Time Series Forecasting and Analysis of Nvidia Stock Prices Using SARIMA and GARCH Models

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Abstract

Stock price movements are inherently unpredictable, influenced by trends, volatility shifts, and external market conditions. This project applies time series modeling to analyze and forecast the daily stock price movements of Nvidia (NVDA), a leading semiconductor company. Given the volatility of tech stocks, developing an accurate forecasting model provides valuable insights for investors, analysts, and risk managers. To achieve this, we implement a combination of Seasonal Autoregressive Integrated Moving Average (SARIMA) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. SARIMA captures short-term price patterns and seasonal trends, while GARCH models volatility clustering to assess market risk. The models are evaluated based on statistical measures such as the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and diagnostic residual tests to determine the best-fitting model. Our findings indicate that SARIMA effectively models short-term price movements, whereas GARCH provides a robust framework for understanding volatility fluctuations, a key factor in financial risk assessment. The integration of these models allows for a more comprehensive analysis of stock price behavior, accounting for both trend-following tendencies and unpredictable volatility spikes. By applying these techniques to Nvidia's stock, this study highlights the strengths and limitations of statistical time series models in financial forecasting and risk management.

1. Introduction

Stock forecasting is a crucial tool in financial markets, helping investors and analysts make informed decisions on market trends, investment strategies, and risk management. Accurate predictions can provide insights into price movements and aid in portfolio optimization. This project applies time series analysis to forecast the closing stock prices of Nvidia (NVDA), a global leader in semiconductor technology and artificial intelligence (AI) hardware (Britannica, 2025). Nvidia plays a pivotal role in the tech industry, as one of the world's leading chip producers, it has positioned itself as a major supplier of AI hardware and software. The company gained further prominence in 2022 when OpenAI's ChatGPT utilized a supercomputer powered by 10,000 Nvidia GPUs (Britannica, 2025). Given Nvidia's rapid growth and the volatility of tech stocks, analyzing its stock price behavior offers valuable insights into broader market trends.

For me, one of the reasons why I chose to focus on Nvidia was because in my own experience as an Nvidia shareholder, I am personally interested in understanding its potential future performance. Beyond that, Nvidia is one of the biggest names in AI and tech, making it an interesting stock to analyze. The company's stock has been all over the place in recent years, influenced by things like AI breakthroughs, gaming demand, and chip shortages. Since tech stocks are known for their volatility, I wanted to see if time series modeling could help make sense of Nvidia's price movements and whether it's a good investment for the long run.

Previous research has shown that time series models like SARIMA and GARCH are effective in forecasting stock prices and identifying market trends. Studies indicate that combining these models improves predictive accuracy, making them useful for investment decisions. Jie Gao from the Institute of Economics at Shanghai University found that an ARIMA-GARCH model provided the best fit for capturing stock market fluctuations and volatility, reinforcing the value of these approaches in financial forecasting (Gao, 2022).

This project explores various time series models, including SARIMA and GARCH, to determine the most effective approach for forecasting Nvidia stock prices. Each model provides unique insights into stock behavior: SARIMA is effective for short- to medium-term predictions, capturing trends and seasonal patterns; it revealed a steady increase in NVDA stock over time. GARCH models volatility clustering, offering a better understanding of Nvidia's market risk.

The results highlight the importance of selecting the right model based on forecasting needs, as Nvidia's stock exhibits both trend-following behavior and significant price fluctuations. This study contributes to the broader field of financial time series analysis and stock price forecasting, providing practical insights for investors, traders, and analysts seeking data-driven strategies in the tech sector.

2. Data

The dataset used for this time series project consists of daily stock prices for Nvidia Corporation (NVDA) from January 2, 2018, to September 30, 2024. However, for this analysis, I chose to focus on the most recent three years, from January 3, 2022, to September 30, 2024, to ensure relevance while maintaining a sufficient number of observations for time series modeling. The dataset, obtained from Kaggle, was originally sourced from Yahoo Finance by Muhammad Dawood and cross-checked with Google Finance and NASDAQ for accuracy. It contains 689 observations and seven columns: Date, Open, High, Low, Close, Adjusted Close, and Volume, with all price values reported in USD. Since stock markets do not operate on weekends and holidays, the dataset follows a 252-trading-day-per-year structure.

I selected this dataset because Nvidia is the only individual stock I own outside of an ETF, making it personally relevant, and because of its prominent role in artificial intelligence, semiconductors, and high-performance computing. Nvidia has experienced substantial growth in recent years, driven by increased demand for AI-driven technologies, gaming hardware, and cloud computing. Its stock has shown significant volatility, making it an ideal candidate for time series forecasting and risk analysis. Understanding these price fluctuations can provide insights into how external factors such as earnings reports, macroeconomic conditions, and advancements in AI influence stock price movements. Predicting stock prices is a common challenge for investors, especially in volatile markets like the technology sector. This project aims to evaluate the effectiveness of SARIMA for short-term stock price forecasting and GARCH for modeling Nvidia's volatility. By applying these models, this study seeks to assess their ability to capture Nvidia's stock price behavior and provide valuable insights for traders, investors, and analysts navigating the complexities of the financial markets.

Date	Open	High	Low	Close ⓘ	Adj Close ⓘ	Volume
Sep 30, 2024	118.31	121.50	118.15	121.44	121.42	226,553,700
Sep 27, 2024	123.97	124.03	119.26	121.40	121.38	271,009,200
Sep 26, 2024	126.80	127.67	121.80	124.04	124.02	302,582,900
Sep 25, 2024	122.02	124.94	121.61	123.51	123.49	284,692,900
Sep 24, 2024	116.52	121.80	115.38	120.87	120.85	354,966,800
Sep 23, 2024	116.55	116.99	114.86	116.26	116.24	206,228,500
Sep 20, 2024	117.06	118.62	115.39	116.00	115.98	382,462,400
Sep 19, 2024	117.35	119.66	117.25	117.87	117.85	293,506,400
Sep 18, 2024	115.89	117.70	113.22	113.37	113.35	310,318,900
Sep 17, 2024	118.17	118.80	114.83	115.59	115.57	231,925,900
Sep 16, 2024	116.79	118.18	114.36	116.78	116.76	248,772,300

Figure 1. NVIDIA Corporation (NVDA) Stock Price Dataset (Refer to Appendix A.1)
Link: https://finance.yahoo.com/quote/NVDA/history/

3. Methodology

This project explores two time series models, SARIMA and GARCH, to analyze and forecast Nvidia's stock prices. Each model captures a different aspect of stock price behavior: SARIMA is used for modeling short-term trends and seasonal patterns, while GARCH focuses on volatility clustering. Before applying these models, I cleaned and prepared the dataset by correcting a labeling error, selecting the closing price as the main variable, checking for missing values, and applying log transformations and differencing to ensure stationarity. To confirm stationarity, I used the Augmented Dickey-Fuller (ADF) test and examined the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots to guide model selection.

The SARIMA (Seasonal Autoregressive Integrated Moving Average) model extends ARIMA by incorporating seasonal components, making it useful for stock prices that follow repeating patterns. Defined by (p, d, q) × (P, D, Q), it includes autoregressive, differencing, and moving average terms along with their seasonal counterparts. Nvidia's stock movements may reflect market cycles, earnings reports, and macroeconomic conditions, which can introduce seasonal patterns. SARIMA was selected as a core forecasting tool based on Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values. ACF and PACF plots were used to determine appropriate model orders, and multiple SARIMA configurations were tested to identify the best-performing model. Forecasting accuracy was evaluated through out-of-sample predictions, and residual diagnostics were conducted to ensure model validity (GeeksforGeeks, 2024).

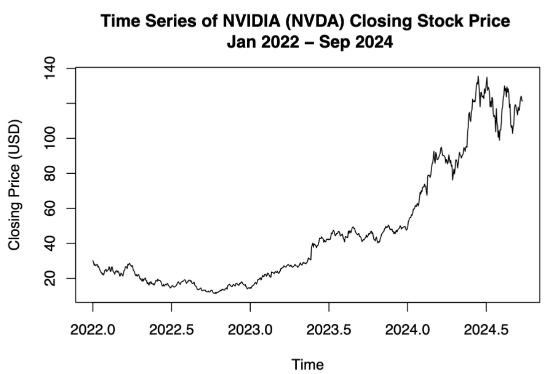
The GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model was used to analyze volatility clustering in Nvidia's stock. Stock price fluctuations often exhibit periods of high and low volatility, meaning past volatility influences future volatility. This characteristic makes traditional time series models like ARIMA or SARIMA insufficient for capturing risk dynamics, necessitating the use of GARCH. To model this, I first fitted an ARMA model to Nvidia's stock returns and examined residuals for heteroskedasticity. The GARCH model parameters (p, q) were selected using AIC and BIC, and the model was validated through ARCH and Ljung-Box tests. Once the final GARCH model was selected, I used it to estimate conditional volatility and assess Nvidia's market risk exposure. Understanding volatility patterns helps investors and analysts anticipate periods of increased market instability (Engle, 2019).

This study builds on research showing that combining ARIMA-based models with GARCH improves stock price forecasting. Prior studies, such as Gao (2022), found that the ARIMA-GARCH model effectively captures both trends and volatility, making it a reliable approach. By implementing SARIMA and GARCH, this project evaluates how well these models forecast Nvidia's stock price behavior and volatility, contributing to financial time series analysis.

4. Results (4.1 SARIMA)

After loading and preprocessing the data the time series plot of Nvidia's stock prices shows a clear upward trend, especially from early 2023 onward, with no obvious seasonality. Volatility increases significantly in 2024, with sharp dips and rises in stock price, suggesting that a GARCH model may help capture these variations. The presence of a trend indicates that differencing is needed to achieve stationarity before applying SARIMA and ARFIMA models for forecasting.

The ACF plot showed strong autocorrelation, indicating non-stationarity, while the PACF dropped off after lag 1, suggesting the presence of an autoregressive (AR) component. To confirm this, an Augmented Dickey-Fuller (ADF) test was performed, yielding a p-value of 0.6194. Since the test's null hypothesis assumes non-stationarity, and a p-value below 0.05 is required to reject it in favor of stationarity, the result confirmed that the data was non-stationary. To address this, a logarithmic transformation and first differencing were applied to stabilize the variance and remove trends before fitting the SARIMA model.



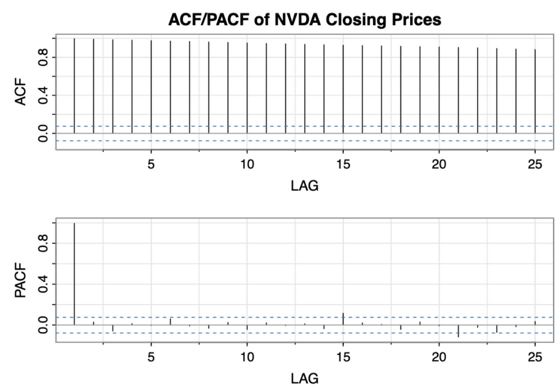


Figure 2. Time Series of Nvidia (NVDA) Closing Stock Price (Refer to Appendix A.1)

Figure 3. ACF and PACF of Nvidia Closing Stock Price (Refer to Appendix A.2)

After applying a logarithmic transformation and first differencing, the time series plot now appears stationary (Figure 4), with no evident trends or seasonality. The ACF and PACF plots (Figure 5) of the transformed data show no significant lags, suggesting stationarity. The Augmented Dickey-Fuller (ADF) test was run and further confirms this, as the p-value is significantly below the threshold of 0.05 at 0.01, indicating that the time series no longer has a unit root.

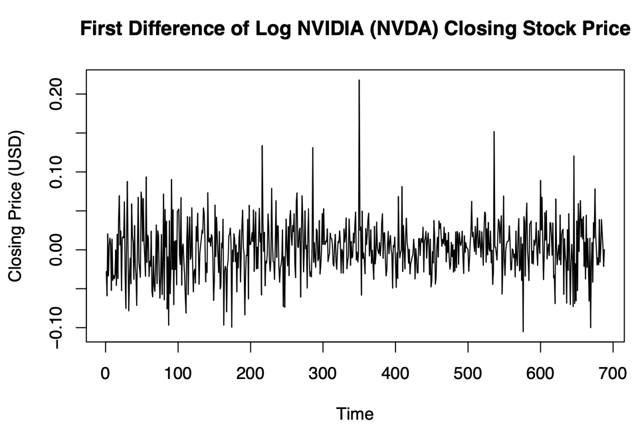


Figure 4. First Difference of Log Closing Stock Price Plot (Refer to Appendix A.3)

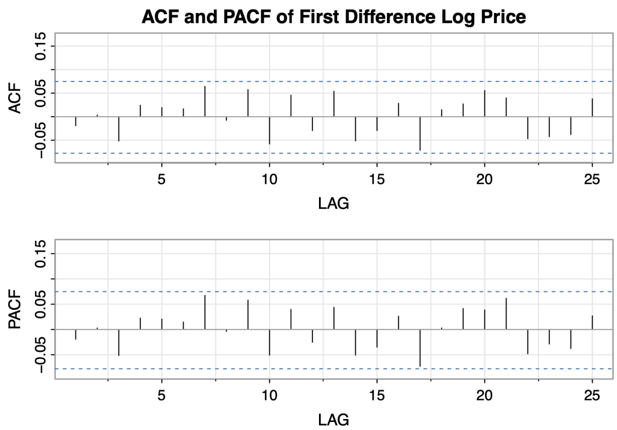


Figure 5. ACF and PACF of First Difference Log Closing Stock Prices (Refer to Appendix A.3)

The ACF and PACF plots of the first-differenced log-transformed stock prices (Figure 5) show no significant seasonal lags, confirming that a SARIMA model is unnecessary. The ACF plot has minor spikes, suggesting little autocorrelation beyond lag 1, while the PACF drops off after lag 1, indicating a first-order AR component. Several ARIMA models were tested using first-order differencing (d=1) to ensure stationarity, with ARIMA(1,1,1) selected based on the lowest AIC (See Appendix A.4).

Residual diagnostics, shown in Figure 6, confirm that the standardized residuals exhibit no major patterns, and the Q-Q plot suggests near-normality. However, the Ljung-Box test indicates some minor autocorrelation, with p-values hovering near 0.05. Despite this, ARIMA(1,1,1) effectively captures short-term dependencies in Nvidia's stock price and remains a reasonable choice for forecasting.

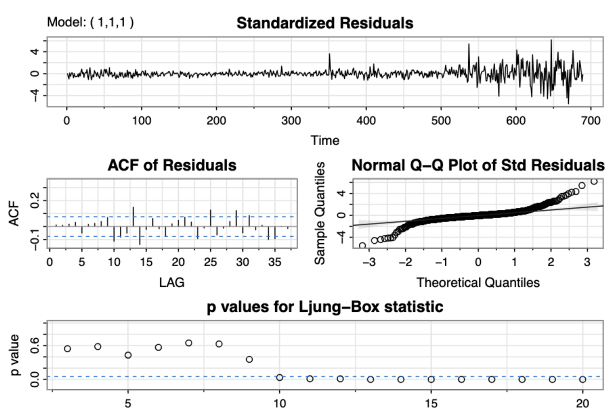


Figure 6. Standardized Residual Plots (Refer to Appendix A.4)

The ARIMA(1,1,1) model was used to generate a one-year forecast, as shown in Figure 7. The forecasted data seems reasonable and suggests a gradual increase in Nvidia's stock price, with confidence intervals widening over time to reflect growing uncertainty. While the model provides a reasonable estimate, the Ljung-Box test results indicate some lingering autocorrelation, suggesting that ARIMA alone may not fully capture the complexities of the stock price movements.

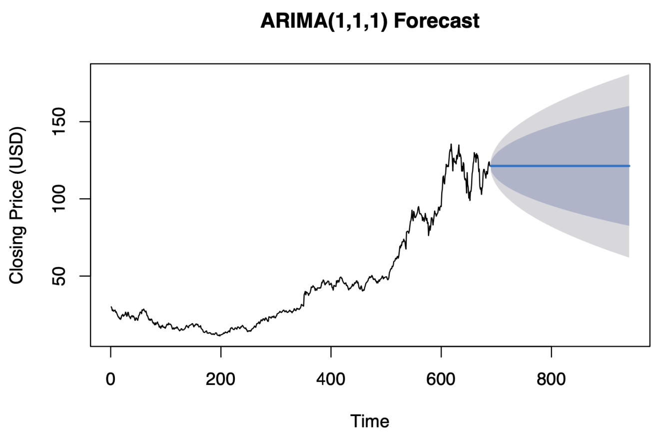


Figure 7. Forecast of ARIMA (1,1,1) Model using Nvidia Corporation Closing Stock Price (Refer to Appendix A.5)

4. Results (4.2 GARCH Model)

To be able to fit a GARCH model onto this Nvidia dataset, we need to first take a look at the ACF and PACF plots of the stock prices as well as the squared residuals of the ARMA model. Figure 5 above shows the ACF and PACF of the stock prices with the transformed data. For this GARCH model the ARMA (1,1) model is used (See Appendix A.5). To determine the parameters of the GARCH models we have to take a look at Figure 8 to see any significant lags.

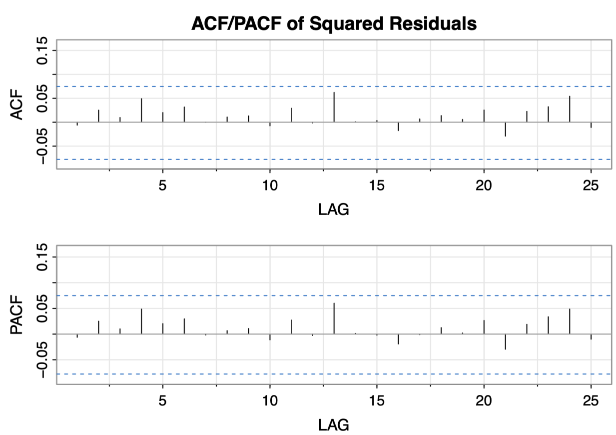


Figure 8. ACF and PACF of Squared Residuals (Refer to Appendix A.6)

Figure 8 indicates weak autocorrelations in squared residuals, suggesting that a low-order GARCH model may be sufficient. Based on this, three different GARCH models were tested: GARCH(1,1) + ARMA(1,1), GARCH(1,0) + ARMA(1,1), and GARCH(1,0) + ARMA(0,0). Each model was fitted using the fGarch package with a standardized t-distribution for the conditional errors. To determine the best-fitting model, we conducted standardized residual tests, including the Ljung-Box test, which assesses whether residuals exhibit serial correlation. The results showed that for the ARMA(1,1) + GARCH(1,1) model, all p-values from the Ljung-Box test were greater than 0.05, indicating that the residuals are consistent with being independently and identically distributed (i.i.d.). This suggests that the model effectively captures the conditional heteroskedasticity in the data.

Moreover, the ARMA(1,1) + GARCH(1,1) model had the lowest AIC value, reinforcing its suitability for modeling Nvidia's stock returns. To further validate the model's performance, several diagnostic plots were generated, including the conditional standard deviation plot, standardized residuals ACF, and Q-Q plot of standardized residuals (See Appendix A.8). These visualizations provide additional confirmation that the selected model appropriately captures the volatility structure and produces residuals that align with the assumptions of the GARCH framework.

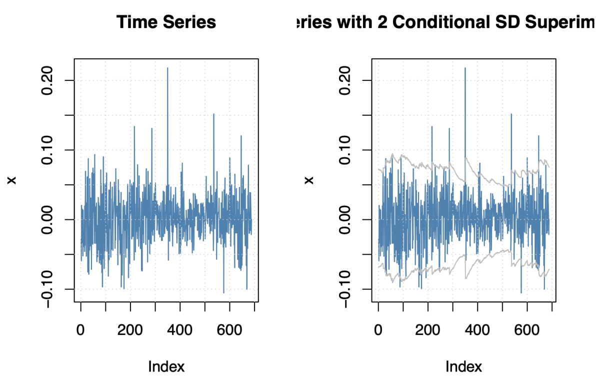


Figure 9. Time Series and 2 Conditional SD Superimposed Plot (Refer to Appendix A.8)

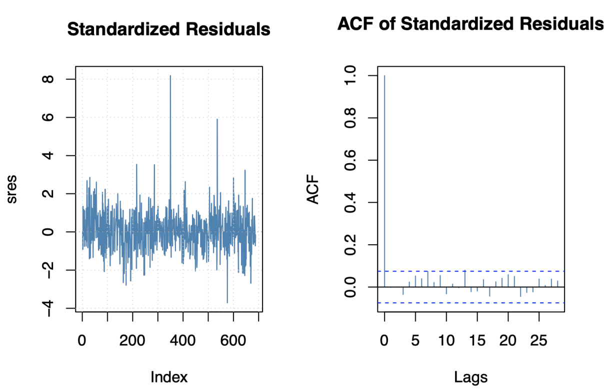


Figure 10. Standardized Residuals and ACF of Standardized Residuals Plot (Refer to Appendix A.8)

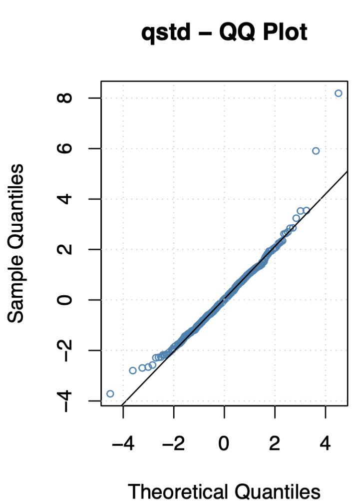


Figure 11. QQ Plot of Standardized Residuals (Refer to Appendix A.8)

The diagnostic plots confirm that the ARMA(1,1) + GARCH(1,1) model is a good fit. Figure 9 shows the time series with two conditional standard deviation estimates, which align with volatility spikes, indicating the model captures market fluctuations. Figure 10 presents the standardized residuals and their ACF, confirming stationarity and minimal autocorrelation. Figure 11's Q-Q plot demonstrates that the residuals follow a near-normal distribution. These results validate the ARMA(1,1) + GARCH(1,1) model for Nvidia's stock return volatility. With well-behaved residuals and strong volatility modeling, this model is selected for forecasting, as shown in Figure 12.

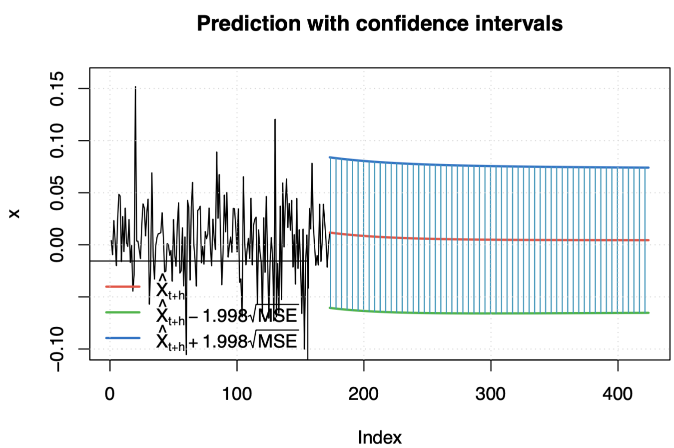


Figure 12. Forecast of GARCH (1,1) Model (Refer to Appendix A.9)

This GARCH model effectively captures the volatility of Nvidia's stock prices, which is essential for accurate forecasting and risk assessment. Previous models struggled to account for the fluctuations in Nvidia's returns, but this approach successfully models the conditional heteroskedasticity present in the data.

Based on our findings, Nvidia's stock exhibits significant volatility, with a wide potential range of future price movements. As shown in the forecast, the confidence intervals expand over time, reflecting the uncertainty in future returns. Investors and analysts should exercise caution when evaluating Nvidia's financial stability, as volatility may impact investment decisions. By integrating this volatility model into ARIMA or ARFIMA frameworks, future stock price predictions can be improved, as the GARCH component ensures that time-varying volatility is properly accounted for.

5. Conclusion

Given the innate complexity of financial time series data, no single model can fully capture all characteristics or provide a perfect forecast. Instead, leveraging a combination of models allows for a more comprehensive analysis by addressing different aspects of the data. In this project, SARIMA was employed to capture the autocorrelation structure in Nvidia's stock prices, making it particularly useful for short- to medium-term forecasting. However, Nvidia's stock, like many in the technology sector, is subject to heightened volatility due to market sentiment, earnings reports, and industry developments. To account for these fluctuations, a GARCH model was integrated to model time-varying risk.

While SARIMA effectively identified underlying trends and seasonal patterns, its assumption of constant variance over time does not fully capture the rapid shifts in volatility characteristic of financial markets. By incorporating a GARCH model, this analysis provided a more dynamic understanding of Nvidia's stock price behavior, offering a better representation of risk and uncertainty. The ARMA(1,1) + GARCH(1,1) model emerged as the best fit based on AIC values and diagnostic tests, highlighting the importance of modeling volatility when analyzing financial time series data.

For short-term investors, SARIMA/ARIMA models are particularly valuable, as they can capture autocorrelations and generate insights into immediate price movements. An investor interested in Nvidia's stock may use an ARIMA model to identify short-term trends and make informed trading decisions. In this project, the ARIMA model suggested that Nvidia's stock prices exhibited predictable short-term fluctuations, which could benefit those focusing on short-term gains.

However, for analysts seeking long-term forecasts, ARIMA models may be insufficient, as they assume constant variance and do not account for the inherent volatility of financial markets. Given Nvidia's position as a high-growth tech company, these fluctuations can be significant. By incorporating a GARCH model, this analysis effectively captured periods of increased uncertainty, providing analysts with a better tool to assess risk and develop more informed financial strategies.

By combining SARIMA/ARIMA for trend forecasting and GARCH for volatility modeling, this project provided a more well-rounded perspective on Nvidia's stock price behavior. Investors and analysts can leverage these insights for strategic financial decisions, whether for short-term trading or long-term portfolio management. This approach underscores the importance of integrating multiple time series models to capture both trend dynamics and volatility, particularly for stocks in fast-evolving industries like Nvidia.

Future research could expand on this analysis by incorporating ARMAX models, which account for external variables such as interest rates, market sentiment, or economic indicators, potentially improving predictive accuracy. ARFIMA models could be explored to better capture long-range dependencies, making them useful for forecasting Nvidia's stock behavior over extended periods. Additionally, deep learning approaches like LSTMs could model complex, nonlinear relationships within the data, offering a more adaptive and robust framework for predicting stock price movements. By integrating these advanced techniques, future studies could enhance forecasting precision and provide deeper insights into Nvidia's market dynamics.

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Appendix

A.1

```{r}
library(astsa)
library(tseries)
library(timeSeries)
library(forecast)
library(lubridate)
library(dplyr)
library(ggplot2)
library(fGarch)
library(rugarch)
library(pander)

NVDA <- read.csv("~/Downloads/NVIDIA_STOCK.csv") %>%
  rename(Date = Price)

NVDA <- NVDA %>%
  mutate(Date = as.Date(Date, format="%Y-%m-%d")) %>%
  filter(Date >= as.Date("2022-01-03") & Date <= as.Date("2024-09-30")) %>%
  arrange(Date)

ClosingPrice <- NVDA$Close

NVDAts <- ts(ClosingPrice, start = c(2022, 1), frequency = 252)

plot(NVDAts,
     main="Time Series of NVIDIA (NVDA) Closing Stock Price \n Jan 2022 - Sep 2024",
     ylab="Closing Price (USD)",
     xlab="Time")

NVDAts <- as.numeric(NVDAts)
```

A.2

```{r}
adf.test(NVDAts)
acf2(NVDAts, 25, main = "ACF/PACF of NVDA Closing Prices")
```

```
```{Output}
Augmented Dickey-Fuller Test

data:  NVDAts
Dickey-Fuller = -1.9029, Lag order = 8, p-value = 0.6194
alternative hypothesis: stationary
```
A.3
```{r}
NVDALogDiff = diff(log(NVDAts))
adf.test(NVDALogDiff)
plot(NVDALogDiff,
    main="First Difference of Log NVIDIA (NVDA) Closing Stock Price",
    ylab="Closing Price (USD)",
    xlab="Time",
    type="l")
acf2(NVDALogDiff, 25, main = "ACF and PACF of First Difference Log Price")
```
```{Output}
Augmented Dickey-Fuller Test

data:  NVDALogDiff
Dickey-Fuller = -7.8345, Lag order = 8, p-value = 0.01
alternative hypothesis: stationary
```
A.4
```{r}
Sarima1 <- sarima(NVDAts, p=1, d=1, q=1)
summary(arima(NVDAts, order=c(1,1,1)))

Sarima2 <- sarima(NVDAts, p=0, d=1, q=1)
summary(arima(NVDAts, order=c(0,1,1)))

Sarima3 <- sarima(NVDAts, p=1, d=1, q=2)
summary(arima(NVDAts, order=c(1,1,2)))

Sarima4 <- sarima(NVDAts, p=2, d=1, q=1)
summary(arima(NVDAts, order=c(2,1,1)))
```
```

```{Output}
Call:
arima(x = NVDAts, order = c(1, 1, 1))

Coefficients:
         ar1     ma1
      -0.7273  0.6312
s.e.   0.0990  0.1096

sigma^2 estimated as 4.081:  log likelihood = -1460,  aic = 2926

Call:
arima(x = NVDAts, order = c(0, 1, 1))

Coefficients:
         ma1
      -0.0821
s.e.   0.0351

sigma^2 estimated as 4.128:  log likelihood = -1463.99,  aic = 2931.98

Call:
arima(x = NVDAts, order = c(1, 1, 2))

Coefficients:
         ar1     ma1     ma2
      -0.7001  0.6187  0.0266
s.e.   0.1192  0.1246  0.0402

sigma^2 estimated as 4.078:  log likelihood = -1459.79,  aic = 2927.57

Call:
arima(x = NVDAts, order = c(2, 1, 1))

Coefficients:
         ar1     ar2     ma1
      -0.6579  0.0304  0.5763
s.e.   0.1603  0.0462  0.1562

sigma^2 estimated as 4.078:  log likelihood = -1459.79,  aic = 2927.58
```

~~~
```
A.5
```{r}
NVDASarima <- arima(NVDAts, order = c(1,1,1))
FcastNVDA <- forecast(NVDASarima, h=252)
plot(FcastNVDA, main="ARIMA(1,1,1) Forecast",
    ylab="Closing Price (USD)", xlab="Time")
```
A.6
```{r}
NVDAarma <- arima(NVDALogDiff, order = c(1,1,1))
residuals <- residuals(NVDAarma)
squaredresiduals = residuals^2
acf2(squaredresiduals, 25, main = "ACF/PACF of Squared Residuals")
```
A.7
```{r}
library(fGarch)

NVDAGarch1 <- garchFit(~ arma(1,1) + garch(1,1), data=NVDALogDiff, cond.dist="std")

NVDAGarch2 <- garchFit(~ arma(1,1) + garch(1,0), data=NVDALogDiff, cond.dist="std")

NVDAGarch3 <- garchFit(~ arma(0,0) + garch(1,0), data=NVDALogDiff, cond.dist="std")

summary(NVDAGarch1)
summary(NVDAGarch2)
summary(NVDAGarch3)
```
A.8
```{r}
par(mfrow=c(1,2))
plot(NVDAGarch1, which = c(1,3,9,10))
plot(NVDAGarch1, which =13)
```
A.9
```{r}
ForecastGARCH <- predict(NVDAGarch1, n.ahead = 252, plot=TRUE)
summary(ForecastGARCH)
```
~~~