

An Analysis Of Blockchain Fundamentals, Technical, And Macroeconomic Factors On Bitcoin Price

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Abstract

Bitcoin has emerged as a prominent digital asset that blends financial innovation, technological advancement, and speculative behavior. However, its growing adoption raises sustainability concerns due to energy-intensive mining and environmental impacts. This study investigates the determinants of Bitcoin prices within the framework of sustainable digital finance by integrating blockchain fundamentals, technical indicators, and macroeconomic variables. Using daily data from 24 November 2021 to 21 November 2024 (753 observations), This analysis examines miner revenue, transactions per block, unique addresses, mining difficulty, and trading volume as internal factors, along with the prices of gold, WTI crude oil, and the S&P 500 index as external factors. Results show that miners' revenue, mining difficulty, trade volume and SP500 have positive and significant effects on Bitcoin prices, emphasizing the importance of mining performance and network activity. Meanwhile, gold and WTI crude oil prices are found to be insignificant, indicating that Bitcoin price dynamics are not strongly driven by traditional safe-haven assets or energy price fluctuations. Overall, the findings suggest that Bitcoin prices are shaped primarily by internal network fundamentals and financial market conditions rather than commodity-based macroeconomic factors.

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1. Introduction

Since its introduction in 2009, cryptocurrency has gained widespread global adoption, attracting considerable attention from investors, regulators, and the general public due to its distinctive nature, as it shares certain characteristics with traditional financial assets while also exhibiting features of highly speculative investments. (Park & Yang, 2024). Although cryptocurrencies are not issued by any central authority, they are considered secure because they employ cryptographic techniques and encryption protocols to verify and authenticate transactions. Cryptocurrency operates on a blockchain system where transactions are sequentially documented in a decentralized public ledger without revealing user identities (Alaminos et al., 2024). Furthermore, as a digital currency that is not subject to conventional financial regulation, cryptocurrency transactions bypass intermediaries, thereby reducing transaction costs (Chaim & Laurini, 2019; Shen et al., 2020).

Despite these advantages, cryptocurrency investment is also associated with high levels of risk, making it susceptible to phenomena such as cryptocurrency bubbles, where asset prices rise rapidly and abnormally within a short period (Diniz et al., 2022). The existing literature reveals ongoing debates on this matter. For instance, some studies describe cryptocurrencies as “virtual gold” due to their scarcity and high value, suggesting their potential as an investment instrument (Dubey, 2022). Others, however, view cryptocurrencies as speculative bubbles or even innovative Ponzi schemes with little or no intrinsic value compared to conventional securities ((Yildirim et al., 2022).

Among cryptocurrencies, Bitcoin stands out as the most representative digital currency. Although Bitcoin was first introduced as a substitute for traditional currency, it is now commonly held as an investment asset (Baur et al., 2018). Its efficiency improves with increasing market demand, making it the most efficient among existing cryptocurrencies (Jiang et al., 2018). Bitcoin is often considered the “parent” of all cryptocurrencies, derived from cryptographic processes (Sovbetov, 2018). As a representative digital currency, Bitcoin attracts considerable interest from investors seeking to understand how past price movements can generate expected returns in the future (Zhu et al., 2017).

The highly volatile nature of Bitcoin prices attracts speculators aiming to sell at higher future prices. According to (Dubey, 2022) several factors determine Bitcoin prices, generally categorized into three groups: fundamental variables, technical variables, and macroeconomic variables. Fundamental factors are particularly important as they reflect the intrinsic value of the asset. These fundamentals capture how market information is passed on and reflected in asset prices, thereby influencing profitability and forming the basis of trading strategies (Sovbetov, 2018). In this study, the fundamental variables considered are miners’ revenue, transactions per block, unique addresses, and mining difficulty.

Second, the technical asset factor employed in this study to capture Bitcoin’s market dynamics is trading volume, which reflects its influence on Bitcoin prices (Bakas et al.,

2022). Trading volume can be utilized by investors as part of technical analysis to predict asset price movements (Fousekis & Grigoriadis, 2021). Prior research has examined the linkage between trading volume and prices across various financial markets, including stock equities (Tsioutsios (2025), commodities (Dwi et al., 2025), interest rates and currency futures (Chang et al. 2025), and real estate (Akinsomi et al 2026). However, within cryptocurrency markets, and particularly in the case of Bitcoin, this relationship remains relatively underexplored (Leirvik (2022); Sapuric et al. (2020).

Third, the macroeconomic factors considered in this study include Gold, WTI, and the S&P 500 Index. The S&P 500 is included because the U.S. equity market is commonly viewed as a key indicator of overall global stock market performance (Hung, 2022). The linkage between Bitcoin and the U.S. equity market emerges because institutional investors, hedge funds, and index funds often reallocate capital between markets depending on prevailing market conditions, suggesting potential interlinkages between the two.

Several studies have documented a negative linkage between the S&P 500 and Bitcoin prices. For example, Bakas et al. (2022) found that Bitcoin exerts a negative influence on S&P 500 stock prices. This implies that when Bitcoin prices increase, the S&P 500 tends to decline, and conversely, when Bitcoin prices decrease, the S&P 500 tends to rise. This dynamic can be explained by substitution effects: when stock prices are lower relative to Bitcoin, investors tend to sell equities and reallocate capital into the more profitable cryptocurrency market. Conversely, when stock prices are higher than Bitcoin, investors prefer equities, driving their prices upward while Bitcoin prices fall. These findings are consistent with those of (Ünvan, (2021); Sovbetov (2018; Kjærland et al (2018); Canoz & Dirican (2017).

However, other studies provide mixed evidence. Bouri et al. (2021); Kudlacik (2023); Budisteanu (2025) reported a positive relationship between U.S. stock market indices and cryptocurrency prices. Similarly, Gil-Alana et al. (2020), show no cointegration between cryptocurrencies and equity indices, indicating that the relationship may not be stable or long-term in nature.

Furthermore, crude oil prices (WTI) and gold are included in the model because both assets are scarce and expensive, making them attractive alternative safe-haven investments during periods when the Bitcoin market experiences downturns (Zhang et al., 2023). During periods of elevated uncertainty, rising inflation, or low returns on risky investments, investors typically reallocate their portfolios toward safer assets such as gold or rare and valuable commodities like crude oil. Consequently, a negative association between crude oil, gold, and Bitcoin prices may be expected. However, with Bitcoin's limited supply and increasing recognition as an inflation hedge, some investors have begun to view it as a safe-haven asset as well (Bakas, 2022).

The empirical literature provides mixed evidence regarding these relationships. For instance, Bouri et al. (2021) reported a negative association between Bitcoin prices and both crude oil

and gold prices. This finding is consistent with Panagiotidis et al. (2018), who also documented an inverse relationship. In contrast, Adebola et al (2019) found only a weak relationship between crude oil, gold, and Bitcoin prices, suggesting that neither gold nor crude oil exerts significant influence on Bitcoin’s price dynamics.

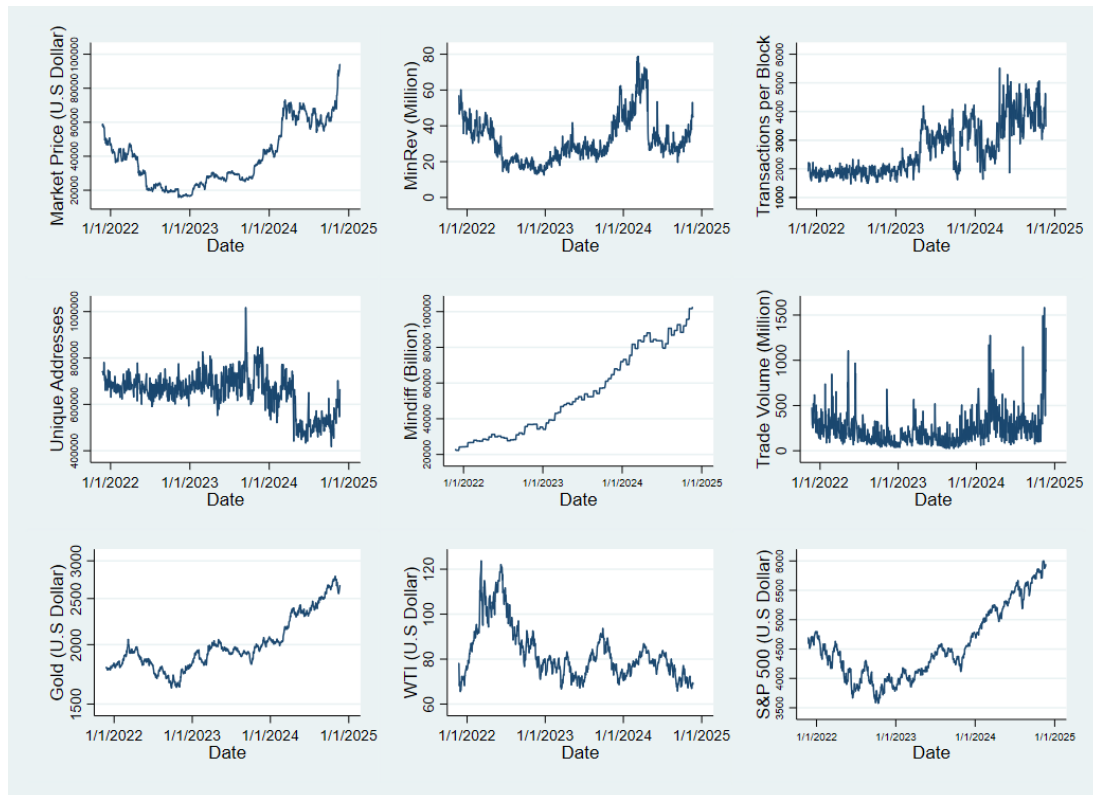


Fig. 1. Illustration of the Research Variables
Data source : Blockchain.com

Based on the observed data, the Bitcoin market has exhibited highly volatile price movements, with sharp surges occurring from November 2021 to 2024. These dynamics have been accompanied by changes in blockchain fundamentals, technical factors, and macroeconomic indicators. This makes it particularly relevant to investigate how fundamental assets, technical assets, and macroeconomic variables influence Bitcoin price movements. Earlier studies suggest that investors commonly use technical analysis because it generates momentum-based trading signals. Therefore, this study seeks to comprehensively address the question of which factors truly drive Bitcoin prices—specifically, to what extent economic and macroeconomic variables explain Bitcoin’s price fluctuations. Should investors rely on fundamentals, technical indicators, or macroeconomic conditions when making investment decisions?

Furthermore, several gaps identified in the existing literature highlight the need for further empirical investigation, which this study aims to address in order to provide more robust insights and potential solutions to the research problem.

2. Literature Review

Bitcoin mining represents a key determinant of Bitcoin's supply dynamics and price movements (Bouoiyour & Selmi, 2016). This process involves using computer hardware to solve complex cryptographic problems to create new Bitcoin units, for which miners are rewarded with a predetermined amount of Bitcoin. The greater the computing power used, the higher the chance of earning a reward, which is then reflected in an increase in miners' revenue, which is an indicator of intensive mining activity and market confidence in the network. Furthermore, transactions per block indicates economic activity within the Bitcoin network the higher the number of confirmed transactions per block, the higher the demand for Bitcoin, which ultimately drives up the price. Unique addresses reflect the number of active participants in the network, so an increase in the number of unique addresses indicates user expansion and potential growth in Bitcoin's market value (Kristoufek, 2015). However, increasing mining difficulty can negatively impact the price because it signals increased costs and complexity of the mining process (Dyhrberg, 2016). Overall, these fundamental blockchain indicators reflect the internal dynamics of the Bitcoin ecosystem, which strongly influence the market price of this digital asset.

H1: Blockchain Fundamental has a significant influence on the price of bitcoin

Trading volume can be used as a benchmark for assessing crypto market dynamics. Low trading volume indicates a lack of investor interest, while high trading volume indicates a high number of investors interested in buying and selling crypto. High investor interest is related to the theory of supply and demand, where investor interest drives increased transaction volume, which in turn drives up the asset's price.

H2 : Technical has a significant influence on the price of bitcoin.

The dynamics of prices and related risks of major financial assets such as the U.S. dollar, crude oil, and gold have long been central topics in financial economics due to their importance for asset allocation, risk management, and valuation. The U.S. dollar is the most widely traded currency globally and is commonly used as a reference point in foreign exchange markets. As the leading international reserve currency, it is held by central banks across the world. Moreover, the U.S. dollar functions as the primary currency for commodity trading, thereby exerting a direct influence on commodity price movements (Grossmann & Kim, 2022; Ayres, Hevia & Nicolini, 2020). Crude oil represents a vital strategic resource for all economies, serving as a fundamental input in numerous industrial processes. As a critical factor in economic activity, fluctuations in the oil market affect not only the energy sector but also broader financial markets, including foreign exchange markets (Ivan, Banti &

Kellard, 2022). In addition, crude oil possesses strong financial characteristics, with oil-based derivatives extensively employed by global investors for both hedging and speculative purposes (Guo, Long & Luo, 2022; Li, 2018). Consequently, volatility in oil prices plays a significant role in influencing the stability of international financial systems.

Gold, by contrast, has historically been regarded as a monetary asset, a commodity, and an investment instrument. Unlike crude oil, gold is not directly tied to macroeconomic production, and the factors driving its market behavior differ substantially. Due to its relatively low correlation with traditional financial assets, gold is widely recognized as a hedge against unfavorable movements across various asset classes (Younis, Shah & Yousaf, 2023; Ansari & Sensarma, 2019). Gold has demonstrated particularly strong performance during periods of financial stress, with prior research confirming its effectiveness during major crises such as the 2007 global financial crisis and the COVID-19 pandemic in 2020 (Choudhry, Hassan & Shabi, 2015).

H3 : Macroeconomics has a significant influence on the price of bitcoin.

3. Research Methods

This study employs daily data from November 24, 2021, to November 21, 2024, comprising a total of 1,095 observations. However, due to the trading schedules of equities (S&P 500), commodities (Gold), and WTI which do not operate on a daily calendar basis like the cryptocurrency market—the number of usable observations, after schedule adjustment, was reduced to 753. The fundamental Bitcoin variables were collected from *Blockchain* (<https://www.blockchain.com/>), while macroeconomic variables were obtained from *Investing* (<https://id.investing.com/>).

The dependent variable is the daily price of Bitcoin, whereas the independent variables include miners' revenue, transactions per block, unique addresses, mining difficulty, trade volume, gold, WTI, and the S&P 500 index. Furthermore, the Bitcoin fundamental variables (miners' revenue, transactions per block, unique addresses, mining difficulty) and the technical factor (trade volume) were transformed into their logarithmic forms prior to statistical modeling. The analysis was conducted using Stata version 16.

Table 1. Operational of Variables

Variable	Definition	Measurement	Formula
Price	Daily closing price of Bitcoin in USD	Transformasi Log	Bitcoin Closing Price
Fundamental Blockchain	Total USD Value Of Coinbase Block Rewards And Transaction	Transformasi Log	(Block Reward + Transaction fees) x BTC Price (USD)

	TranctionperBlock	Number Of Transactions Confirmed In Each Block	Transformasi Log	Total Transactions in Block 1 Block
	Unique Address	Number of unique Bitcoin addresses used (proxy for network activity)	Transformasi Log	Count of distinct bitcoin address
	Mining Difficulty	Difficulty level in mining new blocks	Transformasi Log	Difficulty x 2^{32} / Block Time (seconds)
				2^{32} : Represents the number of possible hashes for one mining attempt.
Technical	Trade Volume	Daily Bitcoin trading volume in USD	Transformasi Log	Total BTC Traded per day x Average BTC Price
	Gold	Price of gold (USD/ounce) traded in the global financial market	In USD	Gold Closing Price
	WTI	Crude oil benchmark price (West Texas Intermediate) in USD	In USD	WTI Closing Price
Macro-Economics	S&P 500	A stock index composed of the 500 largest U.S. publicly traded companies by market value	In USD	S&P 500 Closing Price

4. Results

Table 2. Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Date	753	23156.311	316.585	22608	23701
MarketPrice	753	39393.179	17758.374	15759.61	94354.43
MinersRevenue	753	31881609	12580289	12489766	78889620
TransactionsperBlock	753	2702.652	927.906	1469.646	5517.917
UniqueAddresses	753	652512.14	84736.354	417442	1017545
MiningDifficulty	753	5.374e+13	2.366e+13	2.234e+13	1.023e+14
TradeVolume	753	2.535e+08	2.007e+08	24701118	1.583e+09
Gold	753	2016.307	270.719	1621.57	2786.19
WTI	753	82.625	11.864	65.57	123.7
SP500	753	4558.698	606.637	3577.03	6001.35

Data source : Stata 16, 2025



Table 2 presents the descriptive statistics of the 753 observations for the research variables. The average Bitcoin market price (MarketPrice) was approximately USD 39,393. Miners' revenue recorded a mean value of about USD 31.88 million. On average, there were 2,703 transactions per block (TransactionsperBlock), while the number of unique addresses (UniqueAddresses) reached a mean of 652,512. The mining difficulty (MiningDifficulty) exhibited an average value of 5.37×10^{13} , reflecting the dynamics of the network's computational power. The average daily Bitcoin trade volume (TradeVolume) was USD 253.5 million, with substantial fluctuations ranging from USD 24.7 million to USD 1.58 billion. Furthermore, gold prices averaged USD 2,016 per ounce, while WTI crude oil prices averaged USD 82.62 per barrel, with variations between USD 65.57 and USD 123.7. The S&P 500 index recorded an average level of 4,558 points.

Table 3. Stationary Test

Variable	ADF	Result	PP	Result
MarketPrice	0.9632	NS	0.000	S
MinersRevenue	0.9648	NS	0.000	S
TransactionsperBlock	0.000	S	-	S
UniqueAddresses	0.000	S	-	S
MiningDifficulty	0.9986	NS	0.000	S
TradeVolume	0.000	S	-	S
Gold	0.9047	NS	0.000	S
WTI	0.3940	NS	0.000	S
SP500	0.9353	NS	0.000	S

Table 3 indicates that all data have achieved stationarity, thereby allowing the continuation to subsequent regression tests.

Table 4. Variance inflation factor

	VIF	1/VIF
D logminrev	1.534	.652
logTadeVolume	1.503	.665
logtranctionsperBl~k	1.393	.718
logUniqueAddresses	1.368	.731
D logwti	1.065	.939
D logGold	1.064	.94
D logSP500	1.03	.971
D logmindiff	1.004	.996
Mean VIF	1.245	.

Data source : Stata 16, 2025

Table 4 shows that the regression model is free from multicollinearity issues, as all VIF values are below the threshold of 10, with a relatively low mean VIF of 1.245. This indicates the absence of severe multicollinearity among the independent variables, suggesting that the

regression model in this study is not affected by multicollinearity problems.

Table 5. Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) logmarketprice	1.000								
(2) D_logMinrev	0.079	1.000							
(3) logTranctionsp~k	0.034	0.244	1.000						
(4) logUniqueAddre~s	0.002	-	-	1.000					
(5) D_logmindiff	-	0.010	0.468	-	1.000				
(6) logTadeVolume	0.019	0.047	0.002	-	0.016	1.000			
(7) D_logGold	0.056	0.540	0.210	-	0.030	0.206	1.000		
(8) D_logSP500	-	0.019	-	0.020	-	0.019	0.131	1.000	
(9) D_logwti	0.027	-	0.006	-	0.025	-	0.042	0.097	1.000
	0.012	-	0.049	-	-	0.034	0.217	0.097	1.000
	0.069	0.063	-	0.033	-	0.032	0.217	0.097	1.000
			0.056		0.003				

Data source : Stata 16, 2025

Table 5 indicates that most of the correlations among the variables are relatively low. The findings show that the correlation values are below 0.8, suggesting that the relationships among the variables in the model are not particularly strong.

Table 6. Linear regression

logmarketprice	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
D_logMinrev	2.192	.65	3.37	.001	.913	3.471	***
logTranctionperblock	-.41	.567	-0.72	.47	-1.525	.705	
logUniqueAddresses	-1.831	.903	-2.03	.043	-3.607	-.054	**
D_logminingdifficulty	1.785	.933	1.91	.057	-.051	3.622	*
logTadeVolume	.188	.108	1.74	.083	-.025	.401	*
D_logGold	11.907	7.269	1.64	.103	-2.401	26.215	
D_logSP500	27.514	6.497	4.23	0	14.726	40.302	***
D_logWTI	-1.821	2.818	-0.65	.519	-7.366	3.725	
Constant	-	16.661	-1.36	.174	-55.505	10.084	
	22.711						
Mean dependent var		-4.147	SD dependent var			1.165	
R-squared		0.114	Number of obs			294	
F-test		4.579	Prob > F			0.000	
Akaike crit. (AIC)		905.489	Bayesian crit. (BIC)			938.641	

*** $p < .01$, ** $p < .05$, * $p < .1$

Data source : Stata 16, 2025

According to the regression results reported in Table 6, the model produces an R-squared of



0.114, suggesting that nearly 11.4% of the variation in Bitcoin's market price (logMarketPrice) is explained by the model can be explained by the independent variables included in the model, while the remaining variation is attributable to factors outside the model. The F-statistic of 4.579 with Prob > F = 0.000 indicates that the regression model is significant at the 1% level.

The empirical findings reveal that: (i) miners' revenue statistically significant positive influence on Bitcoin's market price (coefficient = 0.445; $p < 0.01$). This indicates that rising mining revenue corresponds with higher Bitcoin prices. The result is consistent with the cost-based pricing theory, suggesting that miners' profitability is a crucial determinant of Bitcoin's market valuation. (ii) transactions per block (logTransactionperblock) show a negative but statistically insignificant relationship with Bitcoin price (coefficient = -0.41 ; $p = 0.470$). This suggests that variations in the number of transactions processed per block do not significantly influence Bitcoin price dynamics. The limited block size and fixed block time constrain transaction capacity, making this indicator less capable of capturing actual demand pressure. (iii) unique addresses have a statistically significant negative effect (coefficient = -0.1831 ; $p < 0.043$). This evidence implies that a rise in the number of unique addresses tends to depress Bitcoin's price. Such evidence can be interpreted through the lens of information asymmetry theory, where the proliferation of addresses may reflect speculative activities and heightened market uncertainty; (iv) mining difficulty shows a positive effect level (coefficient = 1.785; $p = 0.057$). This suggests that increases in mining difficulty growth are associated with rising Bitcoin prices, although the relationship is only marginally significant. This indicates that the transmission of mining costs to prices occurs gradually rather than immediately. (v) trade volume has a positive and significant effect that is weakly significant at the 10% (coefficient = 0.188; $p < 0.08$), showing that higher trading activity tends to push Bitcoin prices upward, consistent with the role of liquidity and investor interest in driving demand. In addition, the macroeconomic variables, Gold (coefficient = 11.91; $p = 0.103$) and WTI crude oil (coefficient = -1.82 ; $p = 0.519$) do not significantly influence Bitcoin's market price, in contrast, the S&P 500 index demonstrates a positive effect that is statistically robust (coefficient = 27.51; $p < 0.01$). This result highlights that Bitcoin's price dynamics are more strongly tied to global financial markets, as proxied by the S&P 500, than to traditional safe-haven assets (gold) or energy costs (oil).

The evidence presented in this study shows that miners' revenue is consistent with the cost-based pricing theory, as it plays a crucial role in helping miners calculate the profitability of mining activities. According to Bouri et al. (2021) the cost of a product or service is determined based on a specific profit margin calculated from the total costs, including both variable and fixed costs, which holds strong relevance in the context of Bitcoin mining. The analysis further demonstrates that miners' revenue is influenced by hardware efficiency and energy costs, as emphasized by Aslanidis et al. (2021), who noted that the adoption of more advanced technology can effectively reduce mining expenses. However, without sufficient hardware capacity or access to affordable energy, it becomes challenging for miners to

sustain profit margins (Tiwaria et al., 2020). Prior research presents mixed findings regarding the relationship between miners' revenue and Bitcoin prices. For instance, Bakas (2022) showed that increases in miners' revenue are positively and significantly linked to Bitcoin price movement. In contrast, Hanindya (2019) found a significant positive insignificant impact of miners' revenue on Bitcoin prices. Supporting this, Erfanian et al. (2022) also identified a negative but insignificant linkage between miners' revenue and Bitcoin prices.

This outcome is inconsistent with earlier research showing a positive and significant link between transactions per block and Bitcoin prices (Li et al., 2023); (Bakhtiar et al., 2023); (Kukacka & Kristoufek, 2023). The maximum number of transactions per block is determined by the block size and block time parameters of the Bitcoin network. Consequently, even if demand for transactions rises, the maximum number of transactions included per block remains constrained, thereby reducing its ability to capture true demand-side pressure on Bitcoin's price.

The findings on unique addresses, which exhibit a negative and significant effect, indicate that an increase in unique addresses tends to reduce the market price of Bitcoin. This outcome can be associated with information asymmetry theory, which posits that differences in information among market participants may lead to speculative investor behavior. Existing research has similarly documented a negative association between unique addresses and Bitcoin prices (Vo et al., 2022); (Polyzos & Youssef, 2025).

Mining difficulty and Bitcoin prices are closely interconnected through a long-term feedback mechanism within the network. When Bitcoin prices increase, mining becomes more profitable, attracting additional miners and raising the global hash rate, which automatically pushes mining difficulty upward to maintain block time stability. In contrast, falling prices reduce profitability and lead less efficient miners to exit, causing difficulty to decline. Beyond reacting to price movements, mining difficulty also influences the market indirectly by shaping production costs and signaling network strength. Higher difficulty reflects greater security, stronger participation, and increased confidence in the sustainability of the Bitcoin ecosystem, which can support price growth over time. Consequently, mining difficulty can be viewed as both a proxy for production cost and a signal of network maturity that helps explain its positive long-run relationship with Bitcoin prices. Nevertheless, in line with theoretical expectations, mining difficulty is expected to exert a positive influence on Bitcoin prices, a relationship that is also supported by several studies in the existing literature (Dubey, 2022); (Kukacka & Kristoufek, 2023); (Li et al., 2023).

The findings on trade volume indicate that an increase in trading activity drives an upward movement in the price of Bitcoin. This can serve as a signal reflecting the flow of information in the market and the private information held by investors, both of which can influence market value and, consequently, the price received by investors. Such signals provide insights for investors regarding asset liquidity, market interest, price trends, and the credibility of these trends, suggesting that higher trading activity indicates favorable market prospects.

First, greater trading volume implies higher liquidity, making the asset easier to buy or sell in the market (Hakim, 2020). Second, it reflects heightened investor interest, which can affect the demand side of Bitcoin and potentially move its price. Third, increased trading volume may demonstrate that more investors are purchasing the asset, suggesting that the trend is likely to continue. Conversely, if trading volume declines during an upward trend, this may signal waning investor interest and a potential reversal. Fourth, trading volume may indicate the credibility of a price trend. When trading volume rises alongside an upward trend, it provides stronger support for the trend, thereby enhancing its reliability. Several earlier studies also confirm a positive association between trading volume and Bitcoin prices, including Momtaz (2021); dan Bakas et al (2022).

While gold is commonly regarded as a traditional safe-haven asset during periods of financial or geopolitical uncertainty, this finding suggests that Bitcoin does not consistently behave as a hedge in the same manner as gold. One possible explanation is that Bitcoin is increasingly treated by investors as an asset characterized by speculation and elevated risk, rather than a protective safe haven instrument. In addition, the coexistence of both assets in diversified portfolios may weaken their direct linkage, as investors may not view Bitcoin as a substitute for gold but rather as a complement with distinct risk-return characteristics. This outcome contrasts with studies such as (Aliyev & Eylasov, 2025); (Aliyev & Eylasov, 2025) which documented a significant association, suggesting that Bitcoin serves as a protective asset remains context-dependent and varies across time horizons and market conditions.

Similarly, the findings show that WTI crude oil prices are not significantly associated with Bitcoin's market price (coefficient = -0.002 ; $p = 0.25$). Although energy costs are a fundamental component of Bitcoin mining operations, their influence may not directly translate into price dynamics in the secondary market. Several factors could explain this insignificance. First, miners often operate under long-term electricity contracts or in regions with low-cost energy sources, which buffer the immediate effect of oil price volatility. Second, Bitcoin's price is predominantly driven by investor demand, trading activity, and macro-financial variables, which tend to overshadow supply-side cost considerations such as oil prices. Third, the rising share of renewable energy in mining operations reduces the dependence of Bitcoin production costs on global oil prices, thereby weakening the theoretical link. Although previous research, such as Lin et al. (2025) and Jia et al. (2023) identified significant relationships, the present results suggest that such linkages are not robust across all samples and periods.

The observed linkage between Bitcoin and the S&P 500 aligns with Modern Portfolio Theory, underscoring the role of asset diversification. The positive influence of the S&P 500 indicates that investors increasingly consider Bitcoin as part of a diversified portfolio, such that when the stock market strengthens, demand for Bitcoin also rises. This conclusion is consistent with studies including Bakas et al. (2022); Ünvan, (2021), and Yakubu et al. (2023) although it is contradicted (Gil-Alana et al., 2020). Consequently, the positive associations of Bitcoin with gold, WTI, and the S&P 500 suggest that movements in Bitcoin's

price cannot be explained solely by internal dynamics blockchain fundamentals but are also highly responsive to global macroeconomic dynamics.

5. Conclusion

This study concludes that both internal blockchain-based factors and external macroeconomic indicators influence Bitcoin market prices, although their effects vary in strength and significance. Among the internal factors, miners' revenue and trade volume exert a positive and statistically significant influence, which indicates that greater mining profitability and increased trading activity play a role in to upward movements in Bitcoin's market price. Conversely, unique addresses demonstrate a negative and significant effect, suggesting that a greater number of wallet addresses may reflect speculative or fragmented activity, thereby exerting downward pressure on price. Meanwhile, transactions per block and mining difficulty are found to be statistically insignificant, implying that these blockchain metrics do not directly explain price fluctuations once other variables are considered.

Mining difficulty is often correlated with other blockchain variables, such as hashrate and miners' revenue. Once these variables are included in the regression model, the independent effect of mining difficulty may be absorbed, rendering it statistically insignificant.

From an external perspective, the S&P 500 index shows a strong and positive effect, confirming Bitcoin's increasing integration with global financial markets. In contrast, gold and WTI crude oil do not display significant relationships with Bitcoin prices, suggesting that Bitcoin does not consistently act as a traditional safe-haven asset or cost-driven commodity-linked instrument.

Overall, these findings highlight Bitcoin's role primarily as a financial asset driven by investor behavior and market dynamics rather than by macroeconomic or energy-related factors. The results suggest that miner income, stock market movements, and behavioral indicators such as unique addresses play a more central role in explaining Bitcoin returns. Future research could explicitly incorporate energy consumption or environmental variables to better assess the sustainability dimension of cryptocurrency systems.

For policymakers and stakeholders, the results underscore the importance of establishing transparent, sustainability-oriented regulatory frameworks, as well as promoting digital financial literacy and responsible investing. Future research is encouraged to adopt an interdisciplinary perspective by integrating financial indicators with sustainability metrics such as energy consumption, carbon emissions, and renewable energy adoption. Such an approach will contribute to the development of a more resilient, sustainable, and accountable digital financial ecosystem.

Discussion

The empirical findings highlight that internal blockchain and financial market variables play a more prominent role in explaining Bitcoin price movements than traditional macroeconomic commodities. The positive and significant effects of miner revenue and mining difficulty confirm the importance of mining profitability as a key economic driver of Bitcoin valuation. This implies that higher mining rewards encourage the adoption of more efficient technologies and strengthen network participation, ultimately supporting price growth.

The strong and significant relationship between the S&P 500 and Bitcoin indicates that Bitcoin is increasingly behaving as a financial asset integrated into global capital markets rather than as a standalone asset or substitute. This finding suggests that investors view Bitcoin as part of a diversified portfolio, where stock market movements can influence demand for crypto assets. Consequently, portfolio diversification strategies should consider the increasing co-movement between Bitcoin and the equity market.

The negative and significant relationship between unique addresses and Bitcoin price suggests that higher network activity does not necessarily reflect actual user adoption or increased demand. Instead, it may reflect speculative behavior, address fragmentation, or increased market uncertainty during volatile periods. Therefore, researchers and practitioners should exercise caution when using unique addresses as a proxy for Bitcoin's fundamental value.

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