

Short-Term Stock Price Forecasting Using ARIMA: A Case Study on Apple and Amazon

Zikai Feng ^a

Department of Athematics, The Chinese University of HongKong, HongKong, 999077, China

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Abstract: In stock market, predicting stock price has attracted many researchers interest over years because of the non-stationary and highly volatile nature of stock prices. Among various time series forecasting models, the Auto Regressive Integrated Moving Average (ARIMA) model has been widely applied because of its ability to capture the patterns for short term prediction. This study applies the Auto Regressive Integrated Moving Average model to forecast Apple (AAPL) stock value and Amazon (AMZN) stock value. Using the Akaike Information Criterion (AIC) to select the model that fits the best, and ARIMA (0,1,0) is found to be the best option for both stocks. The Root Mean Square Error (RMSE) is used to estimate the accuracy of model forecast. Result of this paper illustrate that ARIMA model exhibits an impressive aptitude for short-term stock price predictions, offering a reference for future research and investment strategies. This study aims to demonstrate the effectiveness of the ARIMA model in short-term stock value predicting, delivering a resource for financial market analysts and financial institutions.

1 INTRODUCTION

With the rapid development of financial markets, stock price prediction has become indispensable for investment decision-making and risk management. Stock prices exhibit complex characteristics such as non-stationarity and nonlinearity, and high volatility influenced by macroeconomic indicators, geopolitical events, and irrational market behaviors traditional analytical approaches often fail to capture these dynamic patterns effectively (Devi, Sundar, & Alli, 2013; Ariyo, Adewumi, & Ayo, 2014). Because of their dependence on static assumptions, classic analytical techniques like linear regression and simple time-series models find it difficult to represent the chaotic patterns created by these intricate interactions. The Auto Regressive Integrated Moving Average (ARIMA) model, proposed by Chen, has been proven highly effective in handling financial time series data with temporal dependencies. By transforming non-stationary data into stationary series after servals difference, the ARIMA model would capture cyclical variations in the data and provides short-term forecasts (Chen, 2022). Stationarity, which requires constant mean, variance,

and autocorrelation structure over time, eliminates spurious correlations caused by trends or seasonal patterns, thereby allowing models to identify genuine relationships within the data, using stationary data to predict the stock price is more trustworthy (Dar et al., 2024).

Several empirical investigations have been conducted to assess the capacity for prediction of the ARIMA model in the stock market. For example, Almasarweh et al. applied an ARIMA (1,1,2) model to predict Banking Stock Market Data and found that the model performed well in forecasting the data (Almasarweh & Wadi, 2018). Similarly Adebayo et al. identified ARIMA (3,1,1) and ARIMA (1,1,4) as optimal specifications for Botswana and Nigeria markets, respectively (Adebayo, Sivasamy, & Shangodoyin, 2014). Additionally, Adebisi et al. employed an ARIMA (2,1,0) model to predict the Nokia Stock Index and an ARIMA (1,0,1) model for the Zenith Bank Index, demonstrating that both models effectively predicted stock price movements (Adebisi et al., 2014). These studies emphasize the prediction capability of ARIMA model by using stationary and accurate stock price.

^a <https://orcid.org/0009-0000-8778-7229>

The aim of this paper is exploring application of the ARIMA model in stock market price forecasting, particularly its ability to predict short-term price fluctuations. By doing so, this study seeks to provide investors with an effective tool for short-term stock price prediction, aiding them in making more rational and efficient investment decisions.

The following is the framework of the paper. Section 2 reviews the fundamental theory and methodology of ARIMA model, as well as data sources and model constructed. Section 3 describe the forecast results obtained and the conclusions are illustrated in section 4.

2 MODEL AND DATA

2.1 ARIMA Model

The ARIMA model is composed of different parts: moving averages (MA), differencing (I), and autoregression (AR).

The Equation (1) shows the equation for the ARIMA model.

$$y_t = \mu + \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \dots + \phi_p y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (1)$$

Where: y_t is the time value of t , μ is the constant mean, $\phi_1, \phi_2, \dots, \phi_p$ are the parameters for the autoregressive terms, $\theta_1, \theta_2, \dots, \theta_q$ are the parameters for moving average terms, ε_t represents the white noise (residuals) at time t .

The ARIMA model is a dynamic univariate predictive method for predicting time series data. Therefore, It is crucial for selecting a suitable model to analyze stock price trends and provide sufficient information for decision-making (Ganesan & Kannan, 2021).

2.2 Data Resources

Yahoo Finance website is used in this study to gather stock price data for Apple (AAPL) and Amazon (AMZN) over the period of January 1st, 2020, to December 31th, 2024. The dataset consists of the following key components: Date, Open Value, High Value, Low Value, Close Value, Adjusted Close Value, and Volume.

The Adjusted Close price is selected as the main variable for investigation. The adjusted closing price, as opposed to the closing price, more closely represents real market returns, as it accounts for

corporate actions such as dividends and stock splits, thereby eliminating non-market factors that could distort price movements. This approach enhances the rigor and reliability of the analysis. The time frame spanning January 1st, 2020, to December 1st, 2024, is designated as the training set, while the period from December 2nd, 2024, to December 31th, 2024, is selected as the test set. By comparing the difference between test set and the predicted value, such as RMSE value, it provides a standard for judging the model projections.

To visually illustrate the stock price trends of the three companies, Figure 1 presents the AAPL price trend, Figure 2 shows the AMZN price movement.

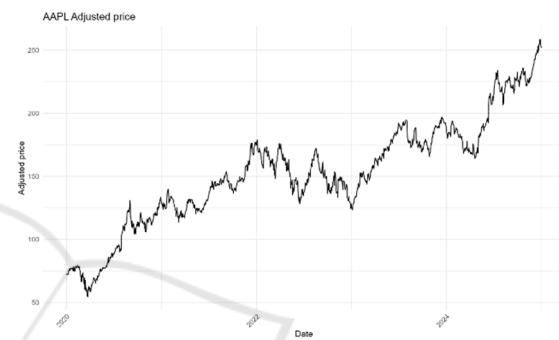


Figure 1: AAPL Adjusted price. (Picture credit: Original)



Figure 2: AMZN Adjusted price. (Picture credit: Original).

2.3 Model Construction

2.3.1 ARIMA (p, d, q) Model for APPL Stock

Figure 3 is the ACF plot of the AAPL stock adjusted price, this picture exhibits a slow decay, indicating that the data is non-stationary.

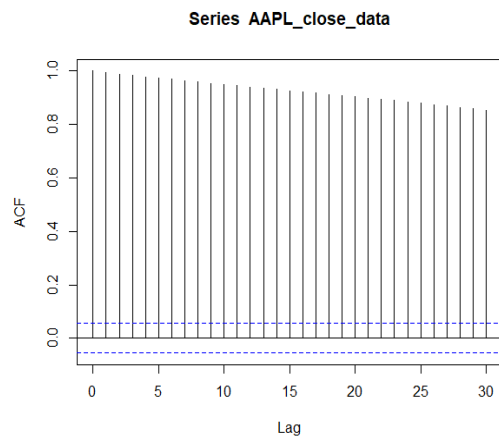


Figure 3: ACF of AAPL. (Picture credit: Original)

Table 1: ADF of AAPL Adjusted price.

Statistic	Value
ADF Test Statistic	-25.5625
1% value of Criticality	-2.58
5% value of Criticality	-1.95
10% value of Criticality	-1.62
z.lag.1 Coefficient	-1.03801
z.lag.1 Standard Error	0.04061
R ²	0.5079
F-Statistic	635.7
F-Statistic p-value	< 2.2e-16

Utilizing the Augmented Dickey-Fuller (ADF) test to determine if this data has reached stationarity following the first difference (Dhyani et al., 2020). The ADF test result verifies that the series is stationary following the first difference, as table 1 illustrates that the test statistic (-25.5625) far below the 1% critical value (-2.58). The unit root hypothesis is rejected at the 99% confidence level ($p < 0.001$).

The best model was thought to be the ARIMA model with the lowest AIC score, since the ARIMA model can be constructed using different values of p , d , and q to accommodate various time series characteristics. The autoregressive order p represents the order of the AR in the model. The number of times the original time series is differentiated is indicated by the difference order d , with the aim of satisfying the stationarity assumption for the series, the moving average order q symbolizes the order of the Moving Average terms (MA) in model, which explains how the real value and the forecast error at the previous q time points are linearly related.

The parameter ranges for p , d , and q are restricted from 0 to 2, because negative values are not meaningful, and values exceeding 2 may lead to

unreliable parameter estimation (Mondal, Shit, & Goswami, 2014).

Table 2: AIC value of different ARIMA model based on AAPL data.

ARIMA	AIC	ARIMA	AIC
(1,0,0)	5949.17	(0,0,1)	11063.27
(1,0,1)	5950.482	(0,1,2)	5936.885
(1,1,1)	5936.876	(0,1,0)	5933.821
(2,0,1)	5952.988	(0,2,0)	6804.786
(2,1,1)	5938.558	(1,0,1)	5935.519

ARIMA (0,1,0) is considered to be the best model to predict the price of AAPL stock, as the value of this model is the smallest in those models, with 5933.821. Some AIC value of different models were listed in the table 2. Table 3 illustrate the coefficient about ARIMA (0,1,0) with drift. This model implies that at each time step, the time series undergoes a fixed change amount, combined with random fluctuations. The ARIMA (0,1,0) with drift equation is given by Equation (2)

$$Y_{t+h} = Y_t + h \times c \quad (2)$$

Where: Y_t is the current stock price, h is the forecast time step, c is the drift term (the fixed trend value estimated by the model).

Table 3: Coefficients value of ARIMA (0,0,1) based on AAPL data

ARIMA (0,1,0) with drift		
Coefficient :	Drift	
	0.1330	
S.E.	0.0757	
sigma ² = 7.097	log likelihood = -2964.37	AIC=5932.74

In figure 4 the residuals were checking with the Ljung-Box test. The results show that the residuals distribution is approximately normal, which means the residuals were white noise and the fitted model sufficiently explains the data, with no systematic information remaining in the residuals. This model is selected to forecast the AAPL stock price from December 2, 2024, to December 31.

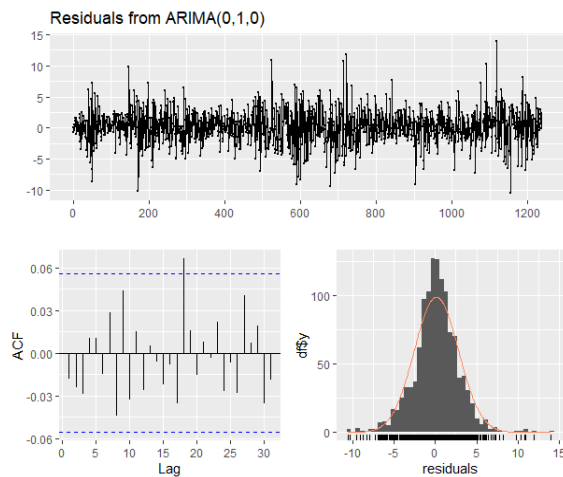


Figure 4: Residuals of ARIMA (0,1,0) based. (Picture credit: Original)

2.3.2 ARIMA (p, d, q) Model for APPL Stock

The Figure 5 exhibit a slowly dies down, indicating that the AMZN data is non-stationary. Following the first difference, the data's stationarity is checked using the ADF test.

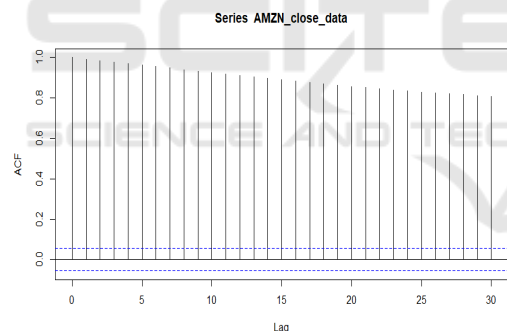


Figure 5: ACF of AMZN. (Picture credit: Original)

Table 4: ADF of AMZN data after first-difference.

Statistic	Value
ADF Test Statistic	-25.4769
1% value of Criticality	-2.58
5% value of Criticality	-1.95
10% value of Criticality	-1.62
z.lag.1 Coefficient	-1.03410
z.lag.1 Standard Error	0.04059
R ²	0.5077
F-Statistic	635.2
F-Statistic p-value	< 2.2e-16

Table 4 shows the result of ADF test of AMZN data after first-difference. It is cleared that the standard error is 0.04059 and a lagged term

coefficient is -1.03410, which means the estimate is deemed to be reasonably accurate. The AMZN stock price after first-difference is a suitable set to design an AIRMA model, as the F-statistic is 635.2 and the p-value is much smaller than 0.05.

Table 5: AIC value of different ARIMA model based on AMZN data.

ARIMA	AIC	ARIMA	AIC
(1,0,0)	6334.658	(0,0,1)	10440.91
(1,0,1)	6336.521	(0,1,2)	6325.42
(1,1,1)	6325.463	(0,1,0)	6322.138
(2,0,1)	6338.182	(0,2,0)	7192.456
(2,1,1)	6327.25	(1,0,1)	6323.851

In table 5 illustrate the ARIMA (0,1,0) was selected as the best fitted model to forecast the AMZN stock price, since the AIC value of this model is the smallest, with 6322.138. The Equation (3) illustrates ARIMA (0,1,0) without drift equation

$$Y_t = Y_{t-1} + \epsilon_t \quad (3)$$

Where: Y_t is the current value, Y_{t-1} is the value from the previous time step, ϵ_t is the white noise term, representing random error, usually following a normal distribution $N(0, \sigma^2)$. It is noticeable that there is a different between Equation (2) and Equation(3) as it shows whether the model has a deterministic temporal trend component or not.

Table 6: Coefficients value of ARIMA (0,1,0) based on AMZN data

ARIMA (0,1,0)		
sigma ² = 9.733	log likelihood = -3160.07	AIC= 6322.14

Table 6 presents the coefficients of the ARIMA (0,1,0) model for AMZN stock prices. The ACF plot in Figure 6 shows that most ACF values fall within the confidence intervals, indicating no significant autocorrelations in the residuals. Additionally, the residuals follow a normal distribution and exhibit white noise characteristics, suggesting that this model effectively fits the stock price data. ARIMA (0,1,0) model is selected to forecast the AMZN stock price.

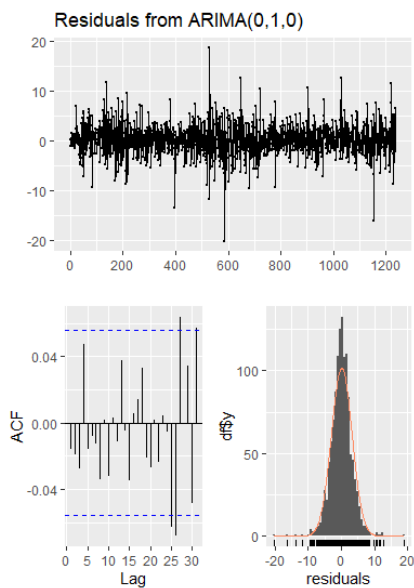


Figure 6: Residuals of ARIMA (0,1,0). (Picture credit: Original)

3 RESULTS AND DISCUSSION

3.1 ARIMA (0,1,0) With Drift based on APPL Data

The figure 7 illustrates the forecasted and actual values of Apple's stock price from December 2, 2024, to December 31, 2024, employing the ARIMA (0,1,0) model. The 95% confidence interval is consisted of areas shaded in blue, whereas the red line represents the expected mean. The black line indicates the actual stock prices. As observed, the actual values totally fall within the predicted confidence interval. The table 7 illustrates the RMSE value of this model is 13.092.

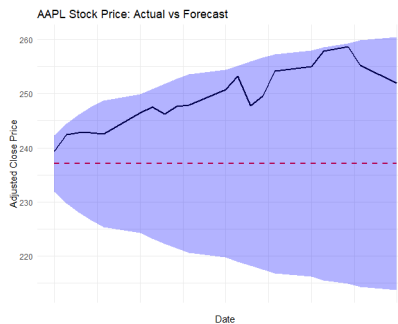


Figure 7: Forecast of APPL stock. (Picture credit: Original)

Table 7: RMSE value of ARIMA (0,1,0) based on APPL data

RMSE of ARIMA (0,1,0)	13.09234
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3.2 ARIMA (0,1,0) based on AMZN Data

The figure 8 illustrates that the actual AMZN stock price (black line) mostly falls within the confidence interval, suggesting the model effectively captures market fluctuations. However, the predicted mean (red dashed line) is noticeably lower than the actual upward trend. The table 8 shows that the RMSE value of this model is 17.34869.

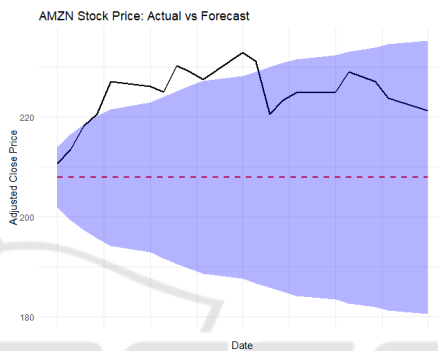


Figure 8: Forecast of AMZN stock (Picture credit: Original)

Table 8: RMSE value of ARIMA (0,1,0) based on AMZN data

RMSE of ARIMA (0,1,0)	17.34896
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4 CONCLUSIONS

Accurate stock price forecasting plays a vital role in financial decision-making, helping investors navigate market fluctuations with data-driven insights. This study selected optimal ARIMA models to forecast stock prices of Apple and Amazon, collecting sufficient stock data from Yahoo Finance. By employing the AIC for parameter optimization and rigorous residual diagnostics to ensure model validity, the analysis identifies ARIMA (0,1,0) with drift is the most effective model for AAPL, while the ARIMA(0,1,0) without drift is the optimal model for AMZN. This can guide investors to make sensible investment decisions. The results illustrate the ARIMA model demonstrates exceptional capability in short-term forecasting. However, given the inherent limitations of ARIMA models, such as their reliance on historical data and assumption of linear relationships, future research may explore hybrid

models or machine learning techniques to enhance forecasting accuracy and robustness.

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