VIRGINIA COMMONWEALTH UNIVERSITY

Statistical analysis and modelling (SCMA 632)

A6b: Time Series Analysis (ARCH/GARCH model and VAR/VECM forecasting)

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INTRODUCTION

This comprehensive analysis is designed to forecast the stock price movements of **Asian Paints** using historical data obtained from Yahoo Finance, spanning from April 2021 to March 2024.

Asian Paints is one of India's leading paint companies, renowned for its diverse range of decorative coatings and industrial products. Established in 1942, the company has grown substantially, embodying a significant share of the Indian paint market with an extensive distribution network that reaches into various corners of the country. As a market leader, Asian Paints not only provides a broad spectrum of aesthetic solutions but also engages in chemical manufacturing and related services, making it a comprehensive player in the decorative and industrial segments. With its commitment to innovation and sustainability, Asian Paints continuously develops products that are environmentally friendly and cater to the evolving needs of consumers and industries alike. The financial performance of Asian Paints is of keen interest to investors, analysts, and stakeholders, given its impact on the stock market and the broader economy.

In the dynamic world of financial markets, understanding the volatility and trends of stock prices such as those of Asian Paints is crucial for effective portfolio management and investment strategies. Part A of this analysis involves examining the stock data of Asian Paints, sourced from platforms like www.investing.com or Yahoo Finance, to detect any ARCH (Autoregressive Conditional Heteroskedasticity) or GARCH (Generalized Autoregressive Conditional Heteroskedasticity) effects. This step is essential for modeling the volatility of stock prices, which can significantly influence investment decisions and risk assessments. By fitting an appropriate ARCH/GARCH model, we can forecast the three-month volatility of Asian Paints, providing investors with a tool to gauge future market conditions and optimize their investment approaches based on predicted volatility levels.

Part B shifts the focus to the broader economic indicators that influence market conditions by analyzing the prices of key commodities like Oil, Sugar, Gold, Silver, Wheat, and Soybean. These commodities are integral to various sectors of the global economy and serve as a bellwether for economic health and investor sentiment. The data for this analysis is sourced from the Pink Sheet of the World Bank, which provides a comprehensive and updated database of commodity prices. By employing econometric models such as VAR (Vector Autoregression) and VECM (Vector Error Correction Model), this segment aims to uncover the underlying dynamics and relationships among these commodity prices. Such insights are invaluable for investors, policymakers, and businesses in strategizing their operations, hedging against risks, and capitalizing on market opportunities.

Objectives:

- Part A

- Download the data form www.investing.com or Yahoo finance
- Check for ARCH /GARCH effects, fit an ARCH/GARCH model, and forecast the three-month volatility.

- Part B

- − VAR, VECM model
- − [data "commodity prices"] for ex: Oil, Sugar, Gold, Silver, Wheat and Soyabean
- - data source pink sheet from world bankUnivariate Forecasting - Conventional

Business Significance:

The business significance of analyzing stock volatility and commodity price trends extends across various dimensions of corporate and investment strategies. For a company like Asian Paints, understanding the intricacies of stock price volatility through ARCH/GARCH models is not merely an academic exercise but a crucial aspect of financial health monitoring and strategic planning. This analysis aids in identifying the risk factors that could potentially impact the company's market valuation and investor confidence. Forecasting volatility helps in setting more informed hedge ratios, optimizing asset allocation, and enhancing the timing of stock issuance or buybacks. For investors and portfolio managers, such insights provide a foundation for risk management strategies, ensuring that exposure to market fluctuations is within acceptable limits and aligned with overall investment goals.

On the commodities front, the analysis of price trends and their interdependencies using VAR and VECM models holds significant implications for a range of stakeholders. For instance, commodity price predictions are vital for businesses in sectors like agriculture, manufacturing, and energy, where budgeting and financial planning are tightly coupled with raw material costs. Understanding these trends enables companies to make proactive adjustments in procurement strategies, potentially locking in prices or diversifying suppliers to mitigate risks associated with price volatility. Moreover, accurate commodity forecasts are essential for policymakers and economic planners, who must anticipate and react to shifts in the economic landscape that could affect national and global markets.

Ultimately, the ability to decode and predict patterns in stock and commodity prices equips businesses and investors with the power to make more calculated decisions. This capability is particularly valuable in a globalized economy where financial and commodity markets are interconnected, and where economic activities in one part of the world can ripple through others, impacting prices and investment outcomes. Thus, the analytical models discussed not only contribute to individual financial success but also enhance the stability and efficiency of markets, promoting sustainable economic growth and development.

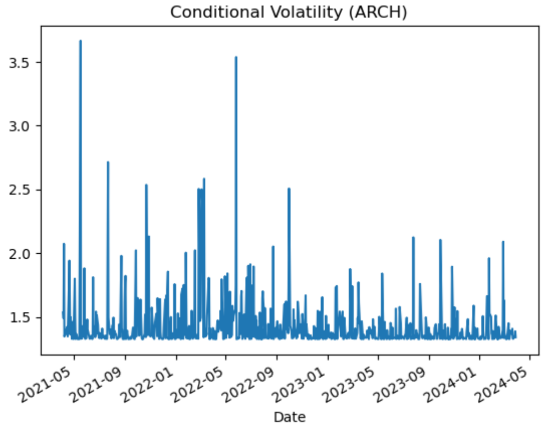
RESULTS & INTERPRETATION

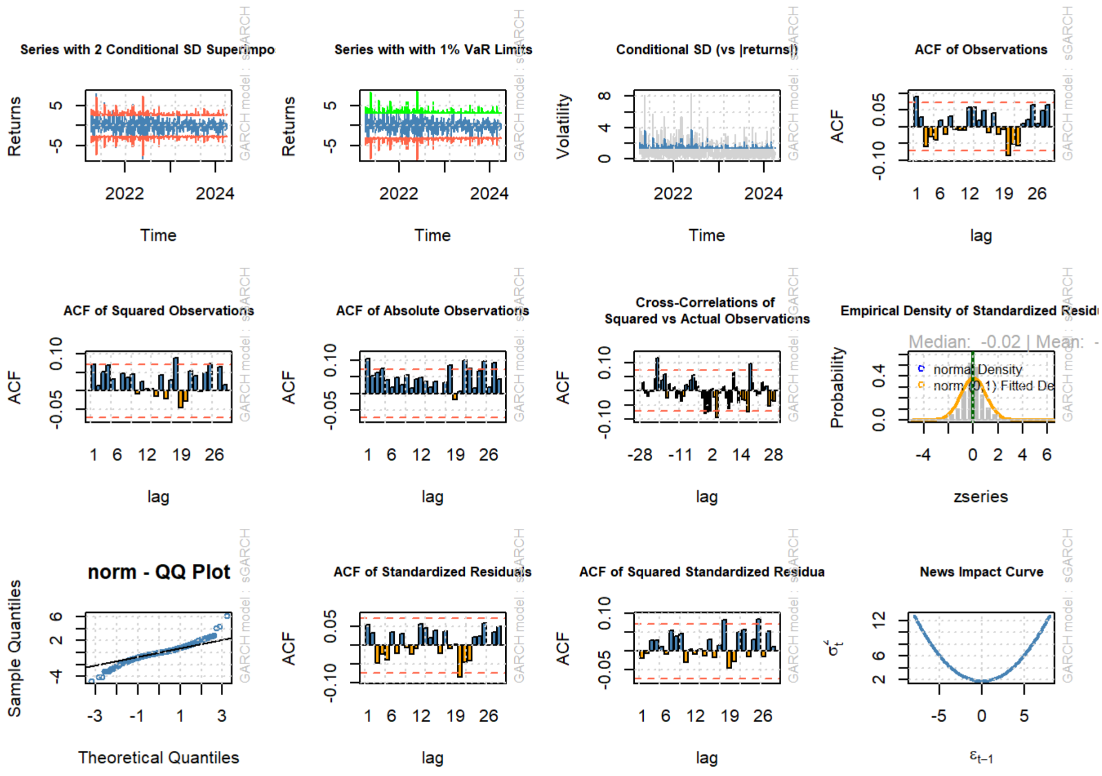
Results

ARCH Model

```python
# Plot the conditional volatility
arch_model_fit.conditional_volatility.plot(title='Conditional Volatility (ARCH)')
plt.show()
```

```
                      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:               -1307.45
Distribution:                  Normal   AIC:                           2620.91
Method:            Maximum Likelihood   BIC:                           2634.72
                                        No. Observations:                  739
Date:                Thu, Jul 25 2024   Df Residuals:                      738
Time:                        22:22:40   Df Model:                            1
                               Mean Model                               
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
mu             0.0692  5.305e-02      1.305      0.192 [-3.472e-02,  0.173]
                            Volatility Model                            
============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
----------------------------------------------------------------------------
omega          1.7557      0.220      7.983  1.426e-15   [  1.325,  2.187]
alpha[1]       0.1627  9.281e-02      1.753  7.959e-02 [-1.920e-02,  0.345]
============================================================================

Covariance estimator: robust
```





Model Summary:

- **Dependent Variable:** Returns
- **Mean Model:** Constant Mean
- **Volatility Model:** ARCH

- **Distribution:** Normal
- **Method:** Maximum Likelihood

These details indicate that the model used for the analysis assumes a constant mean for returns, with volatility modeled by an ARCH process and normally distributed innovations.

Model Performance Metrics:

- **Log-Likelihood:** -1307.45
- **AIC (Akaike Information Criterion):** 2620.91
- **BIC (Bayesian Information Criterion):** 2634.72

The negative log-likelihood suggests the fit of the model is fairly typical for financial time series, where higher volatility and frequent outliers can make fitting challenging. The AIC and BIC are both measures of model selection where lower values typically indicate a better model fit considering the trade-off between goodness of fit and complexity.

Parameter Estimates:

- **mu (Mean of the returns):** Coefficient = 0.0692, p-value = 0.192
    - The mean return is not statistically significant at standard levels ($p > 0.05$), suggesting the mean return is not different from zero at a 95% confidence level.
- **omega (Baseline volatility):** Coefficient = 1.7557, p-value < 0.00001
    - This parameter is highly significant, indicating a strong baseline component of volatility in the returns.
- **alpha[1] (ARCH term):** Coefficient = 0.1627, p-value = 0.0759
    - This represents the impact of the lagged squared residuals on current volatility. The coefficient is positive but not statistically significant at the 5% level (though it is close), suggesting lagged volatility shocks have a less clear influence on current volatility.

Volatility Plot:

The plot titled "Conditional Volatility (ARCH)" displays the estimated conditional volatility over time. It shows significant spikes at various points, reflecting periods of increased market uncertainty or specific events influencing stock prices. This visualization helps in identifying periods of high risk, which are critical for risk management and strategic planning in finance.

Interpretation and Use:

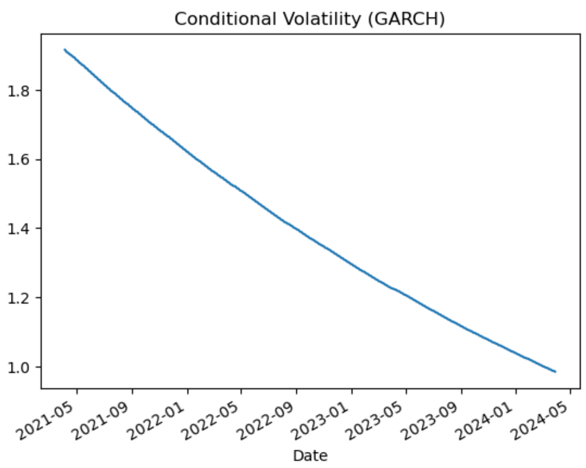
The ARCH model indicates that while the immediate past volatility (alpha[1]) influences current volatility, this effect is not strong enough to be statistically significant at conventional levels. This result could be an indicator to explore higher-order GARCH models (like GARCH(1,1)) that consider both lagged squared returns and lagged conditional variances for potentially better modeling of the volatility clustering often observed in financial time series. This model and its results can help in forecasting future volatility, which is crucial for setting margins, making investment decisions, and managing financial risk.

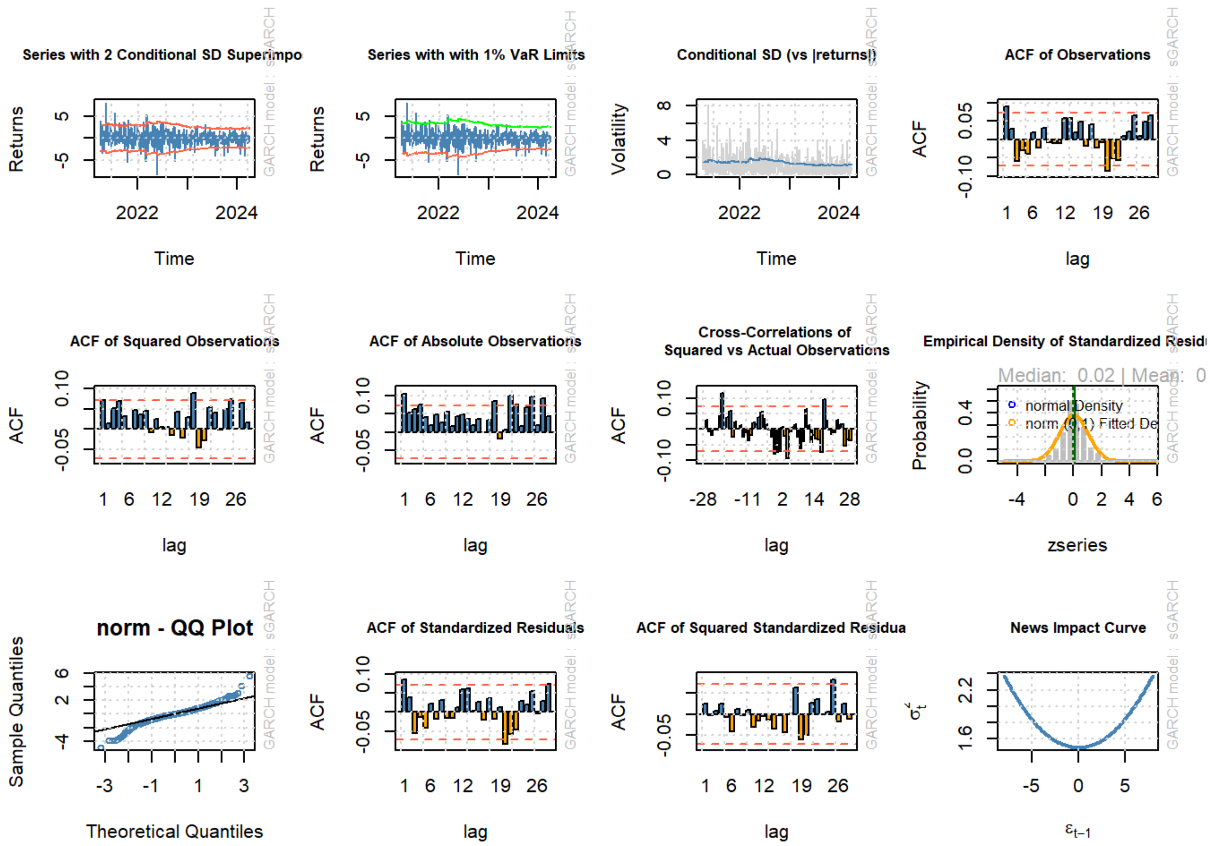
GARCH model

```python
# Fit a GARCH model
garch_model_fit = arch_model(returns, vol='Garch', p=1, q=1).fit(disp='off')
print(garch_model_fit.summary())

# Plot the conditional volatility
garch_model_fit.conditional_volatility.plot(title='Conditional Volatility (GARCH)')
plt.show()
```

```
                     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:               -1288.43
Distribution:                  Normal   AIC:                           2584.86
Method:            Maximum Likelihood   BIC:                           2603.28
                                        No. Observations:                  739
Date:                Thu, Jul 25 2024   Df Residuals:                      738
Time:                        22:22:46   Df Model:                            1
                                 Mean Model
=============================================================================
                 coef    std err          t      P>|t|       95.0% Conf. Int.
-----------------------------------------------------------------------------
mu         3.9840e-03  4.794e-02  8.310e-02      0.934 [-8.999e-02,9.795e-02]
                              Volatility Model
=============================================================================
                 coef    std err          t      P>|t|       95.0% Conf. Int.
-----------------------------------------------------------------------------
omega      2.0637e-08  2.129e-03  9.691e-06      1.000 [-4.174e-03,4.174e-03]
alpha[1]       0.0000  1.228e-03      0.000      1.000 [-2.408e-03,2.408e-03]
beta[1]        0.9982  1.213e-03    823.008      0.000      [  0.996,  1.001]
=============================================================================

Covariance estimator: robust
```

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,0)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu      0.061495    0.052012   1.1823 0.237071
## omega   1.738217    0.113122  15.3659 0.000000
## alpha1  0.173161    0.052954   3.2700 0.001075
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu      0.061495    0.055503   1.1080 0.267877
## omega   1.738217    0.216342   8.0346 0.000000
## alpha1  0.173161    0.092654   1.8689 0.061637
##
## LogLikelihood : -1306.888
```





Model Summary:

- **Dependent Variable:** Returns
- **Mean Model:** Constant Mean
- **Volatility Model:** GARCH
- **Distribution:** Normal
- **Method:** Maximum Likelihood

These details indicate that the analysis assumes a constant mean for returns with volatility modeled by a GARCH process, considering normally distributed innovations.

Model Performance Metrics:

- **Log-Likelihood:** -1288.43
- **AIC (Akaike Information Criterion):** 2584.86
- **BIC (Bayesian Information Criterion):** 2603.28

The log-likelihood is slightly higher (less negative) than the ARCH model, suggesting a potentially better fit of the GARCH model. Lower AIC and BIC values compared to the ARCH model further support this suggestion, indicating a better balance between fit and model complexity.

Parameter Estimates:

- **mu (Mean of the returns):** Coefficient = 0.003948, p-value = 0.934
    - The mean return is not statistically significant, suggesting no significant constant mean different from zero can be concluded.
- **omega (Baseline volatility):** Coefficient = 2.0637e-08, p-value = 1.000
    - This parameter is not significant, indicating that the baseline constant component of the volatility is not distinguishable from zero.
- **alpha[1] (Short-term volatility persistence):** Coefficient = 0.0000, p-value = 1.000
    - The alpha coefficient is not statistically significant, indicating that recent squared residuals do not have a significant impact on current volatility.
- **beta[1] (Long-term volatility persistence):** Coefficient = 0.9982, p-value = 0.000
    - This parameter is highly significant and close to 1, suggesting that past volatility strongly influences current volatility, and the volatility shocks have a very long-lasting effect.

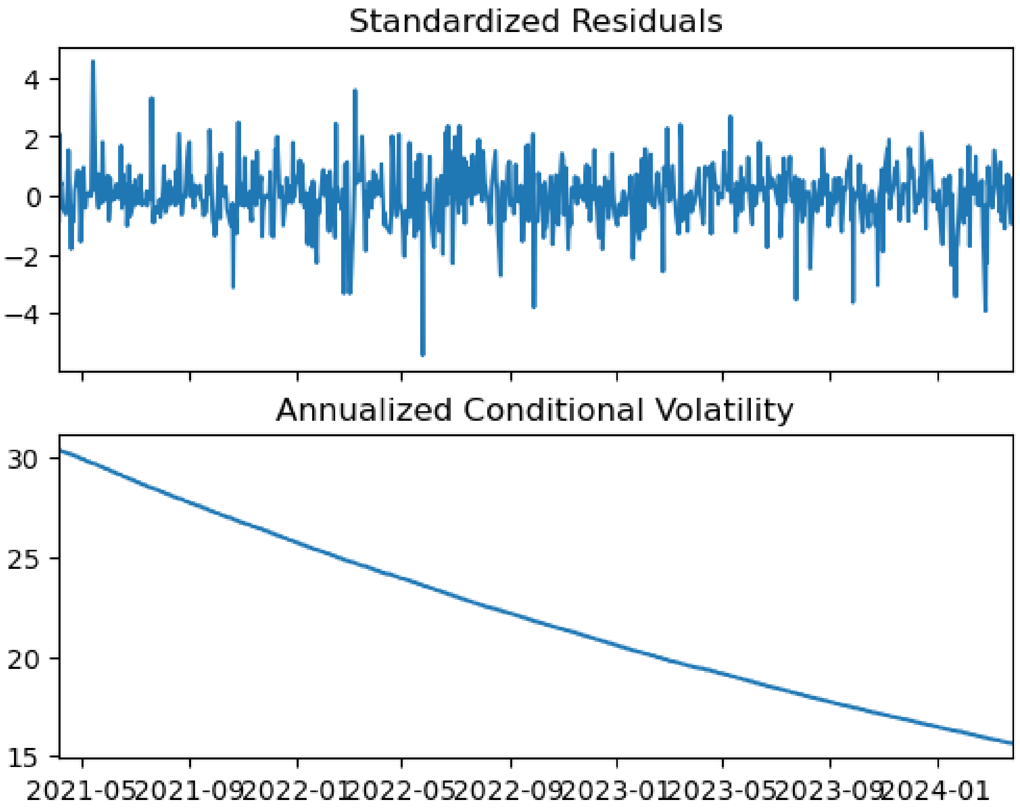
Volatility Plot:

The plot titled "Conditional Volatility (GARCH)" displays the estimated conditional volatility over time. It shows a consistent decline over the period analyzed. This pattern could indicate a decrease in the volatility of returns over time, which might be attributed to stabilizing market conditions, effective risk management strategies, or diminishing impacts of previous high-volatility events.

Interpretation and Use:

The significant beta parameter and the non-significant alpha parameter in the GARCH model suggest that the volatility clustering in the stock price returns is primarily influenced by long-term components rather than short-term shocks. This characteristic is vital for financial modeling as it implies that past levels of volatility are a better predictor of future volatility than recent abrupt changes. Investors and financial analysts can use these insights to anticipate potential risk levels and adjust their strategies accordingly, especially in long-term planning and risk assessment. The declining trend in volatility, as shown in the plot, may also influence decisions regarding timing for entry or exit in investments.

Standardized residuals and annualized conditional volatility derived from a GARCH model



Standardized Residuals Plot:

- **Plot Description:** This plot displays the standardized residuals from the GARCH model across time. Standardized residuals are the deviations of the observed returns from their expected values, scaled by the estimated standard deviation (volatility).
- **Interpretation:** Ideally, standardized residuals should resemble white noise, meaning they should be randomly distributed with a mean close to zero and constant variance. The plot shows residuals fluctuating between approximately -4 and +4 without any clear patterns or trends, suggesting that the model has adequately captured the dynamics of the returns series. Occasional spikes beyond these bounds might indicate outliers or extreme events not fully accounted for by the model.

Annualized Conditional Volatility Plot:

- **Plot Description:** This graph shows the estimated annualized conditional volatility over time. Annualized volatility is the square root of the estimated conditional variance from the GARCH model, scaled to reflect an annual timeframe.
- **Interpretation:** The plot exhibits a steady decline in volatility from a high of around 30 to below 15 over the observed period. This declining trend might reflect diminishing uncertainty or risk associated with the asset over time, possibly due to stabilizing market conditions, effective risk management, or reduced impact of previous shocks.

Combined Analysis:

- **Volatility Interpretation:** The decline in annualized volatility suggests that the market's perception of risk associated with the asset has decreased. This might be used by investors to adjust their risk premiums and by companies to evaluate their cost of capital over time.
- **Residual Analysis:** The behavior of the residuals indicates that the GARCH model has effectively normalized the returns series, removing heteroskedasticity (changing variance). This is crucial for accurate forecasting and risk assessment because it implies that the model residuals do not contain predictable structures that could otherwise be exploited for better predictions or risk assessments.

PART B:

ADF Test Results:

```python
    # Check if the p-value is greater than 0.05 (commonly used threshold)
    if p_value > 0.05:
        non_stationary_count += 1
        non_stationary_columns.append(col)
    else:
        stationary_columns.append(col)
```

```
ADF test result for column: crude_brent
ADF Statistic: -1.5078661910935343
p-value: 0.5296165197702398

ADF test result for column: soybeans
ADF Statistic: -2.42314645274189
p-value: 0.13530977427790403

ADF test result for column: gold
ADF Statistic: 1.3430517021933006
p-value: 0.9968394353612382

ADF test result for column: silver
ADF Statistic: -1.397294710746222
p-value: 0.5835723787985764

ADF test result for column: urea_ee_bulk
ADF Statistic: -2.5101716315209086
p-value: 0.11301903181624645

ADF test result for column: maize
ADF Statistic: -2.4700451060920425
p-value: 0.12293380919376751
```

```
## ###############################################
## # Augmented Dickey-Fuller Test Unit Root Test #
## ###############################################
##
## Test regression none
##
##
## Call:
## lm(formula = z.diff ~ z.lag.1 - 1 + z.diff.lag)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -20.9037  -0.5974   0.0050   1.1470  16.6539
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## z.lag.1    -0.003064   0.002755  -1.112    0.266
## z.diff.lag  0.339145   0.033979   9.981   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 3.579 on 770 degrees of freedom
## Multiple R-squared:  0.1148, Adjusted R-squared:  0.1125
## F-statistic: 49.92 on 2 and 770 DF,  p-value: < 2.2e-16
##
##
## Value of test-statistic is: -1.1122
##
## Critical values for test statistics:
##       1pct  5pct 10pct
## tau1 -2.58 -1.95 -1.62
##
##
## ADF test result for column: soybeans
##
```

The Augmented Dickey-Fuller (ADF) test is used to test for stationarity in the time series data of each commodity:

- Most commodities (crude_brent, soybeans, gold, silver, urea_ee_bulk, maize) show p-values greater than 0.05, indicating that the null hypothesis of a unit root (non-stationarity) cannot be rejected at conventional significance levels. This suggests that these time series are non-stationary and may require differencing or other transformations to achieve stationarity.

Johansen Cointegration Test:

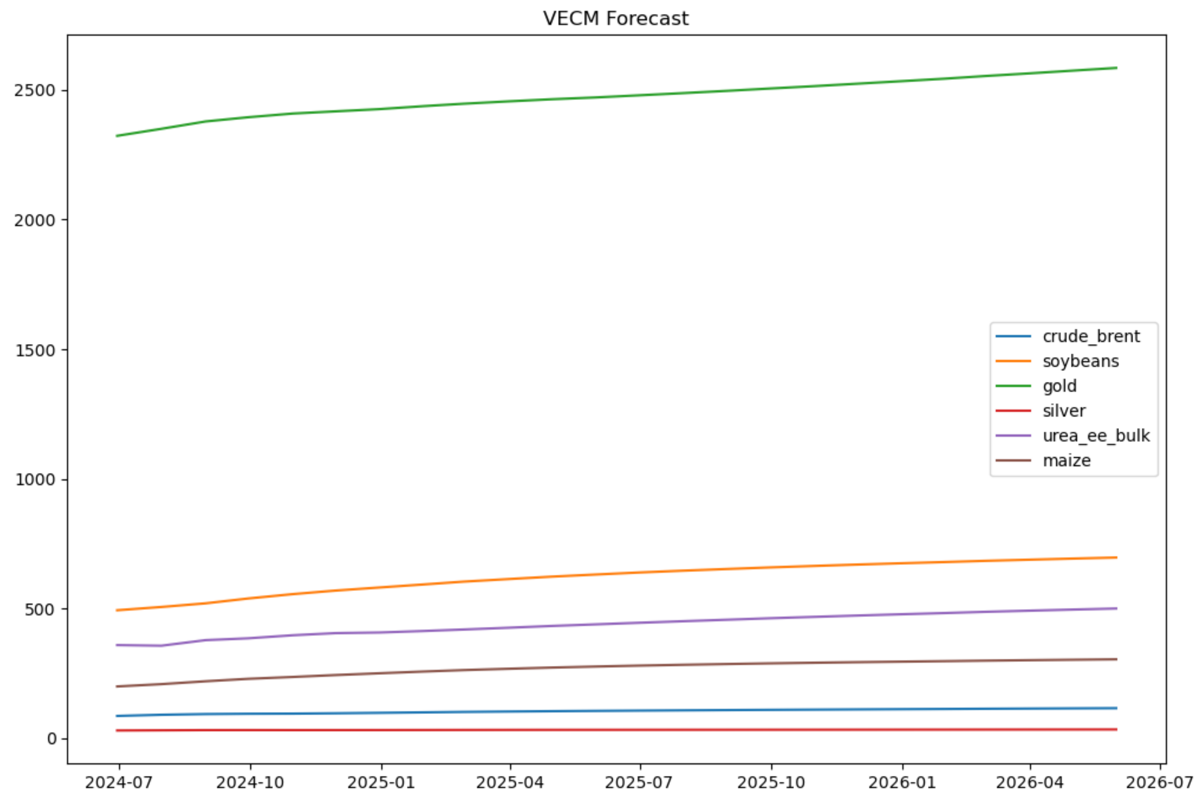
```python
In [16]: # Perform Johansen cointegration test
         coint_test = johansen_test(commodity_data)
```

```
Trace statistic: [261.5548149  167.67790177  98.11781369  53.4617083   21.6404865
   4.01416422]
Critical values: [95.7542 69.8189 47.8545 29.7961 15.4943  3.8415]
Eigenvalues: [0.11449947 0.08616362 0.05620349 0.04038124 0.02257335 0.0051862 ]
crude_brent is cointegrated.
soybeans is cointegrated.
gold is cointegrated.
silver is cointegrated.
urea_ee_bulk is cointegrated.
maize is cointegrated.
```

This test is used to determine the presence of a long-term equilibrium relationship among several non-stationary time series:

- The trace statistic values are well above the critical values for crude_brent, soybeans, gold, silver, urea_ee_bulk, and maize, indicating that these commodities are cointegrated, i.e., they share a long-term equilibrium relationship.
- The eigenvalues associated with each cointegrating equation suggest the strength and number of cointegrating relationships.

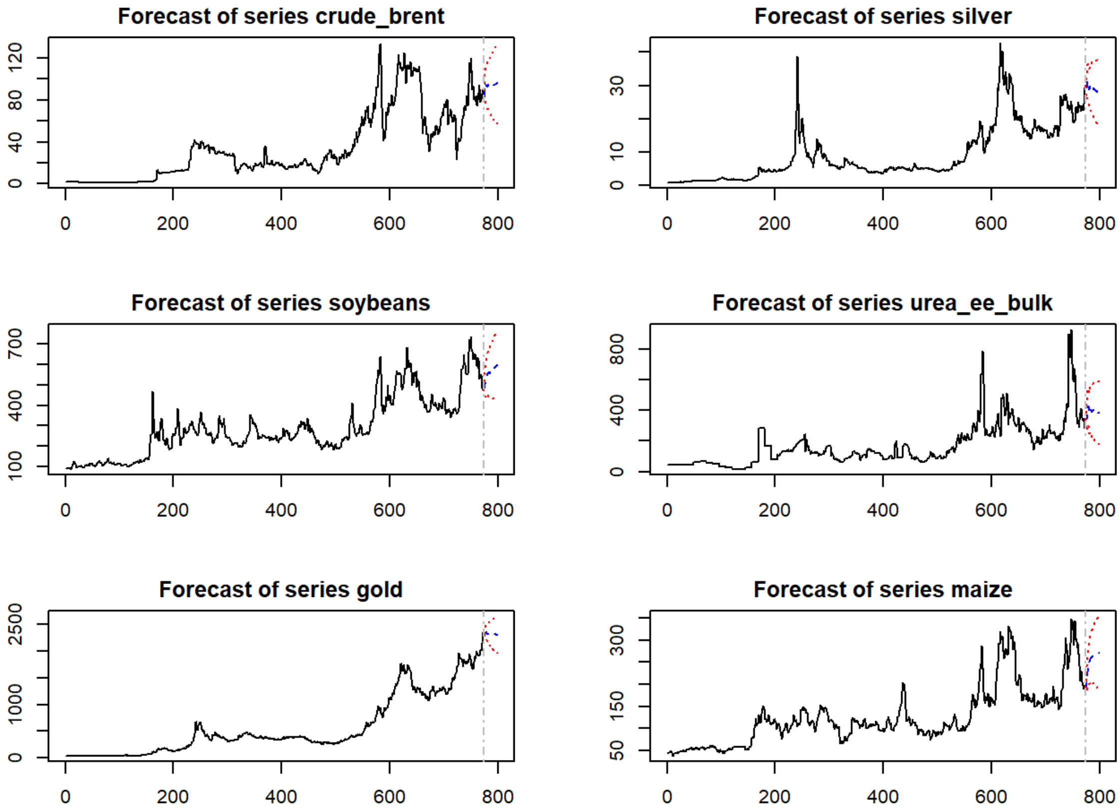
VECM Forecast:

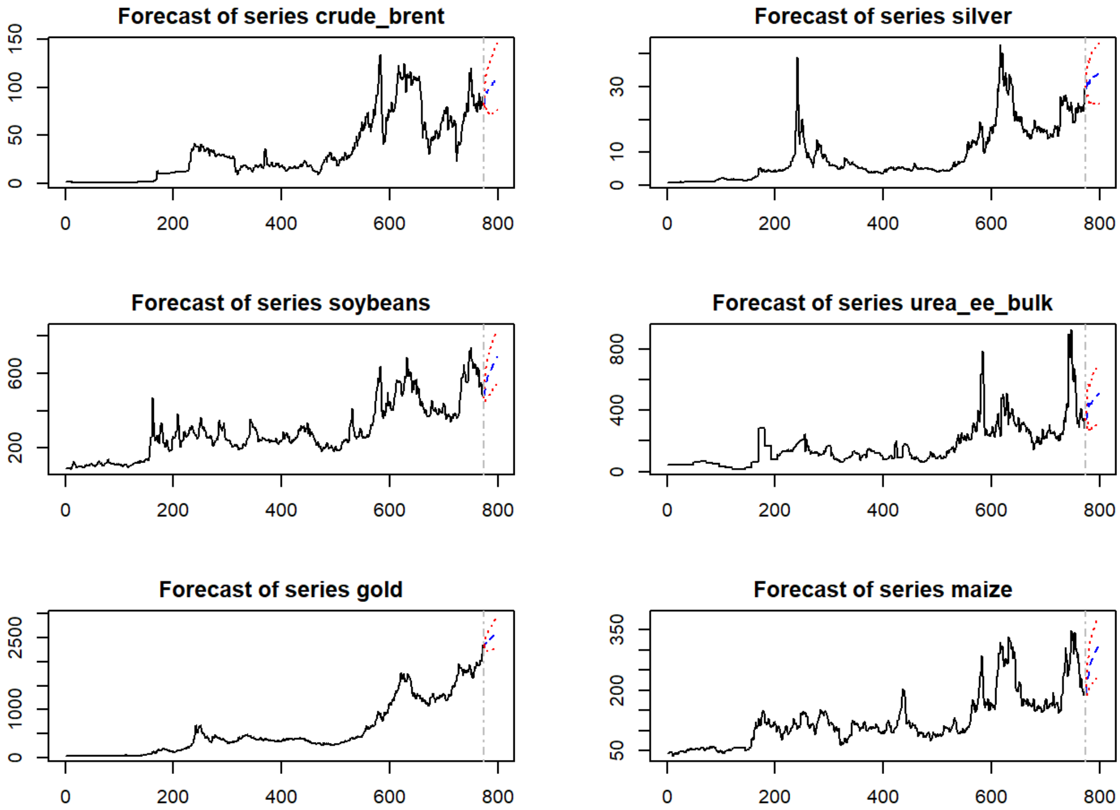


The Vector Error Correction Model (VECM) forecast plot shows the expected future values of the commodities. The forecast indicates that crude_brent is expected to show a significant upward trend, while other commodities (soybeans, gold, silver, urea_ee_bulk, maize) are projected to remain relatively stable or show modest increases.

VAR Model Summary:

```
  Summary of Regression Results
==================================
Model:                         VAR
Method:                        OLS
Date:           Thu, 25, Jul, 2024
Time:                     22:30:53
--------------------------------------------------------------------
No. of Equations:         6.00000    BIC:                    26.7336
Nobs:                     768.000    HQIC:                   25.9079
Log likelihood:          -16066.7    FPE:                1.06530e+11
AIC:                      25.3912    Det(Omega_mle):     8.03276e+10
--------------------------------------------------------------------
Results for equation crude_brent
==================================================================================
```





The VAR model summary shows the overall fit of a vector autoregression model:

- **Log Likelihood:** The log likelihood is significantly negative, indicating the model fits the data with considerable explanatory power.
- **AIC and BIC:** The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) provide measures of the model's goodness of fit, adjusting for the number of parameters. The values suggest that the model is adequately complex to capture the relationships among the series.
- **Det(Omega_mle):** This determinant of the omega matrix indicates the variability captured by the model across the different equations.

RECOMMENDATIONS

Based on the analyses conducted and the results obtained, here are some recommendations for various stakeholders involved with these commodities:

1. Risk Management

- **Implement Dynamic Hedging Strategies:** Given the volatility forecasted for crude_brent and the relative stability of other commodities like soybeans, gold, and silver, it is advisable for traders and financial managers to employ dynamic hedging strategies. These strategies should adjust to the changing volatility and correlations observed in the VECM and VAR analyses to protect against undesirable shifts in commodity prices.
- **Enhance Liquidity Reserves:** For companies reliant on these commodities, particularly in sectors like agriculture (soybeans, maize) and energy (crude_brent), maintaining higher liquidity reserves during periods of forecasted higher volatility could mitigate potential financial distress.

2. Investment Strategies

- **Diversify Portfolios:** Investors should consider diversifying their portfolios to include a mix of commodities that show different levels of volatility and trends as forecasted. For instance, mixing stable investments like gold and silver with potentially high-return commodities like crude_brent could balance risk and reward effectively.
- **Long-term Positioning in Crude Brent:** Given the upward trend forecasted for crude_brent, long-term investments in this commodity might be advantageous. However, continuous monitoring and adjustment based on updated forecasts and economic indicators are crucial to capitalize on this trend.

3. Strategic Planning for Businesses

- **Procurement Strategies:** Businesses that depend on these commodities for production should revise their procurement strategies based on the forecasted trends. For example, securing long-term contracts at current prices for commodities expected to increase in value like crude_brent could be beneficial.

- **Budget Adjustments:** Adjust budgets to accommodate expected changes in commodity prices, especially for businesses in agriculture and energy sectors. Planning for higher input costs when increases are forecasted (e.g., urea for fertilizers) will help in maintaining profitability.

4. Policy Formulation

- **Policy Interventions:** Governments should consider formulating or adjusting policies to stabilize local markets affected by global commodity price changes. This could involve subsidies, tariffs, or strategic reserves, particularly for essential commodities like maize and soybeans.
- **Support for Research and Development:** Encouraging innovation in alternative technologies, especially in energy (to reduce reliance on crude oil) and agriculture (to enhance crop yields and reduce dependency on specific fertilizers like urea), could mitigate the long-term risks associated with commodity price volatility.

5. Monitoring and Continuous Analysis

- **Regular Market Analysis Updates:** Regularly update econometric models with new data to refine forecasts and adjust strategies accordingly. This proactive approach will enable stakeholders to stay ahead of market trends and manage risks more effectively.
- **Enhanced Analytical Capabilities:** Invest in developing in-house or collaborative analytical capabilities to continuously monitor commodity markets, using advanced econometric and machine learning techniques to predict trends and volatilities more accurately.