The Impact of Gold Price Volatility on the Cryptocurrency Market: An Empirical Analysis Based on the VAR Model

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Abstract. With the rapid growth of the cryptocurrency market, researchers increasingly study the price fluctuations and market behavior of digital assets. Gold, as a traditional safe-haven asset, often shows an inverse relationship with high-risk financial assets. Recently, scholars have focused on how gold market volatility affects cryptocurrencies, exploring potential co-movement or substitution effects. This study uses Python and econometric tools, including the Vector Autoregression (VAR) model, Granger causality test, impulse response functions, and forecast error variance decomposition, to analyze the impact of gold price changes on Bitcoin and Ethereum. Using weekly closing prices from 2018 to 2024, the results show that Bitcoin's price is positively influenced by gold futures in the short to medium term, while gold shows a negative feedback response to Bitcoin's returns with a two-period lag. Ethereum appears more independent and less affected by gold or Bitcoin. Strong interlinkages exist between Bitcoin and Ethereum, with Bitcoin playing a dominant role in influencing Ethereum's price. This study has improved the understanding of the connections between cryptocurrencies and traditional assets., which also provides investors with insightful information on portfolio management.

1 Introduction

As an emerging financial market, the cryptocurrency market shares certain similarities with traditional financial markets, while also exhibiting notable differences. One of the most prominent distinctions is the generally higher volatility observed in the cryptocurrency market. Due to low entry barriers and the widespread use of leverage, cryptocurrencies are subject to greater risks and price fluctuations, and are more susceptible to extreme events. Among the numerous cryptocurrencies, Bitcoin (BTC) and Ethereum (ETH) stand out as the most representative.

Gold, as a traditional safe-haven asset, has attracted increasing attention regarding whether it serves as a substitute or complement to cryptocurrencies. Existing research has looked at the connection between gold and Bitcoin, but systematic analysis involving other major cryptocurrencies, such as Ethereum, remains limited. By examining the dynamic links between gold and the main cryptocurrencies, this study aims to close this gap. In order to

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examine the transmission mechanisms via which changes in the price of gold impact the cryptocurrency market, this study uses the Vector Autoregression (VAR) model in conjunction with Granger causality tests, impulse response functions, and prediction error variance decomposition.

2 Literature Review

Recently, a increasing body of literature has focused on the volatility of cryptocurrency prices and the potential influence of traditional safe-haven assets, particularly gold.

Aliu et al. employed VAR, Structural VAR (SVAR) models, and wavelet coherence analysis to study the influence of Bitcoin on gold, the VIX index, and the U.S. dollar index [1]. Their findings suggest a significant interactive relationship between Bitcoin and gold, where positive shocks in Bitcoin tend to increase the price of gold. Additionally, Bouri et al. looked into the ability to hedge of gold, Bitcoin, commodities, and stock markets in various nations using wavelet coherence [2]. They found that under certain extreme conditions, Bitcoin might even outperform gold as a hedge, suggesting a potential substitutability.

Corbet et al. investigated how cryptocurrencies and other financial assets interact dynamically and discovered that while Bitcoin exhibits hedging properties under specific conditions, its behavior can differ significantly depending on the external financial environment [3]. Similarly, Dyhrberg applied GARCH models and demonstrated that Bitcoin shares several volatility characteristics with both gold and the dollar, situating it between traditional currencies and commodities [4]. Klein, Pham Thu, and Walther conducted a comparative analysis of Bitcoin and gold regarding volatility, correlation, and portfolio performance [5]. Their findings reveal that Bitcoin exhibits significantly higher volatility than gold and does not provide the same hedging effectiveness, particularly during periods of market stress. This suggests that although Bitcoin is frequently called "digital gold," it may not yet fulfill the same safe-haven role in financial markets.

Aliyah et al. utilized the Autoregressive Distributed Lag (ARDL) model to analyze the determinants of Ethereum's price, revealing that in the short term, the EUR/USD exchange rate has a significant effect [6]. Within the crypto market, BTC, LTC, and XMR were shown to have significant impacts on ETH, while gold had no notable influence on Ethereum’s price.

Moreover, Phillips, Wu, and Yu introduced the Supremum Augmented Dickey-Fuller (SADF) test to detect explosive behavior in financial time series, laying the foundation for econometric bubble detection. Their framework allows for the identification of periods where asset prices deviate significantly from fundamental values, capturing early signs of exuberance in markets such as the NASDAQ [7]. Ji et al. used a VAR model to examine the dynamic connectedness among major cryptocurrencies, concluding that Bitcoin, as the largest by market capitalization, often acts as the primary source of shocks within the market [8].

Selmi et al. compared Bitcoin and gold in the context of oil price movements, finding that Bitcoin may act as a better diversifier under certain market conditions [9]. Wątorek et al. emphasized the complex, multi-scale nature of cryptocurrency markets and argued that linear models might be insufficient to fully capture their dynamics [10].

Overall, the literature generally supports the view that there exists some form of linkage between gold and the cryptocurrency market, as well as interconnections among various cryptocurrencies. While methodologies differ across studies, most favor models that can capture the dynamic and time-varying relationships among variables. However, existing research tends to focus either on inter-cryptocurrency relationships or the BTC-gold interaction. Few studies incorporate multiple cryptocurrencies in examining their joint relationship with gold. This study addresses this gap by including both BTC and ETH to represent the cryptocurrency market and to analyze their respective relationships with gold.

3 Data and Variable Description

3.1 Data Sources and Processing

This study utilizes weekly time-series data for gold prices, Ethereum prices, and Bitcoin prices spanning the period from 2018 to 2024. This timeframe encompasses several critical phases in the evolution of the cryptocurrency market, such as the "crypto winter" of 2018, the bull market of 2020–2021, the sharp correction in 2022, and the gradual recovery from 2023 to 2024. These variations help to reveal the dynamic interactions among the variables under different market conditions.

Gold prices are represented by the weekly closing prices of London gold futures. Bitcoin and Ethereum prices are sourced from Investing.com and are also recorded as weekly closing prices. To ensure stationarity, all price series are transformed using natural logarithms and differenced once before further modeling.

As cryptocurrency markets operate 24/7, while the gold futures market does not, aligning the frequency of all three variables is necessary. Therefore, all data series are aggregated to a weekly frequency to ensure consistency and comparability across variables.

3.2 Variable Definitions

The variables selected for this study include gold futures prices, Bitcoin prices, and Ethereum prices. The weekly prices of these three assets serve as the primary data for analysis. Bitcoin and Ethereum are chosen due to their status as the most prominent cryptocurrencies, making them suitable representatives for studying the broader crypto market's relationship with gold.

4 Research Method

4.1 Data Preprocessing and Stationarity Test

Following data collection, first-order differencing and logarithmic processing were used to normalize the data and guarantee the time series' stationarity. The Augmented Dickey-Fuller (ADF) test was then used to assess each variable's stationarity. The null hypothesis of a unit root is disproved if the p-value is statistically significant, which shows that the time series is stationary. This provides the framework needed to construct the upcoming VAR model.

4.2 Construction of the VAR Model and Lag Order Selection

In this study, a VAR model was built using the log returns of gold, Bitcoin, and Ethereum. The model is defined as:

$$Y_t=[Gold_t,BTC_t,ETH_t]' \tag{1}$$

where t represents the time index (weekly data). The VAR(p) model is expressed as:

$$Y_t=c+A_1Y_1+A_2Y_2+\cdots+A_pY_p+\varepsilon_t \tag{2}$$

Here, c denotes the vector of constant terms, and A_p represents a 3×3 coefficient matrix that reflects the influence of the p th-order lag. ε_t is the vector of residuals, which is assumed to follow a white noise process with zero mean and a covariance matrix Σ.

The best lag order is then determined in this study using the Bayesian Information

Criterion (BIC) and the Akaike Information Criterion (AIC). A better balance between model fit and parsimony is shown by lower AIC and BIC values. The best lag is chosen based on the criteria by contrasting models with various lag orders.

After estimating the model parameters, significance tests are performed on the regression coefficients of each variable, including a likelihood ratio test for the overall model. Additionally, to ensure that the VAR model assumptions are satisfied, the residuals are tested for autocorrelation and normality. These diagnostic checks are essential to ensure the robustness and validity of the model.

4.3 Granger Causality Test

The Granger causality test is also used in this study to investigate whether there is significant predictive power between pairs of the three variables: gold futures prices, Bitcoin prices, and Ethereum prices. One variable is said to Granger-cause another if the lagged terms of the former greatly increase the prediction accuracy of the latter. In particular, hypothesis testing is carried out using the ideal lag order previously established using the AIC and BIC criteria. A statistically significant p-value indicates that there is a substantial predictive relationship between the first and second variables.

4.4 Impulse Response Function Analysis

Impulse response functions are used to observe how other variables respond over time when one variable in the model receives a one-time shock. Under the VAR framework, the impulse response function effectively captures the pairwise dynamic interactions among the three variables. It makes it easier to see how an abrupt shift to one variable affects another over time.

4.5 Forecast Error Variance Decomposition

The amount that shocks to each variable contribute to the prediction error variance of a target variable over time is measured by forecast error variance decomposition. It is employed in the VAR model framework to examine which external factors influence a target variable's fluctuations over various time periods. Variance decomposition plots are frequently used to show the results. In this case, the time-varying impact of these factors can be evaluated by analyzing the percentage of a target variable's forecast error variation that can be ascribed to shocks from other variables.

5 Empirical Results Analysis

5.1 VAR Model Fitting Results

The code output is shown in Table 1. The results show that the ADF test p-values for the log-differenced time series are significantly below 0.05, confirming that the series are stationary, which satisfies the prerequisite for constructing a VAR model. The AIC and BIC results are presented in Table 2. It is observed that both AIC and BIC reach their lowest values at lag order 0. However, a VAR model with lag 0 only contains constant terms and residuals, which does not meet the objective of this study.

Therefore, to facilitate further analysis and considering the possibility of delayed information transmission in the cryptocurrency market, the lag order was manually set to 2.

Subsequent results confirm that with this lag order, the estimated model parameters are significant and the model effectively captures the relationships between variables, aligning well with the research objectives of this paper.

Table 1. Results of ADF Test

Sequence type	Variable	ADF Statistic	P-value	Stationarity Test
Logarithmic Sequence	Gold	-0.1053	0.9489	Non-stationary
Logarithmic Sequence	BTC	-0.4523	0.901	Non-stationary
Logarithmic Sequence	ETH	-0.8202	0.8131	Non-stationary
Logarithmic Difference Sequence	Gold	-20.8827	0.0	Stationary
Logarithmic Difference Sequence	BTC	-17.3583	0.0	Stationary
Logarithmic Difference Sequence	ETH	-17.7965	0.0	Stationary

Table 2. Results of Lag Order Selection for VAR Model

Lag Order	AIC	BIC	FPE	HQIC
0	-18.02*	-17.99*	1.486e-08*	-18.01*
1	-18.01	-17.88	1.506e-08	-17.96
2	-17.99	-17.76	1.541e-08	-17.90
3	-17.98	-17.65	1.553e-08	-17.85
4	-17.95	-17.52	1.607e-08	-17.78
5	-17.93	-17.41	1.635e-08	-17.72
6	-17.93	-17.30	1.642e-08	-17.68
7	-17.88	-17.16	1.718e-08	-17.59
8	-17.86	-17.04	1.752e-08	-17.54
9	-17.85	-16.93	1.780e-08	-17.48
10	-17.83	-16.82	1.801e-08	-17.43

After determining the optimal lag order, a corresponding VAR model was further constructed in this study. The modeling results are shown in Tables 3, 4, and 5.

Table 3 presents the VAR model estimation results for gold futures. The constant term is significant, with a value of 0.002099, indicating that even when other variables are zero, the average return on gold futures is 0.21%. Among the lagged terms, only the second lag of

BTC is statistically significant, with a coefficient of -0.0432. This suggests that the value of BTC two periods ago has a negative impact on the current return of gold futures, which is consistent with expectations. The possible reason is that when the cryptocurrency market yields higher returns, investors tend to reallocate funds away from safe-haven assets like gold to pursue higher profits. In contrast, all lag terms of ETH are insignificant, indicating that its historical values do not significantly influence gold futures returns.

Table 4 shows the VAR model results for BTC. The constant term is 0.004422, implying that the average return of BTC after controlling for other variables is not statistically significant. Among all lagged terms, only the first lag of BTC itself is significant, with a coefficient of 0.023828. This indicates that the return of BTC in the previous period has a positive effect on its current return. A possible explanation is that a rise in BTC price in the previous period boosts investor sentiment, leading to expectations of continued growth in the current period. Additionally, the second lag of gold futures also has a significant positive effect on BTC returns, with a coefficient of 0.5002. This implies that fluctuations in gold prices may positively influence BTC returns with a delay of two periods. The rationale could be that strong performance in gold two periods ago prompts investors to reconsider their asset allocation strategies to hedge risk, possibly shifting part of their positions to crypto assets like BTC.

Table 5 presents the results for the ETH equation. The constant term is not significant, indicating that after controlling for other variables, the average return of ETH is not statistically significant. Moreover, all lagged terms are insignificant, suggesting that ETH prices cannot be effectively explained by its own or other variables' historical values. Its volatility may be influenced by factors outside the model.

According to the residual correlation matrix shown in Table 6, there is a high residual correlation between BTC and ETH at 0.82708, indicating a potentially deeper underlying relationship between the two, which is not well captured by the VAR model. Meanwhile, the residual correlations between gold futures and BTC/ETH are low, suggesting that the VAR model has effectively explained the relationships among these variables.

Table 3. Data for VAR Model of Gold Futures Prices

Variable	Coefficient	Standard Error	T-Statistic	P-value
const	0.002099	0.001061	1.978	0.048
L1.Gold	-0.095617	0.053125	-1.800	0.072
L1.BTC	0.023828	0.020223	1.178	0.239
L1.ETH	-0.008940	0.015260	-0.586	0.558
L2.Gold	0.001619	0.053269	0.030	0.976
L2.BTC	-0.043189	0.019457	-2.220	0.026
L2.ETH	0.022169	0.014681	1.510	0.131

Table 4. Data for VAR Model of BTC Prices

Variable	Coefficient	Standard Error	T-Statistic	P-value
const	0.004422	0.004921	0.899	0.369

L1.Gold	-0.278845	0.246393	-1.132	0.258
L1.BTC	0.185720	0.093792	1.980	0.048
L1.ETH	-0.078708	0.070774	-1.112	0.266
L2.Gold	0.500157	0.247058	2.024	0.043
L2.BTC	0.054079	0.090240	0.599	0.549
L2.ETH	-0.050822	0.068091	-0.746	0.455

Table 5. Data for VAR Model of ETH Prices

Variable	Coefficient	Standard Error	T-Statistic	P-value
const	0.001758	0.006520	0.270	0.787
L1.Gold	-0.139336	0.326440	-0.427	0.669
L1.BTC	0.173507	0.124262	1.396	0.163
L1.ETH	-0.025164	0.093767	-0.268	0.788
L2.Gold	0.472122	0.327322	1.442	0.149
L2.BTC	-0.026310	0.119557	-0.220	0.826
L2.ETH	0.023867	0.090212	0.265	0.791

Table 6. Residual Correlation Matrix

	Gold	BTC	ETH
Gold	1.000000	0.143087	0.124935
BTC	0.143087	1.000000	0.827080
ETH	0.124935	0.827080	1.000000

5.2 Granger Causality Test Results

The results of the Granger causality tests are shown in Table 7. Regarding the choice of lag order, if the study continues with the previously selected lag order of 2, no significant relationships between variables are observed. Furthermore, this study finds that only when the lag order is set to 3 do significant causal relationships emerge.

As shown in Table 7, only ETH has a significant Granger causal effect on BTC at lag 3. This indicates that historical movements in ETH have some predictive power over BTC. A possible explanation is that, as the second-largest cryptocurrency, changes in ETH prices can influence investor sentiment and trading behavior. However, this transmission effect may require some time to spread to other cryptocurrencies, particularly to major ones like BTC. No significant Granger causality is found among the other variable pairs, suggesting that the historical values of those variables do not significantly improve the prediction of others. This may be due to the fact that financial data often contain a great deal of noise, which can obscure potential causal relationships and lead to non-significant test results.

Table 7. The results of Granger causality analysis

Variable Relationship	Test Statistic	P-value	Causal Relationship
BTC → Gold	6.1075	0.1065	NO
ETH → Gold	2.3915	0.4952	NO
Gold → BTC	5.0132	0.1708	NO
ETH → BTC	9.7747	0.0206	YES
Gold → ETH	3.4465	0.3278	NO
BTC → ETH	5.4685	0.1405	NO

5.3 Impulse Response Function Results

The results of the impulse response functions reflect how other variables dynamically respond after one variable receives a shock. These results are shown in Figure 1. The figure illustrates that for all variables, the response to their own shocks is positive and clear. This indicates that there is momentum in the price movements of financial assets—in other words, When an investment asset's price fluctuates in the near term, this pattern usually lasts for a short time.

For gold futures prices, the short-term response to a BTC shock is negative, but in the long term, it shifts from negative to positive. This suggests the existence of a possible positive transmission mechanism, which is in line with the results from the previous VAR model fitting. However, the confidence interval includes zero in the short term, indicating that the short-term impulse response is not statistically significant and it cannot be conclusively determined whether this effect is deterministic. In the long run, however, the effect appears to be significant.

Other subplots show that the negative impact of ETH on BTC is highly significant, indicating a clear transmission mechanism between the two. Moreover, the negative effect intensifies over time, suggesting a possible substitution effect between BTC and ETH. As the second-largest cryptocurrency, a price shock in ETH may divert some funds away from BTC, thus exerting downward pressure on BTC prices.

Conversely, the impact of BTC on ETH is positive and significant, but the magnitude is very small, making the effect not very noticeable in the short term. As the most important cryptocurrency in the market, BTC's price trends influence overall market sentiment. When BTC prices rise, they may attract more capital into the crypto market, thereby also driving up ETH prices, as ETH is also a major asset in this market. The smaller magnitude of the effect may be because ETH is more driven by technology and application scenarios, while BTC is more speculative in nature.

Other subplots do not show any significant impulse effects.

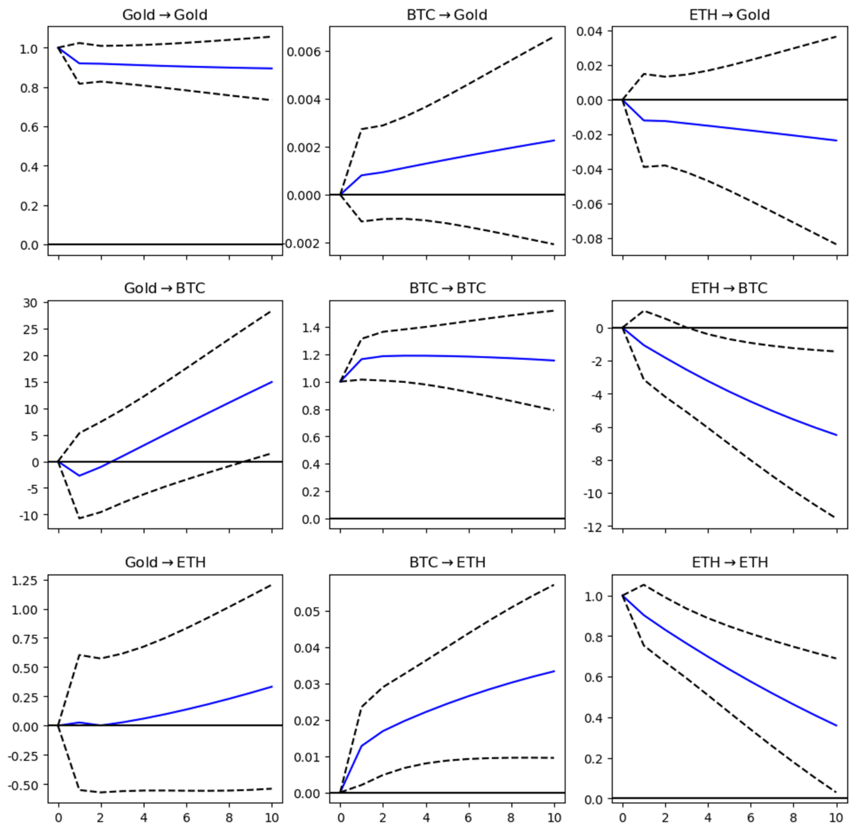

Fig. 1. Impulse Response Function Diagram

5.4 Forecast Error Variance Decomposition Results

The division of variance results according to the VAR model are shown in Figure 2. The results show that fluctuations in gold futures prices are almost entirely explained by their own past values, with other variables having very little influence. This indicates that gold exhibits a high degree of independence within the model. From an economic perspective, as a traditional safe-haven asset, gold prices are typically more influenced by macroeconomic policies and political stability than by the movements of cryptocurrencies.

While BTC's fluctuations are primarily driven by its own factors, the explanatory power of ETH increases as the forecast horizon extends. Although this influence remains relatively small, it still reveals a certain level of interconnection between the two, reflecting the fact that mainstream cryptocurrencies often exhibit correlated behavior within the crypto market. ETH's volatility is significantly influenced by Bitcoin. Moreover, as the number of forecast periods increases, the proportion of its variance explained by BTC rises continuously. This proportion even exceeds the portion explained by ETH's own past values, highlighting BTC's dominant position in the digital asset market.

Overall, the two cryptocurrency variables demonstrate strong interlinkage, while gold appears relatively independent and is less affected by cryptocurrency market fluctuations.

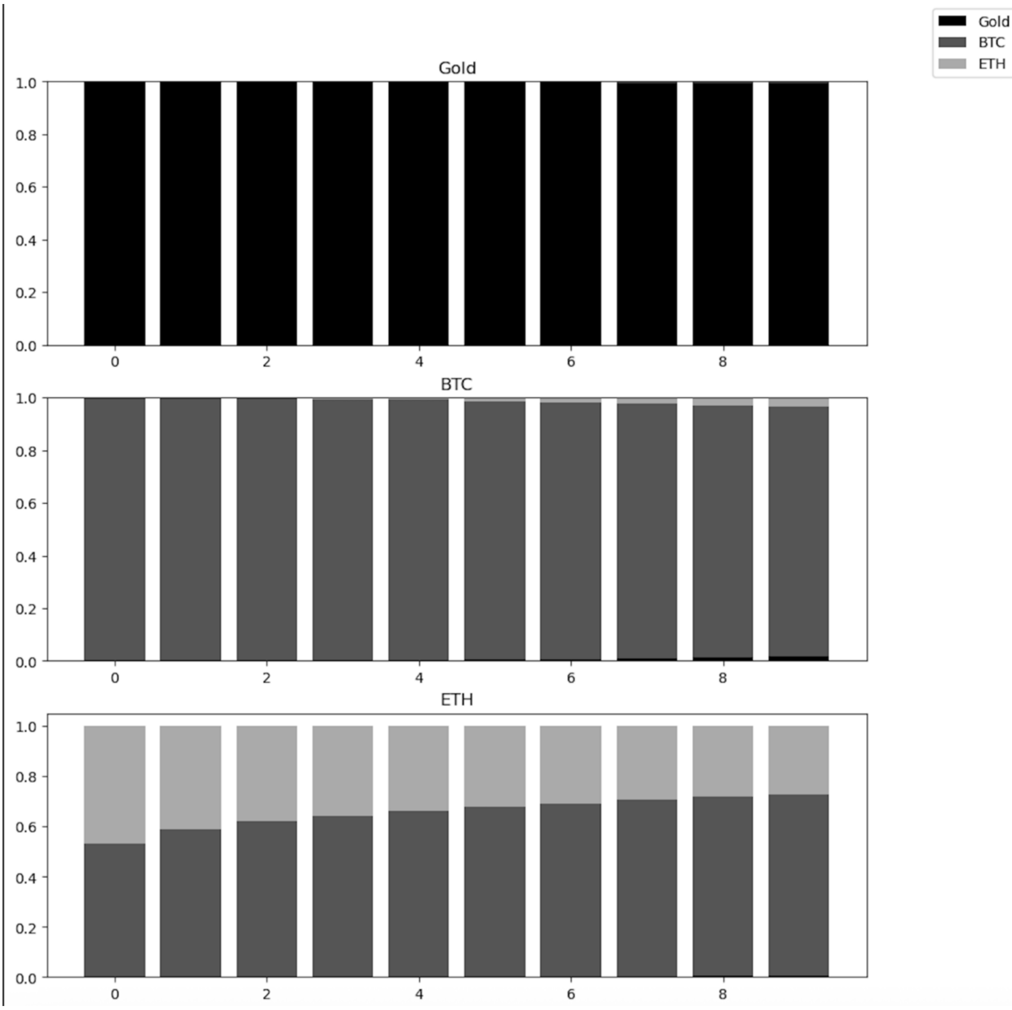

Fig. 2. Forecast Error Variance Decomposition Diagram

6 Conclusions

This paper investigates the relationships among BTC, ETH, and gold futures by constructing a VAR model, conducting Granger causality tests, analyzing impulse response functions, and performing forecast error variance decomposition. According to the VAR model results, BTC is positively influenced by gold futures prices in the short to medium term, while gold futures experience a negative impact from BTC lagged by two periods. ETH, however, does not exhibit significant influence from either BTC or gold futures.

The Granger causality test further validates the mutual influence between cryptocurrencies, demonstrating a linkage between BTC and ETH. Results from the impulse response functions also confirm the interactions between these two cryptocurrencies and verify BTC's response to gold futures within the VAR framework. Similarly, the forecast error variance decomposition illustrates that the influence among cryptocurrencies grows over time, with BTC exerting a relatively stronger and dominant effect on ETH.

Overall, the study confirms the internal connectivity within the cryptocurrency market, especially BTC's leading role, which aligns with Bitcoin's status as the largest cryptocurrency by market capitalization. Meanwhile, it reveals a certain degree of interaction between Bitcoin and gold futures, showing that traditional safe-haven assets and crypto assets are somewhat linked under the current financial environment. The findings suggest that investors could consider gold price movements as an auxiliary indicator for observing short-term trends in the BTC market, particularly when gold prices exhibit abnormal fluctuations that might delay their impact on Bitcoin prices. Moreover, BTC's dominant position and the interconnectedness among cryptocurrencies remind traders to monitor Bitcoin's price trends closely when investing in ETH.

This study has some limitations. Regarding variable selection, only mainstream cryptocurrencies were chosen, excluding emerging coins, which may limit the ability to fully reflect the relationship between the entire cryptocurrency market and traditional safe-haven assets. Additionally, on-chain data was not included, resulting in an incomplete understanding of the factors influencing ETH's price. In terms of model choice, the study employs a VAR model, which is linear and typically unable to capture nonlinear relationships between variables. Future research may consider alternative models that can better account for such nonlinearities.

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