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Forecasting the Volatility of S&P 500 after Covid-19 Pandemic Using GARCH Model

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ABSTRACT

Every country's stock exchanges reflect the health of its financial markets.An understanding of volatility is a prerequisite for calculating the risk-return trade-off in the stock market.In this paper, I made an attempt to predict the volatility of the S&P 500 due to the current COVID-19 pandemic which is affecting the US stock market. In this study, I usedGARCH (Generalized Autoregressive Conditional Heteroscedasticity) model to analyze the volatility pattern of S&P 500 for the period between 1st January, 2000 and 7th December, 2021 which has a total of 3508 observations.According to the analysis, GARCH(2,2) is the most effective method of predicting future volatility of S&P 500. The model predicted the volatility with very good accuracy and finally the volatility prediction was done for next seven days.

Keywords:GARCH, S&P 500, Volatility, Heteroskedasticity.

1. Introduction

The World Health Organization (WHO) on 30thJanuary, 2020 declared COVID-19 as an International health emergency. By the end of 2020, the COVID-19 pandemic had resulted in roughly 31.12 million confirmed cases and over 950,000 deaths (WHO, 2020). Due to this, the governments of the world's largest countries have implemented border closures, travel restrictions, and quarantines, sparking fears of an impending financial recession.Through the shutdown of financial market indices, the COVID-19 pandemic also affected the world economy. As a result of the financial crisis, stock market indices began to behave differently. The S&P 500 index, DJI average, and Nasdaq index, for instance, plunged sharply after the Coronavirus. There have been several papers published recently that explore and confirm the dramatic impact that the COVID-19 crisis has had on financial markets.

In a scenario like COVID-19 pandemic it is difficult to predict the future of the stock market and is full of volatility in the long run. The risk, or volatility, is strongly correlated with the expected returns. Many studies have been conducted on risk, volatility and returns.Pindyck (1984), for instance, notes that "much of the decline in stock prices during the 1970s was due to increases in risk premiums arising from a rise in volatility."

In this paper I have tried to estimate the volatility of the stock and not the price of the stock. Investors usually invest in a stock if the volatility of any stock is not much high. Therefore, this article will help the investors to invest their money in a non-risky stocks.A key component of financial time series is uncertainty. This can be interpreted as a deviation from the mean of the dependent variable. A time-series approach to it has long been familiar to economists. However, there were few attempts to accurately model it before the development of the Autoregressive

Conditional Heteroskedasticity Model (ARCH). Prior to ARCH, economists assumed that the variance of their econometric models was constant over time (Engle, 1982). Therefore, the majority of past research was focused on the dependent variable (e.g., the mean return on an investment) as opposed to its errors (Brailsford, Faff, 1996).Volatility can be interpreted as uncertainty in time series. Volatility tends to cluster around itself. High volatility periods are followed by low volatility periods (Engle, 2001). In turbulent economic times, periods of high volatility tend to occur; the opposite is also true for periods of low volatility (Tsay, 2002).Volatility is a measure of the magnitude of errors made when modeling financial variables. If this volatility can be accurately predicted and modeled, it could become an important key variable (Engle, 2001). Valuing assets and managing risks rely on volatility. As the number of financial crises grows, the studies on volatility are receiving more importance (Brailsford, Faff, 1996).

GARCHor Generalized Autoregressive Conditional Heteroskedasticity, models the variance changes over time in a time series explicitly. The purpose of this article is to identify the importance of GARCH model, especially in finance-related fields. In this analysis, we will model and forecast the volatility of S&P 500 stock price returns after COVID-19 pandemic, then infer some conclusions as to how 'jumpy' the return values are and will be for the next few days. When a stock's returns are low, we are more likely to invest in it with lesser risk than if it were a more volatile or varied stock.

2. Literature Review

Many studies have been done on modelling and forecasting stock prices using ARIMA models. To predict stock prices, Adebiyi et.al. (2014) demonstrated an extensive process to find the best ARIMA model (based on the smallest Schwarz Information Criterion, SIC, and the smallest standard error of regression, S.E. of Regression). Similarly, Kamruzzaman et.al(2017) calculated Dhaka Stock Exchange returns by using the Relative Difference method and chose the ARMA(2,2) model (based on the smallest AIC value) as the most parsimonious model for forecasting the monthly market returns. Furthermore, Abbasi et.al (2017) used the ARIMA model to study the flying cement industry. To achieve stationarity, they first applied log differencing to their data series. In order to determine the order of ARMA models, they used the ACF or PACF patterns. As all points were relatively small and within the confidence interval, they used second order lagged differences and obtained a cut off point of one for both the ACF and PACF plots, suggesting that ARIMA(1,2,1) was an appropriate model for forecasting cement stock prices in their study.

Thus far, the ARCH effect in the models has been ignored by researchers. Almarashiet.al.(2018) extended Abbasi et.al (2017) work by utilizing GARCH(1,1) to model volatility in cement prices. In their study, the ARIMA(1,2,1)-GARCH(1,1) model performed better than the ARIMA(1,2,1) model because its values of AIC and SIC were smaller than those in the ARIMA model. In 2015, Xu et.al used the ARIMA-GJR-GARCH model to predict the exchange rate of the Renminbi against the Hong Kong dollar. It is possible to capture asymmetry in the conditional variance equation using the GlostenJagannathan-Runkle GARCH, GJR-GARCH model. In this study, the authors presented an ARIMA(1,1,1)-GJR-GARCH(1,1) model, which they found to be the best-fitting model for exchange rates and forecasting. To my knowledge this is perhaps the first research article which is done on the volatility of U.S stock market after the COVID-19 pandemic.

3. Methodology

Bollerslev developed ARCH in 1986 as a generalized version of Engle's pioneering ARCH methodology. This generalization is called GARCH. GARCH is analogous to the general autoregressive moving average process (Bollerslev, 1986) in that it extends ARCH to GARCH.According to Bollerslev, the GARCH class of models allow for a more flexible lag structure as opposed to the ARCH model, which usually uses a fixed lag structure to avoid the negative variance estimate. The GARCH model permits a longer memory. The GARCH (p,q) process is described as shown in equation-1.

$$h_t = v + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \beta_i h_{t-i}$$
------------------- (1)

GARCH(p,q) adds an autoregressive component to h_t, the forecasted variance (Fabozzi, 2013). Like ARCH, GARCH also requires positive coefficients to ensure non-negative variance estimates (Bollerslev, 1986). The GARCH process is inherently more complex than ARCH. As a result, many researchers limit (p,q) to (1,1) in order to keep their models parsimonious and easy to estimate (Nelson, 1992).

The arch library in python is used to model the GARCH model which can be installed using the command pip install arch in command prompt.GARCH(2,2) Model is used which is based on two lags i.e., a_{t-1} and a_{t-2}. Also, the timeseries is the function of its volatility which is represented by σ_{t-1} and σ_{t-2} . Therefore, the time series is the function of both the lag values and the volatility or the standard deviation of its lags.

$$a_t = \varepsilon_t \sqrt{\omega + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \beta_1 \sigma_{t-1}^2 + \beta_2 \sigma_{t-2}^2}$$
-------------(2)

$$a_0, a_1 \sim \mathcal{N}(0,1)$$

$$\sigma_0 = 1, \sigma_1 = 1$$

$$\varepsilon_t \sim \mathcal{N}(0,1)$$

where, σ = volatility,

ϵ = white noise,

α, β = coefficients of lagged version of timeseries and volatility respectively,

ω = constant.

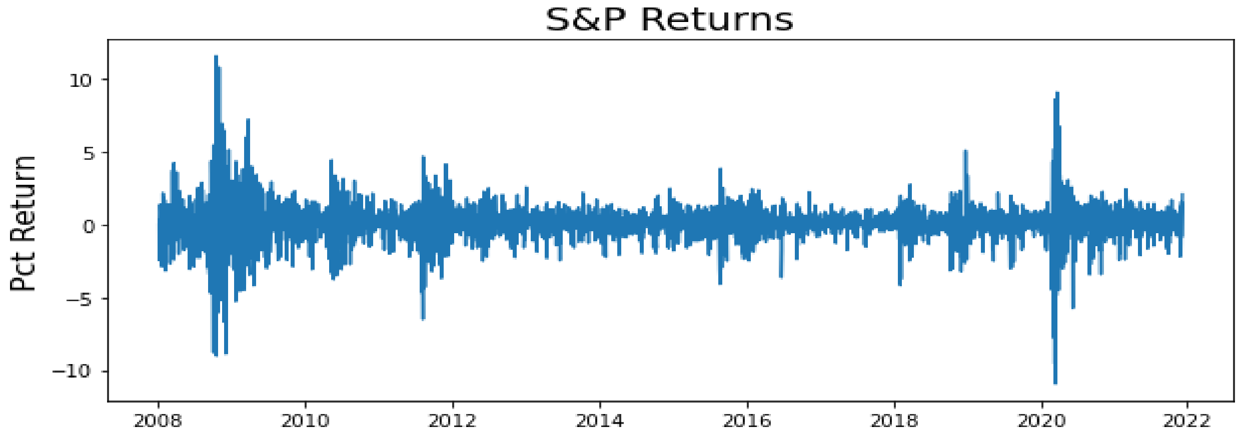
4. Data and Estimation of Results

The S&P 500 data is fetched from the yahoo website by using the code

SPY = web.DataReader('SPY', 'yahoo', start=start, end=end)

The time period of the data was from 1/1/2000 to 07/12/2021. The figure-1 shows the percentage change of S&P 500 returns from 2008-21. This is good data for GARCH model since the data has a high volatility in the year 2008 which was a period of subprime crisis and in year 2020, the year from when the world has been hit by COVID-19. The data is divided into training and testing set. The training set data is from the year 2000 to 2015 and the testing set data is from 2016-2021. The prediction of volatility is done for seven days i.e., from 08/12/21 to 14/12/21.

Figure 1: S&P 500 Returns from 2008-21



The estimated parameters are done by using the code model_fit.summary() and its result is as shown in the table-1. The total number of observations is 3508. Table -3 shows the coefficients of a_ti.e., omega, alpha-1, alpha-2, beta-1 and beta-2 of equation-2. The p-value of all the coefficients is significant expect beta-1.

Table-1: Constant Mean - GARCH Model Results			
Dep. Variable:	Close	**R-squared:**	0.000
Mean Model:	Constant Mean	**Adj. R-squared:**	0.000
Vol Model:	GARCH	**Log-Likelihood:**	-4727.72
Distribution:	Normal	**AIC:**	9467.44
Method:	Maximum Likelihood	**BIC:**	9504.42
		No. Observations:	3508
Date:	Sat, Dec 11 2021	Df Residuals:	3507
Time:	14:00:39	Df Model:	1

Table-2: Mean Model					
	coef	**std err**	**t**	**P>|t|**	**95.0% Conf. Int.**

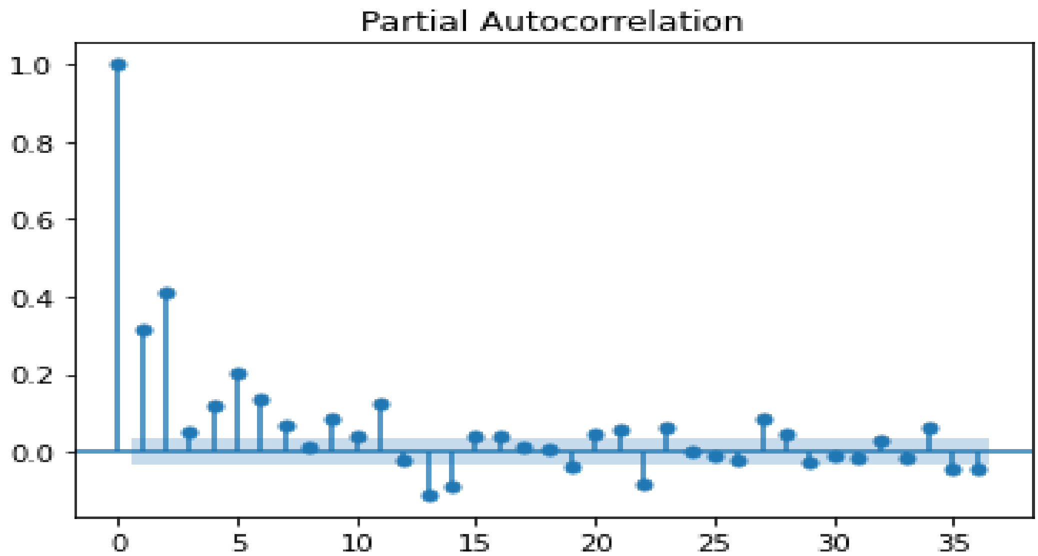
mu	0.0800	1.287e-02	6.218	5.037e-10	[5.479e-02, 0.105]

Table-3: Volatility Model

	coef	std err	t	P>|t|	95.0% Conf. Int.
omega	0.0522	1.285e-02	4.064	4.826e-05	[2.703e-02,7.739e-02]
alpha[1]	0.1225	3.035e-02	4.035	5.470e-05	[6.297e-02, 0.182]
alpha[2]	0.1550	4.168e-02	3.719	2.002e-04	[7.331e-02, 0.237]
beta[1]	0.2269	0.301	0.754	0.451	[-0.363, 0.817]
beta[2]	0.4628	0.254	1.825	6.807e-02	[-3.436e-02, 0.960]

Based on the pacf (partial autocorrelation function) graph which is given in the figure-2, we can select the GARCH(2,2) model since after 2 spikes the bar gets shut down rapidly. Therefore, (p,q) used in this model was (2,2).

Figure 2: Partial Autocorrelation (pacf) graph



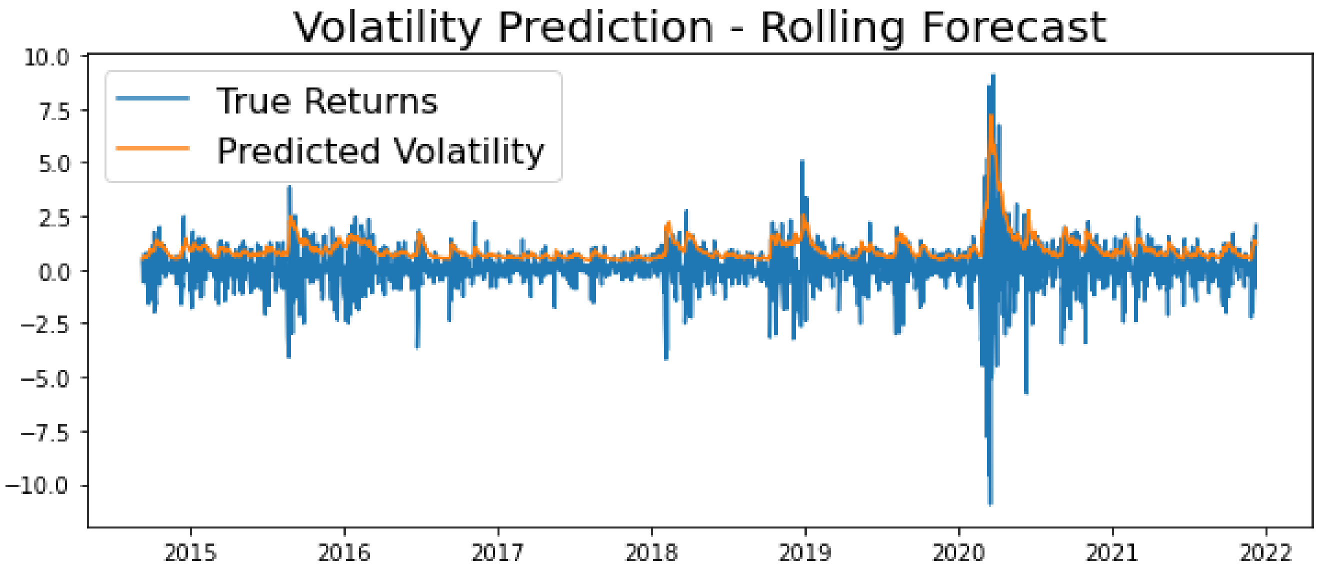
Rolling prediction package is used for the testing data. The period of testing is about 365*5 = 1825 observations. In order to predict the volatility, I have used the command as given below.

rolling_predictions = pd.Series(rolling_predictions, index=returns.index[-365*5:]

In the figure-3, we can see the blue line which is the actual returns and the yellow line is the predicted value of the returns. The yellow line is exactly jumping when the blue line is spiking either high or low. Also, the yellow line is stable whenever the blue line is stable. Therefore, it can be concluded that the predicted and the true returns matches well and the model has performed well.

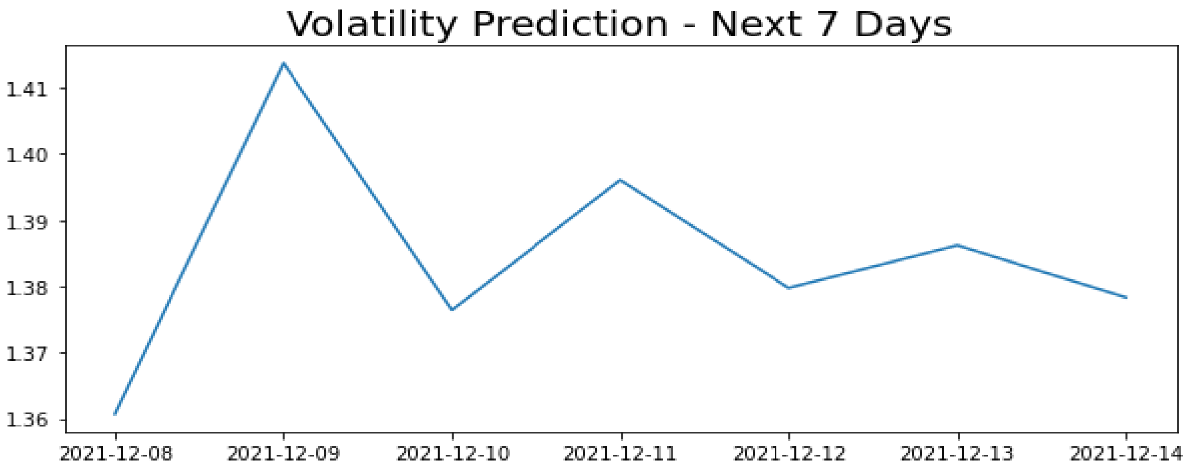
The S&P 500 was stable from 2016 to the end of 2019. But as the COVID-19 pandemic hit the world in the early 2020, we can see that the stocks got very much volatile and of course that was a very uncertain time for investors to invest their money in the stock market. And the GARCH process was able to detect that volatility.

Figure 3: Volatility Prediction



The rolling forecast package is used to forecast the volatility of the S&P 500 for the next 7 days from 08/12/21 to 14/12/21. As shown in the figure-4 the volatility on 08/12/21 is less and then it spikes on 09/12/21 and then again it goes down on 10/12/21.

Figure 4: S&P 500 Volatility Prediction of 7 days from 08/12/21 to 14/12/21



5. Conclusion

This study seeks to identify the best fitting GARCH process that is most predictive of the conditional variance of the Standard and Poor 500 index. In this study, it was found that GARCH with orders (2,2) is the most accurate at forecasting conditional variance. However, this study didn't examine other ARCH variants, such as exponential-GARCH, integrated-GARCH, GJR-GARCH, etc. In my opinion, these other ARCH offshoots are outside the scope of this paper. Consequently, it cannot be said with 100% certainty that the GARCH (2,2) process is the most accurate predictor of volatility of the S&P500.Apart from the technical aspect of predicting the volatility, this article is of practical interest to the investors at all levels because an investor is not only interested in obtaining a higher rate of return, but also a steady (i.e., less volatile) rate of return. Therefore, based on these predictions an investor can take a decision whether he/she should either buy or sell a stock.

References

1. Abbasi U, Almarashi A M, Khan K and Hanif S 2017 Sci. Int. (Lahore), 29(5), p 1039-1043.
2. Adebiyi A A, Adewumi A O and Ayo C K 2014 2014 UK Sim-AMSS 16th International Conference on Computer Modelling and Simulation pp 105-111.
3. Almarashi A M, Abbasi U, Saman H, Alzahrani M R and Khan K 2018 Sci. Int. (Lahore), 30(1), pp 89-94.
4. Box G E P and Jenkins G M 1976 Time series analysis: Forecasting and control 2nd edition (Holden-Day, San Francisco).
5. Engle R F 1982 Econometrica, 50:4 pp 987-1007.
6. Gujarati D N 1995 Basic Econometrics 3rd ed (New York: McGraw-Hill).
7. Kamruzzaman M, Khudri M and Rahman M 2017 Dhaka University Journal of Science 65(2), pp 97-101.
8. Robert F. Engle. Autoregressive conditional heteroskedasticity with estimates of the variance of United Kingdom inflation. Econometrica, 50(4), 1982.
9. Robert W. Faff Timothy J. Brailsford. An evaluation of volatility forecasting techniques. Journal of Banking and Finance, 20, 1996.
10. Robert F. Engle. GARCH 101: The use of arch/GARCH models in applied econometrics. Journal of Economic Perspectives, 15(4), 2001.
11. Ruey S. Tsay. Analysis of Financial Time Series. John Wiley and Sons, 2002.
12. Pindyck, Robert S., 1984, Risk, inflation, and the stock market, American Economic Review 74, 335-351.
13. Tim Bollerslev. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics, 31, 1986.
14. World Health Organization 2020 World Health Organization, Novel Coronavirus (2019-nCOV) Situation Report, 92, (2020). Retrieved From https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports.
15. Xu S N, Zhao K and Sun J J 2015 Proceedings of the AASRI International Conference on Applied Engineering Sciences Vol. 1, pp 83-86.