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INVESTIGATION OF THE EFFECT OF BITCOIN BLOCKCHAIN HASHRATE ON BITCOIN PRICE

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Abstract. As the influence of cryptocurrencies continues to expand globally, understanding the dynamics affecting Bitcoin price becomes increasingly crucial. This study aimed to explore whether the Bitcoin blockchain hashrate – the network's computational power – influences Bitcoin's price. A detailed literature review evaluated and contrasted various scholarly perspectives on the topic. The study employed a Vector Auto-Regression (VAR) model, utilizing secondary data from data.nasdaq.com spanning 2017 to 2023 (May). Contrary to some assumptions, results indicated that the Bitcoin network hashrate does not directly influence Bitcoin's price. Moreover, the study found insufficient statistical evidence to suggest that Bitcoin's price significantly affects the network hashrate. These insights offer valuable implications for investors, cryptocurrency miners, financial institutions, and policymakers as they navigate the implications of cryptocurrencies on the global economy. Furthermore, this study contributes to the broader discussion on blockchain networks and cryptocurrency price valuation, enriching the understanding of Bitcoin price determinants.

Keywords: blockchain, smart contracts, Bitcoin, vector auto-regression (VAR), hashrate, Bitcoin price, cryptocurrency.

Introduction

Cryptography provides scalable digital transactions, facilitating peer-to-peer transfers by eliminating the need for mediators, such as financial institutions, brokers, and payment institutions (Vladimirskaya et al., 2020). As financial technologies evolve, they offer market participants opportunities to provide services at lower cost, faster, and more secure; in particular, the emergence of cryptocurrencies has revolutionized the traditional financial system (Hasyim et al., 2020). The interest of the public and financial institutions has recently been drawn toward cryptocurrencies as an alternative store of value that can also generate passive income through consensus staking (Mohamed, 2021). Moreover, it is important to understand the factors that influence the price of Bitcoin; considering the current valuation and its dominant power of more than 40% market capitalization, the movement in Bitcoin price also affects the prices of other cryptocurrencies at large; for many years, researchers have assessed the relationship between the Bitcoin price and its blockchain network hashrate. However, these studies have yet to provide consistent results. Therefore, the authors of this article find it interesting to understand the present relationship between the price of Bitcoin and its network hashrate; more importantly, the causality direction of Bitcoin price and network hashrate is of great interest.

The research problem. Even though several articles have been published on the determinants of Bitcoin price, there are no sufficient scientific articles on how to assess the effect of Bitcoin network hashrate on the price of Bitcoin.

Main purpose. To investigate the causality effect of Bitcoin blockchain hashrate on the price of Bitcoin.

Hypotheses.

- H0: HASHRATE does not Granger-cause BTC_PRICE.
- H0: BTC_PRICE does not Granger-cause HASHRATE.

The following tasks will be undertaken in the research:

1. Evaluating and contrasting various scholarly perspectives on the causal relationship between Bitcoin network hashrate and the price of Bitcoin to have a foundation of existing knowledge on the topic.

2. Obtain hashrate and Bitcoin price data from a secondary source. This data will be used for analysis.
3. Conduct auto-correlation, VAR estimate, Granger causality, and impulse-response test using R-programming language to analyze the relationship between hashrate and Bitcoin price.
4. Present the research findings in a clear and accessible format, including tables, figures and an explanation of the results.
5. Conduct model diagnosis tests.
6. Draw conclusions based on the literature review and findings, note any limitations, and provide recommendations for future research.

The paper is organized as follows:

1. Section one presents the Literature review.
2. Section two presents the research methodology.
3. Section three presents the research findings.
4. Section four presents Model diagnosis tests.

1. Literature review

1.1. Overview of Bitcoin as a means of payment

Bitcoin is regarded as the most innovative digital currency, created in 2008 by Satoshi Nakamoto. In his first paper in 2008, he called Bitcoin a "peer-to-peer digital cash" with a high level of decentralization, transparent and anonymous (Pan et al., 2021); because of the anonymous feature in the transaction, it is difficult to know the inventors who might be manipulating the market and those that directly bear the risk of high volatility in the price of Bitcoin (European Systemic Risk Board [ESRB], 2023). A genesis block of 50 BTC was mined in 2009, and 10,000 BTC was used to purchase pizza worth $25 by a Florida programmer; the transaction was referred to as the first real-world Bitcoin transaction (Chu et al., 2017). The cryptocurrency market attracted unprecedented interest from investors in 2016. Leading to the price of Bitcoin, the world's largest digital currency, rising (Longo et al., 2020). 1.500% since the beginning of 2017, and the popularity of Bitcoin as an alternative store of value has increased over the decade (Baur & Dimpfl, 2021). However, despite the progressive adoption of Bitcoin as a store of value, it remains a highly volatile and speculative digital asset with no intrinsic value (Mujani et al., 2022); in addition, it is necessary to understand that Bitcoin price follows two market cycles. A bull market cycle is a period of a rising trend in the price of Bitcoin and other cryptocurrencies. It usually occurs after Bitcoin "halving," which occurs every four years while the bear market cycle is a downward trend; during the bear market, the value can go down as much as 80% from an all-time high. Bitcoin transaction records are stored in a public ledger named "blockchain" to protect the network from external attacks and to ensure that anyone can view the details of each transaction (Chen, 2023).

1.2. Application of Blockchain and Smart Contracts

Blockchain technology was of interest for adoption when the fundamental cryptocurrency, Bitcoin, was created in 2008 (Nakamoto, 2008). It was the first time blockchain was implemented to solve the double payment problem regarding digital currency (Bose & Rahman, 2020). Furthermore, due to the transparency in the execution and recording of transactions, it provides a "trustworthy ledger" that cannot be guaranteed by centralized institutions or computers (Sharma et al., 2021). "Blockchain technology is a game changer" when it comes to managing data (Anguiano & Parte, 2023), and as noted by (Taherdoost et al., 2022), blockchain development has created technological breakthroughs. The implementation applies to every sector, and as the world is becoming more digital, businesses are researching the potential of integrating blockchain technology into their system to improve efficiency (Shetty et al., 2022). The blockchain system allows anybody to participate without central authority controlling or determining who can access it (Waheed et al., 2019). The participating clients use the consensus protocol to preserve and protect the data records (Hans et al., 2017). Thereby making it possible to predefine terms of the agreement among various users, i.e., a set of rules was predefined and executed automatically when certain conditions were met (Luu et al., 2016). Blockchain provides an avenue for peer-to-peer distribution of networks where no safekeeping intermediary, such as a bank, acts as a middleman for members to interact (Dehrouyeh & Azmi, 2018); it enables the sharing of resources and solutions, which leads to establishing a marketplace where services can be rendered between different devices (Jing & Li, 2022). For any cryptocurrency to exist, its programable code must be deployed on blockchain technology, either directly or using a smart contract (Pan et al., 2021). Therefore, blockchain is the fundamental requirement for all cryptocurrencies (Kara et al., 2021). A smart contract is regarded as computer programming code embedded with the terms and conditions of an agreement between parties (Talukder et al., 2022); the code is compiled as an executable system code that can be deployed on a blockchain network (Grønbæk, 2016). The word "smart contract" was first mentioned by Nick Szabo in 1993 to explain the goal of creating an innovative internet contract that serves as an agreement between businesses that can be stored and executed digitally on a computer network (Grønbæk, 2016).

A smart contract can be seen as a systematic transaction protocol that automatically executes the terms and conditions of an agreement (Wu et al., 2023); when certain conditions that are coded on the contract are met, the system by itself carries out an operation that was specified, smart contracts are usually deployed on the blockchain, and its ensure that the contract terms are enforced (Zheng et al., 2020). Moreover, it facilitates trusted transactions among unknown parties (Vacca et al., 2021). One of the struggles of smart contracts is ensuring sustainability and mitigating the activities of malicious users who want to take advantage of the computer-based system (Jumaa & Shakir, 2022). In conclusion, non-centralized smart contracts allow participants who do not know each other to safely carry out transactions between themselves by eliminating any trusted intermediaries through which a significant cost will be incurred (Kabiri & Sharifzadeh, 2022).

1.3. Bitcoin network hashrate

Bitcoin hashrate "is the number of computations done by the Bitcoin miners." For a decade, authors such as (Cointelegraph, 2020) have tried to validate the relationship between the price of Bitcoin and the network hashrate. Financial articles from (Hayes, 2019; Aoyagi & Hattori, 2019) have theoretically shown that the hashrate can determine the price of Bitcoin. The price of Bitcoin is very important in determining the number of Bitcoin mints because of the predetermined block reward given to miners who successfully create a new block. Moreover, an increase in the price of Bitcoin will encourage new mining participants due to high rewards (Bouri et al., 2018). Likewise, the decentralization of the Bitcoin network protocol encourages new miners to join the network to increase the robustness and aggravate the network's security system. However, the decentralization of the network has led to the constant demand for more advanced mining devices such as application-specific integrated circuits (ASIC) because as fresh miners are added to the network, then the competition in solving the network block also increases, an increase in hashrate increases the cost of mining for the miners. Authors such as (Fantazzini & Kolodin, 2020; Kjærland et al., 2018) indicates that the price of Bitcoin could be more accurate in measuring the changes in network hashrate. However, the study of (Kubal & Kristoufek, 2022) shows there is no statistical significance in using the price of Bitcoin to measure the changes in hashrate while finding a statistical significance of hashrate to determine Bitcoin price. Bitcoin mining cost can be categorized into two components: electricity cost and depreciation of capital expenditure. Electricity cost involves the amount miners must pay to run a mining machine in a factory or home, accounting for 54% of the total cost. In contrast, 34% can be associated with the depreciation of capital expenditure (Bendiksen et al., 2018). According to the study carried out by (Kjærland et al., 2018), network hashrate is not statistically significant in determining the price of Bitcoin; explained further that only in 2017, when the Bitcoin network experienced substantial hashrate growth, can it be used to determine the price of Bitcoin. There is a discrepancy among previous studies about the effect of hashrate on the price of Bitcoin; authors such as noted by (Kjærland et al., 2018) in their literature that there is no strong connection between the price of Bitcoin and hashrate. According to (bitcoinmagazine, 2023), the recent surge of network hashrate in reaching a new all-time high could result from the recent rise in the price of Bitcoin. Conclusively, network hashrate is very important to the security and protection of the blockchain because the higher the network hashrate, the more difficulty faced by potential hackers or attackers, and this can lead to trust and further adoption, making it an essential factor that needs to be analyzed when investigating the price movement of Bitcoin.

2. Methodology

2.1. Research design and literature review

The quantitative research method is used for this research because it is best suitable to provide a clear understanding of the research problem by utilizing the statistical capability of the quantitative method to identify a causal relationship between blockchain hashrate and the price of Bitcoin. The following steps are undertaken during this research. The research starts with an extensive literature review using logical and comparative analysis of existing scientific articles related to Bitcoin blockchain hashrate and price of Bitcoin to understand the author's perspective better.

2.2. Data collection and processing

Secondary data was obtained from data.nasdaq.com spanning 2017–2023 (May); the data is for quantitative statistical modeling and analysis. Obtained data were converted to monthly time series format; there were no missing values and outliers.

2.3. Model identification

The versatility and difficulties of identifying a direct interaction between economic variables have led to the adoption of a simultaneous system of equations

(Wang, 2022). Moreover, it is very difficult to determine an independent and dependent variable when establishing a relationship between two economic variables, which is why it is necessary to implement an equation system where the variables are not forcefully chosen to be independent or dependent variables, such as the vector auto-regression (VAR) model (Abed & Shamil, 2022). The VAR model is generally used for time series analysis because it establishes a vital relationship between variables without restriction (Tuaneh & Wiri, 2019).

2.4. Model assumptions and implementation

Vector-auto regressive (VAR) model assumptions were carefully tested to guarantee the validity of the data and model persistence by conducting stationary tests using the Augmented Dickey-Fuller test, autocorrelation test using auto-correlation function (ACF), and partial auto-correlation function (PCAF). The following tests were conducted along with VAR estimation: the Optimal lags test to recognize the optimal lags for the model, the Granger causality test to identify the direction of causality of the relationship, and impulse-response analysis to reflect the shock between variables.

2.5. Hypothesis testing and results presentation

The chosen significant level is 0.05 or 5%. Therefore, the P-value, which is the probability obtained from the data, is regarded to be statistically significant; if it is less than 0.05 or 5% null hypothesis is rejected; however, if greater than 0.05 or 5%, then the authors will fail to reject the null hypothesis. Results of the research statistical tests were presented with a brief introduction, explanations, and implications of each test.

2.6. Model diagnoses, conclusion, limitations, and recommendations

The model's validity was examined by conducting the following tests: serial correlation, heteroskedasticity, normal distribution of the residuals, and stability test. Conclusions were drawn based on the literature review and findings, noting limitations and providing recommendations for future research.

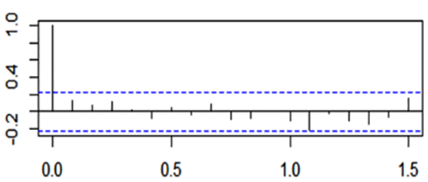

Figure 1a. Auto-correlation function (ACF) for Bitcoin

3. Research results and discussion

3.1. Stationary testing

Stationary testing is very important on time series data to determine if the mean, variance and co-variance do not vary over time because it can lead to inconsistencies in the result of the analysis; stationary of the Bitcoin price and Hashrate data was assessed using the Augmented dickey-fuller test. The stationary test carried out on the original time series data was not statistically significant because the data is a cyclical time series that follows a pattern; therefore, to fulfill the assumption of the VAR model, the data were transformed to stationary using the differentiation and log transformation method. After performing the stationary, the results are shown in Tables 1a and 1b, respectively.

Table 1a. Augmented Dickey-Fuller Test for Bitcoin Price

Dickey-Fuller	Lag order	p-value
–3.8155	4	0.0227

Table 1b. Augmented Dickey-Fuller Test for Hashrate

Dickey-Fuller	Lag order	p-value
–3.6846	4	0.03193

The Dickey-Filler results of –3.8155 and –3.6846, as shown in Table 1a and 1b, respectively, indicate the evidence supporting the rejection of the null hypothesis. The more negative dickey-fuller results, the stronger the evidence to reject the null hypothesis. While the p-values of 0.0227 and 0.03193 show how significant the test therefore, since the p-values are less than 0.05 (significant level), the null hypothesis is rejected, meaning the data is stationary.

3.2. Auto-correlation function (ACF) and Partial auto-correlation function (PACF) testing

The next assumption of the VAR model that must be performed is the Auto-correlation function (ACF) and Partial Auto-correlation function (PACF) to ensure that the time series data is not auto-correlated. In ACF and PACF, the null hypothesis assumes no auto-correlation.

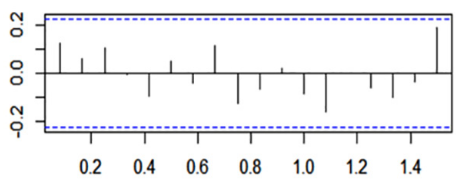

Figure 1b. Partial auto-correlation function (PACF) for Bitcoin

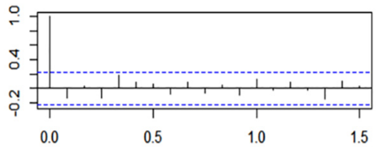

Figure 2a. Auto-correlation function (ACF) for Hashrate

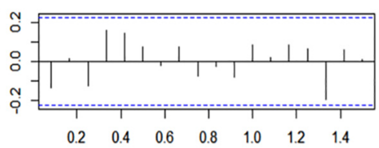

Figure 2b. Partial auto-correlation function (PACF) for Hashrate

The blue lines below and above 0.0 in Figures 1a, 1b and 2a, and 2b mean "Significant bands" when there are many lag indicators above the blue lines or beyond the blue lines on the negative side, it indicates that the null hypothesis is false (there is an autocorrelation). It should be rejected; however, as shown in Figure 1a and 2a, there are only two spikes in the first lags, while Figures 1b and 2b lags are within the "Significant Bands", which means there is no autocorrelation within the time series data and its lagged values, therefore, the assumption of no auto-correlation is met.

3.3. Vector auto-regression (VAR) Estimate

VAR is a widely accepted way of assessing the relationship between two time series variables, even though the estimate does not directly identify the direction of the causality relationship.

Table 2a. Estimation of the relationship between Bitcoin network hashrate and its price

	Coefficient	Std. Error	p-value
BTCPRICE	–0.04739	0.08656	0.585722
HASHRATE	–0.11787	0.12002	0.329354

Table 2b. Estimation of the relationship between Bitcoin network hashrate and its price

	Value
Residual Std. Error	0.1717 (df = 72)
Adjusted R-squared	–0.005347
F-statistic	0.8032 (df = 2 and 72, p-value: 0.4519)

The *coefficients* of BTCPRICE and HASHRATE shown in Table 2a indicate how a one-unit increase in the respective lagged independent variable affects the value of the other as the dependent variable, given that all other factors are constant. A one-unit increase in hashrate resulted in –0.04739 in BTC price. Also, a unit increase in BTC price resulted in –0.11787 in hashrate. However, this theory does not hold since the p-value of 0.585722 corresponding to the relationship between BTCPRICE and HASHRATE, and 0.329354 corresponding to the relationship between HASHRATE and BTCPRICE are not statistically significant at a significant level of 0.05. The *standard error (std. Error)* of BTCPRICE 0.08656 and HASHRATE 0.12002 represents how accurately the data is used to analyze the fact; the smaller the error, as it is in this case, the better the data fit. The *residual std. Error* represents the difference between the predicted and actual values in the error term; a small residual standard error of 0.1717 indicates a better fit to the data. *F-statistics* measure the overall fit of the model; bigger numbers indicate a better fit of the model. *Adjusted R-squares* measure how the independent variable could explain the variation in the dependent variable. Therefore, adjusted r-squares of –0.005347 indicates a very small change in Bitcoin price is due to the influence of hashrate and vice versa. In conclusion, the BTCPRICE p-value of 0.585722 and HASHRATE p-value of 0.329354 indicates the non-linear relationship between Bitcoin price and hashrate, meaning one does not influence another. The adjusted r-squared –0.005347 in Table 2b shows the changes in the price of Bitcoin that can be attributed to the changes in network hashrate; however, since the p-value 0.4519 is not statistically significant, it can be concluded that there is minimum or no influence from the network hashrate in determine the price of Bitcoin.

3.4. Granger causality test

The Granger causality test is a component of the vector auto-regression model that shows the direction of the causality effect between two variables.

Table 3a. HASHRATE Granger causality on BITCOIN

F-Test	df1	df2	p-value
0.87285	7	108	0.5305

The p-value of 0.5305 shown in Table 3a is greater than 0.05. Therefore, the authors fail to reject the null hypothesis because the p-value is not statistically significant. Thus, changes in the Bitcoin blockchain hashrate do not influence the price of Bitcoin either positively or negatively.

Table 3b. BITCOIN PRICE Granger causality on HASHRATE

F-Test	df1	df2	p-value
1.0185	7	108	0.4224

The p-value of 0.4224 shown in Table 3b is greater than 0.05. Hence, the Null hypothesis is not rejected because the p-value is not statistically significant for the rejection of the null hypothesis at a 5% significance level; it can be concluded that there is not enough statistical evidence to believe that changes in the price of Bitcoin influence the Bitcoin blockchain hashrate.

3.5. Impulse-response function analysis

The impulse-response analysis is an important step when conducting econometric analysis, and it helps to understand how a variable responds to the shock from another variable over time. An impulse-response function is conducted after vector auto-regression model estimation.

Table 4 shows the response of each variable when there is a shock from the other; it can be seen from the table that when there is one unit increase in BTCPRICE, there is a response of –0.00469 on HASHRATE in the first period and the effect continue to decrease in some continuous some period of 8. In contrast, the response of BTCPRICE when there is a shock from HASHRATE amounted to 0.00000 in the first period, which means BTCPRICE does not respond immediately to any changes in HASHRATE but that change from the second period. Figure 3a and 3b illustrate graphically how BTCPRICE and HASHRATE respond to shock. However, there is a small effect of HASHRATE on BTCPRICE and vice versa, which is not statistically significant. Therefore, the effect could be just random.

4. Model diagnoses testing

4.1. Serial correlation

The serial correlation was tested using the Portmanteau Test (asymptotic), and the p-value is 0.6235, which means there is no serial correlation. It is a good result because serial correlation in VAR does not make the results reliable.

4.2. Heteroskedasticity testing

Heteroskedasticity was tested using the ARCH (Multivariate) test. The p-value is 0.7155, meaning the model does not suffer from Heteroskedasticity, and it is efficient because the presence of Heteroskedasticity makes the model inefficient.

4.3. Normal distribution of the residuals Test

One of the "rules of thumb" for quantitative analysis is for the data to be normally distributed; even though it is not mandatory in all cases, it provides some confidence in the analysis. Three normality tests were conducted, and the results show the following:

– *JB-Test (Multivariate):* The p-value is 0.1634 above 0.05, meaning the residuals do not deviate from the normal distribution.
– *Skewness:* The p-value is 0.2401, which is above 0.05, meaning the skewness of the residuals does not change significantly from what will be observed if they are normally distributed.
– *Kurtosis:* The p-value is 0.1597, above 0.05, meaning the kurtosis of the residuals does not deviate from a normal distribution.

4.4. Model stability test

The model stability test was conducted using eigenvalues, and the results are less than 1, which is a rule of thumb. Therefore, the model is stable.

Conclusions, limitations, and recommendations

This study investigates the association between Bitcoin's price and network hashrate. Contrary to some assumptions, the study results indicate that Bitcoin hashrate does not directly affect its price. Moreover, we found no significant statistical evidence that the price of Bitcoin affects the network hashrate. These insights challenge the assumption that there is a linear relationship

Table 4. Impulse-response analysis

Period	1	2	3	4	5	6	7	8
HASHRATE	–0.00469	–0.05096	–0.04354	–0.03543	–0.06673	–0.07238	–0.03638	–0.02182
BTC-PRICE	0.00000	0.03383	0.05521	–0.01605	–0.01050	0.04839	0.00273	–0.00018

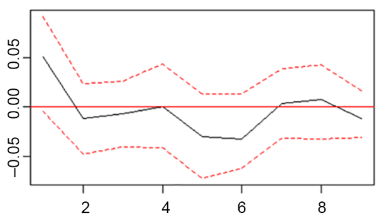

Figure 3a. HASHRATE response from BTC-PRICE shock

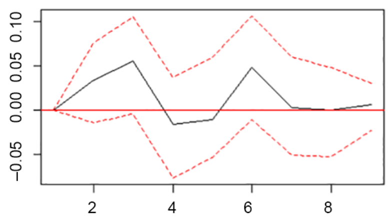

Figure 3b. BTC-PRICE response from HASHRATE shock

between Bitcoin's price and its network hashrate. The implications derived from these findings are substantial for investors, miners, crypto enthusiasts, and policymakers. For example, investors and miners may need to consider factors other than hashrate when predicting Bitcoin price fluctuations. Policymakers and financial Institutions must also reconsider their viewpoints regarding the dynamics influencing Bitcoin pricing as they develop new regulatory schemes and strategies for cryptocurrencies. The continuously evolving dynamics of the cryptocurrency industry play a significant role in our findings because, in a rapidly evolving field such as cryptocurrency, continuous research is necessary to keep up with changes and developments. Future research could investigate other factors influencing the price of Bitcoin, such as market sentiment, regulatory changes, or economic indicators. Additionally, similar studies could be conducted on other cryptocurrencies to determine if these findings are unique to Bitcoin or apply more broadly across the cryptocurrency market. The study's limitation is that the field is still very new, therefore. There are no sufficient latest articles on the relationship between network hashrate and Bitcoin price.

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BITKOINŲ BLOKŲ GRANDINĖS TINKLO GALIOS POVEIKIO BITKOINŲ KAINAI TYRIMAS

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Santrauka. Kriptovaliutų reikšmė pasauliniu mastu vis didėja, todėl ypač svarbu suprasti, kas daro poveikį bitkoinų kainai. Tyrimu siekiama įvertinti, ar bitkoinų blokų grandinės tinklo galia daro poveikį šios kriptovaliutos kainai. Atlikus išsamią literatūros apžvalgą buvo įvertinti ir palyginti įvairūs moksliniai požiūriai šia tema. Tyrime buvo taikomas vektorinės autoregresijos (VAR) modelis, naudojant antrinius 2017–2023 m. (gegužės mėn.) duomenis iš data.nasdaq.com svetainės. Priešingai kai kuriems tyrimams, gauti rezultatai parodė, kad bitkoinų blokų grandinės tinklo galia nedaro tiesioginio poveikio bitkoinų kainai. Tyrimas parodė, kad nepakanka statistinių įrodymų, leidžiančių manyti, kad bitkoinų kaina daro didelę įtaką tinklo galiai. Šios įžvalgos suteikia vertingos informacijos investuotojams, kriptovaliutų kasėjams, finansų įstaigoms ir politikos formuotojams, kai jie tyrinėja kriptovaliutų poveikį pasaulio ekonomikai. Be to, šis tyrimas skatina tolesnę diskusiją apie blokų grandinės tinklus ir kriptovaliutų kainų vertinimą, didindamas supratimą apie bitkoino kainą lemiančius veiksnius.

Reikšminiai žodžiai: blokų grandinė, išmanieji sandoriai, bitkoinas, vektorinė autoregresija (VAR), tinklo galia, bitkoino kaina, kriptovaliuta.