FORECASTING STOCK RETURNS WITH GARCH MODEL

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ABSTRACT

This paper presents the application of GARCH model in forecasting stock returns. I used python on all the calculations and analysis. The first part we select, specify and fit GARCH model so as to forecast daily one step returns for the Apple stock. I extracted the historical data from yahoo finance and the analysis was done in Spyder, a python IDE. The results showed that the best model for the Apple stock is the ARIMA(0,1)-GARCH(1,1) or MA(1)-GARCH(1,1) which is in a family of M-GARCH models.

* *Univariate Volatility Modeling and Multivariate Time Series Analysis*

1 VOLATILITY ANALYSIS

2 FORECASTING APPLE DAILY STOCK RETURN USING A GARCH MODEL

2.1 Data

The historical data used to fit the model is the Apple daily adjusted closing prices from October 1st, 2018 (as the earliest data available) to October 1st, 2019, which corresponds to a total of 252 observations. We save the data from September 15th, 2019 to October 1st, 2019 to perform forecasts and validation latter. The data is compiled from Yahoo Finance using python, and covers a daily database denominated in US dollar. The log-returns are calculated by taking the natural logarithm of the ratio of two consecutive prices, using the formula below:

$$r_i = \ln\left(\frac{S_i}{S_{i-1}}\right)$$

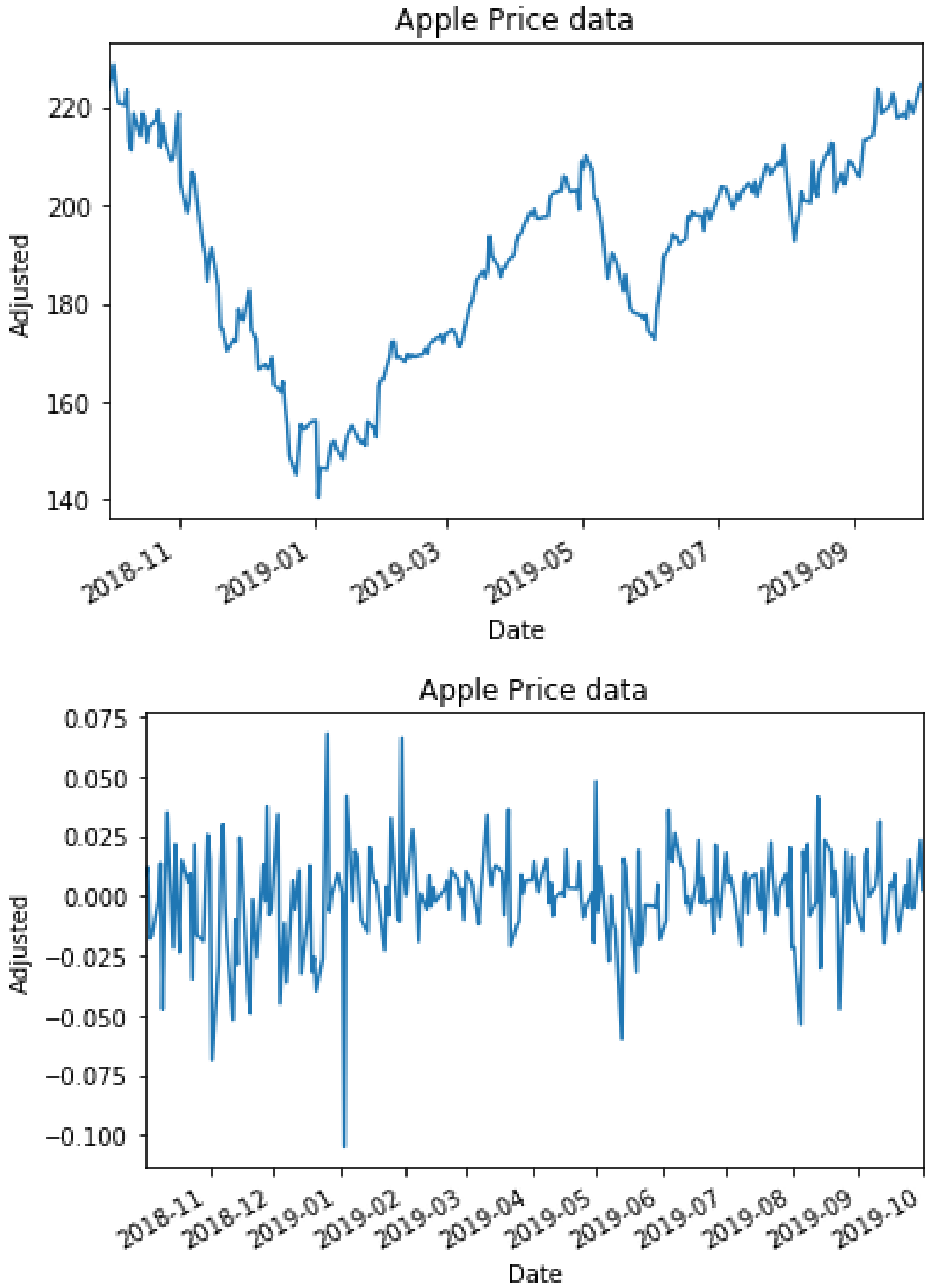

Figure 1: illustrate the Apple daily closing prices and daily returns.

Calculating log returns ensure that our returns follow a log normal distribution as shown from Figure **??**. In most cases these returns are stationary.

3 METHODOLOGY

The plots shows one common observation we can get from economic and financial data: Volatility clustering. If the recent daily returns have been unusually volatile, we might expect that tomorrow's return is also more volatile than usual. We can also observe that the squared returns of an asset are usually positively autocorrelated, that is, if an asset price made a big move yesterday, it is more likely to make a big move today. With economic and financial data, time dependence volatility is more common than constant volatility, and accurate modeling of time dependence volatility is of utmost importance.

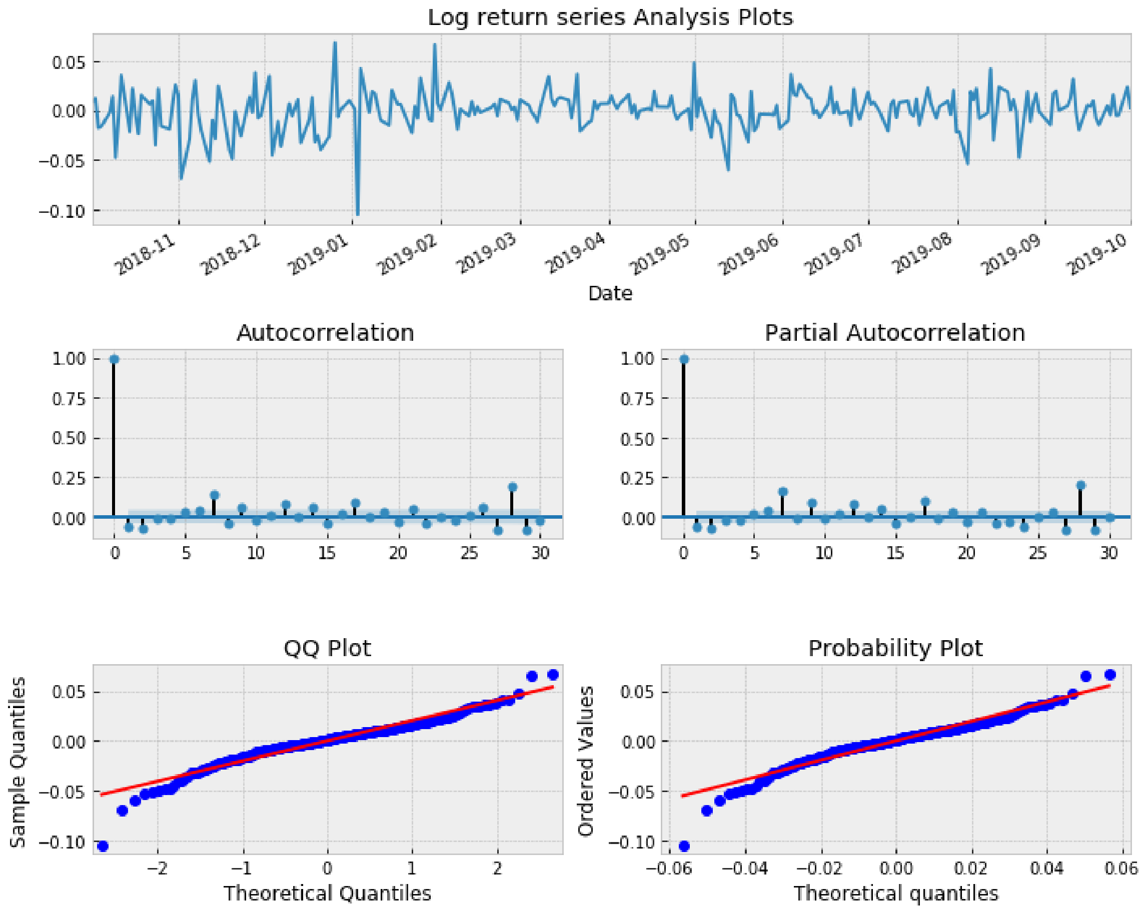

Figure 2: illustrate the Apple daily closing prices and daily returns.

4 JUSTIFICATIONS FOR ARMA-GARCH MODEL

In our case, from Figure 2 we have already known from the QQ plots and Probability plots that an obvious fat/ heavy tails displayed in our series, a typical evidence of heteroskedastic effects as volatility clustering. We can also observe from the squared log-return. 3 illustrates that the squared returns appear to fluctuate around a constant level, but exhibit volatility clustering. Large changes in the squared returns tend to cluster together, and small changes tend to cluster together, which also indicates that the series exhibits conditional heteroscedasticity.

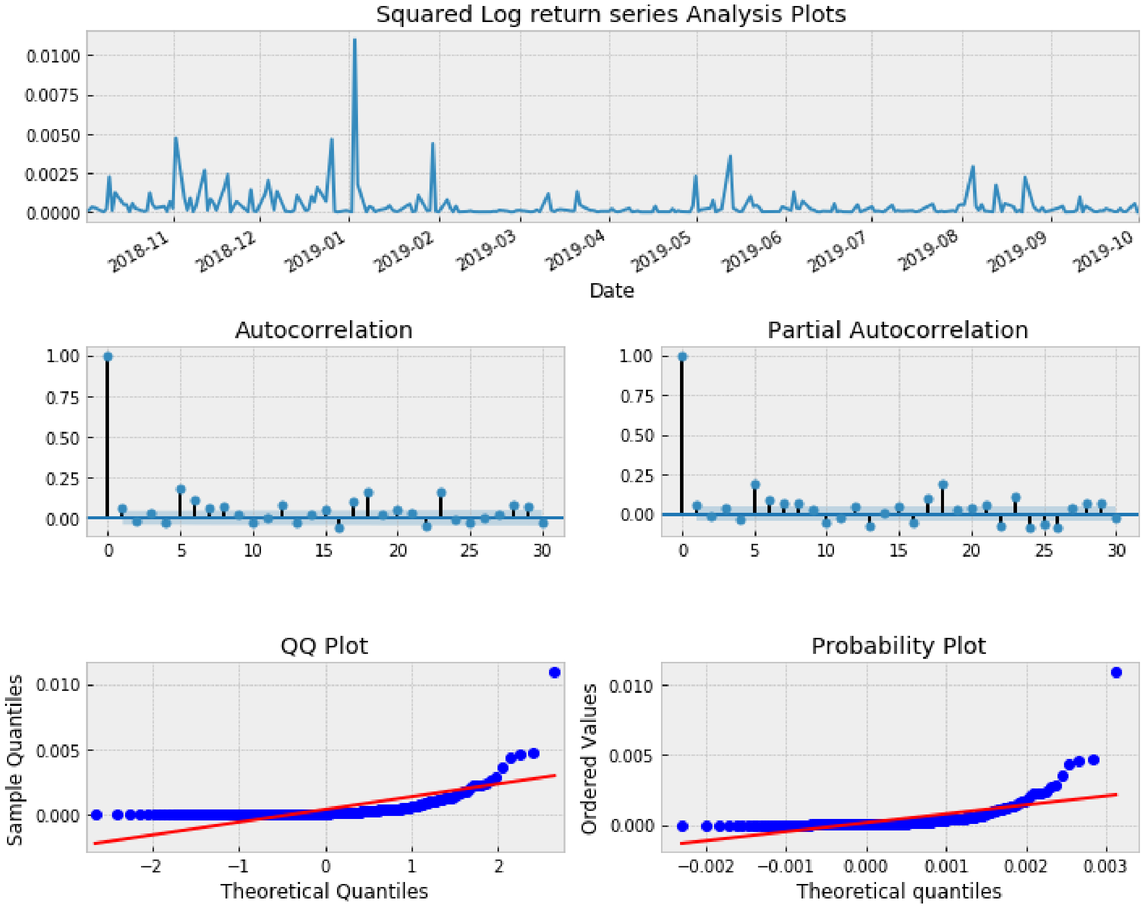

Figure 3: illustrate the Apple daily closing prices and daily returns.

It is even more clear, if we plot the sample autocorrelation function (ACF) and partial autocorrelation function (PACF) of squared log-return, as shown in 3. The sample ACF and PACF show significant autocorrelation in the squared log-return series.

As illustrated in the ACF and PACF plot of squared returns, there is clearly autocorrelation present. The model we select is going to attempt to capture the autocorrelation of squared returns, clustering volatility, as well as the heteroscedasticity. The significance of the lags in both the ACF and PACF indicate we need both AR and MA components for our model. ARMA models are used to model the conditional mean of the process given past information, which however, assumes the conditional variance given the past is constant. ARMA model alone fails to capture the volatility clustering behavior. Thus, we will use GARCH process that has become widely used in econometrics and finance, to correct the heavy tails and model the randomly varying volatility in Apple's return.

ARMA Process

We first model the mean equation as an ARMA process. we recall that the ARMA(m, n) process of autoregressive order of m, and moving average order n can be described as:

$$r_t = \mu + \sum_{a_i}^{r_{t-1}} + \sum_{b_j}^{\varepsilon_{t-j}} + \varepsilon_t$$

With mean μ , autoregressive coefficients a_i , and moving average coefficients b_j .

To choose the best order(m, n), we try out different combinations and select the one with the lowest AIC and BIC in Python using a for loop function.

```
#ARMA Process
# pick best order by aic
# smallest aic value wins
best_aic = np.inf
best_order = None
best_mdl = None

rng = range(5)
for i in rng:
    for j in rng:
        try:
            tmp_mdl = smt.ARMA(apple_daily_returns, order=(i, j)).fit(method='mle', trend='nc')
            tmp_aic = tmp_mdl.aic
            if tmp_aic < best_aic:
                best_aic = tmp_aic
                best_order = (i, j)
                best_mdl = tmp_mdl
        except: continue

p('aic: {:6.5f} | order: {}'.format(best_aic, best_order))

# aic: -1241.05315 | order: (0, 1)
```

Figure 4: Python code for selecting ARMA model

The 4 illustrates that ARMA(0,1) or MA(1) is the best fit for our series. We also plot the residuals and squared residuals of the ARMA(0,1) model.

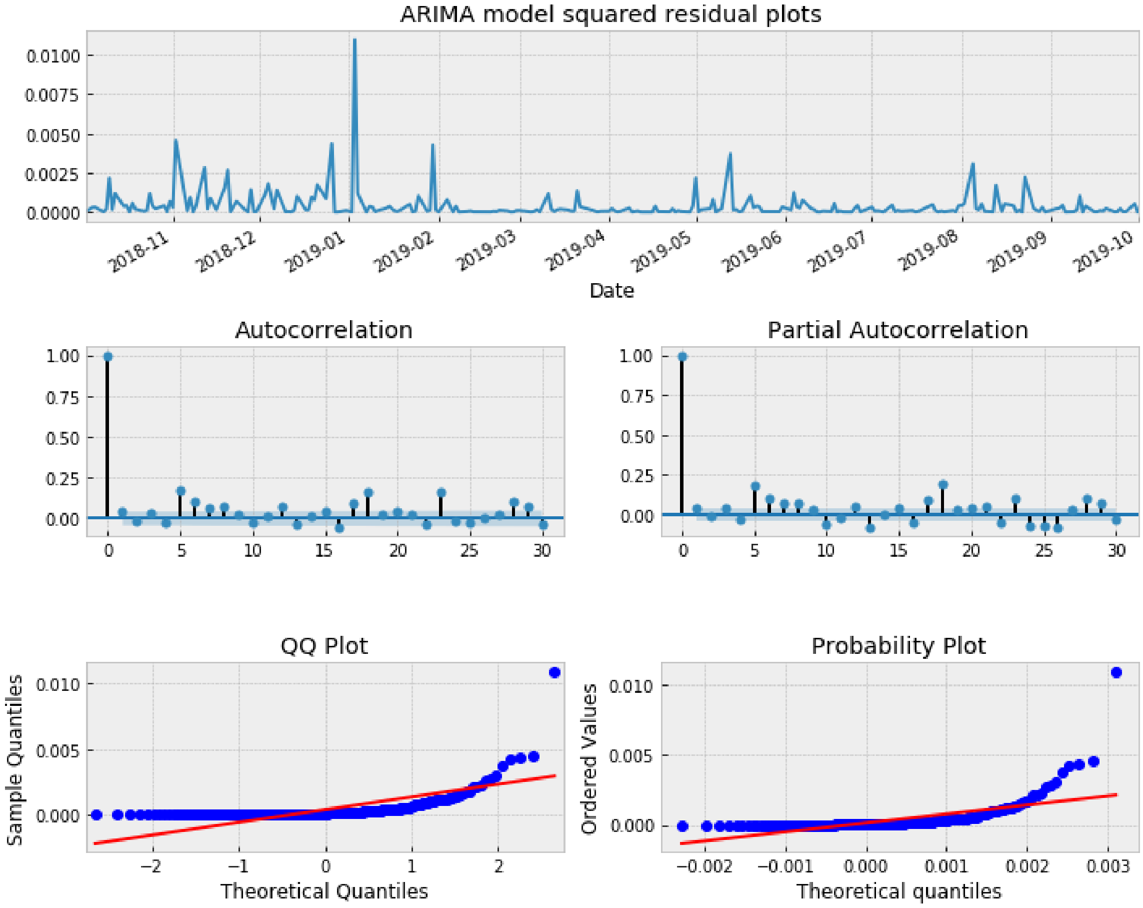

Figure 5: Squared residual plots

GARCH Process

[1] et al. have tackled the merits of applying GARCH (1, 1). We apply the concept due to its simplicity for modelling volatility of use stock returns. Although to better explain the volatility process of returns recommends integrated GARCH and asymmetric GARCH to test for the presence of leverage effects in returns.

We the use ARMA(0,1)-GARCH(1,1) as the best model. And here is the residual plot we get from our fitting our model:

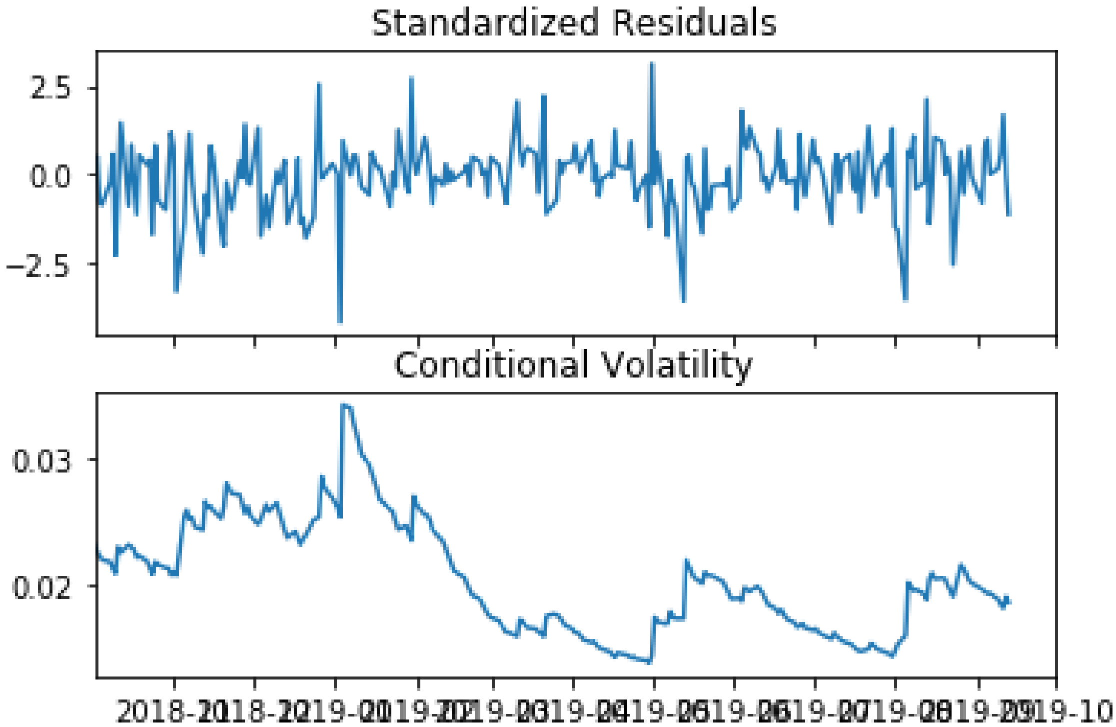

Figure 6: ARMA(0,1)- GARCH(1,1) Residual plots

5 FORECASTING

```
#specifying the model and estimating the parameters
garch11 = arch_model(best_mdl.resid, p=1, q=1)

split_date = '2019-09-15'

res = garch11.fit(last_obs = split_date)
print(res.summary())

#Plot ARMA(0,1) - GARCH(1,1) residuals
res.plot()

#forecasting
forecasts = res.forecast(start=split_date)
forecasts.variance[split_date:].plot()
forecasts.mean[split_date:].plot()
forecasts.variance.dropna()
forecasts.mean.dropna()
```

Figure 7: Python code for forecasting

We obtain:

```
Out[95]:
                 h.1
Date
2019-09-16  0.001289
2019-09-17  0.001289
2019-09-18  0.001289
2019-09-19  0.001289
2019-09-20  0.001289
2019-09-23  0.001289
2019-09-24  0.001289
2019-09-25  0.001289
2019-09-26  0.001289
2019-09-27  0.001289
2019-09-30  0.001289
2019-10-01  0.001289
```

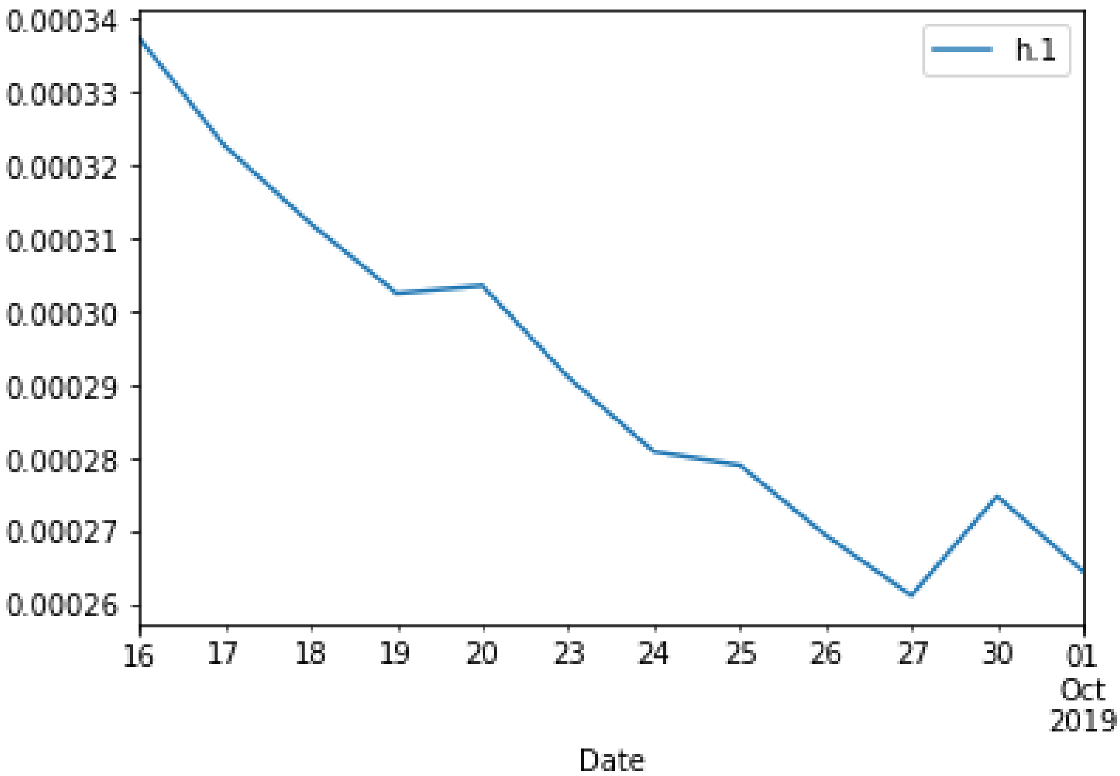

Figure 8: ARMA(0,1)- GARCH(1,1) forecasting results

```
Out[95]:
                 h.1
Date
2019-09-16  0.001289
2019-09-17  0.001289
2019-09-18  0.001289
2019-09-19  0.001289
2019-09-20  0.001289
2019-09-23  0.001289
2019-09-24  0.001289
2019-09-25  0.001289
2019-09-26  0.001289
2019-09-27  0.001289
2019-09-30  0.001289
2019-10-01  0.001289
```

Figure 9: ARMA(0,1)- GARCH(1,1) Mean return forecasting results

6 CONCLUSION

Our model can roughly predict the ups and downs of Apple's return/price movement. However, it fails to capture the high volatility of the daily return/price and thus gives a prediction around a rather constant level relative to the actual return/price.

REFERENCES

[1] Horvath L. Francq C. and Zakoïan J. M. Merits and drawbacks of variance targeting in garch models. *Journal of Applied Econometrics*, 1:5–30, 2011.

[2] Sheppard K. Introduction to python for econometrics, statistics and data analysis. *University of Oxford*, 1:5–9, 2012.

[3] Choirat C. and Seri R. Econometrics with python. *Journal of Applied Econometrics*, 1:8–12, 2009.

[4] Koenker R. and Zeileis A. On reproducible econometric research. *Journal of Applied Econometrics*, 1:3–19, 2009.

[5] Gulde A. M. Ghosh R. and Wolf H. C. Exchange rate regimes: Choices and consequences. *The MIT Press*, 2:6–23, 2003.

[6] Sauer and Bohara A. K. Exchange rate volatility and exports: Regional differences between developing and industrialized countries. *Review of International Economics.*, 1:12–16, 2001.

[7] Ravindran R. and Soroush K. A. Influence of macroeconomic variables on exchange rates. *Journal of Economics, Business and Management.*, 3:54, 2015.