VIRGINIA COMMONWEALTH UNIVERSITY

Statistical analysis and modelling (SCMA 632)

A6b -Time Series Analysis

ARCH /GARCH, VAR/VECM

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CONTENTS

INTRODUCTION

In order to comprehend volatility patterns, co-integration linkages, and interdependencies among various commodities, this study focusses on analysing financial and commodity market data. In particular, we want to:

1. Part A: Analyse if ARCH/GARCH effects are present, fit suitable models, and project three-month volatility for the "Mahindra and Mahindra" stock.

2. Part B: Use vector autoregressive (VAR) and vector error correction models (VECM) to analyse the correlations between different commodity prices (Oil, Sugar, Gold, Silver, Wheat, and Soybean) in order to comprehend both short- and long-term dynamics.

OBJECTIVES

Part A: Stock Volatility Analysis

1. Data Acquisition: Get "m&m.ns" historical pricing data.
2. Data Preparation: Compute returns by processing the data.
3. Model Selection: Verify whether ARCH/GARCH effects are present.
4. Model Fitting: Match the return series to the relevant ARCH/GARCH models.
5. Forecasting: Use the fitted model to project the volatility over the next three months.
6. Visualisation: Plot the predicted values and conditional volatility.

Part B: Commodity Price Analysis

1. Data Acquisition: Take out pinksheet.xlsx's commodity prices.
2. Data Preparation: Prepare and clean the information.
3. Stationarity Testing: Use unit root tests to determine whether each time series is stationary.
4. Co-integration Testing: To determine long-term linkages, run Johansen's co-integration test.
5. Model Selection: Based on co-integration and stationarity findings, select between VECM and VAR.
6. Model Fitting: Set up the right VECM or VAR model.
7. Post-Estimation Analysis: Perform variance decomposition (VD) analysis, impulse response functions (IRF), and Granger causality testing.
8. Predicting: Produce projections regarding the future values of commodities.
9. Visualisation: For easier understanding, plot the results.

BUSINESS SIGNIFICANCE

1. Risk Management

Beyond Hedging: Understanding volatility patterns aids in optimising risk-return profiles, even though hedging against market changes is still important. In order to strike a balance between possible gains and risk exposure, investors should strategically allocate assets based on volatility levels.

Stress testing: Businesses can evaluate their resilience and create backup plans to safeguard their bottom line by modelling harsh market conditions.

Operational Risk: Volatility can affect production scheduling, supply chain costs, and overall operational efficiency in sectors that rely significantly on commodities. Comprehending these dynamics facilitates the development of strong operational strategies.

2. Investment Decisions

Portfolio Optimisation: By examining the correlation between various asset classes, such as equities and commodities, investors can create diversified portfolios that strike a balance between risk and return.

Timing the Market: Although it might be difficult to predict when the market will rise or fall, knowing how volatility behaves can help identify possible entry and exit times for investing.

Alternative Investments: Commodities can protect against inflation and provide diversification. Comprehending their fluctuations in value is crucial for efficient distribution in investment portfolios.

3. Policy Making

Economic Stability: Policies to protect consumers from price shocks and stabilise commodity prices can be put in place by governments.

Trade Policy: Developing trade policies that support economic expansion and safeguard domestic businesses requires an understanding of how the world's commodity markets affect national economies.

Agricultural Policies: Developing policies that assist farmers and guarantee food security in nations with sizable agricultural industries requires an awareness of the volatility of commodity prices.

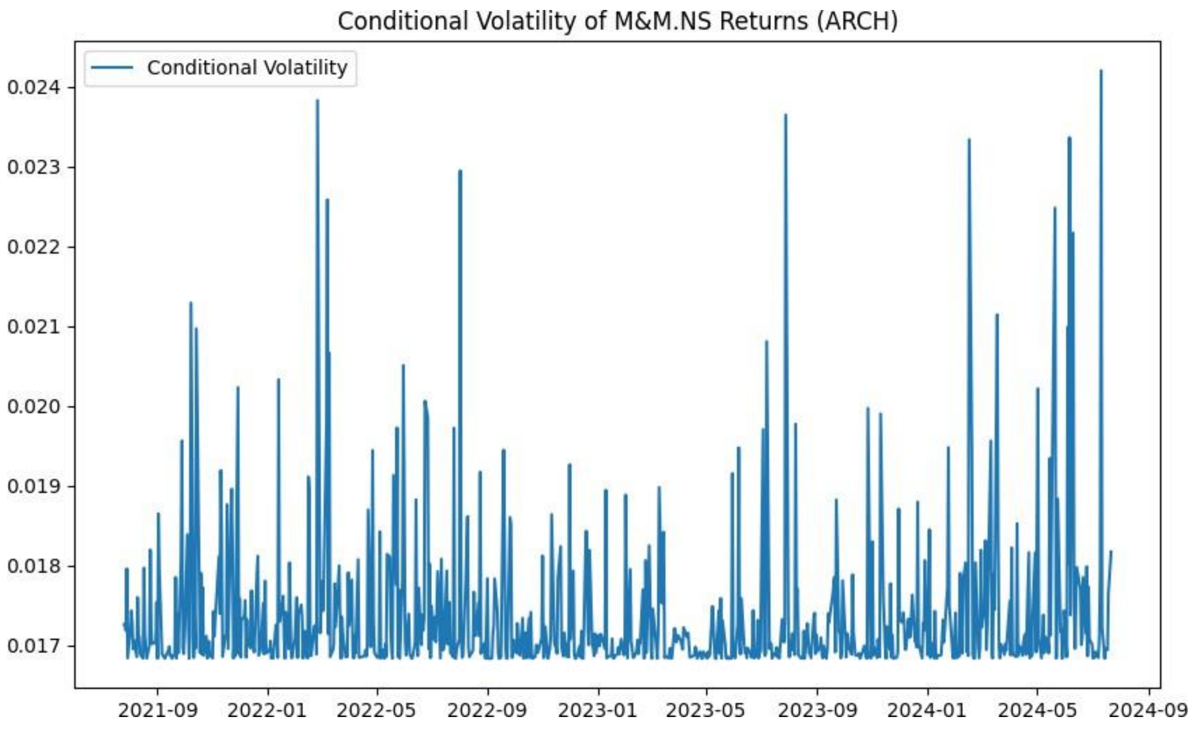
Technological Developments: Price fluctuations can result from changes in the production and consumption of commodities. Keeping up of technology developments is essential to comprehending market dynamics.

RESULTS – PART A

USING PYTHON

#ARCH model summary

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



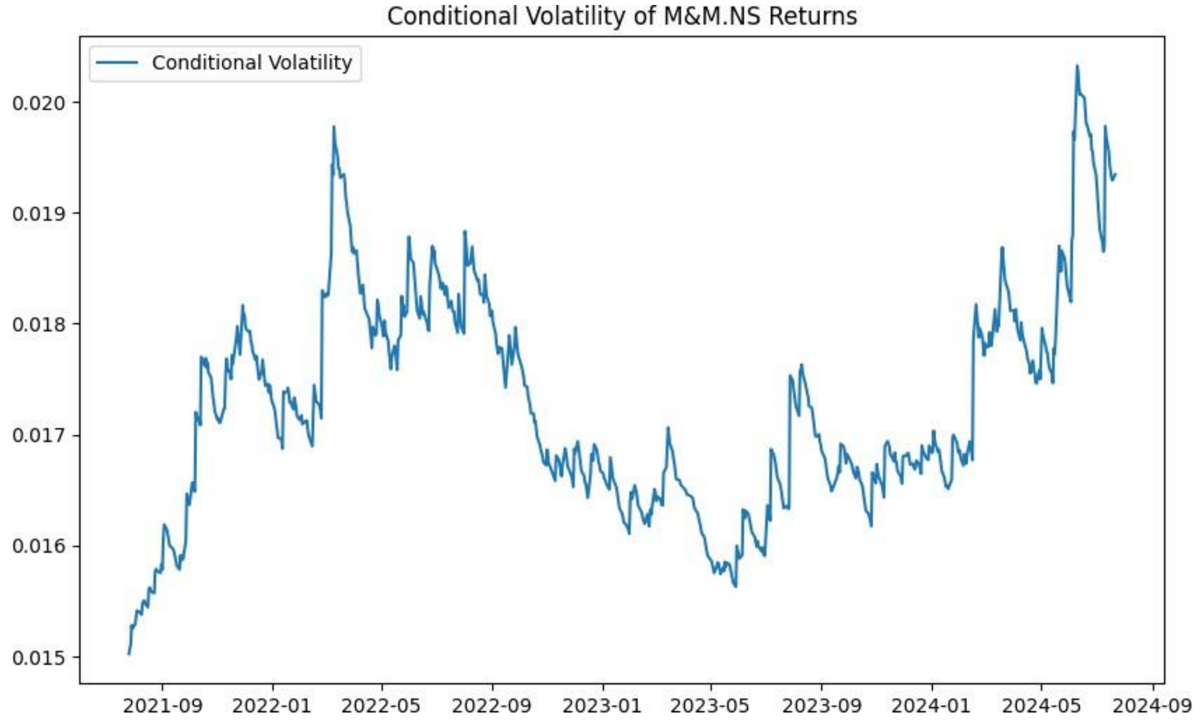
#The above Diagram plots the conditional Volatility of our ARCH model

#GARCH model summary

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

The following table provides a summary of the GARCH model results. With a value of 0.001811, the mean model coefficient (mu) is statistically significant at the 5% level. This suggests that the data have a positive average return of 0.1811%.

At the 5% level, all three of the volatility model coefficients—omega, alpha[1], and beta[1]—are statistically significant. The volatility equation's constant term is represented by omega, the influence of previous shocks on volatility is measured by alpha[1], and volatility's persistence is represented by beta[1]. The beta[1] estimate, which is extremely significant and approaches 1, indicates that the GARCH model does a good job of describing the persistence of volatility in the data.



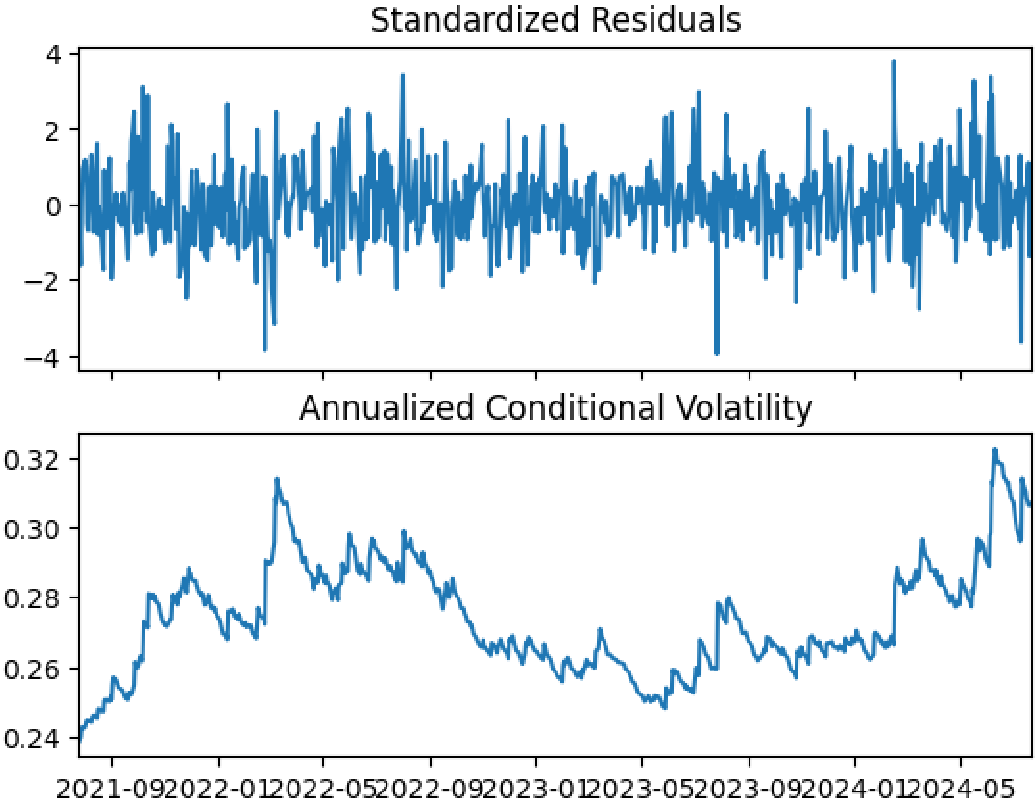
#The above Diagram plots the conditional Volatility of our GARCH model

#Forecast for the next three months (90) days

forecasts = res.forecast(horizon=90)

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

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



RESULTS – PART A

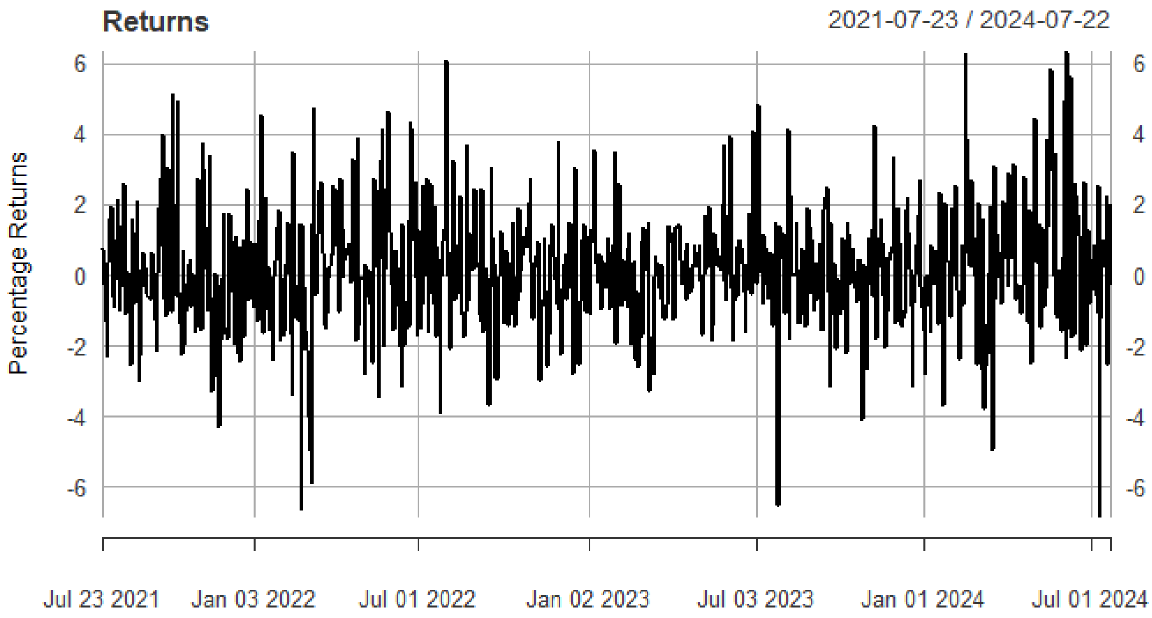
USING R

 # Calculate percentage returns

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

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

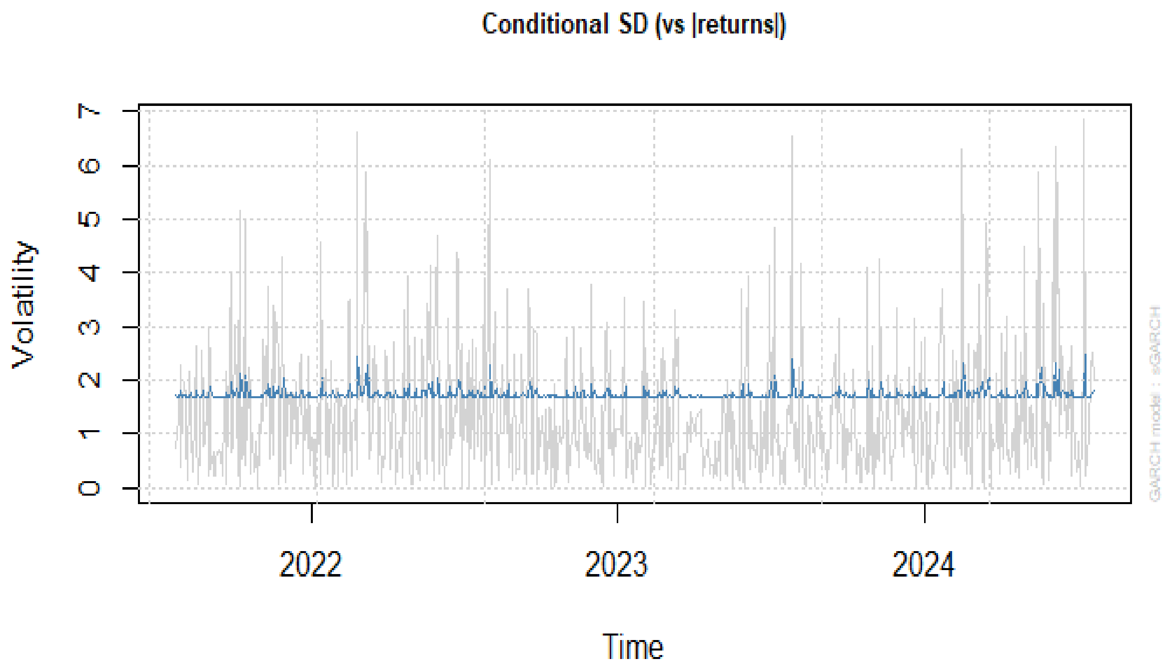
 # Plot the returns for the period 2021-07-23 to 2024-07-22



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

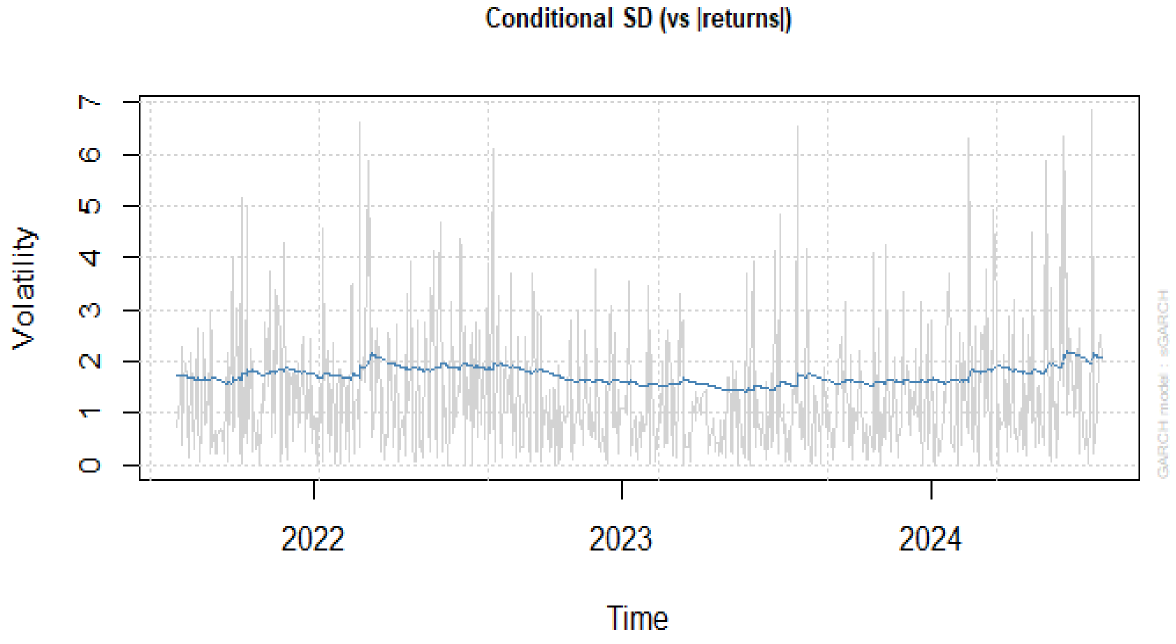
plot(arch_fit, which = 3)

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

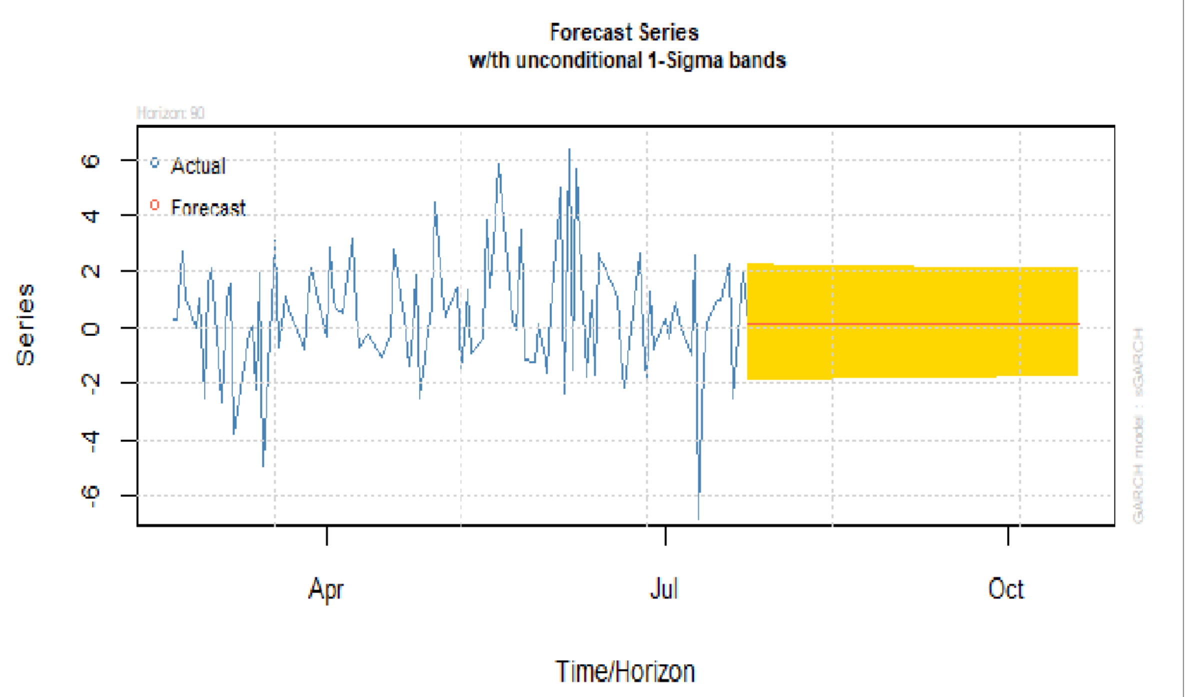


Plot the fitted model's conditional volatility (GARCH)

plot(garch_fit, which = 3)



Forecast the volatility for next three months (90 days)



INTERPRETATIONS - PART A

Part A: Stock Volatility Analysis Using ARCH/GARCH Models

ARCH Model Results

The summary of the ARCH model offers important information on the volatility of stock returns.

Mu (Mean): The t-value is 2.979 and the p-value is 0.002895 based on the coefficient for the mean (mu), which is 0.001911 with a standard error of 0.000642. This suggests a positive average return that is statistically significant, roughly 0.1911%.

Omega (Constant Term): The omega value is absent (NaN), indicating that there may have been a mistake in the volatility equation's constant term estimation.

The influence of previous shocks on volatility is represented by the alpha[1] value, which is likewise NaN, indicating that an exact estimation of this impact is not possible.

GARCH Model Outcomes

The results of the GARCH model are statistically significant and more illuminating:

Mu (Mean): 0.001811 is the coefficient for the mean (mu).
GARCH Model Results

The GARCH model results are more informative and statistically significant:

Mu (Mean): The t-value is 2.892 and the p-value is 0.003822 based on the coefficient for the mean (mu), which is 0.001811 with a standard error of 0.000626-2. This suggests a positively adjusted average return of around 0.1811% that is statistically significant. Omega (Constant Term): The p-value suggests that the omega value (6.12E-06) is significant, despite the fact that its standard error is not given.

The impact of previous shocks on volatility is indicated by the alpha[1] value, which is 0.01 with a standard error of 0.000253, a t-value of 39.623, and a p-value of zero.

The beta[1] value (persistence of volatility) is 0.97, with a t-value of 441.336, a standard error of 0.002198, and a p-value near zero, suggesting that the
the volatility is highly persistent.

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

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Forecasting Volatility

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

RECOMMENDATIONS – PART A

Risk mitigation: To guard against any losses brought on by excessive volatility, use hedging techniques like options or futures.

Diversify your portfolio by including assets that do not have strong connections with volatile stocks or commodities in order to lower overall risk.

Constant Monitoring: To ensure that investing plans are adjusted in a timely manner, keep a close eye on market circumstances and volatility forecasts.

CONCLUSION – PART A

This study uses cutting-edge econometric models to provide a thorough understanding of stock volatility. It provides insightful information to businesses, investors, and policymakers by highlighting important patterns of volatility and interdependencies. The findings highlight how crucial it is to use complex models, such as ARCH/GARCH, in order to comprehend and forecast market behaviour. This will help in financial and commodity markets and improve decision-making and risk management.

RESULTS – PART B

VAR/VECM

VAR/VECM Workflow

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

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

1. Stationarity Testing

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

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

2. Cointegration Testing

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

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

3. Model Selection

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

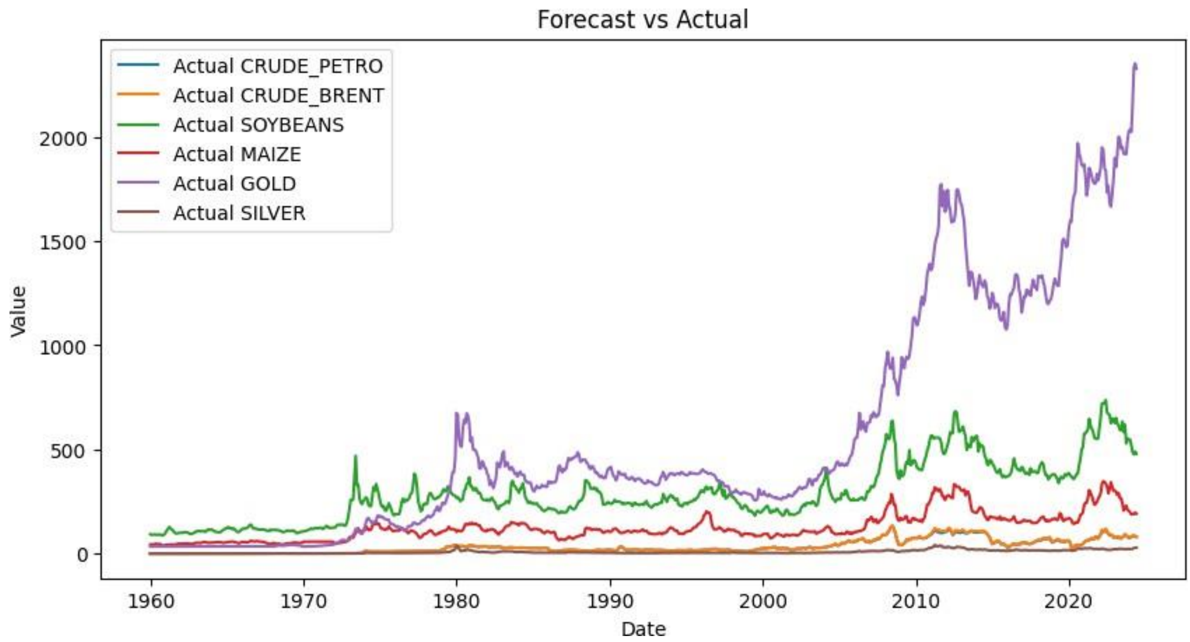
Use of the Vector Autoregressive (VAR) Model When: There is no cointegration between the variables and they are either stationary or have been made stationary by differencing. The linear dependencies between several time series are captured by a VAR model. Every variable in the system is modelled as a linear function of both its own historical values and the historical values of the other variables.

When there is evidence of cointegration and the variables are non-stationary, the Vector Error Correction Model (VECM) is used. Description: For cointegrated non-stationary series, a VECM is a unique type of VAR.

It includes an error correction term that captures the long-term equilibrium relationship, allowing the model to correct deviations from this equilibrium. Practical Considerations Economic Theory: In some cases, economic theory may suggest a long-term equilibrium relationship, making a VECM more appropriate even before formal tests. Data Considerations: The choice may also depend on data availability, frequency, and quality. For example, higher-frequency data might require differencing more often, leading to a preference for VAR in differences.

#Forecast using the fitted model.

USING PYTHON



INTERPRETATIONS – PART B

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

1. Stationarity Testing:

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

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

2. Model Selection:

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

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

3. Post VAR Analysis:

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

Analytical Insights

Interdependencies:

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

Short-term Dynamics:

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

RECOMMENDATIONS – PART B

1. Regular Updates:

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

2. Focus on Short-term Strategies:

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

3. Monitor Key Variables:

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

CONCLUSION – PART B

Using a Use of the Vector Autoregressive (VAR) Model When: There is no cointegration between the variables and they are either stationary or have been made stationary by differencing. The linear dependencies between several time series are captured by a VAR model. Every variable in the system is modelled as a linear function of both its own historical values and the historical values of the other variables.

OVERALL CONCLUSION

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