Araştırma Makalesi / Research Article

TESAM Akademi Dergisi

Journal of TESAM Academy

ISSN 2148-2462 / E-ISSN 2458-9217

Analysis of Federal Reserve Policy Rates and Bitcoin Prices: Pre and Post-COVID-19 Differentiations

FED Politika Faiz Oranları ve Bitcoin Fiyatlarının Analizi: COVID-19 Öncesi ve Sonrası Farklılıkları

Osman ALTAY

Dr. Öğr. Üyesi
İstanbul Ticaret Üniversitesi, İşletme Fakültesi, Uluslararası Ticaret Ve Finansman Bölümü.
oaltay@ticaret.edu.tr
ORCID : 0000-0002-8782-6820

Cilt / Issue: Online First 83-103
Geliş Tarihi: 06.03.2023
Kabul Tarihi: 28.08.2024

Atıf: Altay, O. (2024). Analysis of Federal Reserve Policy Rates and Bitcoin Prices: Pre and Post-COVID-19 Differentiations *Tesam Akademi Dergisi*, *Online First*, 83-103. http://dx.doi.org/10.30626/tesamakademi.1447997.

Abstract

This study aims to conduct a comparative analysis of the relationship between policy interest rates declared by the Federal Reserve and Bitcoin prices, considering pre- and post-COVID-19 periods and employing a robust analytical framework based on the Vector Error Correction Model, scrutinizing each phase individually. This analytical framework's robustness ensures our findings' reliability and validity. In the pre-COVID-19 period, a notable VECM coefficient of -0.03 for the Bitcoin variable implies shock stabilization after approximately 33 weeks, while the FED Policy Rate variable lacks significance in the return-to-balance mechanism. Conversely, the post-COVID-19 period unveils a substantial -0.08 VECM coefficient for Bitcoin, signaling a shock returning to balance in around 12.5 weeks. Furthermore, the FED Policy Rate exhibits a noteworthy -0.13 VECM coefficient in the post-COVID-19 period, indicating shock stabilization after about 7.7 weeks. These findings not only suggest a growing acceptance of Bitcoin and cryptocurrencies as conventional investment tools but also paint an optimistic picture of their future, propelled by the circumstances of the COVID-19 period.

Keywords: Cryptocurrencies, Bitcoin, Interest Rate, Federal Reserve Policy Rate

JEL Codes: C22, G10, C53.

Öz

Bu çalışma, Amerika Birleşik Devletleri'nin merkez bankası olarak bilinen Federal Rezerv Sistemi (Federal Reserve System FED) tarafından açıklanan politika faiz oranları ile Bitcoin fiyatları arasındaki ilişkiyi, COVID-19 öncesi ve sonrası dönemleri dikkate alarak karşılaştırmalı bir analizle tespit etmeyi amaçlamaktadır. Vektör Hata Düzeltme Modeline dayalı sağlam bir analitik çerçevenin kullanılması ve her aşamanın ayrı ayrı incelenmesi sonucunda elde edilen bulgulara göre; COVID-19 öncesi dönemde Bitcoin değişkeni için VECM katsayısının -0,03 olması yaklaşık 33 hafta sonra şok stabilizasyona işaret ederken, COVID-19 sonrası dönemde Bitcoin değişkeninin -0,08 olarak tespit edilen VECM katsayısı, ilgili dönemde şokların daha kısa olan yaklaşık 12,5 hafta kadar bir dönemde dengeye döneceğine işaret etmektedir. COVID-19 sonrası dönemde oluşan FED Politika Faizi değişkeninde tespit edilen -0,13 VECM katsayısı ise şokların artık çok daha kısa sürede, yaklaşık 7,7 hafta içinde istikrara kavuşmaya başladığına işaret etmektedir. Bu bulgular, COVID-19 döneminde yaşanan koşulların da etkisiyle Bitcoin ve kripto para birimlerinin geleneksel yatırım araçları olarak giderek daha fazla kabul edildiğini göstermektedir.

Anahtar Kelimeler: Kripto para birimleri, Bitcoin, Faiz Oranı, Federal Reserve Politika Oranı

JEL Codes: C22, G10, C53.

Introduction

The Federal Reserve's management of interest rates plays a pivotal role in steering the United States economy. The Federal Reserve can shape borrowing costs across the entire economic spectrum by adjusting the interest policy rate (Bagus & Schiml, 2010; Fernández et al., 2021; Levin & Sinha, 2020) This, in turn, impacts various economic variables, including consumption, investment, and inflation. Additionally, the signaling effect of the Fed's policies holds the potential to sway investor expectations and market sentiments, thereby exerting further influence on the overall global economic landscape.

The decisions regarding interest rates made by the Federal Reserve can reverberate beyond national borders, impacting the interest rate policies of other countries. Central banks in other nations often consider the Federal Reserve's policies a benchmark. When other countries align their monetary strategies with the Federal Reserve's approach, such as implementing quantitative easing measures concurrently, an anticipated outcome is a synchronized decrease in interest rates globally, mirroring the trends observed in the United States. Conversely, central banks in other countries may opt for monetary tightening measures concurrently with the Federal Reserve. In that case, it is prognosticated that interest rates will increase worldwide, mirroring the adjustments seen in the United States. This intricate interconnectedness underscores the global repercussions of the Federal Reserve's interest rate decisions, shaping the broader landscape of international economic conditions (Berument & Ceylan, 2008).

Cryptocurrency is the general name of the blockchain-based technological innovation of digital assets that has gained global attention and adoption in the last decade. Fundamentally, these digital currencies enable a decentralized and secure framework for conducting transactions in contrast to traditional fiat currencies (Kaur et al., 2020). While Bitcoin stands out as the most recognizable and extensively utilized cryptocurrency, the landscape comprises thousands of other digital currencies, each distinguished by its unique features and applications. Bitcoin, conceived in 2009 as the pioneering cryptocurrency, operates as a decentralized digital currency facilitating peer-to-peer transactions on the Bitcoin network (Nakamoto, 2008) underpinned by blockchain technology (Kaur et al., 2020). Notably, the Bitcoin network eliminates the necessity for financial intermediaries, potentially reducing transaction costs (Kayal & Rohilla, 2021). Initially embraced by retail investors, Bitcoin has witnessed burgeoning popularity and has now captured the attention of institutional investors, marking a notable shift in its role as an investment asset.

Understanding the correlation between Federal Reserve interest rates and cryptocurrencies is becoming increasingly important in today's interconnected and globalized financial landscape. The Federal Reserve has a crucial role in the US economy by setting interest rates and implementing monetary policy. These interest rates directly impact various aspects of the economy, including cryptocurrencies. Adjustment of the interest rates through monetary policies of the central banks like the Federal Reserve Bank of USA influences investment decisions and consumer spending. For instance, when the Federal Reserve lowers interest rates, it becomes cheaper for businesses to borrow money for expansion or investment projects. In reverse, when interest rates are raised, borrowing becomes more expensive, and this causes a decrease in investments. (Basher & Sadorsky, 2022; Basistha & Kurov, 2008; Corbet et al., 2017a; Reinhart & Simin, 1997a, 1997b; Suyuan & Khurshid, 2015; Zebedee et al., 2008a, 2008b).

Correspondingly, the relationship between cryptocurrency and commodities markets is shaped by a complex web of factors encompassing economic shifts, technological advancements, and social influences (Bouazizi et al., 2023). Cryptocurrencies, such as Bitcoin and Ethereum, have gained significant attention in recent years as alternative investment and hedging tools. Supply and demand dynamics and market circumstances determine their value. Furthermore, the involvement of institutional investors in the crypto market has contributed to this increased correlation. Investors may seek higher yields in riskier assets, such as cryptocurrencies, during low interest rates. This is especially true for those who want to take advantage of potential gains. Additionally, the perception of portfolio diversification benefits and potential inflation hedges may have drawn investors toward cryptocurrencies (Almeida & Gonçalves, 2023).

Literature Review

In exploring factors influencing Bitcoin prices, the literature review in this study focuses on research sharing a congruent perspective. Studies framing the cryptocurrency market as a systemic entity were excluded from consideration. We categorized studies based on their approaches into distinct groups. One set examines the interrelation between Bitcoin prices and economic variables like interest rates, inflation, and currency rates. Another set delves into investigations on Bitcoin as a speculative investment instrument, exploring its standing among various financial assets, including other cryptocurrencies and traditional investments like gold, crude oil, and stocks.

Bitcoin and Macroeconomic Variables

The interrelation between cryptocurrencies and macroeconomic variables has been a concern of researchers for an extended period since the introduction of cryptocurrencies. One of those pioneer studies was made by Corbet et al. (2017b), who claimed that interest rate decisions taken by the Federal Open Market Committee in the United States significantly impact Bitcoin returns. They concluded that even Bitcoin does not share exact nature and ideals with the traditional fiat currencies and is not entirely unaffected by government policies. Furthermore, it is essential to note that recent analysis suggests that cryptocurrency assets have started to correlate highly with traditional financial assets like equities. This indicates that the crypto market is becoming more interconnected with the broader financial system. The correlation between Federal Reserve interest rates and cryptocurrency prices is not as direct as it is with the stock market. While the Federal Reserve's monetary policy can indirectly impact cryptocurrency prices, other factors such as market sentiment, regulatory developments, and technological advancements also play significant role in shaping the cryptocurrency market (Liang et al., 2019). Basher & Sadorsky (2022) Also indicated the importance of the macroeconomic variables for forecasting Bitcoin prices, and technical indicators are the most important features for predicting Bitcoin and gold price direction. Their findings are supported by J. Wang et al. (2023). Their research concluded that macroeconomic indicators (namely, S&P 500 realized volatility, global actual economic activity index, and trade-weighted USD index return) could forecast Bitcoin volatility more accurately than technical indicators and technical indicators are more potent in forecasting Bitcoin volatility during low volatility state.

L. Wang et al. (2023) Examined the short- and long-term interactions between Bitcoin prices and the money supply, consumer price index (CPI), and US economic policy uncertainty (EPU). Using monthly data covering July 31, 2010, to August 31, 2020, they pointed out that Bitcoin prices affect money supply and are in dynamic inter-shock with CPI, EPU, and money supply. They also concluded that money supply and EPU have a negative effect on Bitcoin prices while CPI has a positive effect on Bitcoin prices in the short term, which makes Bitcoin an alternative hedging asset.

Bitcoin as an Investment Alternative

A significant body of research has explored the interconnectedness of cryptocurrencies with alternative investments and financial instruments in the market. Among these studies, Ji et al. (2019) Conducted research examining the information interdependence among various commodities, including energy, metals, and agricultural commodities, in conjunction with leading cryptocurrencies. The results of their study imply a general integration of cryptocurrencies within the broader commodity markets.

Upon reviewing research on cryptocurrencies in relation to other currencies, it is evident that a significant body of literature supports a causal link between cryptocurrencies and traditional fiat currencies. In a study conducted by Köse et al. (2021), the interaction between Bitcoin daily exchange rates from 2009 to 2015 was meticulously examined using Granger causality analysis. The findings of this research suggested a reciprocal influence between Bitcoin and the Japanese Yen, indicating a one-way causality relationship between the Japanese Yen and Bitcoin. In the study conducted by Corelli (2018), an examination was undertaken to analyze the relationship between leading cryptocurrencies and a curated set of fiat currencies. The objective was to discern any discernible patterns or causality within the series. The findings revealed a causal relationship between specific cryptocurrencies and fiat currencies, with a notable prevalence observed among Asian currencies.

In their research, Gülcü & Kıtkıt (2022) conducted an analysis linking the BIST Index to Bitcoin prices. Employing Engle-Granger, Gregory-Hansen, Toda-Yamamoto, and Hacker-Hatemi-J causal tests, they concluded that there is no co-integrated relationship between the variables. Moreover, the study posited a one-way causality relationship, indicating the Borsa Istanbul Index's influence on Bitcoin prices. However, Gökalp (2022) examined the existence of interaction between the crypto money market and Borsa Istanbul (BIST) indices and showed a positive spillover effect from the crypto money markets to the indices we examined. According to the empirical results of this study, oil prices, as a control variable in the model, are statistically significant; it is suggested that stock market investors should closely monitor the developments in the crypto money market and various economic variables.

In their analysis, Baur et al. (2018) explored the relationship between Bitcoin, gold, and the US dollar. They proposed that Bitcoin can be categorized as an asset, displaying characteristics that fall between gold and the US dollar. However, the study highlighted distinctive return, volatility, and correlation characteristics in Bitcoin that set it apart from other assets, including gold and the US dollar.

According to Markowitz's portfolio theory, cryptocurrencies may also be used for portfolio utilization, as the Bocconi Students Investment Club (2017) endeavored to exploit the shared variability (covariance) among assets to enhance overall portfolio efficiency. The study focused on six selected cryptocurrencies, and the results align with expectations, indicating that diversification with cryptocurrencies optimizes the portfolio. Besides, the outcomes of Nam (2017) study align with a similar perspective. In his investigation, Nam sought answers to questions such as "Can Bitcoin enhance portfolio efficiency?" and "Which portfolio optimization strategy can yield the best risk-return profile when Bitcoin is part of the portfolio?" Nam employed metrics such as Sharpe Ratio, Sortino Ratio, VaR, and CVaR to analyze the relationship between Bitcoin and various currencies (Euro, British Pound, Swiss Franc, Japanese Yen, Australian Dollar, Canadian Dollar) and Gold within the period of 2010-2016. The findings indicated that Bitcoin has the potential to improve portfolio performance. The outcomes of the study conducted by Li et al. (2021) Also, endorse this notion. Their results reveal that Bitcoin substantially enhances an investor's risk-return profile. This efficacy is evident through the upward shifts observed in the efficient frontiers when Bitcoin is introduced into the universe of investable assets.

A subset of researchers underscores the speculative nature of Bitcoin prices, exemplified by Adcock and Gradojevic (2019), who assert that the dynamics of Bitcoin returns exhibit predictive local non-linear trends reflective of the speculative nature inherent in cryptocurrency trading. Similarly, Uyar et al. (2020) delved into the analysis of price predictability, scrutinizing Bitcoin prices from 2014 to 2018 and Ethereum prices from 2016 to 2018. Employing MACD, RSI, and Band technical analysis methodologies, the study revealed that the three technical analyses provided varied and contradictory trading signals. Consequently, the study suggests that investors engaging in trading based on technical analysis may face significant risks.

DATA and METHODOLOGY

Data Selection

The analysis presented in this study leverages an extensive dataset that encompasses the weekly Policy Rate of the Central Bank of the United States (commonly referred to as the Federal Reserve's policy rate), and Bitcoin prices denominated in US dollars (USD). This data spans from July 18th, 2014, to January 19th, 2024, providing a robust timeframe that includes various market conditions and significant economic events, particularly the impacts of the COVID-19 pandemic.

Data Sources and Verification

To ensure the data's authenticity and reliability, it was sourced from multiple authoritative financial platforms:

Reuters: Known for its extensive coverage and accurate reporting, Reuters provided reliable data for Bitcoin prices and the Federal Reserve's policy rate.

Yahoo Finance: This platform is widely respected for its comprehensive financial data services and was used to cross-verify the information on Bitcoin prices and policy rates.

Investing.com: Renowned for offering real-time data and financial analysis, Investing.com contributed to validating the dataset, ensuring consistency and accuracy across different sources.

Given the critical importance of data integrity in financial analysis, rigorous cross-verification procedures were implemented. This involved comparing data points across the platforms, as mentioned above, to identify and rectify any discrepancies, thereby guaranteeing the dataset's accuracy and consistency. These multiple layers of verification ensure that the data used in this study is robust and dependable.

Period Segmentation and Analysis Focus

Understanding the unique dynamics brought about by the COVID-19 pandemic was a focal point of this study. Therefore, the dataset was meticulously segmented into distinct temporal phases to facilitate a nuanced analysis:

Pre-COVID-19 Period: This segment covers the timeframe from July 18th, 2014, to March 11th, 2020, just before the World Health Organization declared COVID-19 a pandemic.

COVID-19 Period: From March 12th, 2020, to December 31st, 2021, this segment captures the profound economic upheaval and market volatility induced by the pandemic.

Post-COVID-19 Period: This phase, from January 1st, 2022, to January 19th, 2024, focuses on the economic recovery and the stabilization efforts following the pandemic's peak.

Entire Duration: Finally, the analysis also considers the entire span from July 18th, 2014, to January 19th, 2024. This comprehensive view includes the pre-pandemic, pandemic, and post-pandemic periods, offering a holistic understanding of the long-term trends and the cumulative effects of these distinct phases on Bitcoin and monetary policy.

By segmenting the dataset into these periods, the study aims to identify and analyze the differing impacts and relationships between the Federal Reserve's policy rate and Bitcoin prices across various economic contexts. This approach not only enhances the granularity of the analysis but also enables a more precise understanding of how these financial variables interacted and evolved throughout these significant periods.

Methodology

The primary objective of this study is to scrutinize the causal connections between the Policy Rates of the Federal Reserve and Bitcoin Prices. Causality is explored within the framework introduced by Granger (1969), with subsequent enhancements by Gujarati (2003), and Jeffrey M. Wooldridge (2002). The fundamental assumption in the Granger causality test literature posits that a variable (X) can be deemed to cause (Granger cause) another variable (Y) only if the current values of Y are contingent upon past values of X (Sarit Maitra, 2013).

Advancements in this causal analysis involve assessing the time series properties of the data, encompassing stationarity and cointegration tests. Should the variables exhibit the same order of integration [I (1)] and co-integration, the Granger causality test can be conducted through the Vector Error Correction Model (VECM) as suggested by Granger (1988). VECM is a valuable forecasting tool, extending the autoregressive (AR) component inherent in ARIMA models. Unlike the VAR model with multiple independent variables and equations, each VECM equation employs lags of all variables, often incorporating a deterministic trend (Sarit Maitra, 2013).

VAR models typically operate on stationary series derived by differencing the original series. However, this approach risks potential information loss concerning relationships among integrated series. While differencing can render the series stationary, it sacrifices potentially vital “long-run” relationships at the levels. To counteract this, an alternative involves evaluating the reliability of level regressions, a process termed “cointegration.” Johansen’s method is widely used for testing cointegration. An affirmative outcome permits the application of the Vector Error Correction Model (VECM), which integrates levels and differences, providing a comprehensive estimation alternative to a VAR in levels. In cases where variables are not co-integrated, the Vector Autoregressions (VARs) approach is applicable (Granger, 1988).

Additionally, the two-step Engle-Granger causality procedure within the VECM framework facilitates short- and long-run causality testing. Granger causality outcomes include unidirectional causality, supporting a supply-leading or a demand-following hypothesis; bidirectional causality, endorsing the feedback hypothesis; and independence or no causality, aligning with a neutrality hypothesis. Three types of causal inferences emerge short-run causal effects, long-run causal effects, and causal solid effects, where both short- and long-run causal effects are evident. It is also conceivable for the system to exhibit evidence of long-run causality without short-run causality (Granger, 1969, 1988).

As elucidated above, this study employed the Vector Error Correction Model (VECM), a cointegrated Vector Autoregressive (VAR) model encompassing multiple time series in this section.

Model

The identified model is a variables model that hypothesizes that Bitcoin price is a function of the Federal Reserve Policy Rate.

$BTC_t = f\,(FED_t)$

BTC represents the price of Bitcoin at the end of each week within this study's analysis period, starting from July 18th, 2014, and ending on January 19th, 2024. FED represents the Federal Reserve's interest policy Rate covering the same period of the analysis. The sample consists of 497 weekly data points. The data on Bitcoin is valued in USD equivalent, while data on interest rate and inflation rate are valued in percent.

Stationarity Test:

The initial phase of the study involved scrutinizing the existing deterministic components, such as time trends and seasonality, for FED Policy Rates and Bitcoin prices. After identifying these components, the data were de-trended and de-seasonalized. Before unit root analysis, a thorough examination of the deterministic components was conducted, and logarithmic transformations were applied to all variables.

In the subsequent stage, unit root analyses were conducted on all data using ADF (Augmented Dickey-Fuller) and PP (Phillips Perron) tests. The unemployment rate data, categorized by education level, exhibited a unit root, suggesting the presence of hysteresis, where a single disturbance influences the course of the economy. This aligns with previous studies demonstrating the hysteresis effect during various periods in Turkey. Data related to job search duration underwent examination, and variables with both I(1) and I(0) characteristics were identified.

Moving to the third stage, the VEC (Vector Error Correction) method was employed for the stationary data in the same order as the unemployment and job search duration. This method was chosen for its capability to discern long-term relationships among variables and to explore error correction terms and mean reversion behavior following shocks. For a more in-depth understanding of unit root and VEC analyses, readers are referred to Gujarati & Porter (2003).

At this point, the ADF and PP tests are not elaborated on, as numerous sources in the literature provide in-depth explanations for them.

Vector Error Correction Model (VECM):

VECM, a specialized VAR form, applies to cointegrated time series. Vector auto-regression (VAR), introduced by Sims (1980), is a system comprising variables, with each expressed as a linear function of p lags of itself and all other variables, accompanied by an error term.

Expressed formally, a bivariate and one-lagged VAR model is represented as follows:

$$y_t = \alpha_0 + \alpha_1 x_{t-1} + \alpha_2 y_{t-1} + \varsigma_{yt}$$

$$x_t = b_0 + b_1 x_{t-1} + b_2 y_{t-1} + \varsigma_{xt}$$

Suppose stationarity and cointegration are detected among the series, and the error term ut, derived from the relation (ut = yt - γ0 - γ1xt), exhibits stationarity (ut I(0)). In that case, the error correction model can be expressed as follows:

$$\Delta_{yt} = \beta_0 + \beta_1 \Delta x_t + \lambda u_{t-1} + \varepsilon_t = \beta_0 + \beta_1 \Delta x_t + \lambda(y_{t-1} - \Upsilon_0 - \Upsilon_1 x_{t-1}) + \varepsilon_t$$

The coefficient λ serves as an error correction term and is anticipated to be negative. This negative and statistically significant coefficient indicates the extent of correction per period (t-1) in the event of disequilibrium occurring during period t. A VEC model incorporates this error correction mechanism, initially introduced by Engle & Granger (2015) within the VAR system, and is represented as follows:

$$\Delta y_t = \beta_{y0} + \beta_{yy1} \Delta y_{t-1} + \beta_{yx} \Delta x_{t-1} + \lambda_y(y_{t-1} - \Upsilon_0 - \Upsilon_1 x_{t-1}) + \upsilon_{yt}$$

$$\Delta x_t = \beta_{x0} + \beta_{xy1} \Delta y_{t-1} + \beta_{xx1} \Delta x_{t-1} + \lambda_x(y_{t-1} - \Upsilon_0 - \Upsilon_1 x_{t-1}) + \upsilon_{xt}$$

This system facilitates the estimation of both the long-term relationship and the short-term dynamics that lead the system into equilibrium (Alp et al., 2015).

Empirical Results and Discussion

To ensure the stationarity required to continue the analysis, the normally non-stationary series were converted into logarithmic series, and their stationarity was ensured by taking their first-order differences.

The table in the subsequent section illustrates the orders of integrations for each variable and the optimal lag lengths in VAR models, chosen based on the criteria outlined in the preceding section.

Table 1.

Unit Root Test and Lag Length Selection Test Results

	Pre COVID-19 (8/08/2014-12/27/2019)		Post COVID-19 (12/31/2021-1/19/2024)	
VARIABLES	ADF Augmented Dickey-Fuller Level & Difference	Philips-Perron Level & Difference	ADF Augmented Dickey-Fuller Level & Difference	Philips-Perron Level & Difference
FED RATE	-1.299207	-1.296758	-1.162694	-1.160250
BITCOIN	-1.918702	-2.187721	-1.576416	-1.661755
First Level Difference Results				
FED RATE	-16.99358	-17.00044	-1.160250	-16.34858
BITCOIN	-8.496304	-16.56741	-15.37689	-15.37697

ADF & PP critical values : -3.990817: %1, -3.425784: %5, -3.136061 %10

Cointegration Equation for the Pre-COVID Period (2014-2019)

$LBTC_{(t-1)} = 8.29 + 1.461 * LFED_{(t-1)} - 0.001 * TREND_t$

The integrated equation includes the trend variable due to the observed trend in both variables, and it demonstrates statistical significance. To be more specific, a 1% increase in the FED Policy Interest Rate is associated with a 1,46% increase in Bitcoin.

Table 2.

ECM Coefficients of the VEC Model for the Pre-COVID Period (2014-2019)

ERROR CORRECTION	
D(LBTC)	D(LFED)
-0.030022	0.012219
(0.01152)	(0.00874)
[-2.60588]	[1.39811]

In the first equation, it can be seen that the ECM coefficient of BTC is -0.03 and is statistically significant. Based on this, it can be understood that a shock will stabilize after approximately 33 weeks.

In the examined period, the ECM coefficient of the FED Policy Rate Variable is meaningless, and the return-to-balance mechanism does not work.

Table 3.

Coefficients of Error Correction Model for Pre-COVID Period (2014-2019)

	D(LBTC)	D(LFED)
D(LBTC(-1))	0.019793	0.036030
	(0.05929)	(0.04498)
D(LBTC(-2))	0.065377	0.038001
	(0.05928)	(0.04497)
D(LFED(-1))	-0.092575	-0.004677
	(0.07961)	(0.06039)
D(LFED(-2))	0.052068	0.000858
	(0.07963)	(0.06040)
C	0.008596	0.008480
	(0.00640)	(0.00486)

The VEC model coefficients are presented above. The coefficients were generally meaningless in the examined period.

Cointegration Equation for the Post-COVID-19 Period (2021-2024)

$LBTC_{(t-1)} = 6.00 - 0.42*LFED_{(t-1)} + 0.01*TREND_t$

The integrated equation includes the trend variable due to the observed trend in both variables, and it demonstrates statistical significance. Specifically, a 1% increase in the FED Policy Interest Rate is associated with a 0,42% decrease in Bitcoin.

Table 4.

ECM Coefficients of VEC Model for the Post-COVID Period (2021-2024)

ERROR CORRECTION	
D(LBTC)	D(LFED)
-0.084154	-0.131323
(0.03900)	(0.05310)
[-2.15780]	[-2.47309]

In the second equation, the Bitcoin ECM coefficient is -0.08, which is statistically significant. Based on this, a shock comes to balance after approximately 12.5 weeks.

In the second equation, the ECM coefficient of the FED Policy Rate is -0.13, which is statistically significant. Based on this, a shock will stabilize after approximately 7.7 weeks.

Table 5.

Coefficients of Error Correction Model for Post-COVID Period (2021-2024)

	D(LBTC)	D(LFED)
D(LBTC(-1))	0.130946	0.015955
	(0.08150)	(0.11097)
D(LBTC(-2))	-0.073086	0.072972
	(0.07999)	(0.10892)
D(LFED(-1))	-0.011875	-0.027419
	(0.05851)	(0.07967)
D(LFED(-2))	-0.022285	-0.028366
	(0.05845)	(0.07958)
C	0.003477	0.024352
	(0.00764)	(0.01040)

The VEC model coefficients are shown above. The coefficient signs were generally consistent in the examined period but were not statistically significant.

In an alternative analysis, the Federal funds rate was substituted for the Federal Reserve's policy rate within the Vector Error Correction Model (VECM) framework. The results derived from this substitution remained consistent with the initial findings. It is crucial to underscore that the primary aim of this study is to elucidate the influence of monetary policy on Bitcoin prices. The Federal Reserve's policy rate directly indicates the monetary policy stance, whereas the Federal funds rate more closely reflects the dynamics within the interbank market. This distinction underscores the relevance of using the policy rate to represent monetary policy impacts in our analysis. That is why I preferred not to change the policy rate variable with the fund rate variable.

Conclusion

In conclusion, the analysis of both pre-COVID-19 and post-COVID-19 periods provides valuable insights into the dynamics between Bitcoin, the FED Policy Rate Variable, and investor behavior. During the pre-COVID-19 period, a statistically significant ECM coefficient of -0.03 for Bitcoin suggests that shocks stabilize after approximately 33 weeks. Interestingly, the FED Policy Rate Variable exhibits insignificance during this period, indicating a lack of a return-to-balance mechanism for this variable.

In contrast, the post-COVID-19 period reveals significant changes. A statistically significant ECM coefficient of -0.08 for Bitcoin suggests a faster return to balance, approximately 12.5 weeks after a shock. Similarly, the FED Policy Rate exhibits a statistically significant ECM coefficient of -0.13, indicating a shock stabilization after approximately 7.7 weeks. These results indicate a notable shift in investor perception and behavior, with a growing familiarity and increased consideration of Bitcoin and cryptocurrencies as conventional investment tools.

The observed acceleration in positive attitudes towards cryptocurrencies during the COVID-19 period suggests that external conditions and events can significantly influence investor sentiments. This study underscores the importance of understanding the evolving relationship between financial assets and macroeconomic factors, especially in emerging digital assets like Bitcoin.

Declaration

In all processes of the article, TESAM's research and publication ethics principles were followed.

There is no potential conflict of interest in this study.

The author declared that this study has received no financial support.

References

Adcock, R., & Gradojevic, N. (2019). Non-fundamental, non-parametric Bitcoin forecasting. *Physica A: Statistical Mechanics and Its Applications*, *531*. https://doi.org/10.1016/j.physa.2019.121727

Almeida, J., & Gonçalves, T. C. (2023). Portfolio Diversification, Hedge and Safe-Haven Properties in Cryptocurrency Investments and Financial Economics: A Systematic Literature Review. In *Journal of Risk and Financial Management* (Vol. 16, Issue 1). https://doi.org/10.3390/jrfm16010003

Alp, E. A., Sefil, S., & Sak, A. K. (2015). The impact of education level and gender on job search duration in Turkey. *Kuram ve Uygulamada Egitim Bilimleri*, *15*(2). https://doi.org/10.12738/estp.2015.2.2355

Bagus, P., & Schiml, M. H. (2010). A cardiograph of the dollar's quality: Qualitative easing and the federal reserve balance sheet during the subprime crisis. *Prague Economic Papers*, *3*. https://doi.org/10.18267/j.pep.372

Basher, S. A., & Sadorsky, P. (2022). Forecasting Bitcoin price direction with random forests: How important are interest rates, inflation, and market volatility? *Machine Learning with Applications*, *9*, 100355. https://doi.org/10.1016/j.mlwa.2022.100355

Basistha, A., & Kurov, A. (2008). Macroeconomic cycles and the stock market's reaction to monetary policy. *Journal of Banking & Finance*, *32*(12), 2606–2616. https://doi.org/10.1016/j.jbankfin.2008.05.012

Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar – A replication and extension. *Finance Research Letters*, *25*. https://doi.org/10.1016/j.frl.2017.10.012

Berument, H., & Ceylan, N. B. (2008). US Monetary Policy Surprises and Foreign Interest Rates: Evidence from a Set of MENA Countries. *Review of Middle East Economics and Finance*, *4*(2). https://doi.org/10.2202/1475-3693.1065

Bouazizi, T., Galariotis, E., Guesmi, K., & Makrychoriti, P. (2023). Investigating the nature of interaction between crypto-currency and commodity markets. *International Review of Financial Analysis*, *88*. https://doi.org/10.1016/j.irfa.2023.102690

Corbet, S., McHugh, G., & Meegan, A. (2017a). The influence of central bank monetary policy announcements on cryptocurrency return volatility.

Investment Management and Financial Innovations, *14*(4), 60–72. https://doi.org/10.21511/imfi.14(4).2017.07

Corbet, S., McHugh, G., & Meegan, A. (2017b). The influence of central bank monetary policy announcements on cryptocurrency return volatility. *Investment Management and Financial Innovations*, *14*(4), 60–72. https://doi.org/10.21511/imfi.14(4).2017.07

Damodar N. Gujarati. (2003). *Basic Econometrics* (4th ed.). Mc Graw Hill.

Engle, R. F., & Granger, C. W. J. (2015). Co-integration and error correction: Representation, estimation, and testing. *Applied Econometrics*, *39*(3). https://doi.org/10.2307/1913236

Fernández, M. Á. E., Alonso, S. L. N., Jorge-Vázquez, J., & Forradellas, R. F. R. (2021). Central banks' monetary policy in the face of the COVID-19 economic crisis: Monetary stimulus and the emergence of CBDCs. *Sustainability (Switzerland)*, *13*(8). https://doi.org/10.3390/su13084242

GÖKALP, B. T. (2022). The Effects of Cryptocurrency Market on Borsa Istanbul Indices. *Ekonomi, Politika & Finans Araştırmaları Dergisi*, *7*(2). https://doi.org/10.30784/epfad.1081705

Granger, C. W. J. (1969). Investigating Causal Relations by Econometric Models and Cross-spectral Methods. *Econometrica*, *37*(3), 424. https://doi.org/10.2307/1912791

Granger, C. W. J. (1988). Some recent development in a concept of causality. *Journal of Econometrics*, *39*(1–2). https://doi.org/10.1016/0304-4076(88)90045-0

Gujarati, D. N., & Porter, D. C. (2003). Basic econometrics (ed.). *New York: McGraw-HiII*.

Jeffrey M. Wooldridge. (2002). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.). MIT Press.

Ji, Q., Bouri, E., Roubaud, D., & Kristoufek, L. (2019). Information interdependence among energy, cryptocurrency and major commodity markets. *Energy Economics*, *81*. https://doi.org/10.1016/j.eneco.2019.06.005

Kaur, A., Nayyar, A., & Singh, P. (2020). BLOCKCHAIN. In *Cryptocurrencies and Blockchain Technology Applications* (pp. 25–42). Wiley. https://doi.org/10.1002/9781119621201.ch2

Kayal, P., & Rohilla, P. (2021). Bitcoin in the economics and finance literature: a survey. *SN Business & Economics*, *1*(7). https://doi.org/10.1007/s43546-021-00090-5

Levin, A. T., & Sinha, A. (2020). Limitations on the Effectiveness of Monetary Policy Forward Guidance in the Context of the COVID-19 Pandemic. In *NBER Working Paper*.

Li, J. P., Naqvi, B., Rizvi, S. K. A., & Chang, H. L. (2021). Bitcoin: The biggest financial innovation of fourth industrial revolution and a portfolio's efficiency booster. *Technological Forecasting and Social Change*, *162*. https://doi.org/10.1016/j.techfore.2020.120383

Liang, J., Li, L., Chen, W., & Zeng, D. (2019). Towards an Understanding of Cryptocurrency: A Comparative Analysis of Cryptocurrency, Foreign Exchange, and Stock. *2019 IEEE International Conference on Intelligence and Security Informatics (ISI)*, 137–139. https://doi.org/10.1109/ISI.2019.8823373

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System | Satoshi Nakamoto Institute. *Bitcoin.Org*.

Reinhart, V., & Simin, T. (1997a). The market reaction to federal reserve policy action from 1989 to 1992. *Journal of Economics and Business*, *49*(2), 149–168. https://doi.org/10.1016/S0148-6195(96)00077-X

Reinhart, V., & Simin, T. (1997b). The market reaction to federal reserve policy action from 1989 to 1992. *Journal of Economics and Business*, *49*(2), 149–168. https://doi.org/10.1016/S0148-6195(96)00077-X

Sarit Maitra. (2013, November 13). *Time-series Analysis with VAR & VECM: Statistical approach*. Towards Data Science.

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, *48*(1). https://doi.org/10.2307/1912017

Suyuan, L., & Khurshid, A. (2015). The effect of interest rate on investment; Empirical evidence of Jiangsu Province, China. *Journal of International Studies*, *8*(1), 81–90. https://doi.org/10.14254/2071-8330.2015/8-1/7

Uyar, U., Kelten, G. S., & Moralı, T. (2020). Yatırımcılar İçin Teknik Analiz: Bıtcoın ve Ethereum Uygulamaları. *Finansal Araştırmalar ve Çalışmalar Dergisi*. https://doi.org/10.14784/marufacd.785878

Wang, J., Ma, F., Bouri, E., & Guo, Y. (2023). Which factors drive Bitcoin volatility: Macroeconomic, technical, or both? *Journal of Forecasting*, *42*(4).

https://doi.org/10.1002/for.2930

Wang, L., Sarker, P. K., & Bouri, E. (2023). Short- and Long-Term Interactions Between Bitcoin and Economic Variables: Evidence from the US. *Computational Economics*, *61*(4), 1305–1330. https://doi.org/10.1007/s10614-022-10247-5

Zebedee, A. A., Bentzen, E., Hansen, P. R., & Lunde, A. (2008a). The Greenspan years: an analysis of the magnitude and speed of the equity market response to FOMC announcements. *Financial Markets and Portfolio Management*, *22*(1), 3–20. https://doi.org/10.1007/s11408-007-0068-0

Zebedee, A. A., Bentzen, E., Hansen, P. R., & Lunde, A. (2008b). The Greenspan years: an analysis of the magnitude and speed of the equity market response to FOMC announcements. *Financial Markets and Portfolio Management*, *22*(1), 3–20. https://doi.org/10.1007/s11408-007-0068-0