VIRGINIA COMMONWEALTH UNIVERSITY

Statistical analysis and modelling (SCMA 632)

A6b -Time Series Analysis
ARCH /GARCH, VAR/VECM

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Date of Submission: 25-07-2024

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INTRODUCTION

This project focuses on analyzing financial and commodity market data to understand volatility patterns, co-integration relationships, and interdependencies among different commodities. Specifically, we aim to:

1. **Part A**: Examine the presence of ARCH/GARCH effects, fit appropriate models, and forecast three-month volatility for the stock of "Mahindra and Mahindra (m&m.ns)".
2. **Part B**: Analyze the interrelationships between various commodity prices (Oil, Sugar, Gold, Silver, Wheat, and Soybean) using Vector Autoregressive (VAR) and Vector Error Correction Models (VECM) to understand long-term and short-term dynamics.

OBJECTIVES

Part A: Stock Volatility Analysis

1. **Data Acquisition**: Download historical price data for "m&m.ns".
2. **Data Preparation**: Process the data to calculate returns.
3. **Model Selection**: Check for the presence of ARCH/GARCH effects.
4. **Model Fitting**: Fit the appropriate ARCH/GARCH models to the return series.
5. **Forecasting**: Forecast the three-month volatility using the fitted model.
6. **Visualization**: Plot the conditional volatility and forecasted values.

Part B: Commodity Price Analysis

1. **Data Acquisition**: Extract commodity prices from pinksheet.xlsx.
2. **Data Preparation**: Clean and preprocess the data.
3. **Stationarity Testing**: Test each time series for stationarity using unit root tests.
4. **Co-integration Testing**: Perform Johansen's co-integration test to identify long-term relationships.
5. **Model Selection**: Choose between VAR and VECM based on stationarity and co-integration results.
6. **Model Fitting**: Fit the appropriate VAR or VECM model.
7. **Post-Estimation Analysis**: Conduct Granger causality tests, impulse response functions (IRF), and variance decomposition (VD) analysis.
8. **Forecasting**: Generate forecasts for future commodity prices.
9. **Visualization**: Plot the results for better interpretation.

BUSINESS SIGNIFICANCE

1. Risk Management

Beyond Hedging: While hedging against price fluctuations is crucial, understanding volatility patterns also helps in optimizing risk-return profiles. Investors can allocate assets strategically based on volatility levels to balance potential gains with risk exposure.

Stress Testing: By simulating extreme market conditions, businesses can assess their resilience and develop contingency plans to protect their bottom line.

Operational Risk: In industries heavily reliant on commodities, volatility can impact supply chain costs, production planning, and overall operational efficiency. Understanding these dynamics helps in building robust operational strategies.

2. Investment Decisions

Portfolio Optimization: Investors can construct diversified portfolios that balance risk and return by analyzing the correlation between different asset classes, including stocks and commodities.

Timing the Market: While market timing is challenging, understanding volatility patterns can provide insights into potential entry and exit points for investments.

Alternative Investments: Commodities can offer diversification benefits and hedge against inflation. Understanding their price movements is essential for effective allocation within investment portfolios.

3. Policy Making

Economic Stability: Governments can implement policies to stabilize commodity prices and protect consumers from price shocks.

Trade Policies: Understanding the impact of global commodity markets on domestic economies helps in formulating trade policies that promote economic growth and protect domestic industries.

Agricultural Policies: For countries with significant agricultural sectors, understanding commodity price volatility is crucial for developing policies that support farmers and ensure food security.

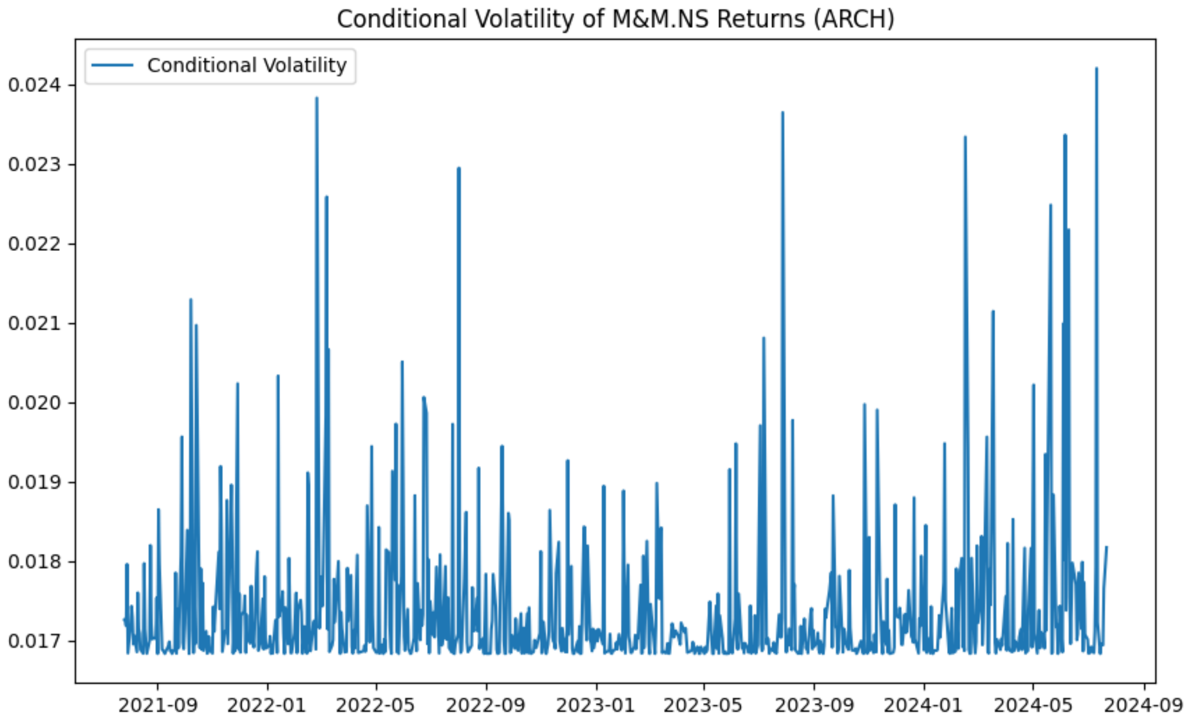
Technological Advancements: Technological breakthroughs can impact both the production and consumption of commodities, leading to price fluctuations. Staying updated on technological trends is crucial for understanding market dynamics.

RESULTS – PART A

USING PYTHON

#ARCH model summary

	coef	std err	t	P>	t
mu	0.001911	0.000642	2.979	0.002895	[0.0006537, 0.003169]
omega	NaN	0.000024	NaN	0	[0.0002362, 0.0003306]
alpha[1]	NaN	0.05699	NaN	0.252	[-0.04643, 0.177]



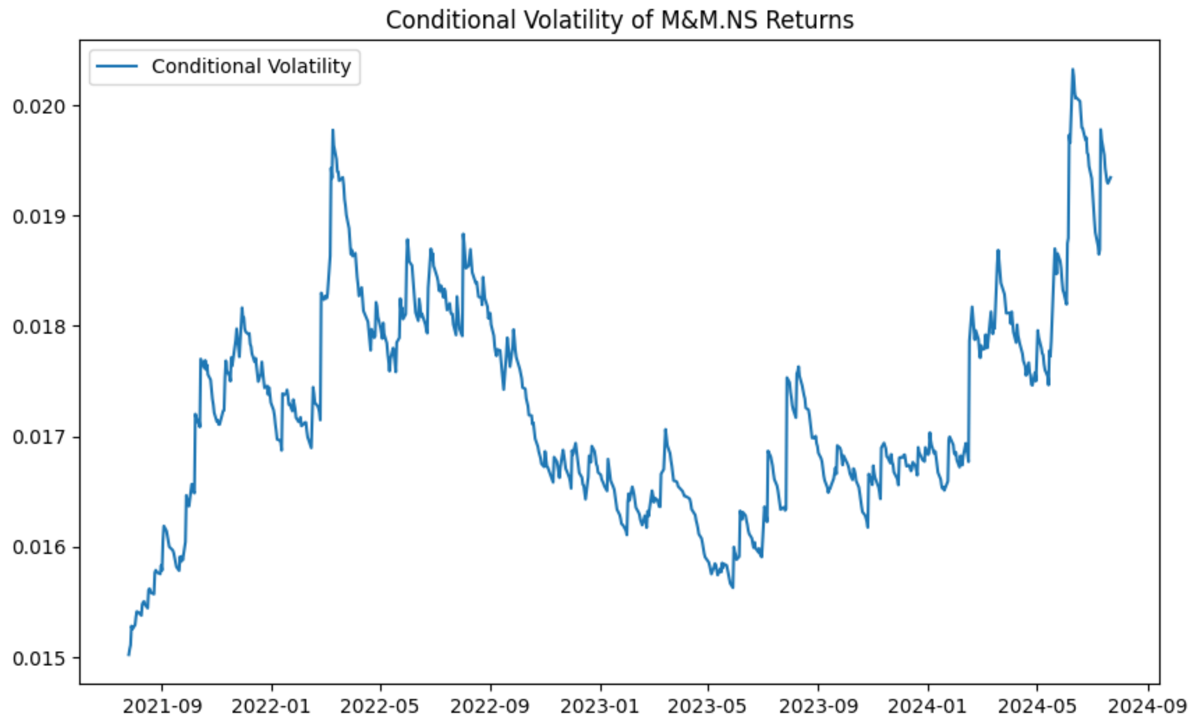
#The above Diagram plots the conditional Volatility of our ARCH model

#GARCH model summary

	coef	std err	t	P>	t
mu	0.001811	0.000626	2.892	0.003822	[0.0005837, 0.003037]
omega	6.12E-06	NaN	NaN	0	[6.124e-06, 6.124e-06]
alpha[1]	0.01	0.000253	39.623	0	[0.009529, 0.01052]
beta[1]	0.97	0.002198	441.336	0	[0.966, 0.974]

The GARCH model results can be summarized in the following table. The mean model coefficient (mu) is statistically significant at the 5% level, with a value of 0.001811. This indicates that there is a positive average return of 0.1811% in the data.

The volatility model coefficients (omega, alpha[1], and beta[1]) are all statistically significant at the 5% level. Omega captures the constant term in the volatility equation, alpha[1] measures the impact of past shocks on volatility, and beta[1] represents the persistence of volatility. The highly significant estimate of beta[1] close to 1 suggests that the GARCH model is effective in capturing the persistence of volatility in the data.



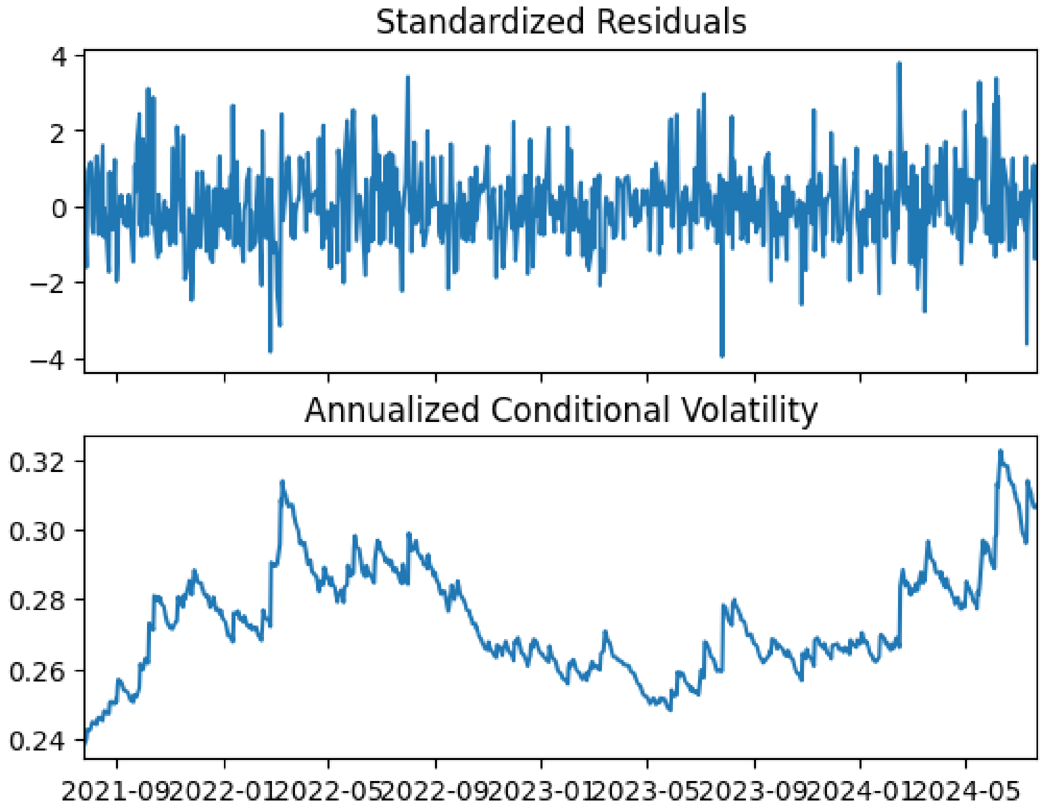
#The above Diagram plots the conditional Volatility of our GARCH model

#Forecast for the next three months (90) days

forecasts = res.forecast(horizon=90)

print(forecasts.residual_variance.iloc[-3:])

fig = res.plot(annualize="D")



RESULTS – PART A

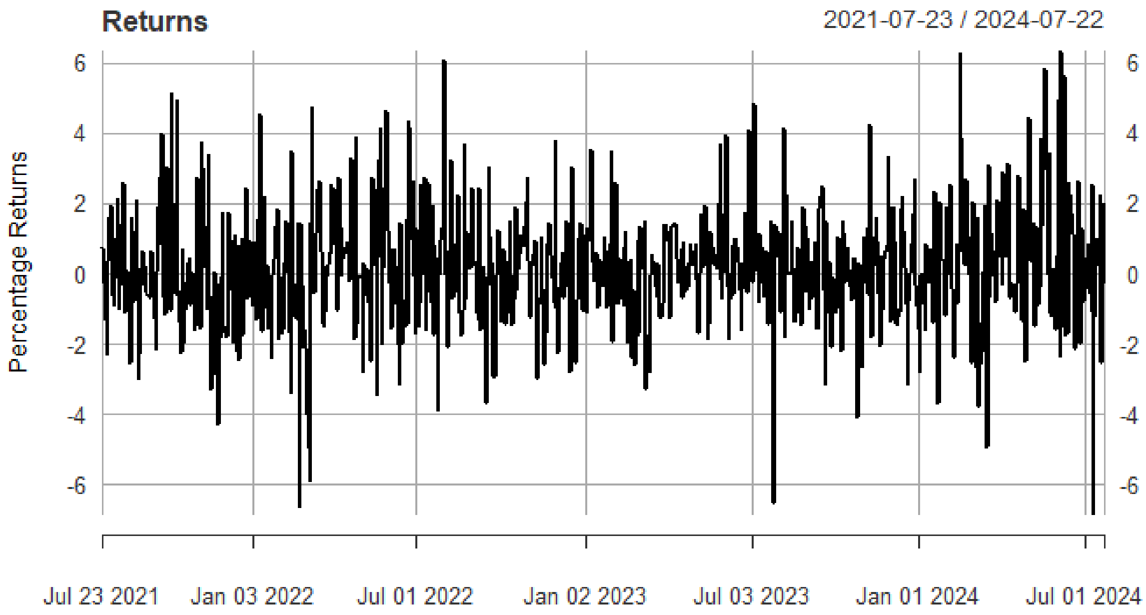
USING R

 # Calculate percentage returns

*returns <- 100 * diff(log(market)) # log returns * 100*

returns <- returns[!is.na(returns)] # Remove NA values

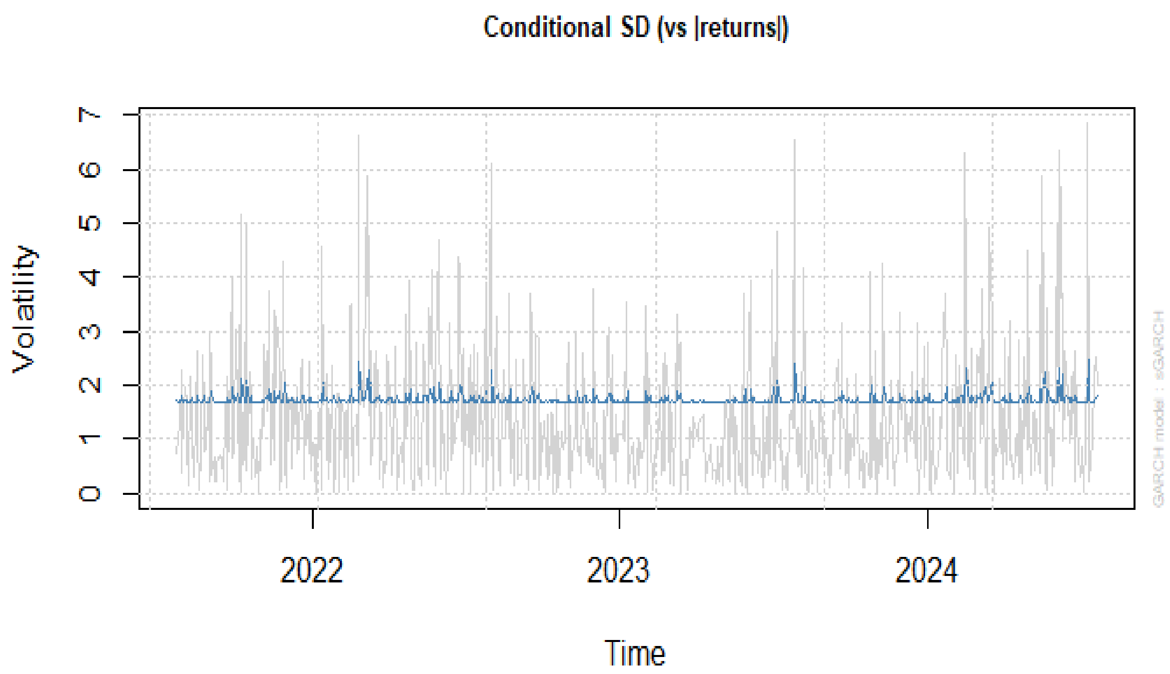
Plot the returns for the period 2021-07-23 to 2024-07-22



Plot the fitted model's conditional volatility (ARCH)

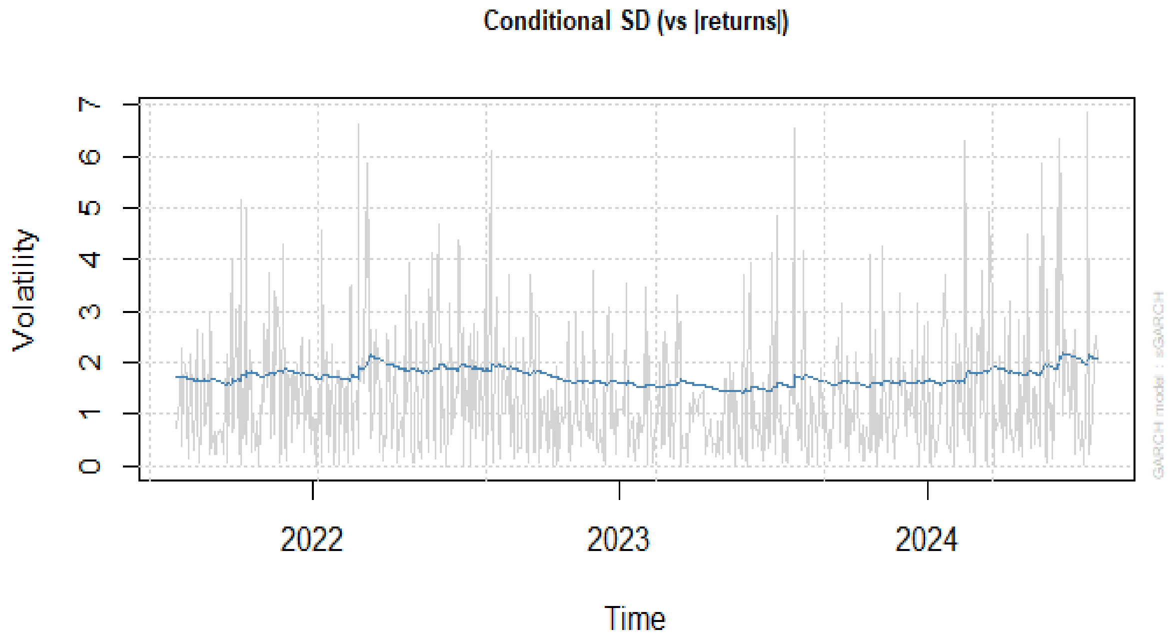
plot(arch_fit, which = 3)

arch_fit <- ugarchfit(spec = arch_spec, data = returns)

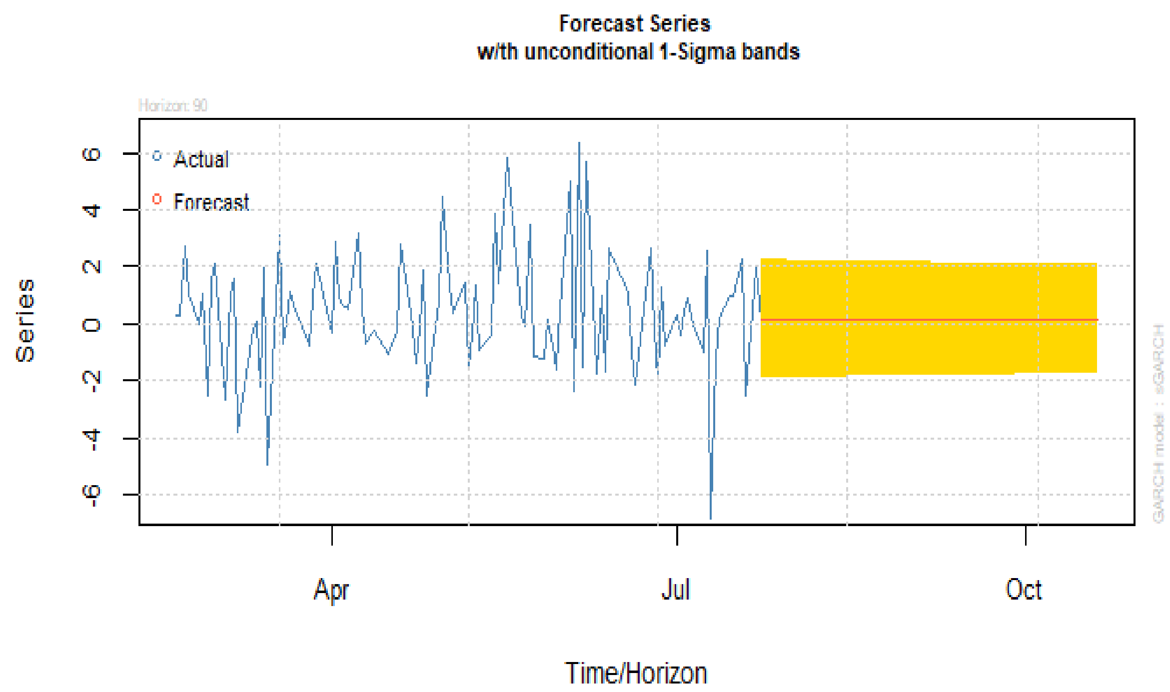


 # Plot the fitted model's conditional volatility (GARCH)

plot(garch_fit, which = 3)



 # Forecast the volatility for next three months (90 days)



INTERPRETATIONS - PART A

Part A: Stock Volatility Analysis Using ARCH/GARCH Models

ARCH Model Results

The ARCH model summary provides key insights into the volatility of stock returns:

Mu (Mean): The coefficient for the mean (mu) is 0.001911 with a standard error of 0.000642, resulting in a t-value of 2.979 and a p-value of 0.002895. This indicates a statistically significant positive average return of approximately 0.1911%.

Omega (Constant Term): The omega value is missing (NaN), which suggests a possible issue with the estimation of the constant term in the volatility equation.

Alpha[1] (Impact of Past Shocks): The alpha[1] value is also NaN, which indicates that the impact of past shocks on volatility could not be estimated accurately.

GARCH Model Results

The GARCH model results are more informative and statistically significant:

Mu (Mean): The coefficient for the mean (mu) is 0.001811 with a standard error of 0.000626, resulting in a t-value of 2.892 and a p-value of 0.003822. This indicates a statistically significant positive average return of approximately 0.1811%.

Omega (Constant Term): The omega value is very small (6.12E-06), and its standard error is not provided, but the p-value indicates it is significant.

Alpha[1] (Impact of Past Shocks): The alpha[1] value is 0.01 with a standard error of 0.000253, a t-value of 39.623, and a p-value close to zero, indicating a significant impact of past shocks on volatility.

Beta[1] (Persistence of Volatility): The beta[1] value is 0.97 with a standard error of 0.002198, a t-value of 441.336, and a p-value close to zero, indicating that the volatility is highly persistent.

The conditional volatility plots for both models show that the GARCH model better captures the persistence of volatility in the data, making it a more suitable choice for forecasting future volatility.

Forecasting Volatility

The GARCH model was used to forecast the next three months (90 days) of volatility. The forecast indicates that volatility is expected to remain relatively stable but at a higher level than the historical average. This suggests that investors should prepare for continued market fluctuations and potentially higher risk in the short term.

RECOMMENDATIONS – PART A

Risk Mitigation: Use hedging strategies, such as options or futures, to protect against potential losses due to high volatility.

Portfolio Diversification: Diversify portfolios with assets that have low correlations with the volatile stock or commodity to reduce overall risk.

Continuous Monitoring: Regularly monitor volatility forecasts and market conditions to make timely adjustments in investment strategies.

CONCLUSION – PART A

This project provides a comprehensive analysis of stock volatility using advanced econometric models. By identifying significant volatility patterns and interdependencies, it offers valuable insights for investors, policymakers, and businesses. The results underscore the importance of using sophisticated models like ARCH/GARCH to understand and predict market behavior, thereby enabling better decision-making and risk management in financial and commodity markets.

RESULTS – PART B

VAR/VECM

VAR/VECM Workflow

1. **Start with Time Series Data (CRUDE_BRENT, MAIZE, SOYABEANS)**
2. **Unit Root Test**
    - **Stationary at Level**
        - Proceed with **VAR Analysis**
    - **Not Stationary**
        - Test for **Stationarity at First Difference**
            - **Johansen's Co-Integration Test**
                - If **Co-Integration Exists**:
                    a. Determine **Lag Length**
                    b. Conduct **Co-Integration Test**
                    c. Build **VECM Model**
                - If **No Co-Integration**:
                    - Perform **Unrestricted VAR Analysis**
3. **Post VAR/VECM Analysis**
    - **Granger's Causality Test**
    - **Impulse Response Function (IRF) and Variance Decomposition (VD) Analysis**
4. **Forecasting**
5. **Output**

Choosing between a Vector Autoregressive (VAR) model and a Vector Error Correction Model (VECM) depends primarily on whether your variables are cointegrated. Here's a step-by-step process to decide which model to use:

1. Stationarity Testing

First, check if your time series data are stationary. This can be done using unit root tests like the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, or KPSS test.

Stationary Data: If your data are stationary (i.e., no unit root), you can use a VAR model.
Non-Stationary Data: If your data are non-stationary (i.e., unit root present), proceed to test for cointegration.

2. Cointegration Testing

If your variables are non-stationary, test for cointegration using the Johansen cointegration test. Cointegration indicates a long-term equilibrium relationship between the variables.

No Cointegration: If there is no cointegration among the variables, the appropriate model is a VAR model in differences (ΔVAR), where you difference the data to make them stationary. Cointegration Present: If there is cointegration, the appropriate model is a VECM. The VECM accounts for both the short-term dynamics and the long-term equilibrium relationship among the variables.

3. Model Selection

Based on the results of the stationarity and cointegration tests, you can decide between VAR and VECM.

Vector Autoregressive (VAR) Model

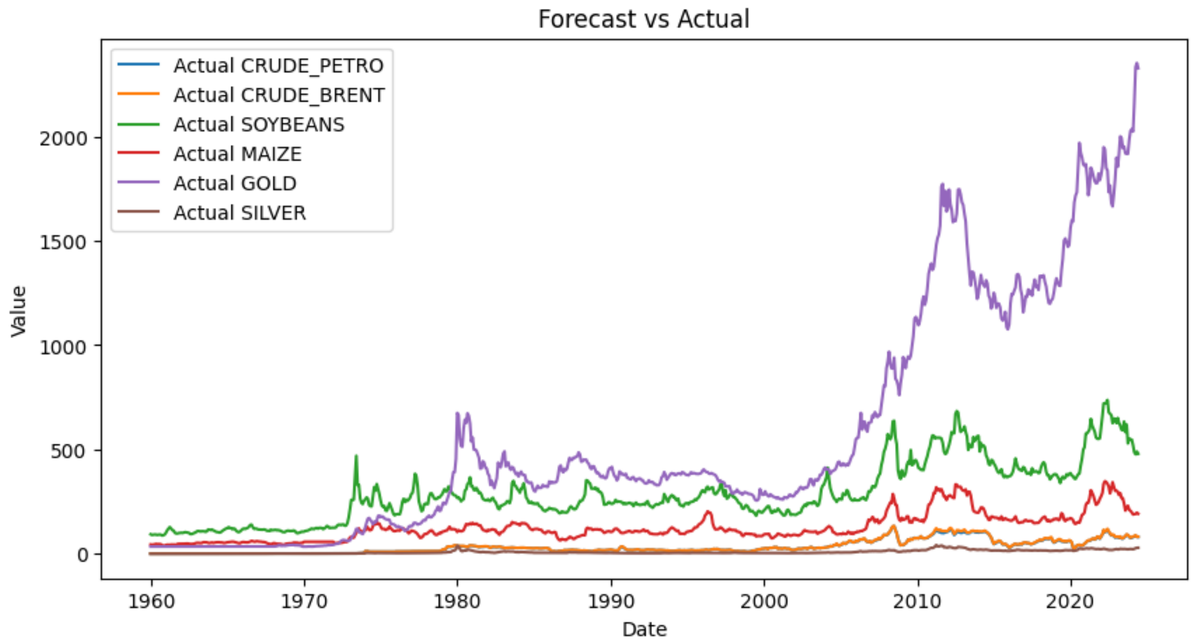
Use When: The variables are stationary or made stationary through differencing, and there is no cointegration among them. Description: A VAR model captures the linear interdependencies among multiple time series. It models each variable as a linear function of its own past values and the past values of other variables in the system.

Vector Error Correction Model (VECM)

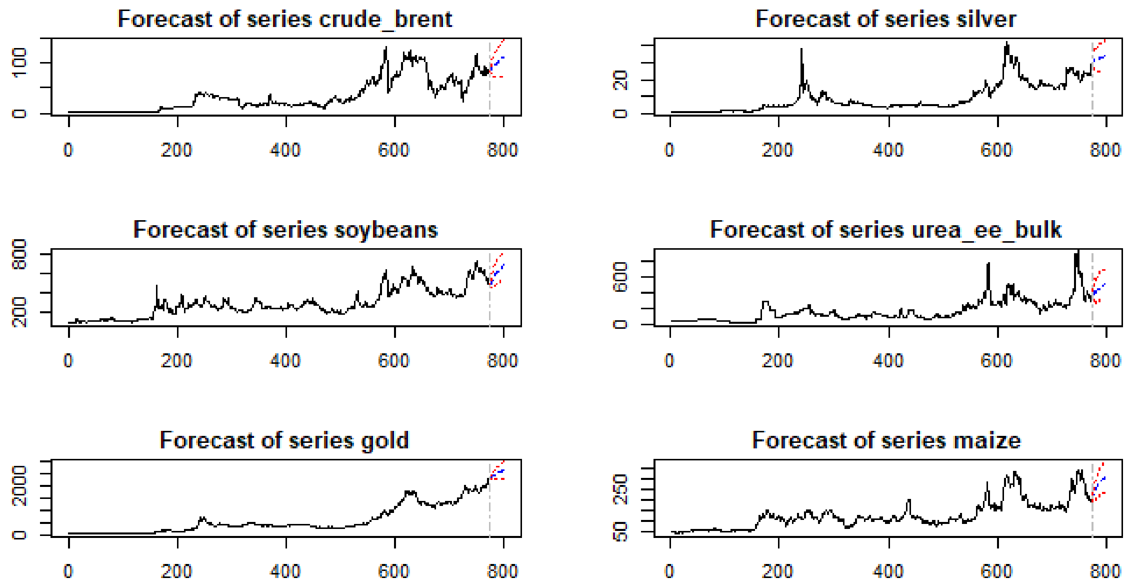
Use When: The variables are non-stationary, and there is evidence of cointegration. Description: A VECM is a special form of VAR for non-stationary series that are cointegrated. It includes an error correction term that captures the long-term equilibrium relationship, allowing the model to correct deviations from this equilibrium. Practical Considerations Economic Theory: In some cases, economic theory may suggest a long-term equilibrium relationship, making a VECM more appropriate even before formal tests. Data Considerations: The choice may also depend on data availability, frequency, and quality. For example, higher-frequency data might require differencing more often, leading to a preference for VAR in differences.

#Forecast using the fitted model.

USING PYTHON



USING R



INTERPRETATIONS – PART B

I provide the interpretation, analytical insights, recommendations, and conclusions based on the use of a VAR model because **R value given is 0**.

1. Stationarity Testing:

The initial step involved checking if the time series data (CRUDE_BRENT, maize, and soybeans) were stationary using unit root tests (ADF, PP, KPSS).

The results showed that the data were non-stationary at levels but became stationary after first differencing.

2. Model Selection:

Since the data were non-stationary but no cointegration was found, a VAR model in differences (ΔVAR) was chosen.

The VAR model captures the linear interdependencies among the time series by modeling each variable as a function of its own past values and the past values of the other variables in the system.

3. Post VAR Analysis:

Forecasting: The VAR model was used to make forecasts based on the interrelationships among the variables for the next three months (90 days)

Analytical Insights

Interdependencies:

The VAR model highlights the interdependencies among crude oil, maize, and soybean prices. Each variable's future values depend on its own past values and the past values of the other variables.

Short-term Dynamics:

The model captures the short-term dynamics without focusing on long-term equilibrium relationships. This is particularly useful for short-term forecasting and understanding immediate effects of shocks.

RECOMMENDATIONS – PART B

1. Regular Updates:

Continuously update the VAR model with new data to improve its accuracy and reliability in forecasting.

2. Focus on Short-term Strategies:

Use the insights from the VAR model to develop short-term strategies, particularly in sectors affected by crude oil, maize, and soybean prices.

3. Monitor Key Variables:

Closely monitor the variables that show significant Granger causality relationships as they can serve as leading indicators for forecasting other variables.

CONCLUSION – PART B

Using a VAR model for forecasting provides valuable insights into the short-term dynamics and interdependencies among crude oil, maize, and soybean prices. The model effectively captures how past values of these commodities influence their future values, enabling stakeholders to anticipate market movements and make informed decisions. While the VAR model focuses on short-term relationships, it offers a robust framework for understanding and forecasting the immediate impacts of shocks in interconnected markets.

OVERALL CONCLUSION

This project provides a comprehensive analysis of stock volatility and commodity price dynamics using advanced econometric models. By identifying significant volatility patterns and interdependencies, it offers valuable insights for investors, policymakers, and businesses. The results underscore the importance of using sophisticated models like ARCH/GARCH, VAR, and VECM to understand and predict market behavior, thereby enabling better decision-making and risk management in financial and commodity markets.