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RESEARCH ARTICLE

Speculative Independence or Monetary Sensitivity? A Structural Cointegration and Causality Analysis of Bitcoin, Growth, and Interest Rates

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Özet

This study examines the dynamic linkages among Bitcoin (BTC) prices, U.S. interest rates, and economic growth using quarterly data from 2012Q3 to 2025Q1 within a nonlinear time series framework that incorporates structural breaks. Stationarity is assessed using the Kruse and Fourier unit root tests, while long-run relationships are evaluated with the Augmented-ARDL cointegration method. Long-run coefficients are estimated with CCR, DOLS, and FMOLS. Causal relationships are explored through the Fourier-Toda-Yamamoto test. Results show a significant and positive long-run effect of interest rates on BTC, implying its role as a speculative hedge during monetary tightening. No cointegration is found between BTC and growth, indicating weak macro-financial integration. Additionally, growth Granger-causes interest rate decisions, consistent with Taylor Rule expectations, while no causality is observed from monetary policy(interest rate) to BTC. These findings highlight the decoupling of cryptocurrency markets from traditional financial tools, underscoring the need for adaptable regulatory strategies.

Keywords: *Cryptocurrency Markets, Monetary Policy, Economic Growth, Interest Rate, Structural Breaks, Nonlinear Time Series.*
Jel Codes: *C32, E52, G12, E44, O16*

Spekülatif Bağımsızlık mı Yoksa Parasal Duyarlılık mı? Bitcoin, Büyüme ve Faiz Oranlarının Yapısal Eşbütünleşme ve Nedensellik Analizi

Abstract

Bu çalışma, Bitcoin (BTC) fiyatları, ABD faiz oranları ve ekonomik büyüme arasındaki dinamik ilişkileri, yapısal kırılmaları içeren doğrusal olmayan zaman serisi çerçevesinde, 2012 üçüncü çeyrek ile 2025 birinci çeyrek arasındaki üçer aylık verilerle incelemektedir. Durağanlık Kruse ve Fourier Kruse birim kök testleriyle değerlendirilirken, uzun dönemli ilişkiler Genişletilmiş ARDL eşbütünleşme yöntemiyle analiz edilmiştir. Uzun dönem katsayıları CCR, DOLS ve FMOLS yöntemleriyle tahmin edilmiştir. Nedensellik ilişkileri ise Fourier-Toda-Yamamoto testiyle araştırılmıştır. Sonuçlar, faiz oranlarının BTC üzerinde anlamlı ve pozitif uzun dönemli bir etkisi olduğunu göstermektedir; bu da BTC'nin parasal sıkılaşma dönemlerinde spekülatif bir korunma aracı olarak işlev gördüğünü ima etmektedir. BTC ile ekonomik büyüme arasında eşbütünleşme bulunmamış, bu da zayıf makro-finansal entegrasyona işaret etmektedir. Ayrıca, ekonomik büyümenin faiz oranı kararlarını Granger nedenselliğiyle etkilediği görülmüş, bu durum Taylor Kuralı beklentileriyle uyumludur. Öte yandan, para politikasından (faiz oranı) BTC'ye doğru herhangi bir nedensellik ilişkisi tespit edilmemiştir. Bu bulgular, kripto piyasalarının geleneksel para politikası araçlarından ayrıştığını vurgulamakta ve esnek düzenleyici stratejilere ihtiyaç olduğunu göstermektedir.

Anahtar kelimeler: *Kripto Para Piyasaları, Para Politikası, Ekonomik Büyüme, Faiz Oranı, Yapısal Kırılmalar, Doğrusal Olmayan Zaman Serileri.*
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1. INTRODUCTION

As of May 2025, Bitcoin (BTC) has emerged as a prominent alternative asset, drawing increasing attention from investors, policymakers, and economists, largely due to its exceptional (approximately 400-fold) appreciation against the U.S. Dollar (USD) over the past decade. Its decentralized structure, high volatility, and potential as a store of value have sparked significant discussions on its interaction with traditional financial markets and central bank policy instruments such as interest rates. The Federal Reserve's monetary policy—particularly its decisions regarding interest rates—is a key tool influencing traditional financial markets, such as equities, bonds, and foreign exchange. However, the impact of these policies on BTC pricing remains an unresolved issue within the economic literature.

The evolving influence of BTC on real economic activity, particularly U.S. growth, remains underexplored despite its increasing market presence and adoption. Operating independently from traditional financial channels, BTC may affect gross domestic product (GDP) through its influence on consumption, investment, and cross-border capital flows. At the same time, the Federal Reserve's interest rate decisions shape macroeconomic conditions that intersect with digital asset behavior. Notably, BTC's volatility—amplified by monetary shifts such as the 2020 rate cuts—could signal new transmission mechanisms to economic growth. This study explores these dynamics through a structurally nuanced empirical framework, capable of capturing nonlinear patterns, asymmetric responses, and hidden structural breaks in the interactions between BTC prices, Federal Reserve policies, and U.S. growth indicators.

Table 1 presents the annual changes in the Federal Reserve's (FED) interest rates and U.S. gross domestic product alongside BTC's price fluctuations.

Table 1: Yearly change of FED interest rates, economic growth and BTCUSD

Period	Change % for FED Interest Rates	US Economic Growth	Change % for BTCUSD	Period
2013	-44%	2%	5290%	2013
2014	33%	4%	-56%	2014
2015	100%	2%	35%	2015
2016	125%	2%	125%	2016
2017	141%	3%	1328%	2017
2018	75%	2%	-72%	2018
2019	-32%	1%	88%	2019
2020	-94%	2%	301%	2020
2021	-11%	4%	60%	2021
2022	5025%	2%	-64%	2022
2023	30%	3%	156%	2023
2024	-16%	2%	122%	2024

Sources: FRED and Investing.com

As seen in Table 1, dramatic declines in the FED's interest rates (e.g., 2013, 2020) are typically associated with substantial increases in BTC's price. The onset of the COVID-19 pandemic in 2020 catalyzed unprecedented shifts in global monetary regimes, prompting the Federal Reserve to enact aggressive interest rate cuts and expansive quantitative easing measures. Similarly, increases in interest rates (e.g., 2014, 2022) often coincide with declines in BTC's value. However, BTC's price behavior does not always conform to traditional financial logic. For instance, in 2016 and 2017, BTC prices surged despite significant interest rate hikes, suggesting that speculative factors and investor sentiment may drive market behavior beyond conventional financial models.

Table 1 illustrates a steady and moderate economic growth despite fluctuations in FED interest rates and BTCUSD prices. The figures suggest that interest rates alone may not determine growth outcomes. As for BTC's price, its correlation with US economic growth appears less direct, implying that BTC's price is influenced more by speculative market behavior and investor sentiment than by economic growth alone. These patterns underscore the necessity of formal econometric analysis to determine whether such associations reflect robust causal relationships or merely temporal co-movements.

Empirical studies examining the relationship between Federal Reserve interest rate changes, economic growth and BTC prices have yielded mixed results. While several researches argue that BTC responds to macroeconomic indicators (Forbes, 2024; S&P Global, 2023; Shaikh, 2020; Zhu et al., 2017), others report temporary, weak or negligible effects suggesting limited macro-financial integration (Benigno & Rosa, 2023; Canöz, 2023; Aboura, 2022). This discrepancy raises important questions about the nature of BTC's market behavior and its integration within the broader financial ecosystem.

The growing prominence of BTC and other cryptocurrencies in global financial markets necessitates a deeper understanding of the factors driving their price volatility. In an environment where central banks continue to adjust monetary policies in response to changing economic conditions, evaluating the impact of traditional economic tools—such as interest rate decisions—on digital assets has become increasingly important. This understanding is crucial not only for policymakers and investors but also for the future of cryptocurrency regulation and its role in financial markets.

BTC's departure from conventional financial logic—evident in episodic volatility and regime-dependent reactions—necessitates a robust analytical framework that accounts for nonlinearity, asymmetry, and endogenous structural shifts. This study integrates advanced cointegration estimators and break-aware causality tests to isolate latent transmission channels across monetary policy, BTC prices and economic growth. To uncover equilibrium linkages and dynamic adjustment mechanisms, the study adopts the Augmented Autoregressive Distributed Lag (AARDL) cointegration model (Sam et al., 2019), Canonical Cointegrating Regression (CCR), Dynamic Ordinary Least Squares (DOLS), and Fully Modified Ordinary Least Squares (FMOLS) and a corresponding Error Correction Mechanism (ECM) to dissect the equilibrium relationships and adjustment processes between BTC, Federal Reserve interest rates, and U.S. economic growth. The study incorporates Fourier-Toda-Yamamoto (FTY) causality tests (Nazlıoğlu et al., 2016) to accommodate structural breaks without imposing restrictive preconditions on stationarity. This multifaceted approach allows for a deeper understanding of how digital assets interact with macroeconomic conditions and monetary policy tools, offering nuanced insights into the financial spillover dynamics operating within the digital economy. Understanding these mechanisms is essential for investors, regulators, and economists to navigate the increasingly complex interface between crypto-assets and real economic activity

The primary motivation for this study stems from the need to decipher the increasingly complex dynamics between BTC, economic growth, and Federal Reserve policy tools – particularly in an era of heightened digital asset volatility and shifting monetary regimes. Past research yields mixed conclusions, revealing that traditional econometric models often fail to capture regime-dependent behavior, structural breaks, and nonlinear spillover effects. This motivates the adoption of more advanced analytical techniques to uncover hidden macro-financial linkages and improve the predictive validity of policy-relevant insights.

This study has four primary objectives: 1) To investigate whether there is a long-run, structurally consistent causal relationship exists among BTC prices, changes in Federal Reserve policy interest rates, and U.S. economic growth—accounting for potential nonstationarity, asymmetries, and structural breaks, 2) To assess the direction and magnitude of causality among these variables, using nonparametric, break-tolerant causality tests, 3) To evaluate the empirical stability and reliability of long-term estimates through alternative cointegration estimators, and 4) To compare the findings with existing literature, discussing the implications for both theoretical frameworks, policy design, and digital asset regulation. By addressing these objectives, the study aims to contribute empirical evidence to a growing strand of literature at the intersection of digital finance and macroeconomic policy.

Four key research questions guide the study: 1) Is there a cointegrating relationship among BTC, FED interest rates, and economic growth, and how stable are parameter estimates across nonlinear estimators? 2) Does Federal Reserve monetary policy (interest rate changes) structurally induce or predict BTC prices or economic growth? 3) What do the findings reveal about the monetary spillover dynamics and transmission mechanisms in the context of digital asset markets?

The paper is structured as follows: Section 2 presents a literature review, Section 3 outlines the methodology, Section 4 presents the theoretical framework, Section 5 introduces data and empirical results and their alignment with previous research, Section 6 concludes the paper, Section 7 offers policy implications.

2. LITERATURE REVIEW

2.1 Literature in the 2010s

Bitcoin's evolving role as a macro-financial asset has sparked extensive debate over its sensitivity to conventional macroeconomic indicators – particularly inflation, economic growth, and monetary expansion. Kristoufek (2015), using wavelet coherence, characterized BTC's dual nature—shifting between speculative behavior and functioning as an economic proxy under varying conditions. Zhu et al. (2017) employed a VECM approach to report weak long-run interactions between BTC and U.S. macroeconomic fundamentals. Their results suggest that although BTC exhibits some asset-like behavior, particularly in relation to the U.S. Dollar Index and equity markets, it diverges from conventional safe-haven assets such as gold.

Dirican and Canöz (2017) contributed an early Turkish perspective, demonstrating long-run cointegration between BTC and major stock indices from the U.S. and China via ARDL bounds testing, implying regional asymmetries in crypto-market integration. Baur et al. (2018) emphasized that crypto-specific characteristics significantly influence BTC's volatility, highlighting its idiosyncratic behavior and the limited explanatory power of conventional financial factors. Similarly, Aysan et al. (2019) introduced geopolitical risk (GPR) as a driver of external uncertainty, finding that BTC returns and volatility respond positively at higher quantiles, suggesting its use as a conditional hedge in turbulent environments.

Guizani & Kahloul Nafti (2019) applied ARDL and Toda–Yamamoto causality tests to uncover the nonlinear effects of money supply and inflation on BTC returns. These early contributions established the foundation for understanding BTC's divergence from traditional assets and its sensitivity to both macroeconomic and geopolitical shocks.

2.2 Literature in the Early 2020s

Shaikh (2020) expanded the perspective through a cross-country lens, showing that BTC reacts negatively to monetary policy uncertainty (MPU) in the U.S. and Japan, but positively in China. His use of quantile regression and Markov regime-switching models supported the view that macro sensitivity is highly regime-dependent. Ünvan (2021) examined the impact of Bitcoin on major stock indices in the U.S., Japan, China, and Turkey, utilizing a VAR model and Granger causality analysis. The results reveal a bidirectional causality between Bitcoin and Turkey's BIST100, along with several unidirectional causal links involving Nikkei225, SSE380, and S&P500, highlighting asymmetric regional interactions.

Jareño et al. (2021), employing NARDL modeling, decomposed oil price shocks and identified demand-side impacts as key drivers of crypto volatility—especially during periods of macroeconomic distress. Sarker and Wang (2022) offered wavelet-based evidence of bidirectional and nonlinear causality between BTC, inflation, MPU, and monetary supply in Japan and the U.K., underscoring the methodological need for frequency-sensitive and break-aware approaches. Liu & Tsyvinski (2020) highlighted that features unique to cryptocurrencies greatly affect BTC's volatility.

Aboura (2022) reported that the influence of Federal Reserve policy on BTC prices is nonlinear and largely temporary, underscoring the regime-dependent and short-lived nature of traditional monetary transmission mechanisms in crypto markets. Benigno & Rosa (2023) posited a partial disconnect between central bank tools and cryptocurrency volatility. Karau (2023), applying a proxy-SVAR approach, documented a regime shift in BTC's monetary response—highlighting that while BTC once behaved as a hedge against U.S. tightening, it has more recently mirrored speculative asset patterns, especially in the post-2020 policy environment. Köse and Ünal (2023) further argued that negative real interest rate shocks trigger stronger causal effects on BTC prices than positive ones, highlighting asymmetric transmission dynamics.

These studies collectively emphasize the conditional and regime-dependent nature of BTC's macroeconomic and monetary policy sensitivity during the early 2020s.

Wang et al. (2023) documented volatility spillovers between BTC and macroeconomic variables, including the consumer price index, money supply, and economic policy uncertainty, across different frequency domains using multiscale wavelet causality. Aydoğan et al. (2024) examined the nonlinear effects of macroeconomic factors on Bitcoin and Ethereum using lag-augmented AR and threshold regression models. Their results reveal that risk appetite and market liquidity are the most consistent drivers of investment decisions, while causal relationships remain unstable and shift over time.

Balhadi (2024) documented that BTC compressed in response to CPI and Fed interest rate hikes in 2022, although its reliance on linear methods limited the robustness of the inference. Ahmadova et al. (2024), Dogan et al. (2022), Febo et al. (2021), Özer et al. (2022), Gürsoy et al. (2024), and Gürsoy (2024) further examined BTC's relationship with macroeconomic and financial variables using cointegration and causality techniques or refined versions of these methodologies.

2.3 Addressing the Gap in The Literature

Despite this growing body of research, few studies jointly analyze BTC prices, Federal Reserve interest rates, and U.S. economic growth through a structurally robust, break-sensitive lens. Existing literature often relies on linear frameworks, shorter-term observations, or segmented causality models, such as Shaikh (2020) and Aysan et al. (2019), which cover 2010–2018; Köse and Ünal (2023), focusing on January 2012–October 2022; Balhadi (2024), examining Fed hikes during 2022; Benigno & Rosa (2023) on post-pandemic volatility; and Canöz (2023) on regime intervals between 2010 and 2019. These approaches fail to detect persistent equilibrium behavior and dynamic feedback mechanisms.

This study addresses this gap by triangulating Fourier-Toda-Yamamoto causality tests to capture nonlinearity and structural shifts, augmented ARDL cointegration modeling to uncover long-run equilibrium relationships under degenerate conditions, and CCR, DOLS, and FMOLS estimators to validate coefficient robustness and prevent distortions caused by autocorrelation and simultaneity. Through this integrated framework, the research provides new empirical insights into BTC's placement within the monetary transmission process, thereby enhancing our understanding of digital asset behavior in the context of central banking and macroeconomic policy.

3. THEORETICAL FRAMEWORK

To ground the empirical strategy in established financial theory, this study integrates insights from both speculative asset pricing literature and the monetary transmission mechanism. Traditional monetary transmission theory posits that changes in policy interest rates affect economic activity through structured channels—such as borrowing costs, liquidity conditions, and asset prices—allowing central banks to influence aggregate demand and inflation expectations (Mishkin, 1995, 2001). However, digital assets like Bitcoin challenge this paradigm due to their decentralized architecture and absence of yield, making them particularly susceptible to speculative dynamics. In this context, speculative asset pricing theory provides a behavioral lens through which to interpret Bitcoin's volatility and its apparent detachment from macroeconomic fundamentals.

Shiller (2014) emphasizes that long-term asset prices are shaped by psychological contagion, social narratives, and fluctuating beliefs about the future, arguing that markets are engineered environments subject to human behaviors rather than perfectly rational mechanisms. Jin (2015) extends this view by modeling a dynamic equilibrium in which misperceptions of crash risk and excessive leverage amplify asset price volatility and financial fragility. These insights are especially relevant for cryptocurrencies, which frequently exhibit nonlinear reactions to macroeconomic uncertainty, policy shifts, and speculative sentiment. Together, these theoretical contributions justify the inclusion of sentiment-sensitive macro variables in the model and support the adoption of a semi-logarithmic specification capable of capturing behavioral asymmetries, volatility clustering, and evolving macro-financial relationships.

4. METHODOLOGY

In this study, a multicomponent empirical approach was employed to identify both short-term and long-term relationships, considering the time series characteristics of the variables. First, descriptive statistics were presented to define the basic statistical structures of the series, followed by an examination of correlation structures and distribution characteristics. Both parametric and non-parametric methods were used in the distribution analysis. In this context, the Jarque-Bera (JB) test, which measures deviations from a normal distribution, was used in conjunction with the kernel density estimate, which visually represents the shape of the distribution. While the JB test measures the conformity of the observed data to the theoretical normal distribution, the kernel distribution reveals the shape of the distribution based on the data without any parameter assumptions. Especially for asymmetric or heavy-tailed distributions, kernel density estimation helps to better understand the reasons for deviations from the normal distribution and thus plays a complementary role.

To determine the stationarity properties of the series, the Kruse (2011) and Fourier Kruse (Güriş, 2019) tests, which allow for the detection of non-linear structures, were applied. The Kruse (2011) test extends the traditional Dickey-Fuller(Dickey & Fuller, 1981) approach to test for nonlinear LSTAR-type structures. The most significant contribution of this test is that it examines the presence of unit roots in series with asymmetric turning points. However, the Kruse test does not directly consider structural breaks. The Fourier Kruse test addresses this shortcoming. Developed by Güriş (2019), this test models unknown structural breaks in the series using non-parametric Fourier terms, providing more robust results. The Fourier-Kruskal test is particularly suitable for identifying structural breaks commonly found in economic series. Other classical tests, such as the ADF (Dickey & Fuller, 1981), PP (Phillips-Perron, 1989), and KPSS (Lumsdaine & Papell, 1992), are based on the assumption of a fixed structure and a linear model. In this study, more advanced methods were employed based on the assumption that non-linear dynamics may be present in the analyzed series.

Before estimating long-run relationships, it is crucial to establish the functional form of the econometric model. Considering the differing measurement units and distribution characteristics of the variables, a semi-logarithmic model was employed to normalize the scale and enhance the interpretability of the coefficients.

$$LBTC_t = \beta_0 + \beta_1 Growth_t + \beta_2 IR_t + \varepsilon_t \quad (1)$$

The logarithmic transformation was applied only to the dependent variable (Bitcoin price, BTC) due to its high dispersion and extreme values. On the other hand, both GDPGR and IR are percentage-based variables, and log-transformation would not only reduce interpretability but also risk distorting the dynamic effects in the model. This specification ensures a more robust interpretation of elasticities while preserving the integrity of macro-financial indicators. Similar modeling strategies are frequently adopted in empirical macro-finance literature when the dependent variable exhibits high volatility (e.g., Corbet et al., 2018; Shahzad et al., 2020). The inclusion of interest rates and growth rates as explanatory variables in the semi-logarithmic specification is also supported by recent studies focusing on macro-financial linkages in cryptocurrency markets (Aydoğan et al., 2024).

To analyze long-term relationships, the Augmented-ARDL cointegration test developed by Sam (2019), which introduces a novel framework in the literature, was employed. This method integrates the strengths of the traditional bounds testing approach by Pesaran et al. (2001) and the bootstrap-based ARDL models developed by McNown et al. (2018), thereby providing a more flexible econometric structure. The Augmented-ARDL model enables the estimation of long-run coefficients by simultaneously using both level and differenced series, while also testing for degenerate cases, which enhances the power of cointegration detection. In addition, its ability to indirectly control for structural breaks and its robustness in small samples were key reasons for its selection in this study. Based on this framework, the following semi-logarithmic form was specified for the empirical model:

$$\begin{aligned}\Delta LBTC_t = \gamma_0 + \gamma_1 LBTC_{t-1} + \gamma_2 Growth_{t-1} + \gamma_3 IR_{t-1} + \sum_{i=1}^{p-1} \theta_{o,i}, \Delta LBTC_{t-i} \\ + \sum_{i=1}^{q_{j-1}} \theta_j \Delta Growth_{t-j} + \sum_{i=1}^{q_{j-1}} \theta_j \Delta IR_{t-j} + \varphi_1 \Delta Growth_t + \varphi_2 \Delta IR_t + \varepsilon_t\end{aligned} \quad (2)$$

In this equation, the short-run dynamics are captured by the differenced terms, while the lagged level terms represent the long-run relationships. The model is particularly suitable for small samples and allows dummy variables to be included to capture sharp and smooth structural shifts if needed. Once cointegration was established, three alternative estimators were employed to estimate long-run parameters more consistently: Canonical Cointegrating Regression (CCR), Dynamic Ordinary Least Squares (DOLS), and Fully Modified Ordinary Least Squares (FMOLS). These estimators address potential problems such as autocorrelation and endogeneity that can bias OLS estimates. The CCR method, developed by Park (1992), eliminates bias by adjusting for long-run correlation in error terms. The DOLS approach, introduced by Stock and Watson (1993), adds lead and lag differences of regressors to account for serial correlation and simultaneity. FMOLS, proposed by Phillips and

Hansen (1990), corrects residuals for serial correlation and endogeneity in the long-run estimation. Using all three estimators enables robustness checks and provides stronger validation of long-run coefficient reliability. For the causality analysis, the Fourier-Toda-Yamamoto (FTY) test was employed. Developed by Nazlıoğlu (2016), this test extends the classical Toda-Yamamoto framework by integrating Fourier terms, allowing for the modeling of unknown structural breaks in a non-parametric way. Unlike standard Granger (1969) causality tests or the Toda-Yamamoto (1995) approach, which require strict stationarity, the FTY test allows for mixed-order integration and better accounts for regime shifts, seasonal patterns, and policy shocks often seen in macroeconomic series. Thanks to these features, the FTY test yields more empirically valid and economically meaningful results than conventional causality tests.

5. EMPRICAL RESULTS

5.1 Data and Preliminary Analysis

Since the empirical framework described in the methodology section is applicable, the variables and data sources used in the study are summarized in Table 2. This table systematically presents information about each variable, including its definition, measurement unit, analysis period, and data source. This study covers the period from the third quarter of 2012 to the first quarter of 2025, encompassing a dataset. The period from 2012Q3 to 2025Q1 encompassed a timeframe during which Bitcoin became more prominent in financial markets, and its interaction with macroeconomic variables intensified. This interval is also reliable and accessible in terms of data continuity. Moreover, the selection of the 2012Q3–2025Q1 period aims to exclude the impact of the 2008 Global Financial Crisis and the subsequent extraordinary macroeconomic conditions. The unconventional monetary policies implemented in the post-crisis era (e.g., quantitative easing) and the heightened uncertainty in financial markets structurally altered the behavior of novel and volatile assets such as Bitcoin. Therefore, to ensure that our study yields more consistent and generalizable results, the third quarter of 2012—when the effects of the crisis had relatively subsided, and market conditions began to normalize—was chosen as the starting point for the analysis. The variables included in the analysis are the Bitcoin price (BTC) expressed in US dollars, the policy interest rate (IR) expressed as a percentage, and the per capita GDP growth rate (GDPGR). BTC data was obtained from Investıng.com, while the other variables were sourced from the FRED database. All series are quarterly in frequency, and the necessary transformations and checks were applied prior to the analysis.

Table 2: Definition of variables

Symbols	Definitions	Measurement Unit	Period	Source
BTC	Bitcoin	USD	2012Q3-2025Q1	Investing.com
IR	Interest Rate	%		FRED
GDPGR	Gross Domestic Product Per Capita Growth	%		FRED

To evaluate the distribution structure and basic statistical properties of the variables included in the analysis, descriptive statistics such as mean, median, maximum, minimum, standard deviation (Std. Dev.), skewness, kurtosis, and coefficient of variation (Coeff. Var.) were calculated. Additionally, the Jarque-Bera statistic and its corresponding probability values were considered to test the normality of the series. These findings are important for understanding the structure of the variables and determining appropriate econometric methods. The relevant descriptive statistics are presented in Table 3. Based on descriptive statistics, the average value of BTC is 17,518.6 USD. The median value of the series is 7,730.6, which is significantly lower than the average. This difference indicates a right-skewed distribution and is supported by a positive skewness coefficient (1.60).

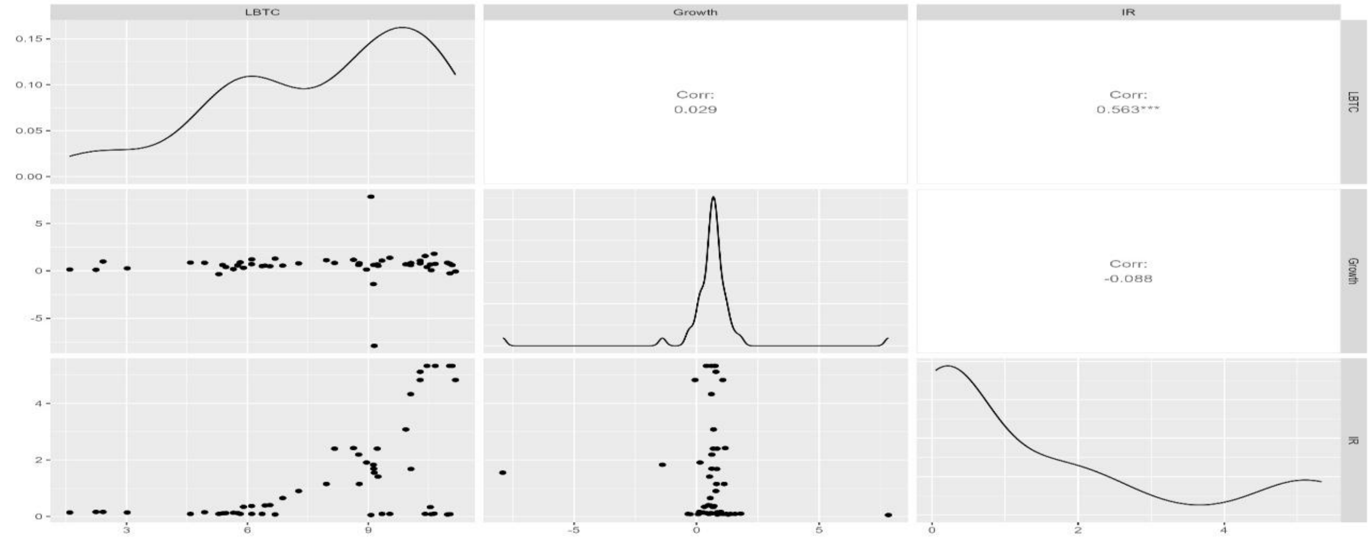
Table 3: Descriptive statistics

	BTC	IR	GDPGR
Mean	17518.6	1.47568	0.60195
Median	7730.60	0.39061	0.67321
Maximum	102470	5.33280	7.83034
Minimum	9.40000	0.05163	-7.90892
Std. Dev.	23564.8	1.82468	1.65996
Coef. Var.	1.34513	1.23650	2.75764
Skewness	1.60473	1.13644	-1.08079
Kurtosis	5.14432	2.83566	21.4902
Jarque-Bera	31.6598	11.0352	736.440
Probability	0.00000	0.00402	0.0000
Observations	51	51	51

Sources: Author’s calculations

The wide range between the maximum and minimum values, along with the high standard deviation (23,564.8), also indicates the series’s high volatility. The Jarque-Bera test result (3,165.98) and its corresponding significance probability value show that the BTC series does not meet the assumption of normal distribution. The average of the FED policy interest rate (IR) series is 1.47%, with a median value of 0.39%. This reflects the impact of the low-interest-rate policy in recent years. The maximum value in the series is 5.33%, and the minimum value is 0.05%. With positive skewness (1.13) and moderate kurtosis (2.83), the Jarque-Bera test result (11.03; $p < 0.01$) also indicates that this series is not normally distributed. The per capita GDP growth rate (GDPGR) averages 0.60%. However, the minimum value of -7.90% and the maximum value of 7.83% indicate significant fluctuations in growth rates. The negative skewness coefficient (-1.08) confirms that the distribution is left-skewed and that the median is higher than the mean. Additionally, the high kurtosis value (21.49) indicates that the series contains extreme values and has a heavy-tailed distribution. The Jarque-Bera statistic is quite high (736.44), indicating that the distribution is not normal. The notable insights from the descriptive statistics in Table 3 show that all three variables deviate from normal distribution—GDPGR in particular exhibits significant skewness and kurtosis—but these findings have been examined in more detail using kernel density estimates and bivariate scatter plots. These graphical tools provide visual information about distribution asymmetries, tail behavior, and relationships between variables. The results shown in Figure 1 support the notion that the series do not follow a normal distribution and may exhibit nonlinear models.

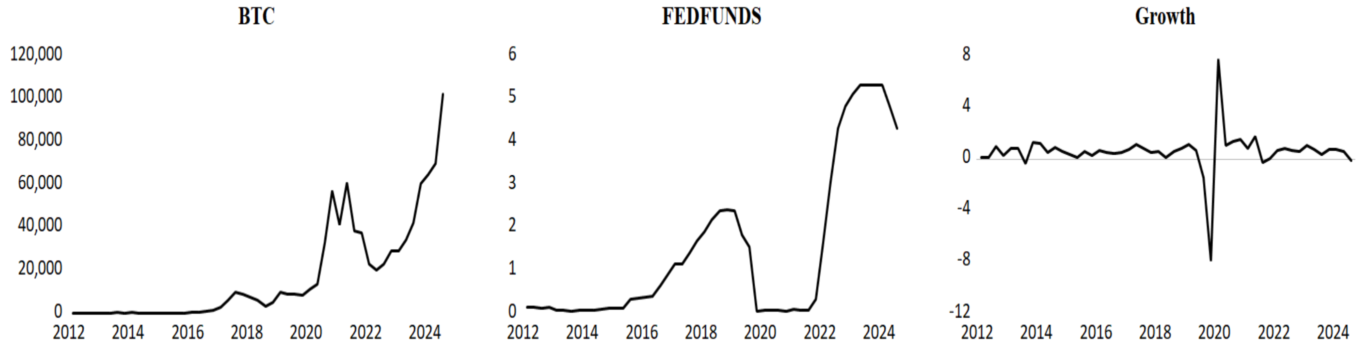
Figure 1: Kernel Densitie, Scatter Plots, and Correlation Coefficients



Sources: Author's Calculations

Figure 1 presents kernel density plots, scatter diagrams, and pairwise correlation coefficients for the variables included in the analysis. The kernel density plots on the diagonal provide insights into the shape and symmetry of each variable's distribution. In particular, the GDPGR series displays a sharp peak and heavy tails, indicating high kurtosis and a deviation from normality. BTC and IR exhibit right-skewed distributions, consistent with the positive skewness values reported in Table 3. These patterns visually reinforce the earlier findings from the Jarque-Bera normality tests, suggesting that standard normality assumptions may not hold. The off-diagonal scatter plots offer a visual inspection of bivariate relationships. The most notable association appears between BTC and FEDFUNDS, with a moderately strong and statistically significant positive correlation (0.563***), suggesting that interest rate movements may be related to BTC price dynamics over the sample period. In contrast, the relationships between GDPGR and the other variables are weak and lack a clear linear form, as indicated by near-zero correlation coefficients. Overall, the visual diagnostics in Figure 1 suggest potential nonlinearities and heterogeneity in the data, supporting the use of flexible econometric methods in subsequent analyses. Although Figure 1 offers valuable insights into the distributional and contemporaneous relationships between the variables, it does not capture how these variables evolve over time. To observe structural breaks, trend shifts, and volatility dynamics, time series plots are presented in Figure 2.

Figure 2: Graphical Summaries of Variables



Sources: Author's Calculations

An analysis of the time series graphs reveals that BTC prices experienced notable spikes in 2017 and 2021, followed by a pronounced upward trend beginning in late 2023. The FED policy interest rate remained at historically low levels for an extended period, before rising sharply from 2022 onward as part of the central bank's tightening cycle, reaching a peak in 2023 and then exhibiting a mild decline. The per capita economic growth rate (GDPGR) underwent a sudden and deep contraction in 2020 due to the Covid-19 pandemic, followed by a sharp but temporary recovery. In the remaining periods, the growth rate appeared relatively stable. These patterns, which reflect both structural changes and responses to external shocks over time, are depicted in Figure 3. Although graphical analysis provides preliminary insights into the dynamic behavior and potential structural shifts in the variables, it does not offer conclusive evidence regarding their stationarity properties. This limitation is particularly relevant in the presence of structural breaks and sudden fluctuations, which can distort visual interpretations (Enders, 2015). To address this issue, the Kruse (2011) test—which allows for nonlinear adjustment but not structural breaks—and the Fourier Kruse (2019) test—which incorporates structural breaks using a non-parametric Fourier function—were employed to assess the stationarity of the series. Both tests were conducted under constant and constant plus trend specifications to capture different forms of deterministic components. The resulting findings offer a methodological basis for selecting appropriate data transformations and econometric techniques in the subsequent analysis. The unit root test results are presented in Table 4.

Table 4: Unit root test results

Panel A: Constant Model							
	Kruse (2011)		Fourier Kruse (2019)				
Variables	Test stat	Lag	Test stat	F stat	l	k	Results
LBTC	4.7882	1	5.1757	53.787	1	1	I(1)
Growth	9.5272*	1	8.5352**	1.7875	1	3	I(0)
IR	8.3425	1	4.1429	235.56	1	1	I(1)
Panel B: Constant and Trend Model							
	Kruse (2011)		Fourier Kruse (2019)				
Variables	Test stat	Lag	Test stat	F stat	l	k	Results
LBTC	6.0472	1	7.0986	21.346	1	3	I(1)
Growth	9.5894	1	8.0381	1.7037	1	3	I(1)
IR	7.1995	1	6.0428	87.915	1	2	I(1)

Sources: Author's Calculations

The Kruse (2011) test found that only the Growth variable was stationary at the 10% significance level under the fixed model (I(0)), while the other variables were classified as I(1). In the fixed + trend model, no significant findings were obtained regarding the stationarity of any variable. In the Fourier Kruse (2019) test, although the Fourier terms for LBTC and IR were significant, the test statistics did not exceed the critical values, so both variables were classified as I(1). Even though the test statistics for Growth were significant, the Fourier term was not significant, so this result cannot be trusted. In conclusion, only the Growth variable is stationary at the level according to the Kruse test, while all other variables contain a unit root and exhibit I(1) properties. This situation indicates the necessity of difference or cointegration analyses in the subsequent modeling process.

5.2 Identifying Structural Breaks

Considering the results of unit root tests applied to the series and, in particular, the presence of structural breaks, it has been understood that traditional cointegration tests may be insufficient for assessing the long-term relationship between variables. Therefore, the Augmented-ARDL method, which takes structural breaks into account and provides a flexible framework that extends the traditional ARDL bounds test approach, has been preferred (Sam et al., 2019). As the analysis, incorporating the structural breaks identified through preliminary testing, revealed no evidence of a long-run cointegration relationship, the findings are presented with due consideration of the underlying financial and economic disruptions. The break points in the series that form the basis for the application of this method and the possible causes of these breaks are presented in detail in Table 5.

Table 5: Structural break periods and related economic events

Dummy Variables	Period	Economic Events / Reasons
D2016	2015 Q4 – 2016 Q4	Start of the Fed's interest rate hike cycle
D2018	2017 Q4 – 2018 Q2	BTC's first major bubble and crash
D2020	2020 Q1 – 2020 Q3	Pandemic shock, interest rate cuts, economic downturn
D2021	2021 Q1 – 2022 Q1	Liquidity boom, BTC rise
D2022	2022 Q2 – 2023 Q3	Fed's aggressive tightening cycle
D2024	2023 Q4 – 2025 Q1	Interest rate cuts and BTC's revival

Sources: Author's Calculations

Table 5 summarizes key structural break periods associated with major macro-financial developments, including the Fed's interest rate hikes (2015–2016, 2022–2023), BTC's speculative bubble and crash (2017–2018), the COVID-19 shock (2020), post-pandemic liquidity effects (2021), and the recent monetary easing phase (2023–2025). Each of these periods reflects abrupt regime changes or policy shocks that could distort or obscure long-term relationships among the variables.

5.3 A-ARDL Cointegration Test

To account for these structural shifts, the identified breakpoints were incorporated into the augmented ARDL cointegration equation as dummy variables. This specification enhances the reliability of long-run estimation by more accurately capturing the underlying equilibrium dynamics. The findings obtained within the scope of the method are presented in Table 6, and these results were used to assess whether there was a statistically significant cointegration relationship between the variables.

Table 6: Augmented ARDL (A-ARDL) bounds test and diagnostic results

<table>
<tr><td></td><td>Model</td><td colspan="3">Lag Order</td><td colspan="2">Dummy</td><td colspan="2">F</td><td colspan="2">t</td><td>$F_{independent}$</td><td>Cointegration</td></tr>
<tr><td></td><td>Case V</td><td colspan="3">1,0,0</td><td colspan="2">D2020</td><td colspan="2">6.092***</td><td colspan="2">-4.094***</td><td>6.1939**</td><td>✓</td></tr>
<tr><td rowspan="2">CV</td><td colspan="6">Peseran et al. (2001)</td><td colspan="4">Narayan (2005)</td><td colspan="2">Sam(2019)</td></tr>
<tr><td colspan="2">I(0)</td><td colspan="4">I(1)</td><td colspan="2">I(0)</td><td colspan="2">I(1)</td><td>I(0)</td><td>I(1)</td></tr>
<tr><td>1%</td><td colspan="2">3.74</td><td colspan="4">5.06</td><td colspan="2">4.31</td><td colspan="2">5.87</td><td>5.12</td><td>8.62</td></tr>
<tr><td>5%</td><td colspan="2">2.86</td><td colspan="4">4.01</td><td colspan="2">3.14</td><td colspan="2">4.42</td><td>3.20</td><td>5.54</td></tr>
<tr><td>10%</td><td colspan="2">2.45</td><td colspan="4">3.52</td><td colspan="2">2.16</td><td colspan="2">3.75</td><td>2.45</td><td>4.33</td></tr>
<tr><td colspan="13">Diagnostic Check</td></tr>
<tr><td>Model</td><td>R²</td><td colspan="2">F-stat</td><td colspan="2">JB</td><td colspan="2">BG-LM</td><td colspan="2">White</td><td>R-R</td><td>ECM</td><td>Stability</td></tr>
<tr><td>Case V</td><td>0.973</td><td colspan="2">163.29***</td><td colspan="2">14.131***</td><td colspan="2">0.422</td><td colspan="2">0.214</td><td>1.756</td><td>-0.384***</td><td>✓</td></tr>
</table>

Notes: CV: critical values. ** and *** show that the null hypothesis was rejected at the 5% and 1% significance levels.

The Case V model, constructed using the Augmented-ARDL method, was estimated with a constant and trend structure. The lag structure of the model is (1, 0, 0). This indicates that a first-order lag is used for the dependent variable, and a zero-order lag is used for the independent variables. To control structural break effects, the D2020 dummy variable representing the COVID-19 shock of 2020, as well as the other dummy variables presented in Table 5, were included in the model.

The F-statistics (6.092) and t-statistics (-4.094) obtained from the model are well above the 1% critical upper bound values proposed by both Pesaran et al. (2001) and Narayan (2005). These results ensure the rejection of the null hypothesis of the absence of a long-run relationship. Moreover, the independent F-test statistic ($F_{independent}$ = 6.1939) also exceeded the upper bound (5.54) at the 5% significance level suggested by Sam (2019). This indicates that the cointegration relationship is supported not only by the one-way explanatory effect of the dependent variable but also within the framework of the holistic structure of the system. Overall, the combined test results confirm the presence of a stable long-run cointegration relationship among the model variables.

Several diagnostic tests were applied to evaluate the statistical validity of the model. The R^2 value was 0.9735, indicating that the model explains a large portion of the variance in the dependent variable. The F-statistics (163.29) were quite high, strongly indicating the overall statistical significance of the model.

The Jarque-Bera (JB) test value is 14.131, which rejects the normal distribution assumption at the 1% significance level. However, it should be noted that such deviations are expected, especially in small samples, in time series analyses, and that the normality assumption is not an absolute condition in the Augmented-ARDL framework. Despite possible distribution deviations, the estimators remain consistent, though the interpretation of confidence intervals in small samples should be handled with greater caution. The Breusch-Godfrey LM test (0.4221) indicates that there is no autocorrelation in the model, while the White test (0.21417) indicates that the assumption of constant variance (homoscedasticity) is satisfied. The Ramsey RESET test (1.7564) also indicates that the functional form of the model is correctly defined.

Additionally, the ECM (Error Correction Mechanism) coefficient is estimated as –0.3844 and is statistically significant at the 1% level. This negative and significant coefficient indicates that short-term deviations from the long-run equilibrium are corrected by approximately 38.44% in each period. Thus, the system gradually converges toward the long-run path, supporting the stability and dynamic consistency of the estimated model.

To more accurately capture the adjustment process, the time required for the system to return to equilibrium after a shock can be calculated using the log-based convergence formula:

$$t = \frac{ln(1-\alpha)}{ln(1-|\lambda|)} \quad (3)$$

where: α represents the desired adjustment level (e.g., 0.90, 0.95, 0.99), λ is the absolute value of the ECM coefficient and t refers to the number of periods (e.g., quarters) required for the system to eliminate the specified proportion (α) of the deviation from equilibrium. This approach is theoretically more accurate than the basic reciprocal method $t=1/|\lambda|$, as it better captures the exponential nature of adjustment in dynamic systems (Enders, 2015).

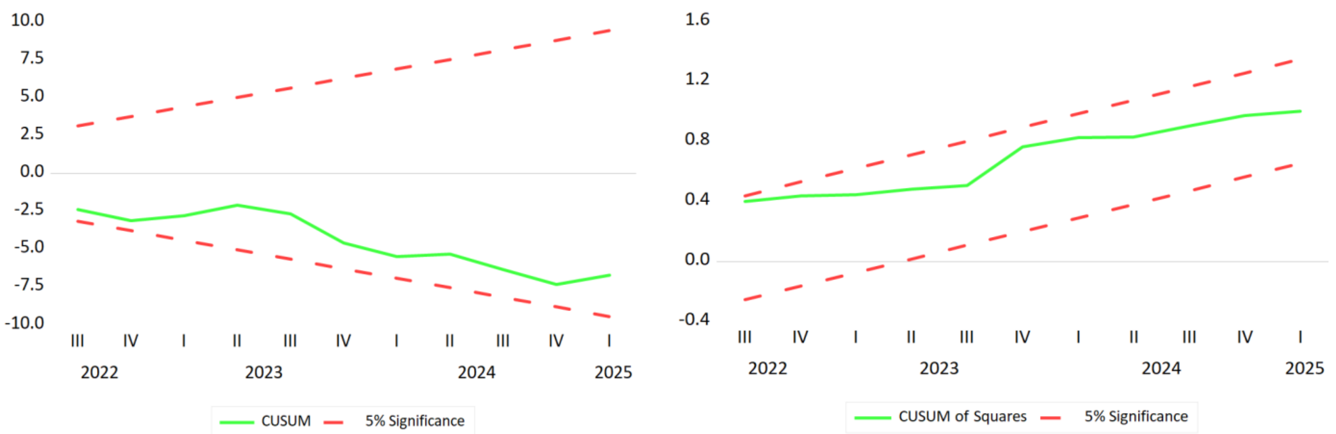
Table 7 presents the estimated number of periods needed for the system to return to equilibrium after a shock at different adjustment levels (90%, 95%, and 99%). As shown, it takes approximately 1 year and 2 months to correct 90% of the deviation, and around 2 years and 4 months to reach 99% convergence. These findings confirm the relatively moderate speed of adjustment in the system, consistent with the semi-rigid dynamics observed in macro-financial relationships.

Table 7: Estimated time to reach long-run equilibrium based on ECM coefficient

Target Adjustment Level	Formula	Estimated Periods (t)	Approximate Time (Quarterly Data)
90%	ln(0.10)/ln(0.6156)	4.75	1 year 2 months
95%	ln(0.05)/ln(0.6156)	6.18	1.5 years
99%	ln(0.01)/ln(0.6156)	9.5	2 years 4 months

Finally, the structural stability of the model is ensured according to the CUSUM and CUSUMSQ tests presented in Figure 3. In both test graphs, the observed lines did not exceed the limits corresponding to the 5% significance level, thus indicating that the model did not experience a structural break during the estimation period.

Figure 3: CUSUM and CUSUMSQ Stability Tests for Model Robustness Diagnostics



Sources: Author's Calculations

5.4 Long-Run Linkages

Following the confirmation of a cointegration relationship among the variables, the long-run coefficients were estimated to be using three alternative methods—Canonical Cointegrating Regression (CCR), Dynamic Ordinary Least Squares (DOLS), and Fully Modified Ordinary Least Squares (FMOLS). The estimation results are presented in Table 8**.**

Table 8: Long-run estimation results

	CCR	DOLS	FMOLS	VIF	Tolerance
Variables	Coefficients				
Constant	5.6108***	5.3919***	5.6407***	-	-
Fedfunds	1.0347***	1.0957**	1.0365***	1.2611	0.7930
Growth	0.0657	0.6905	0.0400	3.6226	0.2760
D2016	0.2101	-0.0419	0.1884***	-	
D2018	1.9168*	1.2476	1.9073*	-	
D2020	3.0596**	4.4246**	2.9744***	-	
D2021	5.2558***	4.2184***	5.2372***	-	
D2022	1.4375*	0.5885	1.3983*	-	
$\overline{R}^2$	0.6798	0.8147	0.6816		
SER	1.3287	0.9366	1.3181		

Sources: Author's Calculations

Table 8 presents long-term coefficient estimates using the CCR, DOLS, and FMOLS methods. As they are compared, the DOLS method shows the strongest model performance with the highest adjusted determination coefficient($\bar{R}^2$ = 0.8147) and the lowest standard error value (SER = 0.9366). Therefore, it is meaningful to focus primarily on the DOLS results when interpreting the long-term relationship between variables. Additionally, the DOLS method is a reliable alternative for long-term coefficient estimates because it addresses potential autocorrelation and endogeneity issues through lagged and forward difference terms (Stock & Watson, 1993).

According to DOLS estimates, the coefficient of the IR(interest rate) variable is 1.0957 and is significant at the 5% level. This indicates that an increase in interest rates has a positive and significant effect on BTC prices. At first glance, this finding may seem to contradict classical financial theories, but the perception of BTC as a 'risky hedge instrument' in recent years explains this effect. According to traditional expectations, when interest rates rise, demand for non-interest-bearing assets decreases. However, in developed markets like the US, increased uncertainty during tightening periods has led some investors to turn to cryptocurrencies, resulting in interest rate hikes boosting BTC demand rather than reducing it. Additionally, interest rate hikes are often perceived as a signal to control inflation expectations, which can make assets like BTC more attractive as a store of value.

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The Growth variable (change in interest rates per capita income) has a positive coefficient (0.6905) but is not statistically significant. This result indicates that no meaningful and stable relationship can be established between economic growth and BTC prices in the long term. This is generally consistent with theoretical expectations, as BTC is an asset that is more sensitive to market expectations, speculative movements, and global financial conditions than to direct economic growth performance. In particular, a decrease in the flow of funds toward assets like BTC during periods of stable growth may weaken the long-term impact of this variable.

Finally, in terms of model evaluation, the Variance Inflation Factor (VIF) and Tolerance values were calculated to assess whether there was a problem of multicollinearity. A VIF value between 1 and 10 is considered to indicate an acceptable level of multicollinearity. For the DOLS model, the VIF for Fedfunds was calculated as 1.26 and for Growth as 3.62, with both variables below the safe threshold values. The Tolerance values, interpreted inversely, were obtained as 0.7930 and 0.2760, respectively. These values are well above 0.1, indicating that there is no serious multicollinearity issue in the model. Therefore, the estimated coefficients can be considered statistically reliable.

D2020 dummy variable represents the pandemic shock of 2020 and is significant at the 5% level with a coefficient of 4.4246. This finding is consistent with the expansionary monetary policies, low interest rates, and individual investors' shift towards crypto assets implemented during the early stages of the pandemic. In particular, increased liquidity and expanded fiscal stimulus packages from the second quarter of 2020 onwards drove up the price of BTC.

The D2021 dummy variable represents the liquidity abundance of 2021 and has a very high coefficient (4.2184) in the DOLS model, as in all estimation methods. This value is significant at the 1% level and shows that central banks' low interest rate and asset purchase policies strongly supported BTC prices during the pandemic. This finding reveals that BTC was adopted by a wider investor base in 2021 with the entry of institutional actors into the crypto markets.

The D2022 variable represents the period when the Fed began raising interest rates, and its coefficient of 0.5885 is significant at the 10% level. While interest rate hikes are traditionally expected to reduce the appeal of interest-free assets like BTC, a limited but positive increase in BTC prices was observed during this period. This result suggests that interest rate hikes did not have as negative an impact as expected and that investors viewed BTC as an alternative safe haven or inflation hedge in some cases.

The D2018 variable represents the period when BTC's first major bubble burst. Although its coefficient in the DOLS model is 1.2476, it is not statistically significant. This result indicates that the correction following the 2017 bubble did not create a meaningful difference within the long-term average. This is a statistically expected outcome given BTC's high volatility.

The D2016 variable (the start of the first interest rate hike cycle) is also not statistically significant in the DOLS model. During this period, BTC had not yet become widely adopted as a global investment asset, which may have contributed to its weak sensitivity to policy changes.

5.5 The Fourier-Toda-Yamamoto Causality Tests

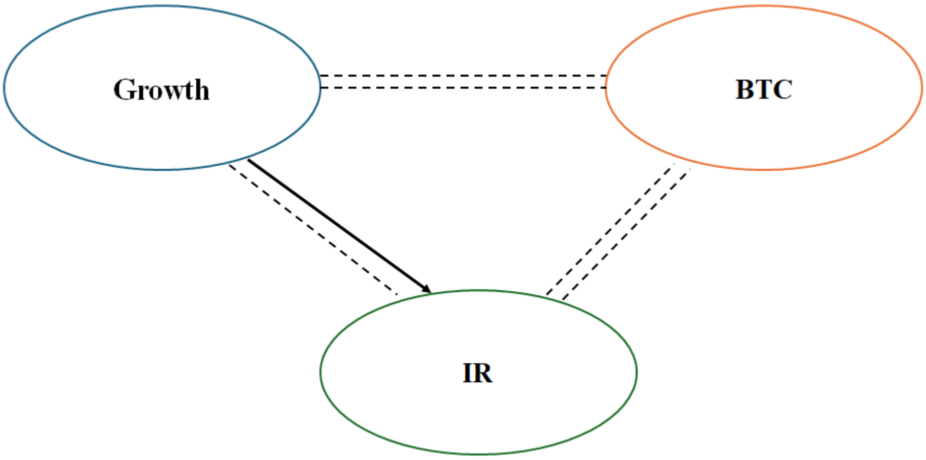
The Fourier-Toda-Yamamoto causality test results are summarized in Figure 4 and Table 9**.** The analysis reveals that only the direction from Growth to IR (Growth → IR) exhibits statistically significant causality at the 10% level (Chi-square = 2.7765, p = 0.0957). This finding aligns with the reactive nature of monetary policy emphasized in the economic literature. Particularly within the framework of the Taylor Rule**,** it is accepted that central banks adjust interest rates in response to real economic indicators such as inflation and output gaps (Taylor, 1993). In this context, changes in growth rates are expected to have a decisive impact on policy interest rates.

Table 9: FTY causality results

Causality direction	Chi-square	prob
BTC→IR	1.1847	0.2764
IR → BTC	0.2951	0.5870
BTC→Growth	0.0297	0.8631
Growth→ BTC	0.9942	0.3187
IR →Growth	2.6785	0.1017
Growth →IR	2.7765	0.0957

Sources: Author's Calculations

Figure 4: Direction of Causality



Sources: Author's Calculations

Conversely, no causal relationship was identified between FED policies and their direct impact on cryptocurrency markets. This suggests that the crypto market operates relatively independently of conventional monetary policy instruments, and that BTC is perceived more as a speculative asset detached from central bank authority. These results are consistent with the argument that cryptocurrencies are driven more by market sentiment, digital innovation, and speculative dynamics than by traditional macroeconomic fundamentals (Sayed et al., 2020; Corbet et al., 2018).

6. CONCLUDING REMARKS

This study examines the long-term and causal relationship between Bitcoin (BTC) prices, the U.S. Federal Reserve's policy interest rate (IR), and per capita economic growth (GDPGR) using a comprehensive time series econometric framework. The empirical findings confirm the existence of a long-term cointegration relationship among the variables. Specifically, policy interest rates exert a statistically significant positive impact on BTC prices, while the effect of economic growth remains statistically insignificant. Furthermore, causality analysis based on the Fourier-Toda-Yamamoto method reveals that economic growth Granger-causes interest rate movements, supporting the theoretical expectations grounded in Taylor-type monetary policy rules. However, no causality was detected between monetary policy and BTC, suggesting that BTC operates outside the influence of conventional macroeconomic levers. Overall, the results reflect the increasing autonomy and speculative nature of the cryptocurrency market in response to economic and policy developments.

Our results are generally in line with previous studies that point to a poor or regime-dependent macro-financial integration of Bitcoin. The lack of a causal relationship between monetary policy and Bitcoin is consistent with Benigno & Rosa's (2023) documentation of the growing "macro-disconnect" in cryptocurrency markets. The results of Zhu et al. (2017) and Shaikh (2020), which show that BTC reacts more strongly to speculative dynamics, policy uncertainty, and investor sentiment than to real activity indicators, are also consistent with the negligible effect of economic growth. The asymmetric monetary transmission suggested by Köse & Ünal (2023) and the speculative-hedge behavior described by Aysan et al. (2019) are compatible with the positive long-run effect of interest rates, despite the fact that this goes against traditional financial theory. All of these trends provide credibility for the idea that Bitcoin is more of a sentiment-driven speculative asset than a macro-sensitive financial instrument. Theoretically, this macro-financial gap is consistent with behavioral viewpoints (Shiller, 2014), highlighting the narrative-driven and sociopsychological processes that influence BTC prices in the face of uncertainty.

7. POLICY RECOMMENDATIONS

This study reveals that traditional monetary levers—particularly interest rate policy—have limited direct influence on cryptocurrency markets, as evidenced by the absence of causality from interest rates to Bitcoin prices. Historical episodes, such as the 2016–2017 BTC rally despite aggressive Fed hikes, indicate that speculative sentiment and perceived macroeconomic uncertainty may override orthodox expectations. During tightening cycles, Bitcoin often serves as a speculative hedge and unregulated store of value, particularly in environments marked by liquidity scarcity and inflation concerns. These dynamics highlight the increasing role of behavioural finance mechanisms in shaping digital asset behavior and call into question the effectiveness of conventional interest rate channels. Policymakers must recalibrate monetary frameworks to account for the sentiment-driven and autonomous nature of crypto price formation, which can distort central bank expectations and complicate forecasting efforts. Conversely, the strong causal impact of economic growth on interest rate decisions, consistent with the Taylor Rule, reaffirms the primacy of real indicators in monetary design. In volatile macro-financial regimes, central banks should prioritize output performance alongside inflation targets.

Finally, regulators must anticipate Bitcoin's rising appeal during financial turbulence and develop responsive, innovation-friendly policy frameworks. These should enhance investor protection and market transparency without stifling the evolving structure of digital finance.

DECLARATIONS

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CONTRIBUTIONS OF AUTHORS

Nijat Gasim: Conceptualization, Data Curation, Methodology, Formal Analysis, Visualization, Writing – Original Draft, Writing – Review & Editing.

İsmail Cem Özgüler: Investigation, Literature Review, Writing – Original Draft, Writing – Review & Editing.

Erhan Demireli: Conceptualization, Writing – Review & Editing, Supervision, Validation.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

DATA AVAILABILITY

The data can be provided upon request by the author(s).

ETHICAL STATEMENT

Ethical approval was not required for this study and therefore was not obtained.

ARTIFICIAL INTELLIGENCE (AI) USAGE STATEMENT

No AI-based tools were used in this study.

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