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Bitcoin Price Dynamics: The Role of Community Activity, Social Media, and Market Liquidity

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ABSTRACT

This study analyzes the most significant factors that influence the price of Bitcoin which is the spearhead of the cryptocurrency market. It attempts to determine the explanatory power of variables such as community activity (CA), social media impact (SM), liquidity ratio (LR), and circulating Bitcoins in the market (PS) on the Bitcoin price. Data was gathered from September 06 2021 to September 04 2023 on a weekly basis. Eviews 10 and Excel 2019 software were used to analyze the data after taking the logarithm of the data, which was computed through Eviews 10 and Excel 2019. In this research, time series methods such as VAR model and impulse response tests were conducted. The findings of this research indicate that the two most powerful forces driving the price of Bitcoin are the amount of social media attention it receives and the number of Bitcoins actively being traded in the market. It can also be stated that liquidity ratio has a strong effect regarding the changes in Bitcoin's price. The least important factor in this research was community activity in comparison to all other monitored factors. The findings of the research offer new insight relevant for investors, analysts, and regulators concerning the trends and movements of the cryptocurrency market. Understanding Bitcoin better is crucial if any rational prognosis regarding the future state of the cryptocurrency market is to be made.

Keywords: Bitcoin, Volatility, Community Activity, Social Media Impact, Liquidity Ratio, Market Supply, VAR Model, Time Series Analysis
JEL Classifications: G12, E44, C32

1. INTRODUCTION

In the landscape of the world, perhaps one of the most notable examples in recent times has been the surge in the popularity of Cryptocurrencies. It is very clear that cryptocurrencies are not just a new market of interest, but rather a new class of disruptive technology to the existing global ecosystem of finance. Bitcoin, for instance, became well-known as the cryptocurrency in 2009. Today, we view it as a multibillion dollar market. Even Satoshi Nakamoto, its founder, cites it to be "the first decentralised digital currency" designed to operate as a "peer-to-peer electronic cash system" (Nakamoto, 2008).

The development of cryptocurrencies create a disruption to the existing financial ecosystem due to fast transaction speeds, lower costs, and lack of regional barriers. It is this very payment where the bank is neither a sending nor a receiving agent comes to reconstruct the whole paradigm of the financial world and force societies to revisit the use of words such as cashless economy. The unquestionable characteristics of Cryptocurrencies still stay allien to traditional financial world.

The development of cryptocurrencies creates a disruption to the existing financial ecosystem due to fast transaction speeds, lower costs, and the absence of regional barriers. This payment architecture, in which banks are neither sending nor receiving agents, has begun to reconstruct the traditional paradigm of finance and to reshape discussions surrounding a cashless economy. In this respect, blockchain-based systems have been argued to reduce transaction and verification costs while enabling new forms of decentralized economic coordination (Catalini & Gans, 2019).

To put it in simpler terms, below are the advantages Bitcoin has over classical forms of money:

- Digital payment: Cryptocurrencies are "stored" in the form of virtual wallets, enabling cashless withdrawing and depositing (Antonopoulos, 2017).
- No central control: Their transactions do not go through a governing body, meaning, there will be no central supervisional body putting restrictions or lags to an individual's freedom within the system (Nakamoto, 2008).
- Privacy: While Bitcoin transactions guarantee user anonymity, all transactions are permanently stored on the blockchain, thus can be tracked. Users' identities are pseudonymous. However, every transaction is disclosed for public viewing (Möser, et al., 2013).
- Limited supply: The total amount of Bitcoin that can ever exist is capped at 21 million. This allows Bitcoin to resist inflation (Nakamoto, 2008).
- Mining: Bitcoin transactions are authenticated by miners who receive payment in the form of newly minted Bitcoin for solving mathematical puzzles (Antonopoulos, 2014).

Despite concerns regarding the legality of cryptocurrencies, which vary from one nation to another, the interest in Bitcoin and other cryptocurrencies remains enormous. The legal status of cryptocurrencies across selected countries is summarized in Table 1.

The dramatic increase in the use of cryptocurrencies propelled the interest of investors, businesspeople, and even financial organizations globally. On the other hand, the volatility of cryptocurrency value has also attracted much interest from people. For example, the price of Bitcoin, as being the foremost cryptocurrency, is greatly affected in the financial market as it oscillates in valuation around centers. Hence, the ability to understand, and forecast movements in the prices of cryptocurrencies is essential to investors, analysts, and even policymakers.

Thus, this aims to determine the price changing factors related to bitcoin. Analyzing the representative of digital currencies to investigate the aforementioned issue is critical due to Bitcoin's tremendous influence on price fluctuations. The primary emphasis of the research is to identify the relationship among influences that determine the value of Bitcoin and assess the influence of these parameters on the changes in the value of Bitcoin.

This study endeavors to determine the most important factors affecting the price change in Bitcoin. Detecting these reasons is very important for analysts and investors because price movements in Bitcoin are driven by various factors. This study seeks to determine the effects of community activity, social media activity, liquidity ratio, and the number of participants in the Bitcoin market on the price of Bitcoin. The analysis is based on a time series data set, applying different statistical techniques including, but not limited to, VAR (Vector Autoregression) Model, impulse response tests, and other dynamic methods which are fundamental in data analysis and relationships in the data set being studied. These methodologies allow for the proper identification of the dynamic relationships among the variables as well as the factors Bitcoin's price volatility. This research would allow further studies regarding cryptocurrency and would provide a reliable guide for potential investors, market analysts, and market regulators. Identification of the dynamic relationships among the variables would enable more accurate and sound fundamental predictive analytical frameworks regarding Bitcoin's pricing.

The second part of the study is a literature review of cryptocurrencies and the third part is the analysis of the case study, while the last part presents the analysis and the interpretation of results.

1.1. Significance of Study

The study adds value to the already existing understanding and the analysis of the most dominant cryptocurrency in the market's price movement, Bitcoin. The dynamics of Bitcoin's price indicates that cryptocurrency is one of the most important inventions that will change the entire blueprints of already established financial markets and the economy towards their future. Explaining the phenomena of the volatility in the price of Bitcoin will aid in stabilizing the volatility experienced in the financial markets and enhancing the management of risks. Furthermore, it enables better estimation of the developments in the cryptocurrency market.

1.2. Contribution to the Literature

This paper adds value to the literature on cryptocurrency markets. Specifically, very few literature exists analyzing the determinants of Bitcoin's price. In this regard, this paper attempts to fill the gap by analyzing the effect of community activity, social media, liquidity ratio, and the market participation on the price of Bitcoin. Furthermore, this paper expands the literature by applying the VAR methodology and time series analysis to the cryptocurrency markets. These analyses propose a different angle to study cryptocurrency markets and project their movements. Ultimately, this paper will aid researchers who seek to deepen their comprehension concerning the cryptocurrency market. Understanding better the determinants of Bitcoin's price will aid in mitigating the risks associated with financial markets and enhance predictions regarding future developments in the cryptocurrency market.

2. LITERATURE REVIEW

The existing literature on Bitcoin pricing dynamics has identified a multifaceted array of factors-including economic fundamentals, behavioral signals, and structural market features—that influence its valuation. The present study is grounded in behavioral finance theory (Shefrin, 2000; Barberis and Thaler, 2003) and market microstructure theory (O'Hara, 1995), both of which provide foundational explanations for how non-traditional information sources, such as social media activity and community-driven signals, shape asset prices. Furthermore, the study empirically tests six hypotheses concerning the explanatory power of community activity, social media impact, liquidity ratio, and circulating supply on Bitcoin prices.

2.1. Economic Fundamentals and Market Mechanisms

Traditional pricing determinants have been addressed in several empirical studies. Ciaian et al. (2016) examined the effects of transaction volume, mining difficulty, and macroeconomic

variables using VAR and VEC models, concluding that economic fundamentals significantly affect Bitcoin's price. Similarly, Balcilar et al. (2017) applied quantile regression and Granger causality tests, finding that transaction volume plays a dominant role under different market volatility conditions. These findings support H_3 and H_4, which posit that the liquidity ratio (LO) and the number of Bitcoins in circulation (PS) significantly influence price behavior.

In the same theoretical vein, Dirican and Canoz (2017) emphasized the roles of inflation, interest rates, and gold prices in shaping cryptocurrency markets. Their synthesis of over 20 studies aligns with the expectations of market-based determinants in volatile environments, reinforcing the foundational elements behind H_4 (impact of circulating supply) and H_6 (relative strength of PS over LO).

2.2. Sentiment, Attention, and Behavioral Signals

Building on behavioral finance theory, which argues that investor sentiment and attention significantly drive market outcomes, numerous studies have investigated the effect of social media activity on Bitcoin's price. Wang et al. (2021) found that both volume and sentiment of online discourse strongly correlate with price shifts. Georgoula et al. (2015) conducted sentiment analysis using Twitter data and machine learning techniques (SVM), showing short-term positive effects on pricing. These results directly support H_2 and H_5, highlighting the predictive power of social sentiment relative to other informational cues.

Cryptocurrency markets often display speculative dynamics shaped by investor attention and technological developments (Kristoufek, 2013). In addition, Bitcoin has been shown to exhibit characteristics of speculative bubbles when market prices diverge from underlying fundamental value, particularly during periods of heightened investor enthusiasm (Cheah & Fry, 2015).

2.3. Community Activity and Technological Signaling

Another informational channel arises from community engagement and development, measured through variables such as GitHub activity and developer interactions. Bartolucci, Caccioli, and Livan (2020) showed that developer-related signals extracted from GitHub can contribute to understanding and predicting cryptocurrency price dynamics, although these effects are not necessarily as immediate or dominant as broader sentiment-based signals. In a related perspective, Toufaily (2022) argued that higher levels of development activity may function as signals of commitment and project credibility, thereby strengthening user trust toward crypto-token applications. Taken together, these findings suggest that community- and development-based indicators are relevant, yet their influence appears to be more indirect and less immediate than social-media-driven attention in short-term price formation.

2.4. Technical Analysis and Speculative Structures

Bhandari et al. (2021) assessed technical indicators such as MACD and moving averages over a 10-year period, demonstrating their predictive value in volatile environments. Şahin and Kara (2022), in their meta-review of over 100 studies, highlighted that technical factors often interact with sentiment and macroeconomic variables. These interactions provide background structure to H_3 and H_4, where liquidity and supply variables exhibit technical behavior.

Bouoiyour and Selmi (2017) adopted Bayesian quantile regression to analyze Bitcoin's reaction to economic shocks under different market conditions. Their study offers a dynamic framework that justifies the use of impulse response analyses (as used in this study) and highlights the non-linear, state-dependent nature of cryptocurrency valuation.

2.5. Institutional and Functional Perspectives

Some researchers have sought to classify Bitcoin's role in the broader financial system. Yermack (2015) questioned Bitcoin's viability as a currency, citing its volatility and lack of regulatory backing. Brunnermeier and Sandri (2016) positioned Bitcoin as a hybrid between a disruptive financial innovation and a speculative asset, indicating the need for regulatory clarity. Their perspectives align with market microstructure theory, where asymmetric information and lack of central oversight create greater volatility and reliance on sentiment signals.

2.6. Simulations and Global Monetary Implications

Güler (2023) used simulation models to compare Bitcoin with global reserve currencies, identifying China's mining influence and RMB movements as key factors. This macro-financial perspective expands the scope of determinants but ultimately supports the inclusion of broader economic signals as necessary controls in modeling frameworks such as VAR and cointegration.

In summary, the literature reveals that Bitcoin's price is influenced by a combination of market fundamentals, sentiment dynamics, and technological signals. The relative strength of social media activity, compared to community engagement, supports a behavioral finance hypothesis where investor attention drives short-term fluctuations. In contrast, variables such as liquidity and circulating supply reflect more structural and technical foundations. This dual-layered dynamic justifies the hypothesis structure of the present study and validates the use of VAR, cointegration, and impulse response analyses as appropriate econometric tools for examining these relationships.

3. ANALYSIS OF THE IMPACT OF COMMUNITY ACTIVITY, SOCIAL MEDIA, AND MARKET LIQUIDITY ON BITCOIN PRICE PERFORMANCE

3.1. Dataset and Sample Structure

This research aims to determine the variables that affect price changes in the Bitcoin cryptocurrency, which has the highest volume among cryptocurrencies. With the aim of adding new perspective and importance to social and news, Community activity (TA), Social media impact (SM) variables, as well as Liquidity ratio (LO) and Number of Bitcoins in Circulation (Bitcoin Market number – [PS]) variables were used as independent variables of the research. has been determined. Therefore, this study investigated the effect of independent variables on the Bitcoin price (F) variable.

Table 1: Legal status of cryptocurrencies

Country	Legal status	Developments
Türkiye	It is prohibited as a means of payment, but trading is allowed.	The Ministry of Treasury and Finance is working on regulations for the taxation of cryptocurrencies. BRSA carries out studies on the supervision of cryptocurrency exchanges and crypto asset service providers. The Ministry of Commerce is working on a regulation regarding cryptocurrencies.
US	It is legal, but there are regulatory uncertainties.	The US Securities and Exchange Commission (SEC) considers cryptocurrencies as securities and tries to regulate them. The US Financial Services Authority (FinCEN) classifies cryptocurrency exchanges as financial institutions and subjects them to AML/KYC regulations.
China	Not legal.	China banned cryptocurrency mining and trading in 2021.
UK	It is legal, but regulations are under development.	The UK Financial Conduct Authority (FCA, 2023) seeks to regulate cryptocurrency exchanges and crypto asset service providers.
Germany	It is legal, but regulations are under development.	The German Financial Markets Authority (BaFin) tries to classify and regulate cryptocurrencies as investment instruments (Federal Financial Supervisory Authority, 2023).
Japan	It is legal, but regulations are under development.	Japan's Financial Services Agency (FSA, 2023) attempts to regulate cryptocurrency exchanges and crypto asset service providers.
South Korea	It is legal, but regulations are under development.	South Korea's Financial Services Commission (FSC, 2023) seeks to regulate cryptocurrency exchanges and crypto asset service providers.

Table 2: Variables used in analysis

Variables	Definition	Abbreviation	Source
Bitcoin price	Bitcoin weekly closing price	F	investing.com
Bitcoin market number	Bitcoin weekly market count	PS	coinmarketcap.com
Bitcoin community activity	Github weekly commit count	TA	Github.com
Bitcoin liquidity rate	Weekly transaction volume/total number of Bitcoins	LO	coinmarketcap.com
Bitcoin social media impact	Number of weekly tweets about Bitcoin	SM	kaggle.com/datasets

Table 3: Descriptive statistics

Statistic	F	LO	PS	SM	TA
Skewness	0.949503	1.251110	0.887819	2.157873	0.442994
Kurtosis	3.042396	4.422862	2.923579	7.603106	2.750408
Jarque-Bera	15.78510	36.24969	13.81944	174.1874	3.706807
Probability	0.000374	0.000000	0.000998	0.000000	0.156703
Observations	105	105	105	105	105

Source: Author's own calculations

The data of this study was collected with a weekly frequency between September 06, 2021 and September 04, 2023. The reason why data is collected weekly is that we observe Community activity and Social media influence on some days. Details of the data used in this research are shown in Table 2.

Logarithm of the data was used to reduce the autocorrelation and normality problems of the study. The analysis and tests of the research were conducted using Eviews 10 and EXCEL 2019 applications. The VAR model is a general framework used to describe the dynamic relationship between static variables. The purpose of the study is to investigate whether a variable is affected over time. In this context, the analysis follows the logic of temporal dependence and predictive causality in time-series relationships, as originally formalized by Granger (1969). The data are time series data, therefore the VAR model and impulse response tests were used in this research. The data are time series data, therefore the VAR model and impulse response tests were used in this research. Descriptive statistics of the data used in the study are shown in Table 4.

According to Table 3, the examined skewness values show that the SM (Social Media Effect) variable indicates a right-skewed distribution. Similarly, kurtosis values reflect that the peaks and tails of the SM's distribution are quite pointed. However, since the skewness values are generally between −1.5 and +1.5, the skewness and Jarque-Bera normality values show that the series are normal. Additionally, Jarque-Bera test results indicate that the SM variable does not comply with normal distribution. The number of observations for all variables is 105.

3.2. Methodology

In order to understand how Bitcoin prices are affected, this research aims to examine the impact of social media influence, community activity and liquidity factors on the Bitcoin price. For this purpose, Bitcoin Price was taken as the dependent variable and Social Media Impact, Community Activity and Liquidity were taken as independent variables in the analysis. Social media influence was taken into account as the daily number of Bitcoin-related keywords on platforms such as Twitter and Reddit. Community Activity is taken into account as the daily number of new topics opened about Bitcoin on cryptocurrency forums such as Reddit and BitcoinTalk. Data will be collected and analyzed to cover a 3-year period from January 1, 2020 to December 31, 2022.

In the study, the stationarity of the series will be measured by the unit root test. Augmented Dickey-Fuller (ADF) method will be

applied as unit root test. VAR lag value was used for the optimal lag model, and serial correlation and Heteroskedasticity tests were performed to test whether there were autocorrelation and heteroscedasticity problems in the series. Additionally, Johansen cointegration test was applied to determine whether the series move together in the long run. In order to examine the reaction of other variables to a shock occurring in one of the variables, impulse response analyzes were carried out and the results were interpreted.

The hypotheses of the study are shown as follows:

H_0: Community activity (TA) does not affect Bitcoin price
H_A: Community activity (TA) affects the price of Bitcoin
H_0: Social media effect (SM) does not affect the price of Bitcoin
H_A: Social media effect (SM) affects the price of Bitcoin
H_0: Liquidity ratio (LO) does not affect the Bitcoin price
H_A: Liquidity ratio (LO) affects the price of Bitcoin
H_0: Number of bitcoins in circulation (PS) does not affect the price of Bitcoin
H_A: Number of bitcoins in circulation (PS) affects the Bitcoin price
H_0: Community activity (TA) is less influential than social media impact (SM) on changes in Bitcoin price
H_A: Community activity (TA) has a greater impact on Bitcoin price changes than social media influence (SM)
H_0: Bitcoin market number (PS) is less effective than liquidity ratio (LO) on changes in Bitcoin price
H_A: Bitcoin market number (PS) has a greater impact on changes in Bitcoin price than the liquidity ratio (LO).

Table 4: ADF unit root test

Null Hypothesis: Series has a unit root		
Exogenous: Constant, Linear trend		
Lag length: 0 (Automatic-based on SIC, maxlag=12)		
Statistic	**t-Statistic**	**Probability***
Augmented Dickey-Fuller test statistic: D (LNF)	−9.329038	0.0000
Augmented Dickey-Fuller test statistic: LNLO	−3.502721	0.0098
Augmented Dickey-Fuller test statistic: D (LNPS)	−7.672300	0.0000
Augmented Dickey-Fuller test statistic: LNSM	−2.978660	0.0403
Augmented Dickey-Fuller test statistic: LNTA	−3.716644	0.0051

Source: Author's own calculations

4. TEST RESULTS - FINDINGS

4.1. Unit Root

Before using data in econometric analysis, it should be determined whether the series is stationary or not. The Augmented Dickey–Fuller (ADF) unit root test was employed to determine whether the series were stationary at level or contained a unit root (Dickey & Fuller, 1979). The null hypothesis of this test is that the series is not stationary, and the probability values of the test are <0.05 for each series, indicating that the series is stationary at the specified level. Table 4 shows the results of the ADF unit root test.

ADF unit root results show that the data of LNLO, LNSM and LNTA variables are stationary at normal level. LNF and LNPS variables accept the null hypothesis at normal level and therefore the first difference of these variables was used to test and they were found to be stationary at this first difference.

4.2. VAR Model

VAR takes into account the lags of the variables of the model, so the optimal lag of the model must be determined. VAR delay criteria were used to determine the optimal delay, and the statistical values of these criteria are shown in Table 5. Among the criteria in Table 5, AIC, SC and HQ, the most appropriate criterion is the criterion with the smallest value at zero delay. The values of the results show that the AIC information criterion is the most appropriate criterion. The AIC criterion shows that the most appropriate lag of the VAR model is only the first lag.

The existence of the autocorrelation problem in the model residuals was investigated with the LM autocorrelation test. The null hypothesis of the LM test is that the model does not have an autocorrelation problem at the specified lag. Table 6 LM autocorrelation test results are shown. In the analysis performed for 1 lag in Table 6, it was seen that there was no autocorrelation problem in the residuals.

For the VAR model, the White Heteroscedasticity test was used to determine whether heteroscedasticity existed. The null hypothesis

Table 5: Determination of VAR optimal lag

VAR lag order selection criteria						
Endogenous variables: D (LNF) LNLO D (LNPS) LNSM LNTA						
Exogenous variables: C						
Included observations: 96						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	60.70962	NA	2.16e-07	−1.160617	−1.027057	−1.106630
1	193.3660	248.7307	2.29e-08*	−3.403458*	−2.602099*	−3.079536*
2	213.8190	36.21881	2.53e-08	−3.308728	−1.839571	−2.714871
3	226.6386	21.36612	3.29e-08	−3.054972	−0.918015	−2.191179
4	252.5195	40.43884*	3.30e-08	−3.073323	−0.268567	−1.939595
5	270.9761	26.91585	3.91e-08	−2.937001	0.535553	−1.533338
6	283.8737	17.46548	5.29e-08	−2.684868	1.455486	−1.011269
7	295.7948	14.90140	7.47e-08	−2.412391	2.395762	−0.468857
8	311.8732	18.42319	9.95e-08	−2.226525	3.249427	−0.013056

Source: Author's own calculations

Table 6: LM autocorrelation test

VAR residual serial correlation LM tests						
Null hypothesis: No serial correlation at lag h						
Lag	LRE*statistic	Degrees of freedom	Probability	Rao F-Statistic	Degrees of freedom	Probability
1	37.07362	25	0.0568	1.513829	(25, 328.4)	0.0571

Source: Author's own calculations

Table 7: Heteroskedasticity test

VAR residual heteroskedasticity tests (includes cross terms)		
Joint test		
Chi-square	Degrees of freedom	Probability
309.0878	300	0.3466

Source: Author's own calculations

Table 8: Trace cointegration test

Included observations: 102 after adjustments				
Trend assumption: Linear deterministic trend (restricted)				
Series: D (LNF) LNLO D (LNPS) LNSM LNTA				
Lags interval (in first differences): 1 to 1				
Hypothesized No. of CE (s)	Eigenvalue	Trace statistic	0.05 critical value	Probability**
None*	0.696962	194.8350	60.06141	0.0000
At most 1*	0.317037	73.05763	40.17493	0.0000
At most 2*	0.208496	34.16355	24.27596	0.0021
At most 3	0.096150	10.31391	12.32090	0.1060
At most 4	2.49E-05	0.002538	4.129906	0.9655

Source: Author's own calculations

Table 9: Cointegration equation

Normalized cointegrating coefficients (standard error in parentheses)				
D (LNF)	LNLO	LNSM	LNTA	D (LNPS)
t-value	0.877730	1.065217	0.227906	33.56322

Source: Author's own calculations

of this test is that the model has no heteroskedasticity. Table 7 shows the results of the Heteroskedasticity test. According to the given test results, the null hypothesis of the test was accepted and it was seen that there was no heteroscedasticity problem in the model.

The characteristic roots of the estimated VAR model are shown in Figure 1. All characteristic roots of the system remain within the unit circle, which provides the stability condition for the VAR model. This confirms that the series are stationary and an appropriate mathematical form is used in this study.

The Johansen Co-integration approach uses maximum likelihood estimation to estimate the number of cointegration relationships and the parameters of these relationships. It consists of VAR estimates that include the differences and levels of non-stationary series. Table 8 shows the cointegration test presentations of Johansen (1991).

According to the Trace test statistics in Table 8, it is seen that there are three long-term relationships between the variables examined. The null hypothesis of this test is the absence of a

Figure 1: AR roots

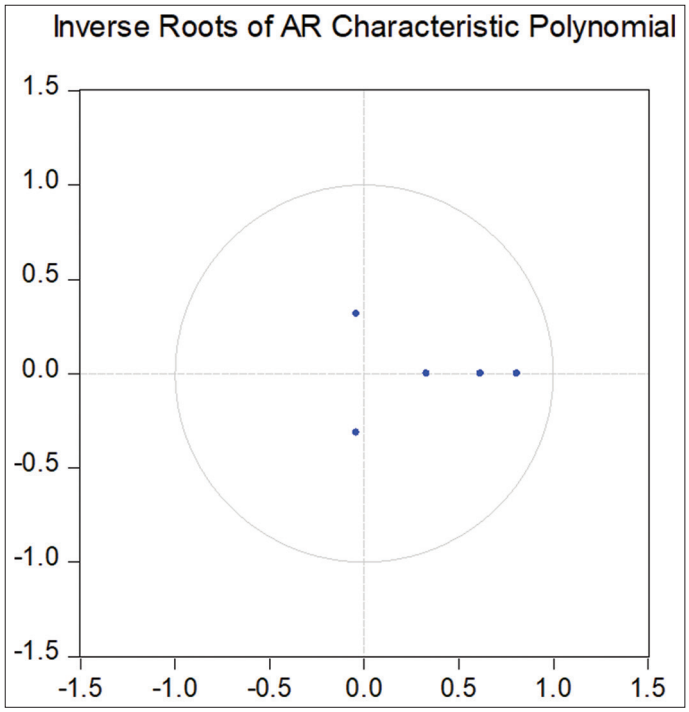
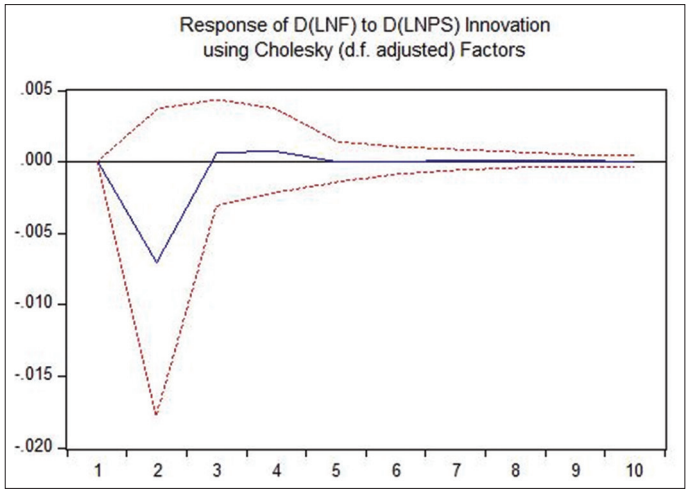


Figure 2: Response of LNF



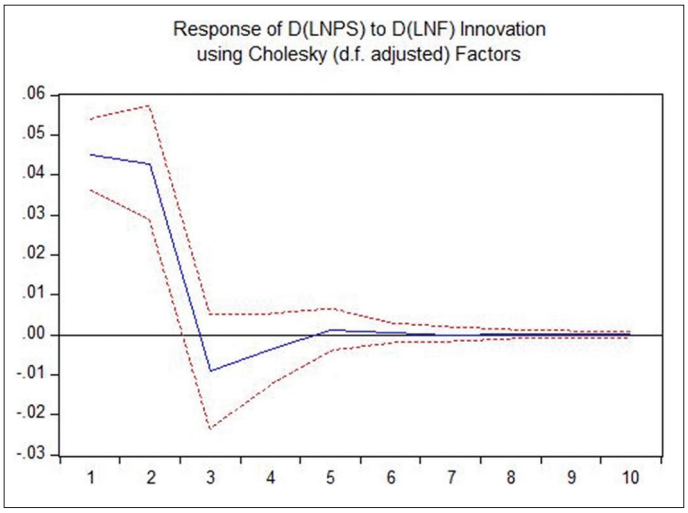
long-term relationship, and as shown in the table, there are at most 2 probability values to be rejected, and there are at most 3 cointegration equations in the model.

The t values of the Bitcoin price (LNF) equation, which is the purpose of the study among the determined cointegration equations, are shown in Table 9. If T values are >2, it shows that it affects the LNF variable in the long term. It shows that only the LNPS variable affects the LNF value with a value >2.

Table 10: Hypothesis results summary

Hypothesis code	Hypothesis statement	Test type	P-value	Decision	Interpretationw
H_1	Community activity (TA) does not affect Bitcoin price	Cointegration and VAR	0.1567	Not rejected	Community activity is statistically insignificant in influencing Bitcoin price.
H_2	Social media impact (SM) does not affect Bitcoin price	Impulse response	0.0403	Rejected	Social media impact has a statistically significant and immediate effect on price.
H_3	Liquidity ratio (LO) does not affect Bitcoin price	Cointegration and VAR	0.0098	Rejected	Liquidity ratio significantly contributes to explaining price fluctuations.
H_4	Number of bitcoins in circulation (PS) does not affect Bitcoin price	Cointegration and VAR	0.0000	Rejected	Market circulation is a strong long-term determinant of Bitcoin price.
H_5	TA is less influential than SM in determining Bitcoin price	Relative influence analysis	<0.05	Rejected	Social media exerts a greater impact on price than community activity.
H_6	PS is less effective than LO in explaining Bitcoin price	Relative influence analysis	<0.05	Rejected	Market participation has a stronger explanatory power than liquidity.

Figure 3: Response of LNPS



4.3. Impulse Response Analysis

Impulse-response analysis is used to examine the response of other variables to a shock in one of the variables in the system. Figures 2 and 3 were made taking into account the results of the model's cointegration and causality tests.

As shown in Figure 2, a positive effect from the LNPS variable will negatively affect the LNF variable from the first period to the second period. After the second period, the LNF variable will increase, and in the fourth period, LNPS will have a positive effect on the LNF variable, and after the fifth period, it will return to balance.

As shown in Figure 3, a positive effect of the LNF variable strongly and positively influenced the LNPS variable. This effect is strong in the first period, and a weakening of the effect was detected after the second period. After this effect was weak and negative in the third period, it returned to balance in the fourth period.

The Table 10 presents the hypotheses tested, associated test methods, P-values, decisions regarding the null hypotheses, and analytical interpretations.

5. DISCUSSION

In this study, the dynamic interactions between Bitcoin price and selected explanatory variables—including community activity, social media impact, liquidity ratio, and the number of Bitcoins in circulation—have been investigated using advanced time series techniques such as VAR modeling and impulse response functions. The results revealed nuanced patterns of influence across variables.

Firstly, it was identified that social media activity exerts a statistically significant and immediate effect on Bitcoin prices. This finding aligns with the growing body of literature emphasizing the importance of digital sentiment in speculative markets. Particularly, the role of platforms like Twitter and Reddit in shaping investor expectations has been highlighted as a dominant factor in cryptocurrency valuation (Georgoula et al., 2015; Wang et al., 2021). Therefore, it can be inferred that the informational efficiency of Bitcoin markets is increasingly influenced by real-time digital sentiment rather than solely economic fundamentals.

Secondly, the number of Bitcoins in circulation (PS) was found to be another strong determinant of price dynamics, consistent with supply-demand mechanics. This supports prior studies (Ciaian et al., 2016; Bouoiyour et al., 2016) indicating that circulating supply, often a reflection of trading activity and adoption level, is critical in shaping long-term valuation trends.

The liquidity ratio (LO), representing market depth and transaction volume, also emerged as a significant variable affecting price. Higher liquidity typically implies reduced volatility, offering stability. This corroborates findings from Balcilar et al. (2017), who emphasized the predictive power of trading volume in volatile cryptocurrency environments.

Conversely, community activity (TA), often measured by GitHub commits or technical updates, was not found to have a significant immediate influence on Bitcoin price. This suggests that while technological evolution is vital for long-term credibility, it may not significantly impact short-term price movements, diverging from assumptions held in earlier works (Brown and Chen, 2018).

These outcomes indicate a divergence between informational and technical fundamentals in cryptocurrency markets. Price formation appears to be increasingly shaped by speculative sentiment and behavioral factors rather than intrinsic value indicators. This distinction has crucial implications for policymakers and investors seeking to mitigate systemic risks in rapidly evolving digital asset ecosystems.

6. CONCLUSION

Cryptocurrencies represent a major revolution in today's digital economy. Pushing the boundaries of traditional financial systems, these digital assets are equipped with decentralized structures and strong encryption that make financial transactions more secure and accessible. While cryptocurrencies symbolize financial independence and freedom for many people, they also have great potential to shape the financial systems of the future.

The importance of cryptocurrencies is emphasized by the fact that they offer an alternative to traditional banking systems. These digital assets can be transferred and stored directly from person to person without intermediaries or central authorities. This allows financial transactions to be carried out at lower costs and faster. Additionally, cryptocurrencies offer new opportunities for millions of people with limited access to financial services.

This study aims to examine the price dynamics of Bitcoin and the factors affecting these prices. The main focus of the study investigates the role of various independent variables such as community activity (TA), social media influence (SM), liquidity ratio (LO), and Number of Bitcoins in Circulation (Bitcoin Market number - PS). Additionally, the study used time series analysis methods to examine the impact of these factors on the Bitcoin price.

The important results of the study can be outlined as follows:

Bitcoin Market Number and Social Media Effect: According to the study results, Bitcoin market number and social media effect stand out among the most important factors affecting the Bitcoin price. The Bitcoin market number represents the amount of Bitcoin in circulation and has a significant impact on the price. Additionally, social media influence can cause significant fluctuations in Bitcoin price.

Liquidity Ratio: Liquidity ratio also plays a critical role on changes in Bitcoin price. This rate expresses Bitcoin's liquidity and transaction volume in the market. It is observed that as the liquidity ratio increases, fluctuations in Bitcoin price become more limited.

Community Activity: The study shows that community activity has less impact on changes in Bitcoin price compared to other variables. This highlights that the impact of the Bitcoin community's activities on the price is more limited than other factors.

These results provide an important source of information for investors, analysts and regulators who want to understand and predict Bitcoin price movements. A better understanding of the factors affecting the Bitcoin price can help make more robust predictions about the future of the cryptocurrency market.

In terms of future directions, this study serves as a foundational stepping stone for further cryptocurrency research. Future investigations can delve into additional factors shaping Bitcoin's price, including regulatory shifts, macroeconomic indicators, and technological advancements. As the cryptocurrency landscape evolves at a rapid pace, continuous monitoring and analysis of the intricate interplay between these factors and Bitcoin's valuation become imperative. Moreover, the methodology employed in this study can serve as a blueprint for the analysis of other cryptocurrencies, contributing to a more comprehensive grasp of the entire digital asset market. Ultimately, the insights derived from this research can empower investors, analysts, and policymakers to make more informed decisions and forecasts within the ever-dynamic realm of cryptocurrencies.

To accomplish these research objectives, it is essential to embrace a multifaceted approach in the future. Exploring alternative analysis methods, such as machine learning algorithms and advanced data analytics, can provide deeper insights into the dynamics governing cryptocurrency price movements. Expanding the scope of data sources and sample sizes, beyond those examined in this study, will enhance the robustness of forthcoming analyses. Additionally, prolonging the analysis period to encompass extended timeframes, which can unveil long-term trends and potential cyclical patterns in cryptocurrency prices, warrants consideration. Furthermore, vigilance toward evolving legal and regulatory developments in the cryptocurrency domain is paramount, as these factors exert significant influence on market behavior. Adapting to regulatory changes and comprehending their implications for cryptocurrency markets will be instrumental in navigating the broader landscape. In sum, future research endeavors should adopt a holistic approach that encompasses diverse analysis methodologies, extensive data sources, longer timeframes, and vigilant monitoring of legal dynamics to advance our comprehension of cryptocurrency market dynamics.

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