

VIRGINIA COMMONWEALTH UNIVERSITY

Statistical analysis and modelling (SCMA 632)

**A6b – ARCH/GARCH**

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**INTRODUCTION**

ARCH (Autoregressive Conditional Heteroskedasticity) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models are powerful statistical tools used to analyze and predict the volatility of time series data. Introduced by Robert Engle in 1982, the ARCH model allows for the modeling of time-varying volatility, recognizing that financial time series often exhibit periods of volatility clustering, where large changes in prices are followed by more large changes. The GARCH model, developed by Tim Bollerslev in 1986, extends the ARCH model by incorporating lagged conditional variances, providing a more comprehensive framework to capture the persistence and long memory effects of volatility. These models are widely utilized in econometrics and finance to forecast future volatility and understand the underlying dynamics of financial markets.

**OBJECTIVES**

Analyze the volatility of Amazon’s stock prices from January 2020 to July 2024 using the dataset "AMZN."

- Perform data cleaning, including handling missing values and converting string attributes to numeric values.

- Check for ARCH/GARCH effects in the data using statistical tests. - Fit an ARCH/GARCH model to the log returns of Netflix’s stock prices.

- Forecast the three-month volatility based on the fitted model.

- Visualize and interpret the forecasted volatility and historical squared log returns

**BUSINESS SIGNIFICANCE**

For a major global corporation like Amazon, employing ARCH/GARCH models can provide significant strategic advantages. By accurately modeling and forecasting the volatility of financial variables such as stock prices, exchange rates, and sales data, Amazon can enhance its risk management strategies. Understanding volatility patterns can aid in optimizing inventory levels, improving pricing strategies, and managing cash flows more effectively. Moreover, these models can support Amazon in making informed decisions regarding investments, mergers, and acquisitions by assessing potential risks and returns with greater precision. In the highly competitive and dynamic e-commerce and tech industry, leveraging ARCH/GARCH models can contribute to Amazon's resilience and adaptability, ultimately driving sustained growth and profitability.

**CODES**

* **R**

# Install and load necessary packages

if (!require("quantmod")) install.packages("quantmod")

if (!require("tseries")) install.packages("tseries")

if (!require("rugarch")) install.packages("rugarch")

if (!require("FinTS")) install.packages("FinTS")

library(FinTS)

library(quantmod)

library(tseries)

library(rugarch)

# Load the dataset

data <- read.csv("D:\\SCMA\\Data\\AMZN.csv")

# Convert the Date column to Date type

data$Date <- as.Date(data$Date, format="%Y-%m-%d")

# Extract the adjusted closing prices

adj\_close <- data$Adj.Close

# Calculate the log returns

log\_returns <- diff(log(adj\_close))

arch\_test <- ArchTest(log\_returns, lags = 1)

print(arch\_test)

# Fit an appropriate GARCH model

# Here we choose a GARCH(1,1) model

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

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

distribution.model = "norm")

garch\_fit <- ugarchfit(spec = spec, data = log\_returns[-1])

print(garch\_fit)

# Forecast the three-month volatility

# Assuming 21 trading days per month, 3 months would be 63 trading days

forecast <- ugarchforecast(garch\_fit, n.ahead = 63)

# Extract the forecasted volatility

forecasted\_volatility <- sigma(forecast)

print(forecasted\_volatility)

* **PYTHON**

import pandas as pd

import numpy as np

from arch import arch\_model

from statsmodels.stats.diagnostic import het\_arch

# Load the dataset

data = pd.read\_csv("D:\\SCMA\\Data\\AMZN.csv")

# Convert the Date column to Date type

data['Date'] = pd.to\_datetime(data['Date'])

# Extract the adjusted closing prices

adj\_close = data['Adj Close']

# Calculate the log returns

log\_returns = np.diff(np.log(adj\_close))

# Perform the ARCH test

arch\_test = het\_arch(log\_returns)

print("ARCH Test Statistic:", arch\_test[0])

print("p-value:", arch\_test[1])

# Fit an appropriate GARCH model

# Here we choose a GARCH(1,1) model

model = arch\_model(log\_returns, vol='Garch', p=1, q=1)

garch\_fit = model.fit(disp="off")

print(garch\_fit.summary())

# Forecast the three-month volatility

# Assuming 21 trading days per month, 3 months would be 63 trading days

forecast = garch\_fit.forecast(horizon=63)

# Extract the forecasted volatility

forecasted\_volatility = forecast.variance.values[-1, :]

print("Forecasted Volatility:")

print(forecasted\_volatility)

**RESULTS**

The ARCH test result shows a Chi-squared value of 0.27674 with a p-value of 0.5988, indicating that there are no significant ARCH effects in the log returns of Amazon's adjusted closing prices. This means that the log returns do not exhibit significant volatility clustering at the chosen lag of 1.

The GARCH(1,1) model fit provides several key parameters. The alpha1 (0.256461) and beta1 (0.620798) values are significant with p-values less than 0.05, indicating that past squared returns and past conditional variances significantly impact the current variance. The model summary also shows that the conditional variance is dynamic, and the combined effect of alpha1 and beta1 (0.877259) being less than 1 indicates a mean-reverting process. The information criteria (Akaike, Bayes, Shibata, and Hannan-Quinn) provide measures of model fit, with lower values indicating better fit.

**INTERPRETATION**

The forecasted volatility values for the next 63 trading days show a gradual increase from approximately 0.01765 to 0.01959, indicating a slight rise in volatility over the three-month forecast period. These values can be used by investors and risk managers to anticipate future market fluctuations and adjust their strategies accordingly. The stable increase suggests that while volatility is expected to rise, it does so in a controlled manner without abrupt spikes, which could imply a relatively stable but slightly riskier market environment in the near term.

Overall, the results suggest that the GARCH(1,1) model is appropriate for modeling the volatility of Amazon's log returns, capturing the dynamics of past volatility and forecasting future trends effectively. The absence of significant ARCH effects in the test, combined with the significant parameters of the GARCH model, highlights the importance of considering both past returns and variances in volatility modeling. This information is crucial for making informed investment decisions and managing financial risk.