Exploring the Relationship Between Gold and Cryptocurrency: A Statistical Analysis

BOCCARDI Maël Aix-Marseille School of Economics
Supervised by: DUFRENOT Gilles

Abstract: This paper offers a nuanced statistical analysis of the relationship between gold, a time-honored store of value, and cryptocurrency, a rapidly emerging digital asset class. Leveraging advanced methodologies such as GARCH for volatility estimation, ARDL for impact assessment, and VAR models for impulse response analysis, the study delves into the complex dynamics between these two asset classes. It seeks to illuminate the evolving role of cryptocurrencies in their potential as a new form of digital gold.

Keywords: Gold, Cryptocurrency, Statistical Analysis, GARCH Model, Volatility, ARDL, VAR Models

1 Introduction

The emergence of digital currencies, particularly cryptocurrencies, has ushered in an unprecedented asset class in global financial markets. This shift raises critical questions about the relationship between these innovative digital assets and traditional assets, notably gold, which has long been a bastion of stability and a hedge against economic volatility.

1.1 Background

Traditionally, gold has been a linchpin in the financial world, valued for its enduring stability and inherent worth. It has consistently acted as a bulwark against inflation and economic downturns. In stark contrast, the advent of cryptocurrencies, epitomized by Bitcoin, signifies a radical move towards digital assets marked by decentralized governance and blockchain technology. The inherent volatility of these assets, coupled with their growing integration into the mainstream financial sphere, has generated significant interest in their potential impact on financial markets and investment strategies.

1.2 Research Problem

Despite extensive research into the distinct attributes of gold and cryptocurrencies, there remains a notable research void in exploring their interrelationship comprehensively. This study aims to bridge this gap by dissecting the statistical interplay between gold and cryptocurrencies, with particular emphasis on aspects like volatility, correlation, and causality. The crux of this research is to ascertain if cryptocurrencies can emulate or surpass the stability and reliability traditionally associated with gold.

1.3 Objectives and Scope

This study's primary goal is to conduct an in-depth statistical analysis to unravel the complex relationship between gold and cryptocurrencies. Employing a range of statistical models, including GARCH for volatility analysis, ARDL for impact evaluation, and VAR models for impulse response examination, the research is confined to scrutinizing historical price data, discerning volatility trends, and analyzing response patterns between these two asset classes. The focus lies on elucidating their interaction and drawing implications for their coexistence in the financial ecosystem.

2 Literature Review

This section reviews existing literature pertinent to the study, laying a foundational understanding of both gold and cryptocurrencies, and scrutinizing the extent of research on their relationship and roles within the financial system.

2.1 Historical Context of Gold as a Store of Value

Gold's status as a universally acknowledged store of value spans several centuries. Its multifaceted role in the financial system encompasses acting as an inflation hedge, a safe haven during economic turmoil, and a diversification tool in investment portfolios. Historical insights underscore gold's stability and intrinsic value, underscoring its resilience during financial crises and its pivotal role in the global monetary framework, particularly under the gold standard system. This subsection explores gold's perpetual value proposition and its evolution as a financial asset through the ages.

2.2 Introduction to Cryptocurrency

Cryptocurrency, a groundbreaking development, has swiftly risen to prominence in global finance. It debuted with Bitcoin in 2009, introducing the concept of a decentralized digital currency based on blockchain technology. This subsection delves into the genesis and growth of cryptocurrencies, emphasizing their technological foundations, market dynamics, volatility characteristics, and increasing adoption. It also addresses the regulatory challenges and market forces shaping the current status of cryptocurrencies in financial arenas.

2.3 Previous Studies and Theories

The nascent field of cryptocurrency research presents diverse viewpoints on its comparison with traditional assets like gold. Initial studies primarily focused on deciphering the fundamental characteristics of cryptocurrencies, contrasting them with fiat currencies and commodities. Later research ventured into understanding the risk-return profiles of cryptocurrencies, their correlation with conventional assets, and their potential role in diversification strategies. This subsection amalgamates pivotal findings from prior research, encompassing empirical studies on the volatility, correlation, and possible cointegration between gold and cryptocurrencies. It also scrutinizes theoretical constructs and hypotheses concerning their interaction and comparative roles as investment assets or speculative vehicles.

3 Methodology

This section outlines the methodologies applied in this study, encompassing data collection, statistical models used for analysis, and the overall analytical approach.

3.1 Data Collection

The study utilizes historical data spanning from December 31, 2014, to December 31, 2023. The data encompasses daily closing prices, trading volume, and volatility measures for various asset classes, including gold and a range of cryptocurrencies. Data sources include major financial databases and cryptocurrency exchanges. Preprocessing steps involve data cleaning, normalization. We decided to drop missing values instead of used an imputation method to avoid additional bias.

3.2 Statistical Tools and Models Used

A suite of statistical models is employed to analyze the data:

The GARCH Models

The GARCH model was developed as an extension of the Autoregressive Conditional Heteroskedasticity (ARCH) model introduced by Engle (1982). The ARCH model itself was a breakthrough in modeling time-varying volatility, but it was limited in its ability to capture long-memory effects. To address this, Bollerslev (1986) proposed the GARCH model.

Mathematical of GARCH Models

A GARCH model is typically denoted as GARCH(p,q), where p and q are non-negative integers that represent the order of the model. The GARCH(1,1) model, which is the most commonly used, is defined by the following equations:

The Conditional Variance Equation

$$\sigma_t^2 = \omega + \alpha\epsilon_{t-1}^2 + \beta\sigma_{t-1}^2 \tag{1}$$

Here, σ_t^2 represents the conditional variance at time t, ω is a constant term, α and β are parameters to be estimated, and ϵ_{t-1} is the lagged error term. The term ϵ_{t-1}^2 captures the ARCH effect (short-run volatility clustering), while σ_{t-1}^2 captures the GARCH effect (long-run volatility persistence).

The Return Equation

$$R_t = \mu + \epsilon_t \tag{2}$$

$$\epsilon_t = \sigma_t z_t \tag{3}$$

In these equations, R_t is the asset return at time t, μ is the expected return, ϵ_t is the error term, σ_t is the standard deviation of the error term (sqrt of σ_t^2), and z_t is an i.i.d. random variable, typically assumed to be standard normal.

Estimation and Application of GARCH Models

The parameters ω, α, and β in the GARCH(1,1) model are estimated using maximum likelihood estimation (MLE). Once estimated, the model can be used to forecast future volatility, which is crucial in risk management, portfolio optimization, and derivative pricing.

GARCH models represent a significant advancement in financial econometrics, providing a flexible framework for modeling and predicting time-varying volatility. Their ability to capture both short-term and long-term dependencies in volatility makes them indispensable tools in financial analysis.

The ARDL Models

Autoregressive Distributed Lag (ARDL) models are econometric models used to analyze dynamic relationships between variables. They are particularly useful when dealing with non-stationary time series data that can be made stationary through differencing.

Behind ARDL Models

ARDL models, introduced by Pesaran et al. (2001), allow for both short-term and long-term analysis within a single framework. They can be applied regardless of whether the regressors are I(0), I(1), or mutually cointegrated.

Mathematical Formulation of ARDL Models
An ARDL model can be specified as follows:

The General ARDL(p,q) Model
Consider a model with one dependent variable Y and one independent variable X. The ARDL(p,q) model is represented as:

$$Y_t = \alpha + \sum_{i=1}^{p} \phi_i Y_{t-i} + \sum_{j=0}^{q} \theta_j X_{t-j} + \epsilon_t \tag{4}$$

where:

- Y_t is the dependent variable at time t.
- X_t is the independent variable.
- α is the intercept.
- ϕ_i are the coefficients for the lags of the dependent variable.
- θ_j are the coefficients for the lags of the independent variable.
- p and q are the lag orders for the dependent and independent variables, respectively.
- ϵ_t is the error term.

The Error Correction Model (ECM)
The ARDL approach is often used in conjunction with an Error Correction Model (ECM) to capture both short-term and long-term dynamics:

$$\Delta Y_t = \alpha + \sum_{i=1}^{p} \phi_i \Delta Y_{t-i} + \sum_{j=1}^{q} \theta_j \Delta X_{t-j} + \lambda ECM_{t-1} + \epsilon_t \tag{5}$$

Here, ECM_{t-1} is the error correction term derived from the long-run relationship between Y and X, and λ measures the speed of adjustment to the long-run equilibrium.

Application of ARDL Models
ARDL models are estimated using Ordinary Least Squares (OLS). They are widely used for cointegration analysis, especially in cases where traditional cointegration tests may not be applicable due to the different integration properties of the variables.

ARDL models provide a versatile approach for analyzing relationships between time series variables, accommodating different levels of integration and allowing for both short-term and long-term analysis. Their flexibility and robustness make them a popular choice in empirical research in economics and finance.

The VAR Models
Vector Autoregression (VAR) models are a staple in time series analysis, particularly in the field of econometrics. They are used to capture the linear interdependencies among multiple time series and are suitable for forecasting systems of interrelated variables and analyzing the impact of random disturbances on the system.

The Origin of VAR Models
VAR models were introduced by Christopher Sims in 1980 as an alternative to structural models, which required strong theoretical assumptions. VAR models, on the other hand, are more data-driven and do not necessitate such assumptions, making them more flexible and widely applicable.

Mathematical Formulation of VAR Models
A VAR model is composed of a set of k equations, where each variable in the system is a linear function of the past values of itself and all the other variables in the system.

The Standard VAR(p) Model
For a system of k endogenous variables $Y_t = (Y_{1t}, Y_{2t}, \ldots, Y_{kt})'$, the VAR(p) model can be written as:

$$Y_t = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} + \epsilon_t \tag{6}$$

Where:

- Y_t is a $k \times 1$ vector of endogenous variables at time t.
- A_0 is a $k \times 1$ vector of constants (intercepts).
- $A_1, A_2, \ldots, A_p$ are $k \times k$ matrices of coefficients.
- p is the number of lags.
- ϵ_t is a $k \times 1$ vector of error terms.

Application of VAR Models
VAR models are typically estimated using Ordinary Least Squares (OLS). Each equation in the VAR system is estimated separately, and the lag order p is often selected based on information criteria such as the Akaike Information Criterion (AIC) or the Schwarz Criterion (SC).

VAR models are extensively used for:

- Forecasting economic and financial time series.
- Impulse response analysis to understand the effect of a shock to one of the variables on the system.
- Variance decomposition to assess the contribution of each variable to the variance of the forecast error.

VAR models represent an essential tool in empirical research, especially for analyzing and forecasting multivariate time series data. Their data-driven nature and flexibility make them particularly useful in situations where theoretical knowledge of the underlying system is limited.

3.3 Analytical Approach

The analysis commences with Principal Component Analysis (PCA) applied to various asset classes. This process involves constructing a singular time series for each asset class, achieved by weighting each component based on its explained variance. Subsequently, GARCH models are employed to extract and compare the volatilities of the asset classes. The analysis then incorporates the ARDL model to investigate both short- and long-term relationships among these assets. To further explore the dynamics, VAR models are utilized for conducting an impulse response analysis specifically between gold and cryptocurrencies. Additionally, a wavelet coherence analysis is performed to comprehend how the volatility of gold behaves in relation to cryptocurrency. This comprehensive approach enables a nuanced examination of the intricate dynamics between gold and cryptocurrencies.

4 Results

4.1 ARDL Model for Gold

The Autoregressive Distributed Lag (ARDL) model for gold was applied to examine the relationship between gold volatility (`vol_Gold_serie_std`) and various financial sectors and assets.

Model Findings

- **Lagged Gold Volatility:** The coefficients of lagged gold volatility (`L(vol_Gold_serie_std)`) are not statistically significant, suggesting that past gold volatility does not significantly impact current volatility.
- **Sector Influence:**
  - *Finance Sector (stocks):* The model indicates a significant negative coefficient for `vol_finance_serie_std`, with a positive coefficient for its lagged value, reflecting a complex, time-sensitive relationship with gold volatility.
  - *Metals Sector (commodities):* The positive coefficients of `vol_metals_serie_std` and its lagged values highlight the significant impact of the metals sector on gold volatility, possibly due to the economic interplay of gold with other metals.
  - *Technology Sector:* The lagged values of `vol_technology_serie_std` show significant positive effects, indicating a delayed but notable influence on gold volatility.
- **Model Fit:** The model explains approximately 19.42% of the variability in gold volatility (Multiple R-squared: 0.1942). The significant F-statistic confirms the model's overall statistical significance, suggesting the model's modest yet meaningful explanation of gold volatility.

4.2 Unrestricted Error Correction Model (UECM) for Gold

The Unrestricted Error Correction Model (UECM) investigates both short-term and long-term relationships between gold volatility and various financial indicators.

Model Findings

- **Lagged Gold Volatility:** A highly significant negative coefficient for the first lag (`L(vol_Gold_serie_std, 1)`) suggests a strong inverse relationship between past and current gold volatility.
- **Sector Influence:**
  - *Technology Sector:* The significant positive coefficient for `L(vol_technology_serie_std, 1)` implies a long-term influence of technology sector volatility on gold.
  - *Metals Sector:* A consistent positive relationship with `L(vol_metals_serie_std, 1)` reaffirms the significant impact of the metals sector on gold volatility.
- **Model Fit:** The model accounts for approximately 60.64% of the variance in gold volatility (Multiple R-squared: 0.6064), indicating a strong explanatory power. The low p-value of the F-statistic confirms the overall statistical significance of the model.

Interpretation and Implications

- **Gold Volatility Dynamics:** The models reveal that gold volatility is influenced by various financial sectors, with the metals and technology sectors playing prominent roles. This suggests gold's sensitivity to broader economic and technological trends.
- **Time-Sensitive Relationships:** The presence of significant lagged effects underscores the market's memory effect, emphasizing the importance of historical data in predicting gold volatility.
- **Model Fit and Utility:** While the ARDL model provides a modest explanation for gold volatility, the UECM's higher explanatory power offers deeper insights into long-term relationships and potential equilibrium adjustments.

These models collectively enhance the understanding of the intricate dynamics governing gold volatility, offering valuable insights for investors, analysts, and policymakers in the financial and commodities markets.

4.3 ARDL Model for Cryptocurrencies

Model Overview The Autoregressive Distributed Lag (ARDL) model for cryptocurrencies, particularly focusing on Bitcoin, examined the relationship between cryptocurrency volatility (`vol_crypto_serie_std`) and various financial sectors.

Key Findings

- **Lagged Cryptocurrency Volatility:** Significant negative coefficients for `L(vol_crypto_serie_std)` at lags 1 to 3 and a positive coefficient at lag 4 indicate a complex, time-dependent influence of past cryptocurrency volatility on current volatility.
- **Sector Influences:**
  - *Finance Sector:* A dynamic relationship is indicated by the negative coefficient for `vol_finance_serie_std` and positive coefficients for its lagged values.
  - *Consumer Goods:* The positive coefficients for `vol_consumer_goods_serie_std` suggest its influence on cryptocurrency volatility.
  - *Real Estate:* Mixed effects are observed with some significant negative coefficients for lagged values of `vol_real_estate_serie_std`.
  - *Metals:* Positive coefficients for lagged values of `vol_metals_serie_std` highlight its influence on cryptocurrency volatility.
- **Model Fit:** The model explains about 56.4% of the variability in cryptocurrency volatility (Multiple R-squared: 0.564). The F-statistic's significance indicates the model's overall statistical significance.

4.4 Unrestricted Error Correction Model (UECM) for Cryptocurrencies

Model Overview The Unrestricted Error Correction Model (UECM) for cryptocurrencies was utilized to ascertain both short-term and long-term dynamics impacting cryptocurrency volatility, particularly focusing on Bitcoin. The UECM incorporated a comprehensive set of financial sector influences, with data spanning from the 7th to the 1390th observation.

Model Findings

- **Lagged Cryptocurrency Volatility:** A highly significant negative coefficient for the first lag (`L(vol_crypto_serie_std, 1)`) indicates a strong inverse relationship between past and current cryptocurrency volatility.
- **Sector Influences:**
  - *Health Sector:* The health sector's volatility showed no significant short-term impact on cryptocurrency volatility.
  - *Consumer Goods Sector:* The consumer goods sector displayed a positive influence on cryptocurrency volatility in the short term, suggesting a reactive interplay.
  - *Technology Sector:* A positive coefficient for technology sector volatility indicates its significance in predicting short-term changes in cryptocurrency volatility.
  - *Real Estate Sector:* The model observed a negative impact from real estate sector volatility on cryptocurrency volatility in the short term.
  - *Energy and Metals Sectors:* Volatility in energy and metals sectors presented a mixed influence on cryptocurrency volatility.
- **Model Fit:** The UECM accounts for approximately 85.87% of the variance in cryptocurrency volatility (Multiple R-squared: 0.8587), signifying a robust model fit. The F-statistic's significance reinforces the overall statistical validity of the model.

Interpretation and Implications

- **Immediate Market Sensitivity:** Cryptocurrency volatility is acutely responsive to its past movements and diverse economic indicators, highlighting a complex and instantaneous feedback loop within the market.
- **Economic Integration:** Significant effects from sectors such as consumer goods and technology reflect cryptocurrencies' growing entanglement with the broader economy.
- **Model Utility:** The UECM's considerable explanatory power demonstrates its usefulness in decoding the volatility of cryptocurrencies, offering critical insights for timely investment and policy decisions.

4.5 Comparative Analysis and Implications

- **Volatility Dynamics:** Cryptocurrency volatility exhibits a more immediate and complex dependence on its past values compared to gold, highlighting the cryptocurrency market's inherent

volatility and reactive nature.
- **Sector Influences:** Cryptocurrencies are influenced by a broader range of sectors, with significant roles played by finance and consumer goods, whereas gold volatility is more strongly tied to the metals sector.
- **Market Behavior:** These findings suggest that the cryptocurrency markets are more reactive to current economic conditions, whereas gold shows a more stable response influenced by fewer sectors.

This comparative analysis underscores the unique characteristics of cryptocurrency as a more volatile and reactive asset compared to gold, with distinct influences from various economic sectors.

4.6 Vector AutoRegression (VAR) Model for Gold and Cryptocurrency

Model Overview The Vector AutoRegression (VAR) model was applied to explore the dynamic relationship between gold volatility (`vol_Gold_serie_std`) and cryptocurrency volatility (`vol_crypto_serie_std`), along with other financial variables. The model spanned over a sample size of 1378 data points, incorporating multiple lagged values of each variable.

Key Findings for Gold Volatility

- **Lagged Influence:** The VAR model results indicate limited predictive power of past values of various financial sectors on gold volatility, with many coefficients being statistically insignificant.
- **Sector Influences:** Notable influences on gold volatility were observed from specific sectors like the food (commodities) sector (`vol_food_serie_std`), though the impact remains marginal.
- **Model Fit:** The model explained a relatively low proportion of the variance in gold volatility (Multiple R-squared: 0.2412), suggesting the need for incorporating additional variables or exploring non-linear relationships.

Key Findings for Cryptocurrency Volatility

- **Lagged Cryptocurrency Influence:** The significant negative coefficients for lagged values of cryptocurrency volatility (`L(vol_crypto_serie_std)`) highlight a strong, immediate influence of past cryptocurrency volatility on its current state.
- **Other Sector Influences:** Metals sector (`vol_metals_serie_std`) and emerging markets index (`vol_emerging_markets_index_serie_std`) among others, showed some level of influence on cryptocurrency volatility.
- **Model Fit:** The model accounted for a higher proportion of the variance in cryptocurrency volatility (Multiple R-squared: 0.6158), indicating a better fit and more substantial explanatory power for cryptocurrency volatility compared to gold.

Interpretation and Implications

- **Volatility Dynamics:** The findings from the VAR model suggest that while cryptocurrency volatility is influenced by its past values and a range of financial sectors, gold volatility is less reactive to these factors. This indicates a more complex and reactive nature of the cryptocurrency market.
- **Comparative Analysis:** The lack of a strong direct relationship between gold and cryptocurrency volatility in the VAR model suggests a more intricate or non-linear interplay, which may be influenced by external factors not captured within the current model structure.
- **Model Utility:** The model's higher explanatory power for cryptocurrency volatility makes it more useful for understanding and predicting movements in the cryptocurrency market than in the gold market.

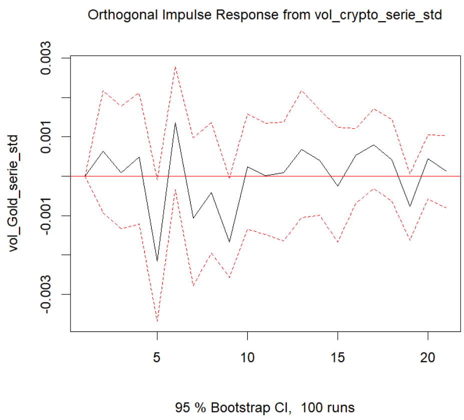
This analysis through the VAR model provides insights into the distinct behaviors of gold and cryptocurrency markets, highlighting the intricate dynamics and varying degrees of responsiveness to different economic sectors.

4.7 Impulse Response Analysis for Gold and Cryptocurrency Volatility

Model Overview An Impulse Response Function (IRF) analysis was conducted as part of the Vector AutoRegression (VAR) model to investigate the dynamic effects of a one standard deviation shock to cryptocurrency volatility (`vol_crypto_serie_std`) on the volatility of gold (`vol_Gold_serie_std`). The IRF traces the path of gold volatility in response to the shock over a horizon of 20 periods.

Key Findings

- **Immediate Response:** The IRF indicates an initial negative response in gold volatility, suggesting an inverse relationship with a shock in cryptocurrency volatility.
- **Time Horizon Dynamics:** Over the span of 20 periods, the response of gold volatility fluctuates



and crosses the zero line multiple times, reflecting the changing impact of the shock over time.

- **Confidence Intervals:** The 95% Bootstrap Confidence Intervals are wide, especially in the long term, implying a significant degree of uncertainty in the response estimates as the horizon extends.
- **Persistence of Shock:** Towards the end of the 20 periods, the response of gold volatility seems to stabilize and the effects of the initial shock appear to dissipate.

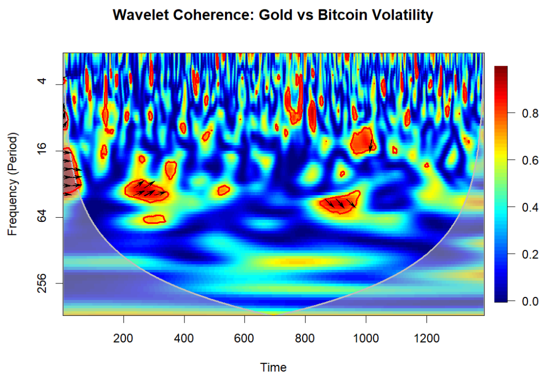
Interpretation and Implications

- **Market Interactions:** The inverse initial response may suggest that investors view gold as a safe-haven asset when cryptocurrency markets are volatile, although this effect does not seem to persist in the long term.
- **Volatility Spillover:** The fluctuating response over time could indicate a complex volatility spillover mechanism between cryptocurrency markets and gold markets, with effects that vary in magnitude and direction over time.
- **Statistical Significance:** The wide confidence intervals, particularly as the horizon extends, suggest that the statistical significance of the response diminishes, highlighting the need for cautious interpretation of long-term impulse response estimates.

These IRF findings contribute to the understanding of how shocks in the cryptocurrency market might transiently influence gold volatility, adding a temporal dimension to the analysis of market interactions between these two asset classes.

4.8 Wavelet Coherence Analysis for Gold and Bitcoin Volatility

Model Overview A Wavelet Coherence (WTC) analysis was performed to examine the coherence between gold volatility (`vol_Gold_serie_std`) and Bitcoin volatility (`vol_Bitcoin_serie_std`) across various frequencies and over time. The WTC is a tool to identify and visualize the time-frequency space where the time series co-move but do not necessarily have a causal relationship.



Key Findings

- **Coherence Across Frequencies:** The analysis revealed areas of high coherence at lower frequencies, indicating a long-term synchronization between gold and Bitcoin volatility.
- **Temporal Variability:** The coherence varies over time, with certain periods showing stronger synchronicity than others, potentially reflecting the influence of external economic factors or market conditions.
- **Short-Term Dynamics:** At higher frequencies, coherence is generally weaker, suggesting that gold and Bitcoin volatilities tend to move independently in the short term.
- **Statistical Significance:** Regions of significant coherence are outlined, showing that the relationship between gold and Bitcoin volatility is not constant but exhibits significant peaks at certain times.

Interpretation and Implications

- **Long-Term Interplay:** The presence of coherent high-power regions at lower frequencies suggests that, over longer cycles, gold and Bitcoin volatilities can exhibit similar responses to long-term economic trends or global financial conditions.
- **Market Sentiment:** The fluctuating coherence over time may reflect changes in market sentiment and the evolving perception of the relationship between gold and Bitcoin by investors.
- **Cone of Influence:** The reliable results within the cone of influence indicate that the edges of the

time series should be interpreted with caution due to potential distortions.

- **Investment Strategies:** For investors and portfolio managers, the WTC findings might be useful for diversification strategies, especially considering the varying degree of co-movement between gold and Bitcoin across different time scales.

This wavelet coherence analysis adds a nuanced perspective to the understanding of how gold and Bitcoin volatilities interact over time, providing insights into the temporal and frequency-based dynamics that characterize these two distinct asset classes.

5 Discussion

5.1 Interpreting Complex Volatility Dynamics

The analysis conducted in the ARDL and UECM models elucidates the intricate dynamics of gold and cryptocurrency volatility. It is evident that gold volatility, while influenced by several financial sectors, exhibits a more stable and predictable pattern compared to the highly reactive and complex nature of cryptocurrency volatility.

5.2 Gold Volatility: Traditional Stability vs. Emerging Trends

Gold has traditionally been seen as a stable investment, often acting as a hedge against market uncertainty. The ARDL and UECM models reinforce this notion, showing modest variability explained by the models. However, the presence of significant lagged effects from the technology and metals sectors suggests an emerging sensitivity to broader economic and technological trends, potentially signaling a shift in gold's traditional market role. This shift is further illuminated by the Impulse Response Analysis, indicating gold's transient inverse reaction to shocks in cryptocurrency volatility, suggesting its evolving role in the face of digital assets.

5.3 Cryptocurrency Volatility: A New Market Dynamic

In contrast to gold, cryptocurrency volatility, as shown in the ARDL model, is significantly influenced by its own past values and various economic sectors. This underlines the asset's sensitivity to immediate market sentiments and broader economic indicators, marking a departure from traditional asset behavior. The findings from the Vector AutoRegression (VAR) model and the Impulse Response Analysis suggest that cryptocurrencies react more rapidly to economic changes, embodying a new dynamic in financial markets.

5.4 The Temporal Interplay: Impulse Response and Wavelet Coherence

The Impulse Response Analysis adds a temporal dimension to our understanding, revealing the volatility spillover and the time it takes for gold to react to cryptocurrency market shocks. Similarly, the Wavelet Coherence Analysis offers a nuanced perspective on the time-frequency interaction between gold and Bitcoin volatilities, presenting investment opportunities based on their coherence across various frequencies and time periods.

6 Conclusion

This study has provided a detailed statistical analysis of the relationship between gold and cryptocurrencies, leveraging methodologies such as GARCH, ARDL, VAR models, and advanced techniques like impulse response and wavelet coherence analysis. The findings reveal distinct dynamics affecting these asset classes, with gold maintaining its traditional stability, albeit showing emerging sensitivity to broader economic trends. Cryptocurrencies, in contrast, exhibit a highly reactive and complex volatility pattern, influenced significantly by past volatility and a diverse array of economic sectors.

Impulse response analysis has highlighted the temporal reactions of gold to cryptocurrency market shocks, while wavelet coherence analysis has uncovered long-term synchronization between gold and Bitcoin volatilities, offering a nuanced perspective on their interaction across various frequencies and time periods.

This research enhances our understanding of the evolving dynamics between gold and cryptocurrencies in financial markets, providing valuable insights for investors, portfolio managers, and policymakers. The comparative analysis underscores the unique characteristics and market behaviors of these asset classes, illuminating the complexities of modern financial ecosystems in the face of emerging digital assets.

References

[1] Engle, R. F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4), 987–1007.

[2] Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics*, 31(3), 307–327.

[3] Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289–326.

[4] Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, 48(1), 1–48.

[5] Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. Retrieved from `https://bitcoin.org/bitcoin.pdf`

A Appendices

A.1 ARDL Regression

```
Time series regression with "ts" data:
Start = 5, End = 1390

Call:
dynlm::dynlm(formula = full_formula, data = data, start = start,
    end = end)

Residuals:
      Min        1Q    Median        3Q       Max
-0.246566 -0.014106  0.000714  0.015045  0.133131

Coefficients:
                                          Estimate Std. Error t value Pr(>|t|)
(Intercept)                              1.187e-05  7.156e-03   0.002 0.998676
L(vol_Gold_serie_std, 1)                -3.469e-02  2.761e-02  -1.256 0.209195
L(vol_Gold_serie_std, 2)                -2.307e-02  2.753e-02  -0.838 0.402161
L(vol_Gold_serie_std, 3)                -4.527e-02  2.756e-02  -1.642 0.100759
L(vol_Gold_serie_std, 4)                -3.622e-02  2.716e-02  -1.334 0.182581
vol_health_serie_std                    -5.985e-03  6.053e-02  -0.099 0.921244
vol_construction_serie_std              -8.319e-03  1.485e-02  -0.560 0.575521
L(vol_construction_serie_std, 1)        -2.729e-02  1.537e-02  -1.775 0.076090 .
vol_finance_serie_std                   -2.751e-01  7.955e-02  -3.458 0.000562 ***
L(vol_finance_serie_std, 1)              2.531e-01  8.038e-02   3.149 0.001677 **
vol_consumer_goods_serie_std            -1.269e-02  4.282e-02  -0.296 0.767052
vol_technology_serie_std                 7.113e-03  1.414e-02   0.503 0.614946
L(vol_technology_serie_std, 1)           2.352e-02  2.048e-02   1.149 0.250936
L(vol_technology_serie_std, 2)           4.690e-02  1.991e-02   2.356 0.018636 *
L(vol_technology_serie_std, 3)           5.527e-02  1.981e-02   2.790 0.005340 **
L(vol_technology_serie_std, 4)           2.529e-02  1.371e-02   1.845 0.065327 .
vol_real_estate_serie_std                2.034e-02  1.141e-02   1.782 0.074919 .
L(vol_real_estate_serie_std, 1)          2.808e-02  1.486e-02   1.890 0.058973 .
L(vol_real_estate_serie_std, 2)         -1.201e-03  1.472e-02  -0.082 0.935028
L(vol_real_estate_serie_std, 3)         -2.813e-02  1.460e-02  -1.928 0.054123 .
L(vol_real_estate_serie_std, 4)         -2.225e-02  1.102e-02  -2.019 0.043657 *
vol_energy_serie_std                    -2.531e-01  1.729e-01  -1.464 0.143565
L(vol_energy_serie_std, 1)               1.718e-01  2.224e-01   0.773 0.439851
L(vol_energy_serie_std, 2)              -2.090e-01  2.058e-01  -1.016 0.309850
L(vol_energy_serie_std, 3)               3.383e-01  1.543e-01   2.193 0.028507 *
vol_metals_serie_std                     1.556e-01  1.430e-02  10.879  < 2e-16 ***
L(vol_metals_serie_std, 1)               5.992e-02  1.630e-02   3.676 0.000247 ***
L(vol_metals_serie_std, 2)              -1.297e-02  1.643e-02  -0.790 0.429917
L(vol_metals_serie_std, 3)               3.727e-02  1.572e-02   2.371 0.017894 *
L(vol_metals_serie_std, 4)               3.535e-02  1.436e-02   2.462 0.013945 *
vol_food_serie_std                       1.727e-01  1.290e-01   1.338 0.181007
L(vol_food_serie_std, 1)                 4.370e-02  1.817e-01   0.240 0.809985
L(vol_food_serie_std, 2)                -2.345e-01  1.297e-01  -1.808 0.070884 .
vol_energy_commodities_serie_std        -2.811e-03  9.165e-03  -0.307 0.759099
L(vol_energy_commodities_serie_std, 1)   2.001e-02  1.247e-02   1.605 0.108836
L(vol_energy_commodities_serie_std, 2)   2.265e-02  9.130e-03   2.480 0.013253 *
vol_emerging_markets_index_serie_std     4.138e-02  4.603e-02   0.899 0.368808
L(vol_emerging_markets_index_serie_std, 1)  1.945e-02  2.824e-02   0.689 0.491173
L(vol_emerging_markets_index_serie_std, 2) -1.060e-03  3.698e-02  -0.029 0.977147
L(vol_emerging_markets_index_serie_std, 3) -3.712e-02  2.361e-02  -1.572 0.116079
L(vol_emerging_markets_index_serie_std, 4) -4.599e-02  1.602e-02  -2.870 0.004174 **
vol_europe_index_serie_std              -4.119e-03  2.362e-02  -0.174 0.861586
L(vol_europe_index_serie_std, 1)        -1.832e-02  2.069e-02  -0.886 0.375976
L(vol_europe_index_serie_std, 2)         4.640e-02  1.800e-02   2.578 0.010060 *
vol_us_index_serie_std                   9.330e-03  4.002e-02   0.233 0.815716
vol_asia_index_serie_std                -2.717e-02  1.570e-02  -1.730 0.083791 .
L(vol_asia_index_serie_std, 1)           3.140e-02  2.120e-02   1.482 0.138696
L(vol_asia_index_serie_std, 2)          -3.610e-02  2.127e-02  -1.697 0.089879 .
L(vol_asia_index_serie_std, 3)          -1.939e-02  2.110e-02  -0.919 0.358271
```

```
L(vol_asia_index_serie_std, 4)                         4.379e-02  1.527e-02   2.868 0.004202 **
vol_emerging_markets_currencies_serie_std              2.868e-03  2.105e-03   1.362 0.173296
L(vol_emerging_markets_currencies_serie_std, 1)       -7.230e-03  2.567e-03  -2.816 0.004934 **
L(vol_emerging_markets_currencies_serie_std, 2)        7.603e-03  2.513e-03   3.026 0.002530 **
L(vol_emerging_markets_currencies_serie_std, 3)       -4.854e-03  2.042e-03  -2.377 0.017616 *
vol_europe_currencies_serie_std                        1.591e-01  1.191e-01   1.336 0.181814
L(vol_europe_currencies_serie_std, 1)                 -2.855e-01  1.377e-01  -2.073 0.038341 *
L(vol_europe_currencies_serie_std, 2)                  2.423e-01  1.436e-01   1.687 0.091936 .
L(vol_europe_currencies_serie_std, 3)                 -3.486e-01  1.366e-01  -2.552 0.010830 *
L(vol_europe_currencies_serie_std, 4)                  2.797e-01  1.123e-01   2.491 0.012877 *
vol_us_currencies_serie_std                           -2.680e-01  1.587e-01  -1.689 0.091443 .
L(vol_us_currencies_serie_std, 1)                      5.879e-02  1.756e-01   0.335 0.737860
L(vol_us_currencies_serie_std, 2)                     -5.826e-02  1.785e-01  -0.326 0.744168
L(vol_us_currencies_serie_std, 3)                      2.197e-01  1.611e-01   1.364 0.172748
vol_asia_currencies_serie_std                         -7.901e-03  1.285e-02  -0.615 0.538685
L(vol_asia_currencies_serie_std, 1)                   -1.084e-03  1.709e-02  -0.063 0.949451
L(vol_asia_currencies_serie_std, 2)                   -3.267e-02  1.683e-02  -1.941 0.052414 .
L(vol_asia_currencies_serie_std, 3)                   -6.879e-02  1.676e-02  -4.105  4.3e-05 ***
L(vol_asia_currencies_serie_std, 4)                   -2.810e-02  1.250e-02  -2.248 0.024761 *
vol_crypto_serie_std                                  -3.717e-03  4.192e-03  -0.887 0.375408
vol_european_corporate_bonds_serie_std                 2.120e-01  9.001e-02   2.355 0.018647 *
L(vol_european_corporate_bonds_serie_std, 1)          -1.209e-01  8.941e-02  -1.352 0.176475
vol_us_government_bonds_serie_std                      7.176e-02  2.078e-01   0.345 0.729924
L(vol_us_government_bonds_serie_std, 1)                2.102e-01  2.728e-01   0.771 0.440973
L(vol_us_government_bonds_serie_std, 2)               -2.916e-01  2.035e-01  -1.433 0.152184
vol_us_corporate_bonds_serie_std                      -1.187e-02  8.097e-03  -1.465 0.143067
L(vol_us_corporate_bonds_serie_std, 1)                 5.047e-03  8.632e-03   0.585 0.558877
L(vol_us_corporate_bonds_serie_std, 2)                 1.236e-02  8.823e-03   1.401 0.161429
L(vol_us_corporate_bonds_serie_std, 3)                -1.481e-02  8.425e-03  -1.758 0.079068 .
L(vol_us_corporate_bonds_serie_std, 4)                 1.332e-02  7.770e-03   1.714 0.086784 .
vol_emerging_markets_government_bonds_serie_std       -3.091e-02  1.505e-02  -2.054 0.040182 *
L(vol_emerging_markets_government_bonds_serie_std, 1)  2.116e-02  1.523e-02   1.389 0.164976
L(vol_emerging_markets_government_bonds_serie_std, 2) -1.421e-02  1.471e-02  -0.966 0.334458
L(vol_emerging_markets_government_bonds_serie_std, 3)  2.216e-02  1.497e-02   1.481 0.138950
L(vol_emerging_markets_government_bonds_serie_std, 4)  2.589e-02  1.449e-02   1.786 0.074285 .
vol_emerging_markets_corporate_bonds_serie_std        -6.930e-02  7.159e-02  -0.968 0.333184
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.02985 on 1301 degrees of freedom
Multiple R-squared:  0.1942,Adjusted R-squared:  0.1422
F-statistic: 3.732 on 84 and 1301 DF,  p-value: < 2.2e-16

    Time series regression with "ts" data:
Start = 7, End = 1390

Call:
dynlm::dynlm(formula = full_formula, data = data, start = start,
    end = end)

Residuals:
     Min       1Q   Median       3Q      Max
-0.58870 -0.04262 -0.00468  0.03317  1.94619

Coefficients:
                                                     Estimate Std. Error t value Pr(>|t|)
(Intercept)                                          0.020993   0.034157   0.615  0.53892
L(vol_crypto_serie_std, 1)                          -0.669694   0.027001 -24.802  < 2e-16 ***
L(vol_crypto_serie_std, 2)                          -0.517164   0.032569 -15.879  < 2e-16 ***
L(vol_crypto_serie_std, 3)                          -0.389478   0.033956 -11.470  < 2e-16 ***
L(vol_crypto_serie_std, 4)                           0.080301   0.032635   2.461  0.01400 *
L(vol_crypto_serie_std, 5)                          -0.169416   0.026992  -6.277 4.72e-10 ***
vol_health_serie_std                                -0.182961   0.649677  -0.282  0.77828
L(vol_health_serie_std, 1)                          -0.772224   0.871054  -0.887  0.37549
L(vol_health_serie_std, 2)                           0.918368   0.646664   1.420  0.15580
vol_construction_serie_std                           0.130301   0.069360   1.879  0.06052 .
```

L(vol_construction_serie_std, 1)	0.064090	0.070283	0.912	0.36200	
L(vol_construction_serie_std, 2)	-0.108849	0.069726	-1.561	0.11875	
vol_finance_serie_std	-0.616518	0.387992	-1.589	0.11231	
L(vol_finance_serie_std, 1)	1.209867	0.517387	2.338	0.01952	*
L(vol_finance_serie_std, 2)	-0.877421	0.387674	-2.263	0.02378	*
vol_consumer_goods_serie_std	0.906151	0.453715	1.997	0.04602	*
L(vol_consumer_goods_serie_std, 1)	0.011638	0.608773	0.019	0.98475	
L(vol_consumer_goods_serie_std, 2)	-0.346404	0.603413	-0.574	0.56602	
L(vol_consumer_goods_serie_std, 3)	-0.809293	0.592774	-1.365	0.17241	
L(vol_consumer_goods_serie_std, 4)	1.289128	0.558874	2.307	0.02123	*
L(vol_consumer_goods_serie_std, 5)	-0.641194	0.400222	-1.602	0.10938	
vol_technology_serie_std	0.101088	0.066044	1.531	0.12611	
L(vol_technology_serie_std, 1)	0.141957	0.095193	1.491	0.13614	
L(vol_technology_serie_std, 2)	0.132747	0.095078	1.396	0.16290	
L(vol_technology_serie_std, 3)	0.071106	0.093159	0.763	0.44544	
L(vol_technology_serie_std, 4)	-0.020270	0.063112	-0.321	0.74813	
vol_real_estate_serie_std	-0.105863	0.052960	-1.999	0.04583	*
L(vol_real_estate_serie_std, 1)	-0.130545	0.068597	-1.903	0.05726	.
L(vol_real_estate_serie_std, 2)	-0.025527	0.068505	-0.373	0.70948	
L(vol_real_estate_serie_std, 3)	-0.029703	0.068064	-0.436	0.66262	
L(vol_real_estate_serie_std, 4)	-0.133933	0.064916	-2.063	0.03930	*
L(vol_real_estate_serie_std, 5)	0.029312	0.062882	0.466	0.64120	
L(vol_real_estate_serie_std, 6)	0.143740	0.048744	2.949	0.00325	**
vol_energy_serie_std	0.580603	0.799441	0.726	0.46781	
L(vol_energy_serie_std, 1)	-0.388304	1.075093	-0.361	0.71802	
L(vol_energy_serie_std, 2)	-1.620815	1.044196	-1.552	0.12086	
L(vol_energy_serie_std, 3)	1.623904	0.746551	2.175	0.02980	*
vol_metals_serie_std	0.084138	0.067481	1.247	0.21268	
L(vol_metals_serie_std, 1)	0.293297	0.073144	4.010	6.42e-05	***
L(vol_metals_serie_std, 2)	-0.133449	0.073248	-1.822	0.06871	.
L(vol_metals_serie_std, 3)	-0.114350	0.066685	-1.715	0.08663	.
vol_food_serie_std	-0.036376	0.130673	-0.278	0.78077	
vol_energy_commodities_serie_std	-0.013721	0.012791	-1.073	0.28360	
vol_emerging_markets_index_serie_std	-0.107893	0.229365	-0.470	0.63815	
L(vol_emerging_markets_index_serie_std, 1)	-0.239023	0.226851	-1.054	0.29224	
L(vol_emerging_markets_index_serie_std, 2)	0.249033	0.200808	1.240	0.21515	
L(vol_emerging_markets_index_serie_std, 3)	0.329642	0.174806	1.886	0.05955	.
vol_europe_index_serie_std	-0.078483	0.137257	-0.572	0.56756	
L(vol_europe_index_serie_std, 1)	0.008741	0.137369	0.064	0.94927	
L(vol_europe_index_serie_std, 2)	-0.115252	0.111143	-1.037	0.29994	
L(vol_europe_index_serie_std, 3)	0.140611	0.101977	1.379	0.16818	
vol_us_index_serie_std	-0.300626	0.242602	-1.239	0.21551	
L(vol_us_index_serie_std, 1)	-0.383388	0.260473	-1.472	0.14129	
L(vol_us_index_serie_std, 2)	0.379405	0.225071	1.686	0.09209	.
L(vol_us_index_serie_std, 3)	0.044929	0.209040	0.215	0.82986	
L(vol_us_index_serie_std, 4)	-0.044460	0.137623	-0.323	0.74671	
L(vol_us_index_serie_std, 5)	-0.163989	0.112205	-1.462	0.14412	
vol_asia_index_serie_std	0.020654	0.071923	0.287	0.77403	
L(vol_asia_index_serie_std, 1)	0.052116	0.097021	0.537	0.59125	
L(vol_asia_index_serie_std, 2)	0.013023	0.096729	0.135	0.89292	
L(vol_asia_index_serie_std, 3)	-0.104040	0.070660	-1.472	0.14115	
vol_emerging_markets_currencies_serie_std	0.005079	0.007179	0.707	0.47942	
vol_europe_currencies_serie_std	0.825318	0.552044	1.495	0.13515	
L(vol_europe_currencies_serie_std, 1)	0.406661	0.635245	0.640	0.52218	
L(vol_europe_currencies_serie_std, 2)	-1.389929	0.659748	-2.107	0.03533	*
L(vol_europe_currencies_serie_std, 3)	0.452233	0.648056	0.698	0.48541	
L(vol_europe_currencies_serie_std, 4)	0.671471	0.607515	1.105	0.26925	
L(vol_europe_currencies_serie_std, 5)	-0.762906	0.516291	-1.478	0.13974	
vol_us_currencies_serie_std	-0.468406	0.434628	-1.078	0.28136	
vol_asia_currencies_serie_std	-0.020041	0.024995	-0.802	0.42282	
vol_Gold_serie_std	0.127196	0.123579	1.029	0.30355	
L(vol_Gold_serie_std, 1)	-0.051030	0.125096	-0.408	0.68340	
L(vol_Gold_serie_std, 2)	0.304286	0.124952	2.435	0.01502	*
L(vol_Gold_serie_std, 3)	-0.032118	0.123453	-0.260	0.79478	
L(vol_Gold_serie_std, 4)	0.072638	0.119797	0.606	0.54440	

```
L(vol_Gold_serie_std, 5)                             0.146054   0.119768   1.219  0.22289
L(vol_Gold_serie_std, 6)                            -0.276798   0.118286  -2.340  0.01943 *
vol_european_corporate_bonds_serie_std               0.671377   0.649102   1.034  0.30118
L(vol_european_corporate_bonds_serie_std, 1)         0.811487   0.746004   1.088  0.27690
L(vol_european_corporate_bonds_serie_std, 2)        -0.266306   0.790702  -0.337  0.73633
L(vol_european_corporate_bonds_serie_std, 3)        -1.038416   0.765014  -1.357  0.17490
L(vol_european_corporate_bonds_serie_std, 4)        -1.731894   0.761899  -2.273  0.02318 *
L(vol_european_corporate_bonds_serie_std, 5)        -0.006198   0.716596  -0.009  0.99310
L(vol_european_corporate_bonds_serie_std, 6)         1.051765   0.602083   1.747  0.08090 .
vol_us_government_bonds_serie_std                    0.377417   1.002531   0.376  0.70663
L(vol_us_government_bonds_serie_std, 1)              0.008282   1.310469   0.006  0.99496
L(vol_us_government_bonds_serie_std, 2)              0.627468   1.317644   0.476  0.63401
L(vol_us_government_bonds_serie_std, 3)             -1.755834   0.990711  -1.772  0.07658 .
vol_us_corporate_bonds_serie_std                     0.047123   0.041285   1.141  0.25391
L(vol_us_corporate_bonds_serie_std, 1)              -0.048974   0.044101  -1.110  0.26700
L(vol_us_corporate_bonds_serie_std, 2)              -0.020104   0.041815  -0.481  0.63075
L(vol_us_corporate_bonds_serie_std, 3)               0.061089   0.038018   1.607  0.10833
vol_emerging_markets_government_bonds_serie_std     -0.021998   0.069439  -0.317  0.75145
vol_emerging_markets_corporate_bonds_serie_std       0.503819   0.716133   0.704  0.48185
L(vol_emerging_markets_corporate_bonds_serie_std, 1) -1.404705   0.933364  -1.505  0.13257
L(vol_emerging_markets_corporate_bonds_serie_std, 2)  0.209884   0.947881   0.221  0.82480
L(vol_emerging_markets_corporate_bonds_serie_std, 3)  1.223152   0.746111   1.639  0.10138
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1356 on 1287 degrees of freedom
Multiple R-squared:  0.564,Adjusted R-squared:  0.5315
F-statistic: 17.34 on 96 and 1287 DF,  p-value: < 2.2e-16
```

A.2 UECM (gold)

```
    Time series regression with "ts" data:
Start = 5, End = 1390

Call:
dynlm::dynlm(formula = full_formula, data = data, start = start,
    end = end)

Residuals:
      Min        1Q    Median        3Q       Max
-0.246566 -0.014106  0.000714  0.015045  0.133131

Coefficients:
                                                   Estimate Std. Error t value Pr(>|t|)
(Intercept)                                       1.187e-05  7.156e-03   0.002 0.998676
L(vol_Gold_serie_std, 1)                         -1.139e+00  5.812e-02 -19.601  < 2e-16 ***
vol_health_serie_std                             -5.985e-03  6.053e-02  -0.099 0.921244
L(vol_construction_serie_std, 1)                 -3.561e-02  2.056e-02  -1.731 0.083603 .
L(vol_finance_serie_std, 1)                      -2.199e-02  4.800e-02  -0.458 0.646947
vol_consumer_goods_serie_std                     -1.269e-02  4.282e-02  -0.296 0.767052
L(vol_technology_serie_std, 1)                    1.581e-01  5.389e-02   2.934 0.003408 **
L(vol_real_estate_serie_std, 1)                  -3.173e-03  4.234e-02  -0.075 0.940275
L(vol_energy_serie_std, 1)                        4.806e-02  4.132e-02   1.163 0.244948
L(vol_metals_serie_std, 1)                        2.751e-01  4.079e-02   6.746 2.28e-11 ***
L(vol_food_serie_std, 1)                         -1.814e-02  2.817e-02  -0.644 0.519827
L(vol_energy_commodities_serie_std, 1)            3.985e-02  2.511e-02   1.587 0.112792
L(vol_emerging_markets_index_serie_std, 1)       -2.334e-02  3.158e-02  -0.739 0.460124
L(vol_europe_index_serie_std, 1)                  2.396e-02  2.686e-02   0.892 0.372618
vol_us_index_serie_std                            9.330e-03  4.002e-02   0.233 0.815716
L(vol_asia_index_serie_std, 1)                   -7.464e-03  3.574e-03  -2.088 0.036971 *
L(vol_emerging_markets_currencies_serie_std, 1)  -1.613e-03  2.005e-03  -0.805 0.421136
L(vol_europe_currencies_serie_std, 1)             4.711e-02  4.545e-02   1.037 0.300074
L(vol_us_currencies_serie_std, 1)                -4.778e-02  1.064e-01  -0.449 0.653407
L(vol_asia_currencies_serie_std, 1)              -1.385e-01  5.137e-02  -2.697 0.007082 **
vol_crypto_serie_std                             -3.717e-03  4.192e-03  -0.887 0.375408
L(vol_european_corporate_bonds_serie_std, 1)      9.109e-02  6.681e-02   1.363 0.173018
```

```
L(vol_us_government_bonds_serie_std, 1)                   -9.597e-03  8.484e-02  -0.113 0.909957
L(vol_us_corporate_bonds_serie_std, 1)                     4.052e-03  8.320e-03   0.487 0.626368
L(vol_emerging_markets_government_bonds_serie_std, 1)      2.409e-02  3.641e-02   0.661 0.508410
vol_emerging_markets_corporate_bonds_serie_std            -6.930e-02  7.159e-02  -0.968 0.333184
d(L(vol_Gold_serie_std, 1))                                1.046e-01  4.943e-02   2.115 0.034596 *
d(L(vol_Gold_serie_std, 2))                                8.149e-02  3.957e-02   2.060 0.039641 *
d(L(vol_Gold_serie_std, 3))                                3.622e-02  2.716e-02   1.334 0.182581
d(vol_construction_serie_std)                             -8.319e-03  1.485e-02  -0.560 0.575521
d(vol_finance_serie_std)                                  -2.751e-01  7.955e-02  -3.458 0.000562 ***
d(vol_technology_serie_std)                                7.113e-03  1.414e-02   0.503 0.614946
d(L(vol_technology_serie_std, 1))                         -1.275e-01  4.111e-02  -3.101 0.001973 **
d(L(vol_technology_serie_std, 2))                         -8.056e-02  3.119e-02  -2.583 0.009915 **
d(L(vol_technology_serie_std, 3))                         -2.529e-02  1.371e-02  -1.845 0.065327 .
d(vol_real_estate_serie_std)                               2.034e-02  1.141e-02   1.782 0.074919 .
d(L(vol_real_estate_serie_std, 1))                         5.159e-02  3.093e-02   1.668 0.095584 .
d(L(vol_real_estate_serie_std, 2))                         5.039e-02  2.326e-02   2.167 0.030435 *
d(L(vol_real_estate_serie_std, 3))                         2.225e-02  1.102e-02   2.019 0.043657 *
d(vol_energy_serie_std)                                   -2.531e-01  1.729e-01  -1.464 0.143565
d(L(vol_energy_serie_std, 1))                             -1.293e-01  1.578e-01  -0.819 0.412873
d(L(vol_energy_serie_std, 2))                             -3.383e-01  1.543e-01  -2.193 0.028507 *
d(vol_metals_serie_std)                                    1.556e-01  1.430e-02  10.879  < 2e-16 ***
d(L(vol_metals_serie_std, 1))                             -5.965e-02  3.113e-02  -1.916 0.055528 .
d(L(vol_metals_serie_std, 2))                             -7.262e-02  2.492e-02  -2.915 0.003621 **
d(L(vol_metals_serie_std, 3))                             -3.535e-02  1.436e-02  -2.462 0.013945 *
d(vol_food_serie_std)                                      1.727e-01  1.290e-01   1.338 0.181007
d(L(vol_food_serie_std, 1))                                2.345e-01  1.297e-01   1.808 0.070884 .
d(vol_energy_commodities_serie_std)                       -2.811e-03  9.165e-03  -0.307 0.759099
d(L(vol_energy_commodities_serie_std, 1))                 -2.265e-02  9.130e-03  -2.480 0.013253 *
d(vol_emerging_markets_index_serie_std)                    4.138e-02  4.603e-02   0.899 0.368808
d(L(vol_emerging_markets_index_serie_std, 1))              8.417e-02  4.262e-02   1.975 0.048499 *
d(L(vol_emerging_markets_index_serie_std, 2))              8.311e-02  2.664e-02   3.119 0.001852 **
d(L(vol_emerging_markets_index_serie_std, 3))              4.599e-02  1.602e-02   2.870 0.004174 **
d(vol_europe_index_serie_std)                             -4.119e-03  2.362e-02  -0.174 0.861586
d(L(vol_europe_index_serie_std, 1))                       -4.640e-02  1.800e-02  -2.578 0.010060 *
d(vol_asia_index_serie_std)                               -2.717e-02  1.570e-02  -1.730 0.083791 .
d(L(vol_asia_index_serie_std, 1))                          1.170e-02  1.564e-02   0.748 0.454674
d(L(vol_asia_index_serie_std, 2))                         -2.440e-02  1.552e-02  -1.572 0.116248
d(L(vol_asia_index_serie_std, 3))                         -4.379e-02  1.527e-02  -2.868 0.004202 **
d(vol_emerging_markets_currencies_serie_std)               2.868e-03  2.105e-03   1.362 0.173296
d(L(vol_emerging_markets_currencies_serie_std, 1))        -2.749e-03  2.119e-03  -1.297 0.194769
d(L(vol_emerging_markets_currencies_serie_std, 2))         4.854e-03  2.042e-03   2.377 0.017616 *
d(vol_europe_currencies_serie_std)                         1.591e-01  1.191e-01   1.336 0.181814
d(L(vol_europe_currencies_serie_std, 1))                  -1.734e-01  1.266e-01  -1.370 0.170785
d(L(vol_europe_currencies_serie_std, 2))                   6.883e-02  1.246e-01   0.553 0.580693
d(L(vol_europe_currencies_serie_std, 3))                  -2.797e-01  1.123e-01  -2.491 0.012877 *
d(vol_us_currencies_serie_std)                            -2.680e-01  1.587e-01  -1.689 0.091443 .
d(L(vol_us_currencies_serie_std, 1))                      -1.615e-01  1.779e-01  -0.907 0.364337
d(L(vol_us_currencies_serie_std, 2))                      -2.197e-01  1.611e-01  -1.364 0.172748
d(vol_asia_currencies_serie_std)                          -7.901e-03  1.285e-02  -0.615 0.538685
d(L(vol_asia_currencies_serie_std, 1))                     1.296e-01  3.671e-02   3.529 0.000431 ***
d(L(vol_asia_currencies_serie_std, 2))                     9.689e-02  2.669e-02   3.630 0.000295 ***
d(L(vol_asia_currencies_serie_std, 3))                     2.810e-02  1.250e-02   2.248 0.024761 *
d(vol_european_corporate_bonds_serie_std)                  2.120e-01  9.001e-02   2.355 0.018647 *
d(vol_us_government_bonds_serie_std)                       7.176e-02  2.078e-01   0.345 0.729924
d(L(vol_us_government_bonds_serie_std, 1))                 2.916e-01  2.035e-01   1.433 0.152184
d(vol_us_corporate_bonds_serie_std)                       -1.187e-02  8.097e-03  -1.465 0.143067
d(L(vol_us_corporate_bonds_serie_std, 1))                 -1.087e-02  9.863e-03  -1.102 0.270620
d(L(vol_us_corporate_bonds_serie_std, 2))                  1.491e-03  9.296e-03   0.160 0.872568
d(L(vol_us_corporate_bonds_serie_std, 3))                 -1.332e-02  7.770e-03  -1.714 0.086784 .
d(vol_emerging_markets_government_bonds_serie_std)        -3.091e-02  1.505e-02  -2.054 0.040182 *
d(L(vol_emerging_markets_government_bonds_serie_std, 1)) -3.384e-02  2.674e-02  -1.266 0.205897
d(L(vol_emerging_markets_government_bonds_serie_std, 2)) -4.805e-02  2.216e-02  -2.168 0.030324 *
d(L(vol_emerging_markets_government_bonds_serie_std, 3)) -2.589e-02  1.449e-02  -1.786 0.074285 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Residual standard error: 0.02985 on 1301 degrees of freedom
Multiple R-squared:  0.6064,Adjusted R-squared:  0.581
F-statistic: 23.86 on 84 and 1301 DF,  p-value: < 2.2e-16
```

A.3 UECM (crypto)

```
    Time series regression with "ts" data:
Start = 7, End = 1390

Call:
dynlm::dynlm(formula = full_formula, data = data, start = start,
    end = end)

Residuals:
     Min       1Q   Median       3Q      Max
-0.58870 -0.04262 -0.00468  0.03317  1.94619

Coefficients:
                                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                                            0.020993   0.034157   0.615  0.53892
L(vol_crypto_serie_std, 1)                            -2.665451   0.114598 -23.259  < 2e-16 ***
L(vol_health_serie_std, 1)                            -0.036817   0.291087  -0.126  0.89937
L(vol_construction_serie_std, 1)                       0.085542   0.114865   0.745  0.45658
L(vol_finance_serie_std, 1)                           -0.284072   0.235718  -1.205  0.22837
L(vol_consumer_goods_serie_std, 1)                     0.410026   0.225919   1.815  0.06977 .
L(vol_technology_serie_std, 1)                         0.426628   0.252772   1.688  0.09169 .
L(vol_real_estate_serie_std, 1)                       -0.252520   0.236643  -1.067  0.28613
L(vol_energy_serie_std, 1)                             0.195387   0.199537   0.979  0.32766
L(vol_metals_serie_std, 1)                             0.129636   0.165423   0.784  0.43338
vol_food_serie_std                                    -0.036376   0.130673  -0.278  0.78077
vol_energy_commodities_serie_std                      -0.013721   0.012791  -1.073  0.28360
L(vol_emerging_markets_index_serie_std, 1)             0.231758   0.156978   1.476  0.14009
L(vol_europe_index_serie_std, 1)                      -0.044383   0.132433  -0.335  0.73758
L(vol_us_index_serie_std, 1)                          -0.468130   0.250952  -1.865  0.06235 .
L(vol_asia_index_serie_std, 1)                        -0.018248   0.016601  -1.099  0.27188
vol_emerging_markets_currencies_serie_std              0.005079   0.007179   0.707  0.47942
L(vol_europe_currencies_serie_std, 1)                  0.202849   0.217843   0.931  0.35194
vol_us_currencies_serie_std                           -0.468406   0.434628  -1.078  0.28136
vol_asia_currencies_serie_std                         -0.020041   0.024995  -0.802  0.42282
L(vol_Gold_serie_std, 1)                               0.290227   0.353070   0.822  0.41122
L(vol_european_corporate_bonds_serie_std, 1)          -0.508184   0.322627  -1.575  0.11547
L(vol_us_government_bonds_serie_std, 1)               -0.742668   0.409771  -1.812  0.07016 .
L(vol_us_corporate_bonds_serie_std, 1)                 0.039134   0.036853   1.062  0.28849
vol_emerging_markets_government_bonds_serie_std       -0.021998   0.069439  -0.317  0.75145
L(vol_emerging_markets_corporate_bonds_serie_std, 1)   0.532151   0.366638   1.451  0.14690
d(L(vol_crypto_serie_std, 1))                          0.995757   0.102536   9.711  < 2e-16 ***
d(L(vol_crypto_serie_std, 2))                          0.478593   0.079075   6.052 1.87e-09 ***
d(L(vol_crypto_serie_std, 3))                          0.089115   0.053169   1.676  0.09396 .
d(L(vol_crypto_serie_std, 4))                          0.169416   0.026992   6.277 4.72e-10 ***
d(vol_health_serie_std)                               -0.182961   0.649677  -0.282  0.77828
d(L(vol_health_serie_std, 1))                         -0.918368   0.646664  -1.420  0.15580
d(vol_construction_serie_std)                          0.130301   0.069360   1.879  0.06052 .
d(L(vol_construction_serie_std, 1))                    0.108849   0.069726   1.561  0.11875
d(vol_finance_serie_std)                              -0.616518   0.387992  -1.589  0.11231
d(L(vol_finance_serie_std, 1))                         0.877421   0.387674   2.263  0.02378 *
d(vol_consumer_goods_serie_std)                        0.906151   0.453715   1.997  0.04602 *
d(L(vol_consumer_goods_serie_std, 1))                  0.507763   0.455960   1.114  0.26565
d(L(vol_consumer_goods_serie_std, 2))                  0.161359   0.431814   0.374  0.70871
d(L(vol_consumer_goods_serie_std, 3))                 -0.647934   0.415732  -1.559  0.11935
d(L(vol_consumer_goods_serie_std, 4))                  0.641194   0.400222   1.602  0.10938
d(vol_technology_serie_std)                            0.101088   0.066044   1.531  0.12611
d(L(vol_technology_serie_std, 1))                     -0.183583   0.194532  -0.944  0.34549
d(L(vol_technology_serie_std, 2))                     -0.050837   0.145277  -0.350  0.72645
d(L(vol_technology_serie_std, 3))                      0.020270   0.063112   0.321  0.74813
```

```
d(vol_real_estate_serie_std)                                  -0.105863   0.052960  -1.999  0.04583 *
d(L(vol_real_estate_serie_std, 1))                             0.016112   0.194289   0.083  0.93392
d(L(vol_real_estate_serie_std, 2))                            -0.009416   0.165691  -0.057  0.95469
d(L(vol_real_estate_serie_std, 3))                            -0.039118   0.134069  -0.292  0.77050
d(L(vol_real_estate_serie_std, 4))                            -0.173051   0.100517  -1.722  0.08538 .
d(L(vol_real_estate_serie_std, 5))                            -0.143740   0.048744  -2.949  0.00325 **
d(vol_energy_serie_std)                                        0.580603   0.799441   0.726  0.46781
d(L(vol_energy_serie_std, 1))                                 -0.003089   0.791078  -0.004  0.99689
d(L(vol_energy_serie_std, 2))                                 -1.623904   0.746551  -2.175  0.02980 *
d(vol_metals_serie_std)                                        0.084138   0.067481   1.247  0.21268
d(L(vol_metals_serie_std, 1))                                  0.247800   0.115777   2.140  0.03252 *
d(L(vol_metals_serie_std, 2))                                  0.114350   0.066685   1.715  0.08663 .
d(vol_emerging_markets_index_serie_std)                       -0.107893   0.229365  -0.470  0.63815
d(L(vol_emerging_markets_index_serie_std, 1))                 -0.578675   0.281128  -2.058  0.03975 *
d(L(vol_emerging_markets_index_serie_std, 2))                 -0.329642   0.174806  -1.886  0.05955 .
d(vol_europe_index_serie_std)                                 -0.078483   0.137257  -0.572  0.56756
d(L(vol_europe_index_serie_std, 1))                           -0.025359   0.147262  -0.172  0.86330
d(L(vol_europe_index_serie_std, 2))                           -0.140611   0.101977  -1.379  0.16818
d(vol_us_index_serie_std)                                     -0.300626   0.242602  -1.239  0.21551
d(L(vol_us_index_serie_std, 1))                               -0.215884   0.309474  -0.698  0.48556
d(L(vol_us_index_serie_std, 2))                                0.163521   0.269010   0.608  0.54339
d(L(vol_us_index_serie_std, 3))                                0.208449   0.155705   1.339  0.18089
d(L(vol_us_index_serie_std, 4))                                0.163989   0.112205   1.462  0.14412
d(vol_asia_index_serie_std)                                    0.020654   0.071923   0.287  0.77403
d(L(vol_asia_index_serie_std, 1))                              0.091018   0.071659   1.270  0.20426
d(L(vol_asia_index_serie_std, 2))                              0.104040   0.070660   1.472  0.14115
d(vol_europe_currencies_serie_std)                             0.825318   0.552044   1.495  0.13515
d(L(vol_europe_currencies_serie_std, 1))                       1.029131   0.583575   1.763  0.07805 .
d(L(vol_europe_currencies_serie_std, 2))                      -0.360798   0.566637  -0.637  0.52441
d(L(vol_europe_currencies_serie_std, 3))                       0.091435   0.556743   0.164  0.86957
d(L(vol_europe_currencies_serie_std, 4))                       0.762906   0.516291   1.478  0.13974
d(vol_Gold_serie_std)                                          0.127196   0.123579   1.029  0.30355
d(L(vol_Gold_serie_std, 1))                                   -0.214061   0.293551  -0.729  0.46600
d(L(vol_Gold_serie_std, 2))                                    0.090225   0.256078   0.352  0.72464
d(L(vol_Gold_serie_std, 3))                                    0.058107   0.216651   0.268  0.78858
d(L(vol_Gold_serie_std, 4))                                    0.130745   0.173566   0.753  0.45142
d(L(vol_Gold_serie_std, 5))                                    0.276798   0.118286   2.340  0.01943 *
d(vol_european_corporate_bonds_serie_std)                      0.671377   0.649102   1.034  0.30118
d(L(vol_european_corporate_bonds_serie_std, 1))                1.991048   0.699088   2.848  0.00447 **
d(L(vol_european_corporate_bonds_serie_std, 2))                1.724742   0.684984   2.518  0.01193 *
d(L(vol_european_corporate_bonds_serie_std, 3))                0.686326   0.650746   1.055  0.29177
d(L(vol_european_corporate_bonds_serie_std, 4))               -1.045567   0.652720  -1.602  0.10943
d(L(vol_european_corporate_bonds_serie_std, 5))               -1.051765   0.602083  -1.747  0.08090 .
d(vol_us_government_bonds_serie_std)                           0.377417   1.002531   0.376  0.70663
d(L(vol_us_government_bonds_serie_std, 1))                     1.128366   1.001865   1.126  0.26026
d(L(vol_us_government_bonds_serie_std, 2))                     1.755834   0.990711   1.772  0.07658 .
d(vol_us_corporate_bonds_serie_std)                            0.047123   0.041285   1.141  0.25391
d(L(vol_us_corporate_bonds_serie_std, 1))                     -0.040985   0.046734  -0.877  0.38066
d(L(vol_us_corporate_bonds_serie_std, 2))                     -0.061089   0.038018  -1.607  0.10833
d(vol_emerging_markets_corporate_bonds_serie_std)              0.503819   0.716133   0.704  0.48185
d(L(vol_emerging_markets_corporate_bonds_serie_std, 1)) -1.433037   0.787828  -1.819  0.06915 .
d(L(vol_emerging_markets_corporate_bonds_serie_std, 2)) -1.223152   0.746111  -1.639  0.10138
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.1356 on 1287 degrees of freedom
Multiple R-squared:  0.8587,Adjusted R-squared:  0.8481
F-statistic: 81.45 on 96 and 1287 DF,  p-value: < 2.2e-16
```

```
VAR Estimation Results:
=========================
Endogenous variables: vol_Gold_serie_std, vol_health_serie_std, vol_construction_serie_std, vol_finance_serie_std,
vol_consumer_goods_serie_std, vol_technology_serie_std, vol_real_estate_serie_std, vol_energy_serie_std,
vol_metals_serie_std, vol_food_serie_std, vol_energy_commodities_serie_std,
vol_emerging_markets_index_serie_std, vol_europe_index_serie_std, vol_us_index_serie_std,
vol_asia_index_serie_std, vol_emerging_markets_currencies_serie_std,
vol_europe_currencies_serie_std, vol_us_currencies_serie_std,
vol_asia_currencies_serie_std, vol_crypto_serie_std, vol_european_corporate_bonds_serie_std,
vol_us_government_bonds_serie_std, vol_us_corporate_bonds_serie_std,
vol_emerging_markets_government_bonds_serie_std, vol_emerging_markets_corporate_bonds_serie_std

Deterministic variables: const
Sample size: 1378
Log Likelihood: 86390.949

Call:
VAR(y = stationarized_data_ts, p = 12, type = "const")


Estimation results for equation vol_Gold_serie_std:
===================================================
vol_Gold_serie_std = vol_Gold_serie_std(l1-l12) + vol_health_serie_std(l1-l12) + vol_construction_serie_std(l1-l12) +
vol_finance_serie_std(l1-l12) + vol_consumer_goods_serie_std(l1-l12) + vol_technology_serie_std(l1-l12) +
vol_real_estate_serie_std(l1-l12) + vol_energy_serie_std(l1-l12) + vol_metals_serie_std(l1-l12) +
vol_food_serie_std(l1-l12) + vol_energy_commodities_serie_std(l1-l12) + vol_emerging_markets_index_serie_std(l1-l12) +
vol_europe_index_serie_std(l1-l12) + vol_us_index_serie_std(l1-l12) + vol_asia_index_serie_std(l1-l12) +
vol_emerging_markets_currencies_serie_std(l1-l12) + vol_europe_currencies_serie_std(l1-l12) +
vol_us_currencies_serie_std(l1-l12) + vol_asia_currencies_serie_std(l1-l12) + vol_crypto_serie_std(l1-l12) +
vol_european_corporate_bonds_serie_std(l1-l12) +
vol_us_government_bonds_serie_std(l1-l12) + vol_us_corporate_bonds_serie_std(l1-l12) +
vol_emerging_markets_government_bonds_serie_std(l1-l12) + vol_emerging_markets_corporate_bonds_serie_std(l1-l12) + const
```

	Estimate	Std. Error	t value	Pr(>|t|)	
vol_Gold_serie_std.l1	-1.479e-02	3.217e-02	-0.460	0.64573	
vol_health_serie_std.l1	-1.417e-01	1.731e-01	-0.818	0.41329	
vol_construction_serie_std.l1	-1.181e-02	1.862e-02	-0.634	0.52606	
vol_finance_serie_std.l1	5.890e-02	5.933e-02	0.993	0.32103	
vol_consumer_goods_serie_std.l1	2.015e-01	1.207e-01	1.670	0.09529	.
vol_technology_serie_std.l1	-9.766e-03	1.785e-02	-0.547	0.58436	
vol_real_estate_serie_std.l1	3.075e-03	1.180e-02	0.261	0.79450	
vol_energy_serie_std.l1	-6.874e-02	2.120e-01	-0.324	0.74579	
vol_metals_serie_std.l1	6.805e-03	1.781e-02	0.382	0.70250	
vol_food_serie_std.l1	3.240e-01	1.547e-01	2.094	0.03649	*
vol_energy_commodities_serie_std.l1	1.150e-02	1.140e-02	1.010	0.31294	
vol_emerging_markets_index_serie_std.l1	5.846e-02	5.458e-02	1.071	0.28443	
vol_europe_index_serie_std.l1	-3.099e-02	5.920e-02	-0.524	0.60073	
vol_us_index_serie_std.l1	-7.130e-02	6.678e-02	-1.068	0.28593	
vol_asia_index_serie_std.l1	-4.709e-03	1.861e-02	-0.253	0.80027	
vol_emerging_markets_currencies_serie_std.l1	-5.385e-03	2.540e-03	-2.120	0.03422	*
vol_europe_currencies_serie_std.l1	-1.489e-01	1.950e-01	-0.764	0.44533	
vol_us_currencies_serie_std.l1	-9.031e-01	4.906e-01	-1.841	0.06591	.
vol_asia_currencies_serie_std.l1	8.566e-03	1.570e-02	0.545	0.58554	
vol_crypto_serie_std.l1	4.955e-03	7.002e-03	0.708	0.47934	
vol_european_corporate_bonds_serie_std.l1	-3.406e-02	1.698e-01	-0.201	0.84105	
vol_us_government_bonds_serie_std.l1	4.471e-01	2.594e-01	1.724	0.08501	.
vol_us_corporate_bonds_serie_std.l1	-3.938e-03	1.230e-02	-0.320	0.74885	
vol_emerging_markets_government_bonds_serie_std.l1	2.918e-02	2.061e-02	1.416	0.15717	
vol_emerging_markets_corporate_bonds_serie_std.l1	-1.689e-01	1.948e-01	-0.867	0.38599	
vol_Gold_serie_std.l2	-1.901e-02	3.253e-02	-0.584	0.55905	
vol_health_serie_std.l2	4.075e-01	2.365e-01	1.723	0.08516	.
vol_construction_serie_std.l2	9.741e-03	1.939e-02	0.502	0.61546	
vol_finance_serie_std.l2	-1.361e-02	6.474e-02	-0.210	0.83348	

vol_consumer_goods_serie_std.l2	-2.630e-01	1.607e-01	-1.637	0.10201	
vol_technology_serie_std.l2	1.986e-02	2.622e-02	0.757	0.44902	
vol_real_estate_serie_std.l2	-6.401e-03	1.453e-02	-0.441	0.65959	
vol_energy_serie_std.l2	-1.282e-02	2.858e-01	-0.045	0.96423	
vol_metals_serie_std.l2	1.226e-02	1.979e-02	0.619	0.53578	
vol_food_serie_std.l2	-5.076e-01	2.206e-01	-2.301	0.02155	*
vol_energy_commodities_serie_std.l2	1.463e-02	1.564e-02	0.935	0.35001	
vol_emerging_markets_index_serie_std.l2	-1.137e-01	6.954e-02	-1.635	0.10231	
vol_europe_index_serie_std.l2	1.078e-01	6.909e-02	1.560	0.11915	
vol_us_index_serie_std.l2	-5.892e-02	7.278e-02	-0.810	0.41833	
vol_asia_index_serie_std.l2	-1.637e-02	2.529e-02	-0.647	0.51746	
vol_emerging_markets_currencies_serie_std.l2	8.291e-03	3.156e-03	2.627	0.00872	**
vol_europe_currencies_serie_std.l2	3.212e-01	2.758e-01	1.165	0.24446	
vol_us_currencies_serie_std.l2	3.446e-01	6.776e-01	0.509	0.61113	
vol_asia_currencies_serie_std.l2	-4.140e-02	2.118e-02	-1.955	0.05086	.
vol_crypto_serie_std.l2	2.955e-03	8.347e-03	0.354	0.72343	
vol_european_corporate_bonds_serie_std.l2	-5.801e-02	2.136e-01	-0.272	0.78597	
vol_us_government_bonds_serie_std.l2	-6.936e-01	3.356e-01	-2.067	0.03900	*
vol_us_corporate_bonds_serie_std.l2	-6.996e-03	1.302e-02	-0.537	0.59131	
vol_emerging_markets_government_bonds_serie_std.l2	-3.718e-02	2.103e-02	-1.768	0.07741	.
vol_emerging_markets_corporate_bonds_serie_std.l2	3.906e-01	2.592e-01	1.507	0.13201	
vol_Gold_serie_std.l3	-6.420e-02	3.283e-02	-1.955	0.05079	.
vol_health_serie_std.l3	-5.247e-01	2.381e-01	-2.204	0.02776	*
vol_construction_serie_std.l3	-4.507e-02	1.939e-02	-2.324	0.02031	*
vol_finance_serie_std.l3	5.981e-02	6.532e-02	0.916	0.36004	
vol_consumer_goods_serie_std.l3	-1.100e-02	1.621e-01	-0.068	0.94592	
vol_technology_serie_std.l3	4.851e-02	2.637e-02	1.840	0.06606	.
vol_real_estate_serie_std.l3	-2.112e-02	1.461e-02	-1.446	0.14858	
vol_energy_serie_std.l3	1.831e-01	2.863e-01	0.640	0.52259	
vol_metals_serie_std.l3	2.125e-02	2.010e-02	1.057	0.29062	
vol_food_serie_std.l3	1.181e-01	2.228e-01	0.530	0.59606	
vol_energy_commodities_serie_std.l3	1.148e-02	1.568e-02	0.732	0.46414	
vol_emerging_markets_index_serie_std.l3	9.845e-02	7.016e-02	1.403	0.16082	
vol_europe_index_serie_std.l3	-5.670e-02	7.061e-02	-0.803	0.42210	
vol_us_index_serie_std.l3	3.129e-02	7.344e-02	0.426	0.67015	
vol_asia_index_serie_std.l3	-1.903e-02	2.542e-02	-0.748	0.45437	
vol_emerging_markets_currencies_serie_std.l3	-4.704e-03	3.191e-03	-1.474	0.14069	
vol_europe_currencies_serie_std.l3	-4.927e-01	2.778e-01	-1.774	0.07640	.
vol_us_currencies_serie_std.l3	8.778e-01	6.822e-01	1.287	0.19845	
vol_asia_currencies_serie_std.l3	-8.323e-02	2.112e-02	-3.940	8.66e-05	***
vol_crypto_serie_std.l3	6.537e-03	9.108e-03	0.718	0.47312	
vol_european_corporate_bonds_serie_std.l3	2.798e-01	2.200e-01	1.272	0.20371	
vol_us_government_bonds_serie_std.l3	2.807e-01	3.404e-01	0.825	0.40976	
vol_us_corporate_bonds_serie_std.l3	6.064e-03	1.317e-02	0.460	0.64533	
vol_emerging_markets_government_bonds_serie_std.l3	2.835e-02	2.094e-02	1.354	0.17601	
vol_emerging_markets_corporate_bonds_serie_std.l3	-2.656e-01	2.683e-01	-0.990	0.32258	
vol_Gold_serie_std.l4	-3.140e-02	3.300e-02	-0.952	0.34149	
vol_health_serie_std.l4	9.432e-02	2.357e-01	0.400	0.68907	
vol_construction_serie_std.l4	5.165e-02	1.958e-02	2.638	0.00846	**
vol_finance_serie_std.l4	3.103e-02	6.577e-02	0.472	0.63715	
vol_consumer_goods_serie_std.l4	9.470e-02	1.621e-01	0.584	0.55916	
vol_technology_serie_std.l4	3.961e-02	2.671e-02	1.483	0.13828	
vol_real_estate_serie_std.l4	-4.479e-04	1.523e-02	-0.029	0.97655	
vol_energy_serie_std.l4	3.185e-02	2.887e-01	0.110	0.91218	
vol_metals_serie_std.l4	2.433e-02	2.003e-02	1.215	0.22472	
vol_food_serie_std.l4	1.306e-01	2.217e-01	0.589	0.55583	
vol_energy_commodities_serie_std.l4	8.302e-04	1.564e-02	0.053	0.95769	
vol_emerging_markets_index_serie_std.l4	-1.444e-02	7.084e-02	-0.204	0.83858	
vol_europe_index_serie_std.l4	5.764e-03	7.184e-02	0.080	0.93606	
vol_us_index_serie_std.l4	-7.892e-02	7.380e-02	-1.069	0.28514	
vol_asia_index_serie_std.l4	1.918e-02	2.545e-02	0.753	0.45140	
vol_emerging_markets_currencies_serie_std.l4	-2.354e-03	3.197e-03	-0.736	0.46166	
vol_europe_currencies_serie_std.l4	5.110e-01	2.778e-01	1.839	0.06618	.
vol_us_currencies_serie_std.l4	-1.063e+00	6.916e-01	-1.538	0.12445	
vol_asia_currencies_serie_std.l4	-3.455e-02	2.119e-02	-1.631	0.10322	

vol_crypto_serie_std.l4	-1.171e-02	9.468e-03	-1.237	0.21632	
vol_european_corporate_bonds_serie_std.l4	-2.097e-01	2.234e-01	-0.939	0.34799	
vol_us_government_bonds_serie_std.l4	3.274e-01	3.436e-01	0.953	0.34089	
vol_us_corporate_bonds_serie_std.l4	5.631e-03	1.305e-02	0.431	0.66621	
vol_emerging_markets_government_bonds_serie_std.l4	6.548e-03	2.086e-02	0.314	0.75362	
vol_emerging_markets_corporate_bonds_serie_std.l4	1.698e-01	2.683e-01	0.633	0.52701	
vol_Gold_serie_std.l5	2.749e-02	3.286e-02	0.836	0.40314	
vol_health_serie_std.l5	8.390e-02	2.351e-01	0.357	0.72130	
vol_construction_serie_std.l5	-2.492e-02	1.949e-02	-1.278	0.20139	
vol_finance_serie_std.l5	-6.126e-02	6.617e-02	-0.926	0.35478	
vol_consumer_goods_serie_std.l5	-4.103e-02	1.611e-01	-0.255	0.79906	
vol_technology_serie_std.l5	-4.890e-04	2.689e-02	-0.018	0.98549	
vol_real_estate_serie_std.l5	6.635e-03	1.516e-02	0.438	0.66176	
vol_energy_serie_std.l5	1.962e-01	2.887e-01	0.679	0.49703	
vol_metals_serie_std.l5	1.142e-02	2.003e-02	0.570	0.56887	
vol_food_serie_std.l5	1.381e-01	2.197e-01	0.629	0.52975	
vol_energy_commodities_serie_std.l5	2.100e-02	1.554e-02	1.352	0.17681	
vol_emerging_markets_index_serie_std.l5	-3.511e-02	7.111e-02	-0.494	0.62158	
vol_europe_index_serie_std.l5	1.343e-01	7.257e-02	1.851	0.06440	.
vol_us_index_serie_std.l5	1.056e-02	7.506e-02	0.141	0.88809	
vol_asia_index_serie_std.l5	-7.926e-03	2.547e-02	-0.311	0.75574	
vol_emerging_markets_currencies_serie_std.l5	5.028e-03	3.155e-03	1.594	0.11125	
vol_europe_currencies_serie_std.l5	-1.007e-01	2.771e-01	-0.363	0.71636	
vol_us_currencies_serie_std.l5	5.233e-01	6.964e-01	0.751	0.45256	
vol_asia_currencies_serie_std.l5	-8.488e-03	2.124e-02	-0.400	0.68954	
vol_crypto_serie_std.l5	2.953e-03	9.448e-03	0.313	0.75471	
vol_european_corporate_bonds_serie_std.l5	-9.241e-02	2.282e-01	-0.405	0.68557	
vol_us_government_bonds_serie_std.l5	-7.800e-01	3.470e-01	-2.248	0.02479	*
vol_us_corporate_bonds_serie_std.l5	4.552e-04	1.308e-02	0.035	0.97225	
vol_emerging_markets_government_bonds_serie_std.l5	4.506e-03	2.073e-02	0.217	0.82798	
vol_emerging_markets_corporate_bonds_serie_std.l5	7.130e-02	2.705e-01	0.264	0.79218	
vol_Gold_serie_std.l6	-3.190e-02	3.291e-02	-0.970	0.33249	
vol_health_serie_std.l6	-3.242e-01	2.363e-01	-1.372	0.17031	
vol_construction_serie_std.l6	3.468e-02	1.964e-02	1.766	0.07766	.
vol_finance_serie_std.l6	4.091e-03	6.711e-02	0.061	0.95141	
vol_consumer_goods_serie_std.l6	1.223e-01	1.609e-01	0.760	0.44722	
vol_technology_serie_std.l6	-2.143e-02	2.695e-02	-0.795	0.42666	
vol_real_estate_serie_std.l6	-3.359e-03	1.501e-02	-0.224	0.82295	
vol_energy_serie_std.l6	-2.136e-01	2.898e-01	-0.737	0.46129	
vol_metals_serie_std.l6	-4.076e-02	1.993e-02	-2.045	0.04108	*
vol_food_serie_std.l6	8.053e-03	2.192e-01	0.037	0.97070	
vol_energy_commodities_serie_std.l6	1.251e-02	1.535e-02	0.815	0.41547	
vol_emerging_markets_index_serie_std.l6	-6.751e-03	7.194e-02	-0.094	0.92525	
vol_europe_index_serie_std.l6	-9.667e-02	7.392e-02	-1.308	0.19123	
vol_us_index_serie_std.l6	7.899e-02	7.500e-02	1.053	0.29248	
vol_asia_index_serie_std.l6	2.373e-02	2.548e-02	0.931	0.35186	
vol_emerging_markets_currencies_serie_std.l6	-8.529e-04	3.163e-03	-0.270	0.78750	
vol_europe_currencies_serie_std.l6	6.445e-02	2.766e-01	0.233	0.81576	
vol_us_currencies_serie_std.l6	-3.731e-01	6.984e-01	-0.534	0.59327	
vol_asia_currencies_serie_std.l6	-2.876e-02	2.119e-02	-1.357	0.17503	
vol_crypto_serie_std.l6	-7.549e-03	9.527e-03	-0.792	0.42828	
vol_european_corporate_bonds_serie_std.l6	3.177e-01	2.330e-01	1.363	0.17307	
vol_us_government_bonds_serie_std.l6	5.957e-01	3.512e-01	1.696	0.09010	.
vol_us_corporate_bonds_serie_std.l6	2.040e-02	1.317e-02	1.549	0.12163	
vol_emerging_markets_government_bonds_serie_std.l6	-9.299e-03	2.073e-02	-0.449	0.65381	
vol_emerging_markets_corporate_bonds_serie_std.l6	-6.049e-01	2.734e-01	-2.213	0.02712	*
vol_Gold_serie_std.l7	5.138e-03	3.286e-02	0.156	0.87578	
vol_health_serie_std.l7	3.943e-01	2.363e-01	1.668	0.09555	.
vol_construction_serie_std.l7	9.188e-03	1.945e-02	0.472	0.63672	
vol_finance_serie_std.l7	4.415e-02	6.717e-02	0.657	0.51106	
vol_consumer_goods_serie_std.l7	-5.187e-02	1.621e-01	-0.320	0.74910	
vol_technology_serie_std.l7	-3.224e-02	2.705e-02	-1.192	0.23350	
vol_real_estate_serie_std.l7	-1.781e-03	1.500e-02	-0.119	0.90554	
vol_energy_serie_std.l7	1.950e-01	2.921e-01	0.667	0.50461	
vol_metals_serie_std.l7	3.273e-03	1.986e-02	0.165	0.86914	

```
vol_food_serie_std.l7                               -1.828e-01  2.168e-01  -0.843  0.39926
vol_energy_commodities_serie_std.l7                 -1.055e-02  1.519e-02  -0.694  0.48767
vol_emerging_markets_index_serie_std.l7             -2.932e-03  7.193e-02  -0.041  0.96749
vol_europe_index_serie_std.l7                        2.704e-02  7.382e-02   0.366  0.71419
vol_us_index_serie_std.l7                           -6.399e-02  7.518e-02  -0.851  0.39486
vol_asia_index_serie_std.l7                         -1.758e-05  2.535e-02  -0.001  0.99945
vol_emerging_markets_currencies_serie_std.l7        -1.188e-04  3.123e-03  -0.038  0.96965
vol_europe_currencies_serie_std.l7                   5.486e-02  2.771e-01   0.198  0.84309
vol_us_currencies_serie_std.l7                      -5.515e-02  6.963e-01  -0.079  0.93689
vol_asia_currencies_serie_std.l7                     5.341e-03  2.119e-02   0.252  0.80103
vol_crypto_serie_std.l7                             -1.159e-02  9.509e-03  -1.219  0.22322
vol_european_corporate_bonds_serie_std.l7           -2.851e-01  2.344e-01  -1.217  0.22400
vol_us_government_bonds_serie_std.l7                 1.080e-01  3.526e-01   0.306  0.75941
vol_us_corporate_bonds_serie_std.l7                  1.526e-02  1.307e-02   1.168  0.24308
vol_emerging_markets_government_bonds_serie_std.l7  -5.275e-03  2.060e-02  -0.256  0.79793
vol_emerging_markets_corporate_bonds_serie_std.l7    1.939e-02  2.746e-01   0.071  0.94372
vol_Gold_serie_std.l8                               -9.862e-03  3.303e-02  -0.299  0.76534
vol_health_serie_std.l8                              3.572e-01  2.355e-01   1.517  0.12959
vol_construction_serie_std.l8                        2.304e-03  1.934e-02   0.119  0.90522
vol_finance_serie_std.l8                            -2.245e-02  6.688e-02  -0.336  0.73716
vol_consumer_goods_serie_std.l8                      5.820e-02  1.610e-01   0.361  0.71784
vol_technology_serie_std.l8                         -4.318e-02  2.691e-02  -1.605  0.10884
vol_real_estate_serie_std.l8                        -1.432e-02  1.516e-02  -0.945  0.34510
vol_energy_serie_std.l8                             -3.352e-01  2.916e-01  -1.150  0.25050
vol_metals_serie_std.l8                              1.389e-02  1.977e-02   0.702  0.48252
vol_food_serie_std.l8                               -2.755e-01  2.151e-01  -1.281  0.20057
vol_energy_commodities_serie_std.l8                  1.099e-02  1.538e-02   0.715  0.47505
vol_emerging_markets_index_serie_std.l8              2.514e-02  7.112e-02   0.353  0.72379
vol_europe_index_serie_std.l8                       -6.888e-02  5.400e-02  -1.276  0.20238
vol_us_index_serie_std.l8                           -1.571e-01  7.261e-02  -2.163  0.03074 *
vol_asia_index_serie_std.l8                         -3.050e-02  2.544e-02  -1.199  0.23091
vol_emerging_markets_currencies_serie_std.l8         5.292e-04  3.050e-03   0.174  0.86228
vol_europe_currencies_serie_std.l8                  -3.272e-01  2.778e-01  -1.178  0.23911
vol_us_currencies_serie_std.l8                       2.716e-01  6.969e-01   0.390  0.69685
vol_asia_currencies_serie_std.l8                     3.575e-02  2.119e-02   1.687  0.09190 .
vol_crypto_serie_std.l8                             -8.102e-03  9.509e-03  -0.852  0.39442
vol_european_corporate_bonds_serie_std.l8            3.927e-01  2.372e-01   1.656  0.09804 .
vol_us_government_bonds_serie_std.l8                -7.666e-02  3.523e-01  -0.218  0.82778
vol_us_corporate_bonds_serie_std.l8                 -2.133e-02  1.295e-02  -1.648  0.09972 .
vol_emerging_markets_government_bonds_serie_std.l8  -1.215e-03  2.007e-02  -0.061  0.95175
vol_emerging_markets_corporate_bonds_serie_std.l8    4.014e-01  2.719e-01   1.476  0.14013
 [ getOption("max.print") est atteint -- 101 lignes omises ]
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.03175 on 1077 degrees of freedom
Multiple R-Squared: 0.2412,Adjusted R-squared: 0.02986
F-statistic: 1.141 on 300 and 1077 DF,  p-value: 0.07135



Estimation results for equation vol_crypto_serie_std:
=====================================================
vol_crypto_serie_std = vol_Gold_serie_std(l1-l12) + vol_health_serie_std(l1-l12) + vol_construction_serie_std(l1-l12) +
vol_finance_serie_std(l1-l12) + vol_consumer_goods_serie_std(l1-l12) + vol_technology_serie_std(l1-l12) +
vol_real_estate_serie_std(l1-l12) + vol_energy_serie_std(l1-l12) + vol_metals_serie_std(l1-l12) +
vol_food_serie_std(l1-l12) + vol_energy_commodities_serie_std(l1-l12) + vol_emerging_markets_index_serie_std(l1-l12) +
vol_europe_index_serie_std(l1-l12) + vol_us_index_serie_std(l1-l12) + vol_asia_index_serie_std(l1-l12) +
vol_emerging_markets_currencies_serie_std(l1-l12) + vol_europe_currencies_serie_std(l1-l12) +
vol_us_currencies_serie_std(l1-l12) + vol_asia_currencies_serie_std(l1-l12) + vol_crypto_serie_std(l1-l12) +
vol_european_corporate_bonds_serie_std(l1-l12) + vol_us_government_bonds_serie_std(l1-l12) +
vol_us_corporate_bonds_serie_std(l1-l12) + vol_emerging_markets_government_bonds_serie_std(l1-l12) +
vol_emerging_markets_corporate_bonds_serie_std(l1-l12) + cons
```

```
                                                Estimate Std. Error t value Pr(>|t|)    
vol_Gold_serie_std.l1                         -0.2216593  0.1406650  -1.576 0.115367    
vol_health_serie_std.l1                       -1.0550264  0.7567534  -1.394 0.163560    
vol_construction_serie_std.l1                  0.0859217  0.0814157   1.055 0.291504    
vol_finance_serie_std.l1                       0.2812173  0.2593929   1.084 0.278547    
vol_consumer_goods_serie_std.l1                0.9923550  0.5277578   1.880 0.060334 .  
vol_technology_serie_std.l1                    0.0479106  0.0780368   0.614 0.539379    
vol_real_estate_serie_std.l1                  -0.0290066  0.0515985  -0.562 0.574125    
vol_energy_serie_std.l1                        0.8307379  0.9268883   0.896 0.370311    
vol_metals_serie_std.l1                        0.2702928  0.0778801   3.471 0.000540 ***
vol_food_serie_std.l1                          0.5463567  0.6764369   0.808 0.419443    
vol_energy_commodities_serie_std.l1            0.0238209  0.0498231   0.478 0.632669    
vol_emerging_markets_index_serie_std.l1       -0.4398480  0.2386601  -1.843 0.065605 .  
vol_europe_index_serie_std.l1                  0.0097071  0.2588320   0.038 0.970090    
vol_us_index_serie_std.l1                     -0.3917109  0.2919886  -1.342 0.180032    
vol_asia_index_serie_std.l1                    0.0528025  0.0813543   0.649 0.516448    
vol_emerging_markets_currencies_serie_std.l1  -0.0093601  0.0111052  -0.843 0.399494    
vol_europe_currencies_serie_std.l1             1.3381762  0.8526989   1.569 0.116862    
vol_us_currencies_serie_std.l1                 0.6340614  2.1449522   0.296 0.767588    
vol_asia_currencies_serie_std.l1               0.0546348  0.0686655   0.796 0.426402    
vol_crypto_serie_std.l1                       -0.6497057  0.0306168 -21.221  < 2e-16 ***
vol_european_corporate_bonds_serie_std.l1      1.0900839  0.7424215   1.468 0.142320    
vol_us_government_bonds_serie_std.l1           0.1179704  1.1341118   0.104 0.917173    
vol_us_corporate_bonds_serie_std.l1            0.0163934  0.0537717   0.305 0.760524    
vol_emerging_markets_government_bonds_serie_std.l1  -0.0025173  0.0901146  -0.028 0.977720    
vol_emerging_markets_corporate_bonds_serie_std.l1   -0.6953612  0.8515217  -0.817 0.414332    
vol_Gold_serie_std.l2                          0.3350965  0.1422237   2.356 0.018645 *  
vol_health_serie_std.l2                        1.5277925  1.0339109   1.478 0.139785    
vol_construction_serie_std.l2                 -0.0339146  0.0847689  -0.400 0.689175    
vol_finance_serie_std.l2                      -0.3312024  0.2830756  -1.170 0.242254    
vol_consumer_goods_serie_std.l2               -0.3886625  0.7026497  -0.553 0.580284    
vol_technology_serie_std.l2                    0.1062241  0.1146628   0.926 0.354444    
vol_real_estate_serie_std.l2                  -0.0608503  0.0635240  -0.958 0.338323    
vol_energy_serie_std.l2                       -2.0229342  1.2494574  -1.619 0.105729    
vol_metals_serie_std.l2                       -0.1437771  0.0865206  -1.662 0.096850 .  
vol_food_serie_std.l2                         -1.0206462  0.9644096  -1.058 0.290151    
vol_energy_commodities_serie_std.l2            0.0556780  0.0684002   0.814 0.415823    
vol_emerging_markets_index_serie_std.l2        0.5798180  0.3040690   1.907 0.056804 .  
vol_europe_index_serie_std.l2                 -0.2414792  0.3021030  -0.799 0.424277    
vol_us_index_serie_std.l2                      0.1387996  0.3182099   0.436 0.662787    
vol_asia_index_serie_std.l2                    0.0412930  0.1105549   0.374 0.708845    
vol_emerging_markets_currencies_serie_std.l2  -0.0022308  0.0137973  -0.162 0.871587    
vol_europe_currencies_serie_std.l2            -2.6827710  1.2059956  -2.225 0.026320 *  
vol_us_currencies_serie_std.l2                -0.6167563  2.9626096  -0.208 0.835128    
vol_asia_currencies_serie_std.l2               0.0623134  0.0926040   0.673 0.501154    
vol_crypto_serie_std.l2                       -0.5193129  0.0364977 -14.229  < 2e-16 ***
vol_european_corporate_bonds_serie_std.l2      0.5581801  0.9338609   0.598 0.550158    
vol_us_government_bonds_serie_std.l2           0.4231568  1.4673813   0.288 0.773115    
vol_us_corporate_bonds_serie_std.l2            0.0004631  0.0569480   0.008 0.993514    
vol_emerging_markets_government_bonds_serie_std.l2   0.0874462  0.0919575   0.951 0.341847    
vol_emerging_markets_corporate_bonds_serie_std.l2   -0.2063996  1.1331049  -0.182 0.855496    
vol_Gold_serie_std.l3                         -0.0674791  0.1435490  -0.470 0.638395    
vol_health_serie_std.l3                       -0.0163000  1.0411438  -0.016 0.987512    
vol_construction_serie_std.l3                 -0.0708702  0.0847992  -0.836 0.403486    
vol_finance_serie_std.l3                       0.3584248  0.2856157   1.255 0.209780    
vol_consumer_goods_serie_std.l3               -0.6908954  0.7088935  -0.975 0.329972    
vol_technology_serie_std.l3                   -0.0318257  0.1152788  -0.276 0.782543    
vol_real_estate_serie_std.l3                   0.0126790  0.0638927   0.198 0.842737    
vol_energy_serie_std.l3                        0.5540194  1.2517738   0.443 0.658153    
vol_metals_serie_std.l3                       -0.0955257  0.0878861  -1.087 0.277313    
vol_food_serie_std.l3                         -0.2690447  0.9739468  -0.276 0.782415    
vol_energy_commodities_serie_std.l3            0.0661620  0.0685368   0.965 0.334586    
vol_emerging_markets_index_serie_std.l3       -0.2677332  0.3067639  -0.873 0.382985    
vol_europe_index_serie_std.l3                  0.4058793  0.3087183   1.315 0.188883    
```

vol_us_index_serie_std.l3	-0.4452954	0.3210866	-1.387	0.165778	
vol_asia_index_serie_std.l3	-0.1559053	0.1111578	-1.403	0.161037	
vol_emerging_markets_currencies_serie_std.l3	0.0216401	0.0139503	1.551	0.121141	
vol_europe_currencies_serie_std.l3	1.9056780	1.2146095	1.569	0.116950	
vol_us_currencies_serie_std.l3	1.5681504	2.9828031	0.526	0.599184	
vol_asia_currencies_serie_std.l3	-0.0846366	0.0923614	-0.916	0.359682	
vol_crypto_serie_std.l3	-0.3776479	0.0398241	-9.483	< 2e-16	***
vol_european_corporate_bonds_serie_std.l3	-1.9036782	0.9620639	-1.979	0.048099	*
vol_us_government_bonds_serie_std.l3	-2.3708602	1.4883722	-1.593	0.111471	
vol_us_corporate_bonds_serie_std.l3	0.0462072	0.0575932	0.802	0.422554	
vol_emerging_markets_government_bonds_serie_std.l3	-0.1132503	0.0915433	-1.237	0.216311	
vol_emerging_markets_corporate_bonds_serie_std.l3	1.9602095	1.1732918	1.671	0.095073	.
vol_Gold_serie_std.l4	-0.0124061	0.1442845	-0.086	0.931496	
vol_health_serie_std.l4	-1.1526769	1.0303681	-1.119	0.263516	
vol_construction_serie_std.l4	0.1368666	0.0855962	1.599	0.110118	
vol_finance_serie_std.l4	-0.5144795	0.2875860	-1.789	0.073902	.
vol_consumer_goods_serie_std.l4	1.1674570	0.7086562	1.647	0.099763	.
vol_technology_serie_std.l4	-0.2191546	0.1167646	-1.877	0.060803	.
vol_real_estate_serie_std.l4	-0.0900495	0.0665944	-1.352	0.176592	
vol_energy_serie_std.l4	1.8551912	1.2623721	1.470	0.141960	
vol_metals_serie_std.l4	0.0410810	0.0875715	0.469	0.639083	
vol_food_serie_std.l4	0.8159310	0.9693927	0.842	0.400147	
vol_energy_commodities_serie_std.l4	0.0668040	0.0683988	0.977	0.328945	
vol_emerging_markets_index_serie_std.l4	0.0081373	0.3097560	0.026	0.979047	
vol_europe_index_serie_std.l4	0.0192092	0.3141032	0.061	0.951247	
vol_us_index_serie_std.l4	0.1967490	0.3226895	0.610	0.542179	
vol_asia_index_serie_std.l4	-0.0408635	0.1112957	-0.367	0.713571	
vol_emerging_markets_currencies_serie_std.l4	-0.0271625	0.0139786	-1.943	0.052259	.
vol_europe_currencies_serie_std.l4	-0.0700363	1.2148125	-0.058	0.954037	
vol_us_currencies_serie_std.l4	0.9103915	3.0239744	0.301	0.763428	
vol_asia_currencies_serie_std.l4	-0.1178332	0.0926330	-1.272	0.203632	
vol_crypto_serie_std.l4	0.0429602	0.0413964	1.038	0.299608	
vol_european_corporate_bonds_serie_std.l4	-0.7590358	0.9765839	-0.777	0.437190	
vol_us_government_bonds_serie_std.l4	1.1474992	1.5022387	0.764	0.445118	
vol_us_corporate_bonds_serie_std.l4	-0.0658293	0.0570615	-1.154	0.248898	
vol_emerging_markets_government_bonds_serie_std.l4	-0.0640852	0.0911898	-0.703	0.482352	
vol_emerging_markets_corporate_bonds_serie_std.l4	-0.2845568	1.1729695	-0.243	0.808365	
vol_Gold_serie_std.l5	0.2138832	0.1436911	1.488	0.136914	
vol_health_serie_std.l5	-0.0103524	1.0280513	-0.010	0.991967	
vol_construction_serie_std.l5	0.0908817	0.0852322	1.066	0.286534	
vol_finance_serie_std.l5	0.3798730	0.2893179	1.313	0.189464	
vol_consumer_goods_serie_std.l5	-0.4223651	0.7044756	-0.600	0.548935	
vol_technology_serie_std.l5	0.0400414	0.1175558	0.341	0.733459	
vol_real_estate_serie_std.l5	-0.0185240	0.0662980	-0.279	0.779987	
vol_energy_serie_std.l5	-2.6384102	1.2624345	-2.090	0.036857	*
vol_metals_serie_std.l5	0.0097119	0.0875992	0.111	0.911742	
vol_food_serie_std.l5	0.2013992	0.9607187	0.210	0.833993	
vol_energy_commodities_serie_std.l5	0.0495768	0.0679519	0.730	0.465802	
vol_emerging_markets_index_serie_std.l5	-0.0428492	0.3109320	-0.138	0.890417	
vol_europe_index_serie_std.l5	-0.0466919	0.3172912	-0.147	0.883035	
vol_us_index_serie_std.l5	-0.3991726	0.3281667	-1.216	0.224110	
vol_asia_index_serie_std.l5	0.0876202	0.1113791	0.787	0.431640	
vol_emerging_markets_currencies_serie_std.l5	0.0125650	0.0137931	0.911	0.362519	
vol_europe_currencies_serie_std.l5	-0.4397151	1.2114321	-0.363	0.716698	
vol_us_currencies_serie_std.l5	-0.7874487	3.0449466	-0.259	0.795987	
vol_asia_currencies_serie_std.l5	-0.0235629	0.0928752	-0.254	0.799772	
vol_crypto_serie_std.l5	-0.2079462	0.0413094	-5.034	5.63e-07	***
vol_european_corporate_bonds_serie_std.l5	-1.3568540	0.9976554	-1.360	0.174101	
vol_us_government_bonds_serie_std.l5	1.0390135	1.5172398	0.685	0.493614	
vol_us_corporate_bonds_serie_std.l5	0.0608651	0.0572012	1.064	0.287543	
vol_emerging_markets_government_bonds_serie_std.l5	0.0665121	0.0906528	0.734	0.463290	
vol_emerging_markets_corporate_bonds_serie_std.l5	0.9950273	1.1828692	0.841	0.400424	
vol_Gold_serie_std.l6	-0.3191844	0.1438752	-2.218	0.026730	*
vol_health_serie_std.l6	1.6251776	1.0332085	1.573	0.116026	
vol_construction_serie_std.l6	-0.0903716	0.0858650	-1.052	0.292813	

vol_finance_serie_std.l6	-0.2684235	0.2934322	-0.915	0.360516	
vol_consumer_goods_serie_std.l6	-0.7506051	0.7033371	-1.067	0.286118	
vol_technology_serie_std.l6	0.3345364	0.1178392	2.839	0.004612	**
vol_real_estate_serie_std.l6	-0.0062721	0.0656311	-0.096	0.923883	
vol_energy_serie_std.l6	1.4505109	1.2673021	1.145	0.252643	
vol_metals_serie_std.l6	-0.0553298	0.0871401	-0.635	0.525594	
vol_food_serie_std.l6	-0.1292765	0.9583909	-0.135	0.892725	
vol_energy_commodities_serie_std.l6	-0.0371387	0.0671257	-0.553	0.580192	
vol_emerging_markets_index_serie_std.l6	0.3634840	0.3145295	1.156	0.248083	
vol_europe_index_serie_std.l6	0.1009473	0.3232164	0.312	0.754857	
vol_us_index_serie_std.l6	0.1397460	0.3279403	0.426	0.670096	
vol_asia_index_serie_std.l6	-0.1504871	0.1114134	-1.351	0.177072	
vol_emerging_markets_currencies_serie_std.l6	0.0068500	0.0138311	0.495	0.620518	
vol_europe_currencies_serie_std.l6	0.2740543	1.2091978	0.227	0.820746	
vol_us_currencies_serie_std.l6	-2.9157392	3.0537628	-0.955	0.339892	
vol_asia_currencies_serie_std.l6	0.0448569	0.0926433	0.484	0.628350	
vol_crypto_serie_std.l6	-0.0164060	0.0416542	-0.394	0.693762	
vol_european_corporate_bonds_serie_std.l6	2.0034668	1.0188266	1.966	0.049504	*
vol_us_government_bonds_serie_std.l6	-0.7172579	1.5354174	-0.467	0.640493	
vol_us_corporate_bonds_serie_std.l6	-0.0549144	0.0575883	-0.954	0.340516	
vol_emerging_markets_government_bonds_serie_std.l6	-0.0654537	0.0906372	-0.722	0.470359	
vol_emerging_markets_corporate_bonds_serie_std.l6	-1.7716928	1.1953127	-1.482	0.138580	
vol_Gold_serie_std.l7	0.2436761	0.1436898	1.696	0.090204	.
vol_health_serie_std.l7	-0.0298924	1.0333213	-0.029	0.976927	
vol_construction_serie_std.l7	-0.0110502	0.0850366	-0.130	0.896633	
vol_finance_serie_std.l7	0.1478525	0.2936693	0.503	0.614740	
vol_consumer_goods_serie_std.l7	-0.0177115	0.7089441	-0.025	0.980073	
vol_technology_serie_std.l7	0.1308391	0.1182665	1.106	0.268841	
vol_real_estate_serie_std.l7	-0.0552579	0.0655996	-0.842	0.399779	
vol_energy_serie_std.l7	-0.4031308	1.2773551	-0.316	0.752369	
vol_metals_serie_std.l7	-0.0606139	0.0868390	-0.698	0.485325	
vol_food_serie_std.l7	-0.2896651	0.9477732	-0.306	0.759948	
vol_energy_commodities_serie_std.l7	-0.0475938	0.0664121	-0.717	0.473749	
vol_emerging_markets_index_serie_std.l7	-0.2915530	0.3144896	-0.927	0.354099	
vol_europe_index_serie_std.l7	0.1135418	0.3227628	0.352	0.725071	
vol_us_index_serie_std.l7	0.1252631	0.3287061	0.381	0.703220	
vol_asia_index_serie_std.l7	0.0380971	0.1108491	0.344	0.731151	
vol_emerging_markets_currencies_serie_std.l7	-0.0001078	0.0136543	-0.008	0.993700	
vol_europe_currencies_serie_std.l7	-0.6850682	1.2115236	-0.565	0.571879	
vol_us_currencies_serie_std.l7	1.0034534	3.0444675	0.330	0.741767	
vol_asia_currencies_serie_std.l7	0.1261485	0.0926499	1.362	0.173621	
vol_crypto_serie_std.l7	-0.1390011	0.0415757	-3.343	0.000856	***
vol_european_corporate_bonds_serie_std.l7	-0.6851285	1.0247496	-0.669	0.503906	
vol_us_government_bonds_serie_std.l7	-0.9466686	1.5415765	-0.614	0.539285	
vol_us_corporate_bonds_serie_std.l7	0.0630051	0.0571313	1.103	0.270354	
vol_emerging_markets_government_bonds_serie_std.l7	-0.0492333	0.0900557	-0.547	0.584699	
vol_emerging_markets_corporate_bonds_serie_std.l7	0.4937691	1.2005258	0.411	0.680939	
vol_Gold_serie_std.l8	-0.1056568	0.1444404	-0.731	0.464639	
vol_health_serie_std.l8	-1.6980151	1.0294925	-1.649	0.099363	.
vol_construction_serie_std.l8	0.0984846	0.0845801	1.164	0.244522	
vol_finance_serie_std.l8	-0.2255329	0.2924251	-0.771	0.440728	
vol_consumer_goods_serie_std.l8	0.8484057	0.7039834	1.205	0.228410	
vol_technology_serie_std.l8	-0.0776411	0.1176599	-0.660	0.509474	
vol_real_estate_serie_std.l8	0.0957136	0.0662866	1.444	0.149048	
vol_energy_serie_std.l8	0.2285669	1.2748579	0.179	0.857745	
vol_metals_serie_std.l8	0.0357934	0.0864620	0.414	0.678973	
vol_food_serie_std.l8	-0.4223347	0.9404509	-0.449	0.653467	
vol_energy_commodities_serie_std.l8	0.0280921	0.0672270	0.418	0.676126	
vol_emerging_markets_index_serie_std.l8	0.2319688	0.3109694	0.746	0.455858	
vol_europe_index_serie_std.l8	-0.4269095	0.2361011	-1.808	0.070860	.
vol_us_index_serie_std.l8	0.0806873	0.3174717	0.254	0.799424	
vol_asia_index_serie_std.l8	0.0152819	0.1112364	0.137	0.890754	
vol_emerging_markets_currencies_serie_std.l8	-0.0033396	0.0133360	-0.250	0.802312	
vol_europe_currencies_serie_std.l8	1.5140425	1.2146682	1.246	0.212864	
vol_us_currencies_serie_std.l8	-1.9698191	3.0470894	-0.646	0.518120	

```
vol_asia_currencies_serie_std.l8                    -0.0030231  0.0926484  -0.033 0.973976
vol_crypto_serie_std.l8                             -0.1141904  0.0415772  -2.746 0.006124 **
vol_european_corporate_bonds_serie_std.l8           -0.7900393  1.0369798  -0.762 0.446307
vol_us_government_bonds_serie_std.l8                 0.6986754  1.5404084   0.454 0.650233
vol_us_corporate_bonds_serie_std.l8                  0.0039878  0.0566155   0.070 0.943860
vol_emerging_markets_government_bonds_serie_std.l8  -0.1553909  0.0877422  -1.771 0.076845 .
vol_emerging_markets_corporate_bonds_serie_std.l8    0.8865093  1.1888200   0.746 0.456008
 [ getOption("max.print") est atteint -- 101 lignes omises ]
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 0.1388 on 1077 degrees of freedom
Multiple R-Squared: 0.6158,Adjusted R-squared: 0.5088
F-statistic: 5.755 on 300 and 1077 DF,  p-value: < 2.2e-16
```