Do Blockchain Activity, Investor Attention and Financial Market Conditions Drive Bitcoin Prices? Evidence From Weekly Data (2017–2024)

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Abstract

With the rising attention, investment, and demand for cryptocurrencies, Bitcoin has become a focal point of discussion in both financial and academic circles. The price of Bitcoin is a crucial aspect for individual investors as well as major financial institutions. To address the growing need for insights into this digital asset, this paper examines the factors that influence Bitcoin price formation. Using various analytical methods, including the Autoregressive Distributed Lag (ARDL) model, this study builds on existing research by incorporating a broader dataset and applying time-series analysis to weekly data from March 8, 2017, to December 31, 2024. Among the 15 variables analyzed, results indicate that 6 independent factors—Overall account of verified transactions, Bitcoin cost per transaction, Bitcoin transaction rate per second, the Dow Jones Industrial Average Index, the exchange rate between the US dollar and Euro, and the number of Bitcoin-related searches on Wikipedia—along with lagged values of the Bitcoin market price, were statistically significant.

Keywords: Bitcoin, Cryptocurrency, ARDL.

JEL Classification: G12, C32, E44, O33, G15

Introduction

Bitcoin is a decentralized digital asset that operates without the control or regulation of central banks or financial institutions. An asset is anything that holds value, such as a house, car, or gold—items that can be sold in the market in exchange for money because people recognize their worth. Similarly, Bitcoin has value, but unlike physical assets, it exists only in digital form. It also functions as a currency, as it can be used for payments worldwide. Its decentralized nature means that no single authority governs or controls it, and its value is determined by the users who trade and invest in it.

Why was Bitcoin Invented?

On October 31, 2008, an individual using the pseudonym Satoshi Nakamoto released a paper online titled "A version of electronic cash that would allow payments to be sent directly from one party to another without going through a financial institution." Nakamoto is widely credited with the creation of Bitcoin, yet his true identity remains unknown. There is no confirmed information regarding who he is, where he resides, or what he does. Additionally, it is uncertain whether Satoshi is a single person or a collective working under a shared alias.

Cryptocurrency is a form of digital asset that operates independently of traditional financial systems. For example, the US dollar is regulated by the Federal Reserve, while the Reserve Bank of India controls the Indian rupee. In contrast, cryptocurrencies are decentralized and lack oversight from any governmental or financial institution. Initially, cryptocurrency was merely a vision in Nakamoto's mind, but today, crypto trading occurs on exchanges, with transactions amounting to significant sums.

To fully grasp Nakamoto's paper and the broader context of cryptocurrency, one must first understand key aspects of economic history. The financial system is fundamentally built on trust. Currency notes and coins derive their value from government guarantees and central bank assurances. Following the Second World War, the United States emerged as the dominant global power, leading other nations to peg their currencies to the US dollar, which, in turn, was backed by gold or silver reserves. Since carrying physical gold and silver was impractical, paper currency was introduced as a more convenient alternative. However, in 1971, the US abandoned the gold standard, allowing central banks worldwide to print currency at their discretion.

However, how does cryptocurrency relate to all this? Understanding the power governments and central banks hold over monetary policy sheds light on its significance. When individuals deposit money in banks, they effectively grant permission for those banks to utilize their funds. Banks leverage these deposits to issue loans to businesses and individuals, generating interest income. However, financial institutions frequently approve large loans without proper due diligence, leading to non-performing assets (NPAs) and bad debts. Government policies can also pose risks to the general public, as seen in India's 2016 demonetization, which rendered 86% of the nation's currency invalid overnight.

Supporters of Bitcoin and cryptocurrency advocate for an alternative financial system, one that eliminates governmental and banking control over money. Nakamoto envisioned Bitcoin as a decentralized system based on software technology, free from third-party intervention. The 2008 global financial crisis, which saw major investment firms like Lehman Brothers collapse, set the stage for cryptocurrencies to emerge. Bitcoin was the first digital currency introduced, followed by the development of numerous other cryptocurrencies in the years that followed.

How does Crypto Technology Work?

To fully grasp this concept, one must have a strong foundation in advanced mathematics and computer science. However, for those looking to get into investing or trading, only basic knowledge is necessary.

Take Bitcoin as an example. It operates on a decentralized digital ledger that records all transactions—the blockchain. Copies of this ledger are stored across all systems participating in the Bitcoin network. The individuals who maintain and validate these transactions are called miners.

When someone, say, A, wants to transfer 2 Bitcoins to B, miners must verify that A has sufficient balance to complete the transaction. To do this, they need to solve complex mathematical equations. Each Bitcoin transaction is assigned a unique identifier, and miners must compute it. Instead of manually solving these equations, powerful computers perform these calculations automatically, as they involve an immense number of possible combinations.

Once the solution is found, other systems within the network verify it, and the transaction is recorded on the blockchain. A group of verified transactions forms a block, which is why this technology is called blockchain. Miners are rewarded with bitcoins for their computational work, following a system known as 'proof of work,' in which they must demonstrate their effort to earn the reward.

This study contributes to the literature by using recent weekly data (2017–2024) and integrating blockchain-specific and macroeconomic variables into an ARDL framework to analyze the short- and long-run determinants of Bitcoin price formation.

Research Question

To analyze the factors influencing Bitcoin price formation, the study examines:

a) The impact of Bitcoin's supply and demand dynamics on its price.

b) The role of investment appeal, measured by the number of weekly Wikipedia searches, in shaping Bitcoin prices.

c) The influence of global macroeconomic and financial trends, including stock market indices, exchange rates, oil prices, S&P 500, and DJIA on Bitcoin valuation.

d) The effect of digital currency-specific attributes, such as Tera Hahes, Miners' Revenue, Miners' Revenue excluding coinbase block reward, Unique Addresses, Estimated Transaction Value, Cost Per Transaction, Transaction Rate Per Second, on Bitcoin price movements.

Literature Review

Since its launch in 2009, Bitcoin has steadily gained traction among investors (Clarke, 2023), particularly in Western countries, where it is viewed as a financial asset and a store of value. Additionally, in nations experiencing hyperinflation, it has served as a medium of exchange (Landormy, 2022). Responding to client demand (Shevlin, 2021b), several leading financial institutions, including Morgan Stanley (Helms, 2021; Morrell & Ramaswamy, 2021), have begun offering Bitcoin-related investment services—primarily catering to high-net-worth individuals—and have gained indirect exposure by investing in companies that hold Bitcoin, such as MicroStrategy (Sinclair, 2021; Cirrone, 2023). Bitcoin's integration into mainstream financial markets has progressed through key milestones, including the launch of Bitcoin futures contracts in December 2017, the introduction of ETFs linked to these futures in October 2021, and, most recently, the approval of 11 Bitcoin spot ETFs in the United States on January 10, 2024 (Mitchelhill, 2024). Alongside its increasing adoption, Bitcoin has demonstrated significant yet highly volatile price growth. Supply and demand are fundamental market forces that influence the price of financial assets, including Bitcoin (Guizani & Nafti, 2019). According to Buchholz et al. (2012), Bitcoin's price is shaped by the interaction between its supply and demand, much like traditional currencies. The supply of Bitcoin is determined by the total number of mined coins that are actively circulating within the network. Bitcoin itself has no intrinsic value, so its demand is primarily driven by its potential for future exchange and its role as a medium of exchange (Ciaian et al., 2016b). According to Kristoufek (2015), the total supply of Bitcoin is governed by a publicly accessible, open-source algorithm that will eventually cap the supply at 21 million units. Additionally, Ciaian et al. (2016b) note that Bitcoin supply grows at a decreasing rate, ultimately reaching zero growth once the supply hits the 21 million limit. Similarly, Kjærland et al. (2018) highlight that Bitcoin's supply is independent of its price but follows a predetermined schedule encoded within the Bitcoin protocol, making it time-dependent.

Since Bitcoin's supply is fixed and externally determined, price movements are largely influenced by demand-side factors. This aligns with the findings of Ciaian et al. (2016b), who suggest that demand-related variables have a more significant impact on Bitcoin's price than its constrained supply. Ciaian et al. (2016) conducted an in-depth study using vector autoregression (VAR) models, vector error correction models (VECMs), and autoregressive distributed lags (ARDL) models based on daily data. Their research highlighted the significant role of supply and demand dynamics in influencing Bitcoin. Regarding attractiveness factors, they found a positive impact on Bitcoin, with Wikipedia having a particularly strong effect. Moreover, their findings supported the idea that investor speculation contributes to Bitcoin's price fluctuations, as both Wikipedia searches and new posts were statistically significant in the short term. However, they did not find evidence of a long-term impact from global macro-financial developments, although a short-term relationship was observed. Bouoiyour and Selmi (2015), using an Auto Regressive Distributed Lag model, conclude that trading volume and exchange transactions play a crucial role in influencing Bitcoin prices. Similarly, DeLeo and Stull (2014) examine Bitcoin transaction volumes as a measure of user demand and find that transaction activity significantly affects Bitcoin's price. Digital currencies, as noted by Kristoufek (2013), are not issued by central banks or governments. Kristoufek (2013) suggests that Bitcoin's demand is primarily driven by the potential profit users anticipate from holding and later selling the asset. Glaser et al. (2014) analyzed the motivations behind users converting traditional currency into Bitcoin, considering two main perspectives: using Bitcoin as a transactional currency or as a speculative asset to generate returns. Similarly, Luis et al. (2019) argue that Bitcoin serves as a speculative asset in the short run, but speculation does not appear to impact long-term demand significantly. Instead, the expectation that Bitcoin might function as a medium of exchange in the future could influence its demand over time.

Kristoufek (2013, 2018) further emphasizes that Bitcoin's appeal as an investment option can affect its price. Ciaian et al. (2016b) suggest that investor interest is influenced by media coverage, as investment opportunities with higher media visibility tend to attract more investors due to reduced search costs. Kristoufek (2015) also finds a strong positive correlation between Bitcoin prices and search trends, indicating that online search interest can be an effective predictor of Bitcoin's market behavior. Supporting these findings, Philippas et al. (2019) highlight the significant role of social media and online networks in shaping Bitcoin's price movements. Similarly, Kjærland et al. (2018) conclude that increased public attention to Bitcoin leads to higher demand and, consequently, higher prices. Van Wijk (2013) investigates how macroeconomic and financial development factors influence Bitcoin prices, utilizing key indicators such as stock market indices, exchange rates, and oil prices. His findings indicate that the Dow Jones Index has a significant positive effect on Bitcoin prices, whereas the euro-dollar exchange rate and West Texas Intermediate (WTI) oil prices exert a significant negative influence.

Ismail and Basah (2021) apply cointegration analysis and a Vector Error Correction Model to investigate the link between Bitcoin and various macroeconomic variables, including oil prices. Their results indicate a significant positive correlation between Bitcoin and the oil market, suggesting a strong relationship between these distinct asset classes. Similarly, Ha (2023) employs Bayesian vector heterogeneous autoregressions to analyze the interactions among crude oil, gold, stock, and cryptocurrency markets during the pandemic. The study highlights that disruptions within the cryptocurrency market can impact traditional commodities such as crude oil, reflecting the growing interconnection between these financial sectors. Additionally, He (2022) examines how the Russia-Ukraine conflict has influenced crude oil prices and fluctuations in the cryptocurrency market. This research provides valuable insights into the impact of geopolitical events on the relationship between oil and digital assets. The findings suggest that while rising crude oil futures prices can boost cryptocurrency returns in the short term, they do not necessarily increase daily volatility.

Bouoiyour et al. (2014) argue that changes in the general price level can negatively impact real income, thereby reducing investors' capacity to allocate funds to Bitcoin or other financial assets. Kjærland et al. (2018) find that the S&P 500 Index positively influences Bitcoin prices, whereas Georgoula et al. (2015) report a long-term negative relationship between Bitcoin and the S&P 500 Index. This suggests that investors may view Bitcoin and stocks as alternative investment options. The profitability of cryptocurrencies has given rise to a new profession known as "cryptocurrency mining" (Xu et al., 2021). Li and Wang (2017) and Guizani and Nafti (2019) highlight that Bitcoin mining can lead to increased expenses due to the need for specialized equipment, ongoing maintenance, electricity consumption, and human resources. Additionally, research by Kjærland et al. (2018) and Guizani and Nafti (2019) suggests a direct correlation between Hash Rate and mining difficulty. As computational power grows, the difficulty of mining also rises, ensuring that Bitcoin production remains within its predetermined supply limit.

Furthermore, Li and Wang (2017) propose that Bitcoin mining influences its market price. As mining difficulty escalates, the value of Bitcoin tends to increase. However, Guizani and Nafti (2019) argue that technological advancements and efficiency improvements lead to increases in computing power. Bouoiyour and Selmi (2015) and Kjærland et al. (2018) suggest that Bitcoin's price influences the Hash Rate rather than the other way around. According to Badev and Chen (2014), Bitcoin miners receive two primary types of rewards: newly generated Bitcoins and transaction fees. The sender of a transaction can opt to include a transaction fee as an incentive for miners. Dwyer (2015) emphasizes that these fees encourage miners to process transactions more promptly. In line with this view, Böhme et al. (2015) explain that both buyers and sellers can contribute to this optional fee, which is awarded to the miner who successfully verifies a transaction. Fantazzini and Kolodin (2020) note that total transaction fees reflect both the level of public interest in Bitcoin and the amount users are willing to pay miners for processing transactions.

Data and Methodology

Data Set

In this paper, the model's dependent variable is the Bitcoin market price in US dollars. The sample includes weekly time series from March 2017 to December 2024.

When assessing data quality, missing values are often encountered. These gaps may arise for various reasons, such as market closures on holidays. Consequently, any days with missing values have been excluded from the dataset. A summary of the dependent variable and all explanatory independent variables, collected from multiple sources, is presented in Table 1.

Table 1: Variables, Description, and Data Sources

Variables	**Description**	**Sources**
BMP	Bitcoin Market Price	Blockchain Chart
Bitcoin Supply	Total amount of Bitcoin mined and is presently in circulation on the network.	Blockchain Chart
Bitcoin Demand	The overall count of verified transactions.	Blockchain Chart
Tera Hashes	Number of Tera Hashes per second Bitcoin Network processed in the past 24 hours.	Blockchain Chart
Unique Addresses	Total number of unique addresses used on The blockchain.	Blockchain Chart
BTC Cost Per Trans	Cost Per Transaction (miners' revenue Divided by number of transactions).	Blockchain Chart
BTC Trans Rate Per Sec	Transaction rate per second (the number of transactions added to the mempool per Second).	Blockchain Chart
BTC Trans Value	Estimated transaction value (Bitcoin).	Blockchain Chart
Miners' Revenue	Miners' revenue (USD), total value in USD of the Coinbase block reward and Transaction fees paid to miners.	Blockchain Chart
Miners' Revenue (excluding coinbase Block reward)	Total USD value of all transaction fees paid to miners excluding coinbase block reward.	Blockchain Chart
DJIA	Dow Jones Industrial Average Index.	St.louisfred.org
S&P 500	S&P 500, index of stocks of 500 leading Companies in the US economy.	St.louisfred.org
Exchange USEU	Exchange rate between US Dollar and Euro.	Stlouisfred.org
Crude oil	Crude oil West Texas Intermediate Futures.	St.louisfred.org
Page views	Number of Bitcoin page views on Wikipedia.	Newhedge.com

Demand and supply play a vital role in determining the price of goods and services. In this study, Bitcoin's supply is represented by the total amount of Bitcoin that has been mined and is currently in circulation on the network. At the same time, its demand is measured by the total number of verified transactions. The independent explanatory variables in this research are categorized into three main groups: investment attractiveness, global macroeconomic and financial factors, and digital currency characteristics.

Investment attractiveness is assessed using the weekly volume of Bitcoin page views on Wikipedia, which helps evaluate the impact of news and information on Bitcoin's price. To analyze global macroeconomic and financial market performance, this study incorporates the S&P 500 Index, the Dow Jones Industrial Average Index, the exchange rate between the US Dollar and the Euro, and West Texas Intermediate (WTI) crude oil futures.

For digital currency characteristics, the study includes the total number of unique addresses used on the blockchain, the Cost Per Bitcoin Transaction, the Bitcoin Transaction Rate Per Second, the estimated transaction value, miners' revenue (the total USD value of block rewards and transaction fees paid to miners), tera hashes, and the total USD value of all transaction fees paid to miners (excluding the coinbase block reward).

Descriptive Statistics

Table 2 presents the descriptive statistics for all variables.

Table 2: Descriptive Statistics

Variables	**Mean**	**Std.Dev.**	**Min.**	**Max.**
BMP	9.701921	1.036027	6.845561	11.556397
Bitcoin Supply	16.72462387	0.05782272	16.60005448	16.80074173
Bitcoin Demand	12.644118	0.319728	11.838878	13.664256
Tera Hashes	18.52690	1.42807	15.02792	20.84740
Unique Addresses	13.2797751	0.1987882	12.6447146	13.7731009
BTC Cost Per Trans	4.1473034	0.6848363	2.0598764	5.7048186
BTC Trans Rate Per Sec	1.2452484	0.2999525	0.4725005	2.2271070
BTC Trans Value	11.7216976	0.5919116	10.0742103	13.5479941
Miners' Revenue	16.8221520	0.8422284	12.3967120	23.5163686
Miners' Revenue (excluding coinbase Block reward	13.395026	1.272729	8.331863	18.210581
DJIA	10.3038393	0.1947229	9.8304829	10.7124302
S&P 500	8.1835659	0.2593388	7.7130698	8.7144477
Exchange USEU	0.11378017	0.05112422	-0.02644665	0.22170251
Crude Oil	4.1541227	0.2985643	2.8033604	4.7999966
Page views	8.5167398	0.6906452	7.4277388	11.2883183

Time Series plot of the Variables and log of the Variables:

Figure: Bitcoin Market Price

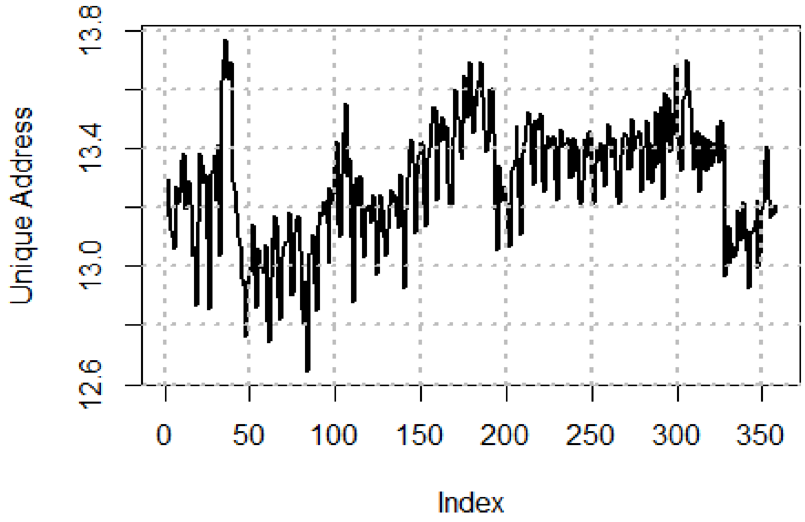


Figure: Unique Addresses used on the blockchain

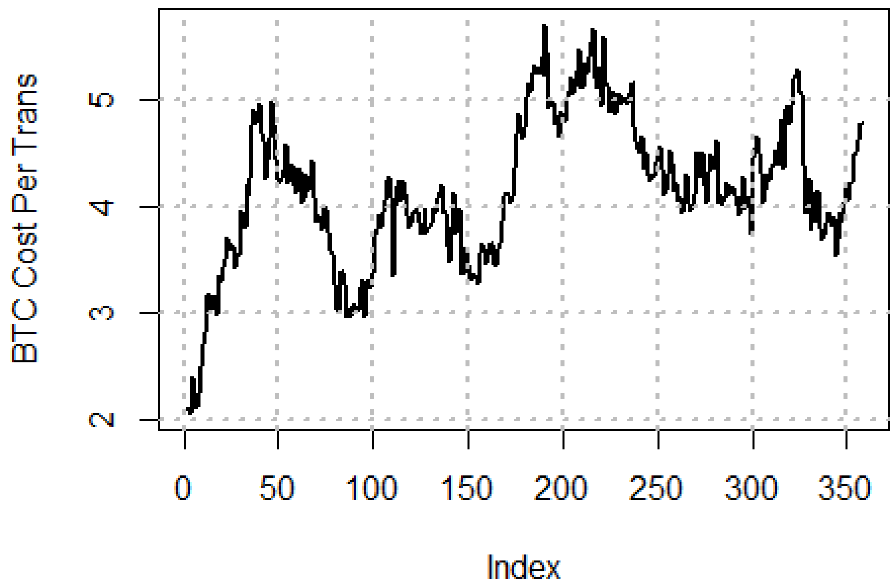


Figure: Bitcoin Cost Per Transaction

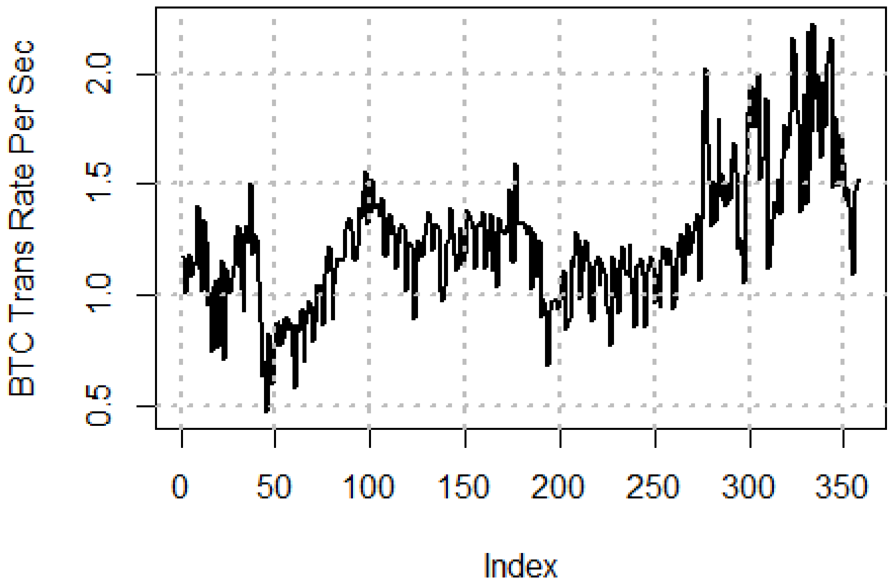


Figure: Bitcoin Transaction Rate Per Second

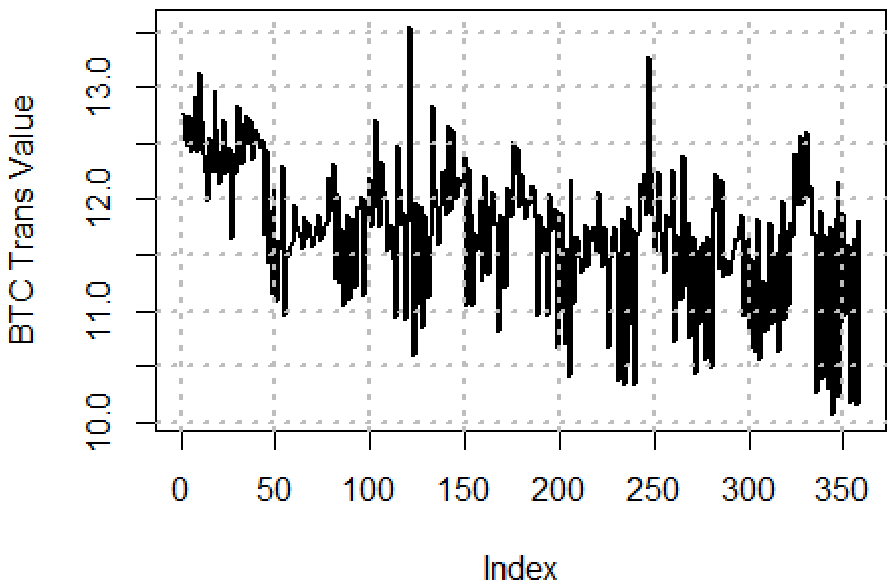


Figure: Bitcoin Transaction Value

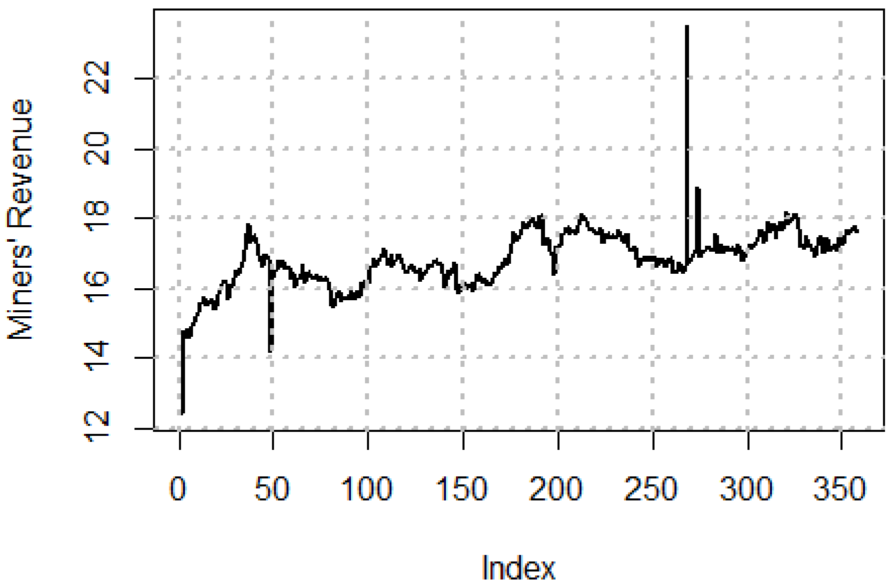


Figure: Miners’ Revenue

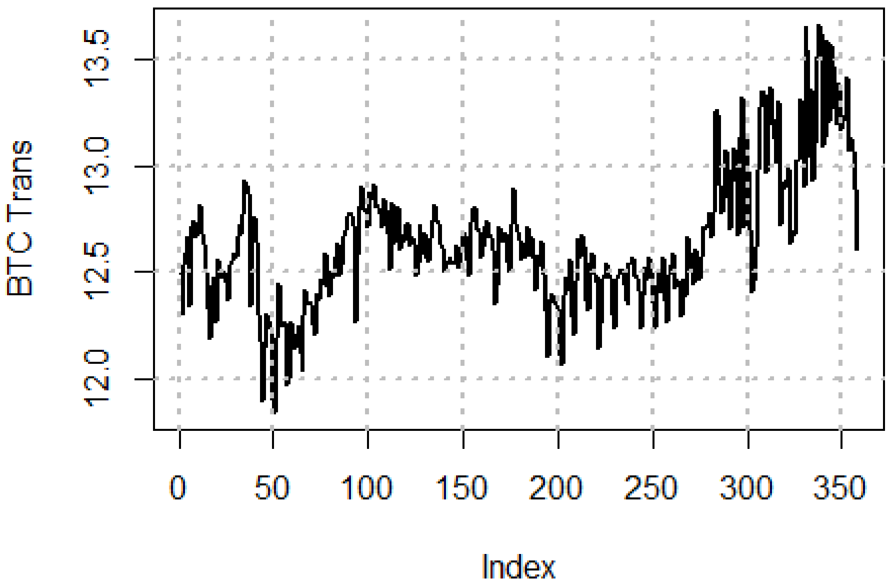


Figure: Overall count of verified Transactions

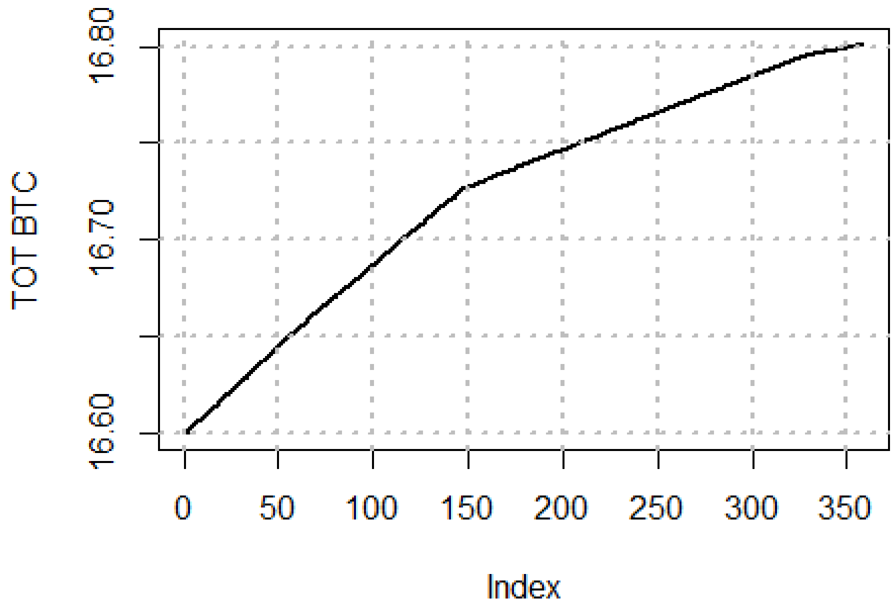


Figure: Total amount of Bitcoin mined and presently in circulation on the network.

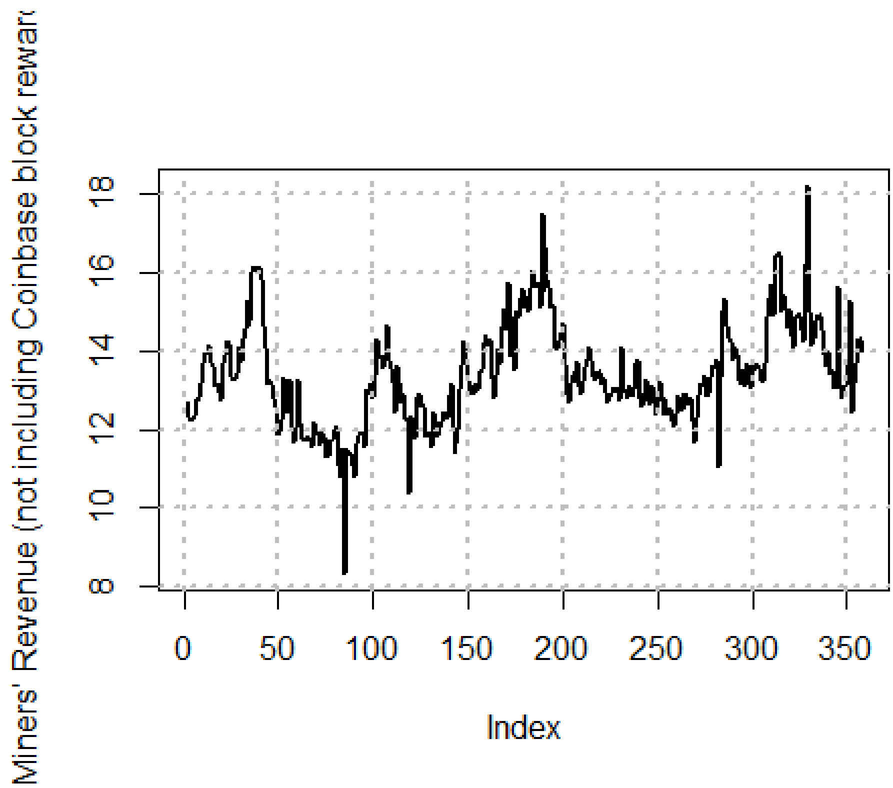


Figure: Miners' Revenue (Excluding coinbase block reward).

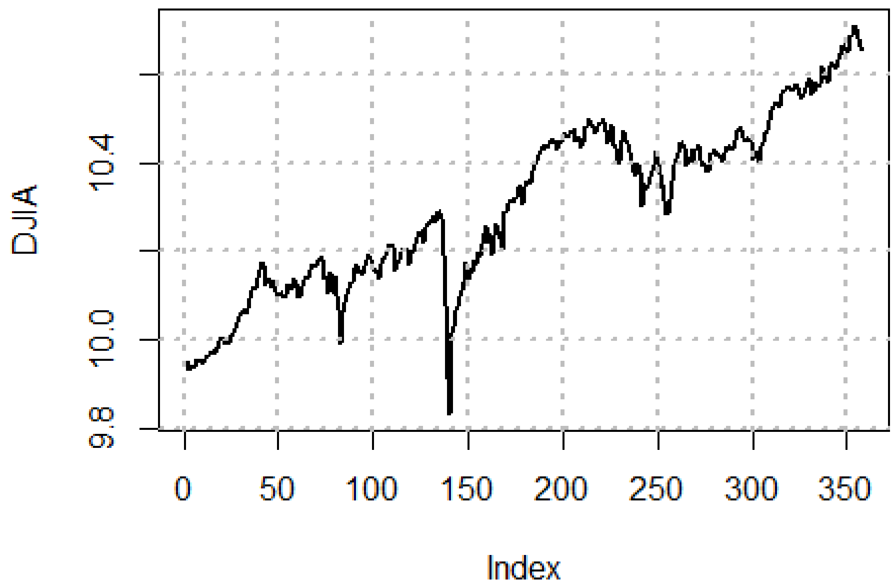


Figure: Dow Jones Industrial Average Index

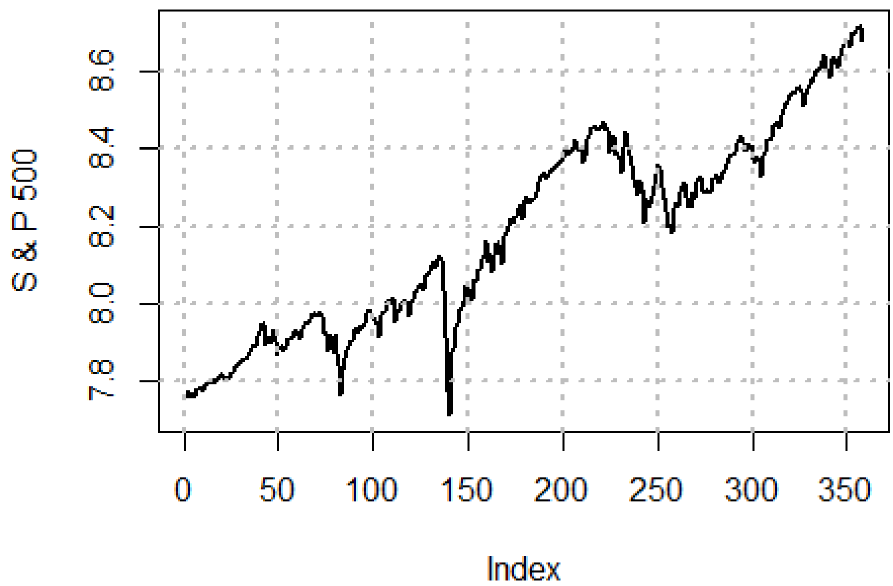


Figure: Standard & Poor 500 Index

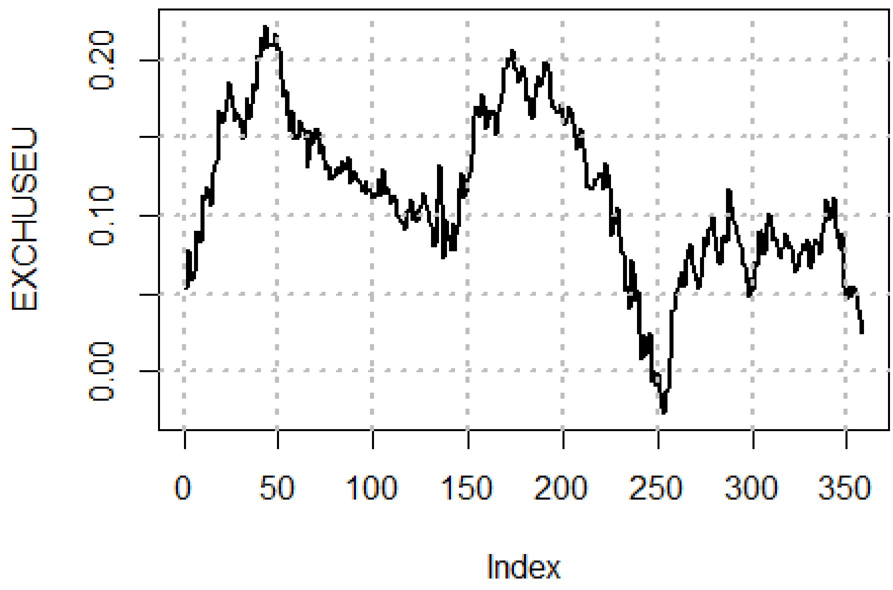


Figure: Exchange Rate between the US Dollar and the Euro.

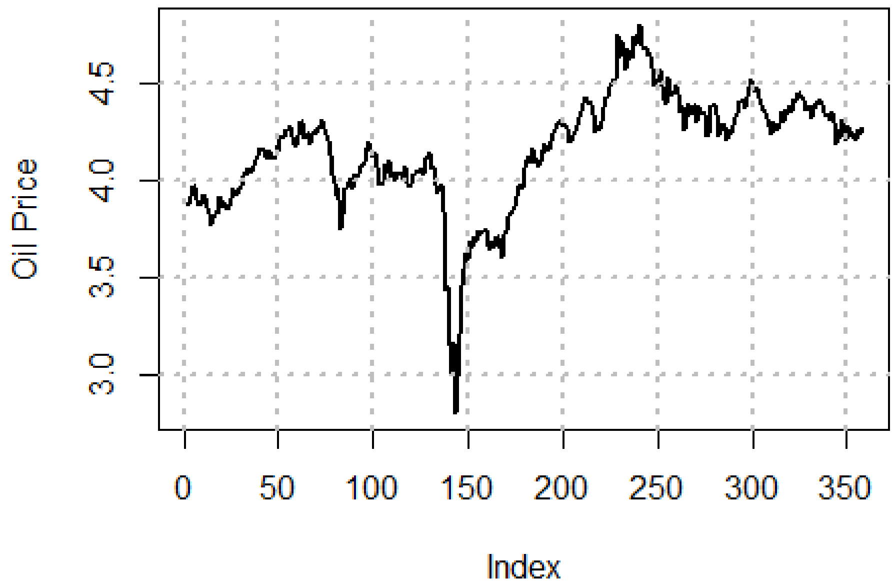


Figure: Crude oil West Texas Intermediate Futures.

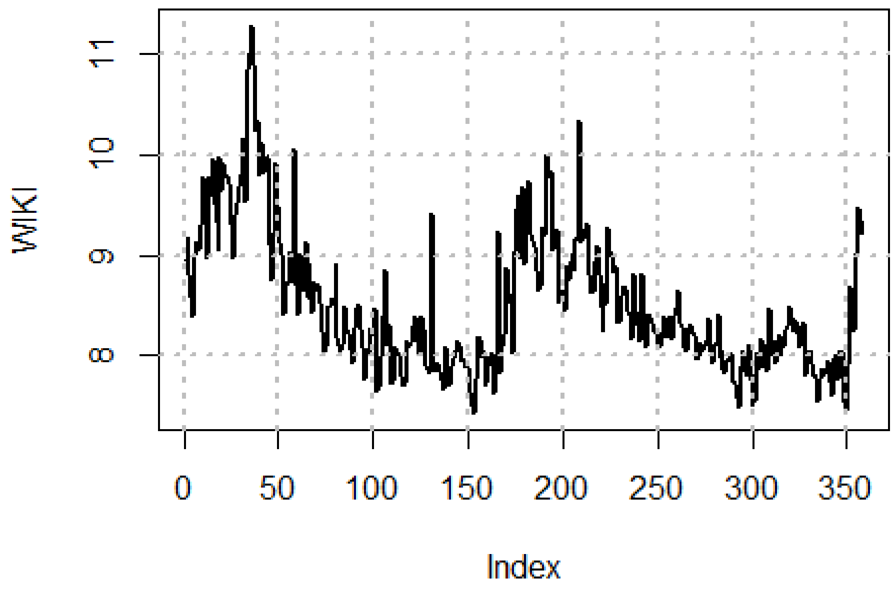


Figure: Number of Bitcoin page views on Wikipedia.

Econometric Method

This study utilizes a specific methodology to identify the key factors influencing Bitcoin price formation, incorporating the Autoregressive Distributed Lag (ARDL) model. To ensure the reliability of the data and avoid spurious regressions, the Augmented Dickey-Fuller (ADF) and Phillips-Perron tests were applied to examine the stationarity of the variables. A general hypothesis for all the variables is given as follows:

H_0: The variables are non- stationary.

H_1: The variables are stationary.

If the p-value is less than 0.05, we reject the null hypothesis, meaning the variable is stationary; if the p-value is greater than 0.05, we accept the null hypothesis, meaning the variable is non-stationary. When considering the overall results of the ADF test, it was found that Estimated Transaction Value, Miners' Revenue including coinbase block reward, Unique Addresses used on the blockchain, and Tera Hashes are stationary, with p-values of –0.01, 0.012, 0.065, and 0.045. However, Bitcoin Market Price, Total amount of Bitcoin mined and is presently in circulation on the network, overall count of verified transactions, Cost Per Transaction , Transaction rate per second, Miners' Revenue Excluding coinbase block reward, Dow Jones Industrial Average Index, S&P 500 Index, Exchange rate between US Dollar and Euro, Crude oil West Texas Intermediate Futures, and number of Bitcoin page views on Wikipedia are non-stationary with p-values as – 0.167, 0.284, 0.194, 0.064, 0.083, 0.122, 0.113, 0.443, 0.230, 0.150, 0.551. A non-stationary time series can be transformed into a stationary one by taking first differences, which involve subtracting each data point from its preceding value. After this transformation, the Augmented Dickey-Fuller (ADF) test is conducted again to analyze the p-values of the differenced series and assess whether stationarity has been achieved.

The analysis revealed that certain variables, which were initially non-stationary at I(0), became stationary after taking their first difference, indicating they are integrated of order one (I(1). In statistical terms, the order of integration, denoted as I(d), represents the number of differencing steps required to achieve stationarity in a time series. When a variable is classified as I(1), it indicates that while the original series is non-stationary, its first-differenced version is stationary. To examine the influence of various factors on Bitcoin price formation, this study employs the Autoregressive Distributed Lag (ARDL) model. The ARDL model is suitable when variables are a mix of I(0) and I(1), or when all variables are I(1). In this study, since the variables are either stationary at I(0) or I(1), the ARDL model is an appropriate choice for analysis. The Autoregressive Distributed Lag (ARDL) model can be employed to analyze both short-term and long-term relationships among variables (Im et al., 2003). Its general form is represented as follows:

$$Y_t = \alpha + \phi_1 Y_{t-1} + +\phi_2 Y_{t-2} + \cdots + +\phi_p Y_{t-p} + \beta_0 X_t + \beta_1 X_{t-1} + \cdots + \beta_q X_{t-q} + \varepsilon_t$$

In this paper, the *auro_ardl()* function from **the ARDL package (**Natsiopoulos et al., 2022) is used, which determines the optimal lag order based on AIC values. The given function calculates the AIC values for all possible combinations and then returns the result based on the minimum AIC value.

Table 3: ARDL specification and associated number of lags.

Variables	**Number of lags**
l BMP	3
l Bitcoin Supply	0
l Bitcoin Demand	1
l Tera Hashes	0
l Unique Addresses	2
l BTC Cost Per Trans	1
l BTC Trans Rate Per Sec	0
l BTC Trans Value	1
l Miners' Revenue	1
l Miners' Revenue (Excluding Coinbase Block reward)	2
l DJIA	2
l S&P 500	2
l Exchange USEU	0
l Crude Oil	0
l Page views	0

To examine the influence of the specified variables on Bitcoin's price, this paper introduces the following model:

$$\Delta lBMP = \alpha + \sum_{i=1}^{a} \alpha_{i1}\Delta lBMP_{t-i} + \sum_{i=0}^{b} \alpha_{i2}\Delta lBitcoinDemand_{t-i} + \sum_{i=0}^{c} \alpha_{i3}\Delta lUniqAddress_{t-1} + \sum_{i=0}^{d} \alpha_{i4}\Delta lBTCCostPerTrans_{t-i} + \sum_{i=0}^{e} \alpha_{i5}\Delta lBTCTransValue_{t-i} + \sum_{i=0}^{f} \alpha_{i6}\Delta lMiners'Revenue_{t-i} + \sum_{i=0}^{g} \alpha_{i7}\Delta lMiners'RevenueExCoin_{t-i} + \sum_{i=0}^{h} \alpha_{i8}\Delta lDJIA_{t-i} + \sum_{i=0}^{i} \alpha_{i9}\Delta lS\&P_{t-i} + \beta_1 lBitcoinSupply + \beta_2 lTeraHash + \beta_3 lBTCTransPerSec + \beta_4 lTeraHash + \beta_5 lCrudeOil + \beta_6 lPageView$$

Here, BMP represents Bitcoin Market Price, BitcoinDemand represents Overall count of verified Transaction, UniqAddress represents total number of Unique addresses used on the blockchain, BTCCostPerTrans represents Bitcoin cost per transaction, BTCTransValue represents Estimated transaction value of Bitcoin, Miners'Revenue represents Miners'Revenue, Miners'RevenueExCoin represents Miners' Revenue excluding Coinbase block reward, DJIA represents Dow Jones Industrial Average Index, S&P represents S&P 500, BitcoinSupply represents represents total amount of Bitcoin mined and is presently in circulation on the network, TeraHash represents number of tera hashes per second Bitcoin network processed in the past 24 hours, BTCTransPerSec represents Transaction rate per second (the number of transactions added to the mempool per second), CrudeOil represents Crude Oil West Texas Intermediate Futures and PageView represents number of Bitcoin page views on Wikipedia.

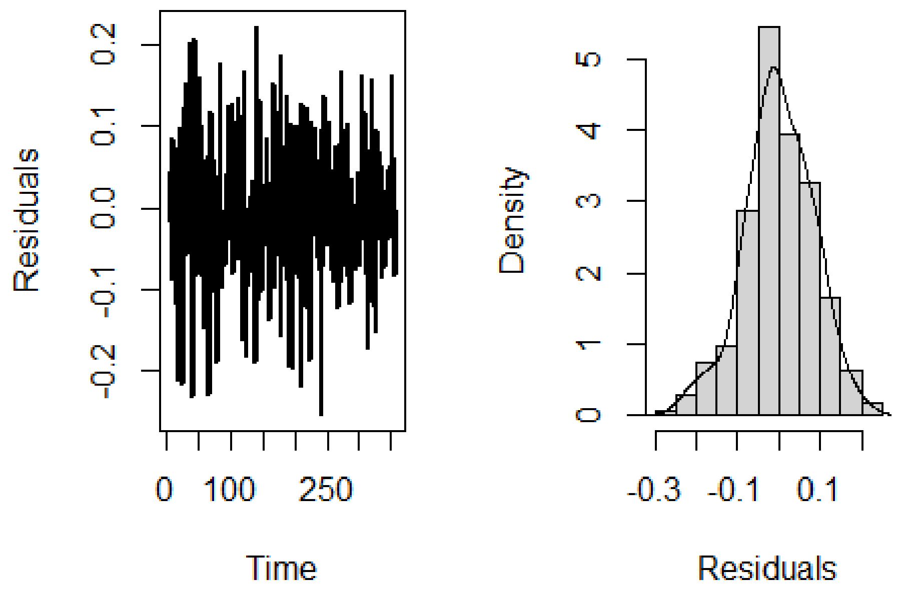
Table 4: ARDL Estimation Results

Variables	Estimate	Std.Error	t-value	p-value
Intercept	-14.25	7.847	-1.816	0.070252 .
L(l BMP,1)	0.7089	0.5907	12.000	<0.0000 ***
L(l BMP,2)	0.2181	0.07200	3.029	0.002651 **
L(l BMP,3)	-0.1200	0.05014	-2.394	0.017239 *
l Bitcoin Supply	0.7935	0.4988	1.591	0.112616
l Bitcoin Demand	0.1100	0.03520	3.126	0.001935 **
L(l Bitcoin Demand,1)	-0.1099	0.03503	-3.137	0.001865 **
l Tera Hashes	0.004341	0.01217	0.357	0.721667
l Unique Addresses	0.05398	0,02916	1.851	0.065080 .
L(l Unique Addresses,1)	-0.06124	0.03006	-2.037	0.042442 *
L(l Unique Addresses,2)	-0.04716	0.02842	-1.659	0.098002 .
l BTC Cost Per Trans	0.2060	0.02908	7.083	0.000000***
L(l BTC Cost Per Trans,1)	-0.1693	0.03090	-5.480	0.000000***
l BTC Trans Rate Per Sec	0.05915	0.02521	2.346	0.019573*
l BTC Trans Value	-0.0003662	0.01009	-0.036	0.971070
L(l BTC Trans Value,1)	0.004563	0.009949	0.459	0.646830
l Miners' Revenue	-0.006274	0.007999	-0.784	0.433391
L(l Miners' Revenue,1)	0.01314	0.007856	1.672	0.095427 .
l Miners' Revenue (excluding coinbase block reward)	0.01969	0.01151	1.711	0.088125 .

L(l Miners' Revenue (excluding Coinbase block reward), 1)	0.01578	0.01162	1.357	0.175665
L(l Miners' Revenue (excluding coinbase block Reward, 2)	0.01928	0.01136	1.696	0.090766.
l DJIA	1.028	0.2887	3.562	0.000424***
L(l DJIA,1)	-0.4421	0.3426	-1.291	0.197761
L(l DJIA,2)	-0.8856	0.3047	-2.906	0.003908**
l S&P 500	-0.1675	0.2959	-0.566	0.571631
L(l S&P 500,1)	-0.02024	0.3214	-0.063	0.949818
L(l S&P 500,2)	0.8037	0.2726	2.949	0.003420 **
l Exchange USEU	0.3579	0.1770	2.022	0.043954*
l Crude Oil	-0.02160	0.03001	-0.720	0.472160
l Page views	0.03646	0.01253	2.910	0.003864 **

Significant Codes: 0-0.001 '***' 0.001-0.01 '**' 0.01-0.05 '*' 0.05-0.1 '.'

The F-statistic is 1596 on 29, and 325 DF, and the corresponding p-value is < 2.2e-16, which is less than 0.05. Hence, we reject the null hypothesis. That means at least one of the variables is significant. Therefore, our fitted model is significant. The R-square is 0.993, and the adjusted R-square is 0.9924, indicating that 99.3% of the variability in Bitcoin market price is explained by the variables included in the model. We have used the bounds F test to assess cointegration and found a p-value of 0.001552465, which is less than 0.05. Hence, we reject the null hypothesis. That means there is possible cointegration in our model.



The histogram indicates that the residuals follow a normal distribution. Additionally, the Jarque-Bera test was conducted, yielding a p-value of 0.231, further confirming the normality of the residuals.

The Breusch–Godfrey Serial Correlation LM Test was applied to examine whether the residuals are autocorrelated. The results indicate that the p-value is greater than 0.05, suggesting that the null hypothesis of no serial correlation cannot be rejected. This confirms that the residuals are free from autocorrelation.

Second, the Breusch–Pagan–Godfrey Test was employed to detect heteroskedasticity in the residuals. The obtained p-value exceeds the 0.05 significance level, indicating that the null hypothesis of homoskedasticity cannot be rejected. Therefore, the variance of the residuals is constant, and the model does not suffer from heteroskedasticity.

The stability of the model parameters was examined using the CUSUM (Cumulative Sum of Recursive Residuals) and CUSUMSQ (CUSUM of Squares) tests. The plots of both tests remain within the 5% critical bounds, indicating that the model is stable over the sample period and that there are no structural breaks.

Overall, the diagnostic test results confirm that the estimated ARDL model is well-specified, stable, and suitable for analyzing the determinants of Bitcoin price formation.

Some of the variables in the ARDL estimation results were found to be insignificant, including: Total amount of Bitcoin mined and is presently in circulation on the network, Tera Hashes, Bitcoin Transaction Value, and Crude Oil West Texas Intermediate Futures.

The findings indicate that the first and second lags of Bitcoin market price have positive coefficients and are statistically significant at the 0.1% and 1% levels, respectively. In contrast, the third lag has a negative coefficient that is significant at the 5% level, suggesting that a 1-unit increase in Bitcoin's price from a week earlier leads to a 0.1200-unit decrease in the current price.

The overall number of verified transactions has a positive coefficient and is significant at the 1% level. However, its first lag has a negative coefficient that is also significant at 1%, implying that a 1-unit increase in verified transactions results in a 0.1099-unit decline in Bitcoin's market price.

Similarly, the first lag of unique blockchain addresses has a negative coefficient. It is significant at the 5% level, indicating that a 1-unit increase in unique addresses is associated with a 0.06124-unit decrease in Bitcoin's price.

Bitcoin cost per transaction has a positive coefficient and is significant at the 0.1% level, meaning that for each 1-unit increase in transaction cost, the Bitcoin market price rises by 0.2060 units. However, its first lag has a negative coefficient that is also significant at the 0.1% level.

The transaction rate per second, which measures the number of transactions added to the mempool, has a positive coefficient and is significant at the 5% level. This suggests that a 1-unit increase in transaction rate leads to a 0.05915-unit rise in Bitcoin's price.

The Dow Jones Industrial Average (DJIA) has a positive coefficient and is highly significant at the 0.1% level, indicating that a 1-unit increase in DJIA raises Bitcoin's price by 1.028 units. However, the second lag of the DJIA has a negative coefficient and is significant at the 1% level, indicating that a 1-unit increase in the DJIA leads to a 0.8856-unit drop in Bitcoin's price.

The second lag of the S&P 500 Index has a positive coefficient. It is significant at the 1% level, indicating that a 1-unit increase in the index is associated with a 0.8037-unit rise in Bitcoin's market price.

The exchange rate between the US Dollar and the Euro also exhibits a positive coefficient that is significant at the 5% level. This means that a 1-unit increase in the exchange rate corresponds to a 0.3579-unit increase in Bitcoin's price.

Additionally, the number of Bitcoin page views on Wikipedia has a positive coefficient. It is significant at the 1% level, implying that a 1-unit rise in page views leads to a 0.03646-unit increase in Bitcoin's market price.

Conclusion

This study aimed to enhance the understanding of factors influencing Bitcoin price formation by analyzing 14 independent variables alongside Bitcoin Market Price as the dependent variable over the period from March 8, 2017, to December 31, 2024. To examine these relationships, a time-series analysis was conducted using the Autoregressive Distributed Lag (ARDL) model.

The findings indicate that six independent variables—Total Verified Transactions, Bitcoin Cost Per Transaction, Bitcoin Transaction Rate Per Second, the Dow Jones Industrial Average (DJIA), the Exchange Rate between the US Dollar and Euro, and the Number of Bitcoin Page Views on Wikipedia—along with the lagged values of Bitcoin Market Price, were statistically significant. These results suggest that various factors related to Bitcoin's supply and demand dynamics play a crucial role in shaping its price.

The study reveals that the overall account of verified transactions exhibits a positive and significant relationship with Bitcoin price, meaning that an increase in transaction verification, which reflects growing Bitcoin demand, drives prices upward. This aligns with the fundamental principle of supply and demand, where increased demand for a particular asset or service leads to higher prices. These results are consistent with previous studies by Ciaian et al. (2016b) and Kristoufek (2015), which also found that the total number of confirmed Bitcoin transactions has a positive and significant impact on Bitcoin pricing.

Additionally, the study finds that Bitcoin Cost Per Transaction and Bitcoin Transaction Rate Per Second have positive and significant effects on Bitcoin prices. The cost per transaction is calculated by dividing miners' revenue in US dollars by the total number of transactions. Since Bitcoin mining operates under a predefined algorithm that limits the number of Bitcoins produced within a given timeframe, increased mining competition makes the cryptographic puzzles more complex. This complexity raises mining costs as additional time and computational power are required, ultimately leading to higher Bitcoin prices.

Moreover, the study identifies a positive and significant relationship between Bitcoin page views on Wikipedia and Bitcoin price. This aligns with Ciaian et al. (2016b), who suggest that Bitcoin-related searches and online interest can influence price movements, regardless of whether the sentiment is positive or negative.

Macroeconomic variables, such as the Exchange Rate between the US Dollar and the Euro and the Dow Jones Industrial Average Index, also play a significant role in determining Bitcoin price fluctuations.

Future research should build upon these findings by incorporating additional independent variables that could impact Bitcoin price formation. Since the variables in this study were found to be non-stationary, the first differences were taken to address potential spurious regression concerns and ensure stationarity. However, these results primarily support short-term estimates rather than long-term trends, which are of greater interest to researchers and investors (Nkoro et al., 2016). The insights from this study, along with further research, can enhance the understanding of key factors influencing the evolving cryptocurrency market.

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