Short-term Stock Price Prediction on Nintendo Co., Ltd. using ARMA Model

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Abstract— **This paper will analyze the use of the Time Series technique known as the Auto-Regressive Moving Average (ARMA) model, popularized by Box & Jenkins, to predict stock prices. In the case of this paper, Nintendo Co. Ltd, from here on will be referred to as Nintendo. Nintendo is a publicly traded Japanese company, and has been selected as the focus of this paper. The short-term prediction of stock prices can be a critical tool for investment strategies, portfolio management, and risk assessment. The main focus of this paper is the effectiveness of an ARMA model's ability to forecast Nintendo's short term stock price.**

I. INTRODUCTION

Predicting stock prices is critical for investment strategies, portfolio management, and risk assessment. Accurate predictions can help investors make timely decisions about buying or selling stocks, hedge against potential losses, and uncover market dynamics and investor behaviour by observing relationships between factors such as product launches, economic conditions, and market trends.

Nintendo was originally founded in 1899 in Kyoto (Nintendo, 2016). The company's business ventures started by producing handmade Hanafuda playing cards. In the 1960s, Nintendo achieved public company status, and by the 1980s, it had become one of the leading video game, consumer electronics, and software companies in the world (Nintendo, 2016). The Nintendo Switch has demonstrated strong financial health over the 2022 to 2024 fiscal years, driven by robust sales of both new releases and established titles. The fiscal year 2023-2024 saw significant contributions from major titles and the positive impact of The Super Mario Bros. Movie, resulting in 31 million-seller titles. Similarly, the fiscal year 2022-2023 also achieved remarkable success with 35 million-seller titles, bolstered by popular games like Pokémon Scarlet and Pokémon Violet, and continued high sales of evergreen titles such as Mario Kart 8 Deluxe (Nintendo, 2023). These results reflect Nintendo's consistent ability to generate substantial revenue and maintain a strong market presence. From January 2022 to June 2024, Nintendo's stock price has ranged from 4821¥ to 8850¥ per share. Dividend payout ratios were roughly 50%, and dividends on net assets were approximately 11% for all of 2022, 2023 (Nintendo, 2023). For 2024, the dividends on net assets are still around 11% (Nintendo, 2024).

Starting October 1, 2022, Nintendo implemented a 10-for-1 stock split. This stock split divided each existing share into ten new shares, thereby lowering the price per share and making it more affordable for a broader range of investors (Kharpal, 2022). This strategic move is expected to potentially increase market liquidity and attract more individual investors, which can positively affect Nintendo's overall market value and perception.

Several significant events have profoundly affected Nintendo's stock price. Notably, the company's stock has been strongly influenced by the release of popular games and the global impact of the COVID-19 pandemic. Nintendo's reputation for consistently developing high-quality and sought-after games is exemplified by titles such as "Animal Crossing: New Horizons," which achieved a global unit sales of 45.36 million copies (Clement, 2024). This game's success notably contributed to a substantial increase in Nintendo's stock prices (Smith, 2020). Moreover, the COVID-19 pandemic brought about a technical challenge in the form of a chip shortage, severely affecting the production and sales of gaming consoles worldwide. This disruption in the global supply chain had a tangible impact on Nintendo's stock performance, resulting in a significant single-day decline of approximately 7%, marking the largest drop in its history (Reuter, 2022).

In general, stock prices are believed to be efficient, reflecting market-related information. However, real-world events often cause stock prices to bias either overreact or underreact, challenging this efficiency hypothesis. Mathematical models offer a framework to understand and potentially exploit these fluctuations. The ARMA model, widely used in finance, provides a method to predict short-term stock price movements (Levenbach, 2017). Understanding these fluctuations is essential for investors aiming to anticipate market movements and optimize their investment strategies. This paper investigates the application of the ARMA model specifically to predict Nintendo's stock prices. By analyzing historical data and significant market events, it aims to evaluate how effectively the model captures price trends amidst dynamic market conditions.

II. LITERATURE REVIEW

Functioning on the principles of supply and demand, the stock market plays a crucial role in transferring economic surplus from those with excess capital (surplus units) to those who need it for investment (deficit units). According to the efficient market hypothesis (EMH) and random walk theory, stock prices reflect all available information, making it nearly impossible for investors to consistently identify undervalued stocks to buy or overvalued stocks to sell for profit. This concept suggests that the market is efficient, incorporating all known information into stock prices instantaneously. As a result, no investor can consistently achieve returns higher than the average market return; whether it is through stock selection or timing trades based on analysis or predictions. EMH challenges the notion that investors can systematically beat the market using information asymmetries or trading strategies. The implications are profound, suggesting that the only way for an investor to potentially earn higher returns is by taking on more risk. Riskier securities offer higher potential proceeds to offset the increased uncertainty and potential for loss associated with them (Downey, 2024). On the other hand, some literature reviews have posited that stock price can be anticipated using economic variables. Ang & Bekaert, BlackRock's senior advisor and professor of finance and economics at Columbia University, asserts that "The predictive ability of the dividend yield is best seen in a bivariate regression with short rates only at short horizons" (p. 28, 2006). In Ang & Bekaert's view, stock prices are not purely random and can be anticipated to some extent using economic indicators like dividend yields and interest rates. Moreover, Campbell & Thompson researchers at National Bureau of Economic Research reveal that, "most of these predictor variables, and almost all that are statistically significant in-sample, perform better out-of-sample than the historical average return forecast, once sensible restrictions are imposed on the signs of coefficients and return forecasts"(p. 17, 2005). In other words, Campbell & Thompson believe that there is predictability in stock returns beyond what can be explained by historical averages. Overall, the general consensus in the above literature is that stock returns exhibit a predictable element (Rounaghi et al., 2016).

Some financial experts believe that the future prices of stocks can be forecasted by the historical patterns of price changes. Essentially, they believe that the past movements of stock prices provide insight into their future value. They developed various models for valuing stock prices focused on patterns and trends in stock prices (Malkiel, 2003, p.4). There are two ways to predict stock price and select stocks that are expected to provide the best returns relative to their risks. The first method is fundamental analysis, where analysts forecast stock prices by evaluating a security's true value using various economic and financial factors directly related to the issuing company. These factors include overall economic health, industry-specific conditions, and the financial performance of the company. Fundamental analysis calculates a value that investors can compare with the current market price of the security. If the current price is deemed undervalued, investors may take a long position to buy the stock in anticipation of its price rise. Conversely, if the current price is considered overvalued, investors may take a short position to sell the stock, betting that its price will fall (Segal, 2023, para. 1). An alternative method is technical analysis, which uses historical price movements of a stock to identify opportunities to buy or sell it. Technical analysts assume that the current stock price reflects all pertinent factors, such as economic conditions, political climate, market sentiment about future prices, and company management strategies. By studying these past patterns, technical analysts believe they can gather valuable information to predict future stock prices (Hayes, 2022, para. 1).

Time series forecasting is a technique within technical analysis. According to Rounaghi et al. (2016), research scientists in finance and economics at the University of Luxembourg, "the task of predicting values of the series based on past and present values in order to achieve the information of the underlying model can be understood under the concept of time series forecasting" (p. 11). Rounaghi et al. (2016) imply that time series forecasting uses historical data and current data to predict future values. It aims to capture underlying patterns or trends in the data, such as seasonality, cyclic behavior, and irregular fluctuations.

One of the most interesting phenomena relating to time series forecasting is Time Series Momentum (TSM). TSM can be most easily explained by the simple statement that across asset classes and markets, there is a "strong positive predictability from a security's own past returns" (Moskowitz et Al., 2012). The existence of TSM opens avenues for investors to predict the future value of their investments over time. An empirical study done on Europe's Equity Market shows that utilizing the effects of a TSM strategy of any lookback period of 1 to 12-month lags generates far better performances in mean-variance terms relative to a simple long passive strategy such as Buy and Hold (Vukovic et Al., 2023). To take advantage of TSM, the ARMA model will be used to predict Nintendo's stock price.

The ARMA model was popularized by Box and Jenkins, and their technique will be used on Nintendo's stock price. The selection of the ARMA model for Nintendo's stock prediction stems from other successful applications. An analysis conducted by Rounaghi and Zadeh (2016), uncovered that using the ARMA model to calculate stock return for the London Stock exchange and the S&P 500 is statistically better than other methods. An application of the ARMA model by H. Tang (2021), gave relative success in terms of predicting AAPL's stock price 5 days into the future with a maximum error rate of 5.5% (pg.203). These examples show that the ARMA model has shown previous success in forecasting.

III. Methodology

A. *Ordinary Least Squares vs. ARMA*

There are a few estimation techniques which can be used to predict the current value. An extremely popular method is the Ordinary Least Squares (OLS) method, which works by creating a continuous linear function explaining the dependent variable based off of certain selected covariates. OLS is a popular method as it is very light in terms of computation, and its interpretability is clear. In a time series context, OLS is seldom used as it has very demanding assumptions that must be met such as the data used must be stationary and samples must be independent and identically distributed which data taken at specific time periods is not. Furthermore, OLS fails to consider past value effects on the present value.

Ordinary Least Squares

$$y_n = \hat{B}_1 x_1 + \hat{B}_2 x_2 + \ldots + \hat{B}_n x_n \tag{1}$$

- Independent Identically Distributed (IID) Random Sample Data Required
- Minimized Residuals
- Must have continuous Output

A model that resolves the issues that OLS cannot solve, is the Auto-Regressive Moving Average Model ARMA model. ARMA works well with Time Series data as it requires periodic time frames. ARMA also considers past values and their errors in calculating the present value.

ARMA Model

- Uses Periodic Time Splits (Good for Time-Series)
- Implements effects of Past Values and Errors

B. Diagnostic Checking

Autocorrelation is "the degree of correlation of a variable's values over time" (Smith, 2023). It ranges from -1 to 1, where -1 represents a perfect negative correlation, and 1 represents a perfect positive correlation. In the context of ARMA, the autocorrelation function (ACF) assists in determining which previous time periods have the most correlation with the present value. Furthermore, a desirable situation for the ARMA model would be to have no autocorrelation as the model would be able to capture the true essence of the time series. This would be beneficial for forecasting future values.

There are two main statistical tests which can help determine autocorrelation within our data. The Durbin Watson test ranges from 0 to 4. Values closer to 0 indicate positive autocorrelation, and closer to 4 indicates negative autocorrelation, with 2 being no autocorrelation. A more insightful statistical test is the Ljung-Box Test, which has the null hypothesis: (H_0 : Autocorrelations up to lag k are zero), in the case of a p-value less than a chosen alpha level, the alternative hypothesis is accepted indicating that there is possibly at least some sort of autocorrelation up to lag k. Using the ACF and the Durbin-Watson Test or Ljung-Box Test, it is possible to get key lags to check for an ARMA model.

C. ARMA Model

As mentioned before, the methodology that is usually used for the ARMA model was popularized by Box & Jenkins. Box & Jenkins implementation goes through a series of steps which verify if the data can be used with ARMA. It is important to understand the mathematical aspect of ARMA. Essentially, it is the combination of 2 series.

ARMA is a mixture of:

Auto-Regressive Model

$$X_t = c + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_p X_{t-p} + \epsilon_t \tag{2}$$

1) X_t is the value of the series
2) C is a constant
3) ϕ_i where $i \in \mathbf{N}$ are the coefficients of the model
4) $\epsilon_t$is the error term
5) p is the number of lags

The AR model considers the impact of the past values on the current value.

Moving Average Model

$$X_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + \ldots + \theta_q \epsilon_{t-q} \tag{3}$$

1) X_t is the value of the series
2) μ is the mean of the series
3) θ_i where $i \in \mathbf{N}$ are the coefficients of the model
4) ϵ_{t-a} where a is the number of time periods before current time, t.

The MA model considers the influence of past errors on the current value.

Together these two series create the ARMA model, which is able to consider the impact of both past values and the past errors on the current value.

ARMA as mentioned before is essentially a series which predicts future values based on the impact of previous terms and previous errors on the current term. For example, an ARMA(1,1) model would forecast future values using the previous time period's (t-1)value as well as the previous time period's (t-1) error term. There are a few assumptions which are required for the ARMA model to work:

- E(ϵ_t) = 0
- Var(ϵ_t) = σ^2
- Cov(ϵ_t, ϵ_s)= 0 : $\forall s \in \mathbb{N} - 0$
- All error terms are independent and identically distributed

Identification of p and q

An ARMA model's notation is written in the form of ARMA(p,d,q), where p is the number of past auto-regressive terms, d is the number of times the data is differenced, and q being the number of past moving average terms.

To select p and q, the best way is to compare different ARMA(p,q) with each other. To judge the best model, a prediction error indicator can be used. In this paper, Akaike Information Criterion (AIC) will be used to compare models, where lower AIC's suggest better modelling. It's important to note that just because a model has lower AIC, it does not necessarily mean that it is a better model in general. Overfit models can give extremely low AIC, but will poorly forecast future values. Using a correlogram, we are able to see the values of ACF/PACF. In very specific situations, it is possible to see the ACF monotonically declining. In this case, spikes in the PACF can suggest that the corresponding time period t_a has some sort of impact on the current value. For example if there is a spike at t_{-1}, then AR(1) could possibly explain the current value of the series at time, t.

IV. Descriptive Statistics Analysis

A. Data Collection

To create an ARMA model, data from the Nikkei 225 provided by NEEDS-financialQUEST was used to get Nintendo's (7974:Tokyo) daily adjusted closing stock price. The use of the adjusted closing stock price, allows for the easy use of data before the stock split. Data from 2022-01-4 to 2024-06-12 was used to construct the ARMA model. The choice of this period is to capture recent trends and relevant events, including the 10-for-1 stock split, significant game releases and the impact of the global chip shortage.

B. Statistical Analysis

By rough inspection of the daily returns and adjusted closing price, it seems that the data has an upward trend and is not stationary.

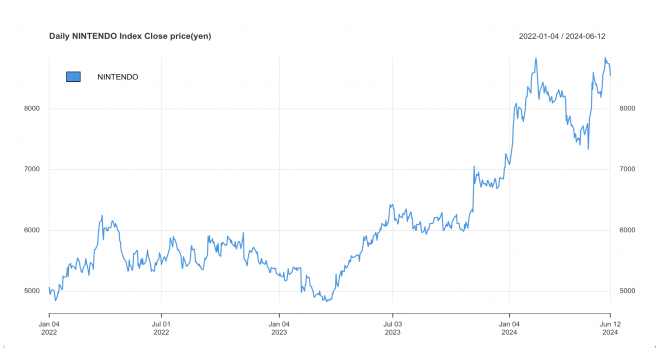

Fig. 1. Daily Nintendo Index Close Price

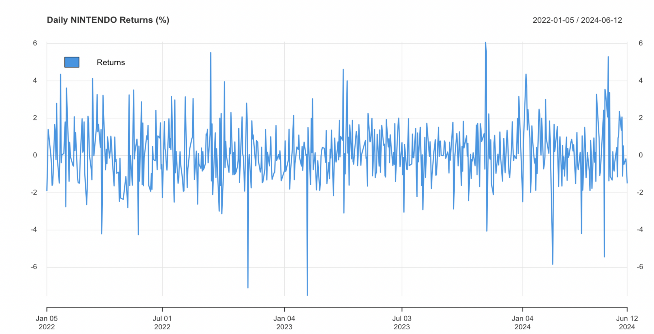

Fig. 2. Daily Nintendo Returns (%)

Mean	6161.5573
SD	1029.6407
Min	4820.8600
Max	8850.0000
Skewness	1.1242
Kurtosis	0.1120
JB Test t-value	126.069
p-value	0.0000
Sample Size	597

TABLE I
Table of Nintendo Index Statistics

- Mean: The average adjusted closing price of the Nintendo stock over the sample period is 6165.5853 yen
- Standard Deviation: The standard deviation of 1029.0178 yen indicates the degree of variation or dispersion of the Nintendo stock prices from the mean
- Minimum and Maximum: The lowest observed stock price is 4820.8600 yen, while the highest observed stock price is 8850.0000 yen. This range provides insight into the fluctuations in the stock price over the sample period.
- Skewness: The skewness value of 1.1208 indicates that the distribution of stock prices is positively skewed, meaning that there are more frequent lower values and a long tail towards the higher values. This suggests that extreme high values (outliers) are more likely than extreme low values.
- Kurtosis: The kurtosis value of 0.1120 suggests that the distribution is platykurtic, meaning it has lighter tails and a flatter peak than the normal distribution. This indicates fewer extreme price changes than would be expected in a normal distribution.
- Jarque-Bera Test: The JB test value of 126.0691 is a measure of whether the data has the skewness and kurtosis matching a normal distribution.
- p-value: The p-value of 0.0000 indicates a strong rejection of the null hypothesis at conventional significance levels.

The low p-value means that the null hypothesis, data is normally distributed, should be rejected. The positive skewness and platykurtic nature imply that the stock prices are more likely to experience mild deviations from the mean with occasional extreme high values. Investors should be aware of this non-normality as it may affect the risk and return profile of the stock. The high variability indicated by the standard deviation suggests that the stock prices can experience significant fluctuations, which is a critical factor for risk assessment and investment decisions.

The descriptive statistics and the results of the normality test provide essential insights into the behaviour of Nintendo stock prices:

- High Mean Value: Indicates the observed time period has a relatively high average stock price over Nintendo's history.
- High Variability: Investors should consider the substantial standard deviation, which suggests a higher risk associated with large price swings.

- Positive Skewness: Indicates a likelihood of experiencing higher stock price spikes, which can be seen as opportunities for high returns.
- Non-Normal Distribution: The rejection of normality suggests that standard models assuming normality may not be appropriate, and alternative models that can capture skewness and kurtosis should be considered for better risk management and pricing strategies.

C. Data Cleaning

There was no need for data cleaning as there were no missing values. The data set was processed in R, with the stock prices being converted into float numeric values.

D. Stationarity

One of the requirements for the ARMA model to be applicable, is that the data must be stationary. This means that the errors and values are not a function of time. Since an absence of a unit root implies that the data has asymptotically stationary properties and will lead to spurious regressions, certain tests such as the Augmented Dickey-Fuller (ADF) test can be used to check. The ADF test has the null-hypothesis that the series has a unit root, setting a designated alpha value of 0.05. If the p-value is less than our alpha level, the alternative hypothesis, the series does not have a unit root, can be accepted. In a similar fashion, the test statistic can be examined to check for a unit root.

The assumption for the ARMA model is the data should be stationary. Here, we do stationarity testing. Perform the Augmented Dickey-Fuller (ADF) test to check for stationarity. If the p-value is high, the series is non-stationary. If the data is non-stationary transformations can be done such as differencing to achieve stationarity. The ADF test can be applied on the transformed data to confirm stationarity.

ADF Test on Nintendo Stock Price

```
        Augmented Dickey-Fuller Test

data:  Nintendo$NINTENDO
Dickey-Fuller = -1.4209, Lag order = 8, p-value = 0.8234
alternative hypothesis: stationary
```

Fig. 3. ADF on Nintendo Stock Price

- Null Hypothesis (H_0): The null hypothesis of the ADF test is that the time series is non-stationary (has unit root)
- Alternative Hypothesis (H_A): Series is stationary (no unit root)

Unfortunately the results of the ADF test indicates that the stock price of Nintendo is an unacceptable dataset to construct an ARMA model.

Log-Difference of Nintendo's Stock Price

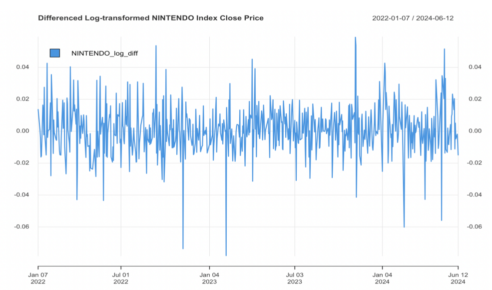

Fig. 4. Log-Difference of Nintendo Index Adjusted Close Price

```
Warning: p-value smaller than printed p-value
        Augmented Dickey-Fuller Test

data:  Nintendo$NINTENDO_log_diff
Dickey-Fuller = -8.6991, Lag order = 8, p-value = 0.01
alternative hypothesis: stationary
```

Fig. 5. ADF on Log-Difference of Nintendo Stock Price

To resolve the problem of non-stationarity, taking the log and first difference on the dataset can usually create stationary data. Performing the ADF test on the log difference, gives a p-value of less than the significance level of 0.05 as well as a highly negative test statistic of -8.6991. This indicates that the null hypothesis should also be rejected. The series Nintendo after taking the natural logarithm and performing the first difference, appears to be stationary. The log-difference is preferred over the first difference as the logarithm has the ability to stabilize trend and variance, making it easier to identify a good ARMA model.

E. Determining Specific Form of the Model

> *Economic variables are generally ARMA models with no more than 5th order* - H.Tang, 2021

In practice, many economic time series can often be adequately modeled using ARMA models with relatively low orders, typically up to order 5. A few characteristics of the ARMA model are below.

1) ARMA(5,5) or higher may overfit the data and fail to generalize well especially with data influenced by a variety of factors
2) Higher Parameter ARMA models have increased complexity and difficulty in interpretation
3) High order ARMA models fail to ignore key characteristics of time series data such as noise and unpredictability

To predict the short-term stock prices of Nintendo, the ARMA model was applied to the daily adjusted closing stock prices. The best-fitting ARMA model will be based on the Akaike Information Criterion (AIC). The data used spans from January 4, 2022, to June 12, 2024, covering the recent period of significant events affecting Nintendo's stock prices.

V. Implementation

A. Best ARMA Model Identification and Fitting

With R, a loop was used to select p and q with the minimum AIC, up to the 5th order. The being p = 4 and q = 2. The equation is below.

ϕ_1	ϕ_2	ϕ_3	ϕ_4	θ_1	θ_2	C
1.0709	-0.8785	-0.0836	-0.0175	-1.1622	1	0.001

TABLE II
Coefficient Values

$$y_t = \phi_1 y_{t-1} + \phi_2 y_{t-2} + \phi_3 y_{t-3} + \phi_4 y_{t-4} + \theta_1 \epsilon_{t-1} + \theta_2 \epsilon_{t-2} + C \quad (4)$$

```
Warning in ARMA( 2 , 0,  5 ): NaNs produced
Best ARMA model: ARMA( 4 , 0,  2 ) with AIC = -3275.55

Call:
arima(x = Nintendo$NINTENDO_log_diff, order = c(best_p, 0, best_q))

Coefficients:
         ar1      ar2      ar3      ar4      ma1     ma2  intercept
      1.0709  -0.8785  -0.0836  -0.0175  -1.1622  1.0000      1e-03
s.e.  0.0419   0.0600   0.0607   0.0416   0.0098  0.0081      6e-04

sigma^2 estimated as 0.0002298:  log likelihood = 1645.78,  aic = -3275.55

Training set error measures:
                        ME       RMSE        MAE  MPE MAPE      MASE          ACF1
Training set -4.255553e-05 0.01516043 0.01119671 -Inf  Inf 0.6637527 -0.0008380946
```

Fig. 6. Further Statistics on ARMA(4,0,2)

- The model selection was based on the AIC.
- The output showed that ARMA(4,0,2) had the lowest AIC of -3275.55
- Autoregressive (AR) terms:
  1) ar1 = 1.0709 with a standard error of 0.0419
  2) ar2 = -0.8785 with a standard error of 0.0600
  3) ar3 = -0.0836 with a standard error of 0.0607
  4) ar4 = -0.0175 with a standard error of 0.0416
- Moving Average (MA) terms:
  1) ma1 = -1.1622 with a standard error of 0.0098
  2) ma2 = 1.0000 with a standard error of 0.0081

The combination of the AR and MA terms work together to determine the value at time t. The intercept was 0.00095392 with a standard error of 0.00057460. This term is not highly significant, indicating that the mean return might be close to zero.

B. Model Diagnostics

- ME (Mean Error): -4.25553e-05
- RMSE (Root Mean Squared Error): 0.01516043
- MAE (Mean Absolute Error): 0.01119671
- MPE (Mean Percentage Error): -Inf (likely due to extremely small or zero values)
- MAPE (Mean Absolute Percentage Error): Inf (same issue as MPE)
- MASE (Mean Absolute Scaled Error): 0.6637527
- ACF1 (Autocorrelation of residuals at $t-1$): -0.0008380946

The different metrics of error show that the ARMA(4,0,2) model are quite effective at explaining the in-sample data. The ACF1 also indicates that the model is without autocorrelation issues.

C. ARMA Coefficient Selection

```
z test of coefficients:

             Estimate  Std. Error   z value  Pr(>|z|)    
ar1        1.07090798  0.04188682   25.5667  < 2e-16 ***
ar2       -0.87853236  0.05995275  -14.6537  < 2e-16 ***
ar3       -0.08357905  0.06065541   -1.3779  0.16822    
ar4       -0.01748946  0.04159545   -0.4205  0.67415    
ma1       -1.16219443  0.00978285 -118.7992  < 2e-16 ***
ma2        0.99998122  0.00811873  123.1697  < 2e-16 ***
intercept  0.00095392  0.00057460    1.6601  0.09689 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Fig. 7. z-test of coefficients

Significance of AR and MA Coefficients: The z test results for the coefficients indicated the significance of each term:

- AR1 (1.0709, p < 2e-16) and AR2 (-0.8785, p < 2e-16) are highly significant, meaning these past values are strong predictors of the current value.
- MA1 (-1.1622, p < 2e-16) and MA2 (1.0000, p < 2e-16) are also highly significant, indicating that past errors in the previous 2 lags significantly influence current values.

The significance levels and very low p-values for these coefficients confirm their importance in the model.

D. Error Measures

- The residual variance (σ^2) was low (0.0002298), and the log likelihood was high (1645.78), suggesting a good fit.
- Training set error measures such as RMSE (0.01516043) and MAE (0.01119671) were reasonable, indicating the model's predictions are close to the actual values.
- The Autocorrelation Function (ACF1) at lag 1 was very close to zero (-0.0008380946), indicating no significant autocorrelation in the residuals at lag 1. This is a good sign as it implies that the residuals do not exhibit patterns and the model has captured the dependency structure in the data well.

E. Interpretation of Results

These findings imply that the ARMA(4,0,2) model can be a reliable tool for short-term stock price prediction of Nintendo. The significant coefficients confirm the influence of historical data on future prices, which aligns with the objectives of using ARMA models in stock price prediction. Further refinement and validation with out-of-sample data could enhance the robustness and predictive accuracy of the model.

In more mathematical terms, the selected model of ARMA(4,0,2) essentially means that for Nintendo's log differenced stock price at time, t, the previous value of the previous 4 time periods and the errors of the previous 2 time periods have some sort of impact. We can predict future values of the log differenced stock price using this model in the short term by finding the values at t_{p+i} where p is the current time, and i is the number of periods ahead of p.

VI. Results & Empirical Analysis (Discussion)

To establish whether the ARMA(4,0,2) model is the best model for our dataset, further diagnostic checks on the residuals must be done in order to assure that there is no autocorrelation. If the model passes further tests, it will be used to forecast the 5 trading days after the last date the model was trained on.

A. Diagnostic Checking

```
	Box-Ljung test

data:  residuals
X-squared = 11.549, df = 20, p-value = 0.9307

The Ljung-Box test indicates no significant autocorrelation in residuals up to
lag 20 (p-value: 0.9307398 )
```

Fig. 8. Box-Ljung Test

The failure to reject the null-hypothesis in the Box-Ljung test indicates that there is probably no autocorrelation. To further inspect, the ACF and PACF will be examined.

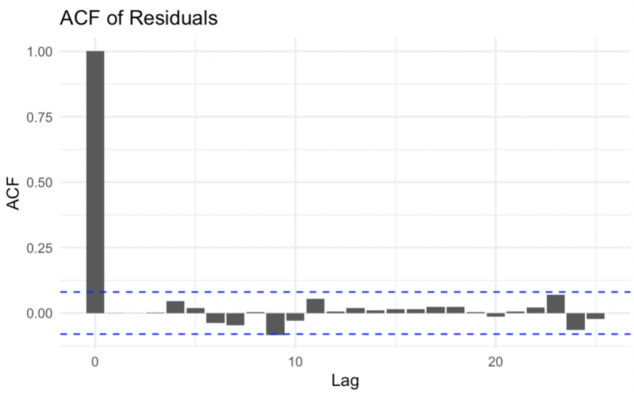

Fig. 9. ACF of Residuals

The ACF plot shows the correlation between the residuals and their own lagged values. The blue dashed lines represent the confidence bounds of 95%. If the autocorrelations fall within these bounds, they are not statistically significant. Since most of the autocorrelations are within the confidence bounds, it indicates that there is no significant autocorrelation in the residuals at most lags. This suggests that the ARMA model can capture the autocorrelation structure of the data.

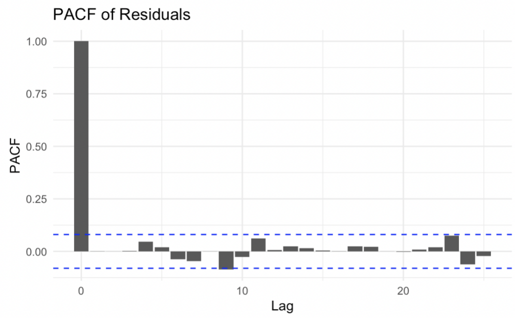

Fig. 10. PACF of Residuals

The PACF plot shows the partial correlation of the residuals with their own lagged values, controlling for the values of the intermediate lags. Similar to the ACF, the spikes outside of the blue dashed lines indicate significance. Most of the partial autocorrelations are within the confidence bounds. This further supports the adequacy of the ARMA model for Nintendo stock price forecasting.

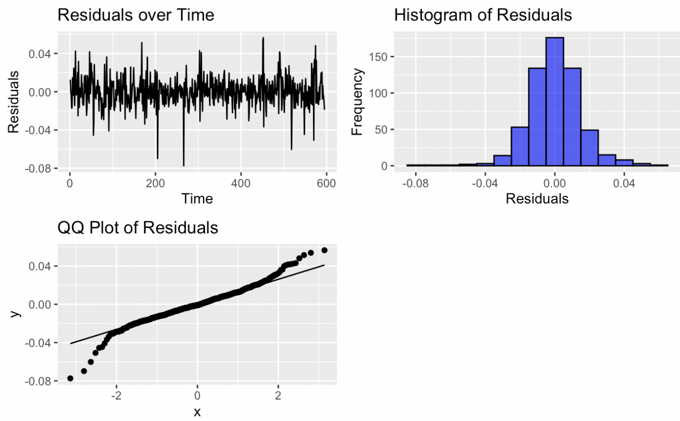

Fig. 11. Residual Data

Residuals over Time:
The Residuals over Time plot shows that the ideal pattern is achieved. The residuals appear to be randomly distributed around zero without any clear pattern, indicating that there are no obvious systematic errors remaining in the residuals, which is a good sign for model adequacy.

Histogram of Residuals:
Ideally, the residuals should be normally distributed. The histogram of residuals shows a symmetric distribution around 0. The histogram further supports good model fitting.

QQ-plot of Residuals:
The QQ plot compares the quantiles of the residuals to the quantiles of a normal distribution. Perfect normal distribution would be all data points lying on the $x = y$ line. The QQ-plot indicates that our data is approximately normally distributed, with potential deviations in the extreme values.

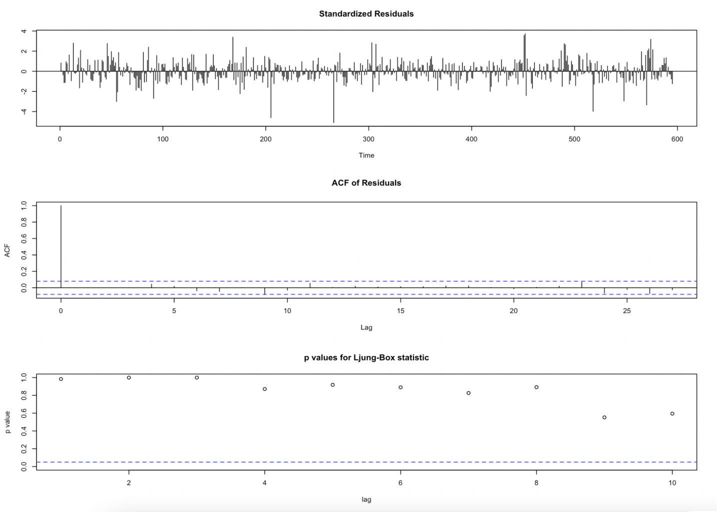

Fig. 12. Residual Diagnostic Tests

After examination of the residual diagnostic tests, the model does not appear to have any statistical problems. The standardized residuals should look random and almost always remain between -2 and +2. The graph shows exactly what is to be expected. The p-values for the Ljung-Box test at all lags are all relatively close to 1. This implies that the null hypothesis, no autocorrelation, should be accepted.

In conclusion, the ARMA(4,0,2) can be established as a method to forecast future values for the Nintendo Stock.

B. Forecasting Comparison

Date <date>	Predicted <dbl>	Actual <dbl>	Error <dbl>
2024-06-13	8544.09	8363	-181.09
2024-06-14	8535.18	8481	-54.18
2024-06-17	8529.11	8411	-118.11
2024-06-18	8524.12	8672	147.88
2024-06-19	8518.54	8581	62.46

Fig. 13. Forecast vs. Actual

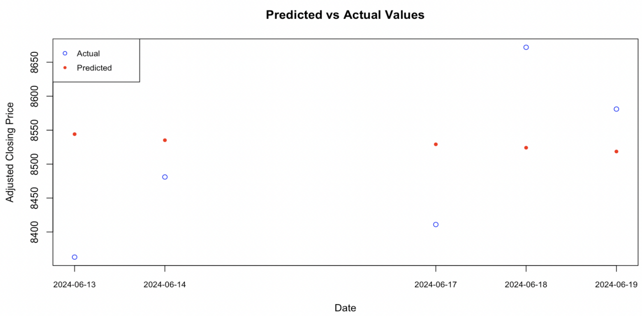

Fig. 14. Forecast vs Actual Visualized

Comparison of Error Metrics

Date	MAE	MSE	RMSE	MAPE
2024-06-13	181.09	32793.59	181.09	2.17
2024-06-14	54.18	2935.47	54.18	0.64
2024-06-17	118.11	13949.97	118.11	1.40
2024-06-18	147.88	21868.49	147.88	1.71
2024-06-19	62.46	3901.25	62.46	0.73

Fig. 15. Error Metrics at each Forecasted Date

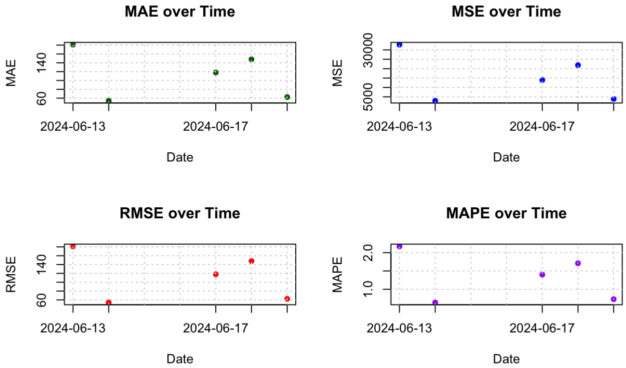

Fig. 16. Error Metrics over Forecast

Error Metrics

Mean Absolute Error (MAE)	112.744
Mean Squared Error (MSE)	15089.76
Root Mean Squared Error (RMSE)	122.84
Mean Absolute Percentage Error (MAPE)	1.328 %

Fig. 17. Average Error Metrics over Forecast

The different error metrics give us insight into how well our ARMA(4,0,2) model is able to predict the future of the Nintendo stock price. Using different metrics of error, the accuracy of the forecasting can be understood empirically. The Mean Absolute Error (MAE) of 112.744 indicates that the model on average was off by 112.744 yen for the 5 forecasted days. The Mean Squared Error (MSE) of 15089.76 is essentially the squared differences between our predicted stock price and the actual stock price of the 5 forecasted days, the high value indicates that either the prediction was off, or the actual price of the stock on one of the days is an outlier. The Root Mean Squared Error (RSME), tells us how close our forecast is to the line of best fit. The Mean Absolute

Percentage Error (MAPE), is perhaps the most interpretable, meaning that over the 5 forecasted days, on average the predicted price was off by 1.328%. Overall, the model seems to be quite accurate over a short period of time.

VII. Concluding Statements

In order to apply the concept of ARMA, the data must be stationary. This was done by taking the log difference of Nintendo's stock price from January 2022 to June 2024. Through theory and empirical work an ARMA(4,0,2) model was created. The model gave a prediction of Nintendo's stock price 5 days into the future. It was only off by an average of 1.33%. In terms of short term forecasting, if the assumptions of the ARMA model are correctly met, it can be a useful tool to assist investors to make financial decisions in the short term. The empirical analysis gives insight into the effects of time momentum, specifically, how the past values and past errors can affect the present value of a stock.

A. Limitations

In the case of Nintendo's stock price, the data became stationary after only one difference. Unfortunately, sometimes data must be differenced multiple times in order to achieve stationarity. In this case the ARMA model would not be interpretable. Moreover, the error terms are expected to be 0 and normally distributed, which is not the case in many scenarios. The ARMA model requires some strong assumptions in order to forecast relatively accurately.

Furthermore, one unfortunate aspect of the ARMA model is the lack of its ability to include other macroeconomic variables such as interest rates, exchange rates, and GDP. The effects of time and macroeconomic conditions can work together, to improve forecasting accuracy.

B. Improvement

In reality, stock prices are nonlinear and dynamic (Shi et al., 2012). Is ARMA, a linear model, good enough to predict nonlinear phenomena? Surprisingly, when ARMA is combined with both an Artificial Neural Network (ANN), and a Markov Model, it can help with predicting the linear and nonlinear aspects in stock price (Shi et al., 2012). Chinese scholars from Dalian University applied their ARMA-ANN-Markov model to forecast China Petroleum's stock price. They were able to predict 5 days using 15 former results with a maximum error of 1.1031% (Shi et. Al., 2012). Another successful application in the field of stock price prediction was when scholars from the Chinese University of Hong Kong, used an ARMA(3,3)-GARCH(3,3) model to predict daily prices of Cheung Kong Holding and HSBC Holding with no more than a mean square error of 2.8 (Tang et Al., 2003). These examples give insight into the possibility of creating models more accurate than a pure ARMA model.

C. Financial Suggestions

There are several ways investors can use ARMA model to exploit the short-term predictions from the ARMA model to identify buying and selling opportunities and make wise financial decisions:

1) Leverage Predicted Price Movements: Use the short-term predictions from the ARMA model to identify buying and selling opportunities.
   - Buy Signal: If the ARMA model predicts an upward trend in Nintendo's stock price, consider purchasing shares to capitalize on the anticipated increase. For instance, if the forecast indicates a price rise over the next week, execute a buy order to maximize potential gains.
   - Sell Signal: Conversely, if the model forecasts a decline, consider selling shares to avoid potential losses. This decision can be particularly beneficial if a short-term trading strategy is in use (Kramer, 2019).
2) Hedging with Options:
   - Call Options: If the ARMA model predicts a significant rise in stock price, purchasing call options can be a cost-effective way to benefit from the price increase without directly buying the stock.
   - Put Options: If a decline is forecasted, buying put options can provide a hedge against potential losses in your portfolio, allowing you to profit from the predicted downturn (Murphy, 2024).
3) Capitalizing on product launches and announcement:
   - Pre-launch Buying: If the ARMA model indicates a positive trend leading up to major product launches or announcements such as new game releases or hardware, invest in Nintendo stock before these events. Historically, successful launches have boosted stock prices, providing a profitable investment opportunity.
   - Post-announcement Selling: After a significant announcement, if the forecast shows a potential peak, consider selling shares to lock in profits before any potential correction.
4) Strategic dividend investments:
   - Dividend Capture Strategy: Based on the forecast, if Nintendo's stock price is expected to rise around the ex-dividend date, buy shares just before this date to capture the dividend payout and benefit from the price increase. Sell the shares after the ex-dividend date if the model predicts a subsequent drop (Mitchell, 2022).

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