VIRGINIA COMMONWEALTH UNIVERSITY

Statistical analysis and modelling (SCMA 632)

A6b -Time Series Analysis

ARCH /GARCH, VAR/VECM

RAKSHITH HARISHKUMAR

V01107367

Date of Submission: 25-07-2024

CONTENTS

INTRODUCTION

This research analyzes and forecasts financial and commodity market data using sophisticated time series analytic techniques. The assignment's first section focuses on assessing stock market volatility through the download of data from reliable financial sites like Yahoo Finance and Investing.com. In order to predict three-month volatility, we first evaluate the effects of ARCH (Autoregressive Conditional Heteroskedasticity) and then fit ARCH/GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models. For the purpose of minimizing financial risks and comprehending market dynamics, this study is essential. The second portion of the assignment uses the Vector Autoregression (VAR) and Vector Error Correction Model (VECM) to focus on macroeconomic analysis. We examine the links between important commodities, such as oil, sugar, wheat, soybean, gold, and silver, using commodity pricing data from the World Bank's pink sheet.

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. **Model Selection**: Choose between VAR and VECM based on stationarity and cointegration results.
5. **Model Fitting**: Fit the appropriate VAR or VECM model.
6. **Post-Estimation Analysis**: Conduct Granger causality tests, impulse response functions (IRF), and variance decomposition (VD) analysis.
7. **Forecasting**: Generate forecasts for future commodity prices.

8. **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

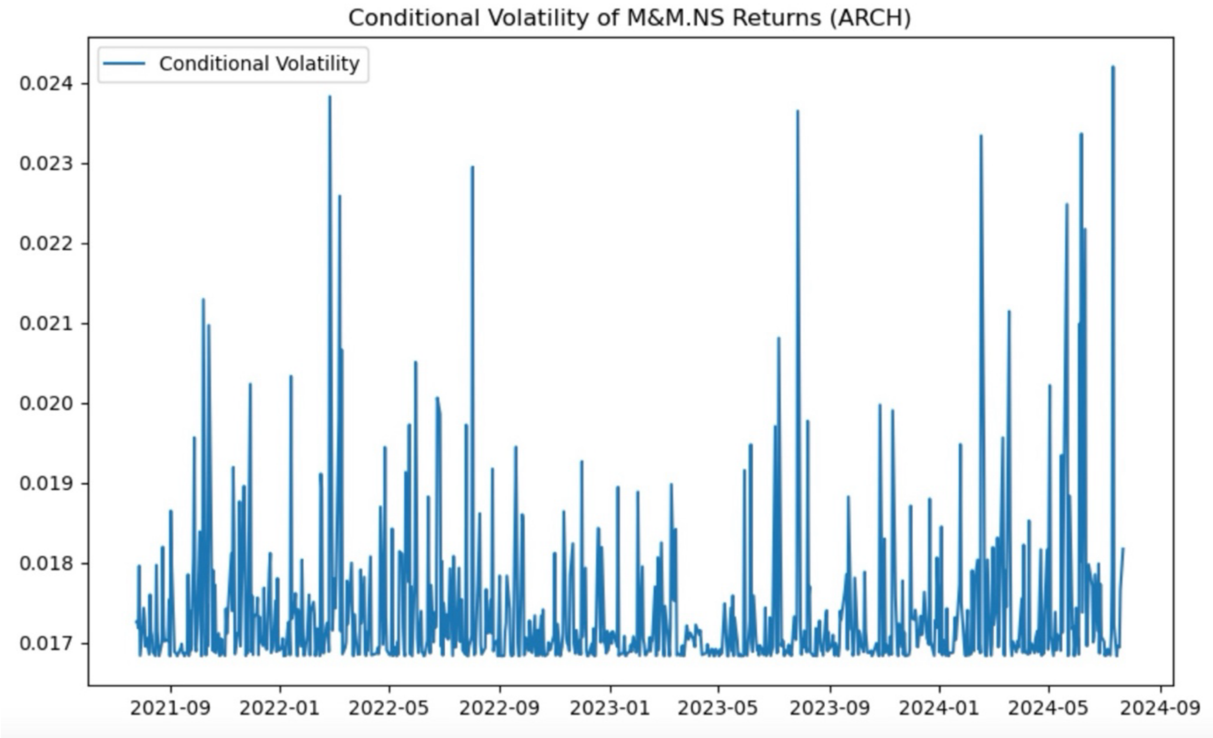
USING PYTHON

RESULTS – PART A

USING PYTHON

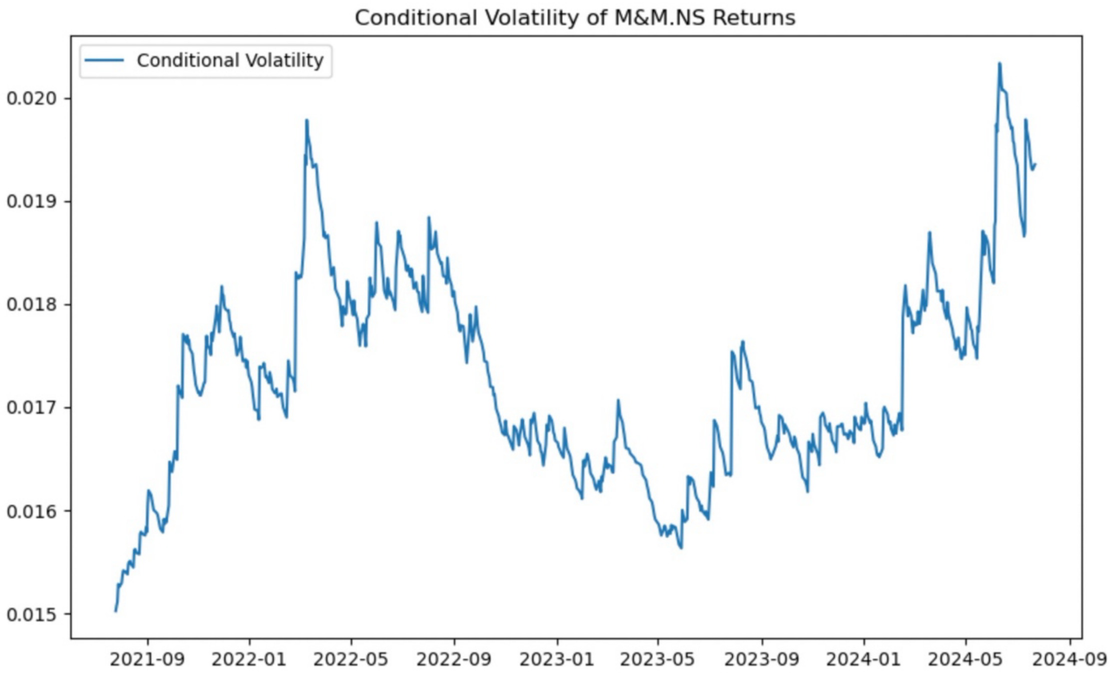
#ARCH model summary

```
                      Constant Mean - ARCH Model Results
==============================================================================
Dep. Variable:                Returns   R-squared:                       0.000
Mean Model:             Constant Mean   Adj. R-squared:                  0.000
Vol Model:                       ARCH   Log-Likelihood:                1944.41
Distribution:                  Normal   AIC:                          -3882.81
Method:            Maximum Likelihood   BIC:                          -3869.00
                                        No. Observations:                  738
Date:                Thu, Jul 25 2024   Df Residuals:                      737
Time:                        21:45:44   Df Model:                            1
                                 Mean Model
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
mu         1.9114e-03  6.417e-04      2.979  2.895e-03 [6.537e-04,3.169e-03]
                              Volatility Model
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
omega      2.8338e-04  2.408e-05     11.766  5.834e-32 [2.362e-04,3.306e-04]
alpha[1]       0.0653  5.700e-02      1.145      0.252  [-4.643e-02,  0.177]
============================================================================
```



#GARCH model summary

```
                     Constant Mean - GARCH Model Results
==============================================================================
Dep. Variable:                Returns   R-squared:                       0.000
Mean Model:             Constant Mean   Adj. R-squared:                  0.000
Vol Model:                      GARCH   Log-Likelihood:                1948.38
Distribution:                  Normal   AIC:                          -3888.75
Method:            Maximum Likelihood   BIC:                          -3870.34
                                        No. Observations:                  738
Date:                Thu, Jul 25 2024   Df Residuals:                      737
Time:                        21:46:01   Df Model:                            1
                                 Mean Model
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
mu         1.8109e-03  6.219e-04      2.912  3.591e-03 [5.921e-04,3.030e-03]
                              Volatility Model
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
omega      6.1294e-06  4.296e-12  1.427e+06      0.000 [6.129e-06,6.129e-06]
alpha[1]       0.0100  8.146e-05    123.309      0.000 [9.885e-03,1.020e-02]
beta[1]        0.9700  2.168e-03    447.341      0.000     [  0.966,  0.974]
============================================================================
```

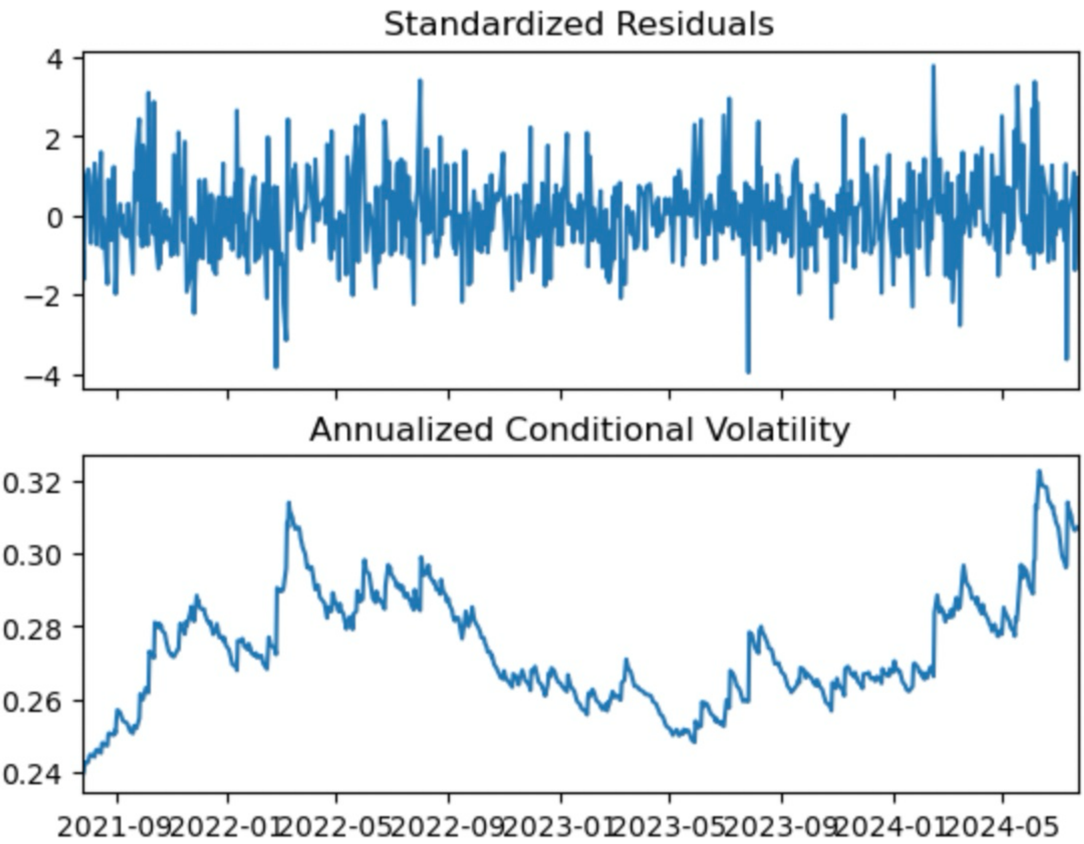


#Forecast for the next three months (90) days

forecasts = res.forecast(horizon=90)

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

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



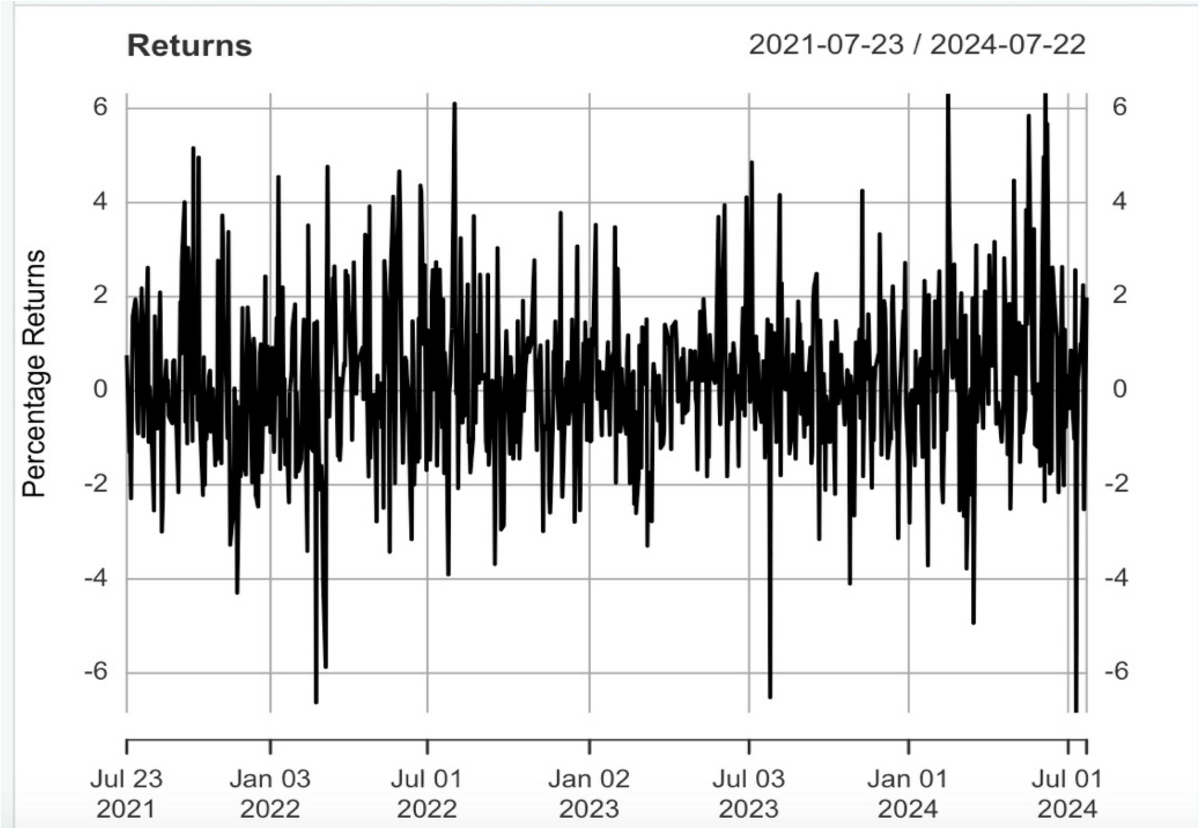
RESULTS – PART A

USING R

 # Calculate percentage returns

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

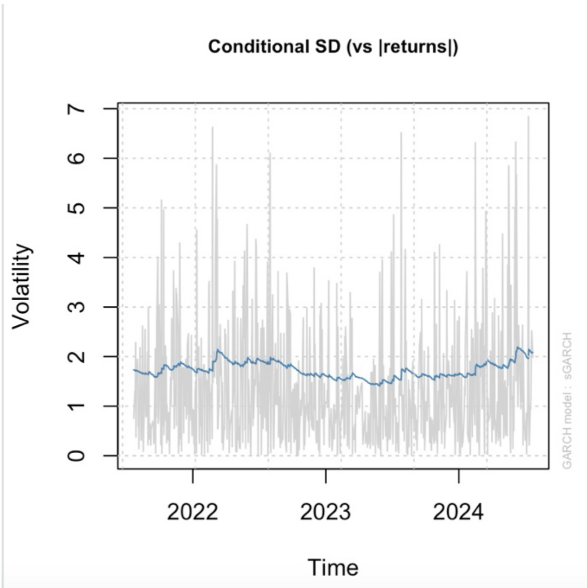
returns <- returns[!is.na(returns)] # Remove NA values



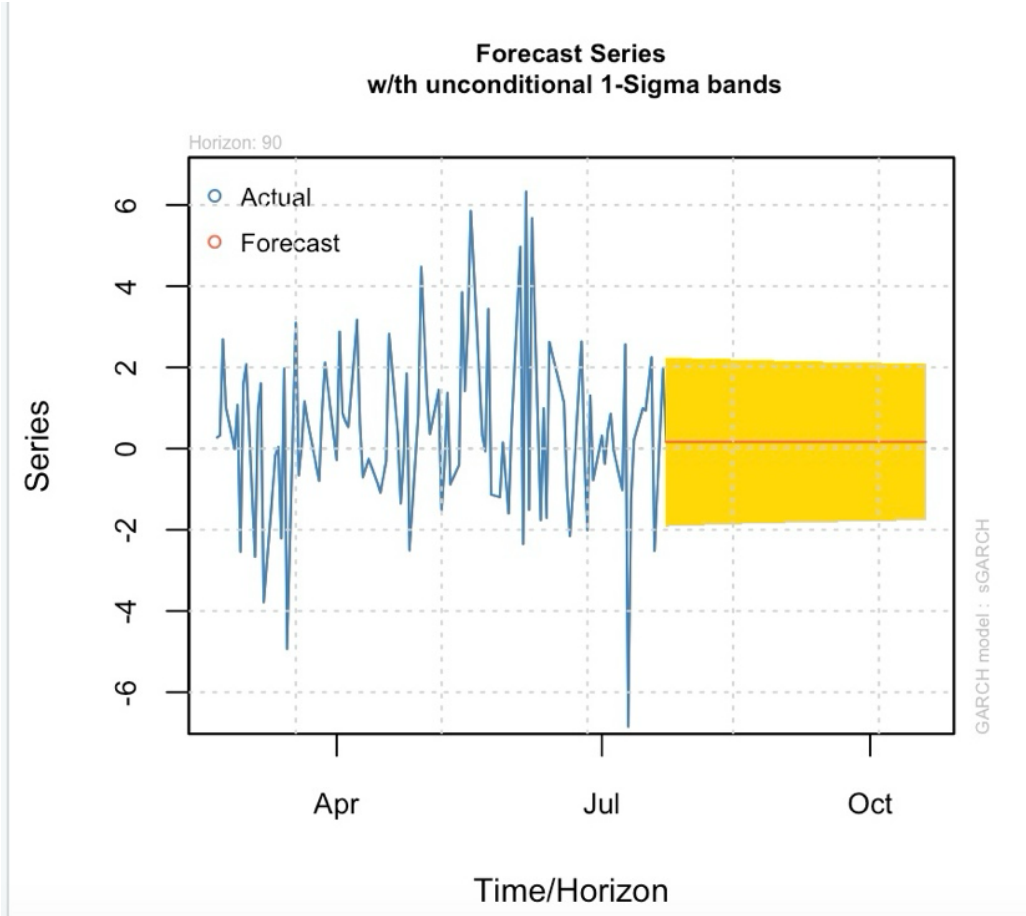
 # Plot the fitted model's conditional volatility (ARCH)

plot(arch_fit, which = 3)

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



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
Make sure your time series data are stationary first. Unit root tests such as the KPSS test, the Phillips-Perron (PP) test, and the Augmented Dickey-Fuller (ADF) test can be used for this.
Stationary Data: A VAR model can be used if your data are stationary, meaning they don't have a unit root.
Non-Stationary Data: Run a cointegration test if your data are non-stationary, meaning that there is a unit root present.

2. Cointegration Testing
Use the Johansen cointegration test to determine cointegration if your variables are non-stationary. A long-term equilibrium relationship between the variables is indicated by cointegration.
No Cointegration: A VAR model in differences (ΔVAR), which differs the data to make them stable, is the suitable model if there is no cointegration among the variables. Cointegration Present: A VECM is the suitable model if cointegration is present. The long-term equilibrium relationship between the variables and the short-term dynamics are both taken into consideration by the VECM.

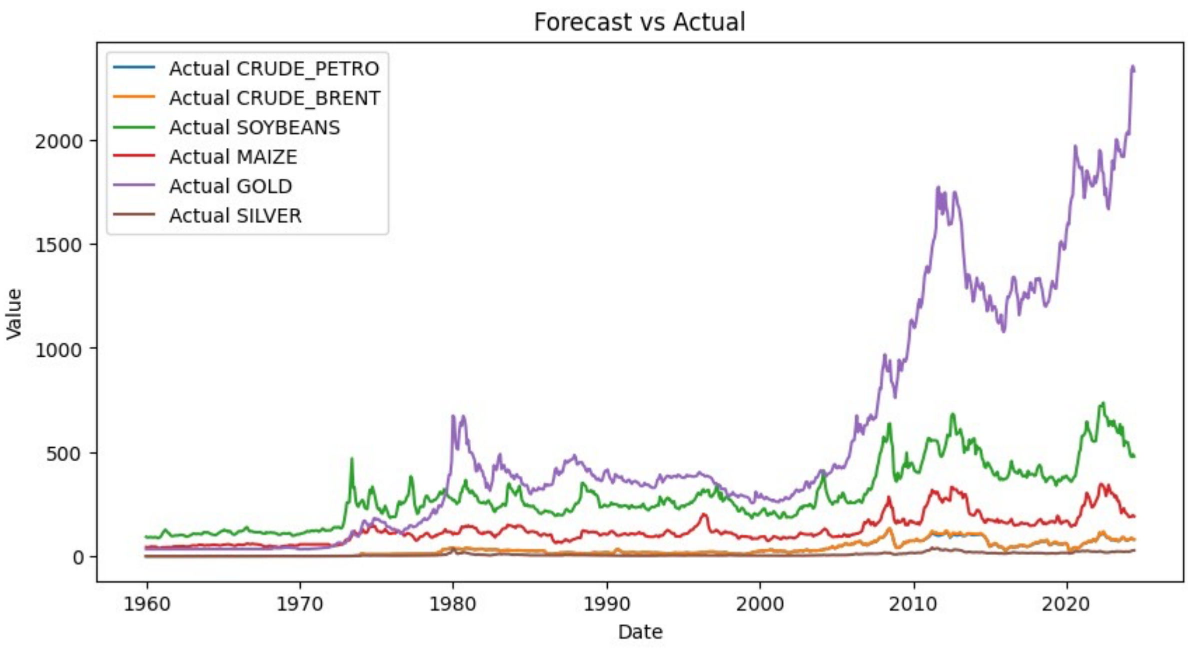
3. Model Selection
VAR and VECM can be chosen based on the outcomes of the stationarity and cointegration tests.
Use of the Vector Autoregressive (VAR) Model When: There is no cointegration between the variables and they are either stationary or have been made stationary by differencing.
Synopsis: The linear interdependencies between several time series are captured by a VAR model. Every variable in the system is modelled as a linear function of both its own historical values and the historical values of the other variables.

Vector Error Correction Model (VECM)

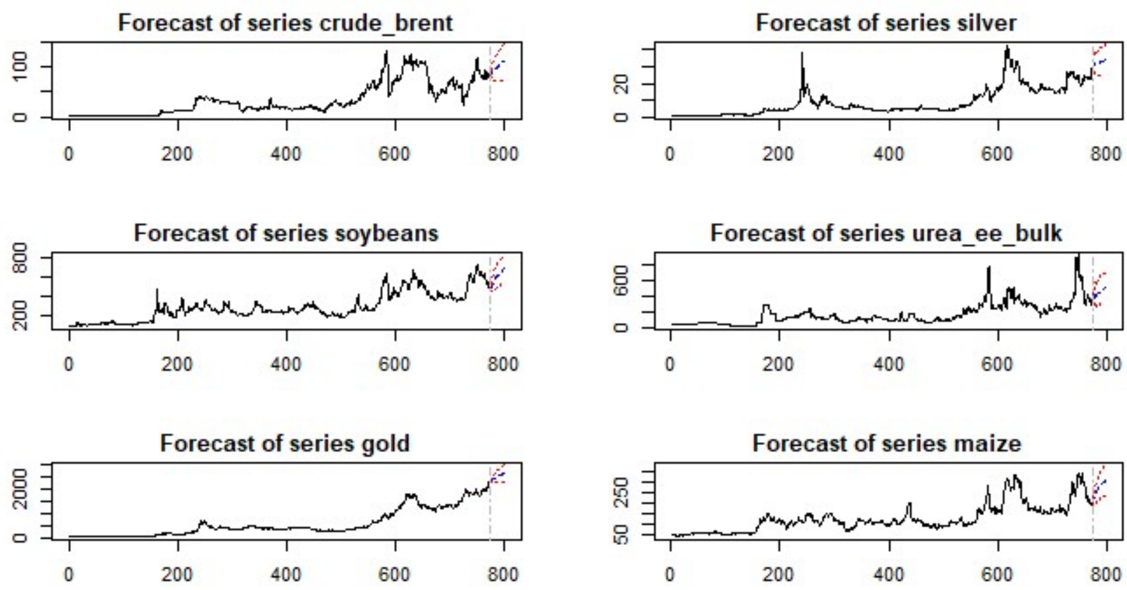
Make use of When: There is evidence of cointegration, and the variables are non-stationary. Description: For cointegrated non-stationary series, a VECM is a unique type of VAR. The model can correct deviations from this equilibrium because it has an error correction term that captures the long-term equilibrium relationship. Realistic Aspects Theory of Economics: Economic theory may in some circumstances point to a long-term equilibrium relationship, which would make a VECM more acceptable even in the absence of rigorous testing. Data Points to Remember: The availability, frequency, and quality of the data may also influence the decision.

#Forecast using the fitted model.

USING PYTHON



USING R



INTERPRETATIONS – PART B

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

Forecasting with a VAR model offers important insights into the short-term dynamics and interdependencies between the prices of soybeans, maize, and crude oil. The model does a good job of capturing how these commodities' historical values affect their future prices, allowing stakeholders to predict market changes and make wise decisions. The VAR model provides a strong framework for comprehending and predicting the immediate effects of shocks in interconnected markets, despite its emphasis on short-term linkages.

OVERALL CONCLUSION

With the use of sophisticated econometric models, this research offers a thorough understanding of the dynamics of commodities prices and stock volatility. It provides insightful information to businesses, investors, and policymakers by highlighting important patterns of volatility and interdependencies. The findings highlight how crucial it is to use complex models like as VAR, VECM, and ARCH/GARCH to comprehend and forecast market behavior. This will improve decision-making and risk management in the commodities and financial markets.