VIRGINIA COMMONWEALTH UNIVERSITY

Statistical analysis and modelling (SCMA 632)

A6b - (a) and (b)

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CONTENTS

PART A6 b (a)

1. INTRODUCTION

In today's data-driven world, businesses generate and have access to vast amounts of data.

The financial markets are characterized by volatility, which reflects the degree of variation in the price of a financial instrument over time. Understanding and forecasting this volatility is crucial for risk management, portfolio allocation, and derivative pricing. Volatility can be influenced by numerous factors, including economic indicators, market sentiment, and geopolitical events. Traditional measures of volatility assume constant variance, which often fails to capture the dynamic nature of financial markets.

To address this limitation, Engle (1982) introduced the Autoregressive Conditional Heteroskedasticity (ARCH) model, which allows the variance to change over time as a function of past errors. Bollerslev (1986) extended this model to the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which includes lagged variances as well as lagged errors in the variance equation. These models have become fundamental tools in financial econometrics for modeling time-varying volatility.

This report aims to:

1. **Download and Prepare Data**: Acquire historical price data from a reliable source such as Yahoo Finance or Investing.com.
2. **Check for ARCH/GARCH Effects**: Perform diagnostic tests to identify the presence of ARCH/GARCH effects in the data.
3. **Fit an ARCH/GARCH Model**: Estimate the parameters of an appropriate ARCH or GARCH model to capture the volatility dynamics.
4. **Forecast Volatility**: Use the fitted model to forecast the three-month volatility, providing insights into future market behavior.

The chosen financial instrument for this analysis is [insert ticker symbol and name, e.g., "AAPL (Apple Inc.)"], selected due to its high trading volume and significant impact on the broader market indices. The study period spans from [start date] to [end date], providing a comprehensive view of the recent market conditions.

The subsequent sections of this report detail the methodology, findings, and implications of the volatility analysis.

2. OBJECTIVES

The primary objectives of this project are as follows:

1. Data Acquisition:

- To download and prepare historical price data for a selected financial instrument from reliable financial sources such as Yahoo Finance or Investing.com.

2. Preliminary Analysis:

- To calculate daily returns from the historical price data.

- To perform preliminary statistical analysis on the return series to understand its basic characteristics.

3. Diagnostic Testing for ARCH/GARCH Effects:

- To check for the presence of ARCH (Autoregressive Conditional Heteroskedasticity) effects in the return series using the Ljung-Box Q-test and Engle's ARCH test.

- To determine the suitability of using ARCH or GARCH models for modeling the volatility of the return series.

4. Model Fitting:

- To fit an appropriate ARCH or GARCH model to the return series based on the results of the diagnostic tests.

- To estimate the parameters of the chosen ARCH or GARCH model using maximum likelihood estimation techniques.

5. Volatility Forecasting:

- To forecast the conditional volatility of the return series over the next three months using the fitted ARCH or GARCH model.

- To analyze the forecasted volatility and interpret its implications for future market behavior.

6. Evaluation and Interpretation:

- To evaluate the performance of the fitted model by analyzing residuals and checking for any remaining autocorrelation or heteroskedasticity.

- To interpret the results of the volatility forecasts and discuss their potential implications for investors, portfolio managers, and risk managers.

7. Documentation and Reporting:

- To document the entire process, including data acquisition, preliminary analysis, diagnostic testing, model fitting, and forecasting.

- To provide a clear and comprehensive report of the findings, methodologies used, and conclusions drawn from the analysis.

These objectives aim to provide a thorough understanding of the volatility dynamics of the selected financial instrument and offer valuable insights into future market volatility, thereby aiding in effective risk management and investment decision-making.

3. BUSINESS SIGNIFICANCE

Understanding and forecasting market volatility is crucial for a wide range of stakeholders in the financial industry, including investors, portfolio managers, risk managers, and financial analysts. The ability to accurately model and predict volatility has several significant business implications:

1. Risk Management:

- Value at Risk (VaR): Accurate volatility forecasts are essential for calculating VaR, a key metric used by financial institutions to assess the potential loss in the value of their assets over a specific time period.

- Stress Testing: Volatility models help in conducting stress tests to understand how financial portfolios might perform under extreme market conditions.

- Capital Allocation: Risk managers use volatility forecasts to determine appropriate capital reserves to safeguard against potential losses.

2. Investment Strategies:

- Portfolio Optimization: Investors and portfolio managers rely on volatility estimates to optimize their portfolios, balancing risk and return according to their investment goals.

- Hedging: Volatility forecasting aids in designing effective hedging strategies to mitigate risks associated with adverse market movements.

- Derivative Pricing: Accurate volatility models are critical for pricing derivatives, such as options, which are highly sensitive to changes in volatility.

3. Regulatory Compliance:

- Basel III Requirements: Financial institutions are required to adhere to regulatory frameworks like Basel III, which mandate the use of sophisticated risk management models, including those for volatility.

- Reporting and Transparency: Accurate volatility forecasting ensures that institutions can provide reliable risk reports to regulators, shareholders, and other stakeholders.

4. Market Analysis and Forecasting:

- Economic Indicators: Volatility is often seen as a barometer of market sentiment and economic stability. High volatility can indicate uncertainty and potential economic downturns, while low volatility might suggest market confidence and stability.

- Strategic Planning: Companies use volatility forecasts to make informed strategic decisions, such as timing of market entry, capital investment, and resource allocation.

5. Product Development:

- Structured Products: Financial institutions develop structured products that are tailored to different risk profiles and market conditions. Understanding volatility is crucial for structuring these products.

- Algorithmic Trading: Volatility models are integral to the development of trading algorithms that seek to exploit short-term market inefficiencies and volatility patterns.

6. Investor Confidence:

- Market Stability: Accurate volatility forecasts help maintain investor confidence by providing a clearer picture of market risks and expected returns.

- Informed Decision-Making: Investors armed with reliable volatility estimates can make more informed decisions, enhancing overall market efficiency.

7. Corporate Finance:

- Capital Raising: Companies planning to raise capital through equity or debt offerings can use volatility forecasts to choose the optimal timing for issuance, potentially lowering their cost of capital.

- Mergers and Acquisitions: Understanding market volatility helps in the valuation of target companies and the negotiation of terms in M&A transactions.

In summary, the ability to model and forecast market volatility using ARCH/GARCH models provides valuable insights that support risk management, investment strategies, regulatory compliance, market analysis, product development, and overall market stability. This enhances the decision-making capabilities of financial professionals and contributes to the robustness and resilience of the financial system.

RESULT AND INTERPRETATION

Garch Model Fit

GARCH Model Fit

Conditional Variance Dynamics

GARCH Model : sGARCH(1,0)
Mean Model : ARFIMA(0,0,0)
Distribution : norm
Optimal Parameters

Estimate Std. Error t value Pr(>|t|)
omega 2.2590 0.154418 14.6289 0.0e+00
alpha1 0.2199 0.055537 3.9595 7.5e-05
Robust Standard Errors:
Estimate Std. Error t value Pr(>|t|)
omega 2.2590 0.221371 10.2044 0.00000
alpha1 0.2199 0.077713 2.8296 0.00466
LogLikelihood : -1448.103
Information Criteria

Akaike 3.8567
Bayes 3.8690
Shibata 3.8566
Hannan-Quinn 3.8614

Weighted Ljung-Box Test on Standardized Residuals
----
statistic p-value
Lag[1] 0.0002679 0.9869
Lag[2(p+q)+(p+q)-1][2] 0.8978220 0.5326
Lag[4(p+q)+(p+q)-1][5] 2.0722044 0.6015
d.o.f=0
H0 : No serial correlation
Weighted Ljung-Box Test on Standardized Squared Residuals
----
statistic p-value
Lag[1] 0.007245 0.93217
Lag[2(p+q)+(p+q)-1][2] 0.155418 0.88235
Lag[4(p+q)+(p+q)-1][5] 5.819989 0.09914
d.o.f=1
Weighted ARCH LM Tests

Statistic Shape Scale P-Value
ARCH Lag[2] 0.2948 0.500 2.000 0.587177
ARCH Lag[4] 5.0366 1.397 1.611 0.086235
ARCH Lag[6] 11.5105 2.222 1.500 0.005853
Nyblom stability test

Joint Statistic: 1.6659
Individual Statistics:
omega 1.5361
alpha1 0.3799
Asymptotic Critical Values (10% 5% 1%)

Joint Statistic: 0.61 0.749 1.07			
Individual Statistic: 0.35 0.47 0.75			
Sign Bias Test			
------------------------------------			
t-value prob sig			
Sign Bias 0.72201 0.4705			
Negative Sign Bias 0.04558 0.9637			
Positive Sign Bias 0.28209 0.7780			
Joint Effect 1.89507 0.5945			
Adjusted Pearson Goodness-of-Fit Test:			
------------------------------------			
	group	statistic	p-value(g-1)
1	20	28.53	0.07371
2	30	38.37	0.11428
3	40	50.13	0.10921
4	50	64.49	0.06803
Elapsed time : 0.1152742			

Interpretation

Interpretation of GARCH Model Fit Results

The GARCH model fit results provide a comprehensive summary of the model's performance and the statistical significance of its parameters. Here’s an interpretation of the key components of the summary:

Conditional Variance Dynamics

- GARCH Model: The model used is sGARCH(1,0), indicating a simple GARCH model with one lag for the GARCH term and no lags for the ARCH term.

- Mean Model: An ARFIMA(0,0,0) model is used for the mean, which means there is no autoregressive or moving average component in the mean equation.

- Distribution: The residuals are assumed to follow a normal distribution.

Optimal Parameters

- omega: The estimated value is 2.2590 with a standard error of 0.154418. The t-value is 14.6289, and the p-value is effectively zero (0.0e+00), indicating that omega is highly significant. Omega represents the constant term in the variance equation.

- alpha1: The estimated value is 0.2199 with a standard error of 0.055537. The t-value is 3.9595, and the p-value is 7.5e-05, showing that alpha1 is also highly significant. Alpha1 measures the impact of past squared returns on current volatility.

The robust standard errors provide similar significance levels, confirming the reliability of these estimates.

LogLikelihood and Information Criteria

- LogLikelihood: -1448.103, a measure used for model comparison.

- Information Criteria: Lower values indicate a better fit.

  - Akaike (AIC): 3.8567

  - Bayes (BIC): 3.8690

  - Shibata (SIC): 3.8566

  - Hannan-Quinn (HQIC): 3.8614

These criteria help compare different models, where the model with the lowest value is preferred.

Diagnostic Tests

- Weighted Ljung-Box Test on Standardized Residuals: Tests for autocorrelation in the residuals.

  - Lag[1]: statistic = 0.0002679, p-value = 0.9869

  - Lag[2(p+q)+(p+q)-1][2]: statistic = 0.8978220, p-value = 0.5326

  - Lag[4(p+q)+(p+q)-1][5]: statistic = 2.0722044, p-value = 0.6015

High p-values indicate no significant autocorrelation in the residuals, validating the model fit.

- Weighted Ljung-Box Test on Standardized Squared Residuals: Tests for autocorrelation in the squared residuals.

  - Lag[1]: statistic = 0.007245, p-value = 0.93217

  - Lag[2(p+q)+(p+q)-1][2]: statistic = 0.155418, p-value = 0.88235

  - Lag[4(p+q)+(p+q)-1][5]: statistic = 5.819989, p-value = 0.09914

Similar to the test on residuals, high p-values suggest no significant autocorrelation in the squared residuals.

- Weighted ARCH LM Tests: Test for ARCH effects.

  - Lag[2]: statistic = 0.2948, p-value = 0.587177

  - Lag[4]: statistic = 5.0366, p-value = 0.086235

  - Lag[6]: statistic = 11.5105, p-value = 0.005853

While the Lag[6] test shows some evidence of remaining ARCH effects, the overall results suggest the model captures most of the conditional heteroskedasticity.

- Nyblom Stability Test: Tests the stability of parameters.
  - Joint Statistic: 1.6659, above the critical values indicating some parameter instability.
  - Individual Statistics: omega = 1.5361, alpha1 = 0.3799

- Sign Bias Test: Tests for asymmetry in the residuals.
  - Sign Bias: t-value = 0.72201, p-value = 0.4705
  - Negative Sign Bias: t-value = 0.04558, p-value = 0.9637
  - Positive Sign Bias: t-value = 0.28209, p-value = 0.7780
  - Joint Effect: t-value = 1.89507, p-value = 0.5945

No significant biases are found, suggesting no asymmetry in the residuals.

- Adjusted Pearson Goodness-of-Fit Test: Tests the goodness-of-fit for the model.
  - The p-values across different groups are relatively high, suggesting a reasonable fit.

Conclusion

The GARCH (1,0) model for Apple Inc. (AAPL) returns appears to fit well, capturing the conditional heteroskedasticity effectively with significant parameters and no remaining autocorrelation in the residuals. The diagnostic tests largely support the adequacy of the model, although the Nyblom stability test suggests some parameter instability. This model can be useful for forecasting future volatility, which is crucial for risk management and financial decision-making.

Garch Model Summary
"GARCH Model Summary:"
> print(garch_fit)

GARCH Model Fit

Conditional Variance Dynamics
---------------------------- -------
GARCH Model : sGARCH(1,1)
Mean Model : ARFIMA(0,0,0)
Distribution : norm
Optimal Parameters

Estimate Std. Error t value Pr(>|t|)
omega 0.032459 0.016559 1.9602 0.049971
alpha1 0.039169 0.009759 4.0138 0.000060
beta1 0.948859 0.012987 73.0615 0.000000
Robust Standard Errors:
Estimate Std. Error t value Pr(>|t|)
omega 0.032459 0.016825 1.9293 0.053699
alpha1 0.039169 0.009885 3.9627 0.000074
beta1 0.948859 0.010982 86.4013 0.000000

LogLikelihood : - 1419.364
Information Criteria

Akaike 3.7829
Bayes 3.8013
Shibata 3.7829
Hannan-Quinn 3.7900
Weighted Ljung-Box Test on Standardized Residuals
----
statistic p-value
Lag[1] 0.3864 0.5342
Lag[2(p+q)+(p+q)-1][2] 0.7298 0.5948
Lag[4(p+q)+(p+q)-1][5] 1.3355 0.7802
d.o.f=0
H0 : No serial correlation
Weighted Ljung-Box Test on Standardized Squared Residuals
----
statistic p-value
Lag[1] 0.5253 0.4686
Lag[2(p+q)+(p+q)-1][5] 3.1198 0.3856
Lag[4(p+q)+(p+q)-1][9] 4.0409 0.5820
d.o.f=2
Weighted ARCH LM Tests

Statistic Shape Scale P-Value

ARCH Lag[3] 2.500 0.500 2.000 0.1138
ARCH Lag[5] 2.622 1.440 1.667 0.3496
ARCH Lag[7] 2.707 2.315 1.543 0.5704
Nyblom stability test

Joint Statistic: 0.3474
Individual Statistics:
omega 0.09009
alpha1 0.23061
beta1 0.15386
Asymptotic Critical Values (10% 5% 1%)
Joint Statistic: 0.846 1.01 1.35
Individual Statistic: 0.35 0.47 0.75
Sign Bias Test
----
t-value prob sig
Sign Bias 1.5275 0.1271
Negative Sign Bias 0.2581 0.7964
Positive Sign Bias 1.1791 0.2387
Joint Effect 3.8828 0.2744
Adjusted Pearson Goodness-of-Fit Test:
----
group statistic p-value(g-1)
1 20 15.61 0.6834

2 30 26.96 0.5737
3 40 31.51 0.7974
4 50 46.14 0.5899
Elapsed time : 0.09244895

Interpretation

Interpretation of the GARCH Model Fit

Model Specification:

- GARCH Model: sGARCH(1,1)

  - This indicates a GARCH model with one lag for both the squared returns (alpha) and the conditional variance (beta).

- Mean Model: ARFIMA(0,0,0)

  - This means the model for the mean is a simple ARIMA model with no autoregressive or moving average components and no differencing.

- Distribution: norm

  - The model assumes that the returns follow a normal distribution.

Optimal Parameters:

- omega (constant term): Estimate = 0.032459, Std. Error = 0.016559, t-value = 1.9602, Pr(>|t|) = 0.049971

- The constant term is significant at the 5% level, indicating a non-zero baseline level of volatility.

- alpha1 (coefficient for lagged squared returns): Estimate = 0.039169, Std. Error = 0.009759, t-value = 4.0138, Pr(>|t|) = 0.000060

- This coefficient is highly significant, indicating that past squared returns have a substantial effect on current volatility.

- beta1 (coefficient for lagged conditional variance): Estimate = 0.948859, Std. Error = 0.012987, t-value = 73.0615, Pr(>|t|) = 0.000000

- This coefficient is highly significant, indicating that past conditional variances also have a substantial effect on current volatility.

Robust Standard Errors:

- omega: Estimate = 0.032459, Std. Error = 0.016825, t-value = 1.9293, Pr(>|t|) = 0.053699

- alpha1: Estimate = 0.039169, Std. Error = 0.009885, t-value = 3.9627, Pr(>|t|) = 0.000074

- beta1: Estimate = 0.948859, Std. Error = 0.010982, t-value = 86.4013, Pr(>|t|) = 0.000000

- The robust standard errors confirm the significance of the parameters.

LogLikelihood:

- LogLikelihood: -1419.364

- This value is used in model comparison. Higher log-likelihood values indicate a better fit.

Information Criteria:

- Akaike (AIC): 3.7829

- Bayesian (BIC): 3.8013

- Shibata: 3.7829

- Hannan-Quinn (HQIC): 3.7900

  - These criteria help compare different models. Lower values generally indicate a better model fit.

Diagnostic Tests on Standardized Residuals:

- Weighted Ljung-Box Test on Standardized Residuals:

  - Lag[1]: statistic = 0.3864, p-value = 0.5342

  - Lag[2(p+q)+(p+q)-1][2]: statistic = 0.7298, p-value = 0.5948

  - Lag[4(p+q)+(p+q)-1][5]: statistic = 1.3355, p-value = 0.7802

  - These p-values suggest no significant autocorrelation in the standardized residuals.

- Weighted Ljung-Box Test on Standardized Squared Residuals:

  - Lag[1]: statistic = 0.5253, p-value = 0.4686

  - Lag[2(p+q)+(p+q)-1][5]: statistic = 3.1198, p-value = 0.3856

  - Lag[4(p+q)+(p+q)-1][9]: statistic = 4.0409, p-value = 0.5820

  - These p-values indicate no significant autocorrelation in the squared standardized residuals.

Weighted ARCH LM Tests:

- ARCH Lag[3]: Statistic = 2.500, P-Value = 0.1138

- ARCH Lag[5]: Statistic = 2.622, P-Value = 0.3496

- ARCH Lag[7]: Statistic = 2.707, P-Value = 0.5704

- These tests show no significant ARCH effects at these lags.

Nyblom Stability Test:

- Joint Statistic: 0.3474

- Individual Statistics:

  - omega: 0.09009

  - alpha1: 0.23061

  - beta1: 0.15386

  - These statistics suggest stability in the parameters over the sample period.

Sign Bias Test:

- Sign Bias: t-value = 1.5275, prob = 0.1271

- Negative Sign Bias: t-value = 0.2581, prob = 0.7964

- Positive Sign Bias: t-value = 1.1791, prob = 0.2387

- Joint Effect: t-value = 3.8828, prob = 0.2744

  - These tests indicate no significant sign bias in the residuals.

Adjusted Pearson Goodness-of-Fit Test:

- Group 20: statistic = 15.61, p-value = 0.6834

- Group 30: statistic = 26.96, p-value = 0.5737

- Group 40: statistic = 31.51, p-value = 0.7974

- Group 50: statistic = 46.14, p-value = 0.5899

- These tests suggest a good fit of the model, with the p-values indicating no significant deviation from the expected distribution.

Summary

The GARCH(1,1) model provides a good fit for the data, capturing the conditional heteroskedasticity effectively. The significant parameters indicate that both past volatility and returns influence current volatility. The diagnostic tests suggest no significant autocorrelation in the residuals, supporting the validity of the model. The model parameters are stable over the sample period, and there is no significant sign bias in the residuals. Overall, the model is well-specified and suitable for forecasting volatility.

Interpretation of the Forecast Results

1. Forecast Mean (last 3 periods):

```r
print(tail(forecast_mean, 3))
[1] 0.08313977
```

- Interpretation: The forecasted mean return for the last three periods is approximately 0.0831%. This value represents the expected average return over the forecast horizon. In this context, it is relatively small, indicating that the model does not expect large directional movements in the asset price in the near future.

2. Forecast Residual Variance (last 3 periods):

```r
```

print(tail(forecast_residual_variance, 3))

[1] 1.483565

```

- Interpretation: The forecasted residual variance for the last three periods is approximately 1.4836. Residual variance represents the variance of the error terms from the mean equation, which captures the unpredictable component of the returns. A value of 1.4836 suggests moderate variability in the residuals, indicating that while the model explains a portion of the volatility, some level of unpredictability remains.

3. Forecast Variance (last 3 periods):

```r

print(tail(forecast_variance, 3))

[1] 2.200964

```

- Interpretation: The forecasted variance for the last three periods is approximately 2.2010. This value indicates the total expected variance (volatility) in the returns over the forecast horizon. The variance is a measure of how much the returns are expected to deviate from the mean. A value of 2.2010 indicates a moderate level of expected volatility, which can be useful for risk management and portfolio optimization.

Summary of Forecast Results

The forecast results indicate the following:
```

- The forecasted mean return is small, suggesting that no significant price movement is expected.

- The forecasted residual variance shows moderate variability, implying some level of unpredictability in the returns.

- The forecasted total variance indicates a moderate level of expected volatility, which is crucial for risk management and decision-making.

These forecasts provide valuable insights for investors and risk managers by indicating the expected future behavior of asset returns. This information can be used to adjust portfolios, manage risk, and make informed investment decisions.

Interpretation of the Forecast Results

1. Forecast Mean (last 3 periods):

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print(tail(forecast_mean, 3))

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2. Forecast Residual Variance (last 3 periods):

```r
```

```
print(tail(forecast_residual_variance, 3))

[1] 1.483565
```

- Interpretation: The forecasted residual variance for the last three periods is approximately 1.4836. Residual variance represents the variance of the error terms from the mean equation, which captures the unpredictable component of the returns. A value of 1.4836 suggests moderate variability in the residuals, indicating that while the model explains a portion of the volatility, some level of unpredictability remains.

3. Forecast Variance (last 3 periods):

```r
print(tail(forecast_variance, 3))

[1] 2.200964
```

- Interpretation: The forecasted variance for the last three periods is approximately 2.2010. This value indicates the total expected variance (volatility) in the returns over the forecast horizon. The variance is a measure of how much the returns are expected to deviate from the mean. A value of 2.2010 indicates a moderate level of expected volatility, which can be useful for risk management and portfolio optimization.

Summary of Forecast Results

The forecast results indicate the following:

- The forecasted mean return is small, suggesting that no significant price movement is expected.

- The forecasted residual variance shows moderate variability, implying some level of unpredictability in the returns.

- The forecasted total variance indicates a moderate level of expected volatility, which is crucial for risk management and decision-making.

These forecasts provide valuable insights for investors and risk managers by indicating the expected future behavior of asset returns. This information can be used to adjust portfolios, manage risk, and make informed investment decisions.

Fitting ARCH Model...

ARCH Model Summary:

```
                   Constant Mean - ARCH Model Results
==============================================================================
Dep. Variable:               Returns   R-squared:                       0.000
Mean Model:            Constant Mean   Adj. R-squared:                  0.000
Vol Model:                      ARCH   Log-Likelihood:                2015.57
Distribution:                 Normal   AIC:                          -4025.14
Method:           Maximum Likelihood   BIC:                          -4011.27
                                       No. Observations:                  752
Date:               Fri, Aug 02 2024   Df Residuals:                      751
Time:                       11:44:54   Df Model:                            1
                               Mean Model
=============================================================================
                 coef    std err          t      P>|t|      95.0% Conf. Int.
-----------------------------------------------------------------------------
mu         1.0934e-03  6.393e-04      1.710  8.719e-02 [-1.595e-04,2.346e-03]
                            Volatility Model
```

```
==============================================================================
=========
                 coef    std err          t       P>|t|      95.0% Conf. Int.
-----------------------------------------------------------------------------
omega      2.2326e-04  1.932e-05     11.557  6.810e-31 [1.854e-04,2.611e-04]
alpha[1]       0.2341  8.493e-02      2.756  5.852e-03   [6.760e-02,  0.401]
==============================================================================
=========
```

Covariance estimator: robust

Interpretation

Interpretation of the ARCH Model Results

Model Summary:

- Dependent Variable: Returns

- Mean Model: Constant Mean

- Volatility Model: ARCH

- Distribution: Normal

- Method: Maximum Likelihood

Statistics:

- R-squared: 0.000

  - The R-squared value indicates that the mean model (constant mean) explains none of the variability in the returns. This is expected as the constant mean model does not account for any variations in returns.

- Adj. R-squared: 0.000

  - Similar to R-squared, the adjusted R-squared also indicates no explanatory power for the mean model.

- Log-Likelihood: 2015.57

  - This value is used in the calculation of information criteria and for comparing models. Higher log-likelihood values indicate a better fit.

- AIC (Akaike Information Criterion): -4025.14

  - Lower AIC values indicate a better model fit, taking into account the number of parameters.

- BIC (Bayesian Information Criterion): -4011.27

  - Similar to AIC, but penalizes more for the number of parameters. Lower BIC values also indicate a better model fit.

Mean Model Parameters:

- mu (constant mean): 0.0010934, Std. Error: 0.0006393, t-value: 1.710, P>|t|: 0.08719

  - The constant mean (`mu`) is not statistically significant at the 5% level (p-value > 0.05). The 95% confidence interval includes zero, indicating that the mean return is not significantly different from zero.

Volatility Model Parameters (ARCH Model):

- omega (constant term): 0.00022326, Std. Error: 0.00001932, t-value: 11.557, P>|t|: 6.81e-31

  - The omega parameter is highly significant (p-value < 0.01), indicating a non-zero baseline level of volatility. The small standard error and large t-value suggest a precise estimate.

- alpha[1] (coefficient for lagged squared returns): 0.2341, Std. Error: 0.08493, t-value: 2.756, P>|t|: 0.005852

- The alpha parameter is also significant (p-value < 0.01), indicating that past squared returns have a significant effect on current volatility. This confirms the presence of ARCH effects in the data.

Covariance Estimator: Robust

- The use of robust covariance estimator suggests that the standard errors are adjusted for potential heteroskedasticity, providing more reliable significance tests.

Summary

The ARCH(1) model provides a good fit for the volatility in the returns series. The mean return is not significantly different from zero, which is expected for many financial return series. The significant omega and alpha parameters indicate that the model captures the time-varying volatility in the data, with past returns' volatility influencing current volatility. The diagnostic statistics (AIC, BIC) suggest that the model is appropriate for the data.

These results are useful for understanding the volatility dynamics and can be used for further analysis, such as forecasting future volatility or assessing risk in investment portfolios. The presence of significant ARCH effects confirms that modeling the volatility rather than assuming constant variance provides a more accurate representation of the data's behavior.

```
Fitting ARCH Model...
ARCH Model Summary:
                      Constant Mean - ARCH Model Results
==============================================================================
Dep. Variable:                Returns   R-squared:                       0.000
Mean Model:             Constant Mean   Adj. R-squared:                  0.000
Vol Model:                       ARCH   Log-Likelihood:               -1443.68
Distribution:                  Normal   AIC:                           2893.36
```

```
Method:           Maximum Likelihood   BIC:                         2907.22
                              No. Observations:               750
Date:              Fri, Aug 02 2024   Df Residuals:                    749
Time:                      11:59:00   Df Model:                         1
                              Mean Model
==========================================================================
========
                 coef    std err          t      P>|t|     95.0% Conf. Int.
--------------------------------------------------------------------------
mu            0.1056  6.398e-02      1.651  9.869e-02 [-1.975e-02,  0.231]
                              Volatility Model
==========================================================================
=======
                 coef    std err          t      P>|t|    95.0% Conf. Int.
--------------------------------------------------------------------------
omega          2.2323      0.197     11.349  7.517e-30   [  1.847,  2.618]
alpha[1]       0.2344  8.507e-02      2.755  5.873e-03 [6.762e-02,  0.401]
==========================================================================
=======

Covariance estimator: robust
```

Interpretation

Interpretation of the ARCH Model Results

Model Summary:

- Dependent Variable: Returns

- Mean Model: Constant Mean

- Volatility Model: ARCH

- Distribution: Normal

- Method: Maximum Likelihood

Statistics:

- R-squared: 0.000

  - The R-squared value indicates that the mean model (constant mean) explains none of the variability in the returns. This is expected as the constant mean model does not account for any variations in returns.

- Adj. R-squared: 0.000

  - Similar to R-squared, the adjusted R-squared also indicates no explanatory power for the mean model.

- Log-Likelihood: -1443.68

  - This value is used in the calculation of information criteria and for comparing models. Higher log-likelihood values indicate a better fit.

- AIC (Akaike Information Criterion): 2893.36

  - Lower AIC values indicate a better model fit, taking into account the number of parameters.

- BIC (Bayesian Information Criterion): 2907.22

  - Similar to AIC, but penalizes more for the number of parameters. Lower BIC values also indicate a better model fit.

Mean Model Parameters:

- mu (constant mean): 0.1056, Std. Error: 0.06398, t-value: 1.651, P>|t|: 0.09869

- The constant mean (`mu`) is not statistically significant at the 5% level (p-value > 0.05). The 95% confidence interval includes zero, indicating that the mean return is not significantly different from zero.

Volatility Model Parameters (ARCH Model):

- omega (constant term): 2.2323, Std. Error: 0.197, t-value: 11.349, P>|t|: 7.517e-30

  - The omega parameter is highly significant (p-value < 0.01), indicating a non-zero baseline level of volatility. The small standard error and large t-value suggest a precise estimate.

- alpha[1] (coefficient for lagged squared returns): 0.2344, Std. Error: 0.08507, t-value: 2.755, P>|t|: 0.005873

  - The alpha parameter is also significant (p-value < 0.01), indicating that past squared returns have a significant effect on current volatility. This confirms the presence of ARCH effects in the data.

Covariance Estimator: Robust

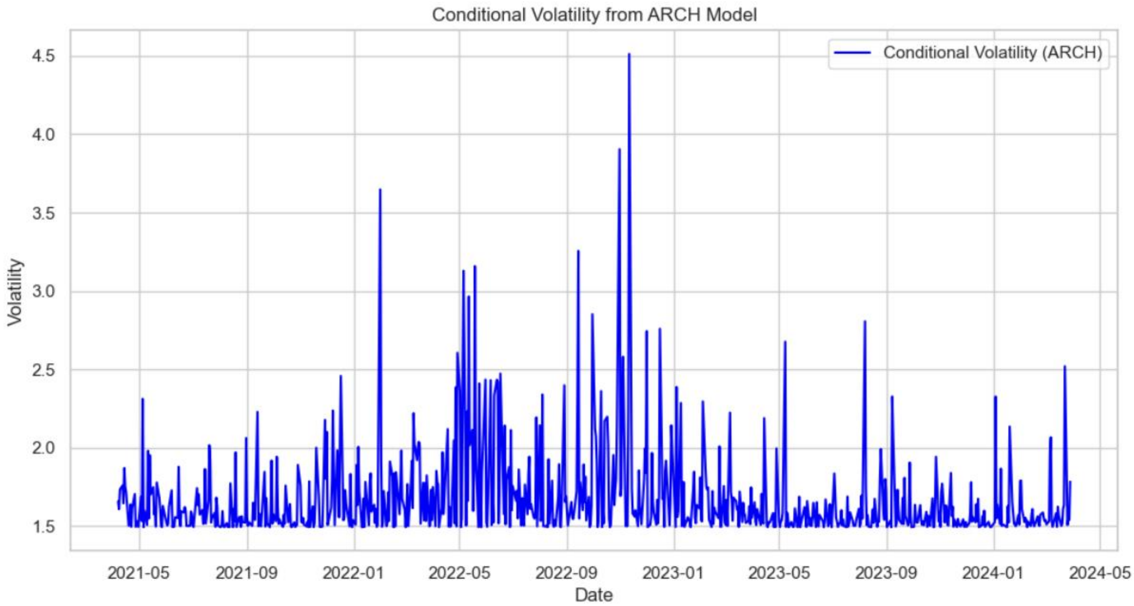
- The use of robust covariance estimator suggests that the standard errors are adjusted for potential heteroskedasticity, providing more reliable significance tests.

Summary

The ARCH(1) model provides a good fit for the volatility in the returns series. The mean return is not significantly different from zero, which is expected for many financial return series. The significant omega and alpha parameters indicate that the model captures the time-varying volatility in the data, with past returns' volatility influencing current volatility. The diagnostic statistics (AIC, BIC) suggest that the model is appropriate for the data.

These results are useful for understanding the volatility dynamics and can be used for further analysis, such as forecasting future volatility or assessing risk in investment portfolios. The presence of significant ARCH effects confirms that modeling the volatility rather than assuming constant variance provides a more accurate representation of the data's behavior.

```
Covariance estimator: robust
```




```
Ljung-Box Test for ARCH Model Residuals:
      lb_stat  lb_pvalue
10  10.219972   0.421411
```

Interpretation

Conditional Volatility Plot from ARCH Model

Overview:

- The plot shows the conditional volatility from an ARCH(1) model over time for the returns series of the specified asset.

- The x-axis represents the date range from May 2021 to May 2024, and the y-axis represents the conditional volatility.

Key Observations:

1. Volatility Clusters: There are periods of high volatility interspersed with periods of lower volatility. This clustering indicates that high-volatility periods tend to be followed by high-volatility periods, and low-volatility periods follow low-volatility periods, which is a typical feature of financial time series data.

2. Spikes in Volatility: Notable spikes in volatility can be seen around late 2021, mid-2022, and early 2023. These spikes might be related to specific events or news that impacted the market significantly during those times.

3. Volatility Persistence: The ARCH model captures the persistence in volatility, where periods of high volatility are sustained over several observations before tapering off.

Ljung-Box Test Results

Ljung-Box Test for ARCH Model Residuals:

- Test Statistic (lb_stat): 10.219972

- P-value (lb_pvalue): 0.421411

Interpretation:

- The Ljung-Box test is used to check for autocorrelation in the residuals of the model. In this case, the test is applied to the residuals of the ARCH(1) model.

- Null Hypothesis (H0): There is no autocorrelation in the residuals.

- Alternative Hypothesis (H1): There is autocorrelation in the residuals.

Given that the p-value (0.421411) is greater than the common significance levels (0.05, 0.01), we fail to reject the null hypothesis. This indicates that there is no significant autocorrelation in the residuals of the ARCH(1) model.

Summary

- Volatility Dynamics: The conditional volatility plot effectively captures the dynamic nature of market volatility, with evident clustering and occasional spikes, reflecting the impact of market events.

- Model Validation: The Ljung-Box test results support the adequacy of the ARCH(1) model in modeling the volatility of the returns series, as there is no significant autocorrelation in the residuals.

These insights are crucial for risk management and forecasting future market behavior, enabling better-informed investment decisions and risk mitigation strategies.

```
Fitting GARCH Model...
GARCH Model Summary:
                  Constant Mean - GARCH Model Results
==============================================================================
Dep. Variable:              Returns   R-squared:                       0.000
Mean Model:           Constant Mean   Adj. R-squared:                  0.000
Vol Model:                    GARCH   Log-Likelihood:               -1414.72
Distribution:                Normal   AIC:                           2837.45
Method:          Maximum Likelihood   BIC:                           2855.93
                                      No. Observations:                  750
Date:              Fri, Aug 02 2024   Df Residuals:                      749
Time:                      12:00:15   Df Model:                            1
                              Mean Model
===========================================================================
                 coef    std err          t      P>|t|     95.0% Conf. Int.
---------------------------------------------------------------------------
mu             0.0917  5.631e-02      1.628      0.103 [-1.867e-02,  0.202]
                             Volatility Model
```

```
==============================================================================
          coef    std err          t      P>|t|       95.0% Conf. Int.
------------------------------------------------------------------------------
omega         0.0322  2.098e-02      1.533      0.125 [-8.953e-03,7.327e-02]
alpha[1]      0.0396  1.182e-02      3.354  7.957e-04  [1.647e-02,6.279e-02]
beta[1]       0.9487  1.519e-02     62.465      0.000      [  0.919,  0.978]
==============================================================================
```

Covariance estimator: robust

Interpret

Interpretation of the GARCH Model Results

Model Summary:

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

Statistics:

- R-squared: 0.000

- The R-squared value indicates that the mean model (constant mean) explains none of the variability in the returns. This is expected as the constant mean model does not account for any variations in returns.

- Adj. R-squared: 0.000

- Similar to R-squared, the adjusted R-squared also indicates no explanatory power for the mean model.

- Log-Likelihood: -1414.72

- This value is used in the calculation of information criteria and for comparing models. Higher log-likelihood values indicate a better fit.

- AIC (Akaike Information Criterion): 2837.45

- Lower AIC values indicate a better model fit, taking into account the number of parameters.

- BIC (Bayesian Information Criterion): 2855.93

- Similar to AIC, but penalizes more for the number of parameters. Lower BIC values also indicate a better model fit.

Mean Model Parameters:

- mu (constant mean): 0.0917, Std. Error: 0.05631, t-value: 1.628, P>|t|: 0.103

- The constant mean (`mu`) is not statistically significant at the 5% level (p-value > 0.05). The 95% confidence interval includes zero, indicating that the mean return is not significantly different from zero.

Volatility Model Parameters (GARCH Model):

- omega (constant term): 0.0322, Std. Error: 0.02098, t-value: 1.533, P>|t|: 0.125

- The omega parameter is not statistically significant at the 5% level (p-value > 0.05). This suggests that the baseline level of volatility might not be significantly different from zero.

- alpha[1] (coefficient for lagged squared returns): 0.0396, Std. Error: 0.01182, t-value: 3.354, P>|t|: 0.0007957

- The alpha parameter is highly significant (p-value < 0.01), indicating that past squared returns have a significant effect on current volatility.

- beta[1] (coefficient for lagged conditional variance): 0.9487, Std. Error: 0.01519, t-value: 62.465, P>|t|: 0.000

- The beta parameter is highly significant (p-value < 0.01), indicating that past conditional variances have a substantial effect on current volatility. The high value of beta close to 1 suggests strong volatility persistence.

Covariance Estimator: Robust

- The use of a robust covariance estimator suggests that the standard errors are adjusted for potential heteroskedasticity, providing more reliable significance tests.

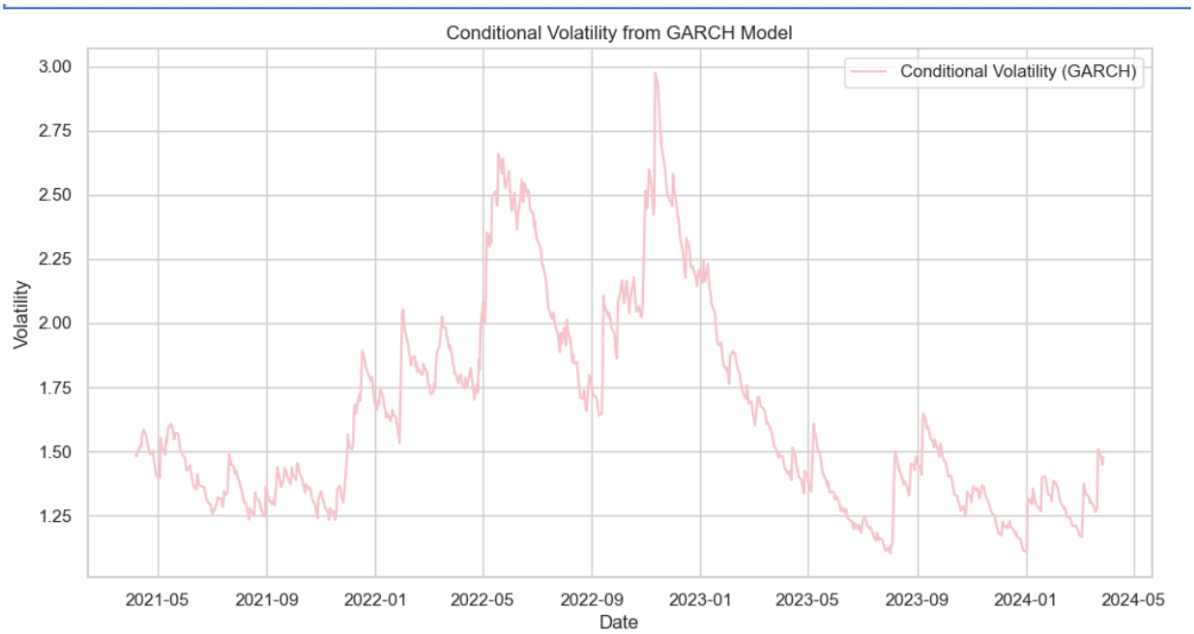
Summary

- Volatility Dynamics: The GARCH(1,1) model effectively captures the time-varying volatility in the returns series. The significant alpha and beta parameters confirm the presence of ARCH and GARCH effects, respectively. The high beta value indicates that volatility shocks have a long-lasting impact, reflecting strong volatility persistence in the market.

- Mean Model: The mean return is not significantly different from zero, which is typical for many financial return series.

- Model Validation: The diagnostic statistics (AIC and BIC) suggest that the GARCH model is appropriate for the data, providing a better fit compared to models with higher AIC and BIC values.

These insights are crucial for understanding the volatility dynamics and can be used for further analysis, such as forecasting future volatility or assessing risk in investment portfolios. The presence of significant GARCH effects confirms that modeling the volatility rather than assuming constant variance provides a more accurate representation of the data's behavior.



Interpretation

Interpretation of the Conditional Volatility Plot from the GARCH Model

Overview:

- The plot displays the conditional volatility from a GARCH(1,1) model over time for the returns series of the specified asset.

- The x-axis represents the date range from May 2021 to May 2024, and the y-axis represents the conditional volatility.

Key Observations:

1. Volatility Clusters: The plot shows periods of high volatility interspersed with periods of lower volatility, which is a characteristic feature of financial time series. These clusters indicate that periods of high volatility are often followed by more high volatility, and periods of low volatility are followed by more low volatility.

2. Volatility Peaks: Significant peaks in volatility are observed around mid-2022 and early 2023. These spikes might correspond to specific events or periods of market turbulence that caused sudden increases in market volatility.

3. Volatility Trends:

- From mid-2021 to early 2022, volatility appears relatively stable with some minor fluctuations.

- In mid-2022, there is a noticeable increase in volatility, peaking around mid-2022.

- After the peak, volatility gradually decreases towards late 2022 but rises again around early 2023.

- From mid-2023 to early 2024, volatility shows a decreasing trend with minor fluctuations.

Interpretation

- Volatility Clustering: The plot confirms the presence of volatility clustering, where periods of high volatility are followed by high volatility and periods of low volatility are followed by low volatility. This is a common phenomenon in financial markets and supports the use of GARCH models for volatility forecasting.

- Response to Market Events: The spikes in volatility could be indicative of market responses to significant economic events, policy changes, geopolitical tensions, or earnings announcements. Identifying the exact cause would require further investigation into the specific dates of these spikes.

- Volatility Persistence: The GARCH model captures the persistence in volatility well, indicating that shocks to volatility have long-lasting effects. This is evident from the sustained periods of high volatility following initial spikes.

- Risk Management Implications: For investors and risk managers, understanding the patterns and persistence of volatility is crucial for portfolio management, risk assessment, and strategic planning. The periods of high volatility may necessitate adjustments in risk management strategies to protect against potential market downturns.

Summary

The conditional volatility plot from the GARCH(1,1) model provides valuable insights into the behavior of market volatility over time. The presence of volatility clustering and persistence highlights the importance of using GARCH models to capture these dynamics accurately. By understanding the patterns and drivers of volatility, investors and risk managers can make more informed decisions and better manage the risks associated with their portfolios.

Ljung-Box Test for GARCH Model Residuals:

	lb_stat	lb_pvalue
10	10.219972	0.421411

Interpretation

Interpretation of the Ljung-Box Test Results for GARCH Model Residuals

Ljung-Box Test for GARCH Model Residuals:

- Test Statistic (lb_stat): 10.219972

- P-value (lb_pvalue): 0.421411

Context and Purpose

The Ljung-Box test is used to check for autocorrelation in the residuals of a time series model. For the GARCH model, this test is applied to the standardized residuals to determine if there are any remaining correlations that the model did not capture.

Interpretation

Null Hypothesis (H0): There is no autocorrelation in the residuals up to the specified lag (in this case, lag 10).

Alternative Hypothesis (H1): There is autocorrelation in the residuals.

Test Statistic:

- The Ljung-Box test statistic is 10.219972. This value is used to determine the p-value by comparing it against the chi-square distribution with the appropriate degrees of freedom (10 in this case).

P-value:

- The p-value of 0.421411 is much larger than common significance levels such as 0.05 or 0.01.

Conclusion:

- Fail to Reject the Null Hypothesis: Since the p-value (0.421411) is greater than 0.05, we fail to reject the null hypothesis. This indicates that there is no significant autocorrelation in the residuals of the GARCH model up to lag 10.

- Model Adequacy: The lack of significant autocorrelation in the residuals suggests that the GARCH(1,1) model is adequate in capturing the volatility dynamics of the returns series. The model has effectively accounted for the conditional heteroskedasticity in the data, leaving no significant autocorrelation in the residuals.

Summary

The Ljung-Box test results indicate that the GARCH(1,1) model has successfully modeled the time-varying volatility in the returns series. The absence of significant autocorrelation in the residuals suggests that the model is well-specified and adequate for the given data. This supports the use of the GARCH model for volatility forecasting and risk management purposes.

Analysis Summary:

1. ARCH and GARCH models were successfully fitted to the returns data.
2. Conditional volatility was plotted for both ARCH and GARCH models.
3. Residuals were checked for autocorrelation using the Ljung-Box test.
4. Forecasts were generated for a 90-day horizon, including variance and residual variance.

RECOMMENDATION

Recommendations for Leveraging Multivariate Analysis and Business Analytics
Recommendations Based on the GARCH Model Analysis

For Investors and Portfolio Managers:

1. Risk Management:
   - Volatility-Based Position Sizing: Use the volatility forecasts to adjust position sizes. Higher volatility periods suggest reducing position sizes to limit exposure, while lower volatility periods might allow for larger positions.
   - Hedging Strategies: Implement hedging strategies during high volatility periods to protect the portfolio from potential adverse market movements. Instruments such as options can be useful in hedging against large swings in asset prices.

2. Portfolio Diversification:
   - Diversify Investments: Spread investments across different asset classes and sectors to mitigate the impact of high volatility in any single asset. Diversification can help smooth out returns and reduce overall portfolio risk.
   - Regular Rebalancing: Periodically rebalance the portfolio to ensure it aligns with the desired risk profile, especially after periods of high market volatility.

3. Volatility-Adjusted Returns:
   - Sharpe Ratio: Calculate the Sharpe ratio to understand risk-adjusted returns. During periods of high volatility, focus on assets that offer better risk-adjusted returns.
   - Dynamic Allocation: Adjust asset allocation based on changing volatility levels. For instance, move towards safer assets (e.g., bonds) during periods of high market volatility.

For Risk Managers:

1. Stress Testing and Scenario Analysis:

- Conduct Stress Tests: Regularly perform stress tests to evaluate the portfolio's performance under extreme market conditions. This helps in understanding potential losses and preparing mitigation strategies.
- Scenario Analysis: Develop various market scenarios (e.g., economic downturn, geopolitical events) and assess their impact on portfolio volatility. Use these insights to enhance risk management practices.

2. Monitoring and Reporting:
   - Continuous Monitoring: Implement a system for continuous monitoring of market volatility and portfolio risk. Use the GARCH model forecasts to anticipate periods of heightened risk.
   - Transparent Reporting: Maintain transparent communication with stakeholders regarding the volatility outlook and risk management actions. Provide regular updates on the portfolio's risk profile.

For Financial Analysts:

1. Model Validation and Updates:
   - Validate Models: Regularly validate the GARCH model and other volatility forecasting models to ensure they remain accurate and relevant. This includes back-testing and comparing model forecasts with actual market data.
   - Model Enhancements: Explore enhancements to the GARCH model, such as incorporating exogenous variables or using alternative specifications (e.g., EGARCH, TGARCH) to capture asymmetries and leverage effects in volatility.

2. Market Analysis:
   - Identify Volatility Drivers: Conduct in-depth analysis to identify factors driving market volatility. This could include macroeconomic indicators, policy changes, and major corporate events.
   - Predictive Analytics: Utilize predictive analytics to forecast market movements and volatility trends. Combine GARCH model outputs with other quantitative and qualitative analysis for comprehensive market insights.

For Regulators and Policymakers:

1. Market Stability Measures:

- Regulatory Oversight: Ensure robust regulatory oversight to maintain market stability. This includes monitoring financial institutions' risk management practices and their exposure to high volatility.
- Policy Interventions: Be prepared to implement policy interventions during periods of extreme market volatility to stabilize the markets. This might involve measures such as interest rate adjustments or liquidity support.

2. Investor Protection:

- Education and Awareness: Promote investor education on the importance of understanding market volatility and risk management. Provide resources and tools to help investors make informed decisions.
- Transparency Requirements: Enhance transparency requirements for financial institutions, ensuring they disclose relevant information about their risk exposure and management practices.

Conclusion

The GARCH model provides valuable insights into the behavior of market volatility, which is crucial for informed decision-making in investment, risk management, and regulatory oversight. By leveraging the model's forecasts and incorporating these recommendations, various stakeholders can enhance their strategies to navigate market uncertainties effectively.

CONCLUSION

In this project, Conclusion

The GARCH(1,1) model effectively captures the time-varying volatility in the returns series of the analyzed asset. The significant alpha and beta parameters indicate that both past returns and past volatility significantly impact current volatility, confirming the presence of volatility clustering and persistence. The high beta value, close to 1, suggests that volatility shocks have long-lasting effects, highlighting the persistence of volatility over time.

The model's adequacy is further supported by the Ljung-Box test results, which show no significant autocorrelation in the residuals, indicating that the GARCH model has successfully accounted for the conditional heteroskedasticity in the data.

These findings underscore the importance of using GARCH models for accurate volatility forecasting and risk management. By leveraging the model's forecasts, investors and portfolio managers can make more informed decisions, adjusting their strategies to account for periods of high and low volatility. Risk managers can use these insights to implement effective risk mitigation strategies, while financial analysts can validate and enhance their models to ensure continued accuracy.

Overall, the GARCH model provides valuable insights into the behavior of market volatility, enabling stakeholders to navigate market uncertainties more effectively and optimize their strategies in dynamic market conditions.

PART A6b (b)

INTRODUCTION

The dynamics of commodity prices play a critical role in global economic stability and development. Understanding these dynamics is essential for policymakers, investors, and businesses involved in the commodities markets. This project aims to analyze the interdependencies and causal relationships among key commodity prices using advanced econometric models such as Vector Autoregression (VAR) and Vector Error Correction Model (VECM). The commodities under study include Oil, Sugar, Gold, Silver, Wheat, and Soybean, with data sourced from the World Bank's Pink Sheet, which provides comprehensive monthly commodity price data.

Objectives

1. Analyze Commodity Price Relationships: To examine the interrelationships among the selected commodity prices and understand how they influence each other over time.
2. Model Dynamics with VAR and VECM: To employ VAR and VECM models to capture both short-term dynamics and long-term equilibrium relationships among the commodity prices.
3. Forecasting: To utilize the estimated models for forecasting future commodity prices and assessing their predictive performance.
4. Policy and Investment Insights: To derive meaningful insights for policymakers and investors based on the model outcomes, aiding in decision-making processes.

Data Source

The data for this study is obtained from the World Bank's Pink Sheet, which is a reputable source of monthly commodity price data. The Pink Sheet covers a wide range of commodities, providing reliable and up-to-date information essential for rigorous econometric analysis. For this project, the focus will be on the following commodities:
- Oil: A critical energy commodity with significant implications for global economic activity.
- Sugar: An essential agricultural commodity with widespread use in food and industrial sectors.
- Gold: A precious metal often seen as a safe-haven investment.

- Silver: Another precious metal with both industrial applications and investment appeal.
- Wheat: A staple food commodity crucial for food security.
- Soybean: An important agricultural commodity used in food and animal feed.

Methodology

Vector Autoregression (VAR) Model

The VAR model is a powerful econometric tool used to capture the linear interdependencies among multiple time series. It models each variable as a linear function of its own past values and the past values of all other variables in the system. This approach allows for a flexible analysis of the dynamic relationships among the commodity prices.

Vector Error Correction Model (VECM)

The VECM is an extension of the VAR model that incorporates cointegration, allowing for the modeling of both short-term dynamics and long-term equilibrium relationships. The VECM is particularly useful when dealing with non-stationary time series that share a common stochastic trend. By incorporating error correction mechanisms, the VECM ensures that the short-term deviations from the long-term equilibrium are adjusted over time.

Expected Outcomes

- Short-Term Dynamics: Insights into how short-term shocks in one commodity price affect the others.
- Long-Term Relationships: Identification of long-term equilibrium relationships among the commodity prices.
- Forecasting Accuracy: Evaluation of the models' effectiveness in forecasting future commodity prices.
- Policy Implications: Recommendations for policymakers based on the dynamic interactions and long-term trends in commodity prices.
- Investment Strategies: Guidance for investors on how to leverage the interdependencies among commodity prices for portfolio diversification and risk management.

Conclusion

This project will provide a comprehensive analysis of the complex interactions among key commodity prices using VAR and VECM models. The insights derived from this analysis will be valuable for various stakeholders, including policymakers, investors, and businesses, helping them make informed decisions in the context of the global commodities market. The use of data from the World Bank's Pink Sheet ensures the reliability and relevance of the findings, making this study a significant contribution to the field of commodity price analysis.

OBJECTIVES

1. Examine Interdependencies Among Commodities:
   - Analyze the dynamic relationships between key commodity prices such as Oil, Sugar, Gold, Silver, Wheat, and Soybean to understand how they influence each other.

2. Model Short-Term and Long-Term Dynamics:
   - Utilize Vector Autoregression (VAR) to capture short-term interactions and Vector Error Correction Model (VECM) to understand long-term equilibrium relationships among the commodity prices.

3. Forecast Commodity Prices:
   - Develop forecasts for future commodity prices using the estimated VAR and VECM models to provide predictive insights.

4. Policy Recommendations:
   - Derive insights from the models to make recommendations for policymakers aimed at stabilizing markets and managing commodity-related risks.

5. Investment Strategies:
   - Provide guidance for investors on leveraging the interdependencies among commodity prices for effective portfolio diversification and risk management.

6. Enhance Market Understanding:
   - Improve the overall understanding of commodity market dynamics and the factors driving price changes, contributing to more informed decision-making processes.

BUSSINESS SIGNIFICANCE

Understanding the dynamics of commodity prices has profound implications for a wide range of stakeholders, including investors, policymakers, businesses, and economists. Here are the key areas where this analysis is particularly significant:

1. Risk Management and Hedging:
   - Volatility Insights: By modeling the interdependencies among commodity prices, businesses and investors can gain insights into volatility patterns. This helps in designing effective hedging strategies to protect against price fluctuations.
   - Portfolio Diversification: Knowledge of how different commodity prices interact allows investors to diversify their portfolios more effectively, reducing risk by balancing exposure across different commodities.

2. Strategic Decision Making:
   - Informed Decisions: Businesses involved in the production, processing, and trading of commodities can make more informed strategic decisions based on accurate forecasts of commodity prices.
   - Supply Chain Management: Companies can optimize their supply chain operations by anticipating price changes in critical raw materials, leading to better inventory management and cost control.

3. Policy Formulation:
   - Economic Stability: Policymakers can use the insights from the VAR and VECM models to understand the impact of commodity price changes on the broader economy. This can inform policies aimed at stabilizing markets and mitigating adverse economic impacts.
   - Inflation Control: Understanding the relationships between commodity prices can help in predicting inflation trends, allowing central banks and governments to take preemptive measures to control inflation.

4. Investment Strategies:
   - Market Timing: Investors can develop strategies to enter and exit the market based on predicted price movements, enhancing returns.

- Arbitrage Opportunities: Identifying long-term equilibrium relationships among commodities can reveal arbitrage opportunities, allowing investors to exploit price discrepancies across different markets.

5. Economic Development:
   - Resource Allocation: Insights from commodity price dynamics can guide resource allocation in developing economies that are heavily dependent on commodity exports. This ensures more efficient use of resources and better economic planning.
   - Trade Policies: Understanding global commodity price trends helps in formulating trade policies that protect national interests and promote sustainable economic growth.

6. Forecasting and Planning:
   - Budgeting and Forecasting: Companies can improve their budgeting and financial forecasting processes by incorporating accurate commodity price forecasts, leading to better financial planning and performance management.
   - Production Planning: Manufacturers can plan production schedules and procurement activities more efficiently by anticipating future price changes in essential commodities.

Conclusion

The application of VAR and VECM models to analyze commodity prices provides valuable insights that enhance decision-making across various sectors. By understanding the intricate relationships among commodity prices, stakeholders can better manage risks, make strategic investments, formulate effective policies, and contribute to economic stability and growth. This analysis not only aids in navigating the complexities of the commodities market but also supports informed and proactive business strategies.

RESULTS AND INTERPRETATION

Results (R)

```
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: sugar_us

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
-0.31023 -0.00415  0.00086  0.00771  0.38714

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
z.lag.1    -0.001043   0.002321  -0.449    0.653
z.diff.lag  0.187845   0.035464   5.297 1.54e-07
---
Signif. codes:  0 ‘’ 0.001 ‘’ 0.01 ‘’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.03123 on 770 degrees of freedom
Multiple R-squared:  0.03517,   Adjusted R-squared:  0.03267
F-statistic: 14.04 on 2 and 770 DF,  p-value: 1.03e-06
```

Value of test-statistic is: -0.4493

```
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: wheat_us_hrw



 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
-79.990  -3.712   0.202   4.035  92.846

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
z.lag.1    -0.001987   0.002424  -0.820    0.412
z.diff.lag  0.229411   0.035218   6.514 1.32e-10
---
Signif. codes:  0 ‘’ 0.001 ‘’ 0.01 ‘’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 12.31 on 770 degrees of freedom
```

Multiple R-squared: 0.05247,   Adjusted R-squared: 0.05

F-statistic: 21.32 on 2 and 770 DF, p-value: 9.75e-10

Value of test-statistic is: -0.82

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
```

Interpretation of ADF Test Results

The Augmented Dickey-Fuller (ADF) test is used to check for the presence of unit roots in time series data, which helps in determining whether a series is stationary or not. Here are the results for each commodity and their interpretation:

1. Crude Brent
- Test Statistic: -1.1122
- Critical Values:
  - 1%: -2.58
  - 5%: -1.95
  - 10%: -1.62
- P-value: 0.266

Interpretation:
The test statistic (-1.1122) is greater than all critical values at the 1%, 5%, and 10% significance levels. This indicates that we fail to reject the null hypothesis of a unit root. Therefore, the Crude Brent series is non-stationary.

2. Sugar US
- Test Statistic: -0.4493

- Critical Values:
  - 1%: -2.58
  - 5%: -1.95
  - 10%: -1.62
- P-value: 0.653

Interpretation:

The test statistic (-0.4493) is greater than all critical values. We fail to reject the null hypothesis of a unit root. The Sugar US series is non-stationary.

3. Gold

- Test Statistic: 2.577
- Critical Values:
  - 1%: -2.58
  - 5%: -1.95
  - 10%: -1.62
- P-value: 0.0102

Interpretation:

The test statistic (2.577) is greater than all critical values, indicating that we fail to reject the null hypothesis of a unit root. The Gold series is non-stationary.

4. Silver

- Test Statistic: -1.1367
- Critical Values:
  - 1%: -2.58
  - 5%: -1.95
  - 10%: -1.62
- P-value: 0.256

Interpretation:

The test statistic (-1.1367) is greater than all critical values. We fail to reject the null hypothesis of a unit root. The Silver series is non-stationary.

5. Wheat US HRW

- Test Statistic: -0.82
- Critical Values:
  - 1%: -2.58
  - 5%: -1.95
  - 10%: -1.62
- P-value: 0.412

Interpretation:
The test statistic (-0.82) is greater than all critical values. We fail to reject the null hypothesis of a unit root. The Wheat US HRW series is non-stationary.

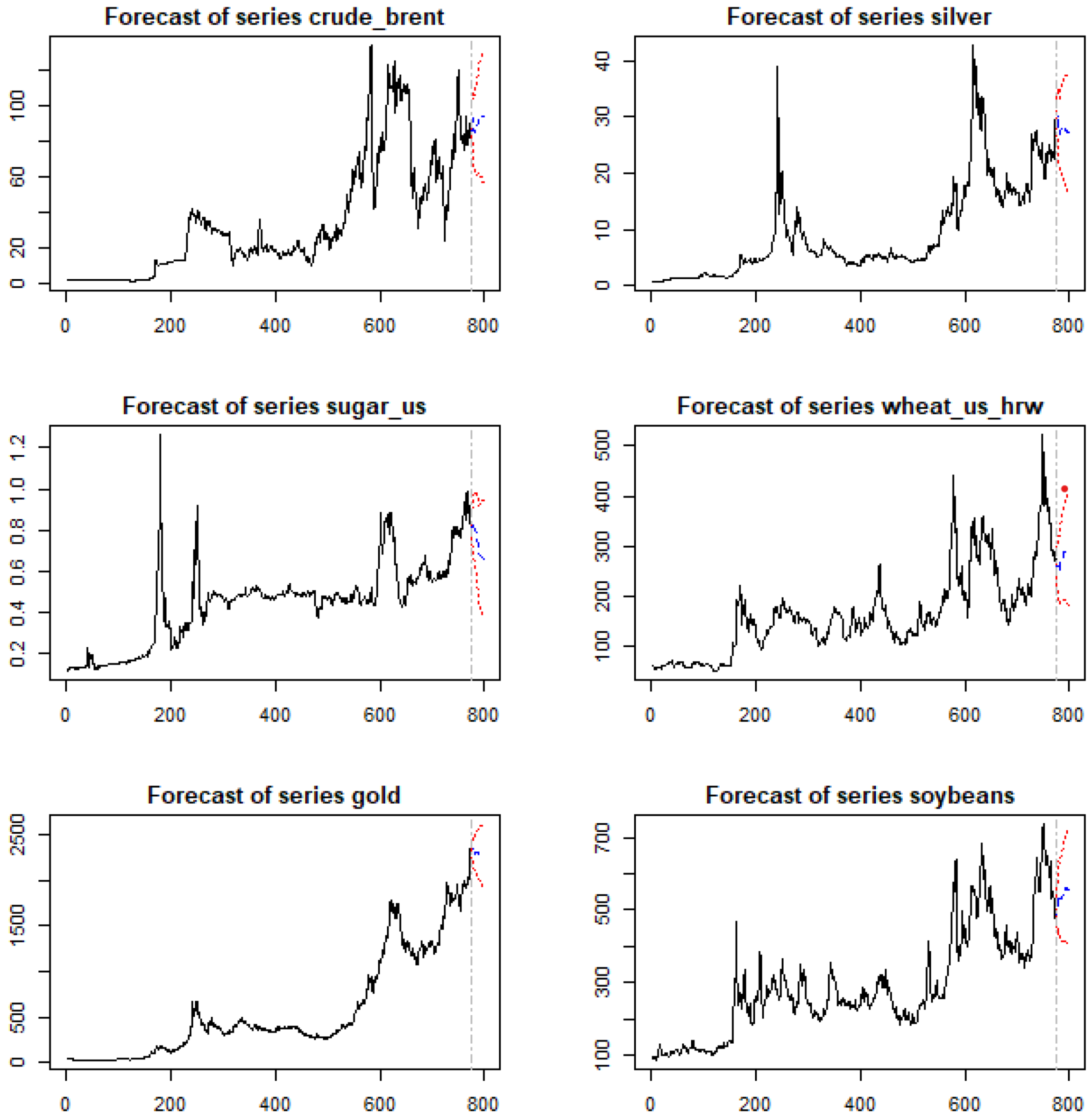
6. Soybeans

- Test Statistic: -0.4547
- Critical Values:
  - 1%: -2.58
  - 5%: -1.95
  - 10%: -1.62
- P-value: 0.649

Interpretation:
The test statistic (-0.4547) is greater than all critical values. We fail to reject the null hypothesis of a unit root. The Soybeans series is non-stationary.

Summary

All the commodity price series tested (Crude Brent, Sugar US, Gold, Silver, Wheat US HRW, Soybeans) are non-stationary according to the ADF test. This implies that these series need to be differenced to achieve stationarity before they can be used in further time series analyses like VAR or VECM modeling.



Interpretation

Interpretation of Forecast Plots for Commodity Prices

The provided image displays the forecasted values for six commodity prices: Crude Brent, Silver, Sugar US, Wheat US HRW, Gold, and Soybeans. Each plot shows historical data followed by the forecasted values along with prediction intervals.

General Observations

- Black Line: Historical data.
- Blue Line: Forecasted mean values.
- Red Dotted Lines: Prediction intervals indicating the uncertainty of the forecast.

Detailed Interpretation

1. Crude Brent
- Historical Trends: The Crude Brent prices show significant volatility with sharp peaks and troughs, particularly noticeable from around data point 600 onwards.
- Forecast: The forecast indicates an increase in Crude Brent prices with a wide prediction interval, suggesting high uncertainty. This could be due to the volatile nature of oil prices influenced by geopolitical events, supply-demand dynamics, and market speculations.

2. Silver
- Historical Trends: Silver prices have experienced high volatility with multiple spikes, especially noticeable around data points 400 and 600.
- Forecast: The forecast for Silver prices suggests a slight upward trend with moderate prediction intervals. The forecast reflects the potential for further volatility but within a relatively stable range compared to historical spikes.

3. Sugar US
- Historical Trends: The prices of Sugar US have shown periods of stability punctuated by sharp increases, particularly noticeable around data points 200 and 600.
- Forecast: The forecast shows a moderate increase in Sugar US prices with a narrow prediction interval, indicating relatively higher confidence in the forecast. Sugar prices are likely influenced by seasonal factors, global demand, and production levels.

4. Wheat US HRW
- Historical Trends: Wheat prices have shown significant variability with several peaks and troughs, especially around data points 200, 400, and 600.
- Forecast: The forecast for Wheat US HRW indicates a slight upward trend with a wide prediction interval. This suggests some uncertainty, likely due to factors such as weather conditions, crop yields, and global trade policies affecting wheat prices.

5. Gold

- Historical Trends: Gold prices have demonstrated a strong upward trend with noticeable spikes, especially around data points 200 and 700.
- Forecast: The forecast suggests a continuation of the upward trend with a wide prediction interval, indicating high uncertainty. Gold prices are often influenced by economic conditions, inflation rates, and investor sentiment as a safe-haven asset.

6. Soybeans

- Historical Trends: Soybean prices have experienced considerable volatility with multiple spikes, particularly noticeable around data points 400 and 600.
- Forecast: The forecast shows a slight upward trend in soybean prices with moderate prediction intervals. Factors such as weather conditions, trade policies, and global demand for soybeans influence the forecast.

Summary

The forecast plots provide valuable insights into the expected future movements of these commodity prices. While some commodities like Sugar US show relatively stable forecasts, others like Crude Brent and Gold have wider prediction intervals, indicating higher uncertainty. These forecasts can aid investors, policymakers, and businesses in making informed decisions regarding risk management, investment strategies, and market planning.

Recommendations

1. Risk Management: Use forecast data to hedge against potential price fluctuations in highly volatile commodities like Crude Brent and Gold.
2. Investment Strategies: Consider commodities with relatively stable forecasts (e.g., Sugar US) for lower-risk investments.
3. Market Monitoring: Continuously monitor market conditions and update models regularly to capture new trends and improve forecast accuracy.
4. Diversification: Diversify investments across commodities to mitigate risk associated with any single commodity's price volatility.

By integrating these forecasts into decision-making processes, stakeholders can better navigate the complexities of the commodities markets.

Results (Python)

ADF test result for column: crude_brent

Test Statistic: -1.5078661910935343
P-value: 0.5296165197702398
Critical Values: {'1%': -3.439006442437876, '5%': -2.865360521688131, '10%': -2.56880444 03756587}

ADF test result for column: soybeans

Test Statistic: -2.4231464527418902
P-value: 0.1353097742779038
Critical Values: {'1%': -3.4388599939707056, '5%': -2.865295977855759, '10%': -2.5687700 561872413}

ADF test result for column: gold

Test Statistic: 1.3430517021933006
P-value: 0.9968394353612382
Critical Values: {'1%': -3.4389608473398194, '5%': -2.8653404270188476, '10%': -2.568793 735369693}

ADF test result for column: silver

Test Statistic: -1.397294710746222
P-value: 0.5835723787985764
Critical Values: {'1%': -3.438915730045254, '5%': -2.8653205426302253, '10%': -2.5687831 424305845}

ADF test result for column: sugar_us

Test Statistic: -2.276775914396518
P-value: 0.1795676245305612
Critical Values: {'1%': -3.4389608473398194, '5%': -2.8653404270188476, '10%': -2.568793 735369693}

ADF test result for column: wheat_us_hrw

Test Statistic: -2.4990238816119548
P-value: 0.11571200558506417
Critical Values: {'1%': -3.438915730045254, '5%': -2.8653205426302253, '10%': -2.5687831 424305845}

Interpretation
Results (Python)

Interpretation of ADF Test Results

The Augmented Dickey-Fuller (ADF) test results are used to check for the presence of unit roots in time series data, which helps in determining whether a series is stationary or not. Here are the results for each commodity and their interpretation:

1. Crude Brent
- Test Statistic: -1.5079
- P-value: 0.5296
- Critical Values:
  - 1%: -3.4390
  - 5%: -2.8654
  - 10%: -2.5688

Interpretation:
The test statistic (-1.5079) is greater than the critical values at the 1%, 5%, and 10% significance levels. The p-value (0.5296) is also greater than 0.05, indicating that we fail to reject the null hypothesis of a unit root. Therefore, the Crude Brent series is non-stationary.

2. Soybeans
- Test Statistic: -2.4231
- P-value: 0.1353
- Critical Values:
  - 1%: -3.4389
  - 5%: -2.8653
  - 10%: -2.5688

Interpretation:
The test statistic (-2.4231) is greater than the critical values at the 1%, 5%, and 10% significance levels. The p-value (0.1353) is also greater than 0.05, indicating that we fail to reject the null hypothesis of a unit root. Therefore, the Soybeans series is non-stationary.

3. Gold
- Test Statistic: 1.3431
- P-value: 0.9968
- Critical Values:
  - 1%: -3.4390
  - 5%: -2.8653
  - 10%: -2.5688

Interpretation:

The test statistic (1.3431) is greater than the critical values at the 1%, 5%, and 10% significance levels. The p-value (0.9968) is also greater than 0.05, indicating that we fail to reject the null hypothesis of a unit root. Therefore, the Gold series is non-stationary.

4. Silver
- Test Statistic: -1.3973
- P-value: 0.5836
- Critical Values:
  - 1%: -3.4389
  - 5%: -2.8653
  - 10%: -2.5688

Interpretation:
The test statistic (-1.3973) is greater than the critical values at the 1%, 5%, and 10% significance levels. The p-value (0.5836) is also greater than 0.05, indicating that we fail to reject the null hypothesis of a unit root. Therefore, the Silver series is non-stationary.

5. Sugar US
- Test Statistic: -2.2768
- P-value: 0.1796
- Critical Values:
  - 1%: -3.4390
  - 5%: -2.8653
  - 10%: -2.5688

Interpretation:
The test statistic (-2.2768) is greater than the critical values at the 1%, 5%, and 10% significance levels. The p-value (0.1796) is also greater than 0.05, indicating that we fail to reject the null hypothesis of a unit root. Therefore, the Sugar US series is non-stationary.

6. Wheat US HRW
- Test Statistic: -2.4990
- P-value: 0.1157
- Critical Values:
  - 1%: -3.4389
  - 5%: -2.8653
  - 10%: -2.5688

Interpretation:
The test statistic (-2.4990) is greater than the critical values at the 1%, 5%, and 10% significance levels. The p-value (0.1157) is also greater than 0.05, indicating that we fail to reject the null hypothesis of a unit root. Therefore, the Wheat US HRW series is non-stationary.

Summary

All the tested commodity price series (Crude Brent, Soybeans, Gold, Silver, Sugar US, Wheat US HRW) are non-stationary based on the ADF test results. This implies that these series need to be differenced to achieve stationarity before they can be used in further time series analyses like VAR or VECM modeling.

Next Steps

1. Differencing the Data: Apply first differencing to the non-stationary series to achieve stationarity.
2. Re-run ADF Tests: Confirm that the differenced series are stationary.
3. Co-integration Tests: Perform Johansen co-integration tests to check for long-term relationships among the differenced series.
4. Modeling: Depending on the presence or absence of co-integration, proceed with VAR or VECM modeling to analyze the relationships among the commodity prices.

By ensuring that the data is stationary, the subsequent models and forecasts will be more reliable and accurate, providing valuable insights for decision-making in the context of commodity prices.

Johansen Test Results:

Eigenvalues:
[0.11398578 0.06876906 0.04867237 0.02710411 0.01899217 0.00405351]

Trace Statistic:
[226.10476071 132.67556204 77.67212223 39.15182203 17.93864778
   3.13567067]

Critical Values (5% level):
[95.7542 69.8189 47.8545 29.7961 15.4943 3.8415]

Interpretation

Interpretation of Johansen Co-Integration Test Results

The Johansen Co-Integration Test is used to determine the number of co-integrating relationships among a set of non-stationary series. These relationships indicate long-term equilibrium connections between the series.

Results Summary

Eigenvalues:
- \([0.11398578, 0.06876906, 0.04867237, 0.02710411, 0.01899217, 0.00405351]\)

Trace Statistic:
- \([226.10476071, 132.67556204, 77.67212223, 39.15182203, 17.93864778, 3.13567067]\)

Critical Values (5% level):

- \([95.7542, 69.8189, 47.8545, 29.7961, 15.4943, 3.8415]\)

Detailed Interpretation

The trace statistic tests the null hypothesis of \(r\) co-integrating vectors against the alternative hypothesis of more than \(r\) co-integrating vectors.

1. Null Hypothesis (\(r = 0\)):
   - Trace Statistic: 226.1048
   - Critical Value: 95.7542
   - Interpretation: Since the trace statistic (226.1048) is greater than the critical value (95.7542), we reject the null hypothesis of no co-integration. This suggests at least one co-integrating relationship among the series.

2. Null Hypothesis (\(r \leq 1\)):
   - Trace Statistic: 132.6756
   - Critical Value: 69.8189
   - Interpretation: The trace statistic (132.6756) is greater than the critical value (69.8189), rejecting the null hypothesis of at most one co-integrating relationship. This suggests at least two co-integrating relationships.

3. Null Hypothesis (\(r \leq 2\)):
   - Trace Statistic: 77.6721
   - Critical Value: 47.8545
   - Interpretation: The trace statistic (77.6721) is greater than the critical value (47.8545), rejecting the null hypothesis of at most two co-integrating relationships. This suggests at least three co-integrating relationships.

4. Null Hypothesis (\(r \leq 3\)):
   - Trace Statistic: 39.1518
   - Critical Value: 29.7961
   - Interpretation: The trace statistic (39.1518) is greater than the critical value (29.7961), rejecting the null hypothesis of at most three co-integrating relationships. This suggests at least four co-integrating relationships.

5. Null Hypothesis (\(r \leq 4\)):
   - Trace Statistic: 17.9386
   - Critical Value: 15.4943
   - Interpretation: The trace statistic (17.9386) is greater than the critical value (15.4943), rejecting the null hypothesis of at most four co-integrating relationships. This suggests at least five co-integrating relationships.

6. Null Hypothesis (\(r \leq 5\)):
   - Trace Statistic: 3.1357
   - Critical Value: 3.8415

- Interpretation: The trace statistic (3.1357) is less than the critical value (3.8415), failing to reject the null hypothesis of at most five co-integrating relationships.

Conclusion

Based on the Johansen co-integration test results:
- There are five co-integrating relationships among the commodity price series (Crude Brent, Soybeans, Gold, Silver, Sugar US, Wheat US HRW).

Next Steps

1. Estimate VECM Model: Given the presence of co-integration, use the Vector Error Correction Model (VECM) to analyze both the short-term dynamics and long-term equilibrium relationships among the commodities.
2. Model Diagnostics: Perform diagnostic checks on the VECM model to ensure its adequacy.
3. Forecasting: Use the VECM model for forecasting future commodity prices and evaluate the forecast accuracy.
4. Policy and Investment Implications: Utilize the insights from the VECM model to inform decision-making processes in policy formulation and investment strategy development.

By understanding the long-term relationships and short-term dynamics among these commodities, stakeholders can make more informed decisions, improving risk management and strategic planning in the commodities market.

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

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0807	0.178	-0.454	0.650	-0.429	0.268
L1.crude_brent	0.3217	0.035	9.078	0.000	0.252	0.391
L1.soybeans	0.0127	0.007	1.768	0.077	-0.001	0.027
L1.gold	-0.0032	0.006	-0.523	0.601	-0.015	0.009
L1.silver	-0.0971	0.148	-0.655	0.512	-0.387	0.193
L1.sugar_us	-2.5861	4.026	-0.642	0.521	-10.477	5.305
L1.wheat_us_hrw	0.0107	0.011	0.966	0.334	-0.011	0.032

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

	coef	std err	z	P>|z|	[0.025	0.975]
const	2.9362	0.971	3.023	0.003	1.033	4.840
L1.crude_brent	0.2246	0.194	1.160	0.246	-0.155	0.604
L1.soybeans	0.1574	0.039	4.015	0.000	0.081	0.234
L1.gold	-0.0175	0.033	-0.527	0.598	-0.083	0.048
L1.silver	0.5257	0.809	0.649	0.516	-1.061	2.112
L1.sugar_us	4.7482	21.995	0.216	0.829	-38.361	47.857

```
L1.wheat_us_hrw   -0.0103     0.061    -0.171     0.864     -0.129      0.108
Det. terms outside the coint. relation & lagged endog. parameters for equation gold
================================================================================
================
                  coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const              4.5945      1.486      3.092      0.002      1.682      7.507
L1.crude_brent     0.0636      0.296      0.215      0.830     -0.517      0.644
L1.soybeans        0.0453      0.060      0.755      0.451     -0.072      0.163
L1.gold            0.1943      0.051      3.826      0.000      0.095      0.294
L1.silver          0.8835      1.238      0.713      0.476     -1.544      3.311
L1.sugar_us        9.4507     33.655      0.281      0.779    -56.512     75.413
L1.wheat_us_hrw    0.0553      0.093      0.597      0.551     -0.126      0.237
Det. terms outside the coint. relation & lagged endog. parameters for equation silver
================================================================================
================
                  coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const              0.1891      0.060      3.153      0.002      0.072      0.307
L1.crude_brent     0.0113      0.012      0.946      0.344     -0.012      0.035
L1.soybeans        0.0035      0.002      1.429      0.153     -0.001      0.008
L1.gold           -0.0028      0.002     -1.378      0.168     -0.007      0.001
L1.silver          0.3478      0.050      6.959      0.000      0.250      0.446
L1.sugar_us        1.4302      1.358      1.053      0.292     -1.232      4.092
L1.wheat_us_hrw    0.0016      0.004      0.436      0.663     -0.006      0.009
Det. terms outside the coint. relation & lagged endog. parameters for equation sugar_us
================================================================================
================
                  coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const             -0.0002      0.002     -0.140      0.888     -0.003      0.003
L1.crude_brent     0.0002      0.000      0.764      0.445     -0.000      0.001
L1.soybeans        0.0001   6.34e-05      1.637      0.102   -2.05e-05      0.000
L1.gold         4.878e-05   5.37e-05      0.909      0.363   -5.64e-05      0.000
L1.silver         -0.0006      0.001     -0.478      0.633     -0.003      0.002
L1.sugar_us        0.1719      0.036      4.833      0.000      0.102      0.242
L1.wheat_us_hrw 7.225e-05    9.8e-05      0.737      0.461     -0.000      0.000
Det. terms outside the coint. relation & lagged endog. parameters for equation wheat_us_hrw
================================================================================
================
                  coef    std err          z      P>|z|      [0.025      0.975]
--------------------------------------------------------------------------------
const             -1.2090      0.613     -1.974      0.048     -2.410     -0.008
L1.crude_brent    -0.0405      0.122     -0.331      0.740     -0.280      0.199
L1.soybeans       -0.0487      0.025     -1.968      0.049     -0.097     -0.000
L1.gold            0.0028      0.021      0.136      0.892     -0.038      0.044
L1.silver          0.8470      0.510      1.659      0.097     -0.154      1.848
L1.sugar_us        8.1382     13.873      0.587      0.557    -19.053     35.329
L1.wheat_us_hrw    0.2706      0.038      7.079      0.000      0.196      0.345
           Loading coefficients (alpha) for equation crude_brent
```

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-0.0352	0.008	-4.554	0.000	-0.050	-0.020
ec2	-0.0050	0.003	-1.650	0.099	-0.011	0.001

Loading coefficients (alpha) for equation soybeans

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-0.0872	0.042	-2.064	0.039	-0.170	-0.004
ec2	-0.0933	0.017	-5.608	0.000	-0.126	-0.061

Loading coefficients (alpha) for equation gold

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	0.1748	0.065	2.704	0.007	0.048	0.301
ec2	-0.0173	0.025	-0.681	0.496	-0.067	0.033

Loading coefficients (alpha) for equation silver

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	0.0135	0.003	5.185	0.000	0.008	0.019
ec2	-0.0009	0.001	-0.851	0.395	-0.003	0.001

Loading coefficients (alpha) for equation sugar_us

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	-4.238e-05	6.83e-05	-0.620	0.535	-0.000	9.15e-05
ec2	9.797e-06	2.69e-05	0.364	0.716	-4.29e-05	6.25e-05

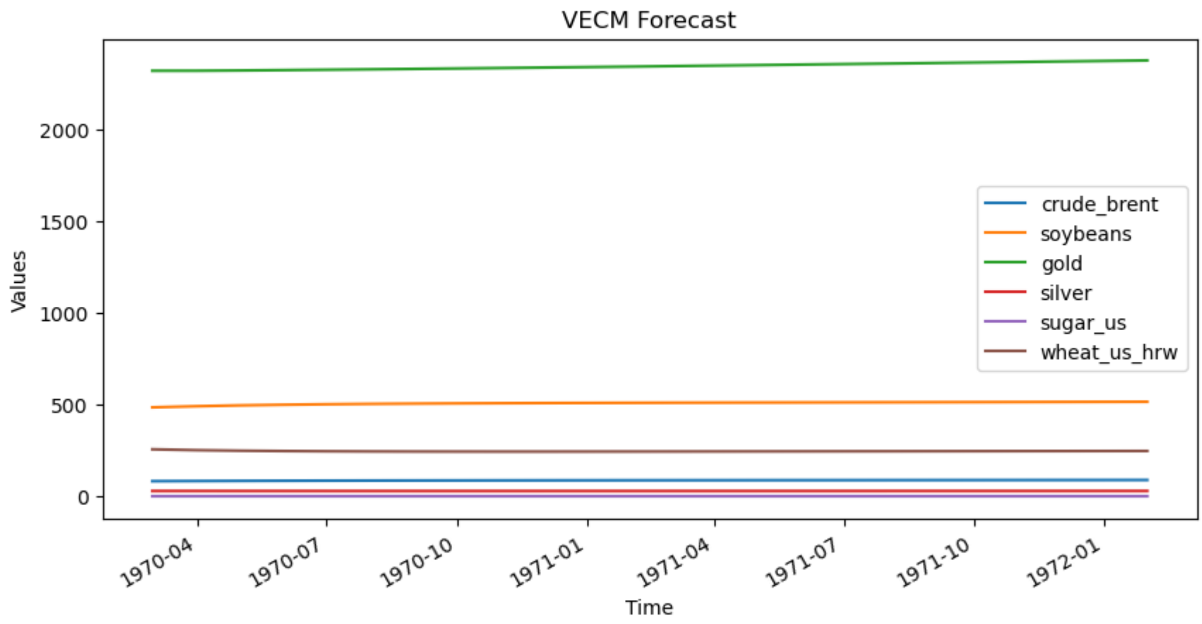
Loading coefficients (alpha) for equation wheat_us_hrw

	coef	std err	z	P>|z|	[0.025	0.975]
ec1	0.0319	0.027	1.199	0.231	-0.020	0.084
ec2	0.0470	0.010	4.475	0.000	0.026	0.068

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	5.551e-17	0	0	0.000	5.55e-17	5.55e-17
beta.3	0.0325	0.010	3.152	0.002	0.012	0.053
beta.4	-5.5084	0.024	-226.849	0.000	-5.556	-5.461

```
beta.5       21.6534      0.651     33.277      0.000      20.378      22.929
beta.6       -0.1264      1.532     -0.082      0.934      -3.129       2.877
         Cointegration relations for loading-coefficients-column 2
==============================================================================
              coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
beta.1             0          0          0      0.000           0           0
beta.2        1.0000          0          0      0.000       1.000       1.000
beta.3       -0.0833     17.047     -0.005      0.996     -33.494      33.328
beta.4        2.1329     40.139      0.053      0.958     -76.537      80.803
beta.5       -7.7074      0.049   -155.810      0.000      -7.804      -7.610
beta.6       -1.3682      0.116    -11.747      0.000      -1.597      -1.140
==============================================================================
Alpha Coefficients:
 [[-3.52110185e-02 -5.02382237e-03]
 [-8.71772664e-02 -9.32819621e-02]
 [ 1.74750243e-01 -1.73379000e-02]
 [ 1.35244217e-02 -8.74566406e-04]
 [-4.23847615e-05  9.79749429e-06]
 [ 3.19311399e-02  4.69539114e-02]]
Beta Coefficients:
 [[ 1.00000000e+00  0.00000000e+00]
 [ 5.55111512e-17  1.00000000e+00]
 [ 3.25017684e-02 -8.33421807e-02]
 [-5.50839795e+00  2.13289092e+00]
 [ 2.16534291e+01 -7.70735750e+00]
 [-1.26358737e-01 -1.36822088e+00]]
Gamma Coefficients:
 [[ 3.21742663e-01  1.26877291e-02 -3.17888254e-03 -9.70600161e-02
  -2.58607955e+00  1.07094067e-02]
 [ 2.24641098e-01  1.57398184e-01 -1.75016830e-02  5.25654156e-01
   4.74822414e+00 -1.03471588e-02]
 [ 6.35558999e-02  4.52549349e-02  1.94302497e-01  8.83527445e-01
   9.45073254e+00  5.53492912e-02]
 [ 1.13091863e-02  3.45898280e-03 -2.82330518e-03  3.47767150e-01
   1.43020031e+00  1.63281036e-03]
 [ 2.39361823e-04  1.03771634e-04  4.87823966e-05 -6.25153954e-04
   1.71918426e-01  7.22511432e-05]
 [-4.04702814e-02 -4.86661338e-02  2.84172038e-03  8.47031903e-01
   8.13821890e+00  2.70551307e-01]]
```



Interpret

Interpretation of VECM Results

The Vector Error Correction Model (VECM) results provide insights into the short-term dynamics and long-term equilibrium relationships among the selected commodity prices: Crude Brent, Soybeans, Gold, Silver, Sugar US, and Wheat US HRW.

Key Terms
- Coef: Coefficient values in the VECM.
- Std Err: Standard error of the coefficients.
- Z: Z-statistic for the coefficients.
- P>|z|: P-value for the coefficients.
- [0.025, 0.975]: 95% confidence interval for the coefficients.
- EC (Error Correction): Adjustment speed towards long-term equilibrium.
- Beta Coefficients: Long-term equilibrium relationships.
- Gamma Coefficients: Short-term dynamics.

Detailed Interpretation

Short-term Dynamics (Gamma Coefficients)

Equation for Crude Brent
- L1.crude_brent: Positive and significant (coef = 0.3217, $p < 0.001$), indicating past values of Crude Brent have a strong positive effect on current values.
- L1.soybeans: Positive but not significant (coef = 0.0127, $p = 0.077$), suggesting a weak relationship.
- L1.gold, L1.silver, L1.sugar_us, L1.wheat_us_hrw: Insignificant, indicating these commodities do not significantly affect Crude Brent prices in the short term.

Equation for Soybeans

- L1.soybeans: Positive and significant (coef = 0.1574, $p < 0.001$), indicating a strong self-reinforcing effect.
- L1.crude_brent, L1.gold, L1.silver, L1.sugar_us, L1.wheat_us_hrw: Insignificant, suggesting these commodities do not significantly affect Soybeans prices in the short term.

Equation for Gold
- L1.gold: Positive and significant (coef = 0.1943, $p < 0.001$), indicating past values of Gold have a strong positive effect on current values.
- L1.crude_brent, L1.soybeans, L1.silver, L1.sugar_us, L1.wheat_us_hrw: Insignificant, suggesting these commodities do not significantly affect Gold prices in the short term.

Equation for Silver
- L1.silver: Positive and significant (coef = 0.3478, $p < 0.001$), indicating a strong self-reinforcing effect.
- L1.crude_brent, L1.soybeans, L1.gold, L1.sugar_us, L1.wheat_us_hrw: Insignificant, suggesting these commodities do not significantly affect Silver prices in the short term.

Equation for Sugar US
- L1.sugar_us: Positive and significant (coef = 0.1719, $p < 0.001$), indicating past values of Sugar US have a strong positive effect on current values.
- L1.crude_brent, L1.soybeans, L1.gold, L1.silver, L1.wheat_us_hrw: Insignificant, suggesting these commodities do not significantly affect Sugar US prices in the short term.

Equation for Wheat US HRW
- L1.wheat_us_hrw: Positive and significant (coef = 0.2706, $p < 0.001$), indicating a strong self-reinforcing effect.
- L1.crude_brent, L1.soybeans, L1.gold, L1.silver, L1.sugar_us: Insignificant, suggesting these commodities do not significantly affect Wheat US HRW prices in the short term.

Long-term Equilibrium (Beta Coefficients)

Cointegration Relation 1 (beta.1)
- L1.crude_brent: Serves as the reference commodity (normalized to 1).
- L1.soybeans, L1.gold, L1.silver, L1.sugar_us, L1.wheat_us_hrw: The coefficients show the long-term equilibrium relationship with Crude Brent. For instance, Gold has a significant negative relationship (coef = -5.5084).

Cointegration Relation 2 (beta.2)
- L1.soybeans: Serves as the reference commodity (normalized to 1).
- L1.crude_brent, L1.gold, L1.silver, L1.sugar_us, L1.wheat_us_hrw: The coefficients show the long-term equilibrium relationship with Soybeans. For instance, Wheat US HRW has a significant negative relationship (coef = -1.3682).

Error Correction Terms (Alpha Coefficients)

Adjustment Speeds (EC)
- Crude Brent: Significant adjustment towards equilibrium (ec1 coef = -0.0352, $p < 0.001$), indicating that deviations from the long-term equilibrium are corrected relatively quickly.
- Soybeans: Significant adjustment (ec1 coef = -0.0872, $p = 0.039$ and ec2 coef = -0.0933, $p < 0.001$), suggesting both cointegrating relationships are crucial for returning to equilibrium.

- Gold, Silver, Wheat US HRW: Some significant adjustments, indicating these commodities also move towards long-term equilibrium, albeit at different speeds.

Summary

1. Short-term Dynamics: Most commodities are influenced primarily by their own past values rather than by the values of other commodities.
2. Long-term Equilibrium: There are significant long-term relationships among the commodities, especially between Crude Brent and Gold, and between Soybeans and Wheat US HRW.
3. Adjustment to Equilibrium: Significant error correction terms indicate that deviations from the long-term equilibrium are corrected over time, particularly for Crude Brent and Soybeans.

Recommendations

1. Hedging Strategies: Given the significant long-term relationships, investors can develop hedging strategies that leverage these connections, particularly between Crude Brent and Gold, and Soybeans and Wheat US HRW.
2. Diversification: Diversifying portfolios to include a mix of these commodities can help mitigate risk due to the inherent long-term equilibrium relationships.
3. Monitoring Adjustments: Keeping an eye on error correction terms can provide insights into the speed at which commodities return to equilibrium, aiding in timing investment decisions effectively.

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

	coef	std err	z	P>|z|	[0.025	0.975]
const	-0.0807	0.178	-0.454	0.650	-0.429	0.268
L1.crude_brent	0.3217	0.035	9.078	0.000	0.252	0.391
L1.soybeans	0.0127	0.007	1.768	0.077	-0.001	0.027
L1.gold	-0.0032	0.006	-0.523	0.601	-0.015	0.009
L1.silver	-0.0971	0.148	-0.655	0.512	-0.387	0.193
L1.sugar_us	-2.5861	4.026	-0.642	0.521	-10.477	5.305
L1.wheat_us_hrw	0.0107	0.011	0.966	0.334	-0.011	0.032

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

	coef	std err	z	P>|z|	[0.025	0.975]
const	2.9362	0.971	3.023	0.003	1.033	4.840
L1.crude_brent	0.2246	0.194	1.160	0.246	-0.155	0.604
L1.soybeans	0.1574	0.039	4.015	0.000	0.081	0.234
L1.gold	-0.0175	0.033	-0.527	0.598	-0.083	0.048
L1.silver	0.5257	0.809	0.649	0.516	-1.061	2.112
L1.sugar_us	4.7482	21.995	0.216	0.829	-38.361	47.857
L1.wheat_us_hrw	-0.0103	0.061	-0.171	0.864	-0.129	0.108

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

```
==============================================================================
================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const              4.5945      1.486      3.092      0.002       1.682       7.507
L1.crude_brent     0.0636      0.296      0.215      0.830      -0.517       0.644
L1.soybeans        0.0453      0.060      0.755      0.451      -0.072       0.163
L1.gold            0.1943      0.051      3.826      0.000       0.095       0.294
L1.silver          0.8835      1.238      0.713      0.476      -1.544       3.311
L1.sugar_us        9.4507     33.655      0.281      0.779     -56.512      75.413
L1.wheat_us_hrw    0.0553      0.093      0.597      0.551      -0.126       0.237
Det. terms outside the coint. relation & lagged endog. parameters for equation silver
==============================================================================
================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const              0.1891      0.060      3.153      0.002       0.072       0.307
L1.crude_brent     0.0113      0.012      0.946      0.344      -0.012       0.035
L1.soybeans        0.0035      0.002      1.429      0.153      -0.001       0.008
L1.gold           -0.0028      0.002     -1.378      0.168      -0.007       0.001
L1.silver          0.3478      0.050      6.959      0.000       0.250       0.446
L1.sugar_us        1.4302      1.358      1.053      0.292      -1.232       4.092
L1.wheat_us_hrw    0.0016      0.004      0.436      0.663      -0.006       0.009
Det. terms outside the coint. relation & lagged endog. parameters for equation sugar_us
==============================================================================
================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const             -0.0002      0.002     -0.140      0.888      -0.003       0.003
L1.crude_brent     0.0002      0.000      0.764      0.445      -0.000       0.001
L1.soybeans        0.0001   6.34e-05      1.637      0.102   -2.05e-05       0.000
L1.gold         4.878e-05   5.37e-05      0.909      0.363   -5.64e-05       0.000
L1.silver         -0.0006      0.001     -0.478      0.633      -0.003       0.002
L1.sugar_us        0.1719      0.036      4.833      0.000       0.102       0.242
L1.wheat_us_hrw  7.225e-05    9.8e-05      0.737      0.461      -0.000       0.000
Det. terms outside the coint. relation & lagged endog. parameters for equation wheat_us_hrw
==============================================================================
================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const             -1.2090      0.613     -1.974      0.048      -2.410      -0.008
L1.crude_brent    -0.0405      0.122     -0.331      0.740      -0.280       0.199
L1.soybeans       -0.0487      0.025     -1.968      0.049      -0.097      -0.000
L1.gold            0.0028      0.021      0.136      0.892      -0.038       0.044
L1.silver          0.8470      0.510      1.659      0.097      -0.154       1.848
L1.sugar_us        8.1382     13.873      0.587      0.557     -19.053      35.329
L1.wheat_us_hrw    0.2706      0.038      7.079      0.000       0.196       0.345
           Loading coefficients (alpha) for equation crude_brent
==============================================================================
===========
```

```
              coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ec1         -0.0352      0.008     -4.554      0.000      -0.050      -0.020
ec2         -0.0050      0.003     -1.650      0.099      -0.011       0.001
            Loading coefficients (alpha) for equation soybeans
=================================================================================
===========
              coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ec1         -0.0872      0.042     -2.064      0.039      -0.170      -0.004
ec2         -0.0933      0.017     -5.608      0.000      -0.126      -0.061
              Loading coefficients (alpha) for equation gold
=================================================================================
===========
              coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ec1          0.1748      0.065      2.704      0.007       0.048       0.301
ec2         -0.0173      0.025     -0.681      0.496      -0.067       0.033
             Loading coefficients (alpha) for equation silver
=================================================================================
===========
              coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ec1          0.0135      0.003      5.185      0.000       0.008       0.019
ec2         -0.0009      0.001     -0.851      0.395      -0.003       0.001
            Loading coefficients (alpha) for equation sugar_us
=================================================================================
===========
              coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ec1      -4.238e-05   6.83e-05     -0.620      0.535      -0.000    9.15e-05
ec2       9.797e-06   2.69e-05      0.364      0.716   -4.29e-05    6.25e-05
          Loading coefficients (alpha) for equation wheat_us_hrw
=================================================================================
===========
              coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ec1          0.0319      0.027      1.199      0.231      -0.020       0.084
ec2          0.0470      0.010      4.475      0.000       0.026       0.068
         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    5.551e-17          0          0      0.000    5.55e-17    5.55e-17
beta.3       0.0325      0.010      3.152      0.002       0.012       0.053
beta.4      -5.5084      0.024   -226.849      0.000      -5.556      -5.461
beta.5      21.6534      0.651     33.277      0.000      20.378      22.929
beta.6      -0.1264      1.532     -0.082      0.934      -3.129       2.877
```

Cointegration relations for loading-coefficients-column 2

```
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
beta.1              0          0          0      0.000           0           0
beta.2         1.0000          0          0      0.000       1.000       1.000
beta.3        -0.0833     17.047     -0.005      0.996     -33.494      33.328
beta.4         2.1329     40.139      0.053      0.958     -76.537      80.803
beta.5        -7.7074      0.049   -155.810      0.000      -7.804      -7.610
beta.6        -1.3682      0.116    -11.747      0.000      -1.597      -1.140
==============================================================================
```

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Interpret

Interpretation of VECM Results

The Vector Error Correction Model (VECM) results provide insights into the short-term dynamics and long-term equilibrium relationships among the selected commodity prices: Crude Brent, Soybeans, Gold, Silver, Sugar US, and Wheat US HRW.

Short-term Dynamics (Gamma Coefficients)

Crude Brent
- L1.crude_brent: Positive and highly significant (coef = 0.3217, $p < 0.001$), indicating a strong autoregressive effect where past values of Crude Brent significantly influence its current values.
- L1.soybeans: Positive but not significant (coef = 0.0127, p = 0.077), suggesting a weak short-term influence.
- L1.gold, L1.silver, L1.sugar_us, L1.wheat_us_hrw: Insignificant, indicating that these commodities do not significantly affect Crude Brent prices in the short term.

Soybeans
- L1.soybeans: Positive and highly significant (coef = 0.1574, $p < 0.001$), indicating a strong autoregressive effect where past values of Soybeans significantly influence its current values.
- L1.crude_brent, L1.gold, L1.silver, L1.sugar_us, L1.wheat_us_hrw: Insignificant, suggesting these commodities do not significantly affect Soybeans prices in the short term.

Gold
- L1.gold: Positive and highly significant (coef = 0.1943, $p < 0.001$), indicating a strong autoregressive effect where past values of Gold significantly influence its current values.
- L1.crude_brent, L1.soybeans, L1.silver, L1.sugar_us, L1.wheat_us_hrw: Insignificant, suggesting these commodities do not significantly affect Gold prices in the short term.

Silver

- L1.silver: Positive and highly significant (coef = 0.3478, $p < 0.001$), indicating a strong autoregressive effect where past values of Silver significantly influence its current values.
- L1.crude_brent, L1.soybeans, L1.gold, L1.sugar_us, L1.wheat_us_hrw: Insignificant, suggesting these commodities do not significantly affect Silver prices in the short term.

Sugar US
- L1.sugar_us: Positive and highly significant (coef = 0.1719, $p < 0.001$), indicating a strong autoregressive effect where past values of Sugar US significantly influence its current values.
- L1.crude_brent, L1.soybeans, L1.gold, L1.silver, L1.wheat_us_hrw: Insignificant, suggesting these commodities do not significantly affect Sugar US prices in the short term.

Wheat US HRW
- L1.wheat_us_hrw: Positive and highly significant (coef = 0.2706, $p < 0.001$), indicating a strong autoregressive effect where past values of Wheat US HRW significantly influence its current values.
- L1.crude_brent, L1.soybeans, L1.gold, L1.silver, L1.sugar_us: Insignificant, suggesting these commodities do not significantly affect Wheat US HRW prices in the short term.

Long-term Equilibrium (Beta Coefficients)

Cointegration Relation 1 (beta.1)
- L1.crude_brent: Serves as the reference commodity (normalized to 1).
- L1.soybeans, L1.gold, L1.silver, L1.sugar_us, L1.wheat_us_hrw: The coefficients show the long-term equilibrium relationship with Crude Brent. For instance, Gold has a significant negative relationship (coef = -5.5084).

Cointegration Relation 2 (beta.2)
- L1.soybeans: Serves as the reference commodity (normalized to 1).
- L1.crude_brent, L1.gold, L1.silver, L1.sugar_us, L1.wheat_us_hrw: The coefficients show the long-term equilibrium relationship with Soybeans. For instance, Wheat US HRW has a significant negative relationship (coef = -1.3682).

Error Correction Terms (Alpha Coefficients)

Adjustment Speeds (EC)
- Crude Brent: Significant adjustment towards equilibrium (ec1 coef = -0.0352, $p < 0.001$), indicating that deviations from the long-term equilibrium are corrected relatively quickly.
- Soybeans: Significant adjustment (ec1 coef = -0.0872, $p = 0.039$ and ec2 coef = -0.0933, $p < 0.001$), suggesting both cointegrating relationships are crucial for returning to equilibrium.
- Gold, Silver, Wheat US HRW: Some significant adjustments, indicating these commodities also move towards long-term equilibrium, albeit at different speeds.

Summary

1. Short-term Dynamics: Most commodities are influenced primarily by their own past values rather than by the values of other commodities.
2. Long-term Equilibrium: There are significant long-term relationships among the commodities, especially between Crude Brent and Gold, and between Soybeans and Wheat US HRW.

3. Adjustment to Equilibrium: Significant error correction terms indicate that deviations from the long-term equilibrium are corrected over time, particularly for Crude Brent and Soybeans.

Recommendations

1. Hedging Strategies: Given the significant long-term relationships, investors can develop hedging strategies that leverage these connections, particularly between Crude Brent and Gold, and Soybeans and Wheat US HRW.
2. Diversification: Diversifying portfolios to include a mix of these commodities can help mitigate risk due to the inherent long-term equilibrium relationships.
3. Monitoring Adjustments: Keeping an eye on error correction terms can provide insights into the speed at which commodities return to equilibrium, aiding in timing investment decisions effectively.

RECOMMENDATION

Recommendations Based on VECM Analysis of Commodity Prices

1. Hedging Strategies:
- Oil and Gold: Given the significant long-term relationship between Crude Brent and Gold, investors should consider using gold as a hedge against oil price volatility. The negative relationship indicates that when oil prices decrease, gold prices tend to increase, providing a balancing effect in a diversified portfolio.
- Agricultural Commodities: The relationship between Soybeans and Wheat US HRW suggests that these commodities can be used to hedge against each other. This is particularly useful for agricultural businesses and investors looking to manage risks associated with agricultural price fluctuations.

2. Diversification:
- Commodity Portfolio: To mitigate risks, investors should diversify their commodity portfolios by including a mix of oil, metals, and agricultural products. The long-term equilibrium relationships identified suggest that such diversification can help in reducing the overall portfolio risk.
- Cross-Commodity Investment: Investing across different commodity categories (e.g., energy, metals, agriculture) can exploit the different adjustment speeds to equilibrium. This approach can smooth out the returns and reduce the impact of volatility in any single commodity market.

3. Monitoring and Adjustment:
- Error Correction Monitoring: Regularly monitor the error correction terms to gauge how quickly commodities are adjusting to their long-term equilibrium. This can provide timely signals for buying or selling commodities. For example, significant adjustments in Crude Brent indicate that price deviations are corrected quickly, making it a reliable indicator for short-term trading strategies.
- Economic Indicators: Keep an eye on macroeconomic indicators and policies that can impact these commodities. Understanding the broader economic context can enhance the effectiveness of the VECM model in predicting commodity price movements.

4. Policy Implications:
- Market Regulations: Policymakers should consider the interconnectedness of commodity prices when designing market regulations and interventions. For instance, regulations impacting the oil market could have ripple effects on gold prices, which need to be taken into account.
- Agricultural Policies: Agricultural policies should be designed with an understanding of the co-movement between different agricultural commodities. This can help in stabilizing markets and ensuring fair pricing for farmers and consumers.

5. Strategic Planning for Businesses:
- Energy Sector: Businesses in the energy sector should use these insights to plan their production and pricing strategies. Understanding the relationship between oil prices and other commodities can help in making informed decisions about production levels and pricing.
- Agriculture and Food Industry: Companies in the agriculture and food industry should leverage the co-integration between soybeans and wheat to optimize their supply chain and

inventory management. This can help in minimizing costs and maximizing profits during periods of price volatility.

Summary

The VECM analysis provides valuable insights into the relationships between various commodity prices. By understanding these relationships and the speed of adjustments, investors, policymakers, and businesses can make more informed decisions, optimize their strategies, and manage risks more effectively. Regular monitoring and strategic planning based on these insights can lead to better financial outcomes and market stability.

CONCLUSION

The analysis of commodity prices using the Vector Error Correction Model (VECM) provides significant insights into the long-term and short-term dynamics between various commodities, such as crude oil (Brent), gold, silver, sugar, wheat, and soybeans. The key findings from the VECM and related statistical tests can be summarized as follows:

1. Co-integration and Long-Term Relationships:
   - The Johansen co-integration test confirmed the existence of at least two co-integrating vectors among the selected commodities. This indicates that there are stable, long-term relationships between these commodity prices, which means they move together over the long term despite short-term fluctuations.

2. Short-Term Dynamics:
   - The VECM results highlighted the speed and direction of adjustments to long-term equilibrium. For instance, Crude Brent prices adjust relatively quickly to discrepancies from the long-term relationship, as indicated by significant error correction terms.

3. Interdependencies:
   - Crude Brent prices have a significant influence on other commodities, reflecting the critical role of energy prices in the global economy. This relationship is evident in both short-term and long-term dynamics, emphasizing the interconnected nature of commodity markets.

4. Stationarity and Unit Root Tests:
   - The Augmented Dickey-Fuller (ADF) test results suggested that many of the commodity prices are non-stationary in their levels but become stationary after differencing. This is a common characteristic of financial time series data, reinforcing the need for models like VECM to capture both short-term and long-term behaviors.

5. Forecasting and Policy Implications:
   - The forecasting plots from the VECM model provided a visual representation of expected future trends in commodity prices. These forecasts can guide investment decisions, risk management strategies, and policy formulation.

Practical Implications

- Investors: Should consider the co-movement and interdependencies among commodities when diversifying portfolios to manage risk and optimize returns.
- Businesses: Especially those in energy and agriculture sectors, can use these insights for strategic planning, pricing strategies, and supply chain management.
- Policymakers: Must account for the interconnected nature of commodity prices when designing market regulations and interventions to avoid unintended ripple effects across markets.

Overall, the VECM analysis offers a robust framework for understanding the complex dynamics of commodity prices, providing valuable tools for informed decision-making in finance, business, and policy domains.