Modeling and Forecasting the Volatility in theIndian Stock Market

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2019B3A70394P
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Abstract

The present paper models the association between stock market returns and stock market volatility in the Indian context and forecasts the model on the covid-19 data. The data used for this paper are daily closing prices of BSE Sensex and Nifty-50 for 16 years (2005-2021). For the purpose of studying the nature of volatility GARCH model is used. The data is tested for stationarity using ADF unit root test and the model is tested for Heteroskedasticity and arch effect using ARCH-LM test. The results of the ADF unit root test showed the presence of stationarity in the prices of both the indices used and the results of the ARCH-LM test showed the presence of heteroskedasticity on the stock indices i.e present period prices are influenced by previous period prices. The results of the GARCH model discloses the existence of volatility clustering in the stock market which says a high volatility period will be followed by a high volatility period. Then the volatility forecasts are generated using the GARCH model.

Introduction

Stock market volatility has long been a variable of interest as it helps Economists, Investors and generally Curious people understand and make forecasts about the economy. Primarily, volatility is a measure of how much the price of an asset varies, Also called the realised (or historical) volatility, a fundamental measure to calculate the same for a period is to use the standard deviation of the asset prices in that period. Another interesting measure is the implied volatility, an indicator which predicts the volatility without calculating any deviations of the stock prices. Various implied volatility indicators exist around the world, one popular example of which is the CBOE-VIX, which calculates the implied volatility based on the demand of S&P 500 call and put options, the analog for India is NVIX. These indicators have mirrored the realised volatility well in the past and are thus fairly reliable.

A higher value of implied volatility is an indicator of expectations of a riskier market by the investors, and thus this indicator is also used as a "fear and greed" indicator to gauge the market sentiment.

The primary motive of our study is to be able to model this very indicator of interest, that is, volatility and be able to make reliable forecasts from that model. For this purpose, we use data on daily returns on the BSE sensex and NSE Nifty-50 indices for the time period of 2005-2021. A

GARCH model is then trained on the logarithm of these data series to yield a regression predictor for the volatility. While GARCH is a standard and popular method used to forecast volatility, it may fail to take into account unprecedented events that may have a significant effect on the economy and markets, and to check this, we test our model on the data of time period during the unfolding of COVID-19 related events from March 2020 and ahead and end up with a not good accuracy on this test data. The model however performs well for most of the training data used to estimate the parameters.

While a lot of existing literature has established the effectiveness of GARCH model for predicting the market volatility, A certain 2013 paper[1] by Amado, Teräsvirta, two parametric alternatives are proposed to the GJR-GARCH model of Glosten et al. (1993) based on additive and multiplicative decompositions of the variance to allow the variance of the model to have a smooth time-varying structure. Another particularly interesting study in the context of COVID-19 is that by Baker et al. (2020)[2] wherein the authors follow a text-based approach based on news-article frequency on economy, market and volatility (EMV) to develop a volatility tracker that mirrors the CBOE-VIX well. The advantage of such a news-based volatility indicator is that you can narrow down on the volatility caused by COVID-19 by looking at the frequency of COVID-19 news articles among the articles considered for calculating the EMV volatility tracker's value.

While the detailed results of the analysis carried out on the data and the model training can be found out in the "Data and Methodology" and "Results" section of this paper, a summary of the findings is that the GARCH(1,1) model detects presence of volatility clustering and the predictions by the model are well fitting the test data as we can see in the graphs presented in the results section that the volatility predictor jumps whenever movements in stock prices are more violent.

Literature review

Trilochan tripaty (2010) : is a comparative study on suitability of different volatility models in predicting stock return in india. It uses different models EMEA , GARCH , EVI and Rolling

[1] Cristina Amado, Timo Teräsvirta, Modelling volatility by variance decomposition, Journal of Econometrics, Volume 175, Issue 2, 2013, Pages 142-153, ISSN 0304-4076, https://doi.org/10.1016/j.jeconom.2013.03.006.

[2] Scott R Baker, Nicholas Bloom, Steven J Davis, Kyle Kost, Marco Sammon, Tasaneeya Viratyosin, The Unprecedented Stock Market Reaction to COVID-19, *The Review of Asset Pricing Studies*, Volume 10, Issue 4, December 2020, Pages 742–758, https://doi.org/10.1093/rapstu/raaa008

moving average models on NSE returns from (2005 -2008). Author suggests using high frequency data such as intra day data so that we get better results. The studies showed that the GARCH performed better in various aspects and concluded that GARCH is the best method for indian stock markets.

Debi bal, Seba Mohanty (2021) : examined the stock market volatility of a few sectors during covid-19. This paper used the GARCH model to study the volatility followed by Diks and pachinko non-linearity tests to find out if there are any causality effects between sectors.The results suggest that there is a huge causality between the volatility of the gas sector, metal sector with a growth rate of a covid-19 pandemic. This paper also talks about the market uncertainties in the market during pandemics that may lead to this volatility. The author concludes that by including lagged information of covid-19 cases the future volatility can be predicted with greater precision.

Astha Agarwal (2020) : compares the short term and long term stock market volatility between the sensex-50 index and nifty-50 index using the GARCH(1,1) model. results show that the volatility of Sensex 50 index is much higher than the nifty 50 index during the period (2015 - 2020) . This paper also talks about the presence of volatility clustering in several sectors of both the indices which makes both upward and downward trends to be persistent for a long period before it changes the trend.

Patil anoop , parab narayan (2018) : studies the impact of demonetization on nifty-50 across different sectoral indices. Authors predicted there should be a negative impact of demonetization on the stock market as people in India were not very familiar with digital transactions in those days. After carrying out the analysis using GARCH model authors noticed that there is a huge negative impact on the stock market due to demonetization from the next day itself as removing a complete currency from the economy stagnated the transactions in the country.

Nisha jindal (2020) investigates if there is presence of leverage effect and volatility clustering in indian stock market as they are most important variable to in understanding the behavior and pattern of stock market volatility.using the GARCH model on data of 10 year (2009 - 2019) authors concluded that there is presence of both leverage effect and volatility clustering in indian stock market. Author believes that this is due to the impact of asymmetric news on the stock market which is a result of interdependence of different economies across the globe.

Banamber mishra (2010) : studied the dynamics of stock market return volatility in the context of india and japan.author uses GARCH model as it is having more flexible lag structure than normal ARCH model . The results show that Indian stock market returns are more predictable than Japan. Indian stock returns respond more to good news whereas japan stock returns respond to bad news.

Rashi choudhary , preeti bakshi (2020) : talks about the performance of indian stock market during covid-19 by analysing the returns. The analysis is made using three different models with three different dependent variables(standard deviation , skewness , kurtosis). It shows that there is strong correlation between volatility and number of covid cases. Also the sectoral analysis shows that healthcare is the only sector with positive return and with stronger rebound against pandemic. Also the comparison of indian stock volatility with uk , us and japan stock markets showed that effect of covid on indian stock volatility is less than that of US and Japan.

Ashri D , sahoo BP (2021) : studied the repercussions of covid-19 on the Indian stock market. The paper talks about the supply chain disruptions and change in patterns of consumption and investments of households due to lockdown and market uncertainties. Market analysis showed that decrease in prices of oil caused a catastrophe to the oil and metal sector which made a huge impact on oil and metal sector indices. Author also talks about the risk assessment by banks in giving loans and found that loans decreased a lot during this period which led to further poor performance of the automobile sector.

Data

The Data for daily closing prices of NSE Nifty 50, and BSE Sensex is taken from official NSE and BSE websites, starting from January 2005, to 1st December 2021.
Log Returns of both the indices are calculated using the formula logarithm of current price divided by previous price times 100.

Methodology

Firstly after calculating the Returns of both indices, the data is tested for stationarity using ADF Unit Root Test. Then the model is tested for Heteroscedasticity, and for arch effect using ARCH-LM test. The ARCH model assumes that the data has an autoregressive behavior and also conditional heteroskedasticity, i.e. the variance is not constant over time.

Then the GARCH(1,1) model is used to model and forecast the volatility.

Model Specification

There are two equations of the model:

1) Mean Equation:

$Y_t = c_1 + c_2(Y_{t-1}) + E$

2) Variance Equation:

$$\sigma^2 t = \alpha 0 + \alpha 1\ u^2\ t-1 + \beta 1\ \sigma^2 t-1$$

In the mean equation, the lag term is considered, if the coefficient of the lag term is significant, that indicates that the current returns are influenced by the previous returns. In the Variance equation, the conditional variance or volatility depends on the previous period variance and also the squared error term of the previous period volatility. The two coefficients alpha1 and beta1, represent the ARCH and GARCH coefficients respectively. If the ARCH coefficient is significant, it indicates that the impact of previous period shocks on current period volatility is significant. If the GARCH coefficient is significant, this indicates that there is a presence of volatility clustering, that means a period of high volatility is followed by a period of high volatility and vice versa. Or that the effect of shocks remain visible for some time in the market.

Empirical Analysis

1) ADF Unit Root Test:

Before testing the stationarity using ADF test, a casual regression is performed, and the Rsquare, is tested with D-Watson statistic:

```
. reg SensexReturns NiftyReturns

      Source |       SS           df       MS      Number of obs   =     4,194
-------------+----------------------------------   F(1, 4192)      >  99999.00
       Model |  1530.19115         1  1530.19115   Prob > F        =    0.0000
    Residual |  25.7038321     4,192  .006131639   R-squared       =    0.9835
-------------+----------------------------------   Adj R-squared   =    0.9835
       Total |  1555.89498     4,193  .371069636   Root MSE        =     .0783

------------------------------------------------------------------------------
SensexRetu~s | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
NiftyReturns |   .9920594   .0019859   499.56   0.000      .988166    .9959528
       _cons |   .0008149   .0012099     0.67   0.501    -.0015572    .0031869
------------------------------------------------------------------------------

. estat dwatson

Number of gaps in sample = 1003

Durbin-Watson d-statistic(  2,   4194) =  1.432269
```

Rsquare = 0.9835

D-Watson statistic = 1.432269.

As Dwatson > Rsquare, indicates that the data is stationary.

ADF Test:

H0:Not stationary

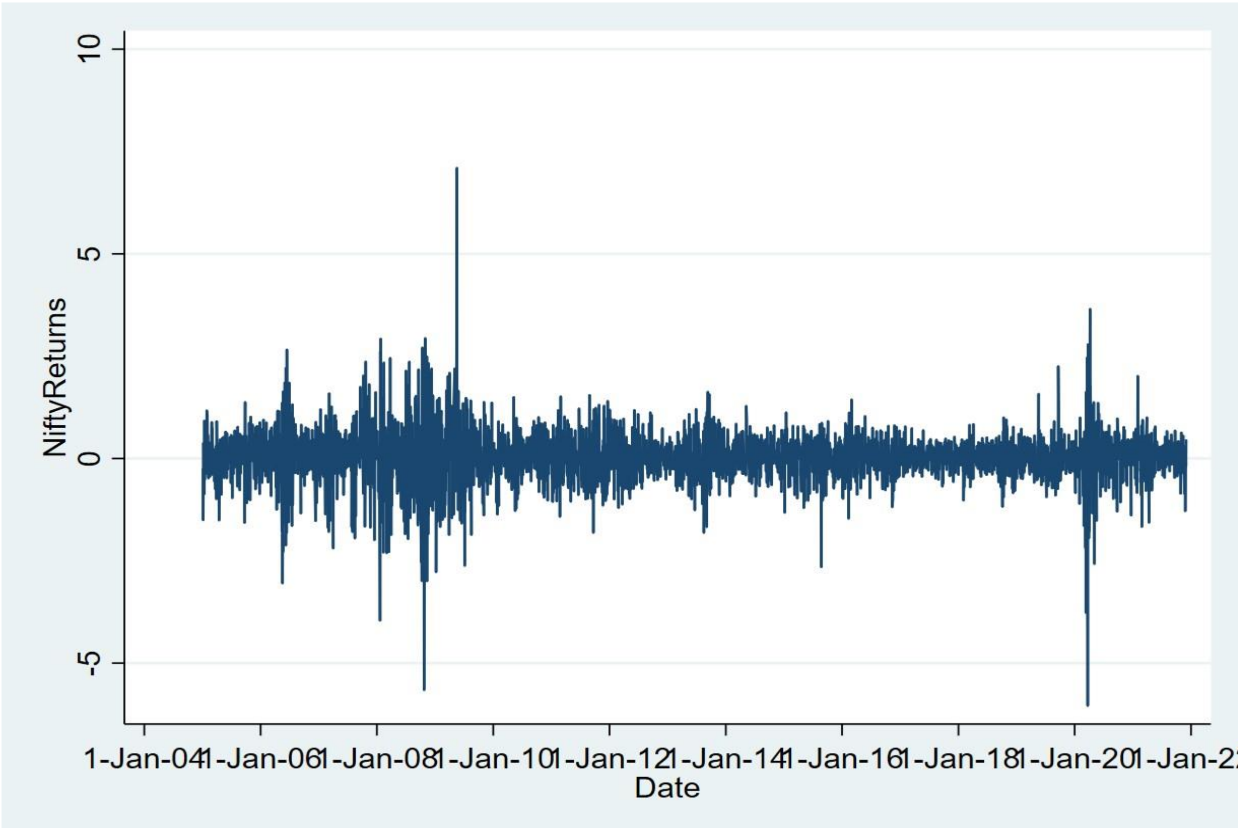
H1:Stationary

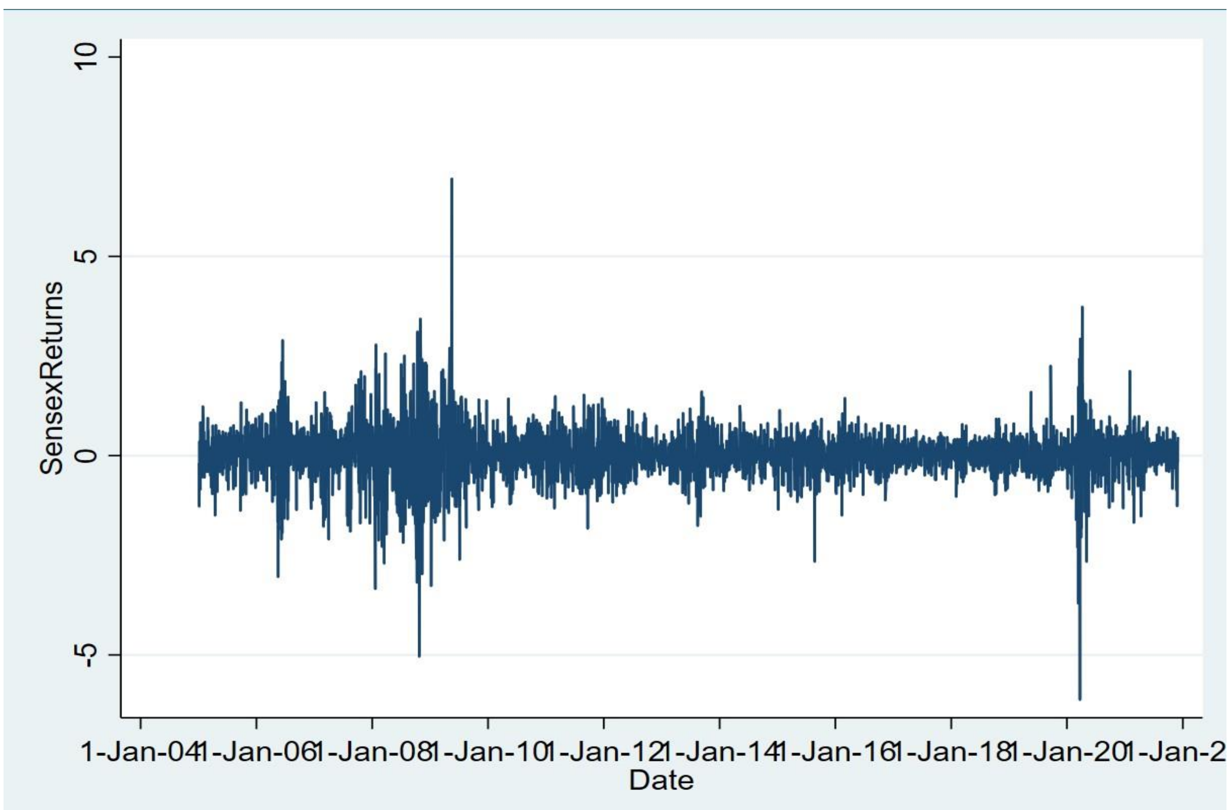
```
. dfuller SensexReturns, trend regress lags(0)

Dickey-Fuller test for unit root          Number of obs  = 3,190
Variable: SensexReturns                   Number of lags =     0

H0: Random walk with or without drift

                                       Dickey-Fuller
                   Test         -------- critical value ---------
              statistic           1%           5%          10%
-----------------------------------------------------------------
 Z(t)           -59.619       -3.960       -3.410       -3.120
-----------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000.
```

As, absolute value of test statistic > absolute value of 1% critical value, we reject H0.

```
. dfuller NiftyReturns, trend regress lags(0)

Dickey-Fuller test for unit root          Number of obs  = 3,190
Variable: NiftyReturns                    Number of lags =     0

H0: Random walk with or without drift

                                       Dickey-Fuller
                   Test         -------- critical value ---------
              statistic           1%           5%          10%
-----------------------------------------------------------------
 Z(t)           -60.404       -3.960       -3.410       -3.120
-----------------------------------------------------------------
MacKinnon approximate p-value for Z(t) = 0.0000.
```

As, absolute value of test statistic > absolute value of 1% critical value, we reject H0.


NiftyReturns
10
5
0
-5
1-Jan-04
1-Jan-06
1-Jan-08
1-Jan-10
1-Jan-12
1-Jan-14
1-Jan-16
1-Jan-18
1-Jan-20
Date


SensexReturns
10
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0
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1-Jan-08
1-Jan-10
1-Jan-12
1-Jan-14
1-Jan-16
1-Jan-18
1-Jan-20
Date

2) ARCH-LM Test for Heteroskedasticity:

The lag terms for both the returns are generated and regressed on the original time series.Then the arch-lm test is performed after the regression results.

1) Nifty returns:

Coefficient of lag: as the p value = 0.012 < 0.05, is significant at 5% level of significance, there is a significant influence of previous period prices on current periods.

ARCH-LM Test:

H0:no ARCH effects

H1:ARCH disturbance present.

As the test statistic of ARCH-LM test is significant at all levels of significance, we reject the null hypothesis, and so ARCH effects are significant in the Nifty data.

```
. reg NiftyReturns lag_nifty

      Source |       SS           df       MS      Number of obs   =     4,193
-------------+----------------------------------   F(1, 4191)      =      6.32
       Model |  2.34026834         1  2.34026834   Prob > F        =    0.0120
    Residual |   1552.3806     4,191  .37040816   R-squared       =    0.0015
-------------+----------------------------------   Adj R-squared   =    0.0013
       Total |  1554.72087     4,192  .37087807   Root MSE        =    .60861

------------------------------------------------------------------------------
NiftyReturns | Coefficient  Std. err.      t    P>|t|     [95% conf. interval]
-------------+----------------------------------------------------------------
   lag_nifty |   .0387994   .0154359     2.51   0.012     .0085368     .069062
       _cons |   .0209062   .0094048     2.22   0.026     .0024677    .0393446
------------------------------------------------------------------------------

. estat archlm, lags(1)

Number of gaps in sample = 1003
LM test for autoregressive conditional heteroskedasticity (ARCH)
---------------------------------------------------------------------------
    lags(p)  |          chi2               df                 Prob > chi2
-------------+-------------------------------------------------------------
       1     |         90.217               1                   0.0000
---------------------------------------------------------------------------
         H0: no ARCH effects      vs.  H1: ARCH(p) disturbance
```

2) Sensex Returns:

Coefficient of lag: as the p value = 0.002 < 0.01, is significant at 1% level of significance, there is a significant influence of previous period prices on current periods.

ARCH-LM Test:

H0:no ARCH effects

H1:ARCH disturbance present.

As the test statistic of ARCH-LM test is significant at all levels of significance, we reject the null hypothesis, and so ARCH effects are significant in the Sensex data.

```
. gen lag_sensex = SensexReturns[_n-1]
(2 missing values generated)

. reg SensexReturns lag_sensex
```

Source	SS	df	MS			
				Number of obs	=	4,193
				F(1, 4191)	=	9.49
Model	3.5149006	1	3.5149006	Prob > F	=	0.0021
Residual	1552.33763	4,191	.370397908	R-squared	=	0.0023
				Adj R-squared	=	0.0020
Total	1555.85253	4,192	.371148028	Root MSE	=	.6086

SensexRetu~s	Coefficient	Std. err.	t	P>|t|	[95% conf.	interval]
lag_sensex	.0475329	.0154302	3.08	0.002	.0172815	.0777843
_cons	.0213186	.009405	2.27	0.023	.0028798	.0397575

```
. estat archlm, lags(1)

Number of gaps in sample = 1003
LM test for autoregressive conditional heteroskedasticity (ARCH)
```

lags(p)	chi2	df	Prob > chi2
1	83.651	1	0.0000

H0: no ARCH effects vs. H1: ARCH(*p*) disturbance

3) GARCH(1,1) Model:

After the confirmation of conditional heteroskedasticity, we performed GARCH(1,1) model on the two indices:

1) Sensex:

Alpha1 = 0.0956, p-value = 7.126e-15

This indicates that the impact of previous period shocks on current period volatility is significant.

Beta1 = 0.8956, p-value = 0.000

This indicates that there is a presence of volatility clustering, that means a period of high volatility is followed by a period of high volatility and vice versa.

Constant Mean - GARCH Model Results

Dep. Variable:	SensexReturns	**R-squared:**	0.000
Mean Model:	Constant Mean	**Adj. R-squared:**	0.000
Vol Model:	GARCH	**Log-Likelihood:**	-2915.76
Distribution:	Normal	**AIC:**	5839.52
Method:	Maximum Likelihood	**BIC:**	5864.89
		No. Observations:	4194
Date:	Mon, Dec 06 2021	**Df Residuals:**	4193
Time:	14:12:18	**Df Model:**	1

Mean Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
mu	0.0371	6.846e-03	5.421	5.910e-08	[2.370e-02,5.054e-02]

Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	3.6328e-03	1.014e-03	3.582	3.408e-04	[1.645e-03,5.620e-03]
alpha[1]	0.0956	1.228e-02	7.782	7.126e-15	[7.151e-02, 0.120]
beta[1]	0.8956	1.232e-02	72.686	0.000	[0.871, 0.920]

Covariance estimator: robust

2) Nifty:

Alpha1 = 0.0984, p value = 1.232e-14

This indicates that the impact of previous period shocks on current period volatility is significant.

Beta1 = 0.8933, p value = 0.000

This indicates that there is a presence of volatility clustering, that means a period of high volatility is followed by a period of high volatility and vice versa.

Constant Mean - GARCH Model Results

Dep. Variable:	NiftyReturns	**R-squared:**	0.000
Mean Model:	Constant Mean	**Adj. R-squared:**	0.000
Vol Model:	GARCH	**Log-Likelihood:**	-2954.39
Distribution:	Normal	**AIC:**	5916.78
Method:	Maximum Likelihood	**BIC:**	5942.14
		No. Observations:	4194
Date:	Mon, Dec 06 2021	**Df Residuals:**	4193
Time:	14:18:35	**Df Model:**	1

Mean Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
mu	0.0358	6.909e-03	5.179	2.227e-07	[2.224e-02,4.933e-02]

Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	3.7523e-03	1.089e-03	3.447	5.669e-04	[1.619e-03,5.886e-03]
alpha[1]	0.0984	1.276e-02	7.713	1.232e-14	[7.339e-02, 0.123]
beta[1]	0.8933	1.255e-02	71.159	0.000	[0.869, 0.918]

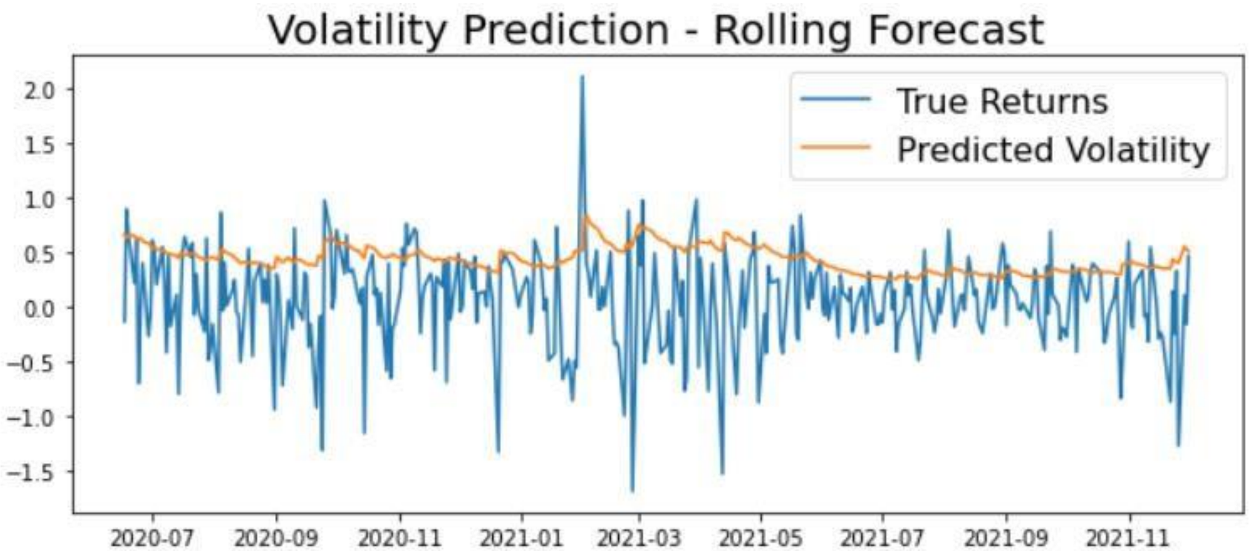
Covariance estimator: robust

Forecasting

The plots show the actual returns and the predicted volatility. These are separate measures, and the graphs are not meant to match each other, but if the model is predicting well, the volatility gets higher when the returns are jumping up and down.

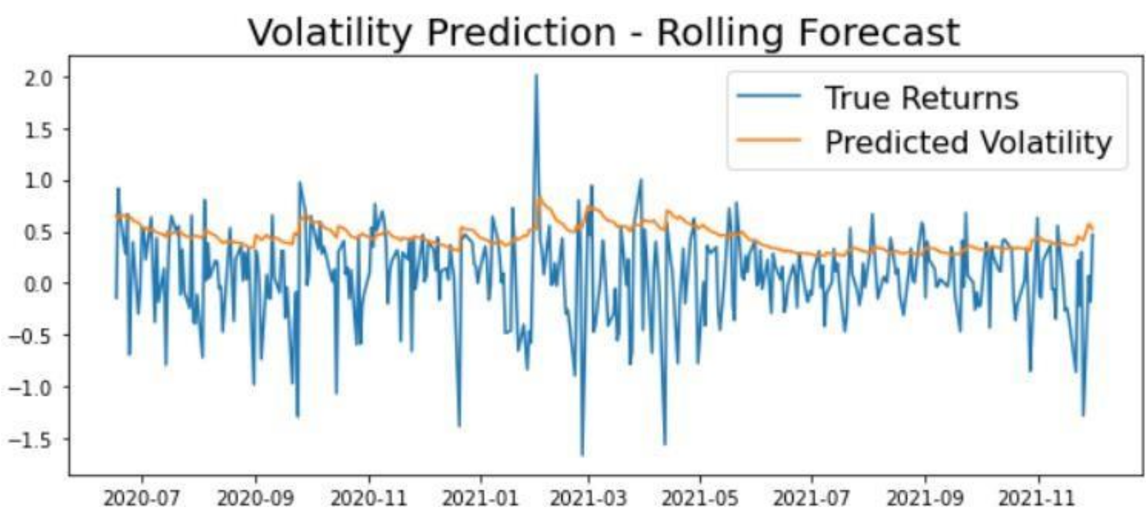
1) Sensex:

Using the above applied GARCH(1,1) models, the forecast for the past 1 year was calculated, using the model trained on the data excluding the past one year.



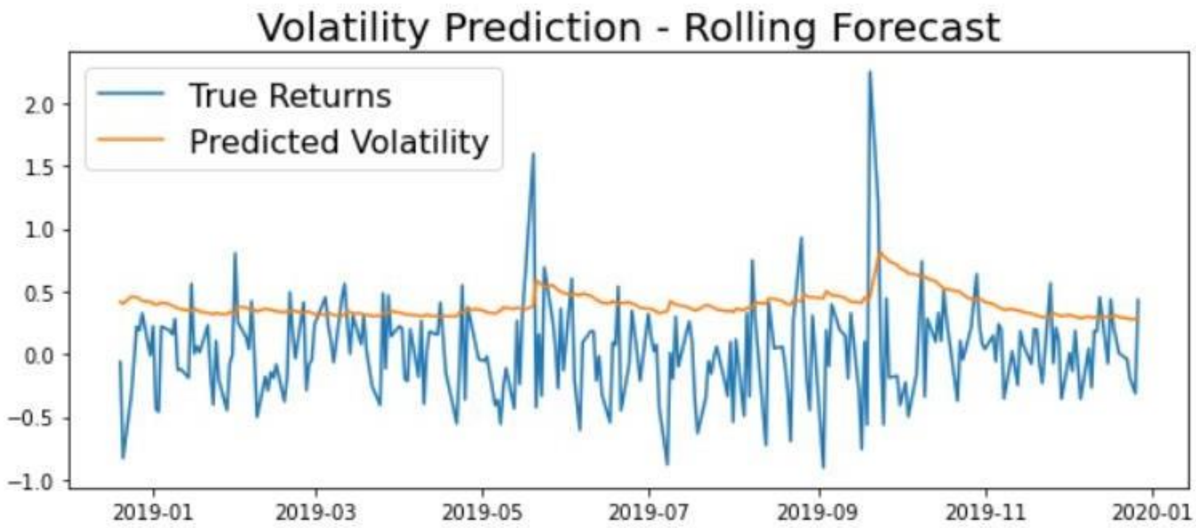
2) Nifty:

Using the above applied GARCH(1,1) models, the forecast for the past 1 year was calculated, using the model trained on the data excluding the past one year.

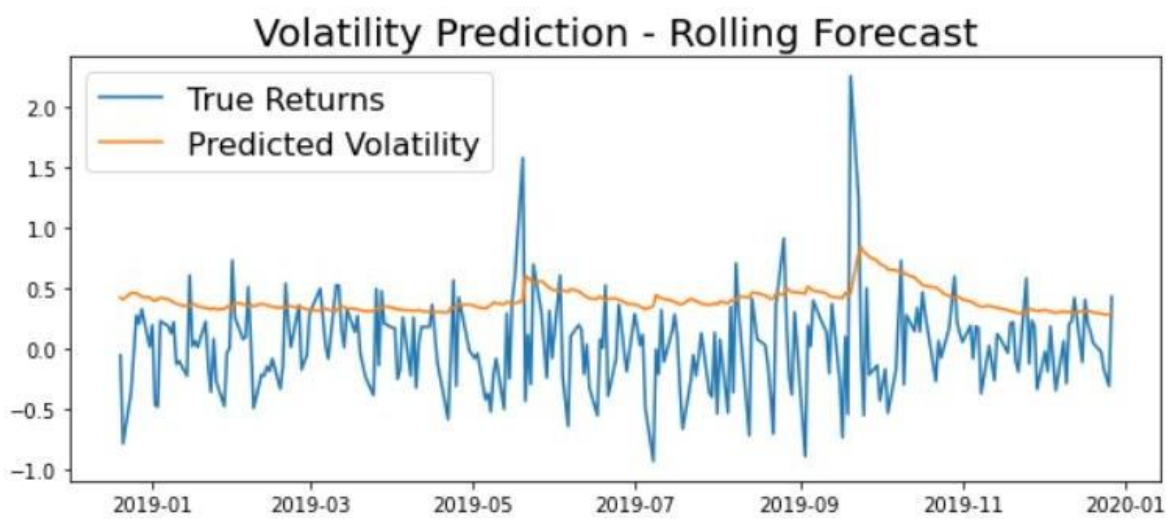


After this the model was trained on data from Jan 2005 to 19 December 2018, and was tested for data from 20 December 2018 to 27 December 2019, when the conditions were normal in the country.

1) Sensex:



2) Nifty:



Conclusion

The returns of both the indices were found to be completely stationary. In both cases the null hypothesis in the ADF unit root test was rejected.

In the ARCH-LM test for heteroskedasticity, for both the indices, null hypothesis was rejected confirming the presence of ARCH effects, and conditional heteroskedasticity.

In the GARCH(1,1) model, on both the indices the ARCH, and GARCH coefficient was found to be significant, which implied the presence of volatility clustering in the data.

The volatility forecasted using the confirmed GARCH(1,1) model trained on precovid data, and forecasted on covid time period, showed the similar trend movement of the volatility with the returns. Volatility dips as the returns stabilize, and increases as the returns swing from positive to negative.

The forecast of volatility on the trained data from 2005 to 2018 and forecasted on data from 2019-2020 showed the similar trend line, signifying that the model works well on both covid and precovid data.

Due to volatility clustering it is seen from the graph that the period of high volatility stays for some time, and also the period of low volatility remains for some time in the economy.

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