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Research paper

The Short-Term Dynamic Effects and Structural Changes in Bitcoin and US Dollar Gold- A Time Series Analysis

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Abstract

This research investigates the dynamic link between Bitcoin and Gold (USD) using an econometric approach that includes structural breaks, cointegration, and Vector Autoregressive (VAR) models. Structural break tests reveal substantial regime changes in the market behavior of both assets, which correspond to large macroeconomic events such as the COVID-19 epidemic and geopolitical tensions. The Johansen cointegration test identifies possible long-term equilibrium correlations, stressing Bitcoin's speculative nature and Gold's conventional safe-haven position. VAR modeling delves further into short-term dynamics, emphasizing the interdependence and causal relationships between the two assets. Impulse response functions and variance decomposition give insights into how Bitcoin and Gold react to shocks, demonstrating their usefulness in diversification methods. The results highlight the significance of combining structural breaks and cointegration studies into financial market modeling and conclusions. This study adds to the burgeoning literature on bitcoin and conventional asset inter-actions, with practical consequences for investors and governments. Future developments might investigate nonlinear dynamics or regime-dependent models to grasp these complicated interactions better.

Keywords: *Bitcoin; Gold; Structural Breaks; Cointegration; Vector Autoregressive (VAR) Model; Financial Markets; Safe-Haven Assets; Cryptocurrency.*

1. Introduction

As a decentralized digital asset, Bitcoin has revolutionized the world of international finance since its creation. Its decentralized nature, high transferability, and fixed quantity have made it a popular cryptocurrency since its launch in 2009 (Nakamoto, 2008). These qualities have made Bitcoin a popular replacement for more traditional kinds of investing; some people even see parallels between the revered precious metal gold (Baur et al., 2015). Many refer to Bitcoin as "digital gold," and the theory that it may be a haven for investors amid economic crisis has generated fierce arguments (Cheah & Fry, 2015). Gold has long been regarded as a fundamental part of investment portfolios because of its historical record of value retention in the face of market volatility and geopolitical upheaval (Blose, 2010). Because of its inverse link with riskier assets like equities, Ghosh et al. (2004) claim it is a good tool for diversifying portfolios and lowering risk. Conversely, Bitcoin is a new asset class with its own unique market dynamics and risk-return profile (Dyhrberg, 2016). Investors, portfolio managers, and legislators should know how Bitcoin and gold interact with one another as they respond differently to economic shocks, market emotion, and world crises (Selmi et al., 2018). Although some research has shown that gold and Bitcoin are interchangeable, others have indicated that in certain cases they could be complementary assets (Bouri et al., 2017; Shahzad et al., 2019). This difference in outcomes emphasizes the necessity of a more robust approach to investigate the equilibrium and dynamic interaction between these two assets over the long term. Conventional models also tend to overlook structural breaks brought on by major economic fluctuations, new laws, or technology advancements (Perron, 1989). Ignoring structural discontinuities (Zivot & Andrews, 1992) would lead to erroneous estimations of the cointegration link between Bitcoin and gold. With an eye on structural fractures, this study looks at Bitcoin's relationship with US dollar gold prices in detail to close these gaps. Using the Chow Test for Structural Breaks, the paper detects significant changes in the time series data. These developments could be the result of changes in investor behavior, regulatory developments, or periods of more market stress (Chow, 1960). By taking these structural breaks into account, the study confirms that the analysis fairly captures the always-shifting character of the relationship between the two assets. The Johansen Cointegration Test is used to determine if Bitcoin and gold are in an equilibrium relationship over the long run after structural flaws are discovered (Johansen, 1988). Should the Johansen test find no cointegration, it implies that gold and Bitcoin have no long-term equilibrium connection. Under these circumstances, the short-term dynamic interactions among many assets are investigated using a Vector Autoregression (VAR) model. In the absence of cointegration, VAR is especially useful here as it does not impose long-term equilibrium limitations, thus fitting for studying short-term fluctuations and interactions. With an eye on how these assets react to economic shocks and market mood, the study investigates short-term dynamics and interactions using the VAR model. In the near run, gold and bitcoin prices are linked; the VAR model helps to represent their dynamic interaction. Understanding their co-movements and temporary changes calls for this method. The results of this research could teach legislators as well as financial professionals a lot. By showing the impact of structural fractures on their link, this research offers a more complex picture of Bitcoin and gold's potential purposes as hedging tools and safe-haven assets. This study might guide investors in portfolio allocation during unpredictable economic times. On the other hand, these results might enable legislators to better understand the wider consequences of digital assets and their interactions with more traditional financial instruments, including gold (Corbet et al., 2019). This research provides pertinent and helpful insights into the evolving dynamics of modern financial markets, which are experiencing rapid growth in both technology and market volatility. Incorporating structural breaks and short-term dynamic analysis helps better grasp the link between digital and traditional safe-haven assets, therefore offering helpful information for negotiating the challenges of a digitalized financial environment.

2. Literature Review

Bouri et al. (2017) used a dynamic conditional correlation model to investigate Bitcoin's potential as a hedge and haven for significant global stock indexes, bonds, oil, gold, the overall commodities index, and the US dollar index. The data for each day and week goes from July 2011 to December 2015. The empirical findings demonstrated that Bitcoin functions inadequately as a hedge and is only appropriate for diversification objectives. But Bitcoin can only be a good haven when Asian markets drop a lot every week. They also demonstrated that Bitcoin's hedging and haven features change over time.

Klein et al. (2018) examined and contrasted the conditional variance characteristics of Bitcoin, Gold, and other assets, revealing structural discrepancies. Second, they used a BEKK-GARCH model to figure out time-varying conditional correlations. Gold is a vital part of the financial markets, especially when things go wrong and people want to buy safe assets. Their findings indicated that Bitcoin functions in direct opposition, exhibiting a positive correlation with declining markets. Finally, they looked at Bitcoin's qualities as a portfolio component and found no proof that it could be used for steady hedging. They concluded that Bitcoin and Gold are fundamentally distinct assets and have different connections to stock markets. Their findings are true for the CRIX index of all cryptocurrencies. Bitcoin currently does not exhibit any unique characteristics of Gold, other than its asymmetric reaction to variance.

Pelagidis and Kostika (2022) discussed euro area digital payments, cryptocurrency trading, and the ECB's plan to develop a central bank digital currency. They showed cointegration between cryptocurrencies, stablecoins, and traditional financial assets. Financial markets and business models may be affected by the digital euro due to rising digital payments and cryptocurrency usage. In the past two years, central banks' unconventional monetary policies, notably quantitative easing (QE), have affected financial markets. To stimulate business investment, accommodating monetary policies have lowered interest rates to zero or negative. Cryptocurrencies (crypto assets) hinder central banks' epidemic response. By establishing a cashless world, private currencies might threaten the central bank's monopoly by denying corporations, families, and financial markets risk-free money. Decentralized Finance (DeFi) seeks to revamp the financial system into an open, permission-free, autonomous one. This research examined the rise of digital payments, cryptocurrency trading, and the ECB's consideration of a central bank digital currency (CBDC). They showed cointegration between cryptocurrencies, stablecoins, and traditional financial assets. Digital payments and cryptocurrency adoption might lead to a digital euro, affecting financial markets and businesses.

Galán-Gutiérrez (2023) committed to the conduct of test agents in the markets of hard commodities by means of an attempt to differentiate between speculating in prices and future price structure management to hedge their holdings. Their triple study included panel data, structural breaks throughout the whole time series, and cointegration on the time series. By means of structural break detection and complete series analysis, we can uncover the link between high prices and the negative future price structure (backwardation) in increasing prices scenarios of tin, copper, aluminum, and zinc. Furthermore, they found that our study using panel data approaches cointegrates the base metals' entire matrix (current and future price structure). For agents in the markets, either as brokers or commodities traders, they felt that these findings were crucial to optimize earnings in their hedging positions.

Hayashi (2023) sought to clarify the stationarity and/or non-stationarity of the key Japanese macroeconomic time series by use of Yamamoto's (1996) enhanced step-wise Chow test and discover temporal and continuous structural changes in these series. It also sought to confirm experimentally that, even in cases of a real model with a structural change, a model supposing no structural change is unlikely to reject a null hypothesis. It is anticipated that structural changes include not only modifications in the drift term's parameters but also in other parameters, in addition to the time trend. The data supported the presence of actual business cycles.

Panigrahi (2023) explored how the bitcoin industry affects India's economy and financial stability. Bitcoin, financial stability, inflation, real GDP, economic volatility, exchange rate, and market volatility index were evaluated quarterly from 2015Q1 to 2022Q4. The findings were robust, utilizing FMOLS and CCR. A growth in bitcoin investments will significantly damage India's financial stability, according to studies. A 1% cryptocurrency increase would reduce financial stability by 5%. Cryptocurrencies hardly affect economic growth. Exchange rate volatility and inflationary pressure damage economic and financial stability, the research found. Data demonstrated a strong positive association between financial stability and economic development. Economic progress depends on the financial sector, which handles most economic transactions. Aggressive monetary policy tightening, capital flow volatility, inflation expectations de-anchoring, economic recovery halting, global supply chain disruptions, and climate change threaten India's financial stability and economic progress.

Foroutan and Lahmiri (2024) compared the top 10 cryptocurrencies to gold and crude oil markets before and after COVID-19. We examine the relationship between these markets and the safe-haven properties of gold and crude oil for cryptocurrencies using cointegration tests, vector autoregressive models, vector error correction models, autoregressive distributed lag models, and Granger causality analyses. During the COVID-19 pandemic, Bitcoin, Litecoin, and Monero are safer in gold than Bitcoin Cash, EOS, Chainlink, and Cardano, according to research. Gold protected Litecoin and Monero before the pandemic. Brent crude oil is a better COVID-19 safe-haven for Bitcoin than Ether, Bitcoin Cash, EOS, and Monero. The causal link switched from gold and crude oil to cryptocurrency markets before COVID-19. Cryptocurrencies affected gold and crude oil markets during the outbreak. These findings affect politicians, hedge fund managers, and cryptocurrency investors. Results show that financial crises like the COVID-19 epidemic need risk exposure adjustments.

Tekin (2024) analyzed the structural breaks and co-movements of Bitcoin (BTC) and Ethereum (ETH) cryptocurrencies during the COVID-19 epidemic. The Bai-Perron test assessed the change in market capitalization average and variance for the two main participants in the cryptocurrency market. Wavelet coherence research identified co-movements between BTC and ETH. The investigation revealed comparable breakdowns in both BTC and ETH series. Only one break was directly linked to the epidemic process. This implied that the epidemic is absorbed and normalized. Wavelet coherence findings show a substantial positive dependency (dark warm colors) between BTC and ETH, with both short and long band gaps proceeding in the same direction.

Kalaiarasi et al. (2024) conducted Granger causality and Chow tests to evaluate the price discovery function and structural break of agricultural, base metals, bullion, and energy commodities futures and spot prices from 2016-2022. The study found bidirectional causation between spot and future markets, except for gold, which showed unidirectional causality, with a bigger future market lead on spot returns.

Understanding dynamic trends throughout the crisis era is crucial for derivative valuation, hedging, and asset allocation. The structural break analysis showed that just a few commodities did not experience a break throughout the crisis era. This implies that commodity demand and supply are in equilibrium, and shocks do not affect commodity prices.
The reviews emphasize the significance of using structural break analysis, cointegration, and VAR modeling to understand commodity and cryptocurrency markets. This study highlights the relevance of financial assets in portfolio diversification, how crises like COVID-19 affect market dynamics, and the ramifications for policymakers, investors, and financial institutions.

3. Research Methodology

3.1. Data collection

Daily pricing data for Bitcoin was acquired from CoinMarketCap (www.coinmarketcap.com), while Gold USD data was collected from the World Gold Council (www.gold.org). The period April 2019–March 2024 was chosen to capture recent market developments, including the COVID-19 pandemic, subsequent monetary policy shifts, and heightened cryptocurrency volatility, ensuring coverage of both expansionary and contractionary market phases.

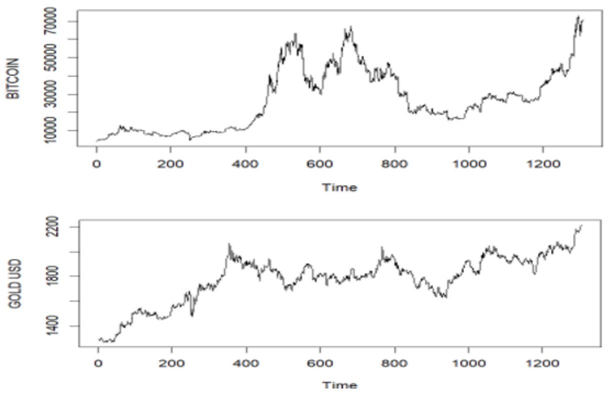

Fig. 1: Daily Price Movements of Bitcoin and Gold (USD), Highlighting Volatility Differences and Major Structural Breakpoints Corresponding to Global Events Such as COVID-19 (2020) and Geopolitical Tensions (2022).

Bitcoin and Gold USD time-series graphs in Figure 1 show significant price trends over time. Bitcoin has sharp ups and downs, with exponential rises followed by significant declines. This behavior shows its speculation and market sensitivity. Gold's steady, moderate rise, with slight volatility, matches its role as a safe-haven commodity amid the economic crisis. Bitcoin is a high-growth, high-risk investment, whereas Gold is a solid store of wealth. Despite their growing trajectories, their volatility differs. Structured variations in Bitcoin's course suggest break points to investigate. The different dynamics justify studying structural breaks, cointegration, and VAR models to understand the two assets' long-term equilibrium link and short-term interdependencies. Bitcoin and Gold respond differently to economic and financial disruptions; therefore, the outcomes will affect portfolio diversification.

Table 1: Descriptive Statistics of Bitcoin and Gold USD

Statistic	Bitcoin	Gold USD
Number of Obs.	1,305	1,305
Missing Values	0	0
Minimum	4,158.18	1,269.50
Maximum	73,083.50	2,214.35
1st Quartile	10,575.53	1,702.60
3rd Quartile	39,845.55	1,920.70
Mean	27,041.76	1,778.79
Median	24,829.15	1,808.45
Sum	35,289,493.24	2,321,320.15
Std. Error Mean	461.95	5.35
95% CI Lower Mean	26,135.50	1,768.29
95% CI Upper Mean	27,948.01	1,789.29
Variance	278,489,600.43	37,378.27
Standard Deviation	16,688.01	193.33
Skewness	0.55787	-0.77341
Kurtosis	-0.66880	0.16580

The descriptive statistics of Bitcoin and USD Gold prices shown in Table 1 reveal significant disparities in their statistical characteristics. Each asset comprises 1,305 observations, guaranteeing a dependable dataset. Bitcoin has a far broader price spectrum (4,158.18 to 73,083.50 USD) in contrast to gold (1,269.50 to 2,214.35 USD), highlighting its greater volatility. This is also shown by the interquartile ranges, where Bitcoin's values exhibit substantially more dispersion than those of gold. The mean price of Bitcoin (27,041.76 USD) exceeds its median (24,829.15 USD), indicating a positively skewed distribution, whereas gold's mean (1,778.79 USD) is closely aligned with its median (1,808.45 USD), demonstrating a symmetrical and stable distribution. The aggregate total of Bitcoin values far surpasses that of gold, owing to its wider spectrum. Moreover, Bitcoin has a bigger standard error of the mean and broader confidence intervals, indicating greater fluctuation in its average price relative to gold.
Moreover, Bitcoin's variance (278,489,600) and standard deviation (16,688 USD) significantly exceed those of gold, which has a variance of 37,378 and a standard deviation of 193.33 USD, thus affirming its pronounced price volatility. The skewness measures indicate that Bitcoin's distribution is favorably skewed, suggesting seldom significant price surges, while gold's negative skewness indicates a little inclination towards elevated prices. Finally, Bitcoin's negative kurtosis implies a distribution that is flatter than usual, whereas gold's near-

normal kurtosis signifies a more pronounced and steady pricing pattern. These results together underscore Bitcoin's speculative and high-risk characteristics, in stark contrast to gold's stability and dependability as a safe-haven asset.

4. Unit root Test

It is imperative to have stationary data, as it will generate spurious regression results otherwise. Establishing a link or forecast is difficult when the series is non-stationary, as its distribution will fluctuate between each period. The data structure of the time series is stable if the series is stationary, which implies that the mean, variance, and covariance remain consistent over time.
To evaluate the unit root issue, the Augmented Dickey-Fuller (ADF) test was implemented (Dickey and Fuller 1981). The null hypothesis assumes that the data are non-stationary.

$$\Delta y_t = \propto_0 + \theta y_{t-1} + \sum_{i=1}^{n} \propto \Delta y_t + e_t \quad (1)$$

In the equation mentioned above (1), 'y_t' represents the data at time t, 'n' is the optimal number of delays, '$\propto_0$ ' is the constant, and 'e_t' is the error term.

Table 2: ADF Test

	Bitcoin	GOLD USD
T Statistics	-1.3651	-2.5279
P-Value	0.8471	0.3548

As observed in Table 2, the ADF test shows that both Bitcoin and Gold (USD) are non-stationary, meaning their prices change over time without warning, and their standards or trends are not stable. The P-value for Bitcoin is $0.8471, and for Gold USD, it is $0.3548, which are both too high to let anyone think otherwise. This means that we cannot use what they did in the past to guess what will happen in the future without doing more work. To look at their relationship, we will need to either make the data stable (stationary) by differencing or investigate their long-term link through cointegration. Also, structure breaks should be checked to see if they have changed in big ways over time.

Table 3: ADF Test at First Level Difference

	Bitcoin	GOLD USD
T Statistics	-10.116	-11.806
P-Value	0.01	0.01

After differencing at level 1, the Augmented Dickey-Fuller (ADF) test in Table 3 indicates that the time series for Bitcoin and GOLDUSD are stationary. Bitcoin and GOLD USD have test statistics of -10.116 and -11.806, respectively, with p-values of 0.01 and 0.01. We reject the null hypothesis of non-stationarity for both assets since their p-values are smaller than the conventional significance threshold of 0.05. The results show that the mean and variance of both time series remain stable throughout the years, which means they may be used for future time series modeling and analysis

5. Chow test

The Chow test assesses the presence of structural change in a regression model at a designated breakpoint. The test entails dividing the data into two subsets (prior to and following the breakpoint) and evaluating the fit of distinct regressions for each subset against the fit of a unified pooled regression across the complete dataset.

The test uses the F-statistic, which may be computed as follows:

$$F = \frac{(SP-(S1+S2))/k}{(S1+S2)/(n1+n2-2k)} \quad (2)$$

In equation 2, SP is the residual sum of squares (RSS) from the pooled regression, $S1$ and $S2$ are the RSS values from the two subsets, $n1$ and $n2$ are the number of observations in the subsets, and k is the number of estimated parameters in each regression. The null hypothesis (H_0) posits that no structural break is present ($\beta_{0,1} = \beta_{0,2}$ and $\beta_{1,1} = \beta_{1,2}$), while the alternative hypothesis (H_1) asserts the existence of a structural break. If the computed F-statistic is above the crucial value, H0 is rejected, indicating the existence of a structural break.

6. Structural Change of Bitcoin

From 1 April 2017 to 31 March 2024, the Chow Test was used to examine the structural stability of Bitcoin values. This test finds structural Changes in time-series data as shown in Table 4. A p-value lower than 0.00000000000000022 accompanied the findings, which showed a sup.F value of 1706.2. The existence of major structural breaks in the time series is confirmed by this extraordinarily tiny p-value, which strongly rejects the null hypothesis of no structural change. These alterations to the underlying structure imply that there have been major changes to the link between Bitcoin prices and fundamental economic or market circumstances over the research period.

Table 4: Result of Structural Change of Bitcoin

Test	Test Statistics	P-value
Chow Test (supF)	1706.2	< 0.00000000000000022

Major market events, such as changes in regulation or technology (such as Bitcoin upgrades or forks), or macroeconomic shocks, such as the COVID-19 pandemic or worldwide inflationary pressures, might be the cause of structural fractures in the cryptocurrency market. These occurrences may have changed the way Bitcoin price dynamics work, which in turn affected how investors and the market felt. To better comprehend the changing character of Bitcoin as a financial asset and to increase the precision of econometric models, it is essential to detect and account for such breakdowns. Further research includes structural breaks since this approach sheds information on the price dynamics of Bitcoin over time.

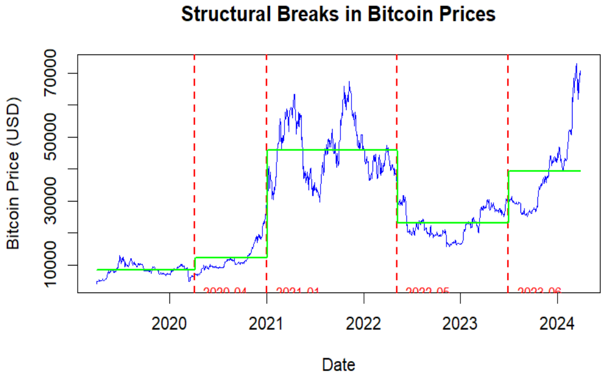

Fig. 2: Structural Breaks in Bitcoin Prices, With Breakpoints Aligned to Events Like COVID-19 (2020), Institutional Adoption (2021), Market Crash (2022), and Recovery Phase (2023).

The structural breaks in Bitcoin prices are visually highlighted in Figure 2, with red dashed lines indicating the breakpoints. The trend within each segment is represented by the green horizontal lines, which indicate periods of relative stability or consistent price behavior between interruptions. The breakpoints are the sites of significant shifts, including the significant market correction that occurred after July 2022 and the precipitous upward trend that occurred after April 2020. These changes are consistent with significant global and crypto-specific events, thereby illustrating the dynamic nature of Bitcoin prices in a clear visual manner.

Table 5: Structural Changes Breakpoints of Bitcoin

Segment	Breakpoint (Observation)	Breakpoint (Break dates)
1	265	10-04-2020
2	460	30-03-2021
3	810	19-07-2022
4	1110	16-05-2023

The structural breakpoints in the Bitcoin price series shown in Table 5 are located at observations 265, 460, 810, and 1110, and correspond to the specific break dates of April 10, 2020, March 30, 2021, July 19, 2022, and May 16, 2023, respectively. These breakpoints separate the data into four parts, indicating important variations in Bitcoin's price behavior. The breaks are most often caused by significant macro-economic events, legislative changes, or market-specific developments, demonstrating Bitcoin's vulnerability to external influences.

The first structural break occurred during the COVID-19 pandemic, which generated economic instability and asset value adjustments. Bitcoin became a hedge against fiat currency depreciation due to extraordinary monetary and fiscal stimulation (Conlon & McGee, 2020). Bitcoin prices began to rise sharply due to individual and institutional investor interest. As a result of prominent institutional adoption, the market reached its peak in 2021, marking the second breakpoint. Bitcoin purchases were disclosed by companies like Tesla, and crypto-currency transactions were made possible via payment networks like PayPal and Square (Bouri et al., 2021). New all-time highs were achieved by Bitcoin prices due to these events, increased retail investment activity, and a positive mood. At this point, before the market became very volatile, speculative fever was at its peak. The third structural break happened at the same time as a big drop in the market after the Terra/Luna environment broke down in May 2022. This event caused a lot of people to sell their crypto, which caused Bitcoin prices to level off for a while. Also, price drops were made worse by crackdowns by regulators in major markets, such as China's ban on cryptocurrency mining and the US's tighter oversight (Kaul et al., 2022). This part shows a change from a lot of instability to a fair amount of steadiness as the market adjusted to these shocks. The fourth breakpoint may indicate the onset of a new upward trend in Bitcoin prices, which may be influenced by the lessening of regulatory uncertainties, the improvement of macroeconomic conditions, and the increasing optimism regarding blockchain technology. This rekindled bullish sentiment was likely influenced by the anticipation of the forthcoming Bitcoin halving event in 2024, which has historically resulted in price increases and a reduction in supply (Kristoufek, 2020). This phase also signifies an increase in investor confidence as Bitcoin resumes its function as a digital store of value.

Table 6: Result of Structural Change in Gold USD

Test	Test Statistics	P-value
Chow Test (supF)	2801.1	< 0.00000000000000022

The structural change in Gold (USD) prices from 1 April 2017 to 31 March 2024 was examined using the Chow Test, a proven method for identifying structural breaks in time series data. The analysis produced in Table 6 shows the sup.F value of 2801.1, with a p-value of less than 0.00000000000000022, much lower than standard significance thresholds. This presents compelling evidence to reject the null hypothesis of no structural change, affirming the existence of substantial changes in the fundamental connection influencing Gold USD prices throughout this period.

Structural breaks in gold prices often signify significant worldwide occurrences, like changes in monetary policy, geopolitical conflicts, or phases of increased market volatility. From 2017 to 2024, notable events include the geopolitical uncertainty surrounding the U.S.-China trade war, the COVID-19 pandemic, and the ensuing monetary policy adjustments by prominent central banks. These events probably disturbed the conventional safe-haven dynamics of gold, resulting in substantial alterations in its price behavior (Baur & McDermott, 2010; Selmi et al., 2018).

Incorporating these structural fractures is essential for precise modeling of Gold USD prices and comprehending its function as a safe-haven asset. Disregarding these changes may result in skewed outcomes in econometric analysis, thereby misleading investment strategies and policy judgments. This research underscores the volatile function of gold in financial markets and its responsiveness to global economic and financial disturbances.

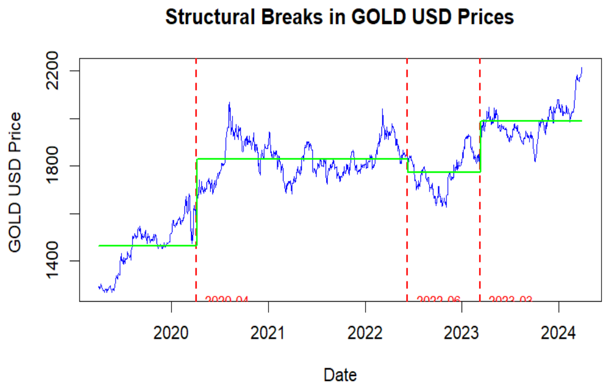

Fig. 3: Structural Breaks in Gold Prices, with Breakpoints Linked to COVID-19 (2020), Russia-Ukraine Conflict and Inflation (2022), and Stabilization Phase (2023).

Structural breaks in the Gold (USD) price series are observed in Figure 3 on April 10, 2020, August 19, 2022, and October 30, 2023, as marked by the red dashed lines. The identified breakpoints correspond to notable changes in the trend and volatility of gold prices. Each segment illustrates variations in market dynamics, including the price increase during the COVID-19 pandemic, fluctuations resulting from geopolitical tensions and inflationary pressures, and the stabilization observed in late 2023. The structural changes highlight the necessity of comprehending external factors influencing gold prices and integrating these alterations into econometric models for precise analysis and forecasting.

Table 7: Structural Changes Breakpoints of Gold USD

Segments	Breakpoint (Observation)	Breakpoint (Break Date)
1	265	April 10, 2020
2	835	August 19, 2022
3	1030	October 30, 2023

The structural breaks in the Gold (USD) series separate the data into three different parts observed in Table 7 on April 10, 2020, August 19, 2022, and October 30, 2023, suggesting major price changes over time. These breaks coincide with significant economic and geopolitical developments that have influenced the gold market. The first structural break coincides with the emergence of the COVID-19 pandemic, which caused unparalleled worldwide uncertainty. During this period, gold prices escalated as investors sought safe-haven assets due to concerns of economic uncertainty. This time signified a strong increase in gold prices, propelled by central bank monetary easing and global fiscal stimulus measures (Conlon & McGee, 2020). The second breakpoint corresponds to the period after the 2022 geopolitical tensions, specifically the Russia-Ukraine conflict, along with increased inflationary pressures. The identified factors contributed to heightened volatility in financial markets, resulting in fluctuations in gold prices as investors navigated between safe-haven demand and increasing interest rates. The Federal Reserve's significant rate increases during this period impacted gold prices, illustrating a complex relationship between monetary policy and risk sentiment (Corbet et al., 2022). The third breakpoint indicates a change in gold market dynamics, likely influenced by the anticipated easing of monetary policy and indications of economic stabilization. With indications of moderating inflationary pressures and central banks signaling a possible halt in rate increases, gold prices have stabilized and may be entering a new growth phase. This period indicates a resurgence of interest in gold as a portfolio diversifier amid a changing economic landscape (Bouri et al., 2023).

7. Cointegration between Bitcoin and Gold USD

The Johansen cointegration test is a prevalent statistical technique for detecting the existence and quantity of cointegrating links among non-stationary time series variables within a Vector Autoregressive (VAR) framework (Johansen, 1988). It ascertains the existence of stationary linear combinations of these variables, indicating a long-term equilibrium connection despite transient perturbations. The test relies on the estimate of the cointegration matrix (Π) derived from the VAR model, articulated as:

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \, \Delta y_{t-1} + \epsilon_t \tag{3}$$

In equation 3, Δy_t is the vector of first-differenced variables, $\Pi = \alpha\beta'$ is the cointegration matrix, α denotes adjustment coefficients, and β signifies cointegrating vectors. The rank (r) of Π establishes the quantity of cointegrating connections. The examination employs two principal statistics: the trace statistic and the maximum eigenvalue statistic. The trace statistic evaluates the null hypothesis that there are at most r cointegrating links, while the maximum eigenvalue statistic assesses r versus $r + 1$ cointegrating relationships. The statistics are juxtaposed with crucial values to ascertain the quantity of cointegrating vectors (Johansen & Juselius, 1990). The Johansen test is especially advantageous in multivariate systems, since it eliminates the need to pre-specify a dependent variable and offers a rigorous method for analyzing long-term equilibrium dynamics in multivariate time series.

Table 8: Johansen Cointegration Test for Bitcoin and Gold USD (Trace and Max Eigenvalue Statistics) without Structural Break

Cointegration	Trace Statistics	5% Critical Value	Prob.	Max Eigen Statistics	5% Critical Value	Prob.
None	6.57	17.95	0.34	6.34	14.90	0.45
At most 1	0.24	8.18	0.87	0.24	8.18	0.87

The Johansen cointegration test was performed to assess the existence of a long-term equilibrium link between Bitcoin and Gold USD prices, excluding structural breaks. Two test statistics were employed: the trace statistic and the maximum eigenvalue statistic, shown in Table 8, both assessing the quantity of cointegrating equations (CEs). The trace test's null hypothesis of no cointegration ($r = 0$) produced a trace statistic of 6.57, which is below the 5% critical value of 17.95, accompanied by a p-value of 0.34. This signifies that the null hypothesis of no cointegration cannot be dismissed, implying the absence of a long-term link between the two assets. Correspondingly, the null hypothesis of a maximum of one cointegrating equation ($r \leq 1$) yielded a trace statistic of 0.24, which remains below the 5% critical value of 8.18, accompanied by a p-value of 0.87. The findings affirm the lack of cointegration between Bitcoin and Gold USD values as determined by the trace test. The maximum eigenvalue test corroborates these results. The null hypothesis of no cointegration ($r = 0$) yielded a maximum eigenvalue statistic of 6.34, which is below the 5% critical value of 14.90, accompanied by a p-value of 0.45. This indicates the absence of a cointegrating link between Bitcoin and Gold USD. Similarly, under the null hypothesis of at most one cointegrating equation ($r \leq 1$), the highest eigenvalue statistic was 0.24, much lower than the 5% critical value of 8.18, accompanied by a p-value of 0.87. The findings affirm that no more cointegrating correlations are present between the two variables. The Johansen cointegration test findings demonstrate a lack of evidence for a long-term equilibrium link between Bitcoin and Gold USD prices over the examined time. Both the trace and maximum eigenvalue tests do not reject the null hypothesis of no cointegration at the 5% significance level. The results indicate that Bitcoin and Gold USD function as separate assets over the long term, consistent with previous research that emphasizes their distinct economic influences and market dynamics.

Table 9: VAR Estimation Results for Bitcoin and Gold USD

Equation	Variable	Estimate	Std. Error	t-value	p-value
	BITCOIN.l1	0.95551	0.02773	34.457	< 2e-16
	GOLD.USD.l1	2.88106	2.19577	1.312	0.19
BITCOIN	BITCOIN.l2	0.04129	0.02776	1.487	0.137
	GOLD.USD.l2	-2.55381	2.19453	-1.164	0.245
	const	-445.42468	374.86133	-1.188	0.235
	BITCOIN.l1	0.00019	0.00035	0.543	0.588
	GOLD.USD.l1	0.97724	0.02776	35.205	< 2e-16
GOLD.USD	BITCOIN.l2	-0.00016	0.00035	-0.446	0.656
	GOLD.USD.l2	0.01687	0.02774	0.608	0.543
	const	10.26591	4.739	2.166	0.031

7.1. Vector autoregressive (VAR) model

The Vector Autoregressive (VAR) model is versatile and commonly used to analyze time series variable dynamics. Unlike univariate models, the VAR model represents all variables as endogenous, enabling each variable to be treated as a function of its previous values and other system variables. General VAR model:

$$y_t = c + \sum_{i=1}^{p} A_i y_{t-i} + \epsilon_t \quad (4)$$

In the above equation 4, y_t is the variable vector, c represents intercepts, A_i holds coefficient matrices for each lag, and ϵ_t holds white noise error terms (Hamilton, 1994). The lag order (p p) is usually chosen using Akaike Information Criterion (AIC) or Bayesian Information Criterion (BIC) methods (Lütkepohl, 2005). The VAR model is ideal for dynamic interactions and forecasting. Impulse response functions (IRFs) and forecast error variance decomposition (FEVD) quantify the impact of one variable's shocks on other variables across time.

The dynamic relationship between Bitcoin and Gold USD prices was investigated using the Vector Autoregression (VAR) model, which was estimated using two delays and a constant term. The model's stability was verified by the fact that all roots of the characteristic polynomial were contained within the unit circle, which suggests stationarity (Lütkepohl, 2005). The findings in Table 9 provide valuable insights into the short-term interactions between these two financial assets. The initial latency of Bitcoin (BITCOIN.l1) in the Bitcoin equation demonstrated a highly significant positive impact on the current price of Bitcoin (estimate = 0.955, $p < 0.001$). This discovery underscores the robust autoregressive nature of Bitcoin, which is characterized by a significant influence of its historical values on its current price. Nevertheless, the delays of Gold USD (GOLD.USD.l1 and GOLD.USD.l2) and the constant term were not statistically significant, indicating that Gold prices do not make a substantial contribution to short-term fluctuations in Bitcoin prices. The model's high R-squared value (99.37%) suggests that it explains nearly all of the variance in Bitcoin prices, emphasizing the importance of its own delays in determining short-term price dynamics. The current value of Gold (GOLD.USD.l1) was significantly positively impacted by the first latency in the Gold USD equation (estimate = 0.977, $p < 0.001$). This is consistent with Gold's status as a stable asset that is influenced by its past prices (Baur & McDermott, 2010). The constant term was marginally significant ($p = 0.031$), suggesting that there may have been a baseline adjustment in gold prices during the sample period. The hypothesis that these two assets operate largely independently in the short term is further supported by the fact that Bitcoin delays did not exhibit any statistically significant influence on Gold USD prices. Which is somewhat surprising. Like the Gold USD equation, the model's strong explanatory power for short-term price movements in Gold was reflected in its R-squared value of 99.25%. The errors of the Bitcoin and Gold USD equations exhibited a low correlation (0.02789) in the residual analysis, indicating that there is minimal short-term interaction between the two assets. This discovery is consistent with prior research that has demonstrated that Bitcoin and Gold, despite their status as "safe-haven" assets, exhibit unique market dynamics and are influenced by distinct factors in the short term (Selmi et al., 2018).

In general, the VAR model indicates that the prices of Bitcoin and Gold USD are primarily influenced by their own historical values, with only a limited degree of short-term interdependence. These findings are instrumental in comprehending the diversification potential of Bitcoin and Gold in financial portfolios, as well as their functions in mitigating market uncertainties.

7.2. Generalized impulse response function (IRF)

To conduct a more in-depth examination of the short-term interactions between Bitcoin and Gold USD, generalized impulse response functions (IRFs) were derived using the estimated VAR model. The IRFs show how each variable reacts to a one-standard-deviation change in the other variable. This gives us information on both self-responses and cross-responses. Table 10 shows the generalized IRF values for horizons 1, 5, and 10. The next figure shows the dynamic adjustment routes with confidence intervals.

Table 10: Generalized Impulse Response Function (IRF) Results for Bitcoin and Gold USD at Horizons 1, 5, and 10

Horizon	Response of Bitcoin to Bitcoin Shock	Response of Bitcoin to Gold Shock	Response of Gold to Bitcoin Shock	Response of Gold to Gold Shock
1.000000	-0.035658	0.030300	0.002698	-0.020549
5.000000	-0.000132	-0.000227	-0.000022	-0.000096
10.000000	0.000000	0.000001	0.000000	0.000000

The generalized impulse response findings shown in Table 10 demonstrate the short-term dynamics between Bitcoin and Gold USD. At horizon 1, Bitcoin has a self-response of –0.0357, whilst Gold shows a self-response of –0.0205, suggesting that immediate shocks in both markets somewhat reduce their eventual prices. Cross-market reactions are negligible: Bitcoin's response to a Gold shock is 0.0303, whereas Gold's response to a Bitcoin shock is 0.0027. Although the responses are positive, they are insufficiently substantial to indicate any significant transmission of shocks between the two assets.

By horizon 5, the reactions to all shocks substantially dissipate (ranging from –0.000227 to –0.000022), and by horizon 10, they entirely converge to zero. This verifies that fluctuations in Bitcoin and Gold rapidly diminish, resulting in no enduring impacts. The findings indicate that Bitcoin and Gold are mostly autonomous, exhibiting few short-term spillovers, in line with the previously identified lack of long-term cointegration.

7.3. Forecast error variance decomposition (FEVD)

In addition to the impulse response analysis, forecast error variance decomposition (FEVD) was employed to assess the proportion of movements in Bitcoin and Gold USD that can be attributed to their own shocks versus shocks originating from the other asset. FEVD provides a quantitative measure of the relative importance of self-driven and cross-market innovations in explaining forecast error variance over different horizons. Table 11 summarizes the decomposition results at horizons 1, 5, and 10.

Table 11: Forecast Error Variance Decomposition (FEVD) Results for Bitcoin and Gold USD at Horizons 1, 5, and 10

Horizon	Bitcoin variance explained by Bitcoin (%)	Bitcoin variance explained by Gold (%)	Gold variance explained by Bitcoin (%)	Gold variance explained by Gold (%)
1	99.2	0.8	1.1	98.9
5	98.7	1.3	1.5	98.5
10	97.9	2.1	1.8	98.2

The prediction error variance decomposition (FEVD) data shown in Table 11 further substantiates the independence of Bitcoin and Gold USD. At horizon 1, 99.2% of Bitcoin's prediction error variation is accounted for by its own shocks, with only 0.8% ascribed to Gold. Likewise, 98.9% of Gold's volatility is accounted for by its own innovations, while a mere 1.1% is attributable to Bitcoin shocks. At horizon 5, self-driven dynamics continue to prevail, with Bitcoin's variation accounted for by its own shocks at 98.7% and Gold's at 98.5%. Cross-market contributions increase somewhat to 1.3% for Bitcoin attributed to Gold, and 1.5% for Gold, attributed to Bitcoin; nonetheless, these figures remain economically insignificant. At horizon 10, both series are mostly accounted for by their respective innovations—97.9% for Bitcoin and 98.2% for Gold—while cross-effects remain under 3%. The findings affirm that fluctuations in Bitcoin and Gold do not significantly affect each other's variance, highlighting the distinct characteristics of the two markets, both in the near term and over extended prediction periods

8. Conclusion

This research analyzed the dynamic relationships between Bitcoin and Gold USD from April 2019 to March 2024 via a multi-method econometric framework. The study used structural break tests, Johansen cointegration analysis, VAR estimation, impulse response functions (IRFs), and forecast error variance decomposition (FEVD) to provide a thorough evaluation of both long-term and short-term connections. The structural break tests indicated that both Bitcoin and Gold experienced regime transitions following significant global events. Bitcoin exhibited fluctuations throughout the COVID-19 pandemic (2020), the surge in institutional use (2021), the market decline linked to cryptocurrency crashes (2022), and the recovery in 2023. Gold showed fewer disruptions but reacted robustly to the pandemic shock and the Russia–Ukraine crisis in 2022. The findings indicate that both assets are susceptible to macroeconomic and geopolitical disruptions, with Bitcoin exhibiting far more volatility and responsiveness.

The cointegration analysis revealed no indication of a long-term equilibrium link between Bitcoin and Gold. This discovery refutes the characterization of Bitcoin as "digital gold" and instead emphasizes its distinct long-term trajectories. Gold remains a conventional safe-haven asset, whereas Bitcoin functions as a speculative and highly volatile instrument.

The VAR calculation indicated that both assets are mostly influenced by their own lagged values, with cross-market effects deemed statistically negligible. This indicates that disturbances in one asset do not consistently affect the other in the near term. The IRF study corroborated this finding. At horizon 1, Bitcoin exhibited a self-response of –0.0357, while Gold demonstrated –0.0205, indicating slight instantaneous self-corrections. The cross-responses—Bitcoin to Gold (0.0303) and Gold to Bitcoin (0.0027)—were economically negligible and statistically inconsequential. By timeframes 5 and 10, all responses neared zero, validating the lack of enduring spillovers between the two markets. The FEVD data provide further confirmation of independence. At horizon 1, 99.2% of Bitcoin's volatility and 98.9% of Gold's variance were attributed to their respective shocks, with cross-market contributions remaining below 2% even at horizon 10. These results highlight the preeminence of self-directed dynamics in both marketplaces.

The data repeatedly indicates that Bitcoin and Gold are distinct but complementary assets. The dynamics of Bitcoin are characterized by internal volatility and speculative cycles, while Gold remains a stable safe-haven asset. The autonomy of both markets indicates potential diversification advantages for investors who include both assets in their portfolios. The results indicate that policymakers and regulators should monitor Bitcoin's volatility independently, rather than supposing it would stabilize via interactions with Gold. The emergence of central bank digital currencies (CBDCs) and the development of legal frameworks may alter these interactions, necessitating more investigation.

This analysis shows that Bitcoin and Gold lack a long-term equilibrium connection and do not substantially impact one another in the near term. Rather, both assets develop autonomously, with Bitcoin marked by speculative volatility and Gold maintaining its status as a haven.

These findings enhance the current discourse on the function of cryptocurrencies in financial markets and provide pertinent insights for portfolio management, regulatory supervision, and prospective scholarly investigation.

References

[1] Ahmed, S. F., Mohsin, A. K. M., & Hossain, S. F. A. (2023). Relationship between FDI Inflows and Export Performance: An Empirical Investigation by Considering Structural Breaks. *Economies*, *11*(3). https://doi.org/10.3390/economies11030073.

[2] Baur, D. G., Hong, K., & Lee, A. D. (2015). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money, 54*(1), 177-189. https://doi.org/10.1016/j.intfin.2015.11.001.

[3] Blose, L. E. (2010). Gold prices, cost of carry, and expected inflation. *Journal of Economics and Business, 62*(1), 35-47. https://doi.org/10.1016/j.jeconbus.2009.07.001.

[4] Bouri, E., Jain, A., Roubaud, D., Kristoufek, L., & Lucey, B. (2017). Cryptocurrencies as hedge and safe-haven for stock markets: A comparative analysis. *Economic Modelling, 67*(1), 257-267. https://doi.org/10.1016/j.econmod.2017.10.020.

[5] Bouri, E. *et al.* (2017) 'On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier?', *Finance Research Letters*, 20, pp. 192–198. https://doi.org/10.1016/j.frl.2016.09.025.

[6] Cheah, E. T., & Fry, J. (2015). Speculative bubbles in Bitcoin markets? An empirical investigation into the fundamental value of Bitcoin. *Economics Letters, 130*(1), 32-36. https://doi.org/10.1016/j.econlet.2015.02.029.

[7] Chow, G. C. (1960). Tests of equality between sets of coefficients in two linear regressions. *Econometrica, 28*(3), 591-605. https://doi.org/10.2307/1910133.

[8] Corbet, S., Lucey, B. M., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis, 62*(1), 182-199. https://doi.org/10.1016/j.irfa.2018.09.003.

[9] Dyhrberg, A. H. (2016). Hedging capabilities of Bitcoin: Comparing to gold and the US dollar. *Finance Research Letters, 16*(1), 85-92. https://doi.org/10.1016/j.frl.2015.10.025.

[10] Engle, R. F., & Granger, C. W. J. (1987). Co-integration and error correction: Representation, estimation, and testing. *Econometrica, 55*(2), 251-276. https://doi.org/10.2307/1913236.

[11] Foroutan, P., & Lahmiri, S. (2024). Connectedness of cryptocurrency markets to crude oil and gold: an analysis of the effect of COVID-19 pandemic. *Financial Innovation*, *10*(1). https://doi.org/10.1186/s40854-023-00596-x.

[12] Galán-Gutiérrez, J. A., Labeaga, J. M., & Martín-García, R. (2023). Cointegration between high base metals prices and backwardation: Getting ready for the metals super-cycle. *Resources Policy*, *81*. https://doi.org/10.1016/j.resourpol.2023.103413.

[13] Ghosh, D., Levin, E. J., Macmillan, P., & Wright, R. E. (2004). Gold as an inflation hedge? *Studies in Economics and Finance, 22*(1), 1-25. https://doi.org/10.1108/eb028786.

[14] Hamilton, J. D. (1994). *Time series analysis*. Princeton University Press. https://doi.org/10.1515/9780691218632.

[15] Hayashi, N. (2005). Structural changes and unit roots in Japan's macroeconomics time series: Is real business cycle theory supported? *Japan and the World Economy*, *17*(2), 239–259. https://doi.org/10.1016/j.japwor.2003.12.006.

[16] Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of Economic Dynamics and Control, 12*(2-3), 231-254. https://doi.org/10.1016/0165-1889(88)90041-3.

[17] Johansen, S., & Juselius, K. (1990). Maximum likelihood estimation and inference on cointegration—with applications to the demand for money. *Oxford Bulletin of Economics and Statistics, 52*(2), 169–210. https://doi.org/10.1111/j.1468-0084.1990.mp52002003.x.

[18] Klein, T., Thu, H. P., & Walther, T. (2018). Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, *59*, 105-116. https://doi.org/10.1016/j.irfa.2018.07.010.

[19] Kalaiarasi, D., Rohini, A., Palanichamy, N. V., Shivakumar, K. M., Selvi, R. P., Murugananthi, D., & Sekhar, K. C. (2024). Structural Dynamics of Indian Commodity Derivatives Market. *Economic Affairs (New Delhi)*, *69*(1), 445–452. https://doi.org/10.46852/0424-2513.2.2024.6.

[20] Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer. https://doi.org/10.1007/978-3-540-27752-1.

[21] Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. Retrieved from https://bitcoin.org/bitcoin.pdf.

[22] Panigrahi, S. (2023). Are cryptocurrencies a threat to financial stability and economic growth of India? Evidence from the cointegration approach. *Investment Management and Financial Innovations*, *20*(2), 307–320. https://doi.org/10.21511/imfi.20(2).2023.26.

[23] Pelagidis, T., & Kostika, E. (2022). Investigating the role of central banks in the interconnection between financial markets and cryptoassets. *Journal of Industrial and Business Economics*, *49*(3), 481–507. https://doi.org/10.1007/s40812-022-00227-z.

[24] Z Perron, P. (1989). The great crash, the oil price shock, and the unit root hypothesis. *Econometrica, 57*(6), 1361-1401. https://doi.org/10.2307/1913712.

[25] Selmi, R., Mensi, W., Hammoudeh, S., & Bouoiyour, J. (2018). Is Bitcoin a hedge, a safe-haven or a diversifier for oil price movements? A comparison with gold. *Energy Economics, 74*(1), 787-801. https://doi.org/10.1016/j.eneco.2018.07.007.

[26] Shahzad, S. J. H., Bouri, E., Roubaud, D., Kristoufek, L., & Lucey, B. M. (2019). Is Bitcoin a better safe-haven investment than gold and commodities? *International Review of Financial Analysis, 63*(1), 322-330. https://doi.org/10.1016/j.irfa.2019.01.002.

[27] Sims, C. A. (1980). Macroeconomics and reality. *Econometrica, 48*(1), 1–48. https://doi.org/10.2307/1912017.

[28] Sinha, A. (2015). India's Services Revolution Amidst Worldwide Structural Change. *Journal of Quantitative Economics*, *13*(2), 253–284. https://doi.org/10.1007/s40953-015-0015-2.

[29] Tekin, B. (2024). Structural Breaks and Co-Movements of Bitcoin and Ethereum: Evidence from the COVID-19 Pandemic Period. *Journal of Central Banking Theory and Practice*, *13*(2), 41–70. https://doi.org/10.2478/jcbtp-2024-0012.

[30] Zivot, E., & Andrews, D. W. K. (1992). Further evidence on the great crash, the oil-price shock, and the unit-root hypothesis. *Journal of Business & Economic Statistics, 10*(3), 251-270. https://doi.org/10.2307/1391541.