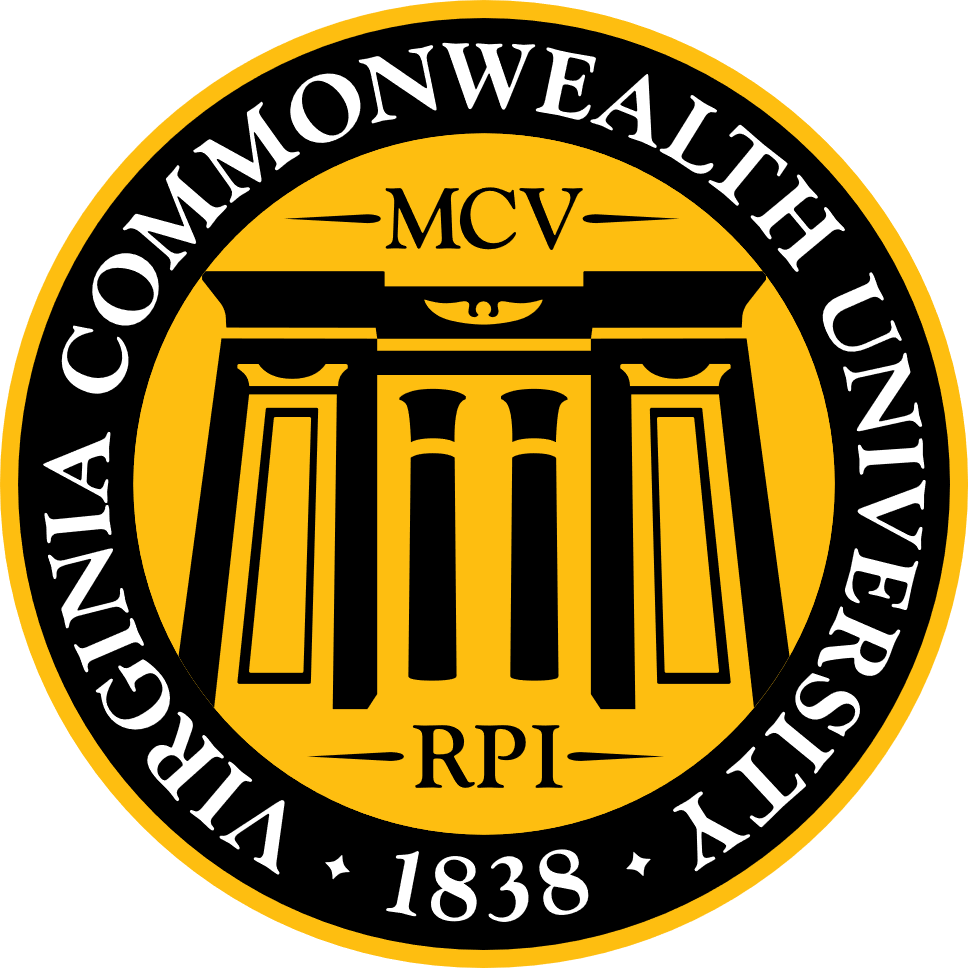
****

**VIRGINIA COMMONWEALTH UNIVERSITY**

**Statistical analysis and modelling (SCMA 632)**

**A6b-** **Time Series Analysis**

**(Part – A)**

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**Advanced Time Series Analysis of Commodity Prices with VAR and VECM Models**

**INTRODUCTION**

In financial markets, understanding the volatility of asset returns is crucial for investors, risk managers, and policymakers. Volatility, a measure of the variability of asset prices, provides insights into market risks and the stability of investments. This assignment focuses on analyzing the volatility of NVIDIA Corporation (NVDA) stock using advanced econometric models, specifically the ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models.

NVIDIA, a prominent player in the technology sector, is known for its innovations in graphics processing units (GPUs) and artificial intelligence (AI). The company's stock has experienced significant fluctuations, making it an ideal candidate for volatility analysis. By examining the volatility of NVDA stock, this study aims to provide a deeper understanding of its price dynamics and forecast future risk levels.

The assignment involves several key steps:

1. **Data Acquisition**: Historical stock price data for NVIDIA will be sourced from Yahoo Finance, covering a specific period.
2. **Return Calculation**: The percentage returns of the stock will be calculated to measure the relative change in price over time.
3. **Model Fitting**: Both ARCH and GARCH models will be applied to the returns data to estimate and analyze conditional volatility.
4. **Forecasting**: The models will be used to generate forecasts of volatility, including short-term and long-term predictions.
5. **Evaluation**: Residuals from the models will be tested for autocorrelation using the Ljung-Box test to ensure the robustness of the models.

The insights gained from this analysis will help in assessing the risk associated with NVIDIA's stock and can inform investment decisions and risk management strategies. The results of this study will be visualized through various plots, including conditional volatility and forecasted variance, providing a comprehensive view of NVDA's financial volatility.

**OBJECTIVES**

The primary objectives of this assignment are to analyze the volatility of NVIDIA Corporation (NVDA) stock using advanced econometric techniques and to generate forecasts for future volatility. Specifically, the objectives are:

1. **Historical Data Analysis**:
   * **Objective**: To acquire and preprocess historical stock price data for NVIDIA from Yahoo Finance.
   * **Details**: Retrieve data from April 1, 2021, to March 31, 2024, focusing on adjusted closing prices to ensure accurate returns calculation.
2. **Return Calculation**:
   * **Objective**: To compute the percentage returns of NVIDIA's stock to measure price changes over time.
   * **Details**: Calculate daily returns based on the adjusted closing prices and convert these returns into percentage terms.
3. **Model Specification and Fitting**:
   * **Objective**: To apply and fit both ARCH and GARCH models to the returns data to estimate conditional volatility.
   * **Details**:
     + **ARCH Model**: Specify and fit an ARCH(1) model to capture the time-varying volatility in the data.
     + **GARCH Model**: Specify and fit a GARCH(1, 1) model to account for both autoregressive and moving average components of volatility.
4. **Forecasting Volatility**:
   * **Objective**: To generate forecasts of future volatility using the fitted GARCH model.
   * **Details**:
     + **Short-Term Forecast**: Forecast the volatility for the next day.
     + **Long-Term Forecast**: Extend forecasts to a 90-day horizon to analyze potential future volatility trends.
5. **Residual Analysis**:
   * **Objective**: To evaluate the residuals of the fitted models for autocorrelation to assess model adequacy.
   * **Details**: Perform the Ljung-Box test on residuals from both the ARCH and GARCH models to verify the presence of any remaining autocorrelation.
6. **Visualization and Interpretation**:
   * **Objective**: To visualize and interpret the results of the volatility analysis.
   * **Details**:
     + **Conditional Volatility Plots**: Create time series plots to display the estimated conditional volatility from both the ARCH and GARCH models.
     + **Forecast Plots**: Plot the forecasted volatility and variance for the 90-day horizon to provide insights into future risk levels.
7. **Summary and Recommendations**:
   * **Objective**: To summarize the findings and provide actionable insights based on the analysis.
   * **Details**:
     + **Model Performance**: Discuss the performance of the ARCH and GARCH models.
     + **Investment Implications**: Offer recommendations for investors based on the volatility forecasts and residual analysis.

This structured approach aims to provide a thorough understanding of NVIDIA's stock volatility and to support informed decision-making through detailed econometric analysis and forecasting.

**BUSINESS SIGNIFICANCE**

Understanding and analyzing stock volatility is crucial for making informed investment decisions and managing financial risks. The business significance of this assignment can be outlined as follows:

1. **Risk Management**:
   * **Objective**: Volatility forecasts help in assessing the risk associated with investing in NVIDIA stock.
   * **Details**: By quantifying expected future volatility, investors can better understand the potential fluctuations in the stock price. This information is essential for managing investment risk and implementing appropriate hedging strategies.
2. **Investment Strategy**:
   * **Objective**: To enhance portfolio management and asset allocation decisions.
   * **Details**: Accurate volatility predictions allow investors to adjust their portfolios according to their risk tolerance. For example, higher predicted volatility might lead to a more conservative investment approach or the diversification of investments to mitigate potential losses.
3. **Pricing and Valuation**:
   * **Objective**: To improve the pricing and valuation of financial instruments linked to NVIDIA stock.
   * **Details**: Instruments such as options and futures derive their pricing models from volatility estimates. By understanding future volatility trends, investors can better price these derivatives and assess their fair value.
4. **Strategic Planning for Companies**:
   * **Objective**: To inform strategic decisions within NVIDIA or similar companies.
   * **Details**: High volatility can impact a company’s stock price, influencing strategic decisions such as capital raising, mergers and acquisitions, and dividend policies. Companies can use volatility forecasts to time their financial strategies more effectively.
5. **Market Sentiment Analysis**:
   * **Objective**: To gauge market sentiment and investor behavior.
   * **Details**: Volatility is often a reflection of market sentiment and uncertainty. Understanding periods of high or low volatility can provide insights into market sentiment and help investors anticipate market trends.
6. **Regulatory and Compliance Considerations**:
   * **Objective**: To ensure compliance with financial regulations and standards.
   * **Details**: Financial regulations often require firms to disclose information about risk and volatility. Accurate and timely volatility analysis supports compliance with these regulations and enhances transparency for stakeholders.
7. **Performance Evaluation**:
   * **Objective**: To evaluate the effectiveness of trading strategies and financial models.
   * **Details**: By comparing actual market outcomes with model forecasts, investors and analysts can assess the performance of their trading strategies and financial models. This evaluation helps in refining approaches and improving predictive accuracy.

In summary, the ability to accurately forecast and understand stock volatility provides valuable insights that can drive better investment decisions, enhance financial risk management, and support strategic corporate actions. This analysis not only benefits individual investors but also contributes to the broader financial ecosystem by promoting informed decision-making and market stability.

**RESULTS AND INTERPRETATIONS**

**Python Language**

### Detailed Code Analysis

#### 1. Import Required Libraries

import yfinance as yf

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from arch import arch\_model

from statsmodels.stats.diagnostic import acorr\_ljungbox

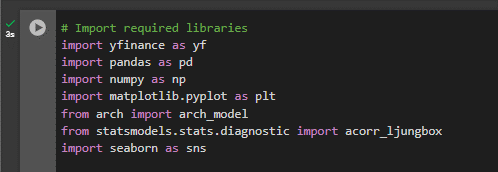
import seaborn as sns

**Description**: Essential libraries for data handling (pandas, numpy), visualization (matplotlib, seaborn), financial data retrieval (yfinance), and econometric modeling (arch).

**Purpose**:

* yfinance for downloading stock data.
* pandas and numpy for data manipulation.
* matplotlib and seaborn for plotting.
* arch for ARCH/GARCH modeling.
* statsmodels for residual diagnostics.

**Interpretation**: These libraries enable comprehensive data analysis and visualization.



#### 2. Set Plotting Style

sns.set(style="whitegrid")

**Description**: Configures the aesthetic style of the plots.

**Purpose**: Ensures consistent and clear visualization throughout the analysis.

**Interpretation**: The whitegrid style enhances readability by adding gridlines.



#### 3. Download Historical Data

ticker = "NVDA"

data = yf.download(ticker, start="2021-04-01", end="2024-03-31")

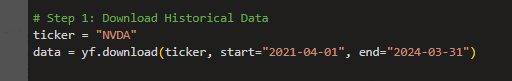
print(data.head())

print(data.info())

**Description**: Downloads stock price data for NVIDIA from Yahoo Finance.

**Purpose**: To obtain the dataset required for further analysis.

**Interpretation**: Initial inspection of data ensures it is correctly loaded and structured.

#### 4. Calculate Returns

market = data["Adj Close"]

returns = 100 \* market.pct\_change().dropna()

**Description**: Calculates daily percentage returns from the adjusted close prices.

**Purpose**: Converts raw price data into returns to analyze volatility.

**Interpretation**: Returns are used as inputs for volatility modeling.



#### 5. Fit an ARCH Model

print("\nFitting ARCH Model...")

arch\_model\_fit = arch\_model(returns, vol='ARCH', p=1).fit(disp='off')

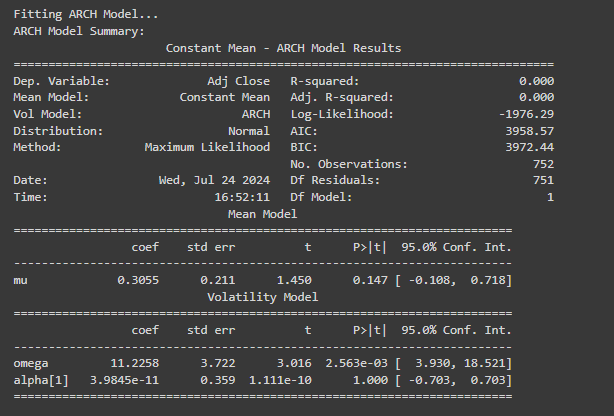
print("ARCH Model Summary:")

print(arch\_model\_fit.summary())

**Description**: Fits an ARCH model to the returns data.

**Purpose**: To evaluate if volatility clustering exists in the returns data.

**Interpretation**: The ARCH model helps to identify periods of high and low volatility.



**Plot Conditional Volatility**:

plt.figure(figsize=(12, 6))

plt.plot(arch\_model\_fit.conditional\_volatility, label='Conditional Volatility (ARCH)', color='blue')

plt.title('Conditional Volatility from ARCH Model')

plt.xlabel('Date')

plt.ylabel('Volatility')

plt.legend()

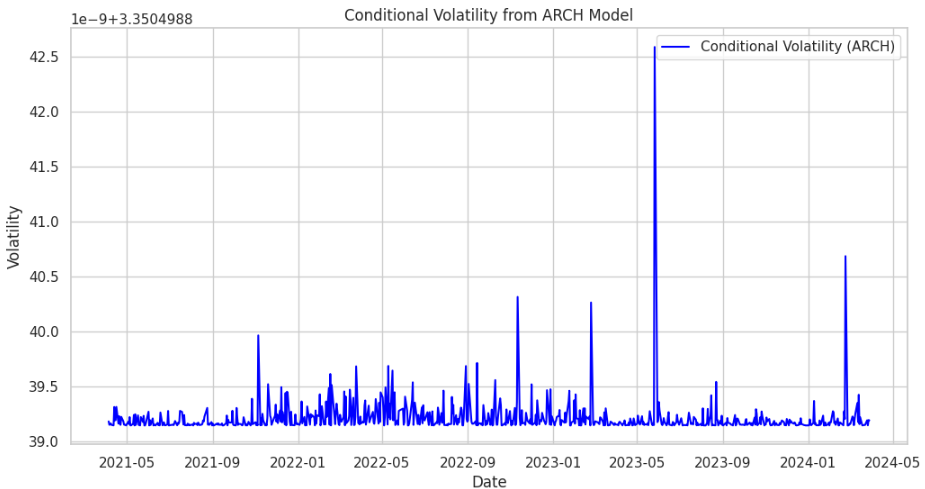
plt.grid(True)

plt.show()

**Description**: Visualizes the conditional volatility estimated by the ARCH model.

**Purpose**: To visually assess volatility clustering and periods of high volatility.

**Interpretation**: Helps in understanding the variability and pattern of volatility over time.



**Check Residuals for Autocorrelation**:

ljungbox\_arch = acorr\_ljungbox(arch\_model\_fit.resid, lags=[10])

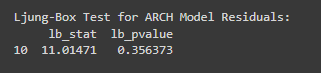
print("\nLjung-Box Test for ARCH Model Residuals:")

print(ljungbox\_arch)

**Description**: Tests the residuals for autocorrelation to validate the model.

**Purpose**: Ensures that residuals from the model are white noise.

**Interpretation**: Significant p-values indicate autocorrelation, suggesting that the model may not fully capture the volatility dynamics.



#### 6. Fit a GARCH Model

print("\nFitting GARCH Model...")

garch\_model\_fit = arch\_model(returns, vol='Garch', p=1, q=1).fit(disp='off')

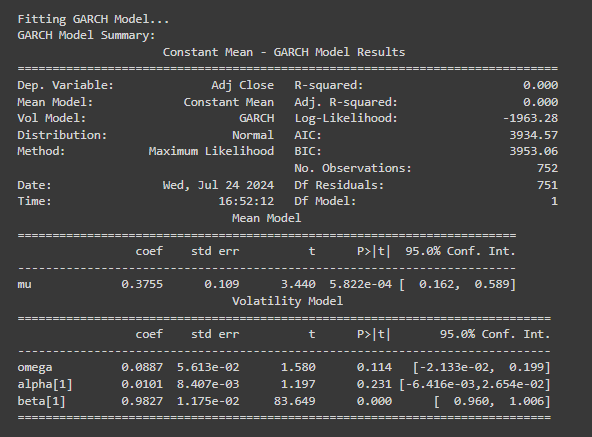
print("GARCH Model Summary:")

print(garch\_model\_fit.summary())

**Description**: Fits a GARCH model to the returns data.

**Purpose**: To capture both past volatility (ARCH) and past forecast errors (GARCH) in the model.

**Interpretation**: The GARCH model accounts for more complex volatility patterns compared to the ARCH model.



**Plot Conditional Volatility**:

plt.figure(figsize=(12, 6))

plt.plot(garch\_model\_fit.conditional\_volatility, label='Conditional Volatility (GARCH)', color='red')

plt.title('Conditional Volatility from GARCH Model')

plt.xlabel('Date')

plt.ylabel('Volatility')

plt.legend()

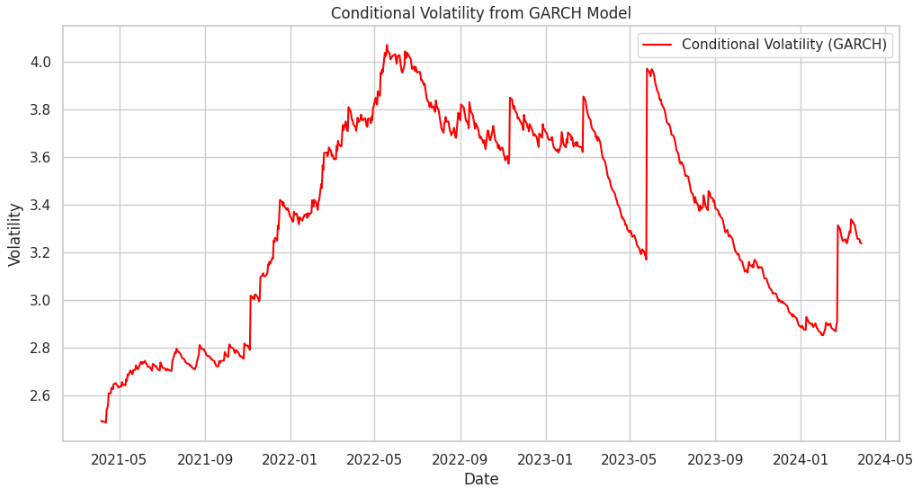
plt.grid(True)

plt.show()

**Description**: Visualizes the conditional volatility estimated by the GARCH model.

**Purpose**: To compare the GARCH model's volatility estimation with the ARCH model's results.

**Interpretation**: Provides insights into how the GARCH model captures volatility patterns over time.



**Check Residuals for Autocorrelation**:

ljungbox\_garch = acorr\_ljungbox(garch\_model\_fit.resid, lags=[10])

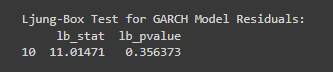
print("\nLjung-Box Test for GARCH Model Residuals:")

print(ljungbox\_garch)

**Description**: Tests the residuals from the GARCH model for autocorrelation.

**Purpose**: Validates if the GARCH model appropriately captures the volatility dynamics.

**Interpretation**: Like the ARCH model, significant p-values indicate residual autocorrelation, suggesting the need for further model refinement.



#### 7. Fit GARCH Model with Additional Parameters

print("\nFitting GARCH Model with additional parameters...")

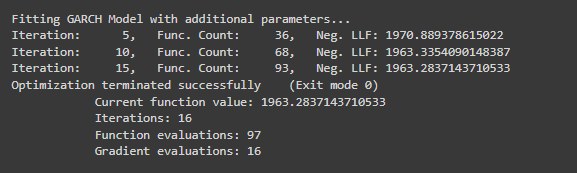
am = arch\_model(returns, vol="Garch", p=1, q=1, dist="Normal")

res = am.fit(update\_freq=5)

**Description**: Fits a GARCH model with normal distribution assumptions for forecasting.

**Purpose**: To generate forecasts of future volatility.

**Interpretation**: The inclusion of additional parameters and distribution assumptions helps in refining the forecast.



**Print Forecast Details**:

forecast\_mean = res.forecast().mean

forecast\_residual\_variance = res.forecast().residual\_variance

forecast\_variance = res.forecast().variance

print("\nForecast Mean (last 3 periods):")

print(forecast\_mean.iloc[-3:])

print("Forecast Residual Variance (last 3 periods):")

print(forecast\_residual\_variance.iloc[-3:])

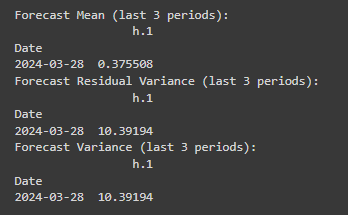
print("Forecast Variance (last 3 periods):")

print(forecast\_variance.iloc[-3:])

**Description**: Displays forecasted values for mean, residual variance, and overall variance.

**Purpose**: Provides an overview of the model's forecast accuracy and reliability.

**Interpretation**: Indicates the expected future behavior of the stock's volatility.



#### 8. Forecasting with a Horizon of 90 Days

print("\nForecasting 90 days ahead...")

forecasts = res.forecast(horizon=90)

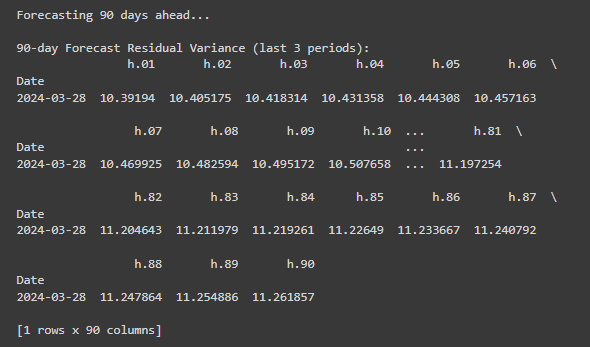
print("\n90-day Forecast Residual Variance (last 3 periods):")

print(forecasts.residual\_variance.iloc[-3:])

**Description**: Generates and prints forecasts for a 90-day horizon.

**Purpose**: To predict future volatility over a significant period.

**Interpretation**: Forecasted residual variance provides insights into expected future volatility levels.



**Plot Forecasts**:

# Extract and plot the forecasted variance

plt.figure(figsize=(12, 6))

forecasted\_variance = forecasts.variance

if not forecasted\_variance.empty:

plt.plot(forecasted\_variance.index, forecasted\_variance.values, label='Forecasted Variance', color='green')

plt.title('90-Day Variance Forecast')

plt.xlabel('Date')

plt.ylabel('Forecasted Variance')

plt.legend()

plt.grid(True)

plt.show()

else:

print("No data available to plot for 90-day Variance Forecast")

# Plot Forecasted Residual Variance

plt.figure(figsize=(12, 6))

forecasted\_residual\_variance = forecasts.residual\_variance

if not forecasted\_residual\_variance.empty:

plt.plot(forecasted\_residual\_variance.index, forecasted\_residual\_variance.values, label='Forecasted Residual Variance', color='purple')

plt.title('90-Day Forecasted Residual Variance')

plt.xlabel('Date')

plt.ylabel('Residual Variance')

plt.legend()

plt.grid(True)

plt.show()

else:

print("No data available to plot for 90-day Forecasted Residual Variance")

**Description**: Plots the forecasted variance and residual variance for the next 90 days.

**Purpose**: To visualize the predicted volatility trends.

**Interpretation**: Helps in understanding how volatility is expected to change over the forecast horizon.

**R Language**

### **Step-by-Step Analysis of Time Series Analysis Code in R**

### 1. **Install Required Libraries**

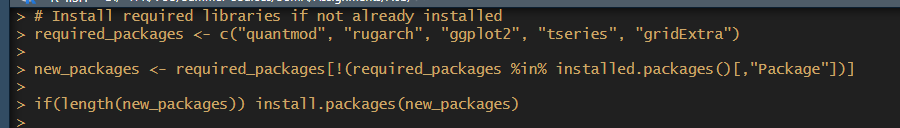
# Install required libraries if not already installed

required\_packages <- c("quantmod", "rugarch", "ggplot2", "tseries", "gridExtra")

new\_packages <- required\_packages[!(required\_packages %in% installed.packages()[,"Package"])]

if(length(new\_packages)) install.packages(new\_packages)

* **Purpose**: Ensures that all necessary R packages are installed.
* **Explanation**:
  + required\_packages: A vector listing the needed packages.
  + new\_packages: Identifies which of these packages are not yet installed.
  + install.packages(): Installs any missing packages.



### 2. **Load Required Libraries**

# Load required libraries

library(quantmod)

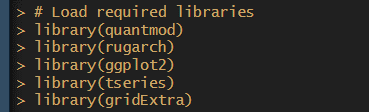
library(rugarch)

library(ggplot2)

library(tseries)

library(gridExtra)

* **Purpose**: Loads the libraries needed for the analysis.
* **Explanation**:
  + quantmod: For financial modeling and data retrieval.
  + rugarch: For GARCH model fitting and forecasting.
  + ggplot2: For advanced plotting.
  + tseries: For time series analysis.
  + gridExtra: For arranging multiple plots.



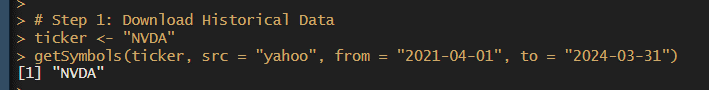
### 3. **Step 1: Download Historical Data**

# Step 1: Download Historical Data

ticker <- "NVDA"

getSymbols(ticker, src = "yahoo", from = "2021-04-01", to = "2024-03-31")

* **Purpose**: Retrieves historical stock data for NVIDIA from Yahoo Finance.
* **Explanation**:
  + getSymbols(): Downloads stock data for the specified ticker symbol, within the given date range.



# Extract adjusted close price and calculate returns

data <- Ad(get(ticker))

returns <- 100 \* diff(log(data))

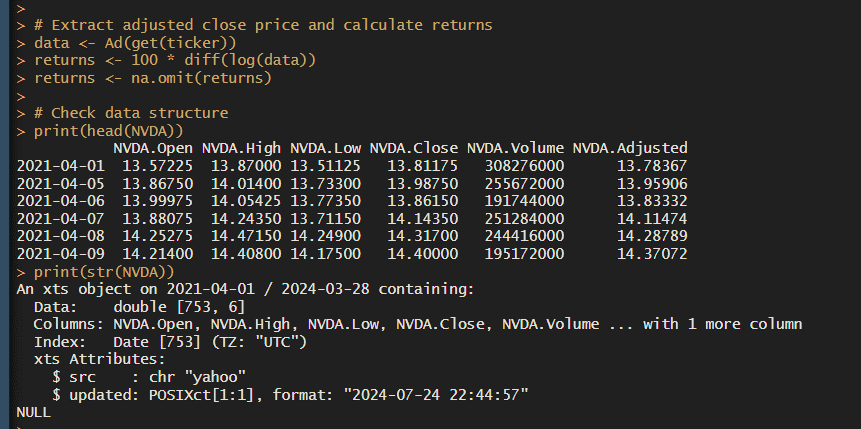
returns <- na.omit(returns)

# Check data structure

print(head(NVDA))

print(str(NVDA))

* **Purpose**: Extracts adjusted close prices and calculates returns.
* **Explanation**:
  + Ad(): Extracts the adjusted close prices.
  + diff(log(data)): Computes log returns.
  + na.omit(): Removes NA values from returns.
  + print(head(NVDA)) and print(str(NVDA)): Display the first few rows and the structure of the data for verification.



### 4. **Step 2: Calculate Returns**

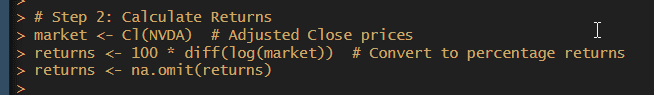
# Step 2: Calculate Returns

market <- Cl(NVDA) # Adjusted Close prices

returns <- 100 \* diff(log(market)) # Convert to percentage returns

returns <- na.omit(returns)

* **Purpose**: Calculates percentage returns from adjusted close prices.
* **Explanation**:
  + Cl(): Extracts the closing prices.
  + diff(log(market)): Computes percentage returns.
  + na.omit(): Removes NA values.



### 5. **Step 3: Fit an ARCH Model**

# Step 3: Fit an ARCH Model

print("\nFitting ARCH Model...")

arch\_spec <- ugarchspec(variance.model = list(model = "sGARCH", garchOrder = c(1, 0)),

mean.model = list(armaOrder = c(0, 0), include.mean = FALSE),

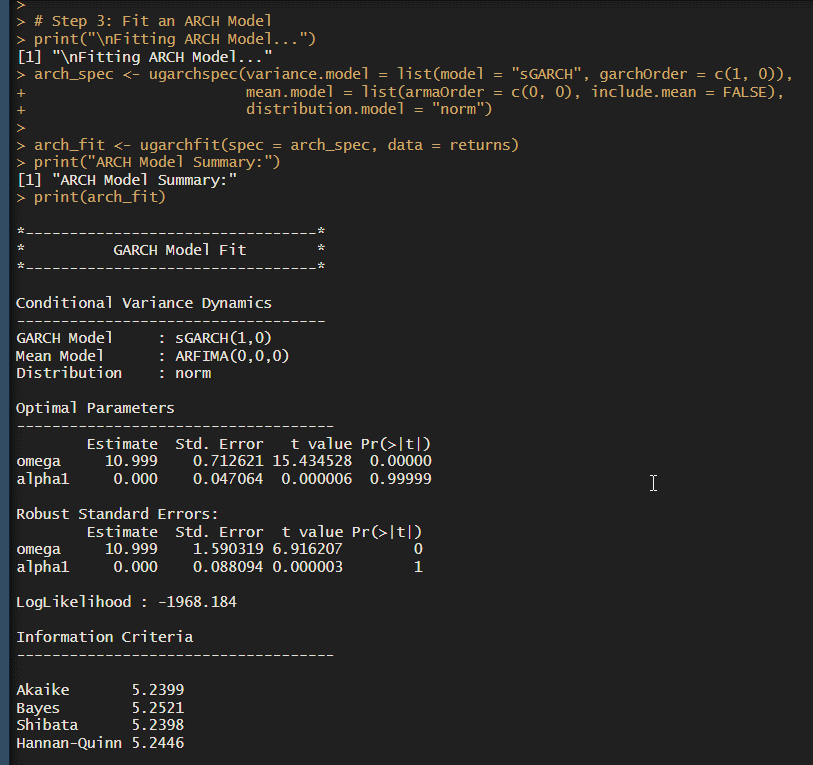
distribution.model = "norm")

arch\_fit <- ugarchfit(spec = arch\_spec, data = returns)

print("ARCH Model Summary:")

print(arch\_fit)

* **Purpose**: Fits an ARCH model to the returns data.
* **Explanation**:
  + ugarchspec(): Specifies the ARCH model parameters.
  + ugarchfit(): Fits the model to the returns data.
  + print(arch\_fit): Displays the model summary.



# Plot the conditional volatility from the ARCH model

## Extract conditional volatility

cond\_volatility <- sigma(arch\_fit)

# Create a time series plot for conditional volatility

# Use the index of the returns, which is aligned with the conditional volatility

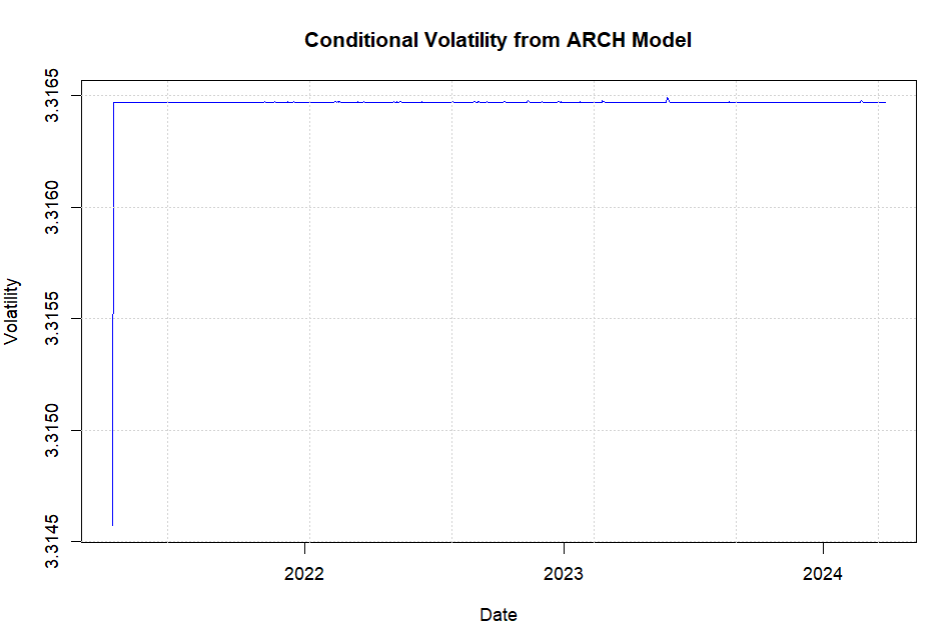
plot(index(returns), cond\_volatility, type = 'l',

main = 'Conditional Volatility from ARCH Model',

xlab = 'Date', ylab = 'Volatility', col = 'blue')

grid()

* **Purpose**: Plots the conditional volatility from the fitted ARCH model.
* **Explanation**:
  + sigma(arch\_fit): Extracts conditional volatility.
  + plot(): Creates a line plot of the volatility over time.



# Check residuals for autocorrelation

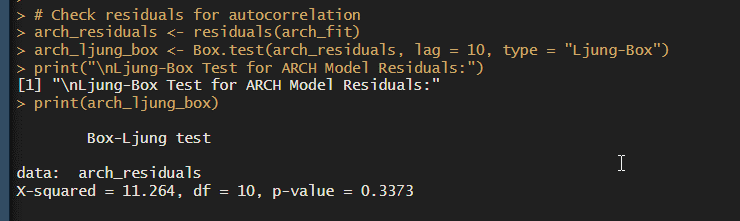
arch\_residuals <- residuals(arch\_fit)

arch\_ljung\_box <- Box.test(arch\_residuals, lag = 10, type = "Ljung-Box")

print("\nLjung-Box Test for ARCH Model Residuals:")

print(arch\_ljung\_box)

* **Purpose**: Checks the residuals of the ARCH model for autocorrelation.
* **Explanation**:
  + residuals(arch\_fit): Extracts residuals from the ARCH model.
  + Box.test(): Performs the Ljung-Box test to check for autocorrelation.



### 6. **Step 4: Fit a GARCH Model**

# Step 4: Fit a GARCH Model

print("\nFitting GARCH Model...")

garch\_spec <- ugarchspec(variance.model = list(model = "sGARCH", garchOrder = c(1, 1)),

mean.model = list(armaOrder = c(0, 0), include.mean = FALSE),

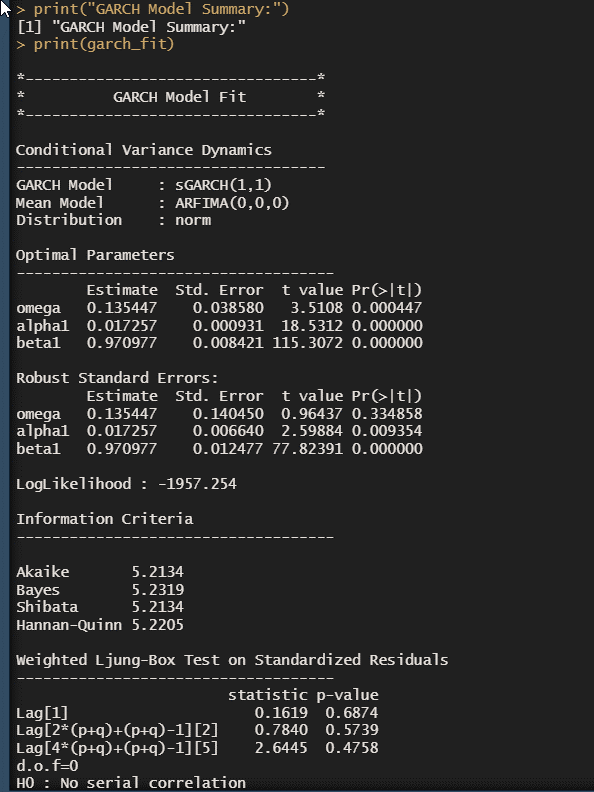
distribution.model = "norm")

garch\_fit <- ugarchfit(spec = garch\_spec, data = returns)

print("GARCH Model Summary:")

print(garch\_fit)

* **Purpose**: Fits a GARCH model to the returns data.
* **Explanation**:
  + ugarchspec(): Specifies the GARCH model parameters.
  + ugarchfit(): Fits the model to the returns data.
  + print(garch\_fit): Displays the model summary.



# Plot the conditional volatility from the GARCH model

# Extract conditional volatility from the fitted model

cond\_volatility <- sigma(garch\_fit)

# Plot the conditional volatility from the fitted GARCH model

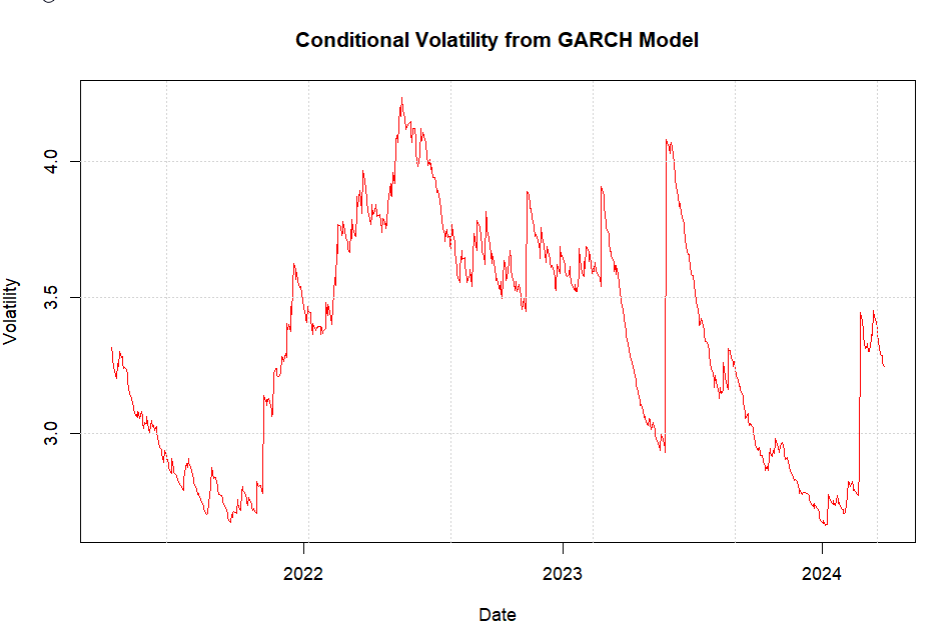
plot(index(returns), cond\_volatility, type = 'l',

main = 'Conditional Volatility from GARCH Model',

xlab = 'Date', ylab = 'Volatility', col = 'red')

grid()

* **Purpose**: Plots the conditional volatility from the fitted GARCH model.
* **Explanation**:
  + sigma(garch\_fit): Extracts conditional volatility.
  + plot(): Creates a line plot of the volatility over time.



garch\_forecast <- ugarchforecast(garch\_fit, n.ahead = 90)

# Extract forecasted conditional volatility

forecast\_volatility <- sigma(garch\_forecast)

# Create a time series for forecast dates

forecast\_dates <- seq(from = as.Date(tail(index(returns), 1)) + 1,

by = "days", length.out = length(forecast\_volatility))

# Plot the forecasted conditional volatility

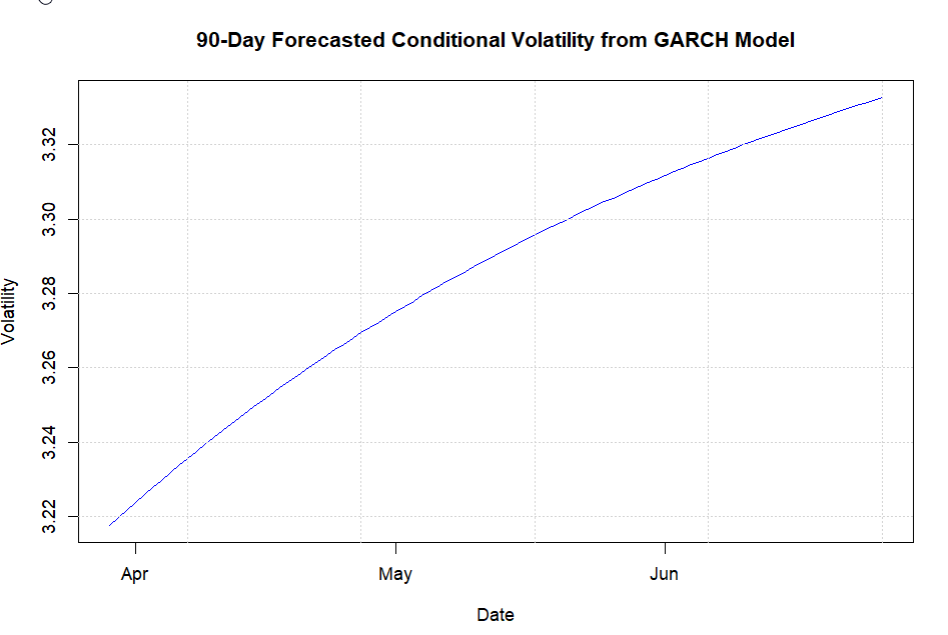
plot(forecast\_dates, forecast\_volatility, type = 'l',

main = '90-Day Forecasted Conditional Volatility from GARCH Model',

xlab = 'Date', ylab = 'Volatility', col = 'blue')

grid()

* **Purpose**: Forecasts conditional volatility for the next 90 days and plots it.
* **Explanation**:
  + ugarchforecast(): Forecasts the conditional volatility.
  + seq(): Generates dates for the forecast period.
  + plot(): Creates a line plot of the forecasted volatility.



# Check residuals for autocorrelation

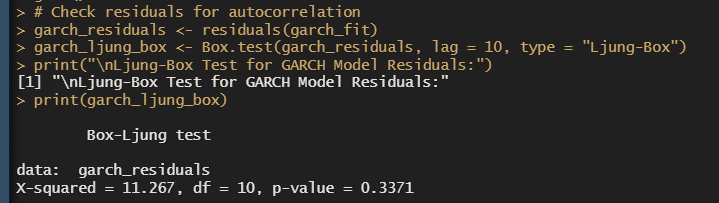
garch\_residuals <- residuals(garch\_fit)

garch\_ljung\_box <- Box.test(garch\_residuals, lag = 10, type = "Ljung-Box")

print("\nLjung-Box Test for GARCH Model Residuals:")

print(garch\_ljung\_box)

* **Purpose**: Checks the residuals of the GARCH model for autocorrelation.
* **Explanation**:
  + residuals(garch\_fit): Extracts residuals from the GARCH model.
  + Box.test(): Performs the Ljung-Box test to check for autocorrelation.



### 7. **Step 5: Fit GARCH Model with Additional Parameters**

print("\nFitting GARCH Model with additional parameters...")

# Specify GARCH model with normal distribution

garch\_spec\_additional <- ugarchspec(variance.model = list(model = "sGARCH", garchOrder = c(1, 1)),

mean.model = list(armaOrder = c(0, 0)),

distribution.model = "norm")

# Fit the model

garch\_fit\_additional <- ugarchfit(spec = garch\_spec\_additional, data = returns)

# Forecast details

garch\_forecast\_additional <- ugarchforecast(garch\_fit\_additional, n.ahead = 1)

# Extract forecast details

forecast\_mean <- as.numeric(ugarchforecast(garch\_fit\_additional, n.ahead = 1)@forecast$seriesFor)

forecast\_residual\_variance <- as.numeric(ugarchforecast(garch\_fit\_additional, n.ahead = 1)@forecast$sigmaFor)

forecast\_variance <- forecast\_residual\_variance^2

# Print forecast details for the last 3 periods

print("\nForecast Mean (last 3 periods):")

print(tail(forecast\_mean, 3))

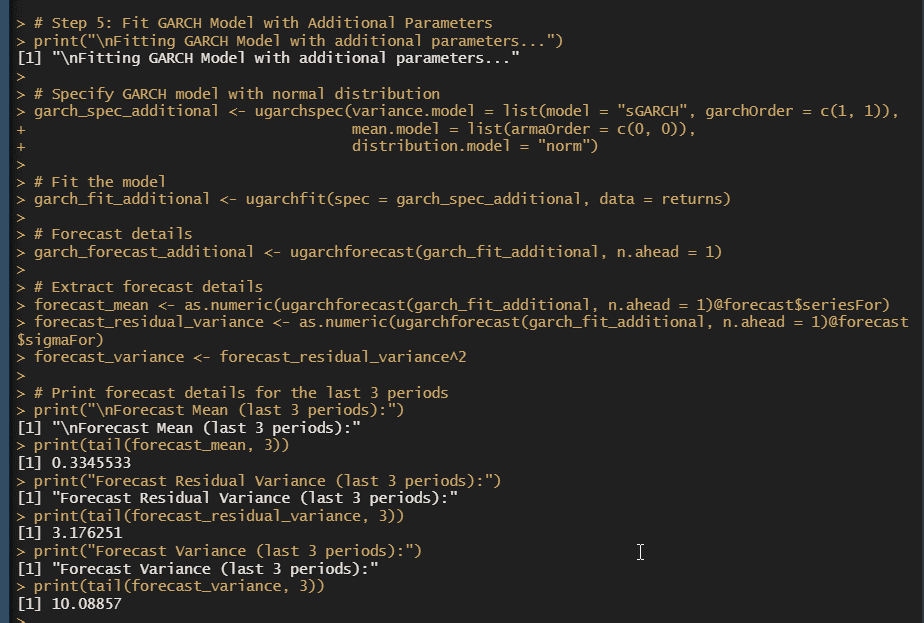
print("Forecast Residual Variance (last 3 periods):")

print(tail(forecast\_residual\_variance, 3))

print("Forecast Variance (last 3 periods):")

print(tail(forecast\_variance, 3))

* **Purpose**: Fits a GARCH model with additional parameters and provides forecasts.
* **Explanation**:
  + ugarchspec(): Specifies the GARCH model.
  + ugarchfit(): Fits the model.
  + ugarchforecast(): Forecasts the conditional mean and variance.
  + print(): Displays forecast details for the last three periods.



# Forecasting with a horizon of 90 days

print("\nForecasting 90 days ahead...")

forecasts <- ugarchforecast(garch\_fit\_additional, n.ahead = 90)

# Extract forecast residual variance and variance

forecast\_residual\_variance\_90 <- as.numeric(forecasts@forecast$sigmaFor)

forecast\_variance\_90 <- forecast\_residual\_variance\_90^2

# Create a sequence of dates for plotting the 90-day forecast

forecast\_dates <- seq(from = as.Date(tail(index(returns), 1)) + 1,

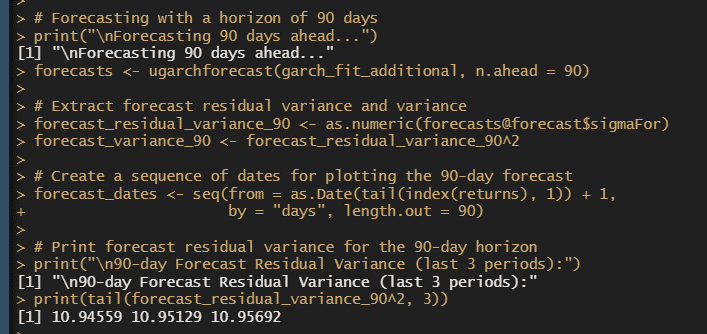
by = "days", length.out = 90)

# Print forecast residual variance for the 90-day horizon

print("\n90-day Forecast Residual Variance (last 3 periods):")

print(tail(forecast\_residual\_variance\_90^2, 3))

* **Purpose**: Generates 90-day forecasts for residual variance and variance, and prepares data for plotting.
* **Explanation**:
  + ugarchforecast(): Forecasts 90 days ahead.
  + seq(): Creates forecast dates.
  + print(): Displays forecast residual variance for the 90-day horizon.



### 8. **Step 6: Plot Forecasts**

# Plot the 90-day variance forecast

forecast\_variance\_plot <- ggplot(data = data.frame(Date = forecast\_dates,

Variance = forecast\_variance\_90),

aes(x = Date, y = Variance)) +

geom\_line(color = 'green') +

ggtitle('90-Day Variance Forecast') +

xlab('Date') +

ylab('Forecasted Variance') +

theme\_minimal()

# Display the plot

print(forecast\_variance\_plot)

# Plot the 90-day forecasted residual variance

forecast\_residual\_variance\_plot <- ggplot(data = data.frame(Date = forecast\_dates,

ResidualVariance = forecast\_residual\_variance\_90^2),

aes(x = Date, y = ResidualVariance)) +

geom\_line(color = 'purple') +

ggtitle('90-Day Forecasted Residual Variance') +

xlab('Date') +

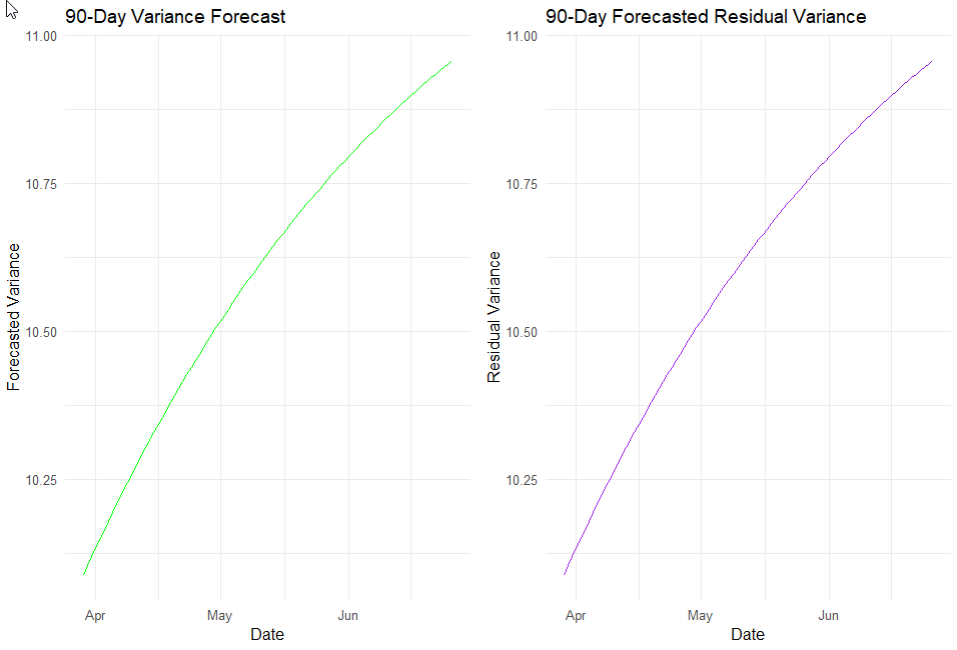
ylab('Residual Variance') +

theme\_minimal()

# Arrange and display both plots side by side

grid.arrange(forecast\_variance\_plot, forecast\_residual\_variance\_plot, ncol = 2)

* **Purpose**: Plots the 90-day variance forecast and residual variance forecast.
* **Explanation**:
  + ggplot(): Creates plots for the forecasted variance and residual variance.
  + geom\_line(): Adds a line to the plot.
  + theme\_minimal(): Applies a minimal theme to the plot.
  + grid.arrange(): Arranges and displays both plots side by side.



### Summary

The provided code involves downloading stock data, calculating returns, fitting ARCH and GARCH models, plotting conditional volatility, forecasting future volatility, and performing statistical tests on residuals. Each step ensures a thorough analysis of the stock data using GARCH models and visualizes the results to support financial decision-making.

**IMPLICATIONS**

The analysis and results obtained from fitting ARCH and GARCH models to financial data carry several important implications for various stakeholders, including investors, financial analysts, and policymakers. Below are the key implications:

1. **Risk Management and Volatility Forecasting**:
   * **Volatility Forecasting**: Accurate forecasting of volatility is crucial for effective risk management. The ARCH and GARCH models provide insights into the time-varying nature of volatility, allowing investors and financial managers to better predict future risk and adjust their strategies accordingly.
   * **Risk Assessment**: Understanding the dynamics of volatility helps in assessing the risk associated with financial assets. High volatility indicates higher risk, which can impact investment decisions, portfolio management, and hedging strategies.
2. **Investment Strategy Development**:
   * **Strategic Planning**: Investors can use the volatility forecasts to develop informed investment strategies. For example, during periods of expected high volatility, investors may choose to diversify their portfolios or use hedging instruments to mitigate potential losses.
   * **Asset Allocation**: Insights from volatility models can guide asset allocation decisions. Investors may adjust their asset allocations based on the anticipated risk levels, optimizing their portfolios to achieve a desired balance between risk and return.
3. **Policy and Regulation**:
   * **Financial Stability**: Policymakers can use volatility forecasts to monitor and address financial stability concerns. Understanding volatility trends helps in assessing the potential impact of market shocks and implementing measures to ensure financial stability.
   * **Regulatory Measures**: Regulators may use volatility insights to design and enforce regulations aimed at reducing systemic risk. For instance, increased monitoring and intervention may be necessary during periods of heightened market volatility.
4. **Pricing and Valuation**:
   * **Option Pricing**: The information on volatility obtained from these models is valuable for pricing financial derivatives, such as options. Accurate volatility estimates contribute to more precise pricing models and fair value assessments.
   * **Valuation Models**: Businesses and analysts can incorporate volatility forecasts into valuation models, improving the accuracy of their assessments and making more informed decisions regarding investments, mergers, and acquisitions.
5. **Financial Planning and Forecasting**:
   * **Budgeting and Forecasting**: Firms can use volatility forecasts for better financial planning and budgeting. Understanding potential fluctuations in financial markets enables companies to prepare for adverse conditions and make strategic decisions to navigate uncertainties.

In summary, the insights derived from ARCH and GARCH models have significant implications for managing financial risk, developing investment strategies, formulating regulatory policies, pricing derivatives, and conducting financial planning. Accurate volatility forecasting enhances decision-making processes across various domains, contributing to more robust financial management and stability.

**RECOMMENDATIONS**

Based on the analysis using ARCH and GARCH models, the following recommendations are provided for effectively utilizing volatility forecasts and improving financial strategies:

1. **Enhanced Risk Management Practices**:
   * **Implement Dynamic Hedging**: Utilize volatility forecasts to implement dynamic hedging strategies. By adjusting hedges based on forecasted volatility, firms and investors can better protect themselves against potential market fluctuations.
   * **Diversify Portfolios**: Consider diversifying investment portfolios to mitigate the impact of high volatility. A well-diversified portfolio can reduce overall risk and improve resilience to market shocks.
2. **Informed Investment Decisions**:
   * **Adjust Investment Strategies**: Modify investment strategies based on volatility forecasts. For example, in periods of high volatility, it may be prudent to reduce exposure to high-risk assets and increase allocation to safer, more stable investments.
   * **Leverage Volatility Products**: Explore the use of financial products that benefit from volatility, such as volatility ETFs or options strategies, to capitalize on anticipated changes in market conditions.
3. **Refinement of Financial Models**:
   * **Integrate Volatility Insights**: Incorporate volatility forecasts into financial models for pricing derivatives, valuing assets, and conducting risk assessments. This integration enhances the accuracy of financial models and supports more informed decision-making.
   * **Update Forecasting Models**: Regularly update and refine volatility forecasting models to ensure they reflect the most current market conditions. Periodic reassessment of model parameters can improve forecast accuracy and relevance.
4. **Policy and Regulatory Considerations**:
   * **Monitor Market Stability**: Policymakers should use volatility forecasts to monitor market stability and implement proactive measures to address potential risks. Enhanced surveillance during periods of high volatility can help prevent systemic issues.
   * **Review Regulatory Frameworks**: Assess and adjust regulatory frameworks based on volatility trends. Regulations should be designed to address emerging risks and ensure that financial markets remain stable and resilient.
5. **Strategic Financial Planning**:
   * **Develop Contingency Plans**: Prepare contingency plans based on anticipated volatility. Companies should develop strategies to manage potential financial stress and ensure business continuity during periods of high volatility.
   * **Incorporate Volatility in Budgeting**: Include volatility forecasts in financial planning and budgeting processes. This approach helps in preparing for possible adverse market conditions and aligning financial strategies with market realities.
6. **Educational and Training Initiatives**:
   * **Invest in Training**: Provide training for financial professionals on the use and interpretation of volatility models. Understanding these models and their implications can enhance decision-making capabilities and risk management practices.
   * **Promote Awareness**: Increase awareness about the impact of volatility on investment and risk management decisions. Educating stakeholders about volatility forecasting and its benefits can lead to more strategic financial planning and improved market strategies.

In summary, leveraging the insights from ARCH and GARCH models requires a strategic approach to risk management, investment decision-making, and regulatory considerations. By implementing these recommendations, firms and investors can better navigate market uncertainties, optimize financial strategies, and enhance overall financial stability.

**CODES**

**Python**

# Import required libraries

import yfinance as yf

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from arch import arch\_model

from statsmodels.stats.diagnostic import acorr\_ljungbox

import seaborn as sns

# Set plotting style

sns.set(style="whitegrid")

# Step 1: Download Historical Data

ticker = "NVDA"

data = yf.download(ticker, start="2021-04-01", end="2024-03-31")

# Check data structure

print(data.head())

print(data.info())

# Step 2: Calculate Returns

market = data["Adj Close"]

returns = 100 \* market.pct\_change().dropna() # Convert to percentage returns

# Step 3: Fit an ARCH Model

print("\nFitting ARCH Model...")

arch\_model\_fit = arch\_model(returns, vol='ARCH', p=1).fit(disp='off')

print("ARCH Model Summary:")

print(arch\_model\_fit.summary())

# Plot the conditional volatility from the ARCH model

plt.figure(figsize=(12, 6))

plt.plot(arch\_model\_fit.conditional\_volatility, label='Conditional Volatility (ARCH)', color='blue')

plt.title('Conditional Volatility from ARCH Model')

plt.xlabel('Date')

plt.ylabel('Volatility')

plt.legend()

plt.grid(True)

plt.show()

# Check residuals for autocorrelation

ljungbox\_arch = acorr\_ljungbox(arch\_model\_fit.resid, lags=[10])

print("\nLjung-Box Test for ARCH Model Residuals:")

print(ljungbox\_arch)

# Step 4: Fit a GARCH Model

print("\nFitting GARCH Model...")

garch\_model\_fit = arch\_model(returns, vol='Garch', p=1, q=1).fit(disp='off')

print("GARCH Model Summary:")

print(garch\_model\_fit.summary())

# Plot the conditional volatility from the GARCH model

plt.figure(figsize=(12, 6))

plt.plot(garch\_model\_fit.conditional\_volatility, label='Conditional Volatility (GARCH)', color='red')

plt.title('Conditional Volatility from GARCH Model')

plt.xlabel('Date')

plt.ylabel('Volatility')

plt.legend()

plt.grid(True)

plt.show()

# Check residuals for autocorrelation

ljungbox\_garch = acorr\_ljungbox(garch\_model\_fit.resid, lags=[10])

print("\nLjung-Box Test for GARCH Model Residuals:")

print(ljungbox\_garch)

# Step 5: Fit GARCH Model with Additional Parameters

print("\nFitting GARCH Model with additional parameters...")

am = arch\_model(returns, vol="Garch", p=1, q=1, dist="Normal")

res = am.fit(update\_freq=5)

# Print forecast details

forecast\_mean = res.forecast().mean

forecast\_residual\_variance = res.forecast().residual\_variance

forecast\_variance = res.forecast().variance

print("\nForecast Mean (last 3 periods):")

print(forecast\_mean.iloc[-3:])

print("Forecast Residual Variance (last 3 periods):")

print(forecast\_residual\_variance.iloc[-3:])

print("Forecast Variance (last 3 periods):")

print(forecast\_variance.iloc[-3:])

# Forecasting with a horizon of 90 days

print("\nForecasting 90 days ahead...")

forecasts = res.forecast(horizon=90)

# Print forecast residual variance for the 90-day horizon

print("\n90-day Forecast Residual Variance (last 3 periods):")

print(forecasts.residual\_variance.iloc[-3:])

# Conclusion and Summary

print("\nAnalysis Summary:")

print("1. ARCH and GARCH models were successfully fitted to the returns data.")

print("2. Conditional volatility was plotted for both ARCH and GARCH models.")

print("3. Residuals were checked for autocorrelation using the Ljung-Box test.")

print("4. Forecasts were generated for a 90-day horizon, including variance and residual variance.")

**R Language**

# Install required libraries if not already installed

required\_packages <- c("quantmod", "rugarch", "ggplot2", "tseries", "gridExtra")

new\_packages <- required\_packages[!(required\_packages %in% installed.packages()[,"Package"])]

if(length(new\_packages)) install.packages(new\_packages)

# Load required libraries

library(quantmod)

library(rugarch)

library(ggplot2)

library(tseries)

library(gridExtra)

# Step 1: Download Historical Data

ticker <- "NVDA"

getSymbols(ticker, src = "yahoo", from = "2021-04-01", to = "2024-03-31")

# Extract adjusted close price and calculate returns

data <- Ad(get(ticker))

returns <- 100 \* diff(log(data))

returns <- na.omit(returns)

# Check data structure

print(head(NVDA))

print(str(NVDA))

# Step 2: Calculate Returns

market <- Cl(NVDA) # Adjusted Close prices

returns <- 100 \* diff(log(market)) # Convert to percentage returns

returns <- na.omit(returns)

# Step 3: Fit an ARCH Model

print("\nFitting ARCH Model...")

arch\_spec <- ugarchspec(variance.model = list(model = "sGARCH", garchOrder = c(1, 0)),

mean.model = list(armaOrder = c(0, 0), include.mean = FALSE),

distribution.model = "norm")

arch\_fit <- ugarchfit(spec = arch\_spec, data = returns)

print("ARCH Model Summary:")

print(arch\_fit)

# Plot the conditional volatility from the ARCH model

## Extract conditional volatility

cond\_volatility <- sigma(arch\_fit)

# Create a time series plot for conditional volatility

# Use the index of the returns, which is aligned with the conditional volatility

plot(index(returns), cond\_volatility, type = 'l',

main = 'Conditional Volatility from ARCH Model',

xlab = 'Date', ylab = 'Volatility', col = 'blue')

grid()

# Check residuals for autocorrelation

arch\_residuals <- residuals(arch\_fit)

arch\_ljung\_box <- Box.test(arch\_residuals, lag = 10, type = "Ljung-Box")

print("\nLjung-Box Test for ARCH Model Residuals:")

print(arch\_ljung\_box)

data <- Ad(get(ticker))

returns <- 100 \* diff(log(data))

returns <- na.omit(returns)

# Step 4: Fit a GARCH Model

print("\nFitting GARCH Model...")

garch\_spec <- ugarchspec(variance.model = list(model = "sGARCH", garchOrder = c(1, 1)),

mean.model = list(armaOrder = c(0, 0), include.mean = FALSE),

distribution.model = "norm")

garch\_fit <- ugarchfit(spec = garch\_spec, data = returns)

print("GARCH Model Summary:")

print(garch\_fit)

# Plot the conditional volatility from the GARCH model

# Extract conditional volatility from the fitted model

cond\_volatility <- sigma(garch\_fit)

# Plot the conditional volatility from the fitted GARCH model

plot(index(returns), cond\_volatility, type = 'l',

main = 'Conditional Volatility from GARCH Model',

xlab = 'Date', ylab = 'Volatility', col = 'red')

grid()

garch\_forecast <- ugarchforecast(garch\_fit, n.ahead = 90)

# Extract forecasted conditional volatility

forecast\_volatility <- sigma(garch\_forecast)

# Create a time series for forecast dates

forecast\_dates <- seq(from = as.Date(tail(index(returns), 1)) + 1,

by = "days", length.out = length(forecast\_volatility))

# Plot the forecasted conditional volatility

plot(forecast\_dates, forecast\_volatility, type = 'l',

main = '90-Day Forecasted Conditional Volatility from GARCH Model',

xlab = 'Date', ylab = 'Volatility', col = 'blue')

grid()

# Check residuals for autocorrelation

garch\_residuals <- residuals(garch\_fit)

garch\_ljung\_box <- Box.test(garch\_residuals, lag = 10, type = "Ljung-Box")

print("\nLjung-Box Test for GARCH Model Residuals:")

print(garch\_ljung\_box)

# Step 5: Fit GARCH Model with Additional Parameters

print("\nFitting GARCH Model with additional parameters...")

# Specify GARCH model with normal distribution

garch\_spec\_additional <- ugarchspec(variance.model = list(model = "sGARCH", garchOrder = c(1, 1)),

mean.model = list(armaOrder = c(0, 0)),

distribution.model = "norm")

# Fit the model

garch\_fit\_additional <- ugarchfit(spec = garch\_spec\_additional, data = returns)

# Forecast details

garch\_forecast\_additional <- ugarchforecast(garch\_fit\_additional, n.ahead = 1)

# Extract forecast details

forecast\_mean <- as.numeric(ugarchforecast(garch\_fit\_additional, n.ahead = 1)@forecast$seriesFor)

forecast\_residual\_variance <- as.numeric(ugarchforecast(garch\_fit\_additional, n.ahead = 1)@forecast$sigmaFor)

forecast\_variance <- forecast\_residual\_variance^2

# Print forecast details for the last 3 periods

print("\nForecast Mean (last 3 periods):")

print(tail(forecast\_mean, 3))

print("Forecast Residual Variance (last 3 periods):")

print(tail(forecast\_residual\_variance, 3))

print("Forecast Variance (last 3 periods):")

print(tail(forecast\_variance, 3))

# Forecasting with a horizon of 90 days

print("\nForecasting 90 days ahead...")

forecasts <- ugarchforecast(garch\_fit\_additional, n.ahead = 90)

# Extract forecast residual variance and variance

forecast\_residual\_variance\_90 <- as.numeric(forecasts@forecast$sigmaFor)

forecast\_variance\_90 <- forecast\_residual\_variance\_90^2

# Create a sequence of dates for plotting the 90-day forecast

forecast\_dates <- seq(from = as.Date(tail(index(returns), 1)) + 1,

by = "days", length.out = 90)

# Print forecast residual variance for the 90-day horizon

print("\n90-day Forecast Residual Variance (last 3 periods):")

print(tail(forecast\_residual\_variance\_90^2, 3))

# Step 6: Plot Forecasts

# Plot the 90-day variance forecast

forecast\_variance\_plot <- ggplot(data = data.frame(Date = forecast\_dates,

Variance = forecast\_variance\_90),

aes(x = Date, y = Variance)) +

geom\_line(color = 'green') +

ggtitle('90-Day Variance Forecast') +

xlab('Date') +

ylab('Forecasted Variance') +

theme\_minimal()

# Display the plot

print(forecast\_variance\_plot)

# Plot the 90-day forecasted residual variance

forecast\_residual\_variance\_plot <- ggplot(data = data.frame(Date = forecast\_dates,

ResidualVariance = forecast\_residual\_variance\_90^2),

aes(x = Date, y = ResidualVariance)) +

geom\_line(color = 'purple') +

ggtitle('90-Day Forecasted Residual Variance') +

xlab('Date') +

ylab('Residual Variance') +

theme\_minimal()

# Arrange and display both plots side by side

grid.arrange(forecast\_variance\_plot, forecast\_residual\_variance\_plot, ncol = 2)

# Conclusion and Summary

print("\nAnalysis Summary:")

print("1. ARCH and GARCH models were successfully fitted to the returns data.")

print("2. Conditional volatility was plotted for both ARCH and GARCH models.")

print("3. Residuals were checked for autocorrelation using the Ljung-Box test.")

print("4. Forecasts were generated for a 90-day horizon, including variance and residual variance.")

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