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The Effect of Heteroscedasticity in Apple Stock Price Towards Predicting its Future Value

Alia Aina Syafika Abdul Rahim Ponniah[1], Shuhaida Ismail[2]*

[1] *Department of Mathematics and Statistics, Faculty of Applied Sciences and Technology, UTHM Kampus Cawangan Pagoh, Hab Pendidikan Tinggi Pagoh, KM 1, Jalan Panchor, 84600Pagoh, Muar, Johor, MALAYSIA*
[2] *Faculty of Computer Science and Information Technology, Universiti Tun Hussein Onn Malaysia, 86400 Parti Raja, Batu Pahat, Johor, MALAYSIA*

*Corresponding Author: shuhaida@uthm.edu.my
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Abstract

The purpose of this study is to examine the effect of heteroscedasticity on the accuracy of predicting Apple Inc.'s stock price using an ARIMA (Autoregressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model. This study uses the ARIMA and GARCH models because these models can predict econometric models such as the daily Apple stock. The research aims to help us understand the potential errors introduced to forecasting models by looking at how these changes affect predictions. Historical Apple Inc. stock price data was studied from January 2008 through June 2022. This study used ARIMA and GARCH methods with an evaluation of forecasting errors using the Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and Mean Absolute Percent Error (MAPE). Next, previous researcher mentioned that ARIMA was an ideal method to handle time series data, especially in predicting the stock market in India and GARCH models are used to forecast daily electricity prices in Spain and California, which outperform the ARIMA model when price spikes and volatility are present. In this study, the ARIMA (8,1,8) was found to be the best model in this study. Next, among the statistical methods ARIMA and GARCH, ARIMA is the most effective method based on the model accuracy measures. The choice between ARIMA and GARCH depends on the specific characteristics of the data and the aspects of the time series you aim to model or forecast.

1. Introduction

In the modern world, the stock market has become one of the things that draws society's attention. Stock market trading has become increasingly popular due to the potential for high returns. In addition, the stock market is also seen diversify investments and reduce the risk of investing in a single asset. As a result, more people have started investing in the stock market. This has led to an increase in market volatility, which can be both challenging and exciting for investors. It has also led to the need for more regulations and oversight to protect investors from fraud and manipulation. Due to this, it is also essential that society is aware of how to deal with the stock market.

Analysing historical stock price data has long been a valuable tool for researchers and traders. Accurate forecasts provide valuable information for developing trading strategies and choosing opportune transaction times [1]. This information is especially crucial in finance and economics, where investors rely on predictions to identify profitable investments and minimize risks [2].

In the financial industry, accurate stock price forecasts serve multiple purposes for investors, traders, and institutions. Investors actively seek methods to maximize returns while mitigating risks. By analysing historical data, market trends, and other relevant factors through stock price forecasts, investors can make informed decisions about buying, selling, or holding stocks [3]. This strategic allocation of capital allows for maximizing growth potential and minimizing potential losses.

Stock price forecasting is the process of predicting the future movements and trends of stock prices [4]. The increasing interest in stock markets has spurred the development of various forecasting methods, including technical analysis, fundamental analysis, and machine learning algorithms, aiming to accurately predict price movements and support investor decisions. Predicting fluctuations and accurately assessing a company's financial performance are crucial for successful investments. Analysing historical data and financial statements provides valuable insights into future stock values. However, forecasting is inherently challenging due to the uncertainties involved [5]. Not only that, but stock price forecasts also play a vital role in risk management. Investing in stocks inherently carries risks, and understanding potential price movements is crucial.

Over the past 50 years, ARIMA has been used in many fields, including finance, economics, and engineering. In finance, ARIMA has been used for modelling stock prices, exchange rates, and interest rates. The ARIMA model has been used in economics to predict macroeconomic variables such as GDP, inflation, and unemployment. In addition [6], suggested that ARIMA was an ideal method to handle time series data, especially in predicting the stock market in India. ARIMA is used to perform one-day-ahead forecasts of tomorrow's federal funds rate. Not only that [7] found that ARIMA worked best for short-term predictions, since its prediction errors increase with prolonged prediction periods.

Generalized Autoregressive Conditional Heteroscedasticity, or GARCH for short, is a statistical model that is frequently used to analyse and forecast the volatility of time series data [8]. The GARCH model was used to forecast Apple stock price due to the heteroscedasticity in the data. Heteroscedasticity describes the irregular pattern of variation of an error term, or variable, in a statistical model. The heteroscedasticity was checked using Breusch Pagan Test. As a result of the GARCH model, the conditional variance of a time series is considered, which is the volatility or fluctuation of the series over time. Using this method, past information is used to estimate the variance of a financial asset's returns over time. GARCH models are used to forecast daily electricity prices in Spain and California, which outperform the ARIMA model when price spikes and volatility are present [9].

In recent years, GARCH models have been applied in finance to investigate spillovers between markets, forecast the volatility of cryptocurrencies, and forecast the volatility of commodities [10]. An earlier study by [11] demonstrated that estimating future market value can be done by examining the heteroskedasticity component of stock market returns. The stock price can be affected by several factors, including political events and general economic conditions [12] that can only be measured through news and bulletins.

This paper explores the potential of ARIMA and GARCH models in forecasting Apple's stock prices. By analyzing historical data and accounting for potential factors like heteroscedasticity, these models can provide valuable insights for investors and other stakeholders in the financial industry. Understanding potential future price movements allows for informed decision-making, strategic investment allocation, and effective risk management.

2. Materials and Method

This section will explain the case study and the methods that are utilized in this study. The study used Apple stock price data between 2nd January 2008 and 17th June 2022. The daily stock prices were recorded and the currency for the prices was recorded as US dollars (USD). It was necessary to conduct a time series analysis to understand past stock price trends. ARIMA and GARCH will be applied to predict the future trend of stock prices. Then, ARIMA and GARCH models will be applied to the time series. The models will be compared to choose the best model. In order to compare the accuracy of two models, some statistics can be used, including MAE, MAPE, and RMSE. A model with a minimum of these evaluation metrics is considered to be the best for forecasting.

2.1 Method

In this study, a preliminary analysis is carried out before proceeding to modelling. The preliminary analysis focuses on determining the characteristics of stationarity of Apple Stock Price. Next, Augmented Dickey-Fuller (ADF) are implemented to test the stationarity of the time series. The next step is to achieve stationarity and forecast the data using the ARIMA and GARCH models. Fig. 1 below shows framework of the study.

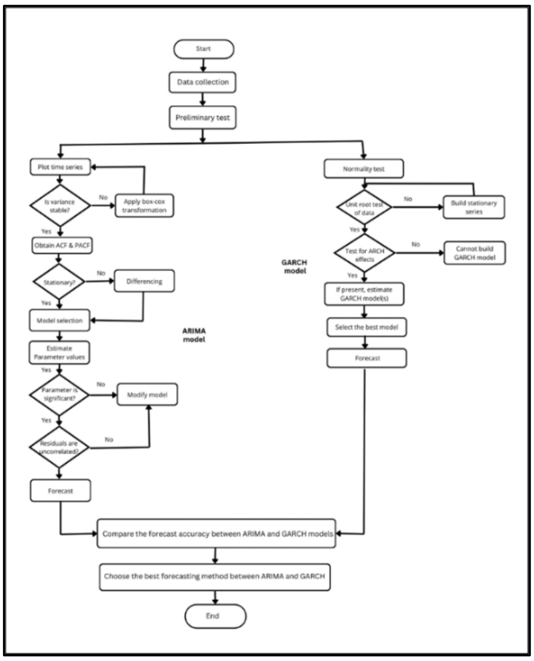


Fig. 1 Flowchart of the ARIMA and GARCH

2.1.1 Stationary Tests

The ADF test is commonly a statistical test used to test stationarity. This test will examine whether data have a unit root. If the series has a unit root, then it is said to be non-stationary. If the p-value of the ADF test is less than the significance level, then the null hypothesis of the stationarity of the series is rejected. For this test, the ADF model in equation (1) is estimated:

$$y'_t = \emptyset y_{t-1} + \beta_1 y'_{t-1} + \beta_1 y'_{t-2} + \cdots + \beta_k y'_{t-k} \tag{1}$$

where the y'_t is the first differenced series, $\emptyset$ is the coefficient on time trend, β is the coefficient presenting process root and k is the number of lags.

As for interpreting the p-value, if it is greater than 0.05, we accept the null hypothesis, while if it is less than 0.05, we reject it and we can conclude that the data is stationary and does not need to be differenced. Otherwise, the data is not stationery and differencing are required to make it stationary [13].

2.1.2 Autoregressive integrated moving average (ARIMA) Model

ARIMA model stands for Auto Regressive Integrated Moving Average model and it is a type of time-series forecasting model used to predict future values based on past data. There are three types of models analyzed in this model: autoregressive (AR), integrated (I), and moving average (MA) [14]. ARIMA (p, d, q) is the notation of the ARIMA model, where p, d and q are parameters for the AR, I and MA models, respectively. p the non-seasonal order of autoregressive, d the order of regular differencing and q the non-seasonal order of moving average. ARIMA (p, d, q) model is employed when the time series is non-stationary and converted into stationary by integrating d times. ARIMA model is shown as equation (2):

$$\emptyset_p(B)\nabla^d y_t = \theta_q(B)a_t \tag{2}$$

where:

$$\nabla = \nabla_1 = (1 - B)^d \tag{i}$$

$$\emptyset_p(B) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p, \tag{ii}$$

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \tag{iii}$$

Substitute the equation (i), (ii) and (iii) into equation (2). Then, the ARIMA model is also equivalent as follow:

$$(1 - \emptyset_1 B - \emptyset_2 B^2 - \ldots - \emptyset_p B^p)(1 - B)^d y_t (1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q) e_t \tag{3}$$

where y_t refers to the i^{th} observation in the series of data, B refers to the backshift operator $B^j y_t = y_{t-j}$, $\emptyset$'s denotes the non-seasonal autoregressive parameters, θ's denotes the non-seasonal moving average parameters and e_t refers to a sequence of independent normal error variables with mean, 0 and variance, σ^2.

2.1.3 Generalized Auto Regressive Conditional Heteroskedasticity (GARCH) Model

Heteroscedasticity in the data led to the use of the GARCH model for forecasting Apple stock price. The GARCH method is a statistical method that can be used to model and forecast financial time series data volatility. Volatility is the amount by which the price of an asset fluctuates over time, such as stock price [13]. GARCH models help analyse and explain nonstationary financial data, such as stock prices. These models can predict future volatility and thus are valuable tools for investors. The GARCH (p, q) model estimates conditional variance as a function of weighted average of the past squared residuals till q lagged term and lagged conditional variance till p terms. The GARCH general equation can be written as equation (4):

$$\sigma_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \quad (4)$$

where σ_t^2 is the conditional volatility, ε_{t-1}^2 is the squared unexpected returns for the previous period and ω is must always be positive.

2.1.4 Forecasting Metrics

Apple stock prices were examined based on a best-fitted proposed model as well as its adequacy and accuracy. The adequacy and accuracy checking involves examining the error terms in the model. Price forecasting models usually use Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) to compare [15].

MAE is a scale-dependent error so it cannot be used to make comparisons with other data sets [16]. However, it is well-known as it is easy to compute and understand as it is just suitable for comparing forecast methods on a single data set. MAE can be written as in equation (5):

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|e_t| \quad (5)$$

where n is the number of errors, Σ is the summation symbol which means add them all up, e_t= represents the absolute differences between the actual (Y) and predicted (Ȳ) values and | | denotes the absolute value.

Next, MAPE is the percentage of absolute difference between the actual values and the predicted values. Percentage errors are typically used to evaluate and compare models with different scales and ranges of data. The smaller the MAPE, the better the model performance [17]. MAPE can be written as in equation (6):

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{e_t}{y_t}\right| \quad (6)$$

where n is the sample size, Σ = summation symbol which means add them all up, e_t=is actual at period t minus forecast value at period t and y_t is actual value at period.

RMSE is an example of a scale-dependent measure that can be used to compare different methods on the same set of data. It is also more sensitive to measure outliers compared to the other errors. The formula of RMSE can be written as equation (7):

$$MSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}e_t^2} \quad (7)$$

where n is the sample size, Σ = summation symbol which means add them all up, e_t is actual at period t minus forecast value at period t.

3. Results

This section will display the analysis output of the Apple Stock Price time series by ARIMA and GARCH model respectively. Besides, the comparison between the models will also be outlined.

3.1 ARIMA Model

After conducting the preliminary test, it was confirmed that the time series is not stationary. Hence, the first difference was applied to the time series. A differencing plot was obtained. ARIMA models described by several researchers have proved to perform well in terms of forecasting as compared to other models. Fig. 2 below displays the time series plot of residuals.

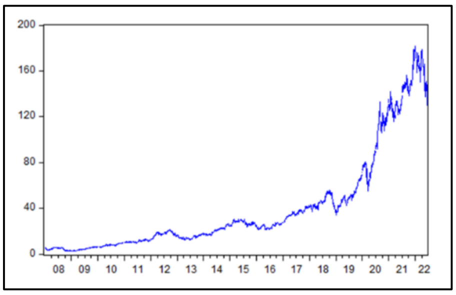


Fig. 2 Time Series Plot of Residuals

From Fig. 2, it can be said there is a trend in the time series, and the mean is increasing. Data are analyzed using a time series plot to determine seasonality and trend. Based on the figure above, we can see that it has a smooth increasing trend. As a result, it is not stationary. The hypothesis testing using the ADF test showed the statistic value of 0.6202 greater than critical values at 1%, 2% and 10% levels. Furthermore, it can be observed that the *p*-value in Table 1 clearly shows that the value is equal to 0.9903 which is greater than 0.05, indicating the data is not stationary. Therefore, the decision is to accept the null hypothesis.

Table 1 ADF test for stationary

Indicators	Value
ADF Test	0.6202
***p*-value**	**0.9903**
1% of Critical Value	-3.4319
5% of Critical Value	-2.8621
10% of Critical Value	-2.5671

Fig. 3 shows the lower control limit of the Box-Cox plot of daily Apple stock price is 0.06 while the upper control limit is 0.12, which means that the plot is not stable in variance as the interval does not contain the value of 1. The rounded value of λ is 0.09 so the transformation could be applied to achieve stable in variance.

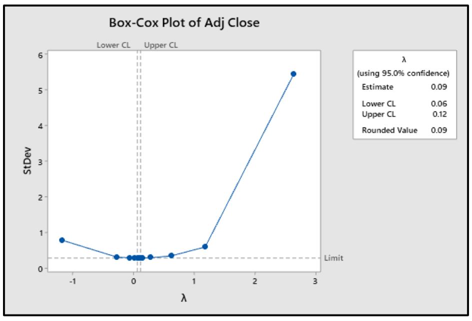


Fig. 3 The Box-Cox plot of daily Apple stock price before transformation

Fig. 4 shows the Box-Cox plot of daily Apple stock price after transformation. The lower control limit of the Box-Cox plot is 0.71 while the upper control limit is 1.25 which means that the variance is stable as the interval contains the value of 1. Therefore, no further transformation is required.

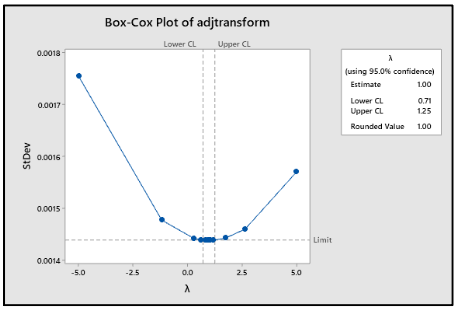
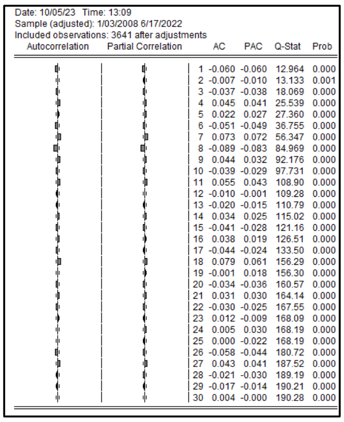


Fig. 4 The Box-Cox plot of daily Apple stock price after transformation

Since the data is still not stationary, as evidenced by the Autocorrelation Function plot (ACF) and Partial Autocorrelation Function plot (PACF) plot and differencing is needed.


Date: 10/05/23 Time: 13:09
Sample (adjusted): 1/03/2008 6/17/2022
Included observations: 3641 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.060	-0.060	12.964	0.000
		2	-0.007	-0.010	13.133	0.001
		3	-0.037	-0.038	18.069	0.000
		4	0.045	0.041	25.539	0.000
		5	0.022	0.027	27.360	0.000
		6	-0.051	-0.049	36.755	0.000
		7	0.073	0.072	56.347	0.000
		8	-0.089	-0.083	84.969	0.000
		9	0.044	0.032	92.176	0.000
		10	-0.039	-0.029	97.731	0.000
		11	0.055	0.043	108.90	0.000
		12	-0.010	-0.001	109.28	0.000
		13	-0.020	-0.015	110.79	0.000
		14	0.034	0.025	115.02	0.000
		15	-0.041	-0.028	121.16	0.000
		16	0.038	0.019	126.51	0.000
		17	-0.044	-0.024	133.50	0.000
		18	0.079	0.061	156.29	0.000
		19	-0.001	0.018	156.30	0.000
		20	-0.034	-0.036	160.57	0.000
		21	0.031	0.030	164.14	0.000
		22	-0.030	-0.025	167.55	0.000
		23	0.012	-0.009	168.09	0.000
		24	0.005	0.030	168.19	0.000
		25	0.000	-0.022	168.19	0.000
		26	-0.058	-0.044	180.72	0.000
		27	0.043	0.041	187.52	0.000
		28	-0.021	-0.030	189.19	0.000
		29	-0.017	-0.014	190.21	0.000
		30	0.004	-0.000	190.28	0.000

Fig. 5 ACF and PACF after differencing

Fig. 5 above shows the ACF and PACF plot after first differencing. As we can see, ACF and PACF plots both tail off to zero relatively quickly, with no significant spikes or dips at higher lags, which means the mean, variance, and autocorrelation of the time series are constant over time and the time series is likely to be stationary. The selected model for the ARIMA will be ARIMA (1,1,1), ARIMA (1,1,7), ARIMA (7,1,7) and ARIMA (8,1,8).

Based on Table 2, the higher the sigma value, the higher the volatility of the model. Higher volatility is not a good forecasting model. As we can see, ARIMA (8,1,8) has a smaller value sigma compared to ARIMA (1,1,1), ARIMA (1,1,7) and ARIMA (7,1,7). Next, the model with the lowest AIC offers the best fit which shows at ARIMA (8,1,8). Therefore, we can conclude that ARIMA (8,1,8) is the most suitable model for the data.

Table 2 Summary ARIMA model

Model	SIGMA	Adjusted R squared	AIC
ARIMA (1,1,1)	1.3429	0.0030	3.1349
ARIMA (1,1,7)	1.3215	0.0173	3.1221
ARIMA (7,1,7)	1.2890	0.0398	3.1024
ARIMA (8,1,8)	**1.2828**	**0.0439**	**3.0993**

Table 3 shows the value of the accuracy measure of MAE, MAPE and RMSE of ARIMA. As we can see MAE value is 1.7261 which is a small value. A lower MAE value indicates better performance. Next, MAPE is 1.5373%, which is also relatively small. The RMSE is the square root of the average squared difference between the predicted and actual values, and it is slightly bigger than MAE and MAPE which is 2.3992 which we can conclude that a small value of RMSE will be better.

Table 3 MAE, MAPE and RMSE of ARIMA

Evaluation Metrics (%)	ARIMA
MAE	1.7261
MAPE (%)	1.5373
RMSE	2.3992

Fig. 6 shows a static forecast which uses the actual value of the lagged dependent variable to compute the next forecast. This is done by only substituting the actual values into the ARIMA model for the previous periods. Static forecast results can be a better prediction of future inflation trends. This is because static forecasts focus on the historical trend of inflation, and the historical trend of inflation can be used to predict future inflation trends when there are no major changes in the economic conditions that affect inflation.

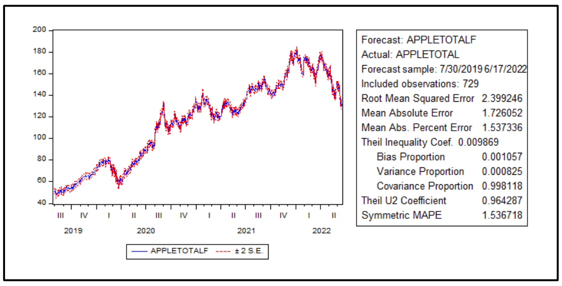
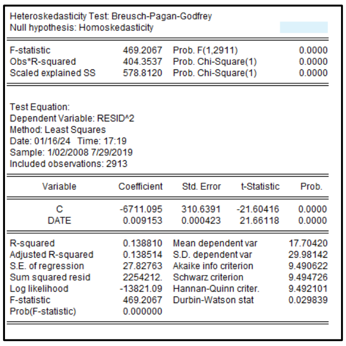


Fig. 6 Static Forecast of Apple Stock Price

3.2 GARCH Model

GARCH models are the most popular instruments for measuring volatility dynamics in financial time series. The GARCH model helps predict how up-and-down swings in a market will change over time, based on past ups and downs. Fig. 7 shows the Breusch Pagan Test's. The Breusch-Pagan test is a statistical test used to detect the presence of heteroscedasticity. The null hypothesis for this test is there is no heteroscedasticity while the alternative hypothesis is there is heteroscedasticity in the model. As we can see in Figure 7, *p* value is less than 0,05, so we can reject the null hypothesis and say that there is a heteroscedasticity.


Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	469.2067	Prob. F(1,2911)	0.0000
Obs*R-squared	404.3537	Prob. Chi-Square(1)	0.0000
Scaled explained SS	578.8120	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 01/16/24 Time: 17:19
Sample: 1/02/2008 7/29/2019
Included observations: 2913

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-6711.095	310.6391	-21.60416	0.0000
DATE	0.009153	0.000423	21.66118	0.0000

R-squared	0.138810	Mean dependent var	17.70420
Adjusted R-squared	0.138514	S.D. dependent var	29.98142
S.E. of regression	27.82763	Akaike info criterion	9.490622
Sum squared resid	2254212.	Schwarz criterion	9.494726
Log likelihood	-13821.09	Hannan-Quinn criter.	9.492101
F-statistic	469.2067	Durbin-Watson stat	0.029839
Prob(F-statistic)	0.000000		

Fig. 7 Breusch Pagan Test's

Fig. 8 showed the time series of Apple stock price plot in blue colour and the return value of GARCH plot in orange colour. The returns value of a stock price is the percentage change in the stock price over a period of time. Return value is the predicted value of the asset price over a certain period. Calculating returns value for GARCH is a useful way to understand and manage the volatility of financial assets. By understanding the volatility of an asset, we can make better investment decisions and manage our risk more effectively. This graph is stationary which exhibits volatility clustering which means periods when large changes are followed by further large changes and periods when small changes are followed by further small changes. Next, as we can see in the graph, the variance of the returns exists so ARCH exists and needs to model the GARCH model. Overall, the graph shows that the Apple stock price has been volatile, but the overall value of the stock has been increasing. This is a good sign for investors who are considering buying Apple stock.

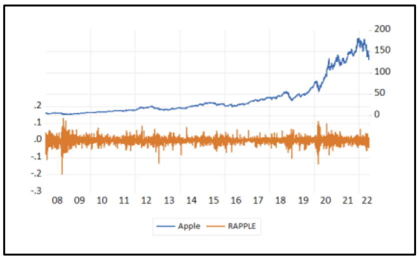


Fig. 8 Apple Stock Price value and Returns value of Apple Stock Price

Fig. 9 below shows the existence of autocorrelation in Apple return squared in all lags by looking at the significance of the *p*-value it shows the existence of the dependency in the variance. Thus, there is a need for the GARCH model to model the heterogenous variance. In conclusion, both correlograms show the need to model the mean and variance equation simultaneously.

Date: 10/29/23 Time: 19:11
Sample (adjusted): 1/03/2008 6/17/2022
Included observations: 3641 after adjustments

Lag	AC	PAC	Q-Stat	Prob
1	0.215	0.215	168.18	0.000
2	0.169	0.128	271.73	0.000
3	0.167	0.115	372.95	0.000
4	0.148	0.083	453.33	0.000
5	0.164	0.096	551.25	0.000
6	0.232	0.160	746.83	0.000
7	0.161	0.055	841.35	0.000
8	0.186	0.090	967.86	0.000
9	0.171	0.063	1074.6	0.000
10	0.259	0.165	1319.0	0.000
11	0.159	0.022	1411.5	0.000
12	0.117	-0.018	1461.7	0.000
13	0.103	-0.019	1500.6	0.000
14	0.110	-0.006	1544.7	0.000
15	0.096	-0.021	1578.3	0.000
16	0.133	0.007	1642.6	0.000
17	0.128	0.022	1702.3	0.000
18	0.098	-0.012	1737.7	0.000
19	0.064	-0.038	1752.6	0.000
20	0.092	-0.004	1783.6	0.000
21	0.096	0.022	1817.0	0.000
22	0.073	-0.002	1836.7	0.000
23	0.077	0.010	1858.7	0.000
24	0.089	0.027	1887.9	0.000
25	0.045	-0.019	1895.3	0.000
26	0.083	0.021	1920.4	0.000
27	0.088	0.021	1948.5	0.000
28	0.077	0.021	1970.2	0.000
29	0.057	0.003	1982.2	0.000
30	0.089	0.036	2011.1	0.000

Fig. 9 ACF and PACF

Fig. 10 shows the significant of the AR (1) coefficient indicating that returns of Apple are determined by its previous returns. The significance for both RESID $(-\mathbf{1})^{\mathbf{2}}$ (ARCH term) and GARCH (-1) (GARCH term) shows that conditional variance depends on past information on conditional variance and past conditional variance. To determine whether the model of AR (1) - GARCH (1,1) is sufficient and adequate, diagnostic checking on standardized residual should be implemented.

Dependent Variable: D(LOG(APPLE))
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 10/30/23 Time: 02:03
Sample (adjusted): 1/04/2008 7/29/2019
Included observations: 2911 after adjustments
Convergence achieved after 29 iterations
Coefficient covariance computed using outer product of gradients
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.001677	0.000293	5.734583	0.0000
AR(1)	0.019240	0.020102	0.957147	0.3385
Variance Equation				
C	1.34E-05	1.59E-06	8.454071	0.0000
RESID(-1)^2	0.101343	0.010738	9.438156	0.0000
GARCH(-1)	0.860255	0.013684	62.86681	0.0000

R-squared	-0.002706	Mean dependent var	0.000739
Adjusted R-squared	-0.003051	S.D. dependent var	0.019470
S.E. of regression	0.019500	Akaike info criterion	-5.288573
Sum squared resid	1.106094	Schwarz criterion	-5.278308
Log likelihood	7702.518	Hannan-Quinn criter.	-5.284875
Durbin-Watson stat	2.032119		
Inverted AR Roots	.02		

Fig. 10 GARCH (1,1)

Result from the correlogram Q-statistics show in Fig. 11 (a) below, shows that insignificant Q-statistics implying the absence of autocorrelation in the standardized residual. Thus, AR (1) is sufficient for modelling the mean equation since there is no autocorrelation problem exists in AR (1) – GARCH (1,1) model. Next, Correlogram squared residuals were used to check for heteroscedasticity problems.

The result from correlogram squared residuals shows in Fig. 11 (b) shows that insignificant Q-statistics imply the absence of heteroscedasticity in the standardized residual. Thus, GARCH (1,1) is sufficient for modelling the variance equation since there is no heteroscedasticity problem exist in the AR (1) - GARCH (1,1) model.

Date: 10/30/23 Time: 02:09
Sample (adjusted): 1/04/2008 7/29/2019
Q-statistic probabilities adjusted for 1 ARMA term

Lag	AC	PAC	Q-Stat	Prob*
1	0.008	0.008	0.2020	
2	-0.003	-0.003	0.2221	0.637
3	-0.013	-0.013	0.6983	0.705
4	0.036	0.037	4.5844	0.205
5	-0.005	-0.006	4.6587	0.324
6	-0.016	-0.016	5.4006	0.369
7	0.023	0.025	7.0092	0.320
8	-0.041	-0.043	11.859	0.105
9	0.003	0.004	11.893	0.156
10	0.025	0.027	13.767	0.131

*Probabilities may not be valid for this equation specification.

(a)

Date: 10/30/23 Time: 02:13
Sample (adjusted): 1/04/2008 7/29/2019
Included observations: 2911 after adjustments

Lag	AC	PAC	Q-Stat	Prob*
1	-0.004	-0.004	0.0431	0.835
2	-0.017	-0.017	0.9141	0.633
3	-0.011	-0.011	1.2776	0.734
4	-0.024	-0.024	2.9337	0.569
5	-0.015	-0.016	3.6087	0.607
6	-0.008	-0.009	3.7937	0.705
7	0.004	0.002	3.8322	0.799
8	0.030	0.029	6.5331	0.588
9	-0.010	-0.011	6.8243	0.655
10	0.003	0.003	6.8519	0.739

*Probabilities may not be valid for this equation specification.

(b)

Fig. 11 Insignificant Q-statistics

Fig. 12 shows the forecasting evaluation consisting of the performance and accuracy of predictive models. When predicting a stock price, it is essential to evaluate how well your model is performing. Several metrics and techniques are commonly used for forecasting evaluation such as visualizations of time series plots and residual plots which can offer insights into the model's behavior over time.

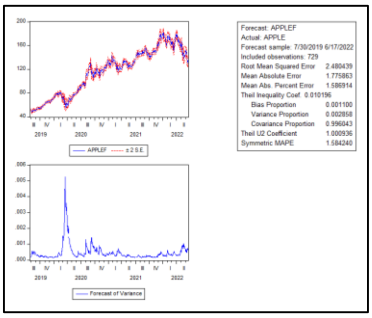


Fig. 12 Forecasting evaluation

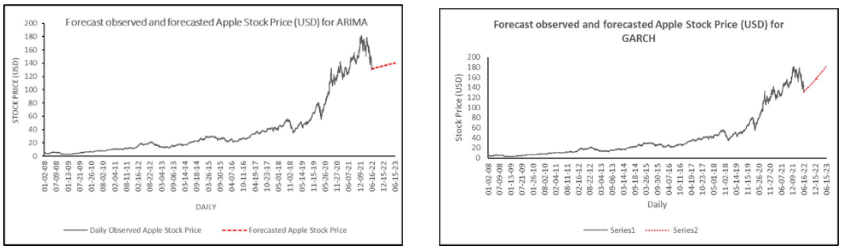
Table 4 shows the accuracy measure for GARCH method. The accuracy measure is a measure of how well the GARCH model can predict future values. The smaller the accuracy measure, the better the results.

Table 4 : MAE, MAPE and RMSE of GARCH

Evaluation Metrics	GARCH
MAE	1.7759
MAPE (%)	1.5869
RMSE	2.4804

3.3 Comparing between ARIMA and GARCH Models

In this section, the comparison between ARIMA and GARCH Models will be presented. Comparing each model would help provide an overview of how well each approach performed. Both Fig. 13 (a) and (b) below show the Apple stock price over time, from Jan 2008 to June 2023. The grey line represents the actual Apple stock price and the red line represents the forecasted Apple stock price. The red line shows that the value of Apple stocks has also increased significantly over time. However, the increase in the real value of Apple shares has not been as dramatic as the increase in the nominal price of Apple shares.



(a) **(b)**

Fig. 13 (a) Forecast the observed and forecasted Apple Stock Price graph for ARIMA; (b) Forecast observed and forecasted Apple Stock Price graph for GARCH

Fig. 14 below shows a combination of two models which are ARIMA (8,1,8) and GARCH (1,1). The ARIMA (8,1,8) - GARCH (1,1) model combines the strengths of these two models to provide a more accurate forecast of the volatility of time series data. The ARIMA (8,1,8) model captures the pattern or trend in the time series data, while the GARCH (1,1) model captures the volatility of the time series data. The benefits of using ARIMA (8,1,8) - GARCH (1,1) are to forecast the volatility of time series data and the model can capture both the pattern and trend in the time series data. To analyze the efficiency of model more comprehensively, three types of evaluation measures were used to evaluate the difference between the predicted and practical data.

Dependent Variable: D(APPLE)
Method: ML ARCH - Normal distribution (BFGS / Marquardt steps)
Date: 11/08/23 Time: 14:04
Sample (adjusted): 1/15/2008 7/29/2019
Included observations: 2904 after adjustments
Convergence achieved after 109 iterations
Coefficient covariance computed using outer product of gradients
MA Backcast: 1/03/2008 1/14/2008
Presample variance: backcast (parameter = 0.7)
GARCH = C(18) + C(19)*RESID(-1)^2 + C(20)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.015060	0.003590	4.194571	0.0000
AR(1)	-0.165550	0.294981	-0.561224	0.5746
AR(2)	-0.144089	0.103345	-1.394249	0.1632
AR(3)	0.052957	0.102640	0.515945	0.6059
AR(4)	-0.103891	0.098705	-1.052543	0.2926
AR(5)	0.032088	0.106216	0.302097	0.7626
AR(6)	0.042487	0.083411	0.509374	0.6105
AR(7)	0.661223	0.081056	8.157627	0.0000
AR(8)	0.143051	0.210923	0.678213	0.4976
MA(1)	0.189241	0.292756	0.646410	0.5180
MA(2)	0.155322	0.102571	1.514289	0.1300
MA(3)	-0.056349	0.105590	-0.533663	0.5936
MA(4)	0.131207	0.099689	1.316164	0.1881
MA(5)	-0.032912	0.112414	-0.292774	0.7697
MA(6)	-0.049786	0.086238	-0.577313	0.5637
MA(7)	-0.646314	0.082600	-7.824650	0.0000
MA(8)	-0.210846	0.205895	-1.024044	0.3058
Variance Equation				
C	2.20E-05	1.61E-05	1.364829	0.1723
RESID(-1)^2	0.032829	0.002040	16.08924	0.0000
GARCH(-1)	0.970173	0.001531	633.6729	0.0000

R-squared	0.012353	Mean dependent var	0.015738
Adjusted R-squared	0.006879	S.D. dependent var	0.394735
S.E. of regression	0.393375	Akaike info criterion	0.250794
Sum squared resid	446.7449	Schwarz criterion	0.291936
Log likelihood	-344.1527	Hannan-Quinn criter.	0.265617
Durbin-Watson stat	2.007275		

Fig. 14 ARIMA (8,1,8) - GARCH (1,1)

4. Discussion

This subtopic will present a discussion comparing the performance of the best model from ARIMA and GARCH respectively. The two models were compared based on the evaluation metrics and determined how well they performed in the forecasting.

A comparison of the forecasted values with the actual price was made, and the values were plotted as illustrated in Fig. 15. As we can see both models deviated away from the actual price. After calculating the MAPE for both forecasting models ARIMA and GARCH, it shows that GARCH got the value of 8.27% and ARIMA got a value of 11.15%. A lower MAPE indicates better performance in predicting the values. In other words, the forecasting model with the smaller MAPE is more accurate relative to the actual values. This shows that GARCH is more accurate than the ARIMA model for forecasting future values.

In Fig. 15, the actual data exhibits significant volatility clustering, which is periods of high and low volatility, GARCH might capture the underlying dynamics better, leading to improved ex-post forecasts. GARCH models are designed to capture time-varying volatility, which is a characteristic often present in financial data. In contrast, ARIMA models assume constant variance, which may not be suitable for highly volatile data like Apple's stock price in 2023. The volatility of Apple's stock price has changed significantly throughout 2023. GARCH models can adapt to these changes, while ARIMA models are limited in their ability to do so. Overall, the superior performance of GARCH in ex post forecasting suggests that it was able to better capture the time-varying volatility of Apple's stock price in 2023. This highlights the importance of using appropriate models that can account for the specific characteristics of the data being analysed.

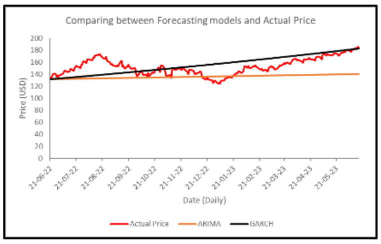


Fig. 15 Comparison of two forecasting model with actual price

5. Conclusion

This study set out to determine a suitable model for forecasting the Apple Stock Price on the accuracy of the models. The two models that were employed in this study included the ARIMA and GARCH models. After comparing the performance of these models, it can be concluded that the ARIMA model is more suitable for forecasting the time series.

In summary, the first objective of this study is to build the hypothesis testing and check for stationarity using Augmented Dickey-Fuller (ADF) was succeeded. The ADF test was used to confirm or deny the presence of unit roots in time series data. If the ADF test rejects the null hypothesis, then the series is said to be stationary. In our case, the p-value is equal to 0.9903 which is more than 0.05 and this means that the data is not stationary, and the null hypothesis is accepted.

Next, the second objective is to predict outcomes using the ARIMA and GARCH models. This objective has been achieved. ARIMA models are better at capturing the autocorrelation of a time series, which is the tendency of past values of the series to influence future values. GARCH models are better at capturing the conditional heteroscedasticity of a time series, which is the tendency of the volatility of the series to change over time.

The last objective is to compare the performance of various models for stock price forecasting through the evaluation of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error

(RMSE). which is already achieved. It clearly shows that the ARIMA method is more accurate than the GARCH method as it has the smallest forecast accuracy values of MAE, MAPE and RMSE.

In conclusion, we can conclude that based on the evaluation metrics results, ARIMA is a better forecasting model for the forecasting historical stock price 2008 to 2022. Meanwhile, the GARCH Method is better in forecasting Apple stock prices in 2023, this might be because external factors. Future researchers would be able to have idea to conduct research on various fields other than stock prices. By looking at the relationship between stock prices and other variables, such as economic news, political events, and natural disasters, researchers can gain a better understanding of how stock prices are impacted by external factors.

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Conflict of Interest

The authors declare that there is no conflict of interest associated with the publication of this paper.

Author Contribution

The authors confirm contribution as follows: ***study conception and design, data collection, analysis and interpretation of results, and manuscript preparation****: Alia Aina Syafika Bt Abdul Rahim Ponniah;* ***supervision and review, editorial oversight, and proofreading****: Shuhaida Ismail*

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