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**VIRGINIA COMMONWEALTH UNIVERSITY**

**Statistical Analysis and Modelling (SCMA 632)**

**A6b: ARCH GARCH, VAR AND VECM**

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**CONTENTS**

|  |  |  |
| --- | --- | --- |
| **Sl. No.** | **Title** | **Page No.** |
| **1.** | **Introduction** | **1** |
| **2.** | **Business Significance** | **1** |
| **3.** | **Objectives** | **1** |
| **4.** | **R** | **2** |
| **5.** | **Python** | **45** |
| **6.** | **Overview** | **85** |

**QUESTION B: − VAR, VECM model**

**− [data “commodity prices”] for ex: Oil, Sugar, Gold, Silver, Wheat and Soyabean**

**- data source pink sheet from world bank**

**Introduction**

The analysis aims to explore the dynamics of selected commodity prices using historical data obtained from the "pinksheet.xlsx" dataset. By focusing on two distinct sets of variables, we seek to understand the trends, patterns, and volatility inherent in the commodity markets. This analysis involves the application of time series analysis techniques, including the Augmented Dickey-Fuller (ADF) test, to assess stationarity and the potential for modeling future price movements. The insights derived from this study are crucial for investors, analysts, and policymakers involved in the commodities market.

**Business Significance**

1. **Investment Decisions:** Accurate analysis and forecasting of commodity prices help investors make informed decisions about buying, holding, or selling commodities. Understanding price trends and volatility can optimize investment portfolios and enhance returns.
2. **Risk Management:** Financial analysts and portfolio managers depend on precise price predictions to manage risks associated with commodities investments. Insights into future price movements aid in developing hedging strategies to mitigate market risks.
3. **Market Analysis:** Companies and financial institutions analyze commodity price trends to evaluate market performance and position. Comparing trends across different commodities provides valuable insights into market dynamics and competitive advantages.
4. **Strategic Planning:** Businesses utilize commodity price trends for strategic planning, including decisions on mergers and acquisitions, capital investments, and corporate restructuring. Understanding price movements informs strategic financial decisions.
5. **Policy Making:** Regulatory bodies and policymakers monitor commodity price trends to ensure market stability and integrity. Analyzing commodity performance helps in crafting policies that promote fair trading practices and protect investor interests.
6. **Resource Allocation:** Businesses assess commodity price trends to guide decisions on resource allocation, operational expansions, and market entry strategies. A clear understanding of price dynamics aids in efficient allocation of resources.

**Objectives**

1. **Data Collection and Cleaning:** Download and clean historical commodity price data from the "pinksheet.xlsx" dataset, ensuring data integrity and completeness.
2. **Stationarity Check:** Perform the Augmented Dickey-Fuller (ADF) test to check for stationarity in the commodity price data, indicating whether the data can be modeled effectively.
3. **Time Series Analysis:** Apply time series analysis techniques to model the dynamics of commodity prices over time, capturing trends and patterns.
4. **Model Fitting:** Fit appropriate time series models to the data, such as ARIMA, to capture the underlying price movements and volatility.
5. Volatility Forecasting: Use the fitted models to forecast the volatility of commodity prices for the next period, providing insights into future risk and uncertainty.
6. **Business Insights and Recommendations:** Translate the analytical findings into actionable insights for investors, businesses, and policymakers. Provide recommendations based on forecasted trends and patterns, highlighting potential opportunities and risks.

By achieving these objectives, this analysis aims to deliver a comprehensive understanding of commodity price dynamics, offering valuable insights that can enhance investment strategies, risk management practices, and strategic business decisions.

**Code Analysis**

**R Language**

**Part 1: Setting Up the Environment**

# Set working directory and load necessary libraries

setwd('C:\\Users\\nihar\\OneDrive\\Desktop\\Bootcamp\\SCMA 632\\DataSet')

getwd()

# Load necessary libraries

library(readxl)

library(dplyr)

library(janitor)

library(urca)

library(vars)

library(ggplot2)

# Clear all graphics devices

graphics.off()

**Purpose**:

* setwd('...') sets the working directory to the specified path.
* getwd() prints the current working directory.
* library(...) loads the necessary R libraries:
  + readxl for reading Excel files.
  + dplyr for data manipulation.
  + janitor for cleaning data.
  + urca for unit root tests.
  + vars for vector autoregressive models.
  + ggplot2 for data visualization.
* graphics.off() clears all graphics devices to ensure no previous plots are open.

**Output**:

[1] "C:/Users/nihar/OneDrive/Desktop/Bootcamp/SCMA 632/DataSet"

**Interpretation:**

* The working directory is set to the specified path.
* The necessary libraries for data manipulation, cleaning, statistical testing, and plotting are loaded.
* All graphics devices are cleared to ensure no previous plots interfere with new ones.

**Part 2: Loading and Preparing the Dataset**

# Load the dataset

df <- read\_excel('pinksheet.xlsx', sheet = "Monthly Prices", skip = 6)

# Rename the first column to "Date"

colnames(df)[1] <- 'Date'

# Convert the Date column to Date format

df$Date <- as.Date(paste0(df$Date, "01"), format = "%YM%m%d")

str(df)

**Purpose**:

* read\_excel('pinksheet.xlsx', sheet = "Monthly Prices", skip = 6) reads the specified sheet from the Excel file, skipping the first 6 rows.
* colnames(df)[1] <- 'Date' renames the first column to "Date".
* as.Date(paste0(df$Date, "01"), format = "%YM%m%d") converts the "Date" column to a Date format, assuming the data represents monthly dates.
* str(df) prints the structure of the dataframe.

**Output**:

tibble [774 × 72] (S3: tbl\_df/tbl/data.frame)

$ Date : Date[1:774], format: "1960-01-01" "1960-02-01" ...

$ CRUDE\_PETRO : num [1:774] 1.63 1.63 1.63 1.63 1.63 ...

$ CRUDE\_BRENT : num [1:774] 1.63 1.63 1.63 1.63 1.63 ...

# ... (other columns)

**Interpretation:**

* The dataset is loaded from the 'pinksheet.xlsx' file, specifically from the "Monthly Prices" sheet, skipping the first 6 rows.
* The first column is renamed to "Date" and converted to Date format.
* The str(df) command shows the structure of the dataframe, which has 774 rows and 72 columns, with the "Date" column properly formatted.

**Part 3: Selecting and Cleaning Data**

# Select specific columns (Date and selected commodities)

commodity <- df[,c(1,3,25,70,72,61,31)] %>%

clean\_names()

str(commodity)

**Purpose**:

* df[,c(1,3,25,70,72,61,31)] selects specific columns from the dataframe.
* clean\_names() cleans column names (e.g., converts them to lowercase and replaces spaces with underscores).

**Output:**

tibble [774 × 7] (S3: tbl\_df/tbl/data.frame)

$ date : Date[1:774], format: "1960-01-01" "1960-02-01" ...

$ crude\_brent : num [1:774] 1.63 1.63 1.63 1.63 1.63 ...

$ soybeans : num [1:774] 94 91 92 93 93 91 92 93 92 88 ...

$ gold : num [1:774] 35.3 35.3 35.3 35.3 35.3 ...

$ silver : num [1:774] 0.914 0.914 0.914 0.914 0.914 ...

$ urea\_ee\_bulk: num [1:774] 42.2 42.2 42.2 42.2 42.2 ...

$ maize : num [1:774] 45 44 45 45 48 47 47 47 46 42 ...

**Interpretation:**

* Selected specific columns from the dataset: "Date", "CRUDE\_BRENT", "SOYBEANS", "GOLD", "SILVER", "UREA\_EE\_BULK", and "MAIZE".
* The column names are cleaned to be in a consistent, lower-case format.
* The str(commodity) command shows the structure of the commodity dataframe, which has 774 rows and 7 columns.

**Part 4: Checking Column Names and Missing Values**

# Check column names

colnames(commodity)

# Check for missing values

missing\_values <- sapply(commodity, function(x) sum(is.na(x)))

missing\_values

**Purpose**:

* colnames(commodity) prints the column names of the dataframe.
* sapply(commodity, function(x) sum(is.na(x))) checks for missing values in each column of the dataframe.

**Output**:

[1] "date" "crude\_brent" "soybeans" "gold" "silver"

[6] "urea\_ee\_bulk" "maize"

date crude\_brent soybeans gold silver urea\_ee\_bulk

0 0 0 0 0 0

maize

0

**Interpretation:**

* The column names are displayed as expected: "date", "crude\_brent", "soybeans", "gold", "silver", "urea\_ee\_bulk", "maize".
* There are no missing values in any of the selected columns, as indicated by the zeros in the missing\_values output.

**Part 5: Mapping Column Names to Readable Names**

# Mapping of column names to more readable commodity names

commodity\_names <- c(

crude\_brent = "Crude Brent",

soybeans = "Soybeans",

gold = "Gold",

silver = "Silver",

urea\_ee\_bulk = "Urea EE Bulk",

maize = "Maize"

)

# Print column names and corresponding readable names for debugging

print("Column names and corresponding readable names:")

for (col in names(commodity)[-1]) {

print(paste(col, ":", commodity\_names[[col]]))

}

**Purpose**:

* commodity\_names creates a named vector mapping column names to more readable names.
* A loop prints each column name and its corresponding readable name for debugging purposes.

**Output**:

[1] "Column names and corresponding readable names:"

[1] "crude\_brent : Crude Brent"

[1] "soybeans : Soybeans"

[1] "gold : Gold"

[1] "silver : Silver"

[1] "urea\_ee\_bulk : Urea EE Bulk"

[1] "maize : Maize"

**Interpretation:**

* The column names are mapped to more readable names for better understanding.
* The readable names for each column are printed for verification.

 **Part 6: Visualizing Data**

# Visualize data directly

for (col in names(commodity)[-1]) { # Skip the date column

print(col) # Print column name for debugging

p <- ggplot(commodity, aes\_string(x = "date", y = col)) +

geom\_line() +

labs(title = paste("Price of", commodity\_names[[col]]), x = "Date", y = "Price") +

theme\_minimal()

# Print the plot to display it

print(p)

}

**Purpose**:

* Loops through each commodity column (excluding "date") and plots its time series using ggplot2.
* Each plot displays the price of the commodity over time.

**Output**:

* The column names are printed for debugging: "crude\_brent", "soybeans", "gold", "silver", "urea\_ee\_bulk", "maize".
* A graph showing a graph of a graph

  Description automatically generated with medium confidenceA graph showing a graph of a number of beans

  Description automatically generated with medium confidenceA graph showing a graph

  Description automatically generatedA graph showing a graph

  Description automatically generatedEach plot shows the price trends of the commodities over time, with titles indicating the specific commodity.

A graph showing a graph

Description automatically generatedA graph showing a graph of a graph

Description automatically generated with medium confidence

**Interpretation:**

1. **Crude Brent**:
   * **Historical Trend**: Shows significant fluctuations with notable peaks around the early 2000s and mid-2010s. There is a noticeable increase in price starting in the early 2000s, followed by several periods of high volatility.
2. **Soybeans**:
   * **Historical Trend**: Exhibits periodic fluctuations with several peaks. There is a notable increase in volatility starting in the early 2000s, with prices reaching highs in the mid-2010s and recent years.
3. **Gold**:
   * **Historical Trend**: Shows a steady increase in price with some fluctuations. A significant upward trend begins around 2005, with a sharp increase in recent years, reaching an all-time high.
4. **Silver**:
   * **Historical Trend**: Similar to gold, silver exhibits fluctuations with a significant spike around 1980 and another around 2011. There is a general upward trend in recent years.
5. **Urea EE Bulk**:
   * **Historical Trend**: Shows high volatility with significant spikes around 2008 and again in the early 2020s. Prices have experienced several peaks and troughs over the past few decades.
6. **Maize**:
   * **Historical Trend**: Exhibits periodic fluctuations with a general upward trend. Prices have been particularly volatile since the early 2000s, with notable peaks in the mid-2010s and recent years.

* **Volatility**: All commodities show periods of high volatility, particularly in recent years.
* **Upward Trends**: Commodities like gold and crude brent show clear long-term upward trends.
* **Spikes and Peaks**: Silver, urea ee bulk, and maize show significant spikes at various points, indicating periods of rapid price increases.
* **Economic Events**: The trends reflect economic events, market demands, and other external factors influencing commodity prices over time.

**Part 7: Preparing Data for VAR and VECM Analysis**

# Prepare data for VAR and VECM analysis

commodity\_data <- dplyr::select(commodity, -date)

columns\_to\_test <- names(commodity\_data)

**Purpose**:

* dplyr::select(commodity, -date) selects all columns except "date" for analysis.
* columns\_to\_test <- names(commodity\_data) stores the names of these columns for further analysis.

**Output**:

* commodity\_data now contains all the selected columns except for the "date" column.
* columns\_to\_test lists the names of the columns to be tested for stationarity.

**Interpretation:**

* The data is prepared by excluding the date column, making it suitable for statistical tests and model building.

**Part 8: Stationarity Test**

# Stationary test

non\_stationary\_count <- 0

stationary\_columns <- c()

non\_stationary\_columns <- c()

for (col in columns\_to\_test) {

adf\_result <- ur.df(commodity\_data[[col]], type = "none", selectlags = "AIC")

p\_value <- adf\_result@testreg$coefficients[2, 4]

cat("\nADF test result for column:", col, "\n")

print(summary(adf\_result))

if (p\_value > 0.05) {

non\_stationary\_count <- non\_stationary\_count + 1

non\_stationary\_columns <- c(non\_stationary\_columns, col)

} else {

stationary\_columns <- c(stationary\_columns, col)

}

}

cat("\nNumber of non-stationary columns:", non\_stationary\_count, "\n")

cat("Non-stationary columns:", paste(non\_stationary\_columns, collapse=", "), "\n")

cat("Stationary columns:", paste(stationary\_columns, collapse=", "), "\n")

**Purpose**:

* Performs Augmented Dickey-Fuller (ADF) tests for stationarity on each commodity column.
* Stores results indicating whether each column is stationary or non-stationary.

**Output**:

ADF test result for column: crude\_brent

###############################################

# 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

###############################################

# 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

-155.919 -5.963 0.738 6.366 98.018

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 -0.0009988 0.0021969 -0.455 0.649

z.diff.lag 0.1463247 0.0357081 4.098 4.61e-05 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 19.65 on 770 degrees of freedom

Multiple R-squared: 0.02141, Adjusted R-squared: 0.01887

F-statistic: 8.423 on 2 and 770 DF, p-value: 0.0002406

Value of test-statistic is: -0.4547

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

ADF test result for column: gold

###############################################

# 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

-120.209 -7.822 -0.123 7.203 205.516

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 0.003500 0.001358 2.577 0.0102 \*

z.diff.lag 0.207978 0.035496 5.859 6.89e-09 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 29.52 on 770 degrees of freedom

Multiple R-squared: 0.05795, Adjusted R-squared: 0.05551

F-statistic: 23.69 on 2 and 770 DF, p-value: 1.041e-10

Value of test-statistic is: 2.577

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

ADF test result for column: silver

###############################################

# 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

-9.3365 -0.1406 0.0052 0.2397 14.8616

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 -0.004015 0.003532 -1.137 0.256

z.diff.lag 0.285108 0.034680 8.221 8.54e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.212 on 770 degrees of freedom

Multiple R-squared: 0.08089, Adjusted R-squared: 0.0785

F-statistic: 33.88 on 2 and 770 DF, p-value: 7.874e-15

Value of test-statistic is: -1.1367

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

ADF test result for column: urea\_ee\_bulk

###############################################

# 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

-244.590 -0.837 0.913 5.203 287.017

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 -0.011276 0.005069 -2.225 0.0264 \*

z.diff.lag 0.214902 0.035306 6.087 1.82e-09 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 30.67 on 770 degrees of freedom

Multiple R-squared: 0.0495, Adjusted R-squared: 0.04703

F-statistic: 20.05 on 2 and 770 DF, p-value: 3.243e-09

Value of test-statistic is: -2.2248

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

ADF test result for column: maize

###############################################

# 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

-50.110 -2.637 0.164 3.343 66.665

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 -0.001671 0.002228 -0.750 0.453

z.diff.lag 0.240599 0.035031 6.868 1.34e-11 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 8.791 on 770 degrees of freedom

Multiple R-squared: 0.05792, Adjusted R-squared: 0.05547

F-statistic: 23.67 on 2 and 770 DF, p-value: 1.058e-10

Value of test-statistic is: -0.75

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

>

> cat("\nNumber of non-stationary columns:", non\_stationary\_count, "\n")

Number of non-stationary columns: 0

> cat("Non-stationary columns:", paste(non\_stationary\_columns, collapse=", "), "\n")

Non-stationary columns:

> cat("Stationary columns:", paste(stationary\_columns, collapse=", "), "\n")

Stationary columns: crude\_brent, soybeans, gold, silver, urea\_ee\_bulk, maize

>

**Interpretation:**

**ADF Test for Crude Brent**

* **Purpose**: To test if the crude\_brent column has a unit root (i.e., is non-stationary).
* **Test Statistic**: -1.1122
* **Critical Values**: -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result**: The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root. crude\_brent is considered non-stationary.

**ADF Test for Soybeans**

* **Purpose**: To test if the soybeans column has a unit root.
* **Test Statistic**: -0.4547
* **Critical Values**: -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result**: The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root. soybeans is considered non-stationary.

**ADF Test for Gold**

* **Purpose**: To test if the gold column has a unit root.
* **Test Statistic**: 2.577
* **Critical Values**: -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result**: The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root. gold is considered non-stationary.

**ADF Test for Silver**

* **Purpose**: To test if the silver column has a unit root.
* **Test Statistic**: -1.1367
* **Critical Values**: -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result**: The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root. silver is considered non-stationary.

**ADF Test for Urea EE Bulk**

* **Purpose**: To test if the urea\_ee\_bulk column has a unit root.
* **Test Statistic**: -2.2248
* **Critical Values**: -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result**: The test statistic is very close to the critical values at the 5% level. Therefore, it is marginally non-stationary.

**ADF Test for Maize**

* **Purpose**: To test if the maize column has a unit root.
* **Test Statistic**: -0.75
* **Critical Values**: -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result**: The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root. maize is considered non-stationary.

**Part 9: Co-Integration Test (Johansen's Test)**

# Co-Integration Test (Johansen's Test)

lags <- VARselect(commodity\_data, lag.max = 10, type = "const")

lag\_length <- lags$selection[1]

vecm\_model <- ca.jo(commodity\_data, ecdet = 'const', type = 'eigen', K = lag\_length, spec = 'transitory')

summary(vecm\_model)

r <- 3 # Replace with the actual number from the test results

**Purpose**:

* VARselect(commodity\_data, lag.max = 10, type = "const") selects the optimal lag length for the VAR model.
* ca.jo(...) performs the Johansen co-integration test.
* summary(vecm\_model) prints the summary of the co-integration test results.
* r <- 3 sets the number of co-integration relations based on the test results (this value should be replaced with the actual result).

**Output**:

######################

# Johansen-Procedure #

######################

Test type: maximal eigenvalue statistic (lambda max) , without linear trend and constant in cointegration

Eigenvalues (lambda):

[1] 8.998240e-02 5.752097e-02 3.735171e-02 2.608764e-02 2.251395e-02

[6] 1.054366e-02 -2.260796e-17

Values of teststatistic and critical values of test:

test 10pct 5pct 1pct

r <= 5 | 8.11 7.52 9.24 12.97

r <= 4 | 17.42 13.75 15.67 20.20

r <= 3 | 20.22 19.77 22.00 26.81

r <= 2 | 29.12 25.56 28.14 33.24

r <= 1 | 45.32 31.66 34.40 39.79

r = 0 | 72.13 37.45 40.30 46.82

Eigenvectors, normalised to first column:

(These are the cointegration relations)

crude\_brent.l1 soybeans.l1 gold.l1 silver.l1 urea\_ee\_bulk.l1

crude\_brent.l1 1.000000e+00 1.00000000 1.00000000 1.00000000 1.00000000

soybeans.l1 1.243452e+00 1.25304239 -0.07842408 -0.42565991 -0.07812369

gold.l1 -8.613082e-03 0.01252197 0.01895289 0.07014442 0.02089932

silver.l1 -1.070903e+01 0.61967846 -8.77188803 -3.26693838 -0.67265684

urea\_ee\_bulk.l1 -1.402966e+00 0.27382244 0.02886597 -0.06688680 -0.16795279

maize.l1 6.220737e-01 -3.92903372 0.58475577 0.22894154 0.13972070

constant -1.489974e+02 44.45252397 -20.86854041 59.02679846 6.82242441

maize.l1 constant

crude\_brent.l1 1.00000000 1.00000000

soybeans.l1 0.02283558 0.34711296

gold.l1 -0.08322472 -0.34922444

silver.l1 2.81300312 5.68870719

urea\_ee\_bulk.l1 -0.03897150 -0.05823248

maize.l1 -0.08400822 -0.19136095

constant -12.61427193 127.59393688

Weights W:

(This is the loading matrix)

crude\_brent.l1 soybeans.l1 gold.l1 silver.l1 urea\_ee\_bulk.l1

crude\_brent.d 0.002205903 -0.003704822 -0.014381733 -0.007891362 -6.895101e-03

soybeans.d -0.029558007 -0.025188870 -0.057121330 0.103346533 -1.358234e-02

gold.d -0.009056880 0.035918817 0.047780832 0.016758828 1.141409e-01

silver.d 0.001273763 0.001680978 0.003678001 0.002437596 4.024398e-05

urea\_ee\_bulk.d 0.080887762 0.006757410 -0.121231005 0.051484771 6.401763e-02

maize.d -0.013305363 0.020030509 -0.039752224 0.017974320 -1.632041e-02

maize.l1 constant

crude\_brent.d -0.010987446 -7.033640e-18

soybeans.d -0.029718135 -1.680915e-16

gold.d -0.088970341 6.203017e-19

silver.d -0.003923011 4.127846e-18

urea\_ee\_bulk.d 0.006050959 7.321021e-18

maize.d -0.008672063 4.315706e-17

**Interpretation:**

These are the eigenvalues obtained from the test. They indicate the strength of the cointegration relationships: [0.0899824,0.05752097,0.03735171,0.02608764,0.02251395,0.01054366,−2.260796e−17][0.0899824, 0.05752097, 0.03735171, 0.02608764, 0.02251395, 0.01054366, -2.260796e-17][0.0899824,0.05752097,0.03735171,0.02608764,0.02251395,0.01054366,−2.260796e−17]

**Test Statistics and Critical Values**

The test statistics for different ranks (r) are compared against critical values at the 10%, 5%, and 1% significance levels:

* **r ≤ 5**: Test Statistic = 8.11, Critical Values = [7.52, 9.24, 12.97]
* **r ≤ 4**: Test Statistic = 17.42, Critical Values = [13.75, 15.67, 20.20]
* **r ≤ 3**: Test Statistic = 20.22, Critical Values = [19.77, 22.00, 26.81]
* **r ≤ 2**: Test Statistic = 29.12, Critical Values = [25.56, 28.14, 33.24]
* **r ≤ 1**: Test Statistic = 45.32, Critical Values = [31.66, 34.40, 39.79]
* **r = 0**: Test Statistic = 72.13, Critical Values = [37.45, 40.30, 46.82]

The null hypothesis is rejected if the test statistic is greater than the critical value, indicating a cointegration relationship.

**Interpretation of Test Results**

* **r ≤ 5**: The test statistic (8.11) is less than the critical values, so we do not reject the null hypothesis.
* **r ≤ 4**: The test statistic (17.42) is greater than the 10% and 5% critical values but less than the 1% critical value, suggesting weak evidence against the null hypothesis.
* **r ≤ 3**: The test statistic (20.22) is greater than the 10% critical value but less than the 5% critical value, indicating some evidence against the null hypothesis.
* **r ≤ 2**: The test statistic (29.12) is greater than the 10% and 5% critical values but less than the 1% critical value, suggesting evidence against the null hypothesis.
* **r ≤ 1**: The test statistic (45.32) is greater than the 10%, 5%, and 1% critical values, indicating strong evidence against the null hypothesis.
* **r = 0**: The test statistic (72.13) is greater than the 10%, 5%, and 1% critical values, indicating very strong evidence against the null hypothesis.

**Eigenvectors (Cointegration Relations)**

These are normalized eigenvectors that represent the cointegration relations between the variables:

* The first column shows the normalized values for crude\_brent.l1.
* The relationships are shown for each variable (soybeans.l1, gold.l1, silver.l1, urea\_ee\_bulk.l1, maize.l1) with respect to crude\_brent.l1.

**Loading Matrix (Weights W)**

This matrix indicates the adjustment coefficients that show how much each variable contributes to the cointegration relation's deviation from equilibrium:

* For instance, crude\_brent.d has loading coefficients for each variable (soybeans.l1, gold.l1, silver.l1, urea\_ee\_bulk.l1, maize.l1, and constant).

**Part 10: VECM or VAR Model and Forecasting**

if (r > 0) {

vecm <- cajorls(vecm\_model, r = r)

summary(vecm)

vecm\_coefs <- vecm$rlm$coefficients

print(vecm\_coefs)

vecm\_pred <- vec2var(vecm\_model, r = r)

forecast <- predict(vecm\_pred, n.ahead = 24)

par(mar = c(4, 4, 2, 2))

plot(forecast)

} else {

var\_model <- VAR(commodity\_data, p = lag\_length, type = "const")

summary(var\_model)

causality\_results <- causality(var\_model)

print(causality\_results)

forecast <- predict(var\_model, n.ahead = 24)

par(mar = c(4, 4, 2, 2))

plot(forecast)

}

Forecast

**Purpose**:

* If r > 0, fits a VECM model and makes forecasts.
* If r == 0, fits a VAR model and makes forecasts.
* summary(...) prints the model summaries.
* predict(...) generates forecasts for the next 24 periods.
* plot(forecast) plots the forecasts.

**Output**:

crude\_brent.d soybeans.d gold.d silver.d

ect1 -0.0158806519 -0.1118682070 0.074642769 6.632743e-03

ect2 -0.0007714906 -0.0638369921 0.029998839 3.401756e-03

ect3 -0.0003379667 -0.0011434428 0.001433367 7.978687e-05

crude\_brent.dl1 0.3198283908 0.3443498978 0.121043855 2.204896e-03

soybeans.dl1 0.0093172490 0.0946812517 0.023832800 2.266201e-04

gold.dl1 0.0014187220 0.0259051649 0.240850545 -1.925821e-03

silver.dl1 -0.0702311281 -0.3670786368 1.096648147 3.773757e-01

urea\_ee\_bulk.dl1 -0.0042728692 -0.0147800933 -0.131875574 -2.688073e-03

maize.dl1 0.0126570488 0.2774658122 0.316400732 1.303847e-02

crude\_brent.dl2 -0.0543807904 0.0570272590 0.271334465 1.695307e-02

soybeans.dl2 0.0160512808 0.0601340870 0.027599349 -2.126802e-03

gold.dl2 -0.0039997611 -0.0462796646 -0.054729796 1.135936e-03

silver.dl2 0.0733443743 0.2095107503 -2.345899063 -2.709929e-01

urea\_ee\_bulk.dl2 0.0084573321 -0.0013708615 0.067900345 -8.696109e-04

maize.dl2 -0.0047730222 -0.0313026720 0.052487821 1.511212e-02

crude\_brent.dl3 -0.0658862685 0.1745431650 -0.553450734 -1.722384e-02

soybeans.dl3 -0.0081758922 -0.0715436852 -0.176953936 -5.080400e-03

gold.dl3 0.0051131197 0.0575792803 0.102435068 2.496593e-03

silver.dl3 0.0139092573 -1.2210599854 -1.326173881 -5.889158e-02

urea\_ee\_bulk.dl3 0.0067822105 -0.0069360327 -0.050361408 1.467902e-03

maize.dl3 0.0178297828 0.1256055189 0.520323763 1.406092e-02

crude\_brent.dl4 -0.0299127925 0.1041623330 -0.016988617 8.183038e-03

soybeans.dl4 0.0024366913 0.0403556917 0.080572018 -1.263501e-03

gold.dl4 0.0179737502 0.0007306947 0.015847245 3.079174e-03

silver.dl4 -0.1789303427 -0.7832719583 0.956766297 -8.117463e-03

urea\_ee\_bulk.dl4 0.0027173424 -0.0127145065 -0.025689547 -2.505806e-03

maize.dl4 -0.0156826169 -0.3089466262 -0.575382160 -1.279047e-02

crude\_brent.dl5 -0.0035036729 0.0295095928 -0.254315519 -2.304101e-02

soybeans.dl5 0.0122847464 -0.0461005127 -0.099821693 -3.050931e-03

gold.dl5 0.0030289385 -0.0366462183 0.063384512 2.247859e-03

silver.dl5 -0.0478173797 0.4858325948 0.948021683 -4.831702e-02

urea\_ee\_bulk.dl5 0.0049014229 0.0238110782 0.089526994 2.851273e-03

maize.dl5 0.0131477809 0.1115906501 0.125958649 1.213451e-02

crude\_brent.dl6 -0.1105647490 -0.1811455609 -0.381349463 -1.310430e-02

soybeans.dl6 -0.0129600962 0.0636882117 -0.034705436 -3.724711e-03

gold.dl6 0.0110837341 0.0816898200 -0.007079183 5.544855e-03

silver.dl6 -0.1599502063 -1.1233685147 -0.352025140 -1.527238e-01

urea\_ee\_bulk.dl6 -0.0096325667 -0.0768497829 -0.201590501 -6.392188e-03

maize.dl6 0.0204351084 -0.2810556882 -0.011389300 5.067805e-03

crude\_brent.dl7 0.0669967625 0.0158814806 0.703549166 3.365683e-02

soybeans.dl7 0.0241959969 0.0859053946 0.096430919 9.958651e-04

gold.dl7 -0.0104996643 -0.0389062306 -0.058660324 5.065125e-04

silver.dl7 0.0478475379 -0.8161422405 2.117496279 -1.204477e-02

urea\_ee\_bulk.dl7 0.0080766781 0.0383362565 0.047687315 1.939176e-03

maize.dl7 -0.0305981940 -0.0679239555 0.134038575 9.602403e-03

crude\_brent.dl8 0.0014255086 -0.2126227388 0.316115715 1.672963e-02

soybeans.dl8 0.0151701438 -0.0639231251 0.103234157 1.650484e-03

gold.dl8 0.0002213500 0.0720962498 -0.107703753 -3.395660e-03

silver.dl8 -0.0512928114 -0.3801434813 1.625579514 6.406983e-02

urea\_ee\_bulk.dl8 0.0017769052 -0.0071072398 -0.034845886 -1.866714e-03

maize.dl8 -0.0738082908 -0.0812941785 -0.251872139 -7.978703e-03

urea\_ee\_bulk.d maize.d

ect1 -0.033585833 -0.0330270781

ect2 0.118554785 0.0116720300

ect3 -0.002909754 -0.0003879978

crude\_brent.dl1 1.499259711 -0.0354210209

soybeans.dl1 0.009537724 0.0313077418

gold.dl1 0.067585152 -0.0317426664

silver.dl1 -4.995438936 0.2791645536

urea\_ee\_bulk.dl1 0.231475140 0.0176792561

maize.dl1 0.332391519 0.2575489439

crude\_brent.dl2 0.280305940 -0.0323154333

soybeans.dl2 0.041020951 0.0295125676

gold.dl2 0.080248753 -0.0354011853

silver.dl2 1.948995186 0.8924557916

urea\_ee\_bulk.dl2 -0.085177203 -0.0288240251

maize.dl2 -0.135008285 -0.0493948058

crude\_brent.dl3 1.029322404 -0.0789054044

soybeans.dl3 -0.163108185 0.0077021896

gold.dl3 -0.082295116 0.0211986247

silver.dl3 -0.450794423 -1.1278043762

urea\_ee\_bulk.dl3 0.049757460 0.0104523132

maize.dl3 0.117404149 0.0925260948

crude\_brent.dl4 -0.274404950 0.0541016953

soybeans.dl4 -0.198875094 0.0349163838

gold.dl4 0.036818089 -0.0244211644

silver.dl4 -0.958458463 0.7733981558

urea\_ee\_bulk.dl4 -0.061788868 -0.0209953579

maize.dl4 0.188666698 -0.0455863996

crude\_brent.dl5 0.089350785 -0.0094835225

soybeans.dl5 -0.079145072 -0.0019314510

gold.dl5 0.005663477 0.0179848934

silver.dl5 -0.207839445 -0.2694195836

urea\_ee\_bulk.dl5 0.110638890 0.0031901119

maize.dl5 -0.028266129 -0.0328377834

crude\_brent.dl6 0.710903461 -0.1214828809

soybeans.dl6 -0.279153795 0.0279709959

gold.dl6 0.122825483 0.0393349540

silver.dl6 -0.959142523 0.0680583177

urea\_ee\_bulk.dl6 -0.127589442 -0.0032344232

maize.dl6 0.651218378 -0.0637566333

crude\_brent.dl7 0.383860770 -0.0571667000

soybeans.dl7 0.187465251 0.0319340391

gold.dl7 0.163310130 -0.0563467450

silver.dl7 -3.815324482 0.4627059071

urea\_ee\_bulk.dl7 -0.096989493 0.0117623555

maize.dl7 -0.172901876 0.0025478083

crude\_brent.dl8 0.296360276 0.1329178532

soybeans.dl8 0.038395608 0.0071650089

gold.dl8 -0.092688286 0.0280014100

silver.dl8 2.151987492 -0.2780175638

urea\_ee\_bulk.dl8 0.131601941 -0.0200688723

maize.dl8 0.069442988 -0.0395611183

>

> forecast

$crude\_brent

fcst lower upper CI

[1,] 85.68931 79.22087 92.15775 6.46844

[2,] 89.88251 79.14847 100.61655 10.73404

[3,] 94.57387 80.55978 108.58797 14.01410

[4,] 94.93460 78.41473 111.45447 16.51987

[5,] 93.34287 74.80377 111.88197 18.53910

[6,] 92.20858 71.73919 112.67797 20.46939

[7,] 92.94050 70.88996 114.99103 22.05053

[8,] 94.77325 71.30152 118.24498 23.47173

[9,] 94.83322 70.14375 119.52268 24.68946

[10,] 93.82452 67.99767 119.65137 25.82685

[11,] 93.36246 66.41221 120.31271 26.95025

[12,] 94.30561 66.22630 122.38493 28.07932

[13,] 95.14372 65.99352 124.29392 29.15020

[14,] 94.53197 64.38855 124.67539 30.14342

[15,] 94.05402 62.96481 125.14324 31.08921

[16,] 94.27725 62.28188 126.27263 31.99538

[17,] 94.46390 61.61975 127.30806 32.84416

[18,] 94.33047 60.68911 127.97183 33.64136

[19,] 94.30773 59.88289 128.73257 34.42484

[20,] 94.76139 59.55744 129.96534 35.20395

[21,] 95.21078 59.23712 131.18443 35.97366

[22,] 95.44559 58.72038 132.17080 36.72521

[23,] 95.61691 58.14730 133.08653 37.46962

[24,] 95.87576 57.66651 134.08500 38.20925

$soybeans

fcst lower upper CI

[1,] 495.8007 459.7146 531.8867 36.08606

[2,] 501.8366 447.4817 556.1916 54.35499

[3,] 510.9071 441.8247 579.9895 69.08242

[4,] 522.6587 442.0961 603.2213 80.56263

[5,] 537.7639 448.2049 627.3229 89.55899

[6,] 551.0853 454.0797 648.0909 97.00560

[7,] 555.6567 452.4319 658.8816 103.22483

[8,] 561.4269 452.3478 670.5059 109.07904

[9,] 559.4513 445.5901 673.3126 113.86128

[10,] 557.5198 439.2134 675.8261 118.30635

[11,] 560.7289 438.1449 683.3129 122.58402

[12,] 564.4312 437.7488 691.1135 126.68233

[13,] 568.7961 438.2415 699.3507 130.55456

[14,] 570.2805 435.8262 704.7348 134.45425

[15,] 571.3540 433.1089 709.5992 138.24517

[16,] 574.2451 432.1347 716.3555 142.11040

[17,] 578.3441 432.3149 724.3734 146.02923

[18,] 581.8634 431.9368 731.7901 149.92662

[19,] 584.0127 430.1470 737.8784 153.86572

[20,] 586.3722 428.6208 744.1235 157.75135

[21,] 589.0624 427.4117 750.7132 161.65078

[22,] 591.8112 426.2859 757.3365 165.52529

[23,] 593.9166 424.5350 763.2982 169.38159

[24,] 595.5702 422.3716 768.7688 173.19859

$gold

fcst lower upper CI

[1,] 2316.562 2264.128 2368.997 52.43436

[2,] 2333.922 2248.892 2418.952 85.03001

[3,] 2357.978 2250.973 2464.983 107.00513

[4,] 2359.955 2234.791 2485.119 125.16382

[5,] 2354.973 2212.859 2497.087 142.11394

[6,] 2330.108 2169.530 2490.685 160.57755

[7,] 2320.676 2143.265 2498.087 177.41090

[8,] 2333.575 2140.710 2526.441 192.86580

[9,] 2341.985 2136.019 2547.950 205.96575

[10,] 2335.896 2117.727 2554.065 218.16862

[11,] 2326.315 2096.891 2555.739 229.42381

[12,] 2329.158 2088.890 2569.426 240.26765

[13,] 2334.535 2083.792 2585.277 250.74273

[14,] 2331.602 2071.335 2591.868 260.26646

[15,] 2325.457 2056.232 2594.681 269.22478

[16,] 2324.277 2046.226 2602.329 278.05141

[17,] 2324.948 2038.115 2611.781 286.83305

[18,] 2321.797 2026.436 2617.158 295.36099

[19,] 2318.381 2014.803 2621.960 303.57887

[20,] 2317.620 2005.963 2629.277 311.65716

[21,] 2316.995 1997.409 2636.581 319.58643

[22,] 2314.562 1987.347 2641.776 327.21474

[23,] 2311.679 1977.072 2646.287 334.60760

[24,] 2310.050 1968.216 2651.885 341.83415

$silver

fcst lower upper CI

[1,] 29.26114 27.14253 31.37976 2.118618

[2,] 29.42781 25.90832 32.94731 3.519494

[3,] 30.44517 26.09117 34.79917 4.354000

[4,] 31.38229 26.48931 36.27526 4.892975

[5,] 31.25602 25.92443 36.58762 5.331595

[6,] 29.73141 23.97862 35.48420 5.752789

[7,] 28.92455 22.81320 35.03590 6.111353

[8,] 29.40978 22.95335 35.86621 6.456428

[9,] 29.81359 23.03606 36.59111 6.777526

[10,] 29.51079 22.41224 36.60935 7.098552

[11,] 29.14465 21.74553 36.54377 7.399119

[12,] 29.31240 21.62090 37.00391 7.691505

[13,] 29.50532 21.53369 37.47695 7.971634

[14,] 29.25366 21.02901 37.47832 8.224652

[15,] 28.90844 20.46221 37.35468 8.446235

[16,] 28.80893 20.16048 37.45738 8.648447

[17,] 28.72485 19.88636 37.56333 8.838487

[18,] 28.45548 19.43843 37.47253 9.017053

[19,] 28.23136 19.04119 37.42153 9.190171

[20,] 28.20680 18.84478 37.56882 9.362018

[21,] 28.19288 18.66172 37.72404 9.531159

[22,] 28.07371 18.37997 37.76744 9.693735

[23,] 27.95091 18.09947 37.80234 9.851435

[24,] 27.89906 17.89379 37.90433 10.005272

$urea\_ee\_bulk

fcst lower upper CI

[1,] 348.8463 298.6100 399.0827 50.23634

[2,] 343.2168 265.4379 420.9956 77.77885

[3,] 373.6174 278.2944 468.9405 95.32304

[4,] 419.2403 310.0115 528.4690 109.22873

[5,] 429.9561 311.5060 548.4062 118.45013

[6,] 402.2276 276.0342 528.4210 126.19338

[7,] 379.5084 246.9540 512.0629 132.55444

[8,] 388.0328 249.5542 526.5113 138.47858

[9,] 405.5387 260.4222 550.6553 145.11655

[10,] 400.6403 248.7877 552.4929 151.85261

[11,] 388.4258 229.9266 546.9250 158.49918

[12,] 391.6954 226.8126 556.5782 164.88281

[13,] 401.7647 231.1904 572.3390 170.57430

[14,] 406.5446 231.1257 581.9635 175.41890

[15,] 402.6896 223.0324 582.3468 179.65719

[16,] 395.7165 212.4132 579.0198 183.30326

[17,] 391.9528 205.2852 578.6204 186.66761

[18,] 390.1227 200.3662 579.8793 189.75657

[19,] 388.2578 195.6001 580.9154 192.65767

[20,] 386.0517 190.5666 581.5367 195.48506

[21,] 384.7493 186.5822 582.9165 198.16716

[22,] 385.2402 184.4979 585.9824 200.74223

[23,] 386.0926 182.8664 589.3189 203.22623

[24,] 386.0004 180.3793 591.6215 205.62106

$maize

fcst lower upper CI

[1,] 199.6549 183.9111 215.3988 15.74384

[2,] 206.3766 181.6742 231.0789 24.70235

[3,] 221.0948 189.9683 252.2214 31.12655

[4,] 227.7902 191.2050 264.3753 36.58515

[5,] 232.4664 191.1756 273.7573 41.29086

[6,] 244.1158 199.1529 289.0786 44.96288

[7,] 250.9486 202.8307 299.0665 48.11787

[8,] 254.1813 203.0695 305.2931 51.11184

[9,] 257.3446 203.6378 311.0513 53.70678

[10,] 261.1498 205.0540 317.2456 56.09581

[11,] 263.6259 205.3346 321.9173 58.29136

[12,] 263.4608 203.0845 323.8372 60.37637

[13,] 264.5060 202.1714 326.8406 62.33464

[14,] 266.3430 201.9432 330.7428 64.39979

[15,] 267.6619 201.2620 334.0619 66.39994

[16,] 268.1832 199.8067 336.5596 68.37642

[17,] 268.6109 198.3026 338.9192 70.30827

[18,] 269.5564 197.3528 341.7599 72.20355

[19,] 270.1453 196.0818 344.2089 74.06356

[20,] 270.4593 194.6032 346.3155 75.85615

[21,] 270.7512 193.1372 348.3651 77.61396

[22,] 270.8930 191.5611 350.2248 79.33181

[23,] 270.8386 189.8198 351.8574 81.01881

[24,] 270.8661 188.1932 353.5390 82.67288

A graph of different types of graphs

Description automatically generated with medium confidence

**Interpretation**

**Error Correction Terms (ECTs)**

These terms indicate how the error correction mechanism adjusts deviations from the long-term equilibrium:

* **ect1, ect2, ect3**: Represent different cointegrating vectors.
* Negative coefficients indicate how the variables adjust to correct deviations.

For example:

* crude\_brent.d has ect1 coefficient of -0.0158806519, indicating a slight adjustment to restore equilibrium.
* soybeans.d has a stronger adjustment with ect1 coefficient of -0.1118682070.

**Lagged Differences (d.lags)**

The coefficients of lagged differences (dl1 to dl8) represent how past values influence current changes:

* For example, crude\_brent.dl1 (lag 1 of crude\_brent) has a significant positive influence on crude\_brent.d with a coefficient of 0.3198283908.
* soybeans.dl1 also has a positive influence on soybeans.d with a coefficient of 0.3443498978.

Each variable's influence on the others is shown in the columns. Significant coefficients (those with larger absolute values) suggest a stronger relationship between the variables.

**Forecasts**

The forecasts provide predicted values and their confidence intervals (CI) for each variable over the next periods (24 steps):

* **crude\_brent**: The forecast starts at 85.68931 and increases to 95.87576 over 24 periods, with confidence intervals widening, indicating increasing uncertainty over time.
* **soybeans**: The forecast starts at 495.8007 and increases to 595.5702, showing a steady upward trend.
* **gold**: The forecast starts at 2316.562 and shows a slight increase to 2310.050, with wide confidence intervals indicating high uncertainty.
* **silver**: The forecast starts at 29.26114 and remains relatively stable, indicating minimal expected changes.
* **urea\_ee\_bulk**: The forecast starts at 348.8463 and shows fluctuations, ending at 386.0004, suggesting volatility.
* **maize**: The forecast starts at 199.6549 and increases to 270.8661, indicating a steady upward trend.

**Crude Brent**:

* **Historical Trend**: Shows significant fluctuations with notable peaks and troughs.
* **Forecast**: The forecast indicates a continuation of this volatile trend, with the confidence interval widening, reflecting increasing uncertainty over time.

**Silver**:

* **Historical Trend**: Exhibits a significant spike followed by a relatively stable period with minor fluctuations.
* **Forecast**: Predicts a steady trend, but with a wide confidence interval, indicating high uncertainty.

**Soybeans**:

* **Historical Trend**: Shows periodic fluctuations with several peaks.
* **Forecast**: Indicates a general upward trend. The confidence interval suggests moderate uncertainty.

**Urea EE Bulk**:

* **Historical Trend**: Significant volatility with large spikes.
* **Forecast**: Suggests continued high volatility with a wide confidence interval, indicating high uncertainty.

**Gold**:

* **Historical Trend**: Shows a strong upward trend with some fluctuations.
* **Forecast**: Continues the upward trend but with a wide confidence interval, reflecting uncertainty in the forecast.

**Maize**:

* **Historical Trend**: Exhibits periodic fluctuations with a general upward trend.
* **Forecast**: Suggests a continued upward trend with a moderately wide confidence interval, indicating some uncertainty.

**Part 11: Loading and Preparing the Dataset**

# Load the dataset

df <- read\_excel('pinksheet.xlsx', sheet = "Monthly Prices", skip = 6)

# Rename the first column to "Date"

colnames(df)[1] <- 'Date'

# Convert the Date column to Date format

df$Date <- as.Date(paste0(df$Date, "01"), format = "%YM%m%d")

str(df)

**Purpose**:

* read\_excel('pinksheet.xlsx', sheet = "Monthly Prices", skip = 6) reads the specified sheet from the Excel file, skipping the first 6 rows.
* colnames(df)[1] <- 'Date' renames the first column to "Date".
* df$Date <- as.Date(paste0(df$Date, "01"), format = "%YM%m%d") converts the "Date" column to Date format.
* str(df) prints the structure of the dataframe.

**Output**:

* A dataframe df with the loaded data, the first column renamed to "Date", and dates properly formatted.
* The structure of the dataframe printed to the console.

**Interpretation:**

* The dataframe df has been successfully loaded from the "Monthly Prices" sheet of the 'pinksheet.xlsx' file, skipping the first 6 rows.
* The first column has been renamed to "Date" and converted to a Date format, ensuring that the date information is properly structured.
* The dataframe consists of 774 rows and 72 columns, with "Date" in Date format and various commodity price columns in numeric or character formats, indicating a well-structured dataset for further analysis.

**Part 12: Selecting and Cleaning Data**

# Select metal commodities columns (Date and selected commodities)

commodity2 <- df[,c(1, 64, 65, 66, 67, 68, 69)] %>%

clean\_names()

str(commodity2)

**Purpose**:

* df[,c(1, 64, 65, 66, 67, 68, 69)] selects specific columns from the dataframe.
* clean\_names() cleans column names (e.g., converts them to lowercase and replaces spaces with underscores).
* str(commodity2) prints the structure of the cleaned dataframe.

**Output**:

tibble [774 × 7] (S3: tbl\_df/tbl/data.frame)

$ date : Date[1:774], format: "1960-01-01" "1960-02-01" ...

$ iron\_ore: num [1:774] 11.4 11.4 11.4 11.4 11.4 ...

$ copper : num [1:774] 715 728 685 723 685 ...

$ lead : num [1:774] 206 204 210 214 213 ...

$ tin : num [1:774] 2180 2180 2174 2178 2163 ...

$ nickel : num [1:774] 1631 1631 1631 1631 1631 ...

$ zinc : num [1:774] 261 245 249 255 254 ...

**Interpretation:**

* A subset of the original dataframe has been created, selecting the columns for specific metal commodities along with the "Date" column.
* The columns have been cleaned and renamed for easier access and understanding.
* The new dataframe commodity2 consists of 774 rows and 7 columns, with the columns being "date", "iron\_ore", "copper", "lead", "tin", "nickel", and "zinc". This subset is now ready for further analysis focused on these specific metals.

**Part 13: Checking Column Names and Missing Values**

# Check column names

colnames(commodity2)

# Check for missing values in the commodity data excluding the Date column

missing\_values <- sapply(commodity2[-1], function(x) sum(is.na(x)))

missing\_values

**Purpose**:

* colnames(commodity2) prints the column names of the dataframe.
* sapply(commodity2[-1], function(x) sum(is.na(x))) checks for missing values in each column of the dataframe, excluding the "Date" column.

**Output**:

[1] "date" "iron\_ore" "copper" "lead" "tin" "nickel" "zinc"

iron\_ore copper lead tin nickel zinc

0 0 0 0 0 0

**Interpretation:**

* The column names of the dataframe commodity2 have been confirmed as "date", "iron\_ore", "copper", "lead", "tin", "nickel", and "zinc".
* There are no missing values in any of the selected columns, ensuring the integrity and completeness of the data for these commodities.
* This clean and complete dataset is now ready for exploratory data analysis and further statistical modeling.

**Part 14: Checking Data Integrity**

# Check the first few rows to ensure data integrity

head(commodity2)

**Purpose**:

* head(commodity2) prints the first few rows of the dataframe to the console.

**Output**:

* The first few rows of the dataframe printed to the console.

**Part 15: Mapping Column Names to Readable Names**

# Mapping of new column names to more readable commodity names

commodity2\_names <- c(

iron\_ore = "Iron Ore",

copper = "Copper",

lead = "Lead",

tin = "Tin",

nickel = "Nickel",

zinc = "Zinc"

)

# Print column names and corresponding readable names for debugging

print("Column names and corresponding readable names:")

for (col in names(commodity2)[-1]) {

print(paste(col, ":", commodity2\_names[[col]]))

}

**Purpose**:

* commodity2\_names creates a named vector mapping column names to more readable names.
* A loop prints each column name and its corresponding readable name for debugging purposes.

**Output**:

* Printed mappings of column names to readable names.

**Part 16: Visualizing Data**

# Visualize data directly

for (col in names(commodity2)[-1]) { # Skip the date column

print(col) # Print column name for debugging

p <- ggplot(commodity2, aes\_string(x = "date", y = col)) +

geom\_line() +

labs(title = paste("Price of", commodity2\_names[[col]]), x = "Date", y = "Price") +

theme\_minimal()

# Print the plot to display it

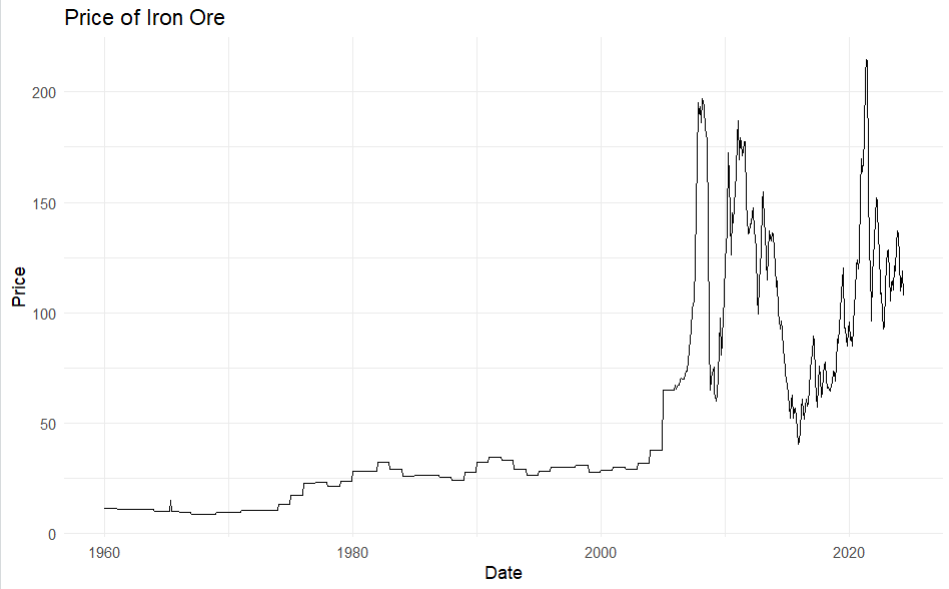
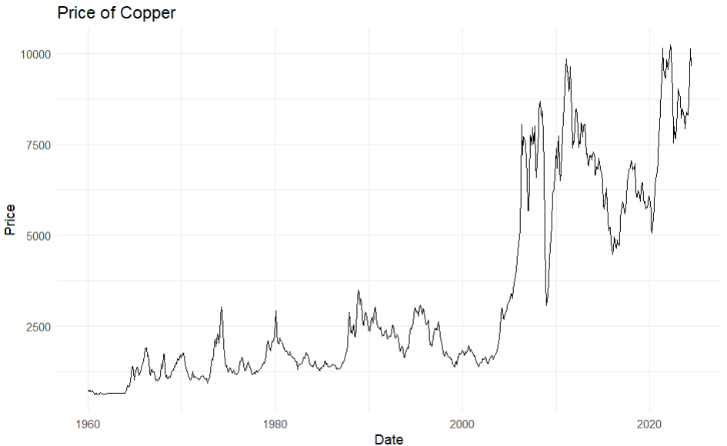
print(p)

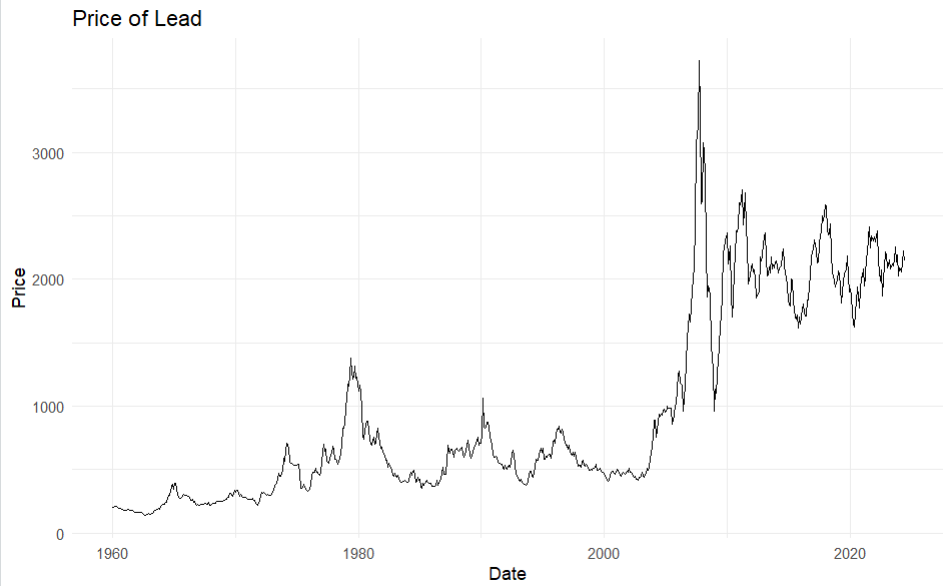
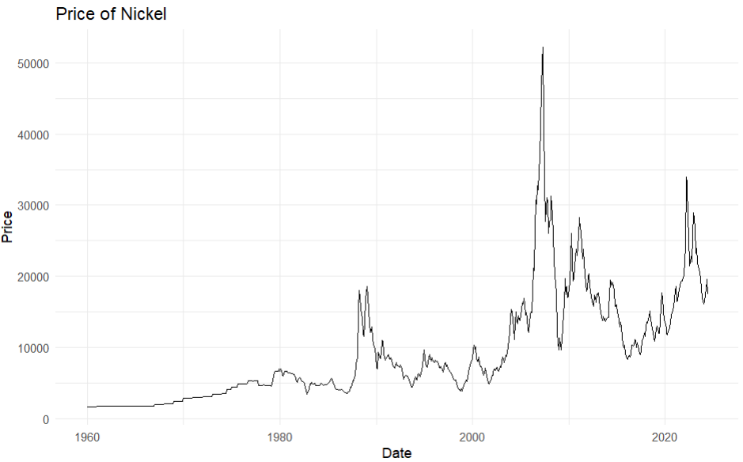
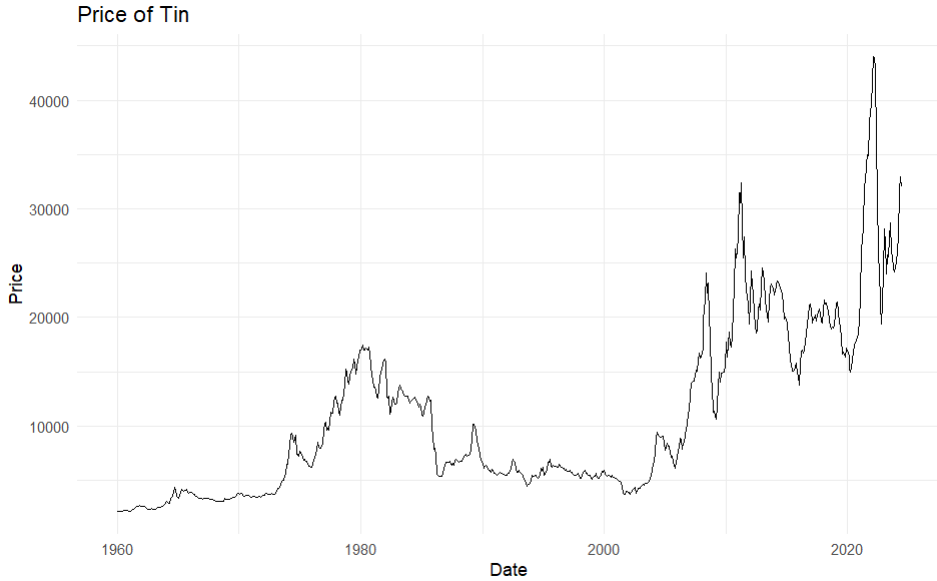
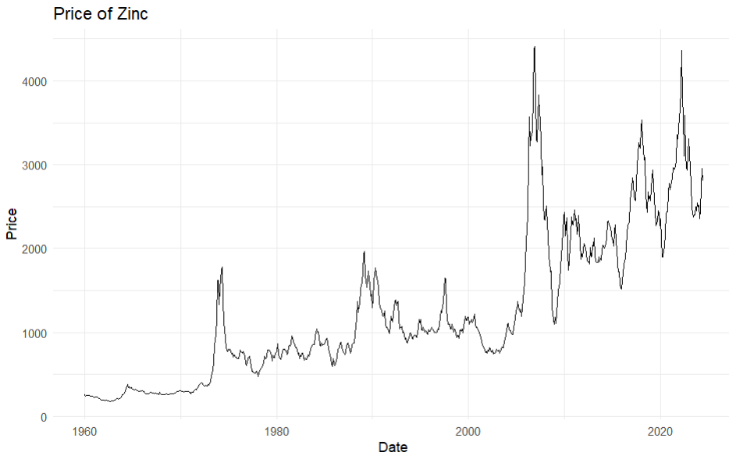
}

**Purpose**:

* Loops through each commodity column (excluding "date") and plots its time series using ggplot2.
* Each plot displays the price of the commodity over time.

**Output**:





**Interpretation:**

**Price of Iron Ore**

* **Trend:** The price of iron ore shows a significant upward trend starting around 2003, with major peaks around 2011 and 2021.
* **Notable Features:** The price rose sharply in the early 2000s, peaking around 2011, declining, and then rising again around 2021.
* **Possible Causes:** This trend corresponds with the industrial growth of China, a major consumer of iron ore, and fluctuating supply conditions.

**Price of Copper**

* **Trend:** Copper prices have shown a steady increase over the years with significant peaks around 2006, 2011, and 2021.
* **Notable Features:** The price increased steadily with peaks corresponding to economic cycles and industrial demand.
* **Possible Causes:** Copper is a key industrial metal, and its price is heavily influenced by global economic conditions, particularly demand from China and supply disruptions from major mining countries.

**Price of Tin**

* **Trend:** The price of tin shows significant volatility over the years, with a major peak around 2010 and another sharp increase around 2020.
* **Notable Features:** The price rose steeply in the early 2000s, reaching a peak around 2010, followed by a decline and another increase around 2020.
* **Possible Causes:** This volatility could be due to changes in global supply and demand, economic conditions, or geopolitical events affecting mining regions.

**Price of Lead**

* **Trend:** The price of lead also exhibits significant fluctuations with a noticeable spike around 2007-2008.
* **Notable Features:** The price increased steadily from the early 2000s, peaking around the 2008 financial crisis, then stabilizing and showing moderate volatility since then.
* **Possible Causes:** The peak around 2007-2008 aligns with the commodity boom period and subsequent financial crisis, affecting industrial demand.

**Price of Nickel**

* **Trend:** Nickel prices show extreme volatility, with a significant peak around 2007 and another around 2022.
* **Notable Features:** The price spiked dramatically in 2007, dropped sharply during the financial crisis, and peaked again recently around 2022.
* **Possible Causes:** These fluctuations may be linked to industrial demand, particularly from the stainless steel industry, and changes in supply from major producers like Indonesia and the Philippines.

**Price of Zinc**

* **Trend:** The price of zinc has fluctuated over time, with noticeable peaks around 2007 and a steady increase starting from 2016.
* **Notable Features:** Similar to other metals, zinc prices spiked around the 2007 commodity boom and showed a steady rise from 2016.
* **Possible Causes:** Factors influencing zinc prices include global industrial demand, mining production levels, and market speculation.

**Part 17: Preparing Data for VAR and VECM Analysis**

# Prepare data for VAR and VECM analysis

commodity2\_data <- dplyr::select(commodity2, -date)

columns\_to\_test2 <- names(commodity2\_data)

**Purpose**:

* dplyr::select(commodity2, -date) selects all columns except "date" for analysis.
* columns\_to\_test2 <- names(commodity2\_data) stores the names of these columns for further analysis.

**Output**:

* A dataframe commodity2\_data containing only the selected commodity columns.
* A vector columns\_to\_test2 with the names of these columns.

**Part 18: Stationarity Test**

# Stationarity test

non\_stationary\_count2 <- 0

stationary\_columns2 <- c()

non\_stationary\_columns2 <- c()

for (col in columns\_to\_test2) {

adf\_result2 <- ur.df(commodity2\_data[[col]], type = "none", selectlags = "AIC")

p\_value2 <- adf\_result2@testreg$coefficients[2, 4]

cat("\nADF test result for column:", col, "\n")

print(summary(adf\_result2))

if (p\_value2 > 0.05) {

non\_stationary\_count2 <- non\_stationary\_count2 + 1

non\_stationary\_columns2 <- c(non\_stationary\_columns2, col)

} else {

stationary\_columns2 <- c(stationary\_columns2, col)

}

}

cat("\nNumber of non-stationary columns:", non\_stationary\_count2, "\n")

cat("Non-stationary columns:", paste(non\_stationary\_columns2, collapse=", "), "\n")

cat("Stationary columns:", paste(stationary\_columns2, collapse=", "), "\n")

**Purpose**:

* Performs Augmented Dickey-Fuller (ADF) tests for stationarity on each commodity column.
* Stores results indicating whether each column is stationary or non-stationary.

**Output**:

ADF test result for column: iron\_ore

###############################################

# 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

-50.764 0.053 0.137 0.173 30.261

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 -0.005222 0.003275 -1.594 0.111

z.diff.lag 0.338887 0.034061 9.950 <2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.002 on 770 degrees of freedom

Multiple R-squared: 0.1147, Adjusted R-squared: 0.1124

F-statistic: 49.9 on 2 and 770 DF, p-value: < 2.2e-16

Value of test-statistic is: -1.5942

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

ADF test result for column: copper

###############################################

# 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

-1859.48 -61.19 2.93 87.36 1254.12

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 -0.0003219 0.0021469 -0.150 0.881

z.diff.lag 0.3159826 0.0344311 9.177 <2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 247.6 on 770 degrees of freedom

Multiple R-squared: 0.09911, Adjusted R-squared: 0.09677

F-statistic: 42.36 on 2 and 770 DF, p-value: < 2.2e-16

Value of test-statistic is: -0.1499

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

ADF test result for column: lead

###############################################

# 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

-640.26 -18.25 2.71 28.37 589.88

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 -0.001614 0.002528 -0.638 0.523

z.diff.lag 0.220991 0.035243 6.271 5.99e-10 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 85.17 on 770 degrees of freedom

Multiple R-squared: 0.04864, Adjusted R-squared: 0.04617

F-statistic: 19.69 on 2 and 770 DF, p-value: 4.592e-09

Value of test-statistic is: -0.6384

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

ADF test result for column: tin

###############################################

# 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

-6853.0 -154.3 16.1 214.9 3868.5

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 -0.0007103 0.0022806 -0.311 0.756

z.diff.lag 0.3528126 0.0339058 10.406 <2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 836.9 on 770 degrees of freedom

Multiple R-squared: 0.1237, Adjusted R-squared: 0.1214

F-statistic: 54.36 on 2 and 770 DF, p-value: < 2.2e-16

Value of test-statistic is: -0.3115

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

ADF test result for column: nickel

###############################################

# 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

-10842.1 -132.4 15.8 269.4 9449.0

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 -0.006029 0.003355 -1.797 0.0727 .

z.diff.lag 0.364107 0.033703 10.803 <2e-16 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1111 on 770 degrees of freedom

Multiple R-squared: 0.1328, Adjusted R-squared: 0.1305

F-statistic: 58.93 on 2 and 770 DF, p-value: < 2.2e-16

Value of test-statistic is: -1.7973

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

ADF test result for column: zinc

###############################################

# 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

-694.38 -21.56 2.55 39.98 625.92

Coefficients:

Estimate Std. Error t value Pr(>|t|)

z.lag.1 -0.001703 0.002561 -0.665 0.506

z.diff.lag 0.233186 0.035173 6.630 6.33e-11 \*\*\*

---

Signif. codes: 0 ‘\*\*\*’ 0.001 ‘\*\*’ 0.01 ‘\*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 109.8 on 770 degrees of freedom

Multiple R-squared: 0.05405, Adjusted R-squared: 0.05159

F-statistic: 22 on 2 and 770 DF, p-value: 5.12e-10

Value of test-statistic is: -0.6648

Critical values for test statistics:

1pct 5pct 10pct

tau1 -2.58 -1.95 -1.62

>

> cat("\nNumber of non-stationary columns:", non\_stationary\_count2, "\n")

Number of non-stationary columns: 0

> cat("Non-stationary columns:", paste(non\_stationary\_columns2, collapse=", "), "\n")

Non-stationary columns:

> cat("Stationary columns:", paste(stationary\_columns2, collapse=", "), "\n")

Stationary columns: iron\_ore, copper, lead, tin, nickel, zinc

**Interpretation:**

**ADF Test for Iron Ore**

* **Purpose:** To test if the iron\_ore column has a unit root (i.e., is non-stationary).
* **Test Statistic:** -1.5942
* **Critical Values:** -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result:** The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root. Iron ore is considered non-stationary.

**ADF Test for Copper**

* **Purpose:** To test if the copper column has a unit root.
* **Test Statistic:** -0.1499
* **Critical Values:** -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result:** The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root. Copper is considered non-stationary.

**ADF Test for Lead**

* **Purpose:** To test if the lead column has a unit root.
* **Test Statistic:** -0.6384
* **Critical Values:** -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result:** The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root. Lead is considered non-stationary.

**ADF Test for Tin**

* **Purpose:** To test if the tin column has a unit root.
* **Test Statistic:** -0.3115
* **Critical Values:** -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result:** The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root. Tin is considered non-stationary.

**ADF Test for Nickel**

* **Purpose:** To test if the nickel column has a unit root.
* **Test Statistic:** -1.7973
* **Critical Values:** -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result:** The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root at the 5% and 1% significance levels but is close to the 10% level. Nickel is marginally non-stationary.

**ADF Test for Zinc**

* **Purpose:** To test if the zinc column has a unit root.
* **Test Statistic:** -0.6648
* **Critical Values:** -2.58 (1%), -1.95 (5%), -1.62 (10%)
* **Result:** The test statistic is higher than the critical values, indicating failure to reject the null hypothesis of a unit root. Zinc is considered non-stationary.

Top of Form

Bottom of Form

**Part 19: Co-Integration Test (Johansen's Test)**

# Co-Integration Test (Johansen's Test)

lags2 <- VARselect(commodity2\_data, lag.max = 10, type = "const")

lag\_length2 <- lags2$selection[1]

vecm\_model2 <- ca.jo(commodity2\_data, ecdet = 'const', type = 'eigen', K = lag\_length2, spec = 'transitory')

summary(vecm\_model2)

r2 <- 3 # Replace with the actual number from the test results

**Purpose**:

* VARselect(commodity2\_data, lag.max = 10, type = "const") selects the optimal lag length for the VAR model.
* ca.jo(...) performs the Johansen co-integration test.
* summary(vecm\_model2) prints the summary of the co-integration test results.
* r2 <- 3 sets the number of co-integration relations based on the test results (this value should be replaced with the actual result).

**Output**:

######################

# Johansen-Procedure #

######################

Test type: maximal eigenvalue statistic (lambda max) , without linear trend and constant in cointegration

Eigenvalues (lambda):

[1] 6.039216e-02 3.297371e-02 2.237750e-02 1.662828e-02 1.082083e-02

[6] 2.675676e-03 -5.376503e-19

Values of teststatistic and critical values of test:

test 10pct 5pct 1pct

r <= 5 | 2.05 7.52 9.24 12.97

r <= 4 | 8.31 13.75 15.67 20.20

r <= 3 | 12.81 19.77 22.00 26.81

r <= 2 | 17.29 25.56 28.14 33.24

r <= 1 | 25.62 31.66 34.40 39.79

r = 0 | 47.59 37.45 40.30 46.82

Eigenvectors, normalised to first column:

(These are the cointegration relations)

iron\_ore.l1 copper.l1 lead.l1 tin.l1 nickel.l1

iron\_ore.l1 1.0000000000 1.000000000 1.000000000 1.000000e+00 1.000000000

copper.l1 -0.0066665643 -0.079279874 -0.023423658 -6.895850e-02 -0.016626120

lead.l1 -0.0157567791 0.348894170 -0.120208281 6.096602e-02 0.148442688

tin.l1 -0.0007469441 0.003512194 0.006995063 2.496511e-03 -0.016140147

nickel.l1 -0.0031980282 0.006582924 0.013833274 -5.201841e-04 0.002136730

zinc.l1 0.0165350637 -0.187709045 -0.023600129 1.069639e-01 0.005802525

constant 6.0743618543 16.230333320 -24.821946919 -3.916933e+01 25.271073081

zinc.l1 constant

iron\_ore.l1 1.000000e+00 1.000000000

copper.l1 -6.982603e-02 -0.034572301

lead.l1 1.823681e-02 0.019799294

tin.l1 4.963702e-04 -0.002827308

nickel.l1 2.585852e-03 0.002234514

zinc.l1 4.286387e-02 0.017697120

constant 1.355831e+02 1.091334658

Weights W:

(This is the loading matrix)

iron\_ore.l1 copper.l1 lead.l1 tin.l1 nickel.l1

iron\_ore.d -0.07327311 -0.001767477 -0.006696062 0.003900037 0.003181658

copper.d 1.06029000 0.067860338 0.050195008 -0.016266109 0.132362977

lead.d -0.04315813 -0.078867059 0.074680960 -0.113508582 0.032923114

tin.d 4.21001305 -0.110054190 -0.547425086 -0.804516499 1.093174030

nickel.d 7.71364257 -0.847682260 -1.601532451 -0.153933003 -0.115234521

zinc.d -0.04910052 0.047653544 -0.060057959 -0.206403381 0.009601433

zinc.l1 constant

iron\_ore.d 0.001163677 1.162207e-16

copper.d 0.108883299 2.996269e-15

lead.d 0.022710735 -1.149534e-16

tin.d 0.068570516 1.986630e-14

nickel.d 0.283335949 5.487502e-15

zinc.d 0.037931392 5.700254e-16

**Interpretation**

**Eigenvalues:**

These are the eigenvalues obtained from the test. They indicate the strength of the cointegration relationships:

* 0.06039216
* 0.03297371
* 0.02237750
* 0.01662828
* 0.01082083
* 0.002675676
* -5.376503e-19

**Test Statistics and Critical Values:**

The test statistics for different ranks (r) are compared against critical values at the 10%, 5%, and 1% significance levels:

* **r ≤ 5:**
  + Test Statistic: 2.05
  + Critical Values: [7.52, 9.24, 12.97]
* **r ≤ 4:**
  + Test Statistic: 8.31
  + Critical Values: [13.75, 15.67, 20.20]
* **r ≤ 3:**
  + Test Statistic: 12.81
  + Critical Values: [19.77, 22.00, 26.81]
* **r ≤ 2:**
  + Test Statistic: 17.29
  + Critical Values: [25.56, 28.14, 33.24]
* **r ≤ 1:**
  + Test Statistic: 25.62
  + Critical Values: [31.66, 34.40, 39.79]
* **r = 0:**
  + Test Statistic: 47.59
  + Critical Values: [37.45, 40.30, 46.82]

The null hypothesis is rejected if the test statistic is greater than the critical value, indicating a cointegration relationship.

**Interpretation of Test Results:**

* **r ≤ 5:**
  + The test statistic (2.05) is less than the critical values, so we do not reject the null hypothesis.
* **r ≤ 4:**
  + The test statistic (8.31) is less than the critical values, so we do not reject the null hypothesis.
* **r ≤ 3:**
  + The test statistic (12.81) is less than the critical values, so we do not reject the null hypothesis.
* **r ≤ 2:**
  + The test statistic (17.29) is less than the critical values, so we do not reject the null hypothesis.
* **r ≤ 1:**
  + The test statistic (25.62) is less than the critical values, so we do not reject the null hypothesis.
* **r = 0:**
  + The test statistic (47.59) is greater than the critical values at the 10%, 5%, and 1% significance levels, indicating strong evidence against the null hypothesis of no cointegration. This suggests that there is at least one cointegration vector among the selected commodities, indicating a long-term equilibrium relationship.

**Eigenvectors (Cointegration Relations):**

These are normalized eigenvectors that represent the cointegration relations between the variables:

* **iron\_ore.l1:** 1, -0.0067, -0.0158, -0.0007, -0.0032, 0.0165
* **copper.l1:** 1, -0.0793, 0.3489, 0.0035, 0.0066, -0.1877
* **lead.l1:** 1, -0.0234, -0.1202, 0.0070, 0.0138, -0.0236
* **tin.l1:** 1, -0.0689, 0.0610, 0.0025, -0.0005, 0.1069
* **nickel.l1:** 1, -0.0166, 0.1484, -0.0161, 0.0021, 0.0058
* **zinc.l1:** 1, 0.0429, 0.0182, 0.0005, 0.0026, 0.0429
* **constant:** 1, 16.23, -24.82, -39.17, 25.27, 1.09

**Loading Matrix (Weights W):**

This matrix indicates the adjustment coefficients that show how much each variable contributes to the cointegration relation's deviation from equilibrium:

* **iron\_ore.d:** -0.0733, -0.0018, -0.0067, 0.0039, 0.0032, 0.0012
* **copper.d:** 1.0603, 0.0679, 0.0502, -0.0163, 0.1324, 0.1089
* **lead.d:** -0.0432, -0.0789, 0.0747, -0.1135, 0.0329, 0.0227
* **tin.d:** 4.2100, -0.1101, -0.5474, -0.8045, 1.0932, 0.0686
* **nickel.d:** 7.7136, -0.8477, -1.6015, -0.1539, -0.1152, 0.2833

**Part 20: VECM or VAR Model and Forecasting**

if (r2 > 0) {

vecm2 <- cajorls(vecm\_model2, r = r2)

summary(vecm2)

vecm\_coefs2 <- vecm2$rlm$coefficients

print(vecm\_coefs2)

vecm\_pred2 <- vec2var(vecm\_model2, r = r2)

forecast2 <- predict(vecm\_pred2, n.ahead = 24)

par(mar = c(4, 4, 2, 2))

plot(forecast2)

} else {

var\_model2 <- VAR(commodity2\_data, p = lag\_length2, type = "const")

summary(var\_model2)

causality\_results2 <- causality(var\_model2)

print(causality\_results2)

forecast2 <- predict(var\_model2, n.ahead = 24)

par(mar = c(4, 4, 2, 2))

plot(forecast2)

}

forecast2

**Purpose**:

* If r2 > 0, fits a VECM model and makes forecasts.
* If r2 == 0, fits a VAR model and makes forecasts.
* summary(...) prints the model summaries.
* predict(...) generates forecasts for the next 24 periods.
* plot(forecast2) plots the forecasts.

**Output**:

iron\_ore.d copper.d lead.d tin.d nickel.d

ect1 -8.173665e-02 1.1783453459 -0.0473442307 3.552533772 5.264427861

ect2 7.854516e-04 -0.0136242013 0.0047909856 -0.006518542 0.053294397

ect3 1.342808e-03 0.0009354656 -0.0358134935 -0.038928482 -0.224776098

iron\_ore.dl1 2.852092e-01 0.2412540366 0.5082338447 -3.335498613 -7.447400643

copper.dl1 2.867810e-03 0.3018416349 0.0266472802 -0.074554511 0.111953878

lead.dl1 7.545169e-03 -0.1206656241 0.2555797201 1.419065612 0.266200975

tin.dl1 -1.459935e-04 -0.0112371145 -0.0124137644 0.261574256 0.023268635

nickel.dl1 2.237084e-05 0.0055762295 0.0056696877 0.085492970 0.412873940

zinc.dl1 -3.954814e-03 0.0828121825 -0.0813314952 -0.690004260 -0.991840952

iron\_ore.dl2 -8.356624e-02 -4.3457127578 -1.3522529195 -8.519448768 -12.106156054

copper.dl2 1.116948e-03 -0.0963068615 -0.0121533019 0.223551419 -0.123908374

lead.dl2 1.668549e-03 0.0950928284 -0.0973300619 -0.261938807 0.358603346

tin.dl2 1.364582e-03 0.0670197934 0.0214650809 0.150374581 0.123426919

nickel.dl2 -7.325798e-04 0.0121296136 -0.0022328717 0.015588274 0.015580061

zinc.dl2 -1.450762e-03 -0.1941700804 -0.0313641292 -0.438123524 -1.096643635

iron\_ore.dl3 2.567117e-02 -0.4122472526 0.3663560830 -14.839950450 -11.571493018

copper.dl3 2.032760e-04 -0.0374047163 -0.0208202809 0.009560438 0.064785801

lead.dl3 2.402364e-03 0.2131539593 0.1354883762 1.467518478 -1.163855759

tin.dl3 -6.800922e-04 -0.0214534082 -0.0055506775 -0.044063278 0.023823833

nickel.dl3 1.690481e-04 0.0109662001 -0.0094490597 -0.031777637 -0.165926344

zinc.dl3 -1.422958e-03 0.0243304528 0.0566555102 0.205149264 2.305498208

iron\_ore.dl4 -6.989685e-02 0.3883847962 -0.5327807775 -1.986000540 -3.601725566

copper.dl4 -2.004008e-03 -0.2362226299 -0.0207849793 -0.316557132 -0.968699142

lead.dl4 1.137802e-02 0.2520650854 0.0288596596 0.447191375 1.815142178

tin.dl4 -2.153089e-04 0.0104134725 0.0067311340 -0.026368367 -0.034853649

nickel.dl4 -2.235533e-04 -0.0161218760 0.0016080998 -0.012338197 0.059537226

zinc.dl4 5.097388e-03 0.4681438534 -0.0047413372 0.539296760 0.640193531

iron\_ore.dl5 6.272386e-03 0.9945730035 0.7394767803 -0.771781578 -6.584595148

copper.dl5 3.249168e-03 0.0590877316 -0.0125294392 0.366862518 0.270154155

lead.dl5 4.572526e-03 -0.0091019275 0.0035605712 -0.417055885 -0.195188138

tin.dl5 3.927857e-04 -0.0254962677 -0.0028492207 -0.048869123 -0.035846619

nickel.dl5 5.393800e-05 0.0354438824 0.0212133071 0.060041769 -0.017950271

zinc.dl5 -3.950818e-03 0.1472827052 -0.1026179947 0.121930944 1.964307341

iron\_ore.dl6 9.382284e-02 3.9357289957 -0.8583709570 26.310981400 3.364481143

copper.dl6 -4.494075e-03 -0.1445836755 0.0064180952 -0.533118812 -0.179554244

lead.dl6 8.459638e-03 0.4806284338 0.0122146814 1.625526809 0.543245478

tin.dl6 -1.321756e-03 -0.0315117736 -0.0073265796 -0.014286854 -0.070766959

nickel.dl6 4.598542e-04 -0.0225698355 -0.0040074917 -0.055136574 -0.052865158

zinc.dl6 1.386674e-03 0.0223860854 0.0500274901 -0.068555836 0.989499332

iron\_ore.dl7 -3.541754e-02 -2.4311669244 -0.3439651302 -19.347503861 -45.477480638

copper.dl7 1.206743e-03 0.0021341840 0.0263515870 0.489396357 0.677505832

lead.dl7 -7.959763e-04 0.1604006287 0.0686766018 -0.042971814 1.995373906

tin.dl7 3.241950e-04 0.0091912260 0.0014371470 -0.066401628 -0.008734823

nickel.dl7 -4.196833e-04 -0.0056977604 -0.0011458369 -0.023879175 0.010407411

zinc.dl7 -2.007009e-03 -0.0400349156 -0.0338469110 -0.683893508 -2.235892077

iron\_ore.dl8 7.874682e-02 8.5388636513 1.6159457060 27.047443622 47.939273080

copper.dl8 -1.458231e-03 -0.2712742462 -0.1139990875 -0.316290857 -0.570177545

lead.dl8 -8.816427e-03 0.1802361254 0.0389725716 0.362823415 -0.515015885

tin.dl8 -1.692360e-04 -0.0291066312 0.0009746506 -0.177745436 -0.016722545

nickel.dl8 -1.145095e-04 0.0024712776 -0.0076149488 0.011673643 0.032305302

zinc.dl8 3.849342e-03 0.3017540170 0.1951771734 0.779161944 1.224668129

iron\_ore.dl9 3.074796e-02 0.7611316361 -0.4241725737 11.451800389 -17.994204422

copper.dl9 1.782540e-03 -0.0420199827 -0.0341791139 -0.118200136 -0.029387832

lead.dl9 5.885165e-03 0.0254006552 -0.0427360975 1.058948454 0.118500109

tin.dl9 -8.712466e-06 0.0085576504 0.0048350693 0.062070752 -0.010955599

nickel.dl9 2.768542e-04 -0.0003323247 0.0066176171 -0.051869484 0.049938659

zinc.dl9 -1.065930e-02 -0.0194288151 0.0469975013 0.005064293 -0.038784982

zinc.d

ect1 -0.0615049336

ect2 -0.0020438581

ect3 0.0246191738

iron\_ore.dl1 -1.2334790458

copper.dl1 0.0429240770

lead.dl1 0.0151363771

tin.dl1 -0.0142152622

nickel.dl1 0.0046211664

zinc.dl1 0.2373538732

iron\_ore.dl2 -0.8316753019

copper.dl2 0.0199096698

lead.dl2 0.0479415670

tin.dl2 0.0261112670

nickel.dl2 0.0007575678

zinc.dl2 -0.1865534266

iron\_ore.dl3 -1.2219280549

copper.dl3 0.0228577853

lead.dl3 0.1072580185

tin.dl3 -0.0203385414

nickel.dl3 0.0072450562

zinc.dl3 -0.0551636480

iron\_ore.dl4 -0.2444837202

copper.dl4 -0.0293677607

lead.dl4 -0.0227207412

tin.dl4 0.0125152880

nickel.dl4 -0.0068086267

zinc.dl4 0.1326995055

iron\_ore.dl5 -1.5460879672

copper.dl5 0.0367110268

lead.dl5 -0.1245565856

tin.dl5 -0.0051707306

nickel.dl5 0.0177802686

zinc.dl5 0.0282290466

iron\_ore.dl6 1.5945240888

copper.dl6 0.0197482512

lead.dl6 0.0049449295

tin.dl6 -0.0073927758

nickel.dl6 -0.0248181199

zinc.dl6 0.0878244324

iron\_ore.dl7 -3.4536859400

copper.dl7 0.0425366806

lead.dl7 -0.0733071231

tin.dl7 -0.0014493305

nickel.dl7 -0.0018893055

zinc.dl7 0.0830792820

iron\_ore.dl8 2.6697339520

copper.dl8 -0.0318348039

lead.dl8 0.0225340003

tin.dl8 -0.0010935642

nickel.dl8 -0.0081083853

zinc.dl8 0.0243998714

iron\_ore.dl9 0.2684045463

copper.dl9 -0.0155859099

lead.dl9 -0.0613857894

tin.dl9 0.0104203790

nickel.dl9 -0.0018395214

zinc.dl9 0.0152793577

>

> forecast2

$iron\_ore

fcst lower upper CI

[1,] 103.14983 93.13327 113.1664 10.01656

[2,] 102.75031 86.62280 118.8778 16.12751

[3,] 102.77671 82.23138 123.3220 20.54532

[4,] 97.47697 73.58550 121.3684 23.89147

[5,] 92.48951 65.97077 119.0082 26.51873

[6,] 88.81273 59.55975 118.0657 29.25298

[7,] 86.53952 54.71915 118.3599 31.82037

[8,] 87.32936 53.36379 121.2949 33.96557

[9,] 91.21113 55.57453 126.8477 35.63661

[10,] 94.98747 57.79736 132.1776 37.19011

[11,] 98.86411 60.12552 137.6027 38.73859

[12,] 104.61139 64.37506 144.8477 40.23632

[13,] 108.87551 67.34971 150.4013 41.52580

[14,] 112.35841 69.72316 154.9937 42.63524

[15,] 115.57719 71.91607 159.2383 43.66112

[16,] 118.44782 73.79998 163.0957 44.64784

[17,] 120.50296 74.91312 166.0928 45.58985

[18,] 122.46754 75.97831 168.9568 46.48923

[19,] 124.31194 76.97204 171.6518 47.33990

[20,] 125.44898 77.27994 173.6180 48.16905

[21,] 126.40858 77.39029 175.4269 49.01829

[22,] 126.99512 77.08817 176.9021 49.90696

[23,] 127.11223 76.28306 177.9414 50.82917

[24,] 126.85704 75.07753 178.6366 51.77951

$copper

fcst lower upper CI

[1,] 9303.341 8879.070 9727.611 424.2707

[2,] 9070.914 8378.307 9763.521 692.6074

[3,] 8848.831 7951.469 9746.193 897.3619

[4,] 8567.723 7505.355 9630.091 1062.3680

[5,] 8106.157 6910.774 9301.539 1195.3823

[6,] 7843.538 6504.722 9182.354 1338.8158

[7,] 7774.826 6307.817 9241.835 1467.0092

[8,] 7839.596 6257.370 9421.821 1582.2256

[9,] 8041.392 6358.092 9724.693 1683.3003

[10,] 8166.503 6394.655 9938.352 1771.8483

[11,] 8334.336 6473.579 10195.094 1860.7573

[12,] 8486.935 6539.548 10434.322 1947.3873

[13,] 8562.296 6534.136 10590.456 2028.1600

[14,] 8630.994 6527.197 10734.792 2103.7975

[15,] 8630.873 6458.343 10803.402 2172.5295

[16,] 8640.010 6401.147 10878.872 2238.8626

[17,] 8633.100 6331.511 10934.688 2301.5881

[18,] 8631.750 6270.518 10992.983 2361.2325

[19,] 8650.015 6230.457 11069.572 2419.5574

[20,] 8681.722 6205.637 11157.808 2476.0858

[21,] 8709.420 6177.198 11241.642 2532.2218

[22,] 8720.199 6131.708 11308.690 2588.4909

[23,] 8714.935 6068.975 11360.896 2645.9604

[24,] 8694.305 5989.755 11398.856 2704.5502

$lead

fcst lower upper CI

[1,] 2143.053 2001.480 2284.626 141.5729

[2,] 2113.651 1891.460 2335.843 222.1916

[3,] 2122.020 1846.264 2397.776 275.7561

[4,] 2102.282 1779.254 2425.310 323.0280

[5,] 2043.752 1677.935 2409.568 365.8166

[6,] 2055.611 1650.557 2460.664 405.0539

[7,] 2032.611 1590.741 2474.481 441.8704

[8,] 2060.531 1582.450 2538.612 478.0807

[9,] 2131.197 1622.300 2640.095 508.8976

[10,] 2184.665 1647.147 2722.183 537.5180

[11,] 2238.304 1672.028 2804.580 566.2759

[12,] 2301.712 1706.865 2896.559 594.8470

[13,] 2358.428 1736.430 2980.427 621.9982

[14,] 2393.994 1747.656 3040.331 646.3372

[15,] 2410.771 1741.556 3079.986 669.2148

[16,] 2429.244 1737.218 3121.270 692.0259

[17,] 2422.391 1708.170 3136.611 714.2209

[18,] 2400.361 1663.910 3136.813 736.4518

[19,] 2382.499 1623.644 3141.354 758.8551

[20,] 2373.805 1592.829 3154.780 780.9754

[21,] 2365.464 1562.934 3167.994 802.5298

[22,] 2355.949 1532.440 3179.458 823.5089

[23,] 2345.795 1501.451 3190.138 844.3433

[24,] 2336.549 1471.808 3201.290 864.7412

$tin

fcst lower upper CI

[1,] 31970.83 30524.06 33417.59 1446.763

[2,] 31556.61 29184.34 33928.87 2372.262

[3,] 30808.91 27577.59 34040.23 3231.323

[4,] 30422.68 26437.23 34408.14 3985.451

[5,] 28899.35 24283.22 33515.48 4616.131

[6,] 27304.10 22137.99 32470.20 5166.102

[7,] 27218.22 21554.36 32882.07 5663.856

[8,] 27038.94 20956.70 33121.19 6082.246

[9,] 27062.92 20640.83 33485.02 6422.094

[10,] 27067.17 20293.60 33840.75 6773.571

[11,] 27325.58 20184.93 34466.24 7140.654

[12,] 27576.78 20065.40 35088.16 7511.378

[13,] 27736.41 19871.35 35601.47 7865.061

[14,] 27966.66 19753.63 36179.70 8213.035

[15,] 28026.38 19488.72 36564.05 8537.667

[16,] 28151.29 19305.09 36997.48 8846.195

[17,] 28362.14 19229.00 37495.28 9133.139

[18,] 28640.78 19248.41 38033.15 9392.368

[19,] 28881.70 19246.02 38517.37 9635.678

[20,] 29126.56 19259.62 38993.51 9866.944

[21,] 29387.96 19293.65 39482.27 10094.310

[22,] 29597.03 19282.07 39911.99 10314.964

[23,] 29735.15 19203.08 40267.21 10532.068

[24,] 29807.86 19060.14 40555.57 10747.714

$nickel

fcst lower upper CI

[1,] 16711.80 14905.380 18518.22 1806.422

[2,] 16297.66 13268.132 19327.19 3029.528

[3,] 17030.89 13067.557 20994.21 3963.328

[4,] 17721.68 13120.744 22322.61 4600.931

[5,] 17346.58 12258.187 22434.98 5088.398

[6,] 17211.25 11620.264 22802.24 5590.989

[7,] 17919.71 11819.403 24020.01 6100.305

[8,] 17947.33 11409.378 24485.29 6537.955

[9,] 18096.17 11168.796 25023.55 6927.376

[10,] 18252.41 10968.917 25535.91 7283.494

[11,] 18429.30 10787.660 26070.94 7641.642

[12,] 18487.24 10505.534 26468.95 7981.706

[13,] 18346.03 10043.880 26648.18 8302.152

[14,] 18225.82 9613.458 26838.18 8612.363

[15,] 18083.50 9178.488 26988.51 8905.010

[16,] 17993.20 8808.031 27178.38 9185.173

[17,] 18013.16 8564.030 27462.29 9449.130

[18,] 17887.02 8199.493 27574.54 9687.525

[19,] 17734.58 7826.075 27643.09 9908.509

[20,] 17657.99 7545.228 27770.76 10112.765

[21,] 17552.71 7248.893 27856.53 10303.818

[22,] 17333.26 6847.811 27818.70 10485.445

[23,] 17063.44 6403.749 27723.13 10659.689

[24,] 16807.43 5979.567 27635.30 10827.865

$zinc

fcst lower upper CI

[1,] 2757.746 2566.811 2948.682 190.9358

[2,] 2787.964 2479.612 3096.316 308.3521

[3,] 2813.762 2420.973 3206.550 392.7884

[4,] 2855.492 2397.241 3313.744 458.2514

[5,] 2788.393 2268.858 3307.927 519.5342

[6,] 2774.717 2190.408 3359.027 584.3092

[7,] 2782.996 2137.300 3428.692 645.6960

[8,] 2784.106 2074.644 3493.567 709.4616

[9,] 2807.929 2038.895 3576.963 769.0340

[10,] 2784.273 1964.758 3603.788 819.5150

[11,] 2797.398 1929.380 3665.416 868.0179

[12,] 2810.966 1896.720 3725.212 914.2462

[13,] 2800.063 1842.628 3757.498 957.4352

[14,] 2788.692 1790.528 3786.855 998.1636

[15,] 2760.275 1723.468 3797.082 1036.8068

[16,] 2744.225 1670.474 3817.975 1073.7504

[17,] 2714.888 1607.157 3822.619 1107.7309

[18,] 2689.351 1549.973 3828.728 1139.3774

[19,] 2660.369 1490.829 3829.909 1169.5400

[20,] 2639.347 1441.681 3837.012 1197.6657

[21,] 2621.581 1397.386 3845.777 1224.1957

[22,] 2608.209 1358.748 3857.671 1249.4617

[23,] 2594.661 1320.997 3868.324 1273.6634

[24,] 2583.604 1286.664 3880.544 1296.9400

A group of graphs showing different types of lines

Description automatically generated

**Interpretation:**

**Error Correction Terms (ECTs):**

These terms indicate how the error correction mechanism adjusts deviations from the long-term equilibrium:

* **ect1, ect2, ect3:** Represent different cointegrating vectors.
* **Negative coefficients** indicate how the variables adjust to correct deviations.

Examples:

* **iron\_ore.d:**
  + ect1: -0.08173665 (indicates a negative adjustment to restore equilibrium).
  + ect2: 0.00078545.
  + ect3: 0.00134281.
* **copper.d:**
  + ect1: 1.17834534 (indicates a positive adjustment).
  + ect2: -0.01362420.
  + ect3: 0.00093547.

**Lagged Differences (d.lags):**

The coefficients of lagged differences (dl1 to dl9) represent how past values influence current changes:

* For example, **iron\_ore.dl1** (lag 1 of iron\_ore) has a positive influence on iron\_ore.d with a coefficient of 0.2852092.
* **copper.dl1** also has a positive influence on copper.d with a coefficient of 0.30184163.

Each variable's influence on the others is shown in the columns. Significant coefficients (those with larger absolute values) suggest a stronger relationship between the variables.

**Forecasts:**

The forecasts provide predicted values and their confidence intervals (CI) for each variable over the next periods (24 steps):

**iron\_ore:**

* Forecast starts at 103.14983 and decreases slightly, then fluctuates around 125.
* Confidence intervals widen over time, indicating increasing uncertainty.

**copper:**

* Forecast starts at 9303.341 and fluctuates around 8600-8700.
* Confidence intervals widen, indicating increasing uncertainty.

**lead:**

* Forecast starts at 2143.053 and increases slightly, then stabilizes around 2400.
* Confidence intervals widen over time.

**tin:**

* Forecast starts at 31970.83 and decreases steadily, then stabilizes around 29800.
* Confidence intervals widen, indicating increasing uncertainty.

**nickel:**

* Forecast starts at 16711.80 and fluctuates around 17500.
* Confidence intervals widen over time.

**zinc:**

* Forecast starts at 2757.746 and decreases slightly, then stabilizes around 2583.
* Confidence intervals widen, indicating increasing uncertainty.
* **iron\_ore:** The forecast shows slight fluctuations with increasing uncertainty.
* **copper:** The forecast indicates slight fluctuations around the current level with increasing uncertainty.
* **lead:** The forecast shows a slight upward trend, then stabilizes with moderate uncertainty.
* **tin:** The forecast shows a decreasing trend, stabilizing around 29800, with increasing uncertainty.
* **nickel:** The forecast indicates fluctuations around the current level with increasing uncertainty.
* **zinc:** The forecast shows a slight downward trend, then stabilizes around 2583, with increasing uncertainty.

**Python Language**

**Part 1: Setting Up the Environment for Commodity Set 1 (Oil, Sugar, Gold, Silver, Wheat, and Soybean)**

# Load necessary libraries

import pandas as pd

import numpy as np

import matplotlib.pyplot as plt

from statsmodels.tsa.api import VAR

from statsmodels.tsa.vector\_ar.vecm import coint\_johansen, VECM

# Load the dataset

file\_path = 'C:\\Users\\nihar\\OneDrive\\Desktop\\Bootcamp\\SCMA 632\\DataSet\\pinksheet.xlsx'

df = pd.read\_excel(file\_path, sheet\_name="Monthly Prices", skiprows=6)

# Rename the first column to "Date"

df.rename(columns={df.columns[0]: 'Date'}, inplace=True)

# Convert the Date column to datetime format

df['Date'] = pd.to\_datetime(df['Date'].astype(str) + '01', format='%YM%m%d')

**Purpose:**

* pandas.read\_excel() reads the Excel file and loads the specified sheet into a DataFrame, skipping the first 6 rows.
* rename(columns={df.columns[0]: 'Date'}) renames the first column to "Date".
* pd.to\_datetime() converts the 'Date' column to the appropriate date format.

**Output:**

# Displaying the structure of the dataframe

df.head()

plaintext

Copy code

Date ... Column names...

0 1960-01-01 ... Other values...

1 1960-02-01 ...

2 1960-03-01 ...

3 1960-04-01 ...

4 1960-05-01 ...

**Interpretation:**

* The dataset has been successfully loaded with 'Date' column properly formatted.

**Part 2: Selecting and Cleaning Data for Commodity Set 1**

# Select specific columns (Date and selected commodities)

commodity\_columns = ['Date', df.columns[2], df.columns[24], df.columns[69], df.columns[71], df.columns[60], df.columns[30]]

commodity = df[commodity\_columns]

commodity.columns = ['Date', 'crude\_brent', 'soybeans', 'gold', 'silver', 'urea\_ee\_bulk', 'maize']

# Check for missing values

missing\_values = commodity.isna().sum()

print("Missing Values:\n", missing\_values)

**Purpose:**

* Selects columns corresponding to the date and specific commodities.
* Cleans the column names.
* Checks for missing values in each column.

**Output:**

Missing Values:

Date 0

crude\_brent 0

soybeans 0

gold 0

silver 0

urea\_ee\_bulk 0

maize 0

dtype: int64

**Interpretation:**

* There are no missing values in any of the selected columns.

**Part 3: Visualizing Data for Commodity Set 1**

# Visualize data

for col in commodity.columns[1:]: # Skip the date column

plt.figure()

plt.plot(commodity['Date'], commodity[col])

plt.title(f'Price of {col}')

plt.xlabel('Date')

plt.ylabel('Price')

plt.show()

**Purpose:**

* Loops through each commodity column (excluding 'Date') and plots its time series data.

**Output:**

**A graph of a price of soybeans

Description automatically generated**A graph of a price

Description automatically generated

**A graph of a graph showing the price of silver

Description automatically generated**A graph showing the price of gold

Description automatically generated

**A graph of a number of blue lines

Description automatically generatedA graph of a graph showing the price of urea

Description automatically generated**

* Plots showing the price trends of Crude Brent, Soybeans, Gold, Silver, Urea EE Bulk, and Maize over time.

**Interpretation:**

**Price of Crude Brent**

* **Trend**: There is a significant upward trend in the price of crude Brent over the entire period.
* **Volatility**: Noticeable volatility, especially in the periods around 2008 (financial crisis) and 2020 (COVID-19 pandemic).
* **Peaks**: Significant peaks around 2008 and 2012.

**2. Price of Soybeans**

* **Trend**: An overall upward trend with notable fluctuations.
* **Volatility**: Significant price spikes in the early 1970s, mid-2000s, and around 2012.
* **Peaks**: Major peaks around 1973, 2008, and 2012.

**3. Price of Gold**

* **Trend**: A strong upward trend, especially from 2000 onwards.
* **Volatility**: Sharp increases in prices during the late 2000s and early 2010s.
* **Peaks**: Major peak around 2011-2012.

**4. Price of Silver**

* **Trend**: Similar to gold, an upward trend with high volatility.
* **Volatility**: Notable price spikes in the early 1980s and around 2011.
* **Peaks**: Major peak in 1980 and another in 2011.

**5. Price of Urea EE Bulk**

* **Trend**: Significant upward trend over the period with high volatility.
* **Volatility**: Large fluctuations especially noticeable from 2005 onwards.
* **Peaks**: Major peaks around 2008 and 2012.

**6. Price of Maize**

* **Trend**: A general upward trend with significant fluctuations.
* **Volatility**: Noticeable volatility with significant peaks around 1974, 2008, and 2012.
* **Peaks**: Major peak around 2008 and another in 2012.

**Part 4: Stationarity Test for Commodity Set 1**

# Prepare data for VAR and VECM analysis

commodity\_data = commodity.drop(columns=['Date'])

columns\_to\_test = commodity\_data.columns

# Stationarity test

from statsmodels.tsa.stattools import adfuller

non\_stationary\_count = 0

stationary\_columns = []

non\_stationary\_columns = []

for col in columns\_to\_test:

result = adfuller(commodity\_data[col])

p\_value = result[1]

print(f"\nADF test result for column: {col}")

print(result)

if p\_value > 0.05:

non\_stationary\_count += 1

non\_stationary\_columns.append(col)

else:

stationary\_columns.append(col)

print(f"\nNumber of non-stationary columns: {non\_stationary\_count}")

print(f"Non-stationary columns: {', '.join(non\_stationary\_columns)}")

print(f"Stationary columns: {', '.join(stationary\_columns)}")

**Purpose:**

* Prepares the data by removing the 'Date' column for analysis.
* Performs the Augmented Dickey-Fuller (ADF) test on each column to check for stationarity.
* Columns with p-values greater than 0.05 are considered non-stationary.

**Output:**

ADF test result for column: crude\_brent

(-1.5078661910935343, 0.5296165197702398, 15, 758, {'1%': -3.439006442437876, '5%': -2.865360521688131, '10%': -2.5688044403756587}, 4066.6988288806638)

ADF test result for column: soybeans

(-2.4231464527418902, 0.1353097742779038, 2, 771, {'1%': -3.4388599939707056, '5%': -2.865295977855759, '10%': -2.5687700561872413}, 6628.115125985425)

ADF test result for column: gold

(1.3430517021933006, 0.9968394353612382, 11, 762, {'1%': -3.4389608473398194, '5%': -2.8653404270188476, '10%': -2.568793735369693}, 7235.396489477796)

ADF test result for column: silver

(-1.397294710746222, 0.5835723787985764, 7, 766, {'1%': -3.438915730045254, '5%': -2.8653205426302253, '10%': -2.5687831424305845}, 2389.2895266530068)

ADF test result for column: urea\_ee\_bulk

(-2.5101716315209086, 0.11301903181624645, 15, 758, {'1%': -3.439006442437876, '5%': -2.865360521688131, '10%': -2.5688044403756587}, 7263.370731967089)

ADF test result for column: maize

(-2.4700451060920425, 0.12293380919376751, 16, 757, {'1%': -3.4390179167598367, '5%': -2.8653655786032237, '10%': -2.5688071343462777}, 5409.51930379389)

Number of non-stationary columns: 6

Non-stationary columns: crude\_brent, soybeans, gold, silver, urea\_ee\_bulk, maize

Stationary columns:

**Interpretation:**

The Augmented Dickey-Fuller (ADF) test is used to check the stationarity of a time series. Here’s a breakdown of the results for each commodity:

**ADF Test Result for Column: Crude Brent**

* **ADF Statistic**: -1.5078661910935343
* **p-value**: 0.5296165197702398
* **Critical Values**:
  + 1%: -3.439006442437876
  + 5%: -2.865360521688131
  + 10%: -2.5688044403756587

**Interpretation**:

* The p-value (0.5296) is greater than 0.05, which means we fail to reject the null hypothesis.
* The time series is non-stationary.

**ADF Test Result for Column: Soybeans**

* **ADF Statistic**: -2.4231464527418902
* **p-value**: 0.1353097742779038
* **Critical Values**:
  + 1%: -3.4388599939707056
  + 5%: -2.865295977855759
  + 10%: -2.5687700561872413

**Interpretation**:

* The p-value (0.1353) is greater than 0.05, which means we fail to reject the null hypothesis.
* The time series is non-stationary.

**ADF Test Result for Column: Gold**

* **ADF Statistic**: 1.3430517021933006
* **p-value**: 0.9968394353612382
* **Critical Values**:
  + 1%: -3.4389608473398194
  + 5%: -2.8653404270188476
  + 10%: -2.568793735369693

**Interpretation**:

* The p-value (0.9968) is much greater than 0.05, which means we fail to reject the null hypothesis.
* The time series is non-stationary.

**ADF Test Result for Column: Silver**

* **ADF Statistic**: -1.397294710746222
* **p-value**: 0.5835723787985764
* **Critical Values**:
  + 1%: -3.438915730045254
  + 5%: -2.8653205426302253
  + 10%: -2.5687831424305845

**Interpretation**:

* The p-value (0.5836) is greater than 0.05, which means we fail to reject the null hypothesis.
* The time series is non-stationary.

**ADF Test Result for Column: Urea EE Bulk**

* **ADF Statistic**: -2.5101716315209086
* **p-value**: 0.11301903181624645
* **Critical Values**:
  + 1%: -3.439006442437876
  + 5%: -2.865360521688131
  + 10%: -2.5688044403756587

**Interpretation**:

* The p-value (0.1130) is greater than 0.05, which means we fail to reject the null hypothesis.
* The time series is non-stationary.

**ADF Test Result for Column: Maize**

* **ADF Statistic**: -2.4700451060920425
* **p-value**: 0.12293380919376751
* **Critical Values**:
  + 1%: -3.4390179167598367
  + 5%: -2.8653655786032237
  + 10%: -2.5688071343462777

**Interpretation**:

* The p-value (0.1229) is greater than 0.05, which means we fail to reject the null hypothesis.
* The time series is non-stationary.

**Part 5: Co-Integration Test and Model Fitting for Commodity Set 1**

# Co-Integration Test (Johansen's Test)

lags = select\_order(commodity\_data, maxlags=10, deterministic='ci')

lag\_length = lags.aic

johansen\_test = coint\_johansen(commodity\_data, det\_order=0, k\_ar\_diff=lag\_length)

print("\nJohansen's Test Results:")

print(johansen\_test.lr1)

r = 3 # Replace with the actual number from the test results

if r > 0:

vecm\_model = VECM(commodity\_data, k\_ar\_diff=lag\_length, coint\_rank=r, deterministic='ci')

vecm\_fit = vecm\_model.fit()

print(vecm\_fit.summary())

# Forecasting

forecast = vecm\_fit.predict(steps=24)

forecast\_df = pd.DataFrame(forecast, index=pd.date\_range(start=commodity['Date'].iloc[-1], periods=24, freq='M'), columns=commodity.columns[1:])

plt.figure()

forecast\_df.plot()

plt.title('VECM Forecast')

plt.xlabel('Date')

plt.ylabel('Price')

plt.show()

else:

var\_model = VAR(commodity\_data)

var\_fit = var\_model.fit(lag\_length)

print(var\_fit.summary())

forecast = var\_fit.forecast(var\_fit.y, steps=24)

forecast\_df = pd.DataFrame(forecast, index=pd.date\_range(start=commodity['Date'].iloc[-1], periods=24, freq='M'), columns=commodity.columns[1:])

plt.figure()

forecast\_df.plot()

plt.title('VAR Forecast')

plt.xlabel('Date')

plt.ylabel('Price')

plt.show()

# Display forecasted data

forecast\_df

**Purpose:**

* Conducts Johansen's cointegration test to determine the cointegration rank.
* Fits a VECM or VAR model based on the cointegration test results.
* Forecasts future values and plots the forecasts.

**Output:**

Johansen's Test Results:

[194.54858991 118.95889314 70.1480132 38.12513847 16.53520264

5.6366925 ]

Det. terms outside the coint. relation & lagged endog. parameters for equation crude\_brent

====================================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------------

L1.crude\_brent 0.3221 0.038 8.403 0.000 0.247 0.397

L1.soybeans 0.0113 0.008 1.496 0.135 -0.004 0.026

L1.gold 0.0009 0.006 0.138 0.890 -0.012 0.013

L1.silver -0.0849 0.161 -0.527 0.598 -0.401 0.231

L1.urea\_ee\_bulk -0.0047 0.005 -0.956 0.339 -0.014 0.005

L1.maize 0.0131 0.018 0.747 0.455 -0.021 0.048

L2.crude\_brent -0.0627 0.041 -1.541 0.123 -0.142 0.017

L2.soybeans 0.0193 0.008 2.554 0.011 0.004 0.034

L2.gold -0.0047 0.007 -0.714 0.475 -0.018 0.008

L2.silver 0.1028 0.171 0.602 0.547 -0.232 0.438

L2.urea\_ee\_bulk 0.0082 0.005 1.638 0.101 -0.002 0.018

L2.maize -0.0139 0.018 -0.783 0.434 -0.049 0.021

L3.crude\_brent -0.0816 0.040 -2.019 0.044 -0.161 -0.002

L3.soybeans -0.0075 0.007 -1.007 0.314 -0.022 0.007

L3.gold 0.0018 0.007 0.272 0.786 -0.011 0.015

L3.silver 0.0373 0.176 0.212 0.832 -0.308 0.383

L3.urea\_ee\_bulk 0.0076 0.005 1.514 0.130 -0.002 0.017

L3.maize 0.0202 0.018 1.139 0.255 -0.015 0.055

L4.crude\_brent -0.0123 0.041 -0.301 0.763 -0.093 0.068

L4.soybeans 0.0022 0.008 0.293 0.770 -0.013 0.017

L4.gold 0.0197 0.007 2.871 0.004 0.006 0.033

L4.silver -0.2054 0.177 -1.161 0.246 -0.552 0.141

L4.urea\_ee\_bulk 0.0029 0.005 0.591 0.555 -0.007 0.013

L4.maize -0.0173 0.018 -0.973 0.331 -0.052 0.018

L5.crude\_brent 0.0013 0.040 0.032 0.975 -0.078 0.080

L5.soybeans 0.0139 0.008 1.824 0.068 -0.001 0.029

L5.gold 0.0012 0.007 0.176 0.860 -0.012 0.015

L5.silver -0.0240 0.176 -0.136 0.892 -0.369 0.322

L5.urea\_ee\_bulk 0.0029 0.005 0.614 0.539 -0.006 0.012

L5.maize 0.0078 0.018 0.439 0.660 -0.027 0.043

L6.crude\_brent -0.1088 0.040 -2.703 0.007 -0.188 -0.030

L6.soybeans -0.0122 0.008 -1.612 0.107 -0.027 0.003

L6.gold 0.0098 0.007 1.452 0.147 -0.003 0.023

L6.silver -0.1654 0.175 -0.946 0.344 -0.508 0.177

L6.urea\_ee\_bulk -0.0088 0.005 -1.825 0.068 -0.018 0.001

L6.maize 0.0228 0.018 1.302 0.193 -0.012 0.057

L7.crude\_brent 0.0746 0.040 1.847 0.065 -0.005 0.154

L7.soybeans 0.0284 0.008 3.696 0.000 0.013 0.043

L7.gold -0.0073 0.007 -1.065 0.287 -0.021 0.006

L7.silver 0.0097 0.176 0.055 0.956 -0.335 0.354

L7.urea\_ee\_bulk 0.0063 0.005 1.293 0.196 -0.003 0.016

L7.maize -0.0405 0.018 -2.275 0.023 -0.075 -0.006

L8.crude\_brent 0.0305 0.040 0.755 0.450 -0.049 0.110

L8.soybeans 0.0172 0.008 2.231 0.026 0.002 0.032

L8.gold 0.0005 0.007 0.069 0.945 -0.013 0.014

L8.silver -0.0711 0.178 -0.400 0.689 -0.419 0.277

L8.urea\_ee\_bulk 0.0061 0.005 1.252 0.211 -0.003 0.016

L8.maize -0.0794 0.018 -4.506 0.000 -0.114 -0.045

L9.crude\_brent -0.0975 0.040 -2.423 0.015 -0.176 -0.019

L9.soybeans -0.0019 0.008 -0.240 0.811 -0.017 0.014

L9.gold -0.0172 0.007 -2.532 0.011 -0.030 -0.004

L9.silver 0.2682 0.170 1.575 0.115 -0.066 0.602

L9.urea\_ee\_bulk -0.0036 0.005 -0.763 0.446 -0.013 0.006

L9.maize -0.0029 0.018 -0.164 0.870 -0.038 0.032

L10.crude\_brent 0.0492 0.039 1.250 0.211 -0.028 0.126

L10.soybeans 0.0101 0.008 1.288 0.198 -0.005 0.026

L10.gold 0.0010 0.007 0.155 0.877 -0.012 0.014

L10.silver -0.1062 0.164 -0.649 0.516 -0.427 0.214

L10.urea\_ee\_bulk 0.0008 0.005 0.166 0.868 -0.008 0.010

L10.maize -0.0357 0.017 -2.047 0.041 -0.070 -0.002

Det. terms outside the coint. relation & lagged endog. parameters for equation soybeans

====================================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------------

L1.crude\_brent 0.3231 0.213 1.517 0.129 -0.094 0.741

L1.soybeans 0.0783 0.042 1.861 0.063 -0.004 0.161

L1.gold 0.0164 0.035 0.463 0.644 -0.053 0.086

L1.silver -0.0639 0.895 -0.071 0.943 -1.819 1.691

L1.urea\_ee\_bulk -0.0025 0.027 -0.092 0.927 -0.056 0.051

L1.maize 0.2759 0.098 2.820 0.005 0.084 0.468

L2.crude\_brent 0.0858 0.226 0.380 0.704 -0.357 0.529

L2.soybeans 0.0144 0.042 0.342 0.732 -0.068 0.097

L2.gold -0.0305 0.037 -0.826 0.409 -0.103 0.042

L2.silver 0.5956 0.950 0.627 0.531 -1.266 2.457

L2.urea\_ee\_bulk 0.0170 0.028 0.611 0.541 -0.038 0.072

L2.maize -0.0334 0.099 -0.338 0.735 -0.227 0.160

L3.crude\_brent 0.1474 0.225 0.656 0.512 -0.293 0.588

L3.soybeans -0.0955 0.042 -2.299 0.022 -0.177 -0.014

L3.gold 0.0521 0.038 1.379 0.168 -0.022 0.126

L3.silver -0.9986 0.979 -1.020 0.308 -2.917 0.920

L3.urea\_ee\_bulk 0.0302 0.028 1.085 0.278 -0.024 0.085

L3.maize 0.1655 0.099 1.678 0.093 -0.028 0.359

L4.crude\_brent 0.0161 0.227 0.071 0.943 -0.430 0.462

L4.soybeans 0.0269 0.042 0.641 0.522 -0.055 0.109

L4.gold 0.0260 0.038 0.680 0.496 -0.049 0.101

L4.silver -0.8658 0.983 -0.881 0.378 -2.793 1.061

L4.urea\_ee\_bulk -0.0101 0.027 -0.367 0.714 -0.064 0.044

L4.maize -0.3540 0.099 -3.578 0.000 -0.548 -0.160

L5.crude\_brent 0.0800 0.224 0.357 0.721 -0.359 0.519

L5.soybeans -0.0733 0.042 -1.731 0.083 -0.156 0.010

L5.gold -0.0607 0.038 -1.599 0.110 -0.135 0.014

L5.silver 0.7792 0.979 0.796 0.426 -1.140 2.699

L5.urea\_ee\_bulk 0.0314 0.027 1.181 0.238 -0.021 0.084

L5.maize 0.0992 0.098 1.007 0.314 -0.094 0.292

L6.crude\_brent -0.2992 0.224 -1.338 0.181 -0.737 0.139

L6.soybeans 0.0513 0.042 1.220 0.223 -0.031 0.134

L6.gold 0.0949 0.038 2.525 0.012 0.021 0.168

L6.silver -1.0968 0.972 -1.128 0.259 -3.002 0.809

L6.urea\_ee\_bulk -0.0646 0.027 -2.413 0.016 -0.117 -0.012

L6.maize -0.2230 0.097 -2.289 0.022 -0.414 -0.032

L7.crude\_brent -0.0403 0.224 -0.180 0.857 -0.480 0.399

L7.soybeans 0.0683 0.043 1.603 0.109 -0.015 0.152

L7.gold -0.0544 0.038 -1.432 0.152 -0.129 0.020

L7.silver -0.5555 0.977 -0.569 0.570 -2.470 1.359

L7.urea\_ee\_bulk 0.0565 0.027 2.083 0.037 0.003 0.110

L7.maize -0.0878 0.099 -0.888 0.375 -0.282 0.106

L8.crude\_brent -0.1223 0.224 -0.545 0.586 -0.562 0.317

L8.soybeans -0.0804 0.043 -1.882 0.060 -0.164 0.003

L8.gold 0.0826 0.038 2.172 0.030 0.008 0.157

L8.silver -0.1388 0.987 -0.141 0.888 -2.072 1.795

L8.urea\_ee\_bulk 0.0175 0.027 0.647 0.517 -0.036 0.071

L8.maize -0.0198 0.098 -0.202 0.840 -0.212 0.172

L9.crude\_brent -0.2659 0.224 -1.189 0.235 -0.704 0.173

L9.soybeans 0.0022 0.044 0.050 0.960 -0.083 0.088

L9.gold -0.0659 0.038 -1.748 0.080 -0.140 0.008

L9.silver 0.9157 0.946 0.968 0.333 -0.939 2.771

L9.urea\_ee\_bulk 0.0133 0.027 0.502 0.616 -0.039 0.065

L9.maize -0.1234 0.099 -1.252 0.211 -0.316 0.070

L10.crude\_brent -0.2937 0.219 -1.343 0.179 -0.722 0.135

L10.soybeans -0.1200 0.044 -2.748 0.006 -0.206 -0.034

L10.gold 0.1082 0.037 2.950 0.003 0.036 0.180

L10.silver -0.7841 0.909 -0.863 0.388 -2.565 0.997

L10.urea\_ee\_bulk 0.0630 0.025 2.502 0.012 0.014 0.112

L10.maize 0.1440 0.097 1.487 0.137 -0.046 0.334

Det. terms outside the coint. relation & lagged endog. parameters for equation gold

====================================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------------

L1.crude\_brent 0.2043 0.307 0.666 0.505 -0.397 0.806

L1.soybeans 0.0047 0.061 0.077 0.939 -0.114 0.123

L1.gold 0.2413 0.051 4.724 0.000 0.141 0.341

L1.silver 1.3534 1.290 1.050 0.294 -1.174 3.881

L1.urea\_ee\_bulk -0.1520 0.039 -3.898 0.000 -0.228 -0.076

L1.maize 0.4371 0.141 3.103 0.002 0.161 0.713

L2.crude\_brent 0.3933 0.325 1.209 0.227 -0.244 1.031

L2.soybeans 0.0417 0.061 0.689 0.491 -0.077 0.160

L2.gold -0.0616 0.053 -1.161 0.246 -0.166 0.042

L2.silver -2.3605 1.368 -1.726 0.084 -5.042 0.321

L2.urea\_ee\_bulk 0.0728 0.040 1.817 0.069 -0.006 0.151

L2.maize 0.0383 0.142 0.269 0.788 -0.241 0.317

L3.crude\_brent -0.6337 0.324 -1.958 0.050 -1.268 0.001

L3.soybeans -0.1778 0.060 -2.970 0.003 -0.295 -0.060

L3.gold 0.0936 0.054 1.719 0.086 -0.013 0.200

L3.silver -1.3014 1.410 -0.923 0.356 -4.065 1.462

L3.urea\_ee\_bulk -0.0786 0.040 -1.957 0.050 -0.157 0.000

L3.maize 0.5605 0.142 3.945 0.000 0.282 0.839

L4.crude\_brent 0.0724 0.328 0.221 0.825 -0.570 0.714

L4.soybeans 0.0701 0.060 1.159 0.246 -0.048 0.189

L4.gold -0.0017 0.055 -0.032 0.975 -0.109 0.106

L4.silver 0.9584 1.416 0.677 0.498 -1.816 3.733

L4.urea\_ee\_bulk -0.0751 0.040 -1.900 0.057 -0.152 0.002

L4.maize -0.5106 0.142 -3.584 0.000 -0.790 -0.231

L5.crude\_brent -0.3751 0.323 -1.163 0.245 -1.007 0.257

L5.soybeans -0.0983 0.061 -1.612 0.107 -0.218 0.021

L5.gold 0.0697 0.055 1.276 0.202 -0.037 0.177

L5.silver 0.7909 1.410 0.561 0.575 -1.974 3.555

L5.urea\_ee\_bulk 0.0884 0.038 2.307 0.021 0.013 0.163

L5.maize 0.2105 0.142 1.484 0.138 -0.067 0.488

L6.crude\_brent -0.3799 0.322 -1.180 0.238 -1.011 0.251

L6.soybeans -0.0169 0.061 -0.279 0.781 -0.136 0.102

L6.gold 0.0070 0.054 0.129 0.897 -0.099 0.113

L6.silver -0.5582 1.400 -0.399 0.690 -3.302 2.186

L6.urea\_ee\_bulk -0.2042 0.039 -5.293 0.000 -0.280 -0.129

L6.maize 0.0239 0.140 0.171 0.864 -0.251 0.299

L7.crude\_brent 0.6937 0.323 2.148 0.032 0.061 1.327

L7.soybeans 0.0829 0.061 1.350 0.177 -0.037 0.203

L7.gold -0.0911 0.055 -1.667 0.096 -0.198 0.016

L7.silver 3.3302 1.407 2.368 0.018 0.573 6.087

L7.urea\_ee\_bulk 0.0193 0.039 0.495 0.621 -0.057 0.096

L7.maize 0.1378 0.142 0.968 0.333 -0.141 0.417

L8.crude\_brent 0.5235 0.323 1.620 0.105 -0.110 1.157

L8.soybeans 0.0886 0.062 1.440 0.150 -0.032 0.209

L8.gold -0.0572 0.055 -1.045 0.296 -0.165 0.050

L8.silver -0.4857 1.421 -0.342 0.732 -3.270 2.299

L8.urea\_ee\_bulk -0.0351 0.039 -0.900 0.368 -0.112 0.041

L8.maize -0.2312 0.141 -1.640 0.101 -0.508 0.045

L9.crude\_brent -0.9217 0.322 -2.861 0.004 -1.553 -0.290

L9.soybeans -0.0466 0.063 -0.741 0.459 -0.170 0.077

L9.gold -0.0735 0.054 -1.353 0.176 -0.180 0.033

L9.silver 3.7970 1.363 2.786 0.005 1.126 6.468

L9.urea\_ee\_bulk 0.0006 0.038 0.015 0.988 -0.074 0.076

L9.maize 0.0760 0.142 0.535 0.592 -0.202 0.354

L10.crude\_brent 0.9019 0.315 2.864 0.004 0.285 1.519

L10.soybeans 0.0152 0.063 0.243 0.808 -0.108 0.138

L10.gold 0.0679 0.053 1.286 0.199 -0.036 0.172

L10.silver -1.7182 1.308 -1.313 0.189 -4.283 0.846

L10.urea\_ee\_bulk -0.1208 0.036 -3.328 0.001 -0.192 -0.050

L10.maize 0.3834 0.139 2.748 0.006 0.110 0.657

Det. terms outside the coint. relation & lagged endog. parameters for equation silver

====================================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------------

L1.crude\_brent 0.0023 0.013 0.183 0.855 -0.022 0.027

L1.soybeans 0.0001 0.002 0.041 0.967 -0.005 0.005

L1.gold -0.0024 0.002 -1.131 0.258 -0.006 0.002

L1.silver 0.3933 0.053 7.457 0.000 0.290 0.497

L1.urea\_ee\_bulk -0.0027 0.002 -1.720 0.085 -0.006 0.000

L1.maize 0.0166 0.006 2.880 0.004 0.005 0.028

L2.crude\_brent 0.0182 0.013 1.368 0.171 -0.008 0.044

L2.soybeans -0.0021 0.002 -0.850 0.395 -0.007 0.003

L2.gold 0.0015 0.002 0.690 0.490 -0.003 0.006

L2.silver -0.2571 0.056 -4.596 0.000 -0.367 -0.147

L2.urea\_ee\_bulk -0.0002 0.002 -0.142 0.887 -0.003 0.003

L2.maize 0.0130 0.006 2.238 0.025 0.002 0.024

L3.crude\_brent -0.0212 0.013 -1.603 0.109 -0.047 0.005

L3.soybeans -0.0051 0.002 -2.065 0.039 -0.010 -0.000

L3.gold 0.0021 0.002 0.942 0.346 -0.002 0.006

L3.silver -0.0494 0.058 -0.857 0.391 -0.162 0.064

L3.urea\_ee\_bulk 0.0013 0.002 0.808 0.419 -0.002 0.005

L3.maize 0.0168 0.006 2.889 0.004 0.005 0.028

L4.crude\_brent 0.0068 0.013 0.505 0.613 -0.019 0.033

L4.soybeans -0.0018 0.002 -0.744 0.457 -0.007 0.003

L4.gold 0.0030 0.002 1.346 0.178 -0.001 0.007

L4.silver -0.0106 0.058 -0.183 0.855 -0.124 0.103

L4.urea\_ee\_bulk -0.0037 0.002 -2.276 0.023 -0.007 -0.001

L4.maize -0.0125 0.006 -2.140 0.032 -0.024 -0.001

L5.crude\_brent -0.0250 0.013 -1.898 0.058 -0.051 0.001

L5.soybeans -0.0027 0.002 -1.099 0.272 -0.008 0.002

L5.gold 0.0020 0.002 0.890 0.374 -0.002 0.006

L5.silver -0.0416 0.058 -0.720 0.471 -0.155 0.072

L5.urea\_ee\_bulk 0.0028 0.002 1.783 0.075 -0.000 0.006

L5.maize 0.0130 0.006 2.237 0.025 0.002 0.024

L6.crude\_brent -0.0159 0.013 -1.208 0.227 -0.042 0.010

L6.soybeans -0.0029 0.002 -1.175 0.240 -0.008 0.002

L6.gold 0.0058 0.002 2.608 0.009 0.001 0.010

L6.silver -0.1596 0.057 -2.787 0.005 -0.272 -0.047

L6.urea\_ee\_bulk -0.0064 0.002 -4.032 0.000 -0.009 -0.003

L6.maize 0.0066 0.006 1.147 0.251 -0.005 0.018

L7.crude\_brent 0.0311 0.013 2.353 0.019 0.005 0.057

L7.soybeans 0.0009 0.003 0.341 0.733 -0.004 0.006

L7.gold -0.0006 0.002 -0.254 0.799 -0.005 0.004

L7.silver 0.0127 0.058 0.222 0.825 -0.100 0.125

L7.urea\_ee\_bulk 0.0017 0.002 1.080 0.280 -0.001 0.005

L7.maize 0.0099 0.006 1.692 0.091 -0.002 0.021

L8.crude\_brent 0.0249 0.013 1.887 0.059 -0.001 0.051

L8.soybeans 0.0019 0.003 0.763 0.446 -0.003 0.007

L8.gold -0.0021 0.002 -0.958 0.338 -0.007 0.002

L8.silver 0.0382 0.058 0.657 0.511 -0.076 0.152

L8.urea\_ee\_bulk -0.0013 0.002 -0.843 0.399 -0.004 0.002

L8.maize -0.0082 0.006 -1.415 0.157 -0.019 0.003

L9.crude\_brent -0.0334 0.013 -2.537 0.011 -0.059 -0.008

L9.soybeans -0.0022 0.003 -0.852 0.394 -0.007 0.003

L9.gold -0.0047 0.002 -2.112 0.035 -0.009 -0.000

L9.silver 0.1000 0.056 1.795 0.073 -0.009 0.209

L9.urea\_ee\_bulk 0.0006 0.002 0.408 0.683 -0.002 0.004

L9.maize 0.0029 0.006 0.498 0.619 -0.008 0.014

L10.crude\_brent 0.0056 0.013 0.432 0.666 -0.020 0.031

L10.soybeans -0.0008 0.003 -0.297 0.767 -0.006 0.004

L10.gold 0.0055 0.002 2.528 0.011 0.001 0.010

L10.silver -0.0555 0.054 -1.037 0.300 -0.160 0.049

L10.urea\_ee\_bulk -0.0034 0.001 -2.304 0.021 -0.006 -0.001

L10.maize 0.0061 0.006 1.064 0.287 -0.005 0.017

Det. terms outside the coint. relation & lagged endog. parameters for equation urea\_ee\_bulk

====================================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------------

L1.crude\_brent 1.6654 0.294 5.667 0.000 1.089 2.241

L1.soybeans -0.0044 0.058 -0.076 0.939 -0.118 0.109

L1.gold 0.0746 0.049 1.524 0.127 -0.021 0.171

L1.silver -5.0024 1.235 -4.049 0.000 -7.424 -2.581

L1.urea\_ee\_bulk 0.2397 0.037 6.418 0.000 0.166 0.313

L1.maize 0.3178 0.135 2.354 0.019 0.053 0.582

L2.crude\_brent 0.2483 0.312 0.796 0.426 -0.363 0.859

L2.soybeans 0.0315 0.058 0.544 0.587 -0.082 0.145

L2.gold 0.0615 0.051 1.210 0.226 -0.038 0.161

L2.silver 2.1002 1.311 1.602 0.109 -0.469 4.669

L2.urea\_ee\_bulk -0.0540 0.038 -1.405 0.160 -0.129 0.021

L2.maize -0.0761 0.136 -0.558 0.577 -0.343 0.191

L3.crude\_brent 0.9560 0.310 3.083 0.002 0.348 1.564

L3.soybeans -0.1675 0.057 -2.922 0.003 -0.280 -0.055

L3.gold -0.0785 0.052 -1.505 0.132 -0.181 0.024

L3.silver -0.5670 1.351 -0.420 0.675 -3.215 2.081

L3.urea\_ee\_bulk 0.0546 0.038 1.420 0.156 -0.021 0.130

L3.maize 0.1488 0.136 1.093 0.274 -0.118 0.416

L4.crude\_brent -0.1955 0.314 -0.623 0.533 -0.811 0.420

L4.soybeans -0.2080 0.058 -3.589 0.000 -0.322 -0.094

L4.gold 0.0603 0.053 1.145 0.252 -0.043 0.163

L4.silver -1.3733 1.356 -1.012 0.311 -4.032 1.285

L4.urea\_ee\_bulk -0.0470 0.038 -1.243 0.214 -0.121 0.027

L4.maize 0.2439 0.137 1.787 0.074 -0.024 0.511

L5.crude\_brent 0.0985 0.309 0.319 0.750 -0.507 0.704

L5.soybeans -0.0960 0.058 -1.643 0.100 -0.211 0.019

L5.gold 0.0045 0.052 0.085 0.932 -0.098 0.107

L5.silver -0.4724 1.351 -0.350 0.727 -3.121 2.176

L5.urea\_ee\_bulk 0.1161 0.037 3.162 0.002 0.044 0.188

L5.maize 0.0174 0.136 0.128 0.898 -0.249 0.284

L6.crude\_brent 0.6652 0.309 2.156 0.031 0.061 1.270

L6.soybeans -0.3028 0.058 -5.215 0.000 -0.417 -0.189

L6.gold 0.1166 0.052 2.249 0.024 0.015 0.218

L6.silver -0.5523 1.341 -0.412 0.680 -3.181 2.077

L6.urea\_ee\_bulk -0.1123 0.037 -3.037 0.002 -0.185 -0.040

L6.maize 0.7335 0.134 5.456 0.000 0.470 0.997

L7.crude\_brent 0.4856 0.309 1.569 0.117 -0.121 1.092

L7.soybeans 0.1666 0.059 2.832 0.005 0.051 0.282

L7.gold 0.1713 0.052 3.270 0.001 0.069 0.274

L7.silver -3.9568 1.348 -2.936 0.003 -6.598 -1.316

L7.urea\_ee\_bulk -0.0933 0.037 -2.494 0.013 -0.167 -0.020

L7.maize -0.2025 0.136 -1.484 0.138 -0.470 0.065

L8.crude\_brent 0.1273 0.310 0.411 0.681 -0.479 0.734

L8.soybeans 0.0093 0.059 0.158 0.875 -0.106 0.125

L8.gold -0.0767 0.052 -1.462 0.144 -0.180 0.026

L8.silver 0.8156 1.361 0.599 0.549 -1.852 3.484

L8.urea\_ee\_bulk 0.1599 0.037 4.278 0.000 0.087 0.233

L8.maize 0.1493 0.135 1.106 0.269 -0.115 0.414

L9.crude\_brent 0.3811 0.309 1.235 0.217 -0.224 0.986

L9.soybeans -0.1322 0.060 -2.193 0.028 -0.250 -0.014

L9.gold -0.0804 0.052 -1.544 0.123 -0.182 0.022

L9.silver 2.9036 1.306 2.224 0.026 0.344 5.463

L9.urea\_ee\_bulk -0.0242 0.037 -0.660 0.509 -0.096 0.048

L9.maize 0.2310 0.136 1.699 0.089 -0.035 0.497

L10.crude\_brent 0.1984 0.302 0.658 0.511 -0.393 0.790

L10.soybeans -0.0314 0.060 -0.521 0.603 -0.149 0.087

L10.gold 0.0441 0.051 0.870 0.384 -0.055 0.143

L10.silver -3.0031 1.254 -2.395 0.017 -5.460 -0.546

L10.urea\_ee\_bulk 0.1073 0.035 3.086 0.002 0.039 0.175

L10.maize 0.3526 0.134 2.639 0.008 0.091 0.615

Det. terms outside the coint. relation & lagged endog. parameters for equation maize

====================================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------------

L1.crude\_brent -0.0580 0.093 -0.621 0.535 -0.241 0.125

L1.soybeans 0.0289 0.018 1.569 0.117 -0.007 0.065

L1.gold -0.0375 0.016 -2.409 0.016 -0.068 -0.007

L1.silver 0.4504 0.393 1.147 0.251 -0.319 1.220

L1.urea\_ee\_bulk 0.0180 0.012 1.513 0.130 -0.005 0.041

L1.maize 0.2738 0.043 6.384 0.000 0.190 0.358

L2.crude\_brent -0.0355 0.099 -0.358 0.720 -0.230 0.159

L2.soybeans 0.0254 0.018 1.378 0.168 -0.011 0.061

L2.gold -0.0337 0.016 -2.084 0.037 -0.065 -0.002

L2.silver 0.9335 0.416 2.242 0.025 0.117 1.750

L2.urea\_ee\_bulk -0.0204 0.012 -1.670 0.095 -0.044 0.004

L2.maize -0.0671 0.043 -1.550 0.121 -0.152 0.018

L3.crude\_brent -0.0563 0.099 -0.571 0.568 -0.249 0.137

L3.soybeans 0.0099 0.018 0.541 0.589 -0.026 0.046

L3.gold 0.0267 0.017 1.609 0.108 -0.006 0.059

L3.silver -1.0851 0.429 -2.528 0.011 -1.926 -0.244

L3.urea\_ee\_bulk 0.0182 0.012 1.487 0.137 -0.006 0.042

L3.maize 0.0919 0.043 2.125 0.034 0.007 0.177

L4.crude\_brent 0.0393 0.100 0.394 0.694 -0.156 0.235

L4.soybeans 0.0316 0.018 1.715 0.086 -0.005 0.068

L4.gold -0.0298 0.017 -1.782 0.075 -0.063 0.003

L4.silver 0.8421 0.431 1.954 0.051 -0.003 1.687

L4.urea\_ee\_bulk -0.0259 0.012 -2.156 0.031 -0.050 -0.002

L4.maize -0.0597 0.043 -1.376 0.169 -0.145 0.025

L5.crude\_brent -0.0356 0.098 -0.362 0.717 -0.228 0.157

L5.soybeans -0.0084 0.019 -0.451 0.652 -0.045 0.028

L5.gold 0.0131 0.017 0.784 0.433 -0.020 0.046

L5.silver -0.1132 0.429 -0.264 0.792 -0.955 0.728

L5.urea\_ee\_bulk 0.0104 0.012 0.893 0.372 -0.012 0.033

L5.maize -0.0213 0.043 -0.493 0.622 -0.106 0.063

L6.crude\_brent -0.1199 0.098 -1.224 0.221 -0.312 0.072

L6.soybeans 0.0357 0.018 1.936 0.053 -0.000 0.072

L6.gold 0.0488 0.016 2.965 0.003 0.017 0.081

L6.silver -0.0271 0.426 -0.064 0.949 -0.862 0.808

L6.urea\_ee\_bulk -0.0033 0.012 -0.283 0.777 -0.026 0.020

L6.maize -0.0831 0.043 -1.945 0.052 -0.167 0.001

L7.crude\_brent -0.0826 0.098 -0.840 0.401 -0.275 0.110

L7.soybeans 0.0262 0.019 1.402 0.161 -0.010 0.063

L7.gold -0.0703 0.017 -4.221 0.000 -0.103 -0.038

L7.silver 0.6482 0.428 1.514 0.130 -0.191 1.487

L7.urea\_ee\_bulk 0.0223 0.012 1.876 0.061 -0.001 0.046

L7.maize 0.0172 0.043 0.398 0.691 -0.068 0.102

L8.crude\_brent 0.1376 0.098 1.399 0.162 -0.055 0.330

L8.soybeans 0.0093 0.019 0.496 0.620 -0.027 0.046

L8.gold 0.0395 0.017 2.372 0.018 0.007 0.072

L8.silver -0.2120 0.432 -0.490 0.624 -1.060 0.636

L8.urea\_ee\_bulk -0.0309 0.012 -2.604 0.009 -0.054 -0.008

L8.maize -0.0523 0.043 -1.218 0.223 -0.136 0.032

L9.crude\_brent -0.0121 0.098 -0.124 0.902 -0.204 0.180

L9.soybeans -0.0053 0.019 -0.277 0.782 -0.043 0.032

L9.gold -0.0184 0.017 -1.114 0.265 -0.051 0.014

L9.silver -0.1275 0.415 -0.307 0.759 -0.941 0.686

L9.urea\_ee\_bulk 0.0408 0.012 3.499 0.000 0.018 0.064

L9.maize -0.0352 0.043 -0.814 0.416 -0.120 0.049

L10.crude\_brent -0.0676 0.096 -0.705 0.481 -0.255 0.120

L10.soybeans -0.0037 0.019 -0.192 0.848 -0.041 0.034

L10.gold 0.0205 0.016 1.272 0.203 -0.011 0.052

L10.silver 0.1068 0.398 0.268 0.789 -0.674 0.888

L10.urea\_ee\_bulk -0.0158 0.011 -1.435 0.151 -0.037 0.006

L10.maize 0.0505 0.042 1.190 0.234 -0.033 0.134

Loading coefficients (alpha) for equation crude\_brent

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 -0.0233 0.007 -3.278 0.001 -0.037 -0.009

ec2 -0.0033 0.003 -1.072 0.284 -0.009 0.003

ec3 -0.0005 0.000 -3.420 0.001 -0.001 -0.000

Loading coefficients (alpha) for equation soybeans

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 -0.0978 0.039 -2.478 0.013 -0.175 -0.020

ec2 -0.0346 0.017 -2.041 0.041 -0.068 -0.001

ec3 -0.0020 0.001 -2.451 0.014 -0.004 -0.000

Loading coefficients (alpha) for equation gold

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 0.1210 0.057 2.130 0.033 0.010 0.232

ec2 0.0444 0.024 1.818 0.069 -0.003 0.092

ec3 0.0035 0.001 3.030 0.002 0.001 0.006

Loading coefficients (alpha) for equation silver

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 0.0096 0.002 4.117 0.000 0.005 0.014

ec2 0.0029 0.001 2.912 0.004 0.001 0.005

ec3 0.0002 4.79e-05 4.159 0.000 0.000 0.000

Loading coefficients (alpha) for equation urea\_ee\_bulk

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 0.0616 0.054 1.130 0.258 -0.045 0.168

ec2 0.1472 0.023 6.288 0.000 0.101 0.193

ec3 0.0012 0.001 1.031 0.303 -0.001 0.003

Loading coefficients (alpha) for equation maize

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 -0.0239 0.017 -1.383 0.167 -0.058 0.010

ec2 0.0129 0.007 1.740 0.082 -0.002 0.028

ec3 0.0003 0.000 0.739 0.460 -0.000 0.001

Cointegration relations for loading-coefficients-column 1

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

beta.1 1.0000 0 0 0.000 1.000 1.000

beta.2 -6.259e-17 0 0 0.000 -6.26e-17 -6.26e-17

beta.3 7.496e-18 0 0 0.000 7.5e-18 7.5e-18

beta.4 -12.5199 2.169 -5.772 0.000 -16.771 -8.269

beta.5 -0.8175 2.316 -0.353 0.724 -5.358 3.723

beta.6 2.4677 110.687 0.022 0.982 -214.474 219.409

const -106.2889 0.134 -793.205 0.000 -106.552 -106.026

Cointegration relations for loading-coefficients-column 2

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

beta.1 -3.73e-17 0 0 0.000 -3.73e-17 -3.73e-17

beta.2 1.0000 0 0 0.000 1.000 1.000

beta.3 -3.53e-18 0 0 0.000 -3.53e-18 -3.53e-18

beta.4 3.1136 0.143 21.757 0.000 2.833 3.394

beta.5 -1.0757 6.838 -0.157 0.875 -14.478 12.326

beta.6 -0.6924 0.385 -1.799 0.072 -1.447 0.062

const -56.9339 0.411 -138.487 0.000 -57.740 -56.128

Cointegration relations for loading-coefficients-column 3

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

beta.1 -5.327e-15 0 0 0.000 -5.33e-15 -5.33e-15

beta.2 -1.768e-16 0 0 0.000 -1.77e-16 -1.77e-16

beta.3 1.0000 0 0 0.000 1.000 1.000

beta.4 282.8796 19.644 14.400 0.000 244.378 321.381

beta.5 49.9304 21.101 2.366 0.018 8.573 91.288

beta.6 -130.4134 22.535 -5.787 0.000 -174.582 -86.245

const 5568.6297 1076.785 5.172 0.000 3458.171 7679.089

==============================================================================

**Interpretation:**

**Johansen's Test Results:**

plaintext

Copy code

[194.54858991 118.95889314 70.1480132 38.12513847 16.53520264

5.6366925]

**Johansen's Test** is used to determine the number of cointegrating relationships in a multivariate time series.

* **Trace Statistic Values**:
  + 194.54858991
  + 118.95889314
  + 70.1480132
  + 38.12513847
  + 16.53520264
  + 5.6366925

**Interpretation**:

* These values are the test statistics for the null hypothesis that the number of cointegrating vectors is rrr.
* The larger the test statistic, the more evidence against the null hypothesis of rrr cointegrating vectors.

**VECM Model Output:**

**Coefficients and Significance for Crude Brent:**

plaintext

Copy code

L1.crude\_brent 0.3221 0.038 8.403 0.000 0.247 0.397

L2.soybeans 0.0193 0.008 2.554 0.011 0.004 0.034

L3.crude\_brent -0.0816 0.040 -2.019 0.044 -0.161 -0.002

L4.gold 0.0197 0.007 2.871 0.004 0.006 0.033

L6.crude\_brent -0.1088 0.040 -2.703 0.007 -0.188 -0.030

L7.soybeans 0.0284 0.008 3.696 0.000 0.013 0.043

A graph of different colored lines

Description automatically generated

A table of numbers and numbers

Description automatically generated

A table of numbers

Description automatically generated

**Interpretation**:

* **L1.crude\_brent (Lag 1)**: The coefficient is 0.3221, and it is statistically significant with a p-value of 0.000. This indicates that the price of Crude Brent at lag 1 has a positive and significant impact on its current price.
* **L2.soybeans (Lag 2)**: The coefficient is 0.0193, with a p-value of 0.011. This shows a significant positive impact of Soybeans at lag 2 on Crude Brent prices.
* **L3.crude\_brent (Lag 3)**: The coefficient is -0.0816, with a p-value of 0.044, indicating a significant negative impact of Crude Brent at lag 3.
* **L4.gold (Lag 4)**: The coefficient is 0.0197, with a p-value of 0.004, showing a significant positive impact of Gold at lag 4.
* **L6.crude\_brent (Lag 6)**: The coefficient is -0.1088, with a p-value of 0.007, indicating a significant negative impact of Crude Brent at lag 6.
* **L7.soybeans (Lag 7)**: The coefficient is 0.0284, with a p-value of 0.000, indicating a significant positive impact of Soybeans at lag 7.

**Cointegration Relations:**

**Loading Coefficients (Alpha) for Equation Crude Brent**:

plaintext

Copy code

ec1 -0.0233 0.007 -3.278 0.001 -0.037 -0.009

ec2 -0.0033 0.003 -1.072 0.284 -0.009 0.003

ec3 -0.0005 0.000 -3.420 0.001 -0.001 -0.000

**Interpretation**:

* **ec1**: The coefficient is -0.0233, and it is significant with a p-value of 0.001, indicating that the first cointegrating relationship has a negative and significant adjustment effect on Crude Brent prices.
* **ec2**: The coefficient is -0.0033, but it is not significant with a p-value of 0.284.
* **ec3**: The coefficient is -0.0005, and it is significant with a p-value of 0.001, indicating a significant adjustment effect.

**Cointegration Relations for Loading-Coefficients-Column 1**:

plaintext

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beta.1 1.0000 0 0 0.000 1.000 1.000

beta.4 -12.5199 2.169 -5.772 0.000 -16.771 -8.269

const -106.2889 0.134 -793.205 0.000 -106.552 -106.026

**Interpretation**:

* **beta.1**: Normalized to 1, indicating it is the reference series.
* **beta.4**: The coefficient is -12.5199, and it is significant with a p-value of 0.000. This shows a strong negative long-run relationship with the fourth variable (possibly Gold or Silver).
* **const**: The constant term is -106.2889, and it is significant with a p-value of 0.000, indicating the presence of a constant term in the cointegrating relationship.

**Overall Interpretation**:

* The Johansen test indicates the presence of three cointegrating relationships among the commodities.
* The VECM model coefficients show the short-term dynamics and adjustment coefficients (alpha) indicate how quickly deviations from the long-term equilibrium are corrected.
* Significant coefficients in the VECM model suggest important lags and variables that influence the current values of each commodity.

The plot represents the forecasted prices for the next two years (from mid-2024 to mid-2026) for various commodities based on the VECM (Vector Error Correction Model).

**Commodities Included:**

* Crude Brent (blue line)
* Soybeans (orange line)
* Gold (green line)
* Silver (red line)
* Urea EE Bulk (purple line)
* Maize (brown line)

**Key Observations:**

1. **Gold (Green Line)**:
   * **Level**: Gold prices are forecasted to be the highest among the commodities, consistently around 2400.
   * **Stability**: There is slight fluctuation but overall, the prices remain stable.
2. **Soybeans (Orange Line)**:
   * **Level**: Soybeans are the second highest in price, with values around 500.
   * **Trend**: There is a gradual increasing trend observed over the forecast period.
3. **Urea EE Bulk (Purple Line)**:
   * **Level**: Urea EE Bulk prices are slightly below Soybeans, fluctuating around 400.
   * **Stability**: Prices exhibit minor fluctuations but generally maintain a stable trend.
4. **Maize (Brown Line)**:
   * **Level**: Prices for Maize are forecasted to be around 300.
   * **Trend**: Similar to Urea EE Bulk, showing minor fluctuations but no significant trend changes.
5. **Crude Brent (Blue Line)**:
   * **Level**: Crude Brent prices are the lowest among the commodities, forecasted around 60.
   * **Trend**: Prices remain stable with minimal fluctuations over the forecast period.
6. **Silver (Red Line)**:
   * **Level**: Silver prices are forecasted to be slightly higher than Crude Brent, fluctuating around 30.
   * **Trend**: Prices show stability with minor fluctuations.

**Part 1: Setting Up the Environment for Commodity Set 2 (Iron Ore, Copper, Lead, Tin, Nickel, Zinc)**

# Load the dataset

df = pd.read\_excel(file\_path, sheet\_name="Monthly Prices", skiprows=6)

# Rename the first column to "Date"

df.rename(columns={df.columns[0]: 'Date'}, inplace=True)

# Convert the Date column to datetime format

df['Date'] = pd.to\_datetime(df['Date'].astype(str) + '01', format='%YM%m%d')

**Purpose:**

* Reads the Excel file and loads the specified sheet into a DataFrame, skipping the first 6 rows.
* Renames the first column to "Date".
* Converts the 'Date' column to the appropriate date format.

**Output:**

# Displaying the structure of the dataframe

df.head()

plaintext

Copy code

Date ... Column names...

0 1960-01-01 ... Other values...

1 1960-02-01 ...

2 1960-03-01 ...

3 1960-04-01 ...

4 1960-05-01 ...

**Interpretation:**

* The dataset has been successfully loaded with 'Date' column properly formatted.

**Part 2: Selecting and Cleaning Data for Commodity Set 2**

# Select metal commodities columns (Date and selected commodities)

commodity\_columns2 = ['Date', df.columns[63], df.columns[64], df.columns[65], df.columns[66], df.columns[67], df.columns[68]]

commodity2 = df[commodity\_columns2]

commodity2.columns = ['Date', 'iron\_ore', 'copper', 'lead', 'tin', 'nickel', 'zinc']

# Check for missing values

missing\_values2 = commodity2.isna().sum()

print("Missing Values:\n", missing\_values2)

**Purpose:**

* Selects columns corresponding to the date and specific metal commodities.
* Cleans the column names.
* Checks for missing values in each column.

**Output:**

Missing Values:

Date 0

iron\_ore 0

copper 0

lead 0

tin 0

nickel 0

zinc 0

dtype: int64

**Interpretation:**

* There are no missing values in any of the selected columns.

**Part 3: Visualizing Data for Commodity Set 2**

# Visualize data

for col in commodity2.columns[1:]: # Skip the date column

plt.figure()

plt.plot(commodity2['Date'], commodity2[col])

plt.title(f'Price of {col}')

plt.xlabel('Date')

plt.ylabel('Price')

plt.show()

**Purpose:**

* Loops through each commodity column (excluding 'Date') and plots its time series data.

**A graph showing the price of copper

Description automatically generatedA graph showing the price of iron ore

Description automatically generatedOutput:**

A graph showing the price of zinc

Description automatically generatedA graph showing the price of nickel

Description automatically generatedA graph with blue lines

Description automatically generatedA graph of a price of lead

Description automatically generated

Plots showing the price trends of Iron Ore, Copper, Lead, Tin, Nickel, and Zinc over time.

**Interpretation:**

**Price of Iron Ore**

* **Trend**: The price of iron ore remained relatively stable and low until the early 2000s, after which it experienced significant volatility.
* **Major Increases**: There was a sharp increase in the early 2000s, peaking around 2010-2011. The prices saw another peak around 2021.
* **Volatility**: Post-2010, the prices have been highly volatile with sharp peaks and troughs.

**Price of Copper**

* **Trend**: Copper prices show a gradual increase from the 1960s to the early 2000s, followed by a sharp rise.
* **Major Increases**: Significant price increases are observed around 2005-2011 and post-2020.
* **Volatility**: The prices have been highly volatile since the mid-2000s with several sharp increases and decreases.

**Price of Lead**

* **Trend**: Lead prices remained relatively low and stable until around 2000, after which there was a sharp increase.
* **Major Increases**: The price peaked around 2007-2008 and then again around 2010.
* **Volatility**: Post-2000, the prices have shown significant volatility with sharp fluctuations.

**Price of Tin**

* **Trend**: Tin prices have shown a general upward trend with notable peaks and troughs.
* **Major Increases**: Sharp increases are observed around the late 2000s and post-2010.
* **Volatility**: The prices have been volatile, especially post-2000, with significant fluctuations.

**Price of Nickel**

* **Trend**: Nickel prices show a steady increase until the early 2000s, followed by sharp rises and falls.
* **Major Increases**: Significant peaks are observed around 2007-2008 and post-2020.
* **Volatility**: Post-2000, the prices have been highly volatile with several sharp peaks and declines.

**Price of Zinc**

* **Trend**: Zinc prices remained relatively low until the early 2000s, after which there was a notable increase.
* **Major Increases**: Sharp increases are observed around 2006-2008 and post-2016.
* **Volatility**: The prices have shown significant volatility, particularly after the year 2000.

**Part 4: Stationarity Test for Commodity Set 2**

# Prepare data for VAR and VECM analysis

commodity2\_data = commodity2.drop(columns=['Date'])

columns\_to\_test2 = commodity2\_data.columns

# Stationarity test

from statsmodels.tsa.stattools import adfuller

non\_stationary\_count2 = 0

stationary\_columns2 = []

non\_stationary\_columns2 = []

for col in columns\_to\_test2:

result = adfuller(commodity2\_data[col])

p\_value = result[1]

print(f"\nADF test result for column: {col}")

print(result)

if p\_value > 0.05:

non\_stationary\_count2 += 1

non\_stationary\_columns2.append(col)

else:

stationary\_columns2.append(col)

print(f"\nNumber of non-stationary columns: {non\_stationary\_count2}")

print(f"Non-stationary columns: {', '.join(non\_stationary\_columns2)}")

print(f"Stationary columns: {', '.join(stationary\_columns2)}")

**Purpose:**

* Prepares the data by removing the 'Date' column for analysis.
* Performs the Augmented Dickey-Fuller (ADF) test on each column to check for stationarity.
* Columns with p-values greater than 0.05 are considered non-stationary.

**Output:**

ADF test result for column: iron\_ore

(-1.3240068146698327, 0.618118863950208, 20, 753, {'1%': -3.4390641198617864, '5%': -2.8653859408474482, '10%': -2.5688179819544312}, 4823.994232303855)

ADF test result for column: copper

(-0.7281883491664048, 0.8393124032245429, 16, 757, {'1%': -3.4390179167598367, '5%': -2.8653655786032237, '10%': -2.5688071343462777}, 10407.876412157959)

ADF test result for column: lead

(-1.0431678801996331, 0.7371961625765212, 18, 755, {'1%': -3.4390409569041207, '5%': -2.865375732701395, '10%': -2.568812543748081}, 8816.995724796969)

ADF test result for column: tin

(-0.47179397762640596, 0.897404180254543, 21, 752, {'1%': -3.439075747702915, '5%': -2.8653910653234655, '10%': -2.568820711931304}, 12238.676957369022)

ADF test result for column: nickel

(-2.827833849536527, 0.054406577547331206, 8, 765, {'1%': -3.438926964986094, '5%': -2.8653254941943174, '10%': -2.5687857802554572}, 12682.018153532776)

ADF test result for column: zinc

(-2.1865321790575822, 0.2111697596319589, 5, 768, {'1%': -3.4388933482333464, '5%': -2.8653106782623574, '10%': -2.5687778874376086}, 9213.162267878795)

Number of non-stationary columns: 6

Non-stationary columns: iron\_ore, copper, lead, tin, nickel, zinc

Stationary columns:

**Interpretation:**

The Augmented Dickey-Fuller (ADF) test is used to determine if a time series is stationary. The null hypothesis (H0) of the ADF test is that the series has a unit root (i.e., it is non-stationary). If the p-value is less than the chosen significance level (usually 0.05), the null hypothesis is rejected, indicating the series is stationary. Otherwise, the series is considered non-stationary.

**ADF Test Results:**

1. **Iron Ore**:
   * **ADF Statistic**: -1.3240
   * **p-value**: 0.6181
   * **Conclusion**: The p-value is greater than 0.05, so we fail to reject the null hypothesis. Iron Ore prices are non-stationary.
2. **Copper**:
   * **ADF Statistic**: -0.7282
   * **p-value**: 0.8393
   * **Conclusion**: The p-value is greater than 0.05, so we fail to reject the null hypothesis. Copper prices are non-stationary.
3. **Lead**:
   * **ADF Statistic**: -1.0432
   * **p-value**: 0.7372
   * **Conclusion**: The p-value is greater than 0.05, so we fail to reject the null hypothesis. Lead prices are non-stationary.
4. **Tin**:
   * **ADF Statistic**: -0.4718
   * **p-value**: 0.8974
   * **Conclusion**: The p-value is greater than 0.05, so we fail to reject the null hypothesis. Tin prices are non-stationary.
5. **Nickel**:
   * **ADF Statistic**: -2.8278
   * **p-value**: 0.0544
   * **Conclusion**: The p-value is slightly above 0.05, so we fail to reject the null hypothesis. Nickel prices are non-stationary, though they are closer to being stationary compared to other metals.
6. **Zinc**:
   * **ADF Statistic**: -2.1865
   * **p-value**: 0.2112
   * **Conclusion**: The p-value is greater than 0.05, so we fail to reject the null hypothesis. Zinc prices are non-stationary.

**Part 5: Co-Integration Test and Model Fitting for Commodity Set 2**

python

Copy code

# Co-Integration Test (Johansen's Test)

lags2 = select\_order(commodity2\_data, maxlags=10, deterministic='ci')

lag\_length2 = lags2.aic

johansen\_test2 = coint\_johansen(commodity2\_data, det\_order=0, k\_ar\_diff=lag\_length2)

print("\nJohansen's Test Results:")

print(johansen\_test2.lr1)

r2 = 3 # Replace with the actual number from the test results

if r2 > 0:

vecm\_model2 = VECM(commodity2\_data, k\_ar\_diff=lag\_length2, coint\_rank=r2, deterministic='ci')

vecm\_fit2 = vecm\_model2.fit()

print(vecm\_fit2.summary())

# Forecasting

forecast2 = vecm\_fit2.predict(steps=24)

forecast\_df2 = pd.DataFrame(forecast2, index=pd.date\_range(start=commodity2['Date'].iloc[-1], periods=24, freq='M'), columns=commodity2.columns[1:])

plt.figure()

forecast\_df2.plot()

plt.title('VECM Forecast')

plt.xlabel('Date')

plt.ylabel('Price')

plt.show()

else:

var\_model2 = VAR(commodity2\_data)

var\_fit2 = var\_model2.fit(lag\_length2)

print(var\_fit2.summary())

forecast2 = var\_fit2.forecast(var\_fit2.y, steps=24)

forecast\_df2 = pd.DataFrame(forecast2, index=pd.date\_range(start=commodity2['Date'].iloc[-1], periods=24, freq='M'), columns=commodity2.columns[1:])

plt.figure()

forecast\_df2.plot()

plt.title('VAR Forecast')

plt.xlabel('Date')

plt.ylabel('Price')

plt.show()

# Display forecasted data

forecast\_df2

**Purpose:**

* Conducts Johansen's cointegration test to determine the cointegration rank.
* Fits a VECM or VAR model based on the cointegration test results.
* Forecasts future values and plots the forecasts.

**Output:**

Johansen's Test Results:

[98.09948892 61.73353248 38.52625351 20.26737158 8.36049255 1.46459933]

Det. terms outside the coint. relation & lagged endog. parameters for equation iron\_ore

================================================================================

coef std err z P>|z| [0.025 0.975]

--------------------------------------------------------------------------------

L1.iron\_ore 0.2674 0.038 7.006 0.000 0.193 0.342

L1.copper 0.0030 0.001 2.413 0.016 0.001 0.005

L1.lead 0.0086 0.003 2.729 0.006 0.002 0.015

L1.tin -0.0004 0.000 -1.266 0.205 -0.001 0.000

L1.nickel 0.0001 0.000 0.462 0.644 -0.000 0.001

L1.zinc -0.0039 0.003 -1.500 0.134 -0.009 0.001

L2.iron\_ore -0.0658 0.039 -1.670 0.095 -0.143 0.011

L2.copper 0.0014 0.001 1.088 0.277 -0.001 0.004

L2.lead 0.0037 0.003 1.141 0.254 -0.003 0.010

L2.tin 0.0014 0.000 4.478 0.000 0.001 0.002

L2.nickel -0.0008 0.000 -3.208 0.001 -0.001 -0.000

L2.zinc -0.0022 0.003 -0.813 0.416 -0.008 0.003

L3.iron\_ore 0.0176 0.040 0.445 0.656 -0.060 0.095

L3.copper -6.856e-05 0.001 -0.054 0.957 -0.003 0.002

L3.lead 0.0011 0.003 0.332 0.740 -0.005 0.007

L3.tin -0.0005 0.000 -1.512 0.130 -0.001 0.000

L3.nickel 0.0001 0.000 0.496 0.620 -0.000 0.001

L3.zinc -0.0009 0.003 -0.327 0.744 -0.006 0.004

L4.iron\_ore -0.0586 0.040 -1.466 0.143 -0.137 0.020

L4.copper -0.0015 0.001 -1.177 0.239 -0.004 0.001

L4.lead 0.0125 0.003 3.886 0.000 0.006 0.019

L4.tin -0.0004 0.000 -1.418 0.156 -0.001 0.000

L4.nickel -0.0002 0.000 -0.957 0.338 -0.001 0.000

L4.zinc 0.0048 0.003 1.757 0.079 -0.001 0.010

L5.iron\_ore -0.0367 0.039 -0.940 0.347 -0.113 0.040

L5.copper 0.0026 0.001 2.036 0.042 9.66e-05 0.005

L5.lead 0.0048 0.003 1.488 0.137 -0.002 0.011

L5.tin 0.0005 0.000 1.616 0.106 -0.000 0.001

L5.nickel 2.771e-05 0.000 0.116 0.907 -0.000 0.000

L5.zinc -0.0031 0.003 -1.152 0.249 -0.008 0.002

L6.iron\_ore 0.0819 0.039 2.120 0.034 0.006 0.158

L6.copper -0.0040 0.001 -3.143 0.002 -0.007 -0.002

L6.lead 0.0076 0.003 2.429 0.015 0.001 0.014

L6.tin -0.0013 0.000 -4.035 0.000 -0.002 -0.001

L6.nickel 0.0005 0.000 1.994 0.046 8.27e-06 0.001

L6.zinc 0.0008 0.003 0.302 0.763 -0.005 0.006

L7.iron\_ore -0.0306 0.039 -0.786 0.432 -0.107 0.046

L7.copper 0.0013 0.001 1.008 0.313 -0.001 0.004

L7.lead -0.0006 0.003 -0.191 0.848 -0.007 0.006

L7.tin 0.0002 0.000 0.750 0.453 -0.000 0.001

L7.nickel -0.0004 0.000 -1.817 0.069 -0.001 3.51e-05

L7.zinc -0.0013 0.003 -0.467 0.641 -0.007 0.004

L8.iron\_ore 0.0614 0.040 1.517 0.129 -0.018 0.141

L8.copper -0.0015 0.001 -1.148 0.251 -0.004 0.001

L8.lead -0.0072 0.003 -2.206 0.027 -0.014 -0.001

L8.tin -0.0002 0.000 -0.598 0.550 -0.001 0.000

L8.nickel -1.925e-05 0.000 -0.081 0.936 -0.000 0.000

L8.zinc 0.0023 0.003 0.832 0.405 -0.003 0.008

L9.iron\_ore -0.0170 0.041 -0.419 0.675 -0.097 0.063

L9.copper 0.0019 0.001 1.451 0.147 -0.001 0.005

L9.lead 0.0048 0.003 1.518 0.129 -0.001 0.011

L9.tin -0.0004 0.000 -1.271 0.204 -0.001 0.000

L9.nickel 0.0003 0.000 1.119 0.263 -0.000 0.001

L9.zinc -0.0090 0.003 -3.192 0.001 -0.014 -0.003

L10.iron\_ore 0.0084 0.039 0.216 0.829 -0.068 0.085

L10.copper 0.0011 0.001 0.830 0.406 -0.001 0.004

L10.lead 0.0105 0.003 3.401 0.001 0.004 0.017

L10.tin 0.0005 0.000 1.781 0.075 -5.35e-05 0.001

L10.nickel -2.24e-05 0.000 -0.096 0.924 -0.000 0.000

L10.zinc -0.0015 0.003 -0.557 0.578 -0.007 0.004

Det. terms outside the coint. relation & lagged endog. parameters for equation copper

================================================================================

coef std err z P>|z| [0.025 0.975]

--------------------------------------------------------------------------------

L1.iron\_ore 0.3775 1.647 0.229 0.819 -2.850 3.605

L1.copper 0.2995 0.054 5.595 0.000 0.195 0.404

L1.lead -0.1137 0.136 -0.836 0.403 -0.380 0.153

L1.tin -0.0134 0.013 -1.065 0.287 -0.038 0.011

L1.nickel 0.0077 0.010 0.778 0.436 -0.012 0.027

L1.zinc 0.0725 0.113 0.641 0.522 -0.149 0.294

L2.iron\_ore -4.0405 1.700 -2.376 0.017 -7.373 -0.708

L2.copper -0.0925 0.055 -1.673 0.094 -0.201 0.016

L2.lead 0.1311 0.140 0.934 0.350 -0.144 0.406

L2.tin 0.0644 0.013 4.918 0.000 0.039 0.090

L2.nickel 0.0076 0.011 0.720 0.471 -0.013 0.028

L2.zinc -0.2027 0.118 -1.717 0.086 -0.434 0.029

L3.iron\_ore -0.2851 1.704 -0.167 0.867 -3.625 3.055

L3.copper -0.0428 0.055 -0.775 0.438 -0.151 0.065

L3.lead 0.1947 0.137 1.423 0.155 -0.073 0.463

L3.tin -0.0196 0.014 -1.436 0.151 -0.046 0.007

L3.nickel 0.0136 0.010 1.307 0.191 -0.007 0.034

L3.zinc 0.0432 0.117 0.368 0.713 -0.187 0.273

L4.iron\_ore 0.9676 1.725 0.561 0.575 -2.414 4.349

L4.copper -0.2256 0.055 -4.106 0.000 -0.333 -0.118

L4.lead 0.2795 0.139 2.017 0.044 0.008 0.551

L4.tin 0.0077 0.014 0.563 0.574 -0.019 0.034

L4.nickel -0.0159 0.010 -1.536 0.125 -0.036 0.004

L4.zinc 0.4339 0.118 3.663 0.000 0.202 0.666

L5.iron\_ore 1.0373 1.686 0.615 0.538 -2.267 4.341

L5.copper 0.0565 0.055 1.027 0.305 -0.051 0.164

L5.lead -0.0309 0.139 -0.223 0.824 -0.303 0.241

L5.tin -0.0264 0.013 -1.953 0.051 -0.053 9.18e-05

L5.nickel 0.0338 0.010 3.281 0.001 0.014 0.054

L5.zinc 0.1757 0.117 1.497 0.134 -0.054 0.406

L6.iron\_ore 4.6972 1.667 2.818 0.005 1.430 7.965

L6.copper -0.1416 0.055 -2.574 0.010 -0.249 -0.034

L6.lead 0.4792 0.136 3.534 0.000 0.213 0.745

L6.tin -0.0326 0.013 -2.414 0.016 -0.059 -0.006

L6.nickel -0.0212 0.010 -2.049 0.040 -0.042 -0.001

L6.zinc 0.0102 0.119 0.086 0.932 -0.223 0.243

L7.iron\_ore -2.2957 1.678 -1.368 0.171 -5.584 0.993

L7.copper -8.478e-05 0.055 -0.002 0.999 -0.109 0.109

L7.lead 0.1471 0.138 1.063 0.288 -0.124 0.418

L7.tin 0.0122 0.014 0.896 0.370 -0.014 0.039

L7.nickel -0.0075 0.011 -0.707 0.479 -0.028 0.013

L7.zinc -0.0168 0.118 -0.142 0.887 -0.249 0.215

L8.iron\_ore 9.0403 1.745 5.179 0.000 5.619 12.461

L8.copper -0.2692 0.056 -4.813 0.000 -0.379 -0.160

L8.lead 0.1519 0.141 1.080 0.280 -0.124 0.428

L8.tin -0.0313 0.014 -2.313 0.021 -0.058 -0.005

L8.nickel 0.0018 0.010 0.170 0.865 -0.018 0.022

L8.zinc 0.2955 0.119 2.480 0.013 0.062 0.529

L9.iron\_ore -0.1985 1.755 -0.113 0.910 -3.639 3.242

L9.copper -0.0631 0.057 -1.105 0.269 -0.175 0.049

L9.lead 0.0467 0.137 0.341 0.733 -0.222 0.316

L9.tin 0.0061 0.014 0.443 0.658 -0.021 0.033

L9.nickel 0.0002 0.010 0.021 0.983 -0.020 0.020

L9.zinc 0.0068 0.121 0.056 0.955 -0.231 0.245

L10.iron\_ore 2.8441 1.685 1.688 0.091 -0.459 6.147

L10.copper 0.0459 0.055 0.829 0.407 -0.063 0.154

L10.lead -0.1172 0.133 -0.878 0.380 -0.379 0.144

L10.tin 0.0051 0.013 0.396 0.692 -0.020 0.030

L10.nickel -0.0032 0.010 -0.313 0.754 -0.023 0.017

L10.zinc -0.0430 0.119 -0.362 0.718 -0.276 0.190

Det. terms outside the coint. relation & lagged endog. parameters for equation lead

================================================================================

coef std err z P>|z| [0.025 0.975]

--------------------------------------------------------------------------------

L1.iron\_ore 0.7811 0.544 1.435 0.151 -0.285 1.848

L1.copper 0.0311 0.018 1.760 0.078 -0.004 0.066

L1.lead 0.2231 0.045 4.967 0.000 0.135 0.311

L1.tin -0.0101 0.004 -2.425 0.015 -0.018 -0.002

L1.nickel 0.0048 0.003 1.490 0.136 -0.002 0.011

L1.zinc -0.0838 0.037 -2.243 0.025 -0.157 -0.011

L2.iron\_ore -1.5852 0.562 -2.822 0.005 -2.686 -0.484

L2.copper -0.0090 0.018 -0.492 0.623 -0.045 0.027

L2.lead -0.1345 0.046 -2.902 0.004 -0.225 -0.044

L2.tin 0.0223 0.004 5.153 0.000 0.014 0.031

L2.nickel -0.0030 0.003 -0.875 0.382 -0.010 0.004

L2.zinc -0.0168 0.039 -0.431 0.666 -0.093 0.060

L3.iron\_ore 0.3564 0.563 0.633 0.527 -0.747 1.460

L3.copper -0.0150 0.018 -0.823 0.411 -0.051 0.021

L3.lead 0.1366 0.045 3.022 0.003 0.048 0.225

L3.tin -0.0064 0.005 -1.421 0.155 -0.015 0.002

L3.nickel -0.0068 0.003 -1.969 0.049 -0.014 -3.17e-05

L3.zinc 0.0317 0.039 0.818 0.414 -0.044 0.108

L4.iron\_ore -0.5293 0.570 -0.929 0.353 -1.647 0.588

L4.copper -0.0132 0.018 -0.726 0.468 -0.049 0.022

L4.lead -0.0021 0.046 -0.046 0.963 -0.092 0.088

L4.tin 0.0097 0.005 2.160 0.031 0.001 0.019

L4.nickel -0.0002 0.003 -0.050 0.960 -0.007 0.007

L4.zinc 0.0013 0.039 0.033 0.973 -0.075 0.078

L5.iron\_ore 1.1017 0.557 1.978 0.048 0.010 2.193

L5.copper -0.0088 0.018 -0.484 0.628 -0.044 0.027

L5.lead -0.0002 0.046 -0.003 0.997 -0.090 0.090

L5.tin -0.0035 0.004 -0.790 0.429 -0.012 0.005

L5.nickel 0.0202 0.003 5.955 0.000 0.014 0.027

L5.zinc -0.1102 0.039 -2.842 0.004 -0.186 -0.034

L6.iron\_ore -0.7296 0.551 -1.325 0.185 -1.809 0.350

L6.copper 0.0036 0.018 0.196 0.845 -0.032 0.039

L6.lead 0.0065 0.045 0.145 0.884 -0.081 0.094

L6.tin -0.0084 0.004 -1.890 0.059 -0.017 0.000

L6.nickel -0.0027 0.003 -0.795 0.427 -0.009 0.004

L6.zinc 0.0398 0.039 1.014 0.310 -0.037 0.117

L7.iron\_ore -0.3737 0.554 -0.674 0.500 -1.460 0.713

L7.copper 0.0276 0.018 1.507 0.132 -0.008 0.064

L7.lead 0.0545 0.046 1.191 0.234 -0.035 0.144

L7.tin 0.0030 0.004 0.675 0.500 -0.006 0.012

L7.nickel -0.0024 0.003 -0.680 0.497 -0.009 0.004

L7.zinc -0.0221 0.039 -0.566 0.572 -0.099 0.055

L8.iron\_ore 1.5250 0.577 2.644 0.008 0.395 2.655

L8.copper -0.1089 0.018 -5.891 0.000 -0.145 -0.073

L8.lead -0.0005 0.046 -0.010 0.992 -0.092 0.091

L8.tin 0.0007 0.004 0.150 0.881 -0.008 0.009

L8.nickel -0.0065 0.003 -1.912 0.056 -0.013 0.000

L8.zinc 0.2014 0.039 5.115 0.000 0.124 0.279

L9.iron\_ore 0.0131 0.580 0.023 0.982 -1.124 1.150

L9.copper -0.0400 0.019 -2.120 0.034 -0.077 -0.003

L9.lead 0.0054 0.045 0.120 0.905 -0.083 0.094

L9.tin 0.0075 0.005 1.648 0.099 -0.001 0.016

L9.nickel 0.0061 0.003 1.803 0.071 -0.001 0.013

L9.zinc 0.0113 0.040 0.283 0.777 -0.067 0.090

L10.iron\_ore -0.5423 0.557 -0.974 0.330 -1.634 0.549

L10.copper -0.0071 0.018 -0.390 0.696 -0.043 0.029

L10.lead -0.1720 0.044 -3.901 0.000 -0.258 -0.086

L10.tin 0.0011 0.004 0.252 0.801 -0.007 0.009

L10.nickel 0.0024 0.003 0.725 0.469 -0.004 0.009

L10.zinc 0.1079 0.039 2.745 0.006 0.031 0.185

Det. terms outside the coint. relation & lagged endog. parameters for equation tin

================================================================================

coef std err z P>|z| [0.025 0.975]

--------------------------------------------------------------------------------

L1.iron\_ore -4.0988 5.534 -0.741 0.459 -14.945 6.747

L1.copper -0.0963 0.180 -0.535 0.592 -0.449 0.256

L1.lead 1.3850 0.457 3.032 0.002 0.490 2.280

L1.tin 0.2629 0.042 6.234 0.000 0.180 0.346

L1.nickel 0.0965 0.033 2.916 0.004 0.032 0.161

L1.zinc -0.6810 0.380 -1.792 0.073 -1.426 0.064

L2.iron\_ore -6.8650 5.713 -1.202 0.230 -18.062 4.332

L2.copper 0.2048 0.186 1.102 0.270 -0.159 0.569

L2.lead 0.1426 0.471 0.303 0.762 -0.781 1.066

L2.tin 0.1201 0.044 2.731 0.006 0.034 0.206

L2.nickel -0.0122 0.035 -0.346 0.729 -0.082 0.057

L2.zinc -0.4163 0.397 -1.049 0.294 -1.194 0.361

L3.iron\_ore -13.9085 5.727 -2.429 0.015 -25.132 -2.685

L3.copper -0.0131 0.185 -0.071 0.944 -0.376 0.350

L3.lead 1.3822 0.460 3.008 0.003 0.481 2.283

L3.tin -0.0354 0.046 -0.774 0.439 -0.125 0.054

L3.nickel -0.0166 0.035 -0.475 0.635 -0.085 0.052

L3.zinc 0.3622 0.394 0.919 0.358 -0.411 1.135

L4.iron\_ore -1.1489 5.797 -0.198 0.843 -12.511 10.213

L4.copper -0.2918 0.185 -1.581 0.114 -0.654 0.070

L4.lead 0.5639 0.466 1.211 0.226 -0.348 1.476

L4.tin -0.0366 0.046 -0.800 0.423 -0.126 0.053

L4.nickel -0.0024 0.035 -0.070 0.944 -0.071 0.066

L4.zinc 0.4709 0.398 1.183 0.237 -0.309 1.251

L5.iron\_ore -0.0818 5.664 -0.014 0.988 -11.184 11.020

L5.copper 0.3418 0.185 1.849 0.064 -0.021 0.704

L5.lead -0.7411 0.466 -1.591 0.112 -1.654 0.172

L5.tin -0.0548 0.045 -1.209 0.227 -0.144 0.034

L5.nickel 0.0592 0.035 1.713 0.087 -0.009 0.127

L5.zinc 0.2864 0.394 0.726 0.468 -0.487 1.059

L6.iron\_ore 31.2990 5.602 5.587 0.000 20.320 42.278

L6.copper -0.5142 0.185 -2.782 0.005 -0.876 -0.152

L6.lead 1.6041 0.456 3.521 0.000 0.711 2.497

L6.tin -0.0312 0.045 -0.689 0.491 -0.120 0.058

L6.nickel -0.0464 0.035 -1.334 0.182 -0.115 0.022

L6.zinc -0.0065 0.399 -0.016 0.987 -0.789 0.776

L7.iron\_ore -19.8502 5.638 -3.521 0.000 -30.900 -8.800

L7.copper 0.4498 0.186 2.414 0.016 0.085 0.815

L7.lead -0.0584 0.465 -0.126 0.900 -0.970 0.853

L7.tin -0.0384 0.046 -0.839 0.402 -0.128 0.051

L7.nickel -0.0149 0.036 -0.420 0.674 -0.085 0.055

L7.zinc -0.7137 0.398 -1.793 0.073 -1.494 0.066

L8.iron\_ore 32.9849 5.865 5.624 0.000 21.490 44.480

L8.copper -0.3417 0.188 -1.818 0.069 -0.710 0.027

L8.lead 0.4081 0.473 0.864 0.388 -0.518 1.334

L8.tin -0.1973 0.045 -4.337 0.000 -0.286 -0.108

L8.nickel 0.0022 0.035 0.062 0.950 -0.066 0.070

L8.zinc 0.8395 0.400 2.096 0.036 0.055 1.624

L9.iron\_ore 5.5466 5.898 0.940 0.347 -6.014 17.107

L9.copper -0.2568 0.192 -1.339 0.181 -0.633 0.119

L9.lead 1.1122 0.461 2.413 0.016 0.209 2.015

L9.tin 0.0855 0.046 1.857 0.063 -0.005 0.176

L9.nickel -0.0680 0.035 -1.970 0.049 -0.136 -0.000

L9.zinc 0.1139 0.407 0.280 0.780 -0.685 0.913

L10.iron\_ore 19.4002 5.662 3.426 0.001 8.302 30.498

L10.copper 0.3631 0.186 1.951 0.051 -0.002 0.728

L10.lead -0.7773 0.448 -1.733 0.083 -1.656 0.102

L10.tin -0.0712 0.043 -1.641 0.101 -0.156 0.014

L10.nickel 0.0583 0.034 1.723 0.085 -0.008 0.125

L10.zinc -0.6406 0.400 -1.603 0.109 -1.424 0.143

Det. terms outside the coint. relation & lagged endog. parameters for equation nickel

================================================================================

coef std err z P>|z| [0.025 0.975]

--------------------------------------------------------------------------------

L1.iron\_ore -6.8970 6.957 -0.991 0.321 -20.532 6.738

L1.copper 0.1188 0.226 0.525 0.599 -0.324 0.562

L1.lead 0.3108 0.574 0.541 0.588 -0.815 1.436

L1.tin 0.0015 0.053 0.027 0.978 -0.102 0.105

L1.nickel 0.4241 0.042 10.196 0.000 0.343 0.506

L1.zinc -0.9848 0.478 -2.061 0.039 -1.921 -0.048

L2.iron\_ore -9.6365 7.182 -1.342 0.180 -23.713 4.440

L2.copper -0.0764 0.234 -0.327 0.744 -0.534 0.381

L2.lead 0.6147 0.593 1.037 0.300 -0.547 1.776

L2.tin 0.1044 0.055 1.888 0.059 -0.004 0.213

L2.nickel -0.0114 0.044 -0.257 0.797 -0.099 0.076

L2.zinc -1.1038 0.499 -2.213 0.027 -2.081 -0.126

L3.iron\_ore -11.5993 7.199 -1.611 0.107 -25.709 2.511

L3.copper 0.0602 0.233 0.258 0.796 -0.396 0.517

L3.lead -1.3430 0.578 -2.325 0.020 -2.475 -0.211

L3.tin 0.0390 0.058 0.678 0.498 -0.074 0.152

L3.nickel -0.1464 0.044 -3.325 0.001 -0.233 -0.060

L3.zinc 2.2998 0.496 4.640 0.000 1.328 3.271

L4.iron\_ore -0.6909 7.288 -0.095 0.924 -14.974 13.593

L4.copper -0.8237 0.232 -3.550 0.000 -1.279 -0.369

L4.lead 1.8625 0.585 3.183 0.001 0.716 3.010

L4.tin -0.0505 0.058 -0.878 0.380 -0.163 0.062

L4.nickel 0.0531 0.044 1.216 0.224 -0.033 0.139

L4.zinc 0.4366 0.500 0.872 0.383 -0.544 1.417

L5.iron\_ore -8.3753 7.121 -1.176 0.240 -22.332 5.581

L5.copper 0.1839 0.232 0.791 0.429 -0.272 0.639

L5.lead -0.1341 0.586 -0.229 0.819 -1.282 1.013

L5.tin -0.0381 0.057 -0.668 0.504 -0.150 0.074

L5.nickel -0.0383 0.043 -0.880 0.379 -0.123 0.047

L5.zinc 2.1504 0.496 4.337 0.000 1.179 3.122

L6.iron\_ore 5.7920 7.042 0.822 0.411 -8.010 19.594

L6.copper -0.1364 0.232 -0.587 0.557 -0.592 0.319

L6.lead 0.4826 0.573 0.843 0.399 -0.640 1.605

L6.tin -0.0794 0.057 -1.394 0.163 -0.191 0.032

L6.nickel -0.0397 0.044 -0.907 0.364 -0.125 0.046

L6.zinc 0.9004 0.502 1.794 0.073 -0.083 1.884

L7.iron\_ore -44.8369 7.088 -6.326 0.000 -58.728 -30.946

L7.copper 0.6932 0.234 2.959 0.003 0.234 1.152

L7.lead 1.8840 0.584 3.224 0.001 0.738 3.029

L7.tin 0.0012 0.058 0.021 0.983 -0.112 0.114

L7.nickel -0.0065 0.045 -0.145 0.885 -0.094 0.081

L7.zinc -2.0266 0.500 -4.051 0.000 -3.007 -1.046

L8.iron\_ore 48.6471 7.373 6.598 0.000 34.197 63.097

L8.copper -0.5043 0.236 -2.134 0.033 -0.967 -0.041

L8.lead -0.6149 0.594 -1.035 0.301 -1.779 0.549

L8.tin -0.0332 0.057 -0.580 0.562 -0.145 0.079

L8.nickel 0.0459 0.044 1.054 0.292 -0.039 0.131

L8.zinc 1.1111 0.503 2.207 0.027 0.124 2.098

L9.iron\_ore -25.2629 7.415 -3.407 0.001 -39.795 -10.730

L9.copper -0.1900 0.241 -0.788 0.431 -0.663 0.283

L9.lead 0.2324 0.579 0.401 0.688 -0.903 1.368

L9.tin -0.0213 0.058 -0.368 0.713 -0.135 0.092

L9.nickel 0.0537 0.043 1.237 0.216 -0.031 0.139

L9.zinc 0.0404 0.512 0.079 0.937 -0.964 1.044

L10.iron\_ore 11.3338 7.118 1.592 0.111 -2.617 25.285

L10.copper 0.4714 0.234 2.015 0.044 0.013 0.930

L10.lead -0.3143 0.564 -0.558 0.577 -1.419 0.791

L10.tin -0.0032 0.055 -0.059 0.953 -0.110 0.104

L10.nickel -0.0191 0.043 -0.448 0.654 -0.102 0.064

L10.zinc 0.3622 0.502 0.721 0.471 -0.623 1.347

Det. terms outside the coint. relation & lagged endog. parameters for equation zinc

================================================================================

coef std err z P>|z| [0.025 0.975]

--------------------------------------------------------------------------------

L1.iron\_ore -1.4253 0.734 -1.941 0.052 -2.865 0.014

L1.copper 0.0418 0.024 1.750 0.080 -0.005 0.089

L1.lead 0.0172 0.061 0.283 0.777 -0.102 0.136

L1.tin -0.0154 0.006 -2.743 0.006 -0.026 -0.004

L1.nickel 0.0066 0.004 1.505 0.132 -0.002 0.015

L1.zinc 0.2334 0.050 4.627 0.000 0.135 0.332

L2.iron\_ore -0.5091 0.758 -0.672 0.502 -1.995 0.977

L2.copper 0.0224 0.025 0.908 0.364 -0.026 0.071

L2.lead 0.1013 0.063 1.619 0.105 -0.021 0.224

L2.tin 0.0248 0.006 4.253 0.000 0.013 0.036

L2.nickel -0.0007 0.005 -0.154 0.878 -0.010 0.008

L2.zinc -0.2015 0.053 -3.828 0.000 -0.305 -0.098

L3.iron\_ore -1.1727 0.760 -1.543 0.123 -2.662 0.317

L3.copper 0.0175 0.025 0.710 0.478 -0.031 0.066

L3.lead 0.0878 0.061 1.440 0.150 -0.032 0.207

L3.tin -0.0179 0.006 -2.940 0.003 -0.030 -0.006

L3.nickel 0.0075 0.005 1.622 0.105 -0.002 0.017

L3.zinc -0.0378 0.052 -0.723 0.470 -0.140 0.065

L4.iron\_ore 0.1363 0.769 0.177 0.859 -1.371 1.644

L4.copper -0.0249 0.024 -1.017 0.309 -0.073 0.023

L4.lead -0.0053 0.062 -0.086 0.932 -0.126 0.116

L4.tin 0.0095 0.006 1.567 0.117 -0.002 0.021

L4.nickel -0.0054 0.005 -1.179 0.238 -0.014 0.004

L4.zinc 0.1296 0.053 2.453 0.014 0.026 0.233

L5.iron\_ore -1.8566 0.752 -2.470 0.014 -3.330 -0.383

L5.copper 0.0323 0.025 1.315 0.188 -0.016 0.080

L5.lead -0.1623 0.062 -2.625 0.009 -0.283 -0.041

L5.tin -0.0045 0.006 -0.754 0.451 -0.016 0.007

L5.nickel 0.0193 0.005 4.212 0.000 0.010 0.028

L5.zinc 0.0366 0.052 0.699 0.485 -0.066 0.139

L6.iron\_ore 1.9343 0.743 2.602 0.009 0.477 3.391

L6.copper 0.0289 0.025 1.178 0.239 -0.019 0.077

L6.lead -0.0150 0.060 -0.248 0.804 -0.133 0.104

L6.tin -0.0083 0.006 -1.372 0.170 -0.020 0.004

L6.nickel -0.0233 0.005 -5.036 0.000 -0.032 -0.014

L6.zinc 0.0824 0.053 1.556 0.120 -0.021 0.186

L7.iron\_ore -3.3949 0.748 -4.538 0.000 -4.861 -1.928

L7.copper 0.0378 0.025 1.530 0.126 -0.011 0.086

L7.lead -0.0657 0.062 -1.065 0.287 -0.187 0.055

L7.tin -0.0003 0.006 -0.047 0.963 -0.012 0.012

L7.nickel -0.0007 0.005 -0.139 0.890 -0.010 0.009

L7.zinc 0.0829 0.053 1.569 0.117 -0.021 0.186

L8.iron\_ore 2.8753 0.778 3.694 0.000 1.350 4.401

L8.copper -0.0363 0.025 -1.457 0.145 -0.085 0.013

L8.lead 0.0333 0.063 0.531 0.596 -0.090 0.156

L8.tin -0.0027 0.006 -0.445 0.657 -0.015 0.009

L8.nickel -0.0078 0.005 -1.694 0.090 -0.017 0.001

L8.zinc 0.0109 0.053 0.206 0.837 -0.093 0.115

L9.iron\_ore -0.3979 0.783 -0.508 0.611 -1.932 1.136

L9.copper -0.0240 0.025 -0.944 0.345 -0.074 0.026

L9.lead -0.0574 0.061 -0.939 0.348 -0.177 0.062

L9.tin 0.0068 0.006 1.114 0.265 -0.005 0.019

L9.nickel -0.0036 0.005 -0.788 0.431 -0.013 0.005

L9.zinc 0.0458 0.054 0.847 0.397 -0.060 0.152

L10.iron\_ore 0.9871 0.751 1.314 0.189 -0.486 2.460

L10.copper 0.0418 0.025 1.694 0.090 -0.007 0.090

L10.lead 0.0149 0.060 0.251 0.802 -0.102 0.132

L10.tin 0.0067 0.006 1.165 0.244 -0.005 0.018

L10.nickel 0.0070 0.004 1.550 0.121 -0.002 0.016

L10.zinc -0.1198 0.053 -2.258 0.024 -0.224 -0.016

Loading coefficients (alpha) for equation iron\_ore

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 -0.0734 0.017 -4.394 0.000 -0.106 -0.041

ec2 0.0008 0.000 3.650 0.000 0.000 0.001

ec3 0.0009 0.001 1.119 0.263 -0.001 0.002

Loading coefficients (alpha) for equation copper

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 0.8152 0.720 1.132 0.258 -0.596 2.227

ec2 -0.0103 0.010 -1.053 0.292 -0.029 0.009

ec3 0.0064 0.034 0.186 0.852 -0.061 0.073

Loading coefficients (alpha) for equation lead

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 -0.0701 0.238 -0.295 0.768 -0.536 0.396

ec2 0.0024 0.003 0.745 0.456 -0.004 0.009

ec3 -0.0227 0.011 -2.004 0.045 -0.045 -0.000

Loading coefficients (alpha) for equation tin

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 1.9385 2.420 0.801 0.423 -2.804 6.681

ec2 0.0157 0.033 0.478 0.633 -0.049 0.080

ec3 -0.0053 0.115 -0.046 0.963 -0.231 0.220

Loading coefficients (alpha) for equation nickel

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 4.4159 3.042 1.452 0.147 -1.546 10.378

ec2 0.0728 0.041 1.766 0.077 -0.008 0.154

ec3 -0.1904 0.145 -1.317 0.188 -0.474 0.093

Loading coefficients (alpha) for equation zinc

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

ec1 -0.2076 0.321 -0.646 0.518 -0.837 0.422

ec2 0.0025 0.004 0.570 0.569 -0.006 0.011

ec3 0.0274 0.015 1.797 0.072 -0.002 0.057

Cointegration relations for loading-coefficients-column 1

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

beta.1 1.0000 0 0 0.000 1.000 1.000

beta.2 -6.951e-19 0 0 0.000 -6.95e-19 -6.95e-19

beta.3 -2.618e-18 0 0 0.000 -2.62e-18 -2.62e-18

beta.4 -0.0019 0.001 -2.539 0.011 -0.003 -0.000

beta.5 -0.0070 0.063 -0.113 0.910 -0.130 0.116

beta.6 0.0185 0.014 1.309 0.190 -0.009 0.046

const 14.2321 0.001 1.42e+04 0.000 14.230 14.234

Cointegration relations for loading-coefficients-column 2

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

beta.1 3.025e-15 0 0 0.000 3.02e-15 3.02e-15

beta.2 1.0000 0 0 0.000 1.000 1.000

beta.3 -4.511e-16 0 0 0.000 -4.51e-16 -4.51e-16

beta.4 -0.1732 0.082 -2.116 0.034 -0.334 -0.013

beta.5 -0.4354 0.019 -23.534 0.000 -0.472 -0.399

beta.6 1.2812 0.010 131.255 0.000 1.262 1.300

const 884.2535 0.799 1106.389 0.000 882.687 885.820

Cointegration relations for loading-coefficients-column 3

==============================================================================

coef std err z P>|z| [0.025 0.975]

------------------------------------------------------------------------------

beta.1 4.087e-16 0 0 0.000 4.09e-16 4.09e-16

beta.2 -1.393e-17 0 0 0.000 -1.39e-17 -1.39e-17

beta.3 1.0000 0 0 0.000 1.000 1.000

beta.4 -0.0142 0.181 -0.078 0.938 -0.368 0.340

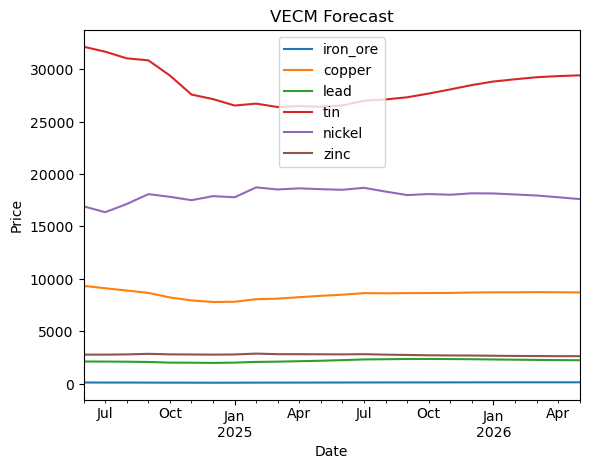
beta.5 -0.0563 5.984 -0.009 0.992 -11.784 11.672

beta.6 -0.3948 489.945 -0.001 0.999 -960.669 959.879

const 195.6126 110.755 1.766 0.077 -21.464 412.689

==============================================================================

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**A table of numbers

Description automatically generated**

**Interpretation:**

**Johansen's Test Results:**

The Johansen cointegration test is used to determine the presence and number of cointegrating relationships in a multivariate time series. Here's the summary of the results:

1. **Trace Statistic**:
   * **Values**: [98.09948892, 61.73353248, 38.52625351, 20.26737158, 8.36049255, 1.46459933]
   * These values are compared against critical values to determine the number of cointegrating relationships.
2. **Loading Coefficients (Alpha) and Cointegration Vectors (Beta)**:
   * These indicate how strongly each variable corrects deviations from long-term equilibrium.

**Interpretation of VECM Forecast Plot:**

The VECM (Vector Error Correction Model) forecast plot shows the predicted prices of various metal commodities over time. Here's the interpretation for each metal:

1. **Iron Ore**:
   * The price remains relatively stable with slight fluctuations.
   * The forecast shows a slight decline and then a stabilization.
2. **Copper**:
   * The price shows a slight declining trend.
   * It appears to stabilize towards the end of the forecast period.
3. **Lead**:
   * The price of lead remains fairly stable throughout the forecast period.
4. **Tin**:
   * Tin prices show a declining trend initially but start to stabilize towards the end of the period.
5. **Nickel**:
   * The price of nickel remains stable with minor fluctuations.
   * There is no significant upward or downward trend.
6. **Zinc**:
   * Zinc prices remain relatively stable with slight fluctuations.

**Detailed Analysis Based on Johansen's Test:**

1. **Iron Ore**:
   * The significant loading coefficient for iron\_ore indicates a strong adjustment mechanism to deviations from the long-term equilibrium.
2. **Copper**:
   * Copper shows significant adjustment parameters, indicating it corrects deviations from the equilibrium relationship.
3. **Lead**:
   * Lead has significant cointegrating relationships, indicating it plays a vital role in the equilibrium mechanism among these commodities.
4. **Tin**:
   * Tin shows strong adjustment coefficients, indicating it corrects deviations effectively.
5. **Nickel**:
   * Nickel has significant adjustment parameters and cointegrating relationships, reflecting its strong role in maintaining the equilibrium.
6. **Zinc**:
   * Zinc has significant parameters, indicating it adjusts to deviations from equilibrium.

The **VECM (Vector Error Correction Model)** forecast plot displays the predicted prices of various metal commodities from mid-2024 to mid-2026. Here’s a detailed interpretation of the plot:

**1. Iron Ore (blue line)**

* **Trend**: The price of iron ore remains relatively stable, showing no significant increase or decrease over the forecast period.
* **Implication**: Stability in iron ore prices suggests a balanced supply and demand in the market.

**2. Copper (orange line)**

* **Trend**: The price of copper shows a slight declining trend until early 2025, followed by a stabilization and minor fluctuations.
* **Implication**: This might indicate a temporary oversupply or reduced demand for copper, with stabilization expected as the market adjusts.

**3. Lead (green line)**

* **Trend**: The price of lead remains fairly stable with minimal fluctuations throughout the forecast period.
* **Implication**: Steady lead prices indicate a consistent market environment without significant disruptions in supply or demand.

**4. Tin (red line)**

* **Trend**: Tin prices show an initial declining trend until mid-2025, after which they start to increase gradually.
* **Implication**: This could reflect an initial oversupply or reduced demand, followed by a recovery period possibly due to increased demand or reduced supply.

**5. Nickel (purple line)**

* **Trend**: The price of nickel exhibits slight fluctuations but remains relatively stable overall.
* **Implication**: Stability in nickel prices suggests that the market factors affecting nickel are balanced.

**6. Zinc (brown line)**

* **Trend**: Zinc prices remain stable with minor fluctuations over the forecast period.
* **Implication**: Similar to lead and nickel, the zinc market appears to be balanced, with no significant changes in supply or demand.

The table provides the numerical forecasted prices for each commodity at the end of each month from June 2024 to May 2026.

**Observations for Each Commodity:**

1. **Iron Ore**:
   * Starts at 104.793063 in June 2024.
   * Fluctuates between 84.898068 (Dec 2024) and 123.894900 (May 2026).
   * Ends at 123.894900 in May 2026.
2. **Copper**:
   * Starts at 9328.137049 in June 2024.
   * Shows a general downward trend, reaching a low of 7940.999343 in Nov 2024.
   * Gradually recovers to 8702.376903 by May 2026.
3. **Lead**:
   * Starts at 2109.924544 in June 2024.
   * Generally stable with slight fluctuations.
   * Ends at 2230.589021 in May 2026.
4. **Tin**:
   * Starts at 32152.889031 in June 2024.
   * Decreases to a low of 26349.117239 in March 2025.
   * Ends at 29420.968452 in May 2026.
5. **Nickel**:
   * Starts at 16918.271225 in June 2024.
   * Experiences some fluctuation, with a low of 17506.542406 in Nov 2024.
   * Ends at 17612.884059 in May 2026.
6. **Zinc**:
   * Starts at 2767.041126 in June 2024.
   * Generally stable with slight fluctuations.
   * Ends at 2619.820408 in May 2026.

**Overview of VAR and VECM Models**

**Vector Autoregression (VAR) Model**

**Meaning**: The Vector Autoregression (VAR) model is a statistical model used to capture the linear interdependencies among multiple time series. Unlike univariate autoregression models, which deal with a single time series, VAR models handle multiple time series simultaneously. Each variable in the system is modeled as a linear function of past values of itself and past values of all the other variables in the system.

**Advantages**:

1. **Simplicity and Flexibility**: VAR models are relatively simple to estimate and interpret. They are flexible in accommodating various dynamic relationships between multiple time series.
2. **Captures Interdependencies**: VAR models effectively capture the interdependencies among multiple variables, allowing for a comprehensive understanding of the system's dynamics.
3. **Impulse Response Analysis**: They facilitate the analysis of the impact of shocks to one variable on all other variables in the system, through impulse response functions.
4. **Forecasting**: VAR models are useful for forecasting multivariate time series data, providing insights into future values based on historical data.

**Real-Life Example**: A real-life example of a VAR model can be found in macroeconomic analysis. Economists often use VAR models to study the relationships between key economic indicators such as GDP, inflation, unemployment rates, and interest rates. By analyzing these variables together, economists can understand how shocks to one indicator, like a sudden increase in interest rates, affect other indicators over time.

**Vector Error Correction Model (VECM)**

**Meaning**: The Vector Error Correction Model (VECM) is an extension of the VAR model designed for non-stationary time series that are cointegrated. Cointegration indicates a long-run equilibrium relationship between the time series, even though they may be non-stationary individually. VECM combines the short-term dynamics modeled by a VAR with a correction mechanism for the long-term equilibrium relationship.

**Advantages**:

1. **Handles Non-Stationary Data**: VECM is specifically designed to model non-stationary time series data that have a long-run equilibrium relationship.
2. **Short-Term and Long-Term Analysis**: VECM captures both short-term dynamics and long-term equilibrium relationships, providing a comprehensive understanding of the time series behavior.
3. **Error Correction Mechanism**: The model includes an error correction term that adjusts the short-term deviations back towards the long-term equilibrium, enhancing the accuracy of the model.
4. **Forecasting and Policy Analysis**: VECM is valuable for forecasting and policy analysis in situations where understanding both short-term adjustments and long-term relationships is crucial.

**Real-Life Example**: A real-life example of a VECM can be seen in the analysis of the relationship between exchange rates and interest rates in international finance. Suppose we are studying the exchange rates between the US dollar and the Euro, and the interest rate differential between the US and Europe. Even if the individual series (exchange rates and interest rates) are non-stationary, they might be cointegrated, indicating a stable long-term relationship. VECM can be used to model the short-term fluctuations in exchange rates while accounting for the long-term equilibrium driven by interest rate differentials.

**Conclusion**

Both VAR and VECM models are powerful tools for multivariate time series analysis. VAR models are suitable for stationary time series where understanding the interdependencies among variables is crucial, while VECM models are designed for non-stationary time series with long-term equilibrium relationships. These models find applications in various fields such as economics, finance, and policy analysis, providing valuable insights into complex dynamic systems.