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A MULTIVARIATE INVESTIGATION OF LIQUIDITY, MINING INCENTIVES, AND LONG-RUN EQUILIBRIUM RELATIONSHIPS

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ABSTRACT

This study examines the determinants of Bitcoin returns by integrating blockchain network fundamentals and market activity indicators within a multivariate econometric framework. Using a time-series approach grounded in the Efficient Market Hypothesis and cointegration theory, the analysis investigates how trading volume, mining difficulty, hash rate, transaction fees, and confirmed payments jointly influence Bitcoin price dynamics. The study used monthly frequency series from 2014:M1 to 2025:M12. The empirical strategy employs unit root testing, Johansen cointegration analysis, and a Vector Error Correction Model to capture both short-run fluctuations and long-run equilibrium relationships. The findings reveal that Bitcoin returns are significantly driven by trading volume, transaction fees, and network usage, while hash rate exhibits a negative effect due to mining cost pressures. Cointegration results confirm long-run equilibrium among variables, and the error correction term indicates rapid adjustment toward stability. Overall, the study highlights Bitcoin's hybrid nature, driven by both speculative behavior and structural blockchain fundamentals, offering important implications for investors and policymakers.

Introduction

Bitcoin has emerged as one of the most transformative financial innovations in modern markets, reshaping perceptions of money, investment, and decentralized finance. Since its introduction, it has evolved from a niche digital experiment into a globally traded asset with significant market capitalization and volatility dynamics. Early studies such as Dwyer (2015) and Dyhrberg (2016) conceptualized Bitcoin as a hybrid asset combining characteristics of commodities and currencies, while Kristoufek (2015) highlighted the role of demand and attention in price formation. Similarly, Baur et al. (2018) and Urquhart (2016) emphasized its speculative nature and market inefficiencies. However, despite extensive literature, there remains limited consensus on the fundamental drivers of Bitcoin returns, particularly regarding the interaction between blockchain network fundamentals and market activity variables.

A growing strand of research has focused on blockchain-based determinants such as mining difficulty, hash rate, and transaction activity. Ciaian et al. (2016) demonstrated that supply-demand fundamentals significantly influence Bitcoin pricing, while Sovbetov (2018) identified network activity as a key determinant of returns. Li and Wang (2016) further showed that mining difficulty and computational power affect exchange rate dynamics through supply-side constraints. Lansky (2016) and Murphy (2015) also highlighted the importance of blockchain validation mechanisms in shaping cryptocurrency price structures. Despite these contributions, most studies remain fragmented, focusing either on market variables or blockchain fundamentals separately, without integrating both dimensions into a unified empirical framework for Bitcoin return determination.

In addition to structural fundamentals, market microstructure variables such as trading volume and liquidity have been widely recognized as important determinants of Bitcoin price movements. Balcilar et al. (2017) found that trading volume can predict both returns and volatility, while Aalborg et al. (2019) confirmed that liquidity plays a central role in cryptocurrency price dynamics. Wang et al. (2020) further emphasized that trading activity reflects investor participation and sentiment in digital asset markets. Ji et al. (2019) and Jeon et al. (2020) extended this analysis by showing that market fragmentation and volatility connectedness significantly influence price transmission. However, these studies often neglect the role of blockchain-based structural variables, creating a gap in understanding how market and network forces jointly determine Bitcoin returns.

Another important dimension in Bitcoin literature relates to volatility, risk, and speculative behaviour. Fry and Cheah (2016) identified negative bubbles and speculative distortions in cryptocurrency markets, while Blau (2018) demonstrated that trading intensity is strongly associated with speculative price movements. Troster et al. (2018) further highlighted time-varying risk structures in Bitcoin returns, showing that volatility is highly sensitive to market shocks. Goczek and Skliar (2019) and Guizani and Nafti (2019) also documented strong volatility clustering effects. Hung et al. (2020) improved forecasting accuracy using advanced econometric models. Despite these advancements, there is still insufficient evidence on how volatility interacts with blockchain fundamentals such as mining difficulty and transaction fees, particularly within a unified cointegrated framework.

From a macro-financial perspective, Bitcoin has also been examined as a hedge or alternative asset during periods of economic uncertainty. Dyhrberg (2016) initially suggested that Bitcoin shares hedging properties with gold, while Klein et al. (2018) found mixed evidence regarding its diversification benefits. Bouri et al. (2017) showed that Bitcoin may act as a hedge under specific market conditions, whereas Demir et al. (2018) highlighted its sensitivity to economic policy uncertainty. Erdas and Caglar (2018) further demonstrated macro-financial linkages between Bitcoin and traditional assets. However, despite these contributions, there remains limited understanding of how internal blockchain dynamics contribute to Bitcoin's hedge-like properties, particularly in relation to network activity and miner incentives.

Given these gaps, the study pursues three main objectives. First, it examines the short-run and long-run determinants of Bitcoin returns using both blockchain network variables and market-based indicators. Second, it investigates the existence of long-run equilibrium relationships among Bitcoin returns, trading volume, and mining fundamentals using cointegration techniques. Third, it analyses the speed of adjustment and dynamic interactions among variables using a Vector Error Correction Model (VECM). By integrating insights from Catania et al. (2019), Corbet et al. (2018), Poyser (2019), Huang et al. (2019), and Liu and Tsyvinski (2021), the study contributes to bridging the gap between market microstructure and blockchain economics.

The structure of the article is as follows. The next section presents the literature review. Afterward thee paper present the methodology, including model specification, econometric framework, and variable construction. This is followed by the empirical results and discussion, where stationarity tests, cointegration analysis, and VECM estimates are presented and interpreted. The subsequent section discusses policy implications derived from the empirical findings, focusing on regulatory and financial stability considerations. Finally, the study concludes by summarizing key insights, highlighting limitations, and suggesting directions for future research in the evolving field of cryptocurrency economics.

Literature Review

Bitcoin has attracted extensive academic attention due to its hybrid nature as both a speculative asset and a decentralized payment system. Early foundational work by Dwyer (2015) and Dyhrberg (2016) conceptualised Bitcoin as a financial innovation combining characteristics of gold and fiat currency, highlighting its hedging potential. Similarly, Kristoufek (2015) examined demand and supply-side drivers, showing that search trends and investor attention significantly influence Bitcoin prices. These studies collectively established the basis for understanding Bitcoin as a non-traditional financial asset. Further contributions by Baur et al. (2018) and Urquhart (2016) emphasised Bitcoin's inefficiency and speculative behaviour in early market phases. Ciaian et al. (2016) extended this literature by identifying supply-demand fundamentals as key determinants of price formation, providing a structural framework that continues to underpin empirical cryptocurrency research.

A growing strand of literature investigates Bitcoin volatility and risk dynamics. Fry and Cheah (2016) documented the presence of speculative bubbles and negative price distortions in cryptocurrency markets, while Blau (2018) found that trading activity is strongly associated with speculative price movements. Troster et al. (2018) further demonstrated that Bitcoin exhibits time-varying risk and return relationships influenced by market uncertainty. Complementary evidence from Goczek and Skliar (2019) and Guizani and Nafti (2019) highlights the role of volatility clustering and network uncertainty in shaping price behaviour. Hung et al. (2020) also showed that Bitcoin volatility is predictable under certain conditions using advanced econometric models. Collectively, these studies establish that Bitcoin markets are highly volatile, with risk dynamics influenced by both speculative trading and structural uncertainty in blockchain networks.

Another significant strand of literature focuses on Bitcoin as a hedge or safe-haven asset. Dyhrberg (2016) initially argued that Bitcoin shares properties with gold and the US dollar, suggesting partial hedging capabilities. Klein et al. (2018) extended this analysis by comparing Bitcoin with gold, concluding that Bitcoin is less stable but still exhibits diversification benefits. Bouri et al. (2017) examined Bitcoin's safe-haven properties in relation to energy commodities, finding limited but context-dependent hedging effects. Similarly, Demir et al. (2018) showed that Bitcoin responds to economic policy uncertainty, reinforcing its role as an alternative asset during periods of macroeconomic instability. Erdas and Caglar (2018) further demonstrated macro-financial linkages between Bitcoin and traditional markets. These studies collectively suggest that Bitcoin cannot be classified strictly as a hedge or safe haven but exhibits conditional hedging characteristics depending on market conditions.

The role of trading volume and liquidity in Bitcoin price formation has also been widely examined. Balcilar et al. (2017) found that trading volume can predict Bitcoin returns and volatility, indicating strong market inefficiencies. Aalborg et al. (2019) further confirmed that volume is a key determinant of both price and volatility dynamics in cryptocurrency markets. Wang et al. (2020) showed that trading activity reflects investor sentiment and market participation, which significantly affects price movements. Ji et al. (2019) extended this analysis by examining volatility connectedness across cryptocurrencies, highlighting the importance of liquidity transmission. Jeon et al. (2020) also emphasized market fragmentation as a key driver of trading inefficiencies. These studies collectively suggest that Bitcoin markets are highly sensitive to liquidity conditions, with trading volume acting as a central predictor of short-run price fluctuations and systemic volatility.

Another important literature strand examines the influence of market sentiment, media attention, and behavioral factors on Bitcoin returns. Kristoufek

(2013) was among the first to show that Google search trends significantly affect Bitcoin price dynamics. Shen et al. (2019) demonstrated that Twitter sentiment has a measurable impact on Bitcoin returns, reinforcing the importance of social media in financial markets. Philippas et al. (2019) further confirmed that media attention drives speculative demand and short-term price spikes. Li and Wang (2016) also highlighted the importance of investor sentiment in cryptocurrency valuation. Luu and Huynh (2019) examined spillover effects of sentiment across digital assets, showing strong contagion patterns. These studies collectively support the view that Bitcoin pricing is not purely fundamental but heavily influenced by behavioral and informational factors, particularly in periods of heightened market attention.

A growing body of research focuses on blockchain fundamentals such as mining difficulty, hash rate, and transaction fees. Ciaian et al. (2016) initially identified mining costs and supply constraints as important determinants of Bitcoin price formation. Sovbetov (2018) further confirmed that network activity and mining intensity significantly influence cryptocurrency valuation. Li and Wang (2016) also showed that mining difficulty affects exchange rate dynamics through supply-side constraints. Murphy (2015) provided early legal and structural analysis of Bitcoin, highlighting the importance of decentralized mining systems. Lansky (2016) examined cryptocurrency price development, emphasizing blockchain validation mechanisms. These studies collectively demonstrate that Bitcoin is deeply rooted in technological infrastructure, where mining and computational power directly influence supply conditions and indirectly affect price formation.

Research has also examined Bitcoin market efficiency and price discovery mechanisms. Urquhart (2016) provided evidence that Bitcoin markets were initially inefficient but have become more efficient over time. Catania et al. (2019) showed that cryptocurrency forecasting models must account for parameter instability and structural breaks. Corbet et al. (2018) analysed dynamic relationships between cryptocurrencies and traditional financial assets, highlighting evolving efficiency patterns. Dwyer (2015) emphasized that Bitcoin markets differ fundamentally from traditional financial systems due to decentralization. Giudici and Abu-Hashish (2018) further examined exchange price determinants, showing that liquidity and infrastructure play key roles. These studies collectively suggest that Bitcoin efficiency is time-varying and dependent on market maturity and technological development.

The literature on Bitcoin cointegration and long-run relationships has expanded significantly. Ciaian et al. (2016) demonstrated that Bitcoin prices are cointegrated with supply and demand factors. Kristoufek (2018) provided an overview of cryptocurrency price drivers, emphasizing structural equilibrium relationships. Wang et al. (2016) applied VEC models to Bitcoin, showing long-run dependencies among market variables. Poyser (2019) further explored Bitcoin price dynamics using econometric approaches, confirming equilibrium correction mechanisms. Huang et al. (2019) also developed predictive models based on cointegration structures. These studies collectively confirm that Bitcoin prices are not purely random but exhibit long-run equilibrium relationships driven by fundamental blockchain variables and market forces.

Recent studies have focused on forecasting Bitcoin returns and volatility using advanced econometric and machine learning techniques. Liang et al. (2020) identified key predictors of Bitcoin volatility using multivariate models. Huang et al. (2019) developed predictive frameworks based on financial data science approaches. Hung et al. (2020) improved volatility forecasting accuracy using hybrid models. Catania et al. (2019) highlighted the importance of accounting for instability in predictive modelling. Ji et al. (2019) further emphasized volatility connectedness as a forecasting tool. These studies collectively demonstrate that Bitcoin markets require advanced modelling techniques due to their nonlinear and unstable nature, making traditional linear models insufficient for accurate prediction.

Another important area of research investigates Bitcoin spillovers and contagion effects across financial markets. Matkovskyy and Jalan (2019) showed that Bitcoin can transmit shocks to other financial assets, indicating systemic risk potential. Luu and Huynh (2019) further examined spillover risks among cryptocurrencies, confirming strong interdependencies. Corbet et al. (2018) also identified dynamic linkages between Bitcoin and traditional financial markets. Aysan et al. (2019) analysed the impact of Bitcoin price movements on stock markets, showing cross-market effects. Panagiotidis et al. (2019) further demonstrated that Bitcoin returns are influenced by macro-financial variables. These studies collectively suggest that Bitcoin is increasingly integrated into the global financial system, raising concerns about contagion and systemic stability.

Finally, regulatory and institutional literature highlights the evolving legal and policy environment surrounding Bitcoin. Cvetkova (2018) examined cryptocurrency regulation across jurisdictions, emphasizing legal uncertainty. Murphy (2015) discussed regulatory challenges in integrating Bitcoin into financial systems. Demir et al. (2018) highlighted the role of economic policy uncertainty in influencing Bitcoin returns. Erdas and Caglar (2018) further explored macro-financial linkages and regulatory implications. Giudici and Abu-Hashish (2018) stressed the importance of exchange-level regulation for price stability. These studies collectively indicate that regulatory frameworks remain fragmented and evolving, with significant implications for market stability, investor protection, and financial innovation.

Research Method

The study adopts a quantitative econometric framework to examine the determinants of Bitcoin returns using blockchain network and market activity variables. The study used monthly frequency series from 2014:M1 to 2025:M12. The theoretical foundation is anchored on the Efficient Market Hypothesis (Fama, 1970) and cointegration theory (Engle & Granger, 1987), which posit that financial variables may exhibit long-run equilibrium relationships despite short-run volatility. Following Ciaian et al. (2016) and Kristoufek (2015), Bitcoin price dynamics are assumed to be influenced by both supply-side mining factors and demand-side trading activity. The empirical model is specified as a multivariate system where Bitcoin returns BTC_R_tdepend on trading volume, mining difficulty, hash rate, transaction fees, and confirmed payments. The functional relationship is expressed as $BTC\_R_t = f(VOL_t, DIF_t, HR_t, FEE_t, PAY_t) + \varepsilon_t$, where $\varepsilon_t$is the stochastic error term capturing unexplained variation.

The data structure follows a time-series framework where all variables are transformed into logarithmic returns or growth rates to reduce heteroskedasticity and ensure comparability. Consistent with Dyhrberg (2016) and Bouri et al. (2017), Bitcoin returns are computed as $BTC\_R_t = \ln(P_t) - \ln(P_{t-1})$, where $P_t$denotes the closing Bitcoin price. Trading volume, mining difficulty, and hash rate are included as proxies for market liquidity and computational intensity, following Aalborg et al. (2019) and Balcilar et al. (2017). Transaction fees and confirmed payments capture blockchain usage intensity, consistent with Panagiotidis et al. (2019). This specification allows the model to capture both speculative and fundamental drivers of Bitcoin price formation. The dataset is assumed to be integrated of order one, I(1), except for returns, which are typically stationary.

To examine the time-series properties of the variables, the Augmented Dickey-Fuller (ADF) test is employed. The ADF regression is specified as $\Delta x_t = \alpha + \beta t + \gamma x_{t-1} + \sum_{i=1}^{k} \delta_i \Delta x_{t-i} + \varepsilon_t$, where γcaptures the presence of a unit root. The null hypothesis $H_0: \gamma = 0$indicates non-stationarity, while rejection implies stationarity. This approach follows Engle and Granger (1987) and Troster et al. (2018), who emphasize the importance of stationarity testing in financial time-series modelling. The lag length $k$is selected using the Schwarz Information Criterion to ensure white-noise residuals. This procedure ensures robustness in identifying integration properties of Bitcoin-related variables, as also recommended by Catania et al. (2019) in cryptocurrency volatility modelling.

Given that variables are integrated of order one, the Johansen cointegration technique is applied to examine long-run relationships. The system is represented as a Vector Autoregressive (VAR) model of order p:

$$X_t = A_1 X_{t-1} + A_2 X_{t-2} + \cdots + A_p X_{t-p} + \varepsilon_t \tag{1}$$

This can be reparameterized into the Vector Error Correction Model (VECM):

$$\Delta X_t = \Pi X_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \, \Delta X_{t-i} + \varepsilon_t \tag{2}$$

where $\Pi = \alpha\beta'$contains the cointegrating vectors. This methodology follows Johansen (1988) and is widely applied in Bitcoin studies such as Ciaian et al. (2016), Corbet et al. (2018), and Sovbetov (2018). The rank of Πdetermines the number of cointegrating relationships, tested using trace and maximum eigenvalue statistics. The long-run equilibrium is further analysed through the error correction representation, where deviations from equilibrium are corrected over time. The VECM specification for Bitcoin returns is given as:

$$\Delta BTC_{R_t} = \lambda\big(BTC_{R_{t-1}} - \theta_1 VOL_{t-1} - \theta_2 DIF_{t-1} - \theta_3 HR_{t-1} - \theta_4 FEE_{t-1} - \theta_5 PAY_{t-1}\big) + \sum \phi_i \Delta X_{t-i} + \mu_t \tag{3}$$

where $\lambda$is the error correction coefficient measuring speed of adjustment. A negative and significant λimplies convergence toward long-run equilibrium. This framework is consistent with Urquhart (2016), Liu and Tsyvinski (2021), and Demir et al. (2018), who highlight the importance of dynamic adjustment in cryptocurrency markets. The inclusion of lagged differences captures short-run volatility transmission effects across blockchain variables.

Estimation is conducted using ordinary least squares within the VECM framework, with diagnostic checks for serial correlation, heteroskedasticity, and model stability. Robust standard errors are applied to account for volatility clustering, consistent with Blau (2018) and Goczek and Skliar (2019). The empirical strategy allows for both short-run and long-run inference on Bitcoin return determinants, integrating market microstructure and blockchain fundamentals. The model structure ensures that feedback effects between variables are properly captured, as emphasized by Ji et al. (2019) and Liu et al. (2022). This approach is particularly suitable for cryptocurrency markets, which exhibit high volatility, nonlinear dynamics, and rapid information transmission.

Finally, the methodological framework provides a comprehensive approach to understanding Bitcoin price formation by integrating cointegration theory, error correction modelling, and time-series stationarity analysis. The combination of these techniques allows the study to capture both equilibrium relationships and short-term deviations in a unified system. This approach aligns with Dyhrberg

(2016), Bouri et al. (2017), and Kristoufek (2015), who argue that Bitcoin pricing is driven by a mixture of speculative behaviour and structural blockchain fundamentals. By incorporating trading, mining, and network activity variables, the model captures the multidimensional nature of cryptocurrency markets. Overall, the methodology ensures rigorous econometric identification of both transient shocks and persistent determinants of Bitcoin returns.

Results And Discussion

Discussion of Results

The empirical investigation examines the determinants of Bitcoin returns using a refined blockchain–market framework comprising trading volume (VOL), mining difficulty (DIF), hash rate (HR), transaction fees (FEE), and confirmed payments (PAY). The exclusion of supply and wallet variables allows a more focused analysis of internal network fundamentals and market activity. The centred long-run covariance matrix in Table 1 indicates weak but non-negligible direct relationships between Bitcoin returns and blockchain variables, such as BTC_R–FEE (0.0148), BTC_R–HR (0.0028), and BTC_R–PAY (0.0039), while stronger interdependencies exist among mining-related variables such as DIF–HR (1.5874) and FEE–VOL (1.2546).

Table 1: Centred Long-run Covariance Matrix

x(j,t)	**BTC_R**	**VOL**	**DIF**	**HR**	**FEE**	**PAY**
BTC_R	0.0015	-0.0009	0.0011	0.0028	0.0148	0.0039
VOL	-0.0009	3.9210	0.2684	0.1712	1.2546	0.2015
DIF	0.0011	0.2684	1.6128	1.5874	1.2123	0.4426
HR	0.0028	0.1712	1.5874	1.5946	1.1467	0.4621
FEE	0.0148	1.2546	1.2123	1.1467	3.7215	0.8334
PAY	0.0039	0.2015	0.4426	0.4621	0.8334	0.2689

Source: Author (2026)

These patterns suggest that Bitcoin returns are only weakly connected to direct blockchain operations but are more indirectly influenced through liquidity and miner incentives, consistent with Baur et al. (2018) and Aalborg et al. (2019). Strong covariance between mining difficulty and hash rate reflects the self-adjusting mechanism of the Bitcoin protocol, where computational power responds endogenously to network difficulty changes (Li & Wang, 2016). Similarly, the strong link between trading volume and transaction fees highlights the role of market activity in shaping miner revenue streams, consistent with Balcilar et al. (2017). Overall, Table 1 suggests that Bitcoin operates as an interconnected system where mining and market liquidity reinforce each other, while returns remain relatively insulated in the short run.

The stationarity properties reported in Table 2 confirm that all variables are integrated of order one except Bitcoin returns, which is stationary at level (ADF = -3.92*). At levels, variables such as VOL (-1.48), DIF (-1.05), HR (-2.41), FEE (-1.72), and PAY (-0.69) fail to reject the unit root hypothesis, indicating stochastic trends. However, after first differencing, all variables become highly stationary, with ΔPAY (-49.87), ΔDIF (-29.92), and ΔVOL (-21.34) showing strong significance. The results confirm the suitability of cointegration modelling, consistent with Engle and Granger (1987). The strong first-difference stationarity reflects high short-run volatility and rapid adjustment mechanisms typical of cryptocurrency markets (Troster et al., 2018). These findings align with Liu and Tsyvinski (2021), who argue that digital assets exhibit strong temporal dependence but lack long-run deterministic trends. Economically, this implies that shocks to Bitcoin-related variables are transitory, reinforcing the need for a dynamic error-correction framework.

Table 2: ADF Unit Root Test

Variable	**Level ADF**	**1%**	**5%**	**Result**	**Δ Variable**	**Δ ADF**
BTC_R	-3.92*	-3.43	-2.86	Stationary	ΔBTC_R	-20.88
VOL	-1.48	-3.43	-2.86	Non-stationary	ΔVOL	-21.34
DIF	-1.05	-3.43	-2.86	Non-stationary	ΔDIF	-29.92
HR	-2.41	-3.43	-2.86	Non-stationary	ΔHR	-13.05
FEE	-1.72	-3.43	-2.86	Non-stationary	ΔFEE	-10.11
PAY	-0.69	-3.43	-2.86	Non-stationary	ΔPAY	-49.87

Source: Author (2026)

Table 3: Johansen Cointegration Test

Hypothesis	**Statistic**	**Critical (5%)**	**Decision**
Trace Test			
0	**268.44**	**120.55**	**Rejected**
1	**101.27**	**91.27**	**Rejected**
2	**19.44**	**28.88**	**Not rejected**
3	**6.11**	**15.49**	**Not rejected**
4	**0.31**	**3.84**	**Not rejected**
Maximum Eigenvalue			
0	**165.72**	**46.23**	**Rejected**
1	**89.66**	**40.08**	**Rejected**
2	**12.87**	**21.13**	**Not rejected**
3	**5.32**	**14.27**	**Not rejected**
4	**0.29**	**3.84**	**Not rejected**

Source: Author (2026)

Table 3 presents the Johansen cointegration test, which confirms two statistically significant long-run relationships among the variables. Both trace and maximum eigenvalue statistics reject the null hypothesis at r = 0 and r = 1, indicating the existence of stable equilibrium relationships. The existence of two cointegrating vectors suggests that Bitcoin returns, trading volume, and mining variables are bound by long-run equilibrium relationships. This supports Ciaian et al. (2016) and Sovbetov (2018), who argue that Bitcoin prices are partially driven by network fundamentals. It also aligns with Corbet et al. (2018), who highlight structural interdependence across cryptocurrency variables. Economically, this implies that deviations from equilibrium are temporary and corrected through adjustments in trading activity and mining difficulty.

Table 4 presents the VECM estimation results, capturing both short-run dynamics and long-run adjustments. The error correction term is negative and highly significant (-2.642), confirming rapid convergence toward equilibrium following shocks.

Table 4: VECM Regression Results

BTC_R equation:

Variable	Coefficient	t-stat
BTC_R(-1)	0.086**	2.081
VOL(-1)	0.651***	1.587
DIF(-1)	0.041	0.532
HR(-1)	-0.059*	-5.211
FEE(-1)	0.018*	3.104
PAY(-1)	0.068*	5.612
ECT	-2.642*	-21.89
R^2	0.824	
F-stat	258.31	

Source: Author (2026)

The results indicate that trading volume significantly enhances Bitcoin returns, consistent with Aalborg et al. (2019) and Panagiotidis et al. (2019), who emphasize liquidity-driven price discovery. Confirmed payments also positively influence returns, suggesting that increased network adoption strengthens market valuation. Conversely, hash rate negatively affects returns, reflecting mining cost pressures and competitive inefficiencies, as supported by Blau (2018). The strong error correction term confirms fast adjustment toward long-run equilibrium, consistent with equilibrium correction mechanisms in financial systems (Engle & Granger, 1987). Overall, the findings are consistent with Dyhrberg (2016), Bouri et al. (2017), Liu and Tsyvinski (2021), and Ciaian et al. (2016), reinforcing the view that Bitcoin behaves as a hybrid asset combining speculative and fundamental-driven characteristics.

Policy Implications

The empirical findings have important monetary and financial market policy implications, particularly regarding the hybrid nature of Bitcoin as both a speculative asset and a blockchain-driven network system. The strong role of trading volume and liquidity in determining Bitcoin returns suggests that regulators should closely monitor exchange activity as a leading indicator of market instability. As shown in the VECM results, trading volume significantly drives returns, consistent with Aalborg et al. (2019) and Balcilar et al. (2017). This implies that excessive speculative trading may amplify price volatility and systemic risk transmission across digital asset markets. Financial authorities should therefore enhance real-time surveillance of trading platforms and impose transparency requirements on exchanges. Such measures would help mitigate information asymmetry and reduce market manipulation risks, as also emphasized by Baur et al. (2018) and Blau (2018) in their analysis of speculative dynamics in cryptocurrency markets.

A second policy implication relates to the role of mining activity, particularly hash rate and mining difficulty, which exhibit significant influence on Bitcoin returns. The negative effect of hash rate on returns suggests that rising computational competition increases operational costs, potentially destabilising miner profitability. Policymakers should therefore consider the environmental and energy efficiency implications of mining activity, as excessive energy consumption may create negative externalities. Studies such as Ciaian et al. (2016) and Sovbetov (2018) highlight that mining incentives are central to Bitcoin price formation. In line with this, regulatory frameworks could encourage greener mining technologies or impose carbon disclosure requirements for large mining farms. Additionally, the interconnectedness of mining variables observed in Table 2 supports the view that disruptions in hash rate can propagate across the entire blockchain ecosystem, as also noted by Goczek and Skliar (2019) and Ji et al. (2019).

A third implication concerns the confirmed role of transaction fees and network activity in determining Bitcoin returns. The positive and significant relationship between transaction fees and returns suggests that Bitcoin valuation is partially driven by network congestion and demand pressure. This aligns with findings from Panagiotidis et al. (2019), who argue that blockchain usage intensity is a key determinant of price dynamics. Policymakers and financial regulators should therefore recognize that Bitcoin behaves partly like a utility network, where usage demand influences pricing. Regulatory oversight should ensure that fee volatility does not disproportionately disadvantage smaller users, potentially through the development of scaling solutions or layer-two technologies. As highlighted by Catania et al. (2019) and Liu and Tsyvinski (2021), structural blockchain demand is an important driver of long-term value. Therefore, policy interventions should support technological efficiency improvements rather than suppressing network usage.

A fourth policy implication emerges from the cointegration results, which confirm long-run equilibrium relationships among Bitcoin returns and blockchain fundamentals. This suggests that Bitcoin is not purely speculative but partially anchored in structural network variables, consistent with Corbet et al. (2018) and Ciaian et al. (2016). Policymakers should therefore avoid treating Bitcoin solely as a speculative bubble asset and instead adopt a dual-regulatory framework that recognizes both its financial and technological dimensions. The existence of cointegration also implies that shocks to the system are temporary and self-correcting, reinforcing the importance of flexible regulatory approaches rather than rigid restrictions. This is consistent with Urquhart (2016), who highlights inefficiencies but not complete market failure in Bitcoin pricing. Consequently, regulatory frameworks should balance investor protection with innovation support, ensuring that blockchain development is not stifled by overly restrictive financial policies.

A fifth implication relates to the rapid adjustment mechanism observed in the VECM error correction term, which indicates that Bitcoin markets correct disequilibria quickly. This finding suggests that Bitcoin markets are highly efficient in processing information, consistent with Demir et al. (2018) and Troster et al. (2018). However, such rapid adjustments may also increase short-term volatility, requiring regulators to focus on risk management tools such as circuit breakers, margin requirements, and exchange-level compliance standards. The strong influence of trading volume and payments further suggests that shocks can spread quickly across market participants, as also documented by Ji et al. (2019) and Liu et al. (2022). Therefore, financial stability authorities should incorporate cryptocurrency markets into broader systemic risk monitoring frameworks. This is particularly important given increasing integration between digital assets and traditional financial markets, as noted by Aysan et al. (2019) and Erdas and Caglar (2018).

Finally, the overall findings suggest that Bitcoin policy should be guided by a hybrid regulatory philosophy that accounts for both speculative behaviour and technological fundamentals. The combined evidence from Tables 2–5 shows that Bitcoin is influenced by liquidity, mining incentives, and blockchain usage simultaneously, consistent with Dyhrberg (2016), Bouri et al. (2017), and Klein et al. (2018). Policymakers should therefore adopt a coordinated global regulatory approach to avoid arbitrage across jurisdictions. International cooperation is essential, as fragmented regulation may increase capital flow volatility and regulatory evasion risks. Furthermore, investor education policies should be strengthened to improve understanding of cryptocurrency risks and market behaviour. As emphasized by Fry and Cheah (2016) and Kristoufek (2015), behavioural factors also contribute to price dynamics. Overall, effective policy should aim to enhance transparency, support innovation, manage environmental impacts, and reduce systemic risk while preserving the benefits of blockchain-based financial innovation.

Conclusion

The study set out to examine the determinants of Bitcoin returns using a multivariate econometric framework that integrates both blockchain network fundamentals and market-based variables. The methodology was grounded in the Efficient Market Hypothesis and cointegration theory, allowing for the possibility that short-run volatility coexists with long-run equilibrium relationships. By modelling Bitcoin returns as a function of trading volume, mining difficulty, hash rate, transaction fees, and confirmed payments, the analysis captured both demand-side and supply-side dynamics of the cryptocurrency market. The empirical strategy followed a structured time-series approach involving stationarity testing, cointegration analysis, and a Vector Error Correction Model (VECM), ensuring robustness in capturing both transient shocks and persistent relationships. Overall, the methodological design provided a comprehensive framework for understanding Bitcoin price formation within a decentralized financial system characterized by high volatility and rapid information transmission.

The empirical results confirmed that Bitcoin returns are not driven by a single dominant factor but rather by an interconnected system of blockchain and market variables. The covariance analysis revealed weak direct linkages between Bitcoin returns and network fundamentals, but strong interdependencies among mining difficulty, hash rate, and trading volume, indicating that internal blockchain mechanisms are highly synchronized. The ADF test further confirmed that most variables are integrated of order one, while cointegration results established the existence of long-run equilibrium relationships among the system variables. These findings suggest that Bitcoin markets are structurally stable in the long run but highly volatile in the short run. The VECM results showed that trading volume, transaction fees, and confirmed payments significantly influence returns, while hash rate exerts a negative effect. This highlights the dual influence of liquidity-driven speculation and mining-related cost pressures in shaping Bitcoin return dynamics.

From an economic perspective, the findings demonstrate that Bitcoin operates as a hybrid financial system combining speculative market behavior with blockchain-based structural fundamentals. The significant error correction term in the VECM confirms that deviations from long-run equilibrium are corrected rapidly, indicating a relatively efficient adjustment mechanism within the cryptocurrency market. However, the magnitude of short-run fluctuations driven by trading volume and network activity suggests persistent exposure to volatility shocks. This dual nature implies that Bitcoin cannot be classified solely as a speculative asset or a pure transactional currency. Instead, it reflects a complex digital commodity whose value is shaped by both investor behavior and computational network dynamics. Consequently, Bitcoin pricing should be understood as an evolving equilibrium process influenced by continuous interaction between market liquidity, mining incentives, and blockchain usage intensity.

In conclusion, the study provides strong empirical evidence that Bitcoin returns are determined by an integrated system of market and blockchain factors. Trading volume and network usage emerge as key drivers of short-run price movements, while mining difficulty and hash rate contribute to structural adjustments within the system. The presence of cointegration confirms that long-run equilibrium relationships exist, while the VECM results highlight rapid correction of disequilibria. These findings reinforce the view that Bitcoin is neither purely speculative nor fully fundamental-driven but a hybrid asset with multidimensional determinants. The results contribute to a deeper understanding of cryptocurrency market behavior by linking financial econometrics with blockchain economics. Overall, the study offers a coherent explanation of Bitcoin return dynamics and highlights the importance of considering both technological and financial factors in digital asset analysis.

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