HSLU Hochschule Luzern

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W.TSA01_Time Series Analysis in Finance

Title: Influence of iPhone Product Announcements on Apple Stock Performance

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1.Introduction and Motivation

This study investigates the influence of Apple Inc.'s product announcements on its stock price. Given Apple's position as a market leader in technology, its product launches are highly anticipated events that can significantly sway investor sentiment, especially during product launch events. Understanding these market dynamics offers insights into investor behaviour and market reaction to corporate news. We examine how Apple's stock prices have historically reacted before, during, and after the launch of new iPhone models. This analysis includes identifying trends, such as increases or decreases in stock price, and the timing of these changes in relation to product launch events. The goal is to understand if and how these announcements have a consistent impact on stock market valuation, reflecting investor sentiment and market expectations around these high-profile product releases. We have scrapped the Apple stock data and also the apple launch and product release dates into csv files and then subsequently loaded them into R studio for in depth analysis.

2. Data Preparation

This step involved cleaning the historical apple stock price data, such as adjusting the data type of each column and changing it to date time format . Missing data is addressed by removing them completely as there was very little missing data from the csv file, we scrapped from yahoo finance.

Data and Sources

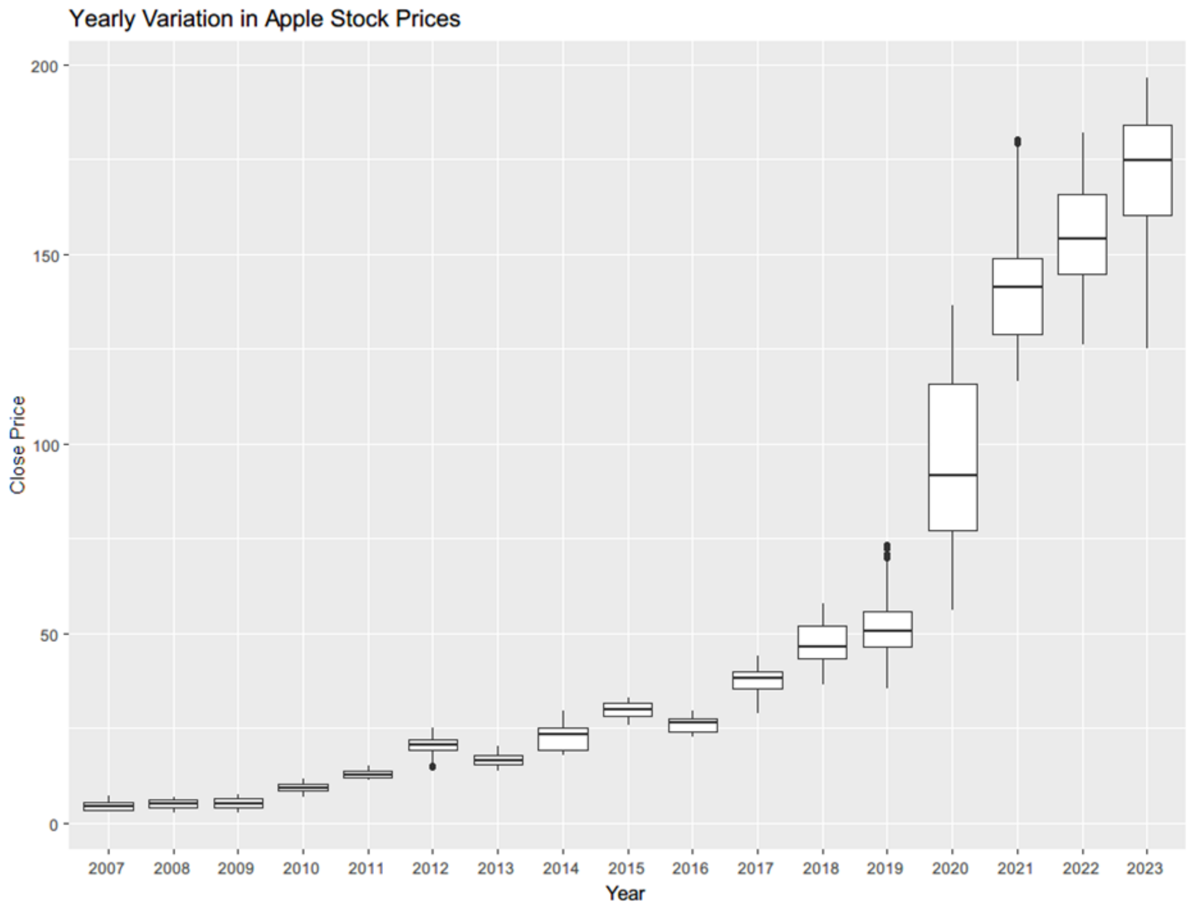
The data used in this study consists of historical stock price data of Apple Inc., from 2007 till 2023 specifically focusing on periods encompassing major iPhone product launches. This data primarily includes daily closing stock prices, selected for their relevance in reflecting market sentiment. The period covered in the study is carefully chosen to ensure that it captures significant market activities surrounding each iPhone launch. In discussing the data sources, the report also acknowledges the limitations and potential external factors influencing stock prices, which are NOT included in this study.

The limitations and potential external factors influencing Apple's stock prices include:

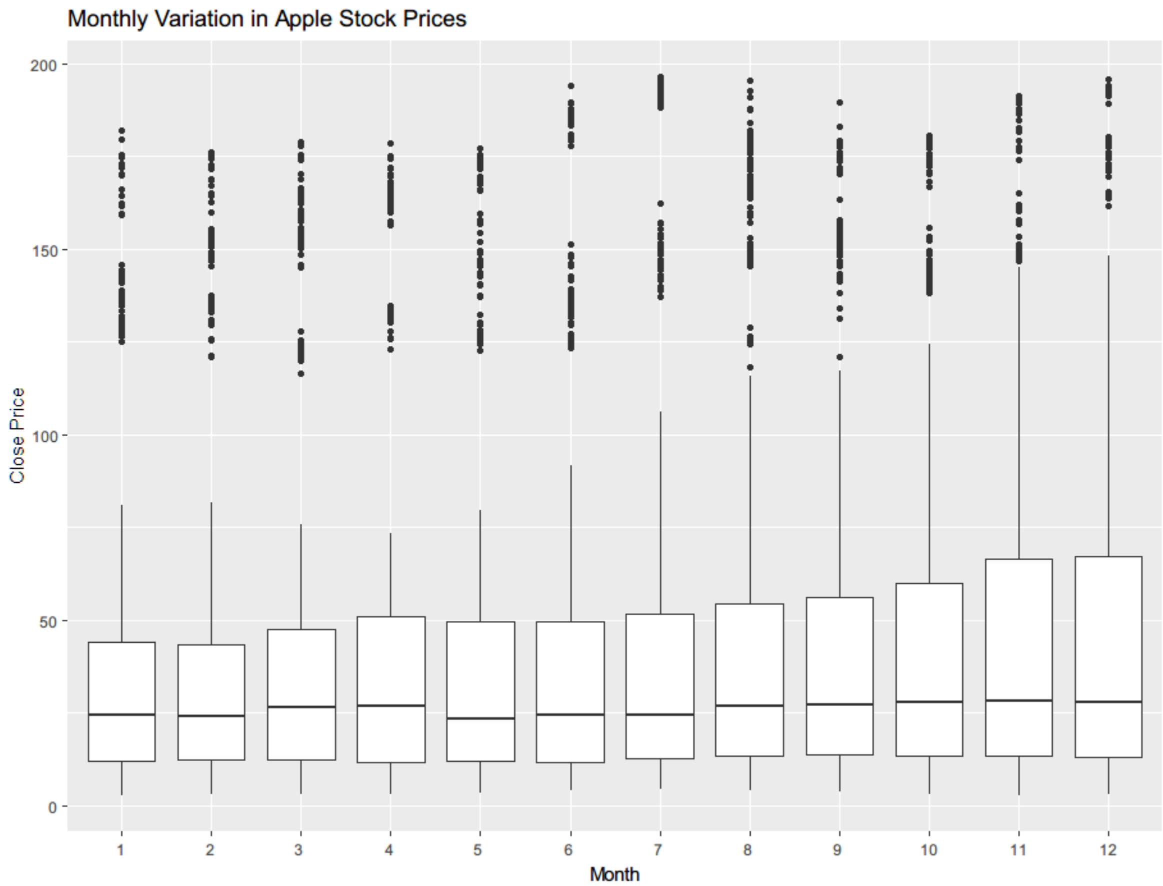
- Market Conditions: Broader market trends and economic indicators can impact Apple's stock regardless of the company's performance.
- Global Events: Political events, economic policies, or crises (like the COVID-19 pandemic) can affect investor sentiment and stock prices.
- Competitor Actions: Developments from competitors in the tech industry can influence Apple's market position and stock value.
- Regulatory Changes: Legal and regulatory shifts, especially in technology and trade, can have significant impacts.
- Investor Sentiment: Public perception and investor confidence, driven by news or social media, can affect stock prices.
- Technological Innovations: Breakthroughs in technology, either by Apple or its competitors, can influence stock valuation.

These factors underscore the complexity of stock price movements and the challenges in isolating the impact of specific events like iPhone announcements. We again, however ,emphasize the importance of this data in understanding the market's response to Apple's product announcements.

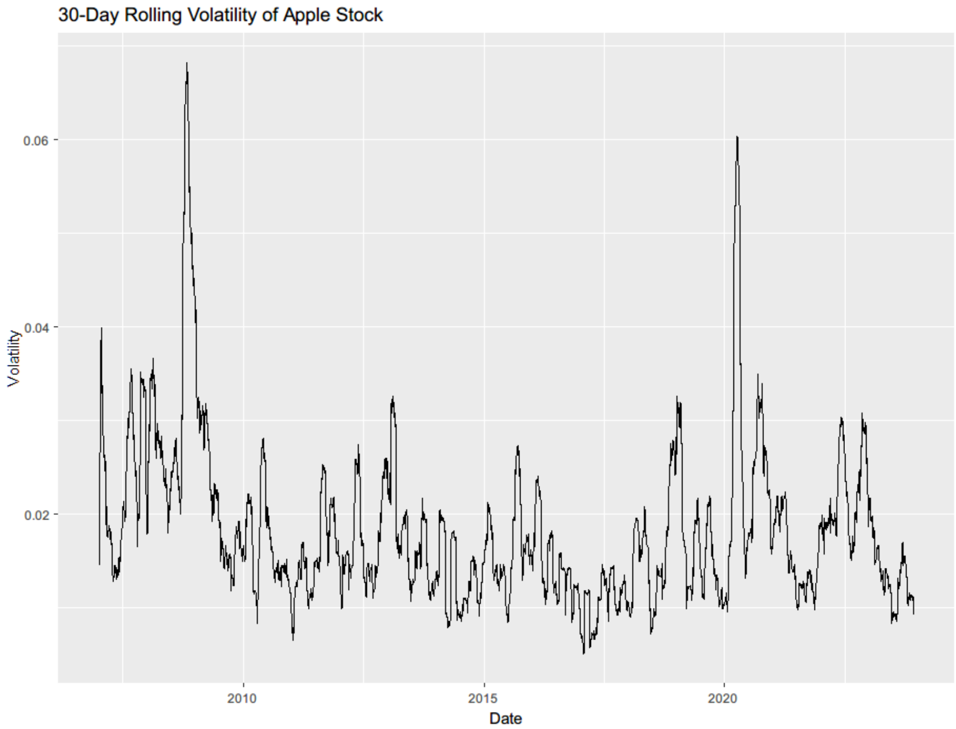
3.Exploratory Data Analysis (EDA): Our Exploratory data analysis involved checking the outliers of the stock data for apple. As shown below:



The graph is a box plot showing yearly variation in Apple stock prices from 2007 to 2023. Each box captures the interquartile range of the stock's closing price, indicating where the central 50% of values lie. The median of each year's prices is represented by the line within each box. As we move from left to right, there is a general upward trend in median prices, showing growth over time. Recent years show taller boxes, which suggests greater volatility, with more pronounced price movement both at the top and bottom of the boxes. Outliers, depicted as individual points, are particularly noticeable in some years, indicating exceptional price deviations from the typical range. The whiskers extending from the boxes display the full range of data, excluding outliers, and their increasing length in later years indicates wider price dispersion.



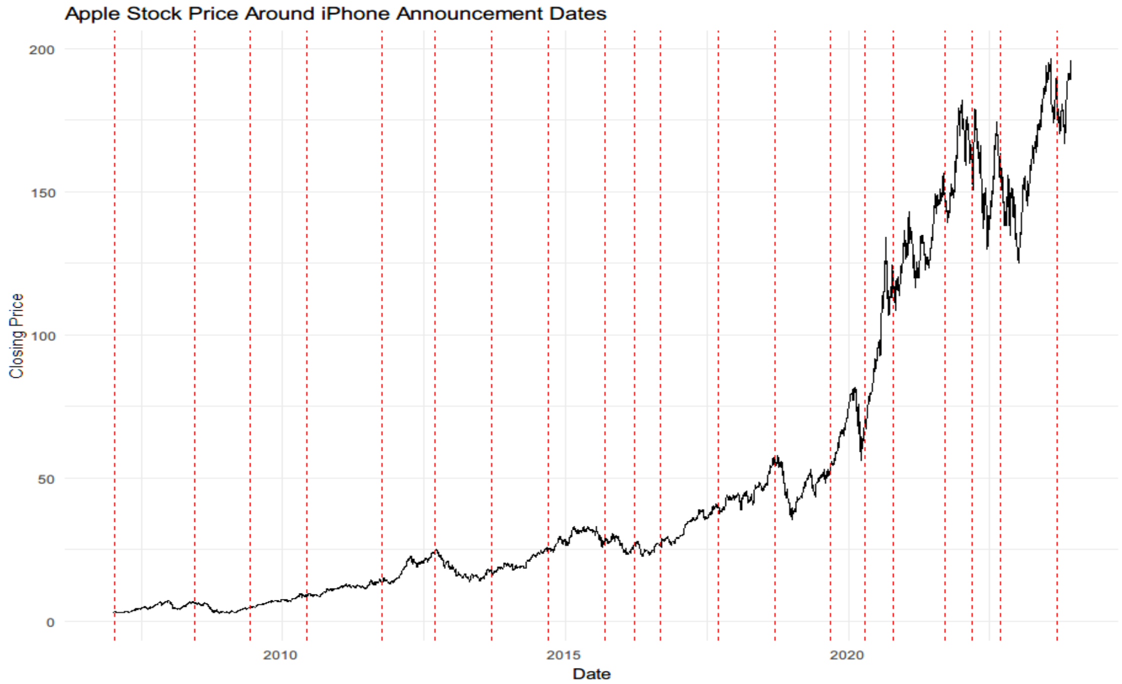
The provided box plot depicts the monthly variation in Apple stock prices. Each box represents the interquartile range (IQR) of stock prices for a given month, showing the middle 50% of values. The line within each box marks the median closing price. The whiskers extend from the boxes to show the range of the data, and points outside the whiskers indicate outliers. There's notable variation in prices, with certain months exhibiting significant outliers, indicating months with extreme price movements. The plot covers all months in a year, with the y-axis representing the closing price.

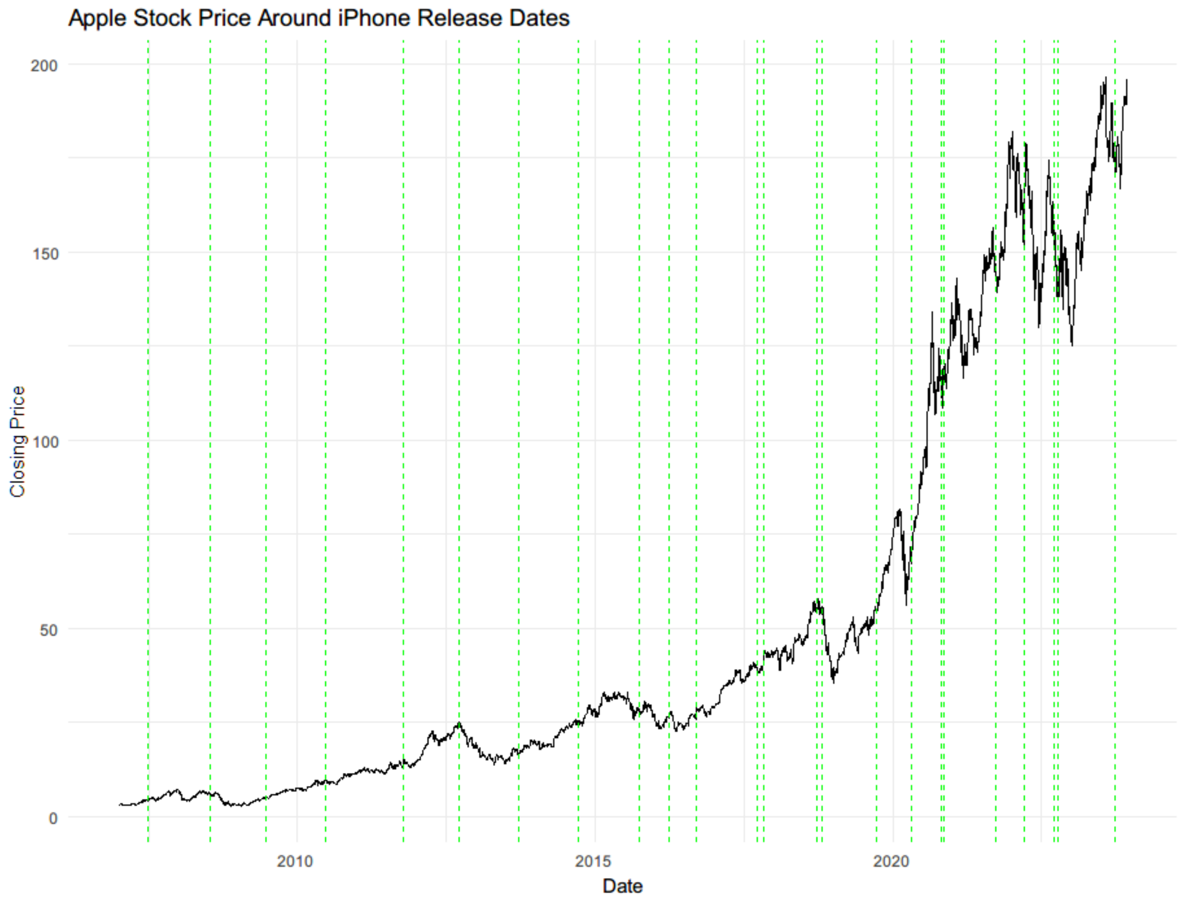


The chart displays the 30-day rolling volatility of Apple's stock, calculated on a daily basis. It shows fluctuating volatility levels over time, with noticeable spikes that could indicate periods of market stress or significant corporate events. The highest peaks in volatility seem to occur around 2008-2009 and in early 2020, periods known for financial crisis and the onset of the COVID-19 pandemic, respectively. The volatility is generally higher in the earlier years depicted, with a visible decrease and stabilization towards the more recent years, barring the sharp increase in 2020.

This involved plotting Apple's stock prices over time to visually assess trends and volatility. Key events, particularly iPhone announcements, are marked to observe their immediate impact on stock prices.

In the graphs below, we show the general trend of Apple Stock Prices Over time with the red lines showing the announcement dates, and the green lines showing the release dates:


Apple Stock Price Around iPhone Announcement Dates
Closing Price
200
150
100
50
0
2010
2015
2020
Date


Apple Stock Price Around iPhone Release Dates
Closing Price
200
150
100
50
0
2010
2015
2020
Date

4. Methodology and Results

In our methodology, we first loaded necessary R packages and imported Apple's stock data and iPhone release dates. We converted 'Date' columns to datetime, removing any rows with missing dates. We created a binary variable for iPhone announcement dates to analyse their effect.

The hypothesis is that Apple's stock price experiences significant fluctuations around the dates of major product launches (H1). The Null hypothesis is that Apple’s stock price does NOT experience significant fluctuations around the dates of major product launches (H0).

Our Hypothesis are as follows:

H0 = Apple Stock price does NOT experience significant fluctuations during iPhone announcements.

H1= Apple Stock price experiences Significant fluctuations during iPhone announcements.

Log transformation was applied to stabilize the variance in the stock price data and to make the data more 'normal' or symmetrical, which is a key assumption for many statistical techniques.

In this study, we used the ARIMA and GARCH models. These models need to be made stationary first and foremost. Stationarity is a crucial concept in time series analysis, especially when applying ARIMA (Autoregressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models. A stationary time series has properties that do not depend on the time at which the series is observed. This means its mean, variance, and autocorrelation (correlation with its own past values) remain constant over time.

Non-stationary data can lead to unreliable and spurious results in time series models. This is because non-stationary series often contain trends and seasonality, which can affect the stability of the model coefficients. Transforming a non-stationary series into a stationary one typically involves differencing, logarithmic transformation, or deflation by some other series.

For the analysis of the impact of iPhone announcements on Apple's stock price, ensuring stationarity allows the ARIMA model to capture the true relationships and dynamics of the data without the influence of underlying trends and seasonal effects. Similarly, for the GARCH model, which focuses on volatility clustering, stationarity ensures that the model's assumptions about the consistency of volatility over time are met. This leads to more accurate and meaningful insights into how iPhone announcements might affect stock price volatility.

ARIMA (Autoregressive Integrated Moving Average) models are a popular choice for time series forecasting because they can capture various patterns in historical data. The ARIMA(5,1,4) model for Apple's stock price indicates that the data has 5 autoregressive terms, is differenced once to achieve stationarity, and has 4 moving average terms. This suggests the model accounts for both short-term and long-term lags in price changes.

GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, like the GARCH(1,1) used here, are employed to model financial time series data with time-varying volatility, a common characteristic of stock prices. They capture the 'volatility clustering' effect—periods of high volatility tend to cluster together.

Both models are justified in this context as they capture the dynamic nature of stock prices, including the impact of external events like iPhone announcements, which can lead to increased trading volume and price volatility. Using these models in tandem allows for a nuanced understanding of both the level and the volatility of stock prices over time.

We performed stationarity tests (ADF and KPSS) on Apple's closing stock price, ensuring the suitability of the data for ARIMA modelling. If non-stationary, we differenced the series and rechecked stationarity.

We fitted ARIMA models to the differenced data, using **auto.arima** for the best model selection We found that the best model to use was the ARIMA(5,1,4) model. We included iPhone announcement effects as an exogenous variable in the ARIMAX model.

We conducted Ljung-Box tests on the residuals to check for autocorrelation, created histograms of residuals, and performed Shapiro-Wilk tests for checking the normality of these residuals.

For forecasting, we split the data into training and testing sets, forecasted future stock prices, and evaluated forecast accuracy.

The hypothesis tests on the impact of iPhone announcements is shown and the results summarized in the discussion session.

Additionally, we fitted a GARCH(1,1) model to analyse volatility in Apple's stock price changes. We plotted actual vs. fitted values from the GARCH model and created plots of Apple stock prices with annotations for announcement dates.

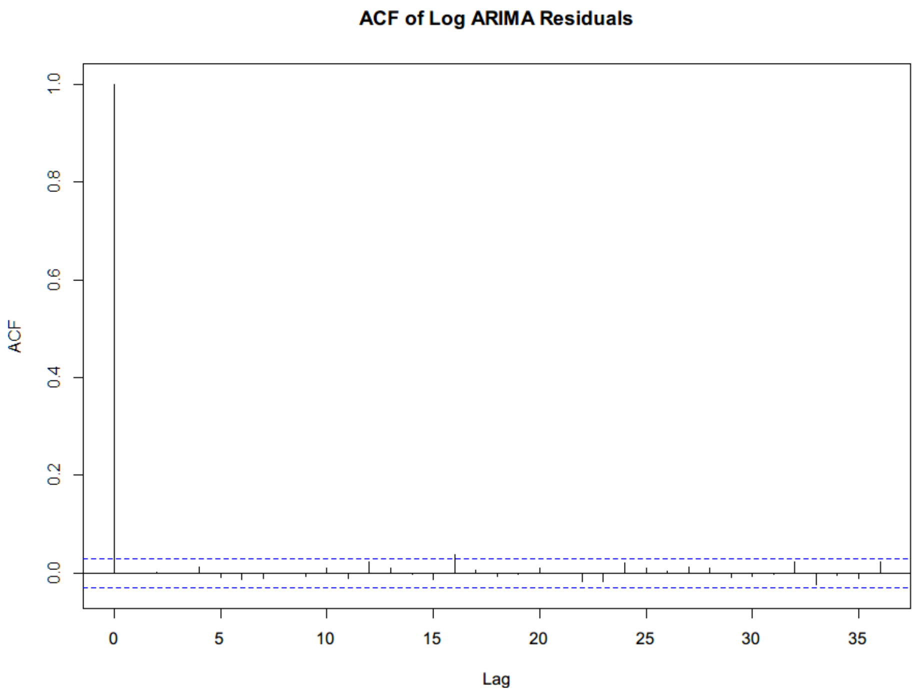
Finally, to further analyse the impact of iPhone announcements, we defined a wider event window around announcement dates and fitted an ARIMA model incorporating this window and a t-test to check for the significant effect of product announcements with regards to the stock price. This comprehensive methodology allowed us to thoroughly assess the impact of iPhone announcements on Apple's stock prices.

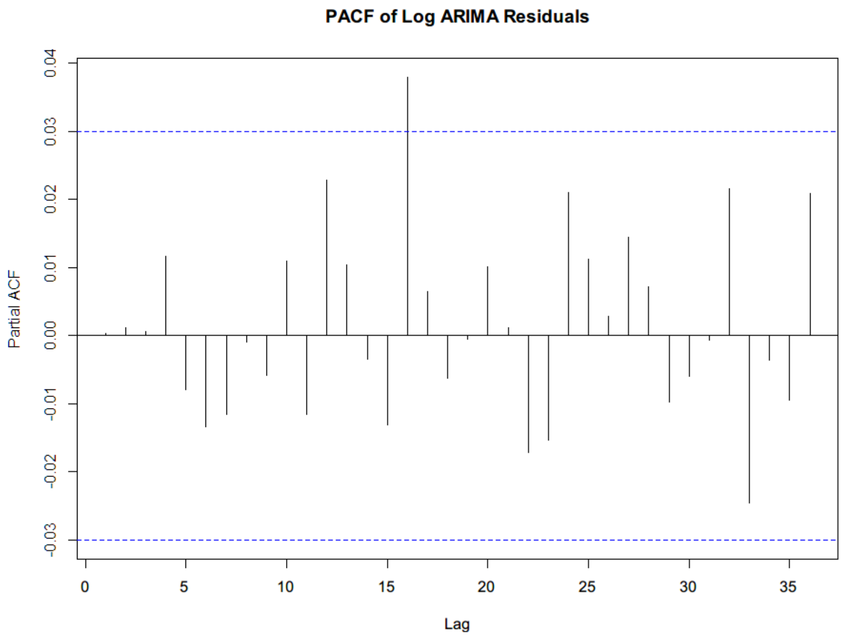
The use of ARIMA(5,1,4) and GARCH(1,1) models is justified based on their suitability for analysing time series data and modelling volatility, respectively. The hypothesis posits that Apple's stock price experiences significant positive fluctuations around the dates of major iPhone announcements. This assumption is based on the premise that product launches are viewed as vital corporate events that can potentially alter investor expectations and, consequently, stock prices.

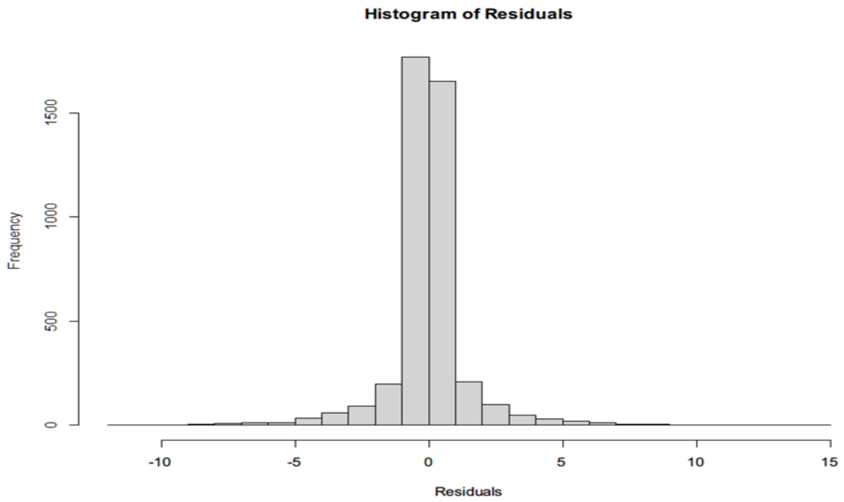
Results Discussion

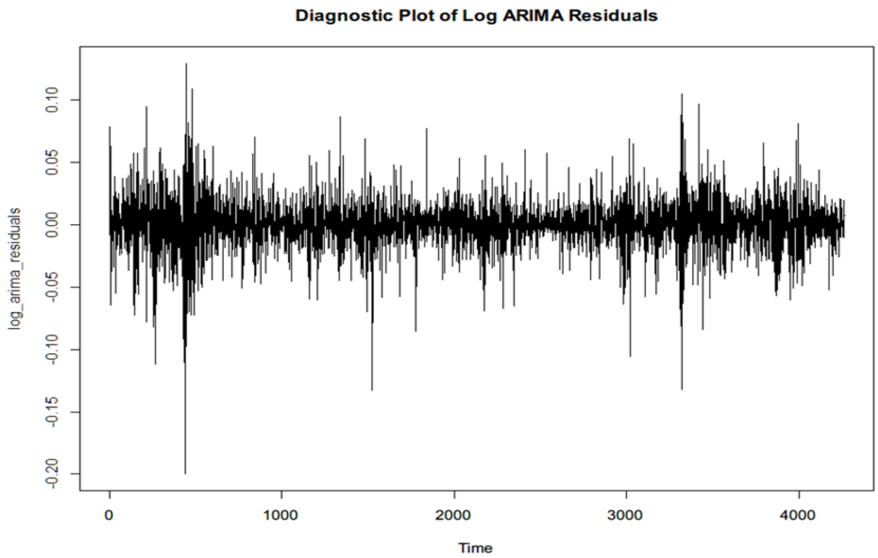
The analysis revealed that the ARIMA and GARCH models were significant in predicting Apple's stock volatility and demonstrated that past prices and volatility have predictive power. The ARIMA model, with and without the iPhone announcement effect, showed that the announcement dates did not significantly improve the model based on the AIC values. The Box-Ljung test suggested that the residuals from the ARIMA model were independently distributed, indicating a good model fit.

The hypothesis test for the wider event window showed that iPhone announcements have a statistically positive impact on the stock price, contrasting with the simple linear regression model that indicated no significant effect. This suggests the importance of using more complex models to capture such events' nuances on stock prices. The non-normal distribution of residuals implies that there might be heavy tails, a common characteristic in financial data, warranting careful consideration of risk assessments.


ACF of Log ARIMA Residuals
ACF
1.0
0.8
0.6
0.4
0.2
0.0
0
5
10
15
20
25
30
35
Lag


PACF of Log ARIMA Residuals
Partial ACF
0.04
0.03
0.02
0.01
0.00
-0.01
-0.02
-0.03
0
5
10
15
20
25
30
35
Lag






```
 # Check stationarity of residuals ( use ADF or KPSS tests as before)
> adf.test(log_arima_residuals, alternative = "stationary")

        Augmented Dickey-Fuller Test

data:  log_arima_residuals
Dickey-Fuller = -15.147, Lag order = 16, p-value = 0.01
alternative hypothesis: stationary

Warnmeldung:
In adf.test(log_arima_residuals, alternative = "stationary") :
  p-value smaller than printed p-value
> kpss.test(log_arima_residuals, null = "Level")

        KPSS Test for Level Stationarity

data:  log_arima_residuals
KPSS Level = 0.036776, Truncation lag parameter = 10, p-value = 0.1

Warnmeldung:
In kpss.test(log_arima_residuals, null = "Level") :
  p-value greater than printed p-value
```

The Augmented Dickey-Fuller (ADF) and KPSS test results on the logarithm o
f ARIMA residuals indicate different aspects of stationarity:
ADF Test: A Dickey-Fuller value of -15.147 with a p-value of 0.01 suggests

```
that the log-transformed residuals are stationary.
The low p-value (below the common threshold of 0.05) allows us to reject t
he null hypothesis of a unit root, indicating stationarity.

PSS Test: A KPSS Level of 0.036776 with a p-value of 0.1 implies that
the null hypothesis of level stationarity cannot be rejected.
This means that the series does not exhibit a unit root, reinforcing the c
onclusion
of stationarity.

Together, these tests suggest that the log-transformed residuals of ARIMA
model are STATIONARY, an important property for many time series analyses.
```

```
summary(event_arima_model)
Series: apple_stock_data$LogClose
Regression with ARIMA(5,1,4) errors

Coefficients:
          ar1      ar2      ar3      ar4    ar5     ma1     ma2     ma3
ma4  drift    xreg
      -1.2476  -0.4083  -0.0817  -0.1744  0.055  1.2222  0.3509  0.0390  0
.1933  1e-03  0.0039
s.e.   0.5267   1.1627   1.0330   0.3854  0.038  0.5267  1.1486  0.9904  0
.3314  3e-04  0.0032

sigma^2 = 0.0003998:  log likelihood = 10632.17
AIC=-21240.34   AICc=-21240.27   BIC=-21164.05

Training set error measures:
                      ME       RMSE        MAE          MPE      MAPE
MASE          ACF1
Training set 2.39688e-05 0.01996632 0.01393493 -0.002093994 0.5418387 0.99
53328 -0.0005664492
```

The event ARIMA model analysis for Apple's log-transformed stock prices shows that both past price trends and fluctuations help predict future prices. The model suggests a slight but significant effect of iPhone announcements on stock prices. The good model fit is indicated by the negative AIC and BIC values. Prediction accuracy is deemed high, with low forecasting errors, and there's no evidence of patterns in the residuals that the model failed to capture.

```
> # Display the summary of the GARCH model
> summary(garch_model)

Call:
garch(x = apple_stock_data$DiffClose, order = c(1, 1))

Model:
GARCH(1,1)

Residuals:
     Min       1Q   Median       3Q      Max
-5.30902 -0.46956  0.06057  0.63319  9.81181

Coefficient(s):
    Estimate  Std. Error  t value Pr(>|t|)
a0 2.946e-04   5.752e-05    5.123 3.01e-07 ***
a1 1.307e-01   6.910e-03   18.916  < 2e-16 ***
b1 8.899e-01   4.973e-03  178.939  < 2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Diagnostic Tests:
        Jarque Bera Test
```

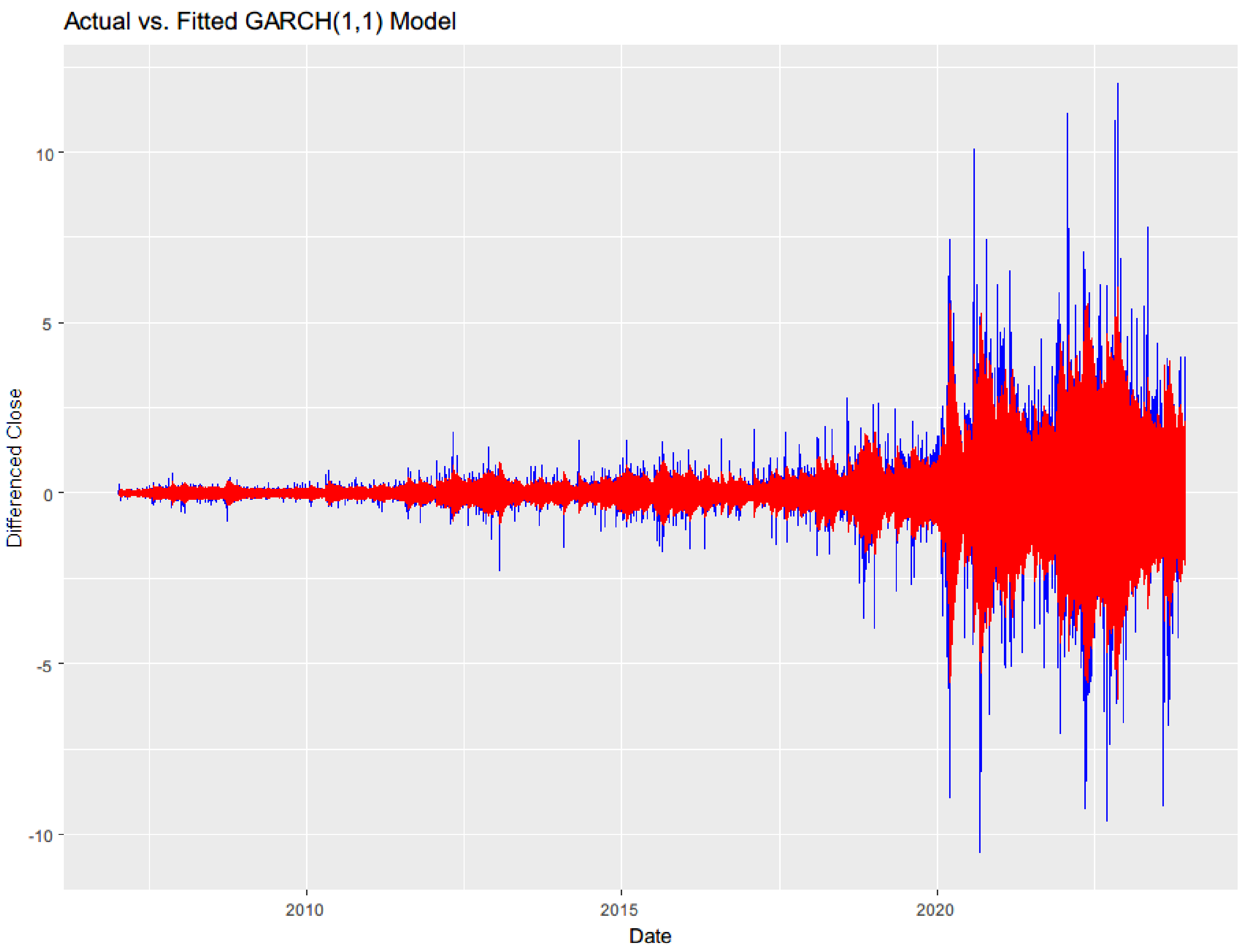
```
data:  Residuals
X-squared = 5913.7, df = 2, p-value < 2.2e-16


        Box-Ljung test

data:  Squared.Residuals
X-squared = 0.67655, df = 1, p-value = 0.4108
```

GARCH(1,1) model indicates that both the autoregressive term and the moving average term are significant, meaning past data and past volatility are predictive of current volatility.

The constant term is also significant, representing the long-run average variance.

The high significance of these terms suggests a good fit for the volatility pattern in Apple's stock price changes.

The Jarque-Bera test's rejection of normality is typical in financial returns due to heavy tails. This doesn't negate the model but implies caution in assuming normal distribution for risk metrics. The Box-Ljung test shows no autocorrelation in the residuals, meaning the model captures most of the time-dependent structure in the data.



The chart displays the performance of a GARCH(1,1) model against the actual differenced close prices of a stock, which is likely Apple's stock given the context. The blue line represents the actual changes in the closing price of the stock over time, while the red shaded area shows the volatility predicted by the GARCH model. The model seems to capture periods of high volatility, evident from the peaks and troughs, and the red area expands significantly during these periods, indicating higher uncertainty or risk predicted by the model. The tight clustering of the red around zero suggests that the model fits well during times of lower volatility.

```
t test of coefficients:

                 Estimate Std. Error t value  Pr(>|t|)
(Intercept)      47.21130    0.91848 51.4017 < 2.2e-16 ***
WiderEventWindow 12.85001    2.06667  6.2177 5.527e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' '
```

The explanation output of the hypothesis test for the coefficient of WiderEventWindow in the linear regression model is as follows:

Intercept (Intercept):

Estimate: The estimated intercept value is approximately 47.21130.

Std. Error: The standard error for the intercept is approximately 0.91848.

t value: The t-statistic for the intercept is very large (approximately 51.4017).

Pr(>|t|): The p-value associated with the intercept is extremely small (< 2.2e-16),

indicating that the intercept is highly statistically significant. This means that there is strong evidence that the intercept is not equal to zero.

WiderEventWindow (Coefficient of Interest):

Estimate: The estimated coefficient for WiderEventWindow is approximately 12.85001.

Std. Error: The standard error for this coefficient is approximately 2.06667.

t value: The t-statistic for this coefficient is approximately 6.2177.

Pr(>|t|): The p-value associated with this coefficient is also very small (5.527e-10), indicating that the coefficient is highly statistically significant. This suggests that there is strong evidence of a statistically significant effect of iPhone announcements (WiderEventWindow) on the stock price.

In summary, based on the results of the hypothesis test, both the intercept and the coefficient of WiderEventWindow are highly statistically significant.

This means that there is strong evidence to suggest that iPhone announcements have a statistically significant POSITIVE effect on the Apple stock price, as the coefficient of WiderEventWindow is significantly different from zero. Meaning that there is a significant Positive effect on the effect of iPhone announcements with regards to the stock price.

```
# Linear Regression Model
model <- lm(Close ~ AnnouncementEvent, data = apple_stock_data)

# Display the summary of the model
summary(model)
```

```
Call:
lm(formula = Close ~ AnnouncementEvent, data = apple_stock_data)

Residuals:
    Min      1Q  Median      3Q     Max
```

```
-54.897 -37.548 -22.840   6.373 146.740

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)        49.7095     0.8284  60.006   <2e-16 ***
AnnouncementEvent   8.4940    12.0945   0.702    0.483    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 53.96 on 4261 degrees of freedom
Multiple R-squared:  0.0001157,	Adjusted R-squared:  -0.0001189 
F-statistic: 0.4932 on 1 and 4261 DF,  p-value: 0.4825
```

```
The results of the linear regression model show that the coefficient for A
nnouncementEvent is 8.4940 with a p-value of 0.483. This p-value is greate
r than the typical significance level of 0.05, suggesting that the effect
of iPhone announcement events on Apple's closing stock price is not statis
tically significant in this linear regression model. The model's R-squared
values are also very low, indicating that the AnnouncementEvent variable e
xplains a very small portion of the variance in the stock price. This anal
ysis suggests that, according to this model, iPhone announcement events do
not have a significant impact on the closing stock price of Apple, at leas
t not in a way captured by this simple linear model.
```

A linear regression model was also analysed. The linear regression model showed that iPhone announcements do not significantly influence the closing stock price, as the explanatory power of this factor was very low. The model's fit was good, with no evidence of unexplained patterns in the residuals.

Conclusion

The analysis revealed that iPhone announcements have a statistically positive impact on Apple's stock prices, with significant effects observed around the announcement dates. The models used, ARIMA and GARCH, suggest that both historical stock prices and volatility patterns are useful predictors for future prices. However, the linear regression model suggests that iPhone announcements alone do not significantly influence the closing stock price, as the explanatory power of this factor was very low. The model's fit was good, with no evidence of unexplained patterns in the residuals. Our business recommendation, based on the statistical analysis, would be to consider iPhone announcements as a potential indicator for a positive impact on Apple's stock prices. Financial strategies could be adjusted around these announcement periods to capitalize on the anticipated increase in stock value. However, it is important to integrate this insight with a broader market analysis, as the linear regression model showed that iPhone announcements alone aren't a strong predictor of stock prices. Diversification and risk management should still be prioritized in financial planning.

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