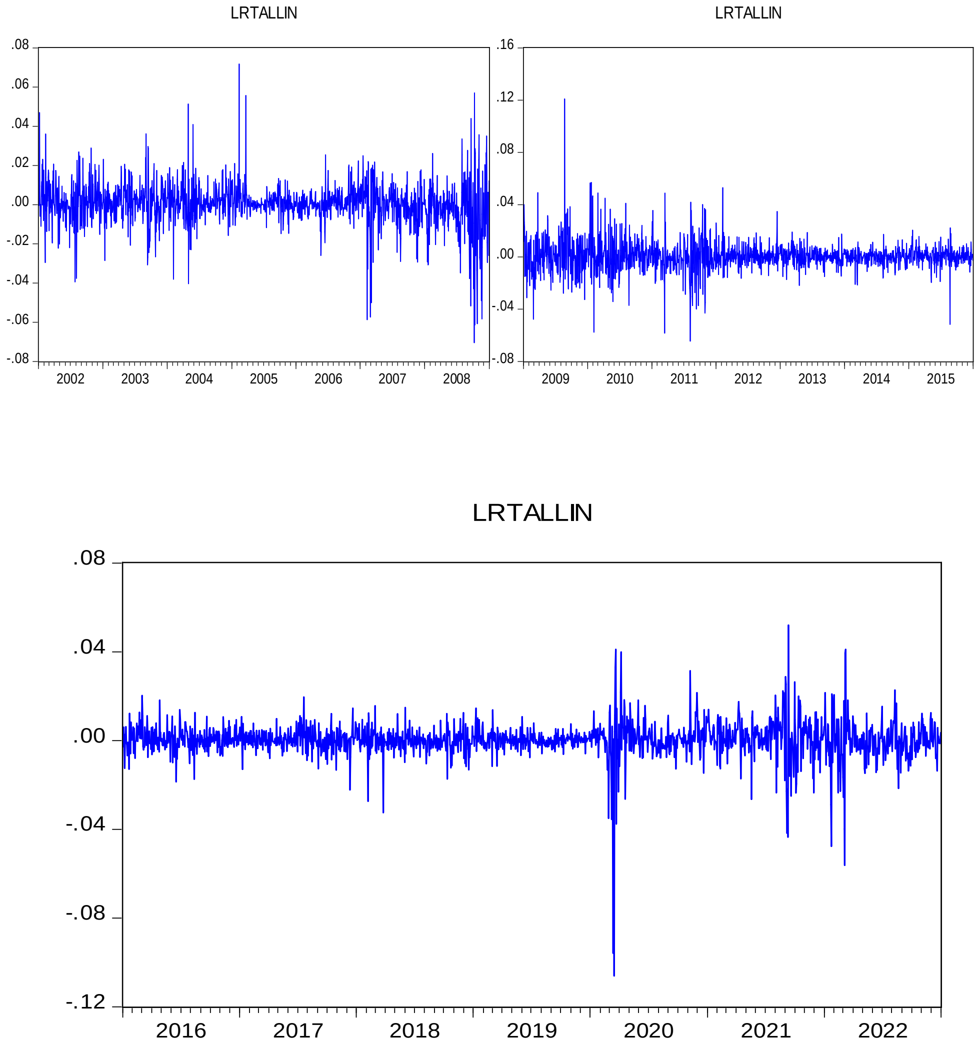






For the purpose of formulating the two asymmetric GARCH Models i.e. EGARCH and TGARCH, log returns have been ascertained for the 21 years of OMX Tallinn Index. This has made all the data of all the three phases, stationary. Again, the stationarity of the data has been checked with the help of unit root test i.e. Augmented Dickey Fuller Test with the inclusion of test equation as Intercept, Trend and Intercept and None and found that all the data of six companies are stationary as the probability values in all the cases are significant even at 1% level of significance. in data of the results The succeeding sections are based on the testing the appropriate hypothesis required to formulate PARCH model along with the results and model for each company. The log returns of all the selected six companies are plotted on the graphs to visualize the existence of volatility clustering which are given below.

Figure No. 2. Line graphs of Log Returns of Three Phases of OMX Tallinn Index



By visualizing the above Graphs of Log Returns of Crude Oil depicts that there is presence of volatility clustering i.e. small variations tracked by small variations and large variations tracked by large variations which implies that volatility models can be formulated. Moreover, large fluctuations in prices could be seen in all the three phases which shows that there is existence of asymmetric volatility caused by various important events during 2002 to 2022.

Testing ARCH Effects in the data of all the 3 phases of OMX Tallin 2002-2008

Heteroskedasticity Test: ARCH

F-statistic	328.7169	Prob. F(1,1823)	0.0000
Obs*R-squared	278.8045	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 02/17/23 Time: 14:24
Sample (adjusted): 1/03/2002 12/31/2008
Included observations: 1825 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	6.69E-05	8.11E-06	8.250109	0.0000
RESID^2(-1)	0.390879	0.021559	18.13055	0.0000

R-squared	0.152770	Mean dependent var	0.000110
Adjusted R-squared	0.152305	S.D. dependent var	0.000360
S.E. of regression	0.000331	Akaike info criterion	-13.18612
Sum squared resid	0.000200	Schwarz criterion	-13.18009
Log likelihood	12034.34	Hannan-Quinn criter.	-13.18390
F-statistic	328.7169	Durbin-Watson stat	2.126770
Prob(F-statistic)	0.000000		

2009-2015

Heteroskedasticity Test: ARCH

F-statistic	34.31508	Prob. F(1,1822)	0.0000
Obs*R-squared	33.71772	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 02/17/23 Time: 15:43
Sample (adjusted): 1/05/2009 12/31/2015
Included observations: 1824 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000103	1.09E-05	9.474430	0.0000
RESID^2(-1)	0.135964	0.023210	5.857908	0.0000

R-squared	0.018486	Mean dependent var	0.000119
Adjusted R-squared	0.017947	S.D. dependent var	0.000453
S.E. of regression	0.000449	Akaike info criterion	-12.57929
Sum squared resid	0.000367	Schwarz criterion	-12.57325
Log likelihood	11474.31	Hannan-Quinn criter.	-12.57706
F-statistic	34.31508	Durbin-Watson stat	2.016057
Prob(F-statistic)	0.000000		

2016-2022

Heteroskedasticity Test: ARCH

F-statistic	58.51205	Prob. F(1,1822)	0.0000
Obs*R-squared	56.75368	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 02/18/23 Time: 12:13
Sample (adjusted): 1/05/2016 12/30/2022
Included observations: 1824 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	5.20E-05	8.81E-06	5.905801	0.0000
RESID^2(-1)	0.176394	0.023060	7.649317	0.0000

R-squared	0.031115	Mean dependent var	6.32E-05
Adjusted R-squared	0.030583	S.D. dependent var	0.000377
S.E. of regression	0.000371	Akaike info criterion	-12.95886
Sum squared resid	0.000251	Schwarz criterion	-12.95282
Log likelihood	11820.48	Hannan-Quinn criter.	-12.95663
F-statistic	58.51205	Durbin-Watson stat	2.153496
Prob(F-statistic)	0.000000		

The above table reveals the results of Heteroscedasticity Test of OMX Tallinn Index in Estonia in all the three phases which could show the presence of ARCH effect in the data. The ARCH effect can be judged from lag range multiplier (LM) statistics which is shown in the form of Observed R Squared. The Observed R Squared statistics of all these three companies are considered significant as its probability value is less than 0.05. Moreover, the F statistics are also significant as its significant value is less than 0.05. This proves that there is an existence of ARCH effect in the index price volatility of all these 3 phases which indicate that PARCH models are suitable for the data.

Formulation of PARCH Model of OMX Tallinn Index from 1st January, 2002 to 31st December, 2008

Dependent Variable: LRTALLIN
Method: ML ARCH - Normal distribution
Date: 02/18/23 Time: 16:15
Sample (adjusted): 1/02/2002 12/31/2008
Included observations: 1826 after adjustments
Convergence achieved after 39 iterations
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(7) = C(3) + C(4)*(ABS(RESID(-1)) - C(5)*RESID(
-1))^C(7) + C(6)*@SQRT(GARCH(-1))^C(7)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000457	0.000193	2.369955	0.0178
LRTALLIN(-1)	0.234461	0.022856	10.25799	0.0000
		Variance Equation		
C(3)	1.92E-05	9.97E-06	1.921072	0.0457
C(4)	0.134088	0.008451	15.86718	0.0000
C(5)	-0.083096	0.026472	-3.138940	0.0017
C(6)	0.888384	0.007153	124.1946	0.0000
C(7)	1.413073	0.103013	13.71748	0.0000

R-squared	0.043909	Mean dependent var	0.000358
Adjusted R-squared	0.043385	S.D. dependent var	0.010715
S.E. of regression	0.010480	Akaike info criterion	-6.665083
Sum squared resid	0.200347	Schwarz criterion	-6.643960
Log likelihood	6092.220	Hannan-Quinn criter.	-6.657291
Durbin-Watson stat	2.064699		

Formulation of PARCH Model of OMX Tallinn Indexfrom 1st January, 2009 to 31st December, 2015

Dependent Variable: LRTALLIN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 02/18/23 Time: 17:35
Sample (adjusted): 1/02/2009 12/31/2015
Included observations: 1825 after adjustments
Convergence achieved after 39 iterations
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(7) = C(3) + C(4)*(ABS(RESID(-1)) - C(5)*RESID(
-1))^C(7) + C(6)*@SQRT(GARCH(-1))^C(7)

Longitudinal Volatility Analysis of OMX Tallinn Index in the case of the emerging stock market of Estonia using PARCH Model

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000295	0.000169	1.747008	0.0806
LRTALLIN(-1)	0.072268	0.023641	3.056827	0.0022
		Variance Equation		
C(3)	0.000103	4.81E-05	2.151610	0.0314
C(4)	0.154966	0.008156	19.00038	0.0000
C(5)	0.039559	0.030332	1.304201	0.1922
C(6)	0.871305	0.006131	142.1151	0.0000
C(7)	1.114716	0.085762	12.99784	0.0000

R-squared	0.007481	Mean dependent var	0.000635
Adjusted R-squared	0.006936	S.D. dependent var	0.010965
S.E. of regression	0.010927	Akaike info criterion	-6.613054
Sum squared resid	0.217667	Schwarz criterion	-6.591922
Log likelihood	6041.412	Hannan-Quinn criter.	-6.605259
Durbin-Watson stat	1.960692		

Formulation of PARCH Model of OMX Tallinn Indexfrom 1st January, 2016 to 31st December, 2022

Dependent Variable: LRTALLIN
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 02/18/23 Time: 17:44
Sample (adjusted): 1/04/2016 12/30/2022
Included observations: 1825 after adjustments
Convergence achieved after 47 iterations
Presample variance: backcast (parameter = 0.7)
@SQRT(GARCH)^C(7) = C(3) + C(4)*(ABS(RESID(-1)) - C(5)*RESID(
-1))^C(7) + C(6)*@SQRT(GARCH(-1))^C(7)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000358	0.000123	2.901042	0.0037
LRTALLIN(-1)	0.082521	0.022989	3.589592	0.0003
		Variance Equation		
C(3)	0.000170	0.000105	1.610861	0.1072
C(4)	0.275088	0.018559	14.82260	0.0000
C(5)	0.122675	0.032853	3.734103	0.0002
C(6)	0.688054	0.021498	32.00481	0.0000
C(7)	1.275441	0.123792	10.30313	0.0000

R-squared	0.015731	Mean dependent var	0.000373
Adjusted R-squared	0.015191	S.D. dependent var	0.008024

S.E. of regression	0.007963	Akaike info criterion	-7.438731
Sum squared resid	0.115599	Schwarz criterion	-7.417600
Log likelihood	6794.842	Hannan-Quinn criter.	-7.430936
Durbin-Watson stat	1.895002		

Conclusion

From the above analysis and discussion, it is clear that there is presence of asymmetric volatility in the crude oil due to the spread of COVID-19 pandemic, in other words the news related to spreading of the pandemic COVID-19 pandemic has an effect on the price volatility of crude oil with is also statistically proven as asymmetric term within the equation i.e. λ is negative and also statistically significant. But there is absence of leverage effect of the pandemic on the price volatility of natural gas as asymmetric term within the equation i.e. λ is positive and also statistically significant. The forecasting graphs of crude oil represents that there is a possibility that volatility will be higher in the even in the succeeding few months but it is difficult to assess the expected volatility of natural gas for the succeeding month as the volatility graph is continuously fluctuating. Once the lockdown will be over and the demand for crude oil and natural will be shoot up which may again change the trend of price volatility of both the commodities. The prediction of volatility may be more accurate when more succeeding months, where the effect of COVID-19 pandemic is still continuing, will be considered for the formulation of volatility models. Moreover, if model will be formulated using high frequency data, then the minute or hour wise volatility may also be possible to predict. These are the few gaps where the future researchers could work on.

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Authors' Contributions:

The authors contributed equally to this work.

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