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Analysis of the Impact of Bitcoin Mining Ecosystem Growth on Global Electricity Consumption 2018-2022

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ABSTRACT

Advances in technology have greatly improved efficiency in various aspects such as work, production, and communication. Among the fastest-growing innovations is cryptocurrency, which relies on cryptographic techniques to validate transactions and employs consensus mechanisms to manage records without the need for third-party involvement. This [A1] [A2] study examines the relationship between the Bitcoin mining ecosystem and global primary electricity consumption using variables such as hashrate, Bitcoin market value, mining difficulty, adjusted transaction value, and the number of Bitcoin transactions. A quantitative method is employed, utilizing Vector Error Correction Model (VECM) analysis with E-Views 12. Granger causality analysis reveals a relationship between the number of Bitcoin transactions and hashrate, as well as between Bitcoin market value and Bitcoin transactions. Long-term findings show that Bitcoin hashrate and market value significantly increase global primary electricity consumption, while mining difficulty, adjusted transaction value, and transaction number do not. However, in the short term, mining difficulty positively impacts energy consumption, while the number of transactions does not have a significant effect.

INTRODUCTION

Technological advancements have significantly enhanced efficiency in work, production, and communication. One of the rapidly developing technologies is cryptocurrency, which utilizes cryptography to verify transactions and consensus mechanisms to maintain ledgers without third-party intermediaries (Miśkiewicz et al., 2022; Morey et al., 2024; Schinckus et al., 2020; Truby, 2018; Wisanggeni, 2021). Cryptocurrency has become the focus of analysis across various disciplines such as economics, sociology, engineering, and political science. Since its introduction by Satoshi Nakamoto in 2009, over 2,500 cryptocurrencies have been traded, creating a new ecosystem known as blockchain technology. Cryptocurrency transactions are conducted and verified digitally within a decentralized system, making them immutable and irreversible (Bisht et al., 2022; Zheng et al., 2023).

Cryptocurrency has evolved rapidly and is now used across various economic and financial sectors, offering a novel alternative to traditional systems. Mastercard's support for cryptocurrency payments in 2021 enabled users to use cryptocurrency as a global payment tool. Major companies such as Tesla, Square, and PayPal have shown significant interest in cryptocurrency (Fadhilah, 2023). Tesla invested in Bitcoin and plans to accept it as payment, while Square and PayPal introduced services for buying, selling, and trading Bitcoin, accelerating cryptocurrency adoption among consumers (Appiah-Otoo, 2023; Harm et al., 2016; Julianto, 2023; William, 2023).

The growth of cryptocurrency is marked by an increase in the number of crypto miners who validate transactions and secure the blockchain network. The global cryptocurrency mining market is projected to reach USD 7 billion by 2032 from USD 1.92 billion in 2022, with an annual growth rate of 12.90%. The Bitcoin mining ecosystem, which involves miners, users, exchanges, financial service providers, and blockchain technology companies, continues to expand. Riot Platforms, a large Bitcoin mining company in North America, increased its production by 19% and its revenue by 20% in 2022.

The cryptocurrency industry has grown significantly due to distributed ledger technology and increased venture capital investment. Digital currencies are widely used for efficient, secure, and transparent transactions, with support from major companies like NVIDIA, which launched specialized graphics cards for crypto mining (Franedya, 2020; Giovanny, 2021; Náñez Alonso et al., 2021; Østbye, 2020; Pamela., 2023). Cryptocurrency, particularly Bitcoin, has garnered significant attention, becoming a focal point for investors and developers. Bitcoin's high market capitalization underscores its position as a market leader, with its value rising since 2009. The growth of the cryptocurrency ecosystem is influenced by increased interest and adoption of crypto. An important indicator is the hashrate, which measures the computational power used for mining. The higher the hashrate, the faster the mining process and the higher the energy consumption. The increasing Bitcoin hashrate reflects network growth, enhanced security, and strong interest in Bitcoin as a valuable digital asset (Bhutoria, 2019; Giovanny, 2023; Rahma, 2022; Rizatu, 2023; Sandria, 2021).

Hut 8 Mining has significantly increased its hashrate capacity to 1,370 PH/s and is expected to surpass 2,500 PH/s by the end of 2022. This increase in computational power strengthens the blockchain ecosystem for further growth and adoption. The cryptocurrency ecosystem is rapidly expanding, driven by the increasing hashrate and high Bitcoin market capitalization. The rising hashrate and Bitcoin market value solidify its position as a leading digital asset in the transformation of the global digital financial ecosystem.

Despite its speculative and volatile nature, Bitcoin attracts investors with its high potential returns. Institutional and individual adoption has increased, as seen in efforts by companies like Hut 8 Mining. This reflects the growing interest and confidence in Bitcoin as a valuable digital asset. Bitcoin's market value surged rapidly, especially in 2021, although high price fluctuations indicate the volatility of the crypto market. Nonetheless, the growing focus on regulation and the continued development of blockchain technology position Bitcoin as a key focus in the global financial ecosystem. This digital currency has had a significant impact on how we understand and use digital assets.

Although Bitcoin's market value often changes quickly, it is important to view a more stable picture to understand the overall growth of the Bitcoin ecosystem. One indicator that provides deeper insights is the adjusted transaction value. This value reflects the actual economic activity on the Bitcoin network, independent of market speculation.

There has been a significant increase in adjusted transaction value from 2020 to 2022, indicating a rise in interest and adoption of Bitcoin in the market. This is influenced by the rise in Bitcoin prices, increased adoption, and growing interest from investors and individuals. However, Bitcoin adoption also faces significant challenges, including rising operational costs and declining profitability. The high mining difficulty level makes the process more expensive, causing many small and medium-sized miners to cease operations.

Geopolitical tensions and economic recession concerns also affect Bitcoin prices. For instance, even a slight increase in geopolitical tensions can result in a significant drop in Bitcoin trading volume. Bitcoin is introduced through the mining process, where the Proof-of-Work (PoW) consensus system used by Bitcoin requires complex computing and high energy consumption. This has become controversial due to perceived inefficiencies in energy use and detrimental environmental impacts.

Challenges in the Bitcoin mining ecosystem include technical difficulties in securing new blocks, price fluctuations that affect profitability, and the energy-intensive process of Proof-of-Work (PoW). PoW requires solving complex mathematical problems to prevent double-spending, and the increasing mining difficulty indicates stiff competition and the need for substantial computational power. The continually rising mining difficulty highlights the increasing competition and need for greater computational power, impacting profitability and the ecosystem's growth. These prospects underscore the significant technical challenges faced by the Bitcoin mining industry, as well as its implications for operational efficiency and the debated environmental impact. These challenges affect profitability, operational efficiency, and environmental impact. Bitcoin mining energy consumption accounts for 0.14% of the global electricity supply, demonstrating the high energy intensity of this technology.

Cryptocurrency, particularly Bitcoin, uses the Proof of Work (PoW) consensus to mine and release new units, which is highly energy-intensive and leaves a significant carbon footprint. This mining has sparked debates about environmental impact and energy sustainability, as much of the energy used comes from fossil sources like coal, gas, and oil. With increasing energy consumption, efforts are needed to transition to more sustainable energy sources. The Bitcoin mining process faces significant challenges, especially due to the Bitcoin halving event every 4 years, which reduces the block reward by half, with the most recent reward being 6.25 BTC per block since February 2021.

The Bitcoin halving event slows the rate of Bitcoin production, with a total supply limited to 21,000,000 BTC. The limited supply of Bitcoin, unchanged mining technology, and consistent infrastructure have made the Bitcoin mining ecosystem stable. However, the challenges for Bitcoin's future growth appear significant. From January 2018 to December 2022, the number of Bitcoin transactions peaked in January 2018 and gradually declined until October 2022, although remaining above 6 million transactions. There was an increase at the end of 2018, mid-2020, and early 2021, but overall, there was a decline in transactions during this period.

The debate over the carbon emissions from Bitcoin mining is intense. This activity is criticized as a trigger for the energy crisis and harmful to the environment, although some argue that Bitcoin mining is more environmentally friendly than gold mining. Since 2015, countries have committed to reducing carbon emissions to limit global warming to 1.5ºC, yet global carbon dioxide emissions continue to rise (European Commission, 2023). Similarly, the findings of the UN indicate that coal, oil, and gas production is expected to exceed twice the limit set by the world by 2030. The sustainability of the cryptocurrency network is key to reducing environmental impact and maintaining a balance between high exchange value and efficient energy consumption. Bitcoin mining requires significant computational resources to complete transactions on the blockchain network.

Several previous studies have addressed the development and challenges of cryptocurrency, particularly Bitcoin, from both economic and environmental perspectives. De Vries (2021) highlights that the Proof-of-Work (PoW) mechanism used in Bitcoin mining contributes significantly to global energy consumption, making sustainability a pressing concern. Meanwhile, Corbet et al. (2020) analyzed the volatility and systemic risk of cryptocurrency markets, showing that high fluctuations reduce investor confidence and hinder broader adoption. Both studies, however, tend to examine Bitcoin either from the perspective of energy consumption or financial volatility in isolation, without exploring the intersection between technological performance, sustainability, and economic stability.

This research aims to analyze how mining difficulty, hashrate growth, and halving mechanisms jointly impact operational efficiency, profitability, and environmental sustainability in Bitcoin's ecosystem. The novelty lies in combining technical and economic-environmental perspectives to provide a more integrated understanding of Bitcoin's long-term viability. The results are expected to benefit policymakers by informing regulatory strategies on energy and taxation, assist investors in evaluating risks and opportunities in cryptocurrency, and contribute to academic discourse on balancing innovation with sustainability in digital finance.

RESEARCH METHOD

This study employs a quantitative approach to measure and analyze numerical data from the variables used, combined with a descriptive approach to provide an overview of the impact of Bitcoin mining ecosystem growth on global primary electricity consumption. The combination of these approaches is expected to offer a comprehensive and in-depth understanding of the research topic.

Table 1. Datasets From Various Sources

Global Primary Electricity Consumption (Y)	U.S. Energy Information Administration
Bitcoin Hashrate (X1)	Coinmetrics.io
Bitcoin Market Value (X2)	Coinmetrics
Mining Difficulty (X3)	Coinmetrics
Adjusted Transaction Value (X4)	Coinmetrics
Bitcoin Transaction Count (X5)	Coinmetrics

The research involves the use of Vector Autoregressive (VAR) and Vector Error Correction Model (VECM) methods. The VAR/VECM analysis method was chosen to understand the relationships between all variables in this study, both directly and indirectly, using Eviews 12 software.

The Vector Autoregressive (VAR) method has several advantages, including:

1. No need to distinguish between dependent and independent variables.
2. Ordinary Least Squares (OLS) method is used in estimating each equation.
3. Estimation using the VAR method is superior compared to complex simultaneous equations.

The VECM model used can be formulated as follows:

$$LnY_t = \alpha_{it} + \beta_1 LnY_{t-i} + \beta_2 LnX1_{t-i} + \beta_3 LnX2_{t-i} + \beta_4 LnX3_{t-i} + \beta_5 LnX4_{t-i} + \beta_6 LnX5_{t-i} + \varepsilon_t$$

Where:

Ln : Natural logarithm of the dependent variable Y at time t

α_{it} : Model constant

β_1 :

Regression coefficients measuring the influence of each independent variable
Ln : on the dependent variable
Natural logarithm of the dependent
Ln : variable Y at time *t-i*
Natural logarithm of the first
ε_t : independent variable at time *t-i*
Error term or residual at time *t*, representing the influence of variables not included in the model

RESULTS AND DISCUSSION

Stationarity Test

The first step in estimating the VAR model is testing for data stationarity, as time series data is usually non-stationary. Unit root tests, such as the Augmented Dickey-Fuller Test (ADF) and Phillips Perron, are often used to assess data stationarity. If the ADF t-statistic is smaller than the MacKinnon critical values, the data is considered non-stationary. A probability greater than 1%, 5%, or 10% also indicates non-stationary data (Winarno, 2017). If the data is non-stationary, a differencing test is performed until the data becomes stationary, typically after the first or second difference.

Table 2. Results of Augmented Dickey-Fuller Test

Variable	Level	1st difference
	Prob.	Prob
LnY	0.42 0.13	0.00
LnX1	0.59	0.00
LnX2	0.88	0.00
LnX3	0.23	0.00
LnX4		0.00

The tests in Table 2 show that the ADF test at the level does not indicate any stationary variables, as the probability values are greater than 5%. Therefore, the ADF test was conducted at the first difference, and the results show that all variables became stationary with probability values below 5% or critical values less than the ADF t-statistic.

Determination of Optimal Lag Length

The purpose of the lag test is to determine the optimal number of lags to be used in the analysis and to find parameter estimates for the Vector Autoregressive (VAR) model. In the VAR model, the number of lags represents degrees of freedom. Parameters used to determine the optimal lag length include the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC).

Table 3. Results Of Optimal Lag Length Test

Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	15.50147	NA	2.83e-08	-0.3551906	-0.130908*	-0.266676
1	54.12234	67.22892	2.59e-08*	-0.448976	1.098012	0.147637
2	89.17852	53.23346*	2.82e-08	-0.414019	2.458958	0.693975
3	124.0217	45.16704	3.36e-08	-0.371173	3.827794	1.248204
4	163.2073	42.08823	3.90e-08	-0.489158	5.0355798	1.641601
5	207.8725	38.04819	4.65e-08	-0.810093*	6.040852	1.832048

Based on Table 3, the optimal lag length was determined based on the lowest AIC value. The optimal lag was found at lag 5, with the smallest AIC value of -0.81. Therefore, the model used for causality testing and VAR analysis is at lag 5.

VAR Stability Test

The VAR stability test evaluates whether the estimated VAR model and the error correction model are stable. The model must be stable for valid IRF and VD results. This test uses the AR Roots Table; a model is considered stable if all characteristic root inverses have a modulus of no more than one and are within the unit circle. If the modulus is greater than one, the model is considered unstable.

Table 4. Results of VAR Stability Test

Root	Modulus
0.679718 + 0.648410i	0.939389
0.679718 - 0.648410i	0.939389
0.487283 + 0.800318i	0.936992
0.487283 - 0.800318i	0.936992
-0.525096 + 0.757757i	0.921912
-0.525096 - 0.757757i	0.921912
-0.793841 + 0.444610i	0.909869
-0.793841 - 0.444610i	0.909869
0.819506 - 0.377977i	0.902472
0.819506 + 0.377977i	0.902472
0.358475 - 0.804532i	0.880782
0.358475 + 0.804532i	0.880782
-0.835399 - 0.180307i	0.854636
-0.835399 + 0.180307i	0.854636
0.849455	0.849455
-0.180574 + 0.821901i	0.841503
-0.180574 - 0.821901i	0.841503
0.811527 - 0.191347i	0.833780
0.811527 + 0.191347i	0.833780
0.069710 + 0.756415i	0.759621
0.069710 - 0.756415i	0.759621
-0.175076 - 0.642740i	0.666158
	0.666158
	0.665537
	0.665537
	0.659913
	0.659913
	0.498926
	0.498926
	0.046001

Root	Modulus
-0.175076 + 0.642740i	
-0.636269 - 0.195194i	
-0.636269 + 0.195194i	
-0.523759 - 0.401450i	
-0.523759 + 0.401450i	
0.442685 + 0.230124i	
0.442685 - 0.230124i	
-0.046001	

Based on Table 4, the model has proven to be stable and passed the stability test, as indicated by the modulus values below one. Therefore, the VAR model used can be continued.

Cointegration Test

The cointegration test determines whether non-stationary variables become stationary at the same degree (degree 1) and have a stable long-term relationship. Variables are said to be cointegrated if they produce a stationary linear combination. If not cointegrated, VAR analysis is used; if cointegrated, VECM is used. The Johansen cointegration test is used, and the data is considered cointegrated if the trace statistic value is greater than the critical value at a 0.05 significance level; otherwise, the analysis is conducted using VAR.

Table 5. Results of Cointegration Test

Cointegration Level	Trace Statistic	Critical Value (0.05)	Prob.
None *	0.598817	95.75366	0.0001
At most 1 *	0.444434	69.81889	0.0130
At most 2	0.331094	47.85613	0.0827
At most 3	0.279025	29.79707	0.1946
At most 4	0.095159	15.49471	0.6011
At most 5	0.027901	3.841466	0.2207

The results of the Johansen cointegration test in Table 4 show that the probability values in the "None" and "At most 1" rows are 0.000 and 0.0130, respectively, which are smaller than 0.05. This indicates the presence of cointegration equations and suggests a long-term equilibrium relationship.

Granger Causality Test

The Granger causality test determines the cause-and-effect relationship between variables in the VAR model. This test identifies the influence of variables on each other in both the short and long term, determining whether there is a unidirectional or bidirectional influence. If event x occurs before y, x may influence y, but not vice versa.

Table 6. Results of Granger Causality Test

Null Hypothesis	Obs	F-Statistic	Prob.
LNX1 does not Granger Cause LNY	55	2.15013	0.0771
LNY does not Granger Cause LNX1		1.64275	0.1687
LNX2 does not Granger Cause LNY	55	0.39188	0.8517
LNY does not Granger Cause LNX2		1.19270	0.3284
LNX3 does not Granger Cause LNY	55	0.35720	0.8748
LNY does not Granger Cause LNX3		0.60064	0.6996
LNX4 does not Granger Cause LNY	55	0.83609	0.5313
LNY does not Granger Cause LNX4		1.28766	0.2865
LNX5 does not Granger Cause LNY	55	1.42829	0.2330
LNY does not Granger Cause LNX5		0.78080	0.5690
LNX2 does not Granger Cause LNX1	55	1.73859	0.1458
LNX1 does not Granger Cause LNX2		1.69345	0.1562
LNX3 does not Granger Cause LNX1	55	0.65170	0.6617
LNX1 does not Granger Cause LNX3		0.19003	0.9648
LNX4 does not Granger Cause LNX1	55	0.58962	0.7078
LNX1 does not Granger Cause LNX4		1.00258	0.4275
LNX5 does not Granger Cause LNX1	55	0.64415	0.6673
LNX1 does not Granger Cause LNX5		3.55768	0.0087
LNX3 does not Granger Cause LNX2	55	0.64531	0.6664
LNX2 does not Granger Cause LNX3		1.01601	0.4198
LNX4 does not Granger Cause LNX2	55	1.52486	0.2017
LNX2 does not Granger Cause LNX4		0.41931	0.8328
LNX5 does not Granger Cause LNX2	55	1.80662	0.1313
LNX2 does not Granger Cause LNX5		5.05303	0.0010
LNX4 does not Granger Cause LNX3	55	0.42096	0.8316
LNX3 does not Granger Cause LNX4		0.74210	0.5961
LNX5 does not Granger Cause LNX3	55	0.57700	0.7173
LNX3 does not Granger Cause LNX5		1.17774	0.3354
LNX5 does not Granger Cause LNX4	55	0.87266	0.5072
LNX4 does not Granger Cause LNX5		2.08960	0.0847

Based on Table 6, the Granger causality test results show that there is no bidirectional causality between most of the tested variables. However, there are significant ($p < 0.05$) unidirectional causality relationships between some pairs of variables. First, there is a unidirectional causality from hashrate (LNX1) to Bitcoin transaction volume (LNX5), where LNX1 affects LNX5 with a p-value of 0.0087. Second, there is a unidirectional causality from Bitcoin market value (LNX2) to Bitcoin transaction volume (LNX5), where LNX2 affects LNX5 with a p-value of 0.0010. In conclusion, changes in hashrate and Bitcoin market value can impact Bitcoin transaction volume in the long term.

Uji Vector Error Correction Model (VECM)

Table 7. Long-term VECM Test Results

Variable	Coefficient	T-Statistic (T-table: 2.0010)
LNX1	3.043858	3.84140
LNX2	0.801949	3.47994
LNX3	-0.692566	-2.91937
LNX4	-0.010911	-0.09460
LNX5	0.602606	0.54830

Based on Table 7, the long-term VECM test results indicate the following findings: Hashrate (LNX1) and Bitcoin market value (LNX2) have a significant positive correlation with global primary electricity consumption (LNY), with coefficients of 3.043858 and 0.801949, respectively. Conversely, mining difficulty (LNX3) has a significant negative correlation with LNY, with a coefficient of -0.692566. Adjusted transaction value (LNX4) and Bitcoin transaction volume (LNX5) show negative and positive correlations, respectively, but are not significant with LNY.

Table 8. VECM Short Term Test

Variable	Coefficient	T-Statistic (T-table: 2.0010)
CointEq1	-0.022678	-0.28128
D(LNY(-1),2)	-0.662858	-3.05682
D(LNY(-2),2)	0.077517	0.35548
D(LNY(-3),2)	-0.886715	-5.87835
D(LNY(-4),2)	-0.928827	-3.58304
D(LNY(-5),2)	-0.005126	-0.02162
D(LNX1 (-1),2)	-0.085443	-0.34293
D(LNX1(-2),2)	-0.018233	-0.06305
D(LNX1(-3),2)	0.082036	0.29240
D(LNX1(-4),2)	-0.297511	-1.26496
D(LNX1(-5),2)	-0.227727	-1.21630
D(LNX2(-1(,2)	0.124532	1.93845
D(LNX2(-2),2)	0.160753	2.39738
D(LNX2(-3),2)	0.078950	0.97870
D(LNX2(-4),2)	0.059907	0.93620
D(LNX2(-5),2)	0.061989	1.01897
D(LNX3(-1),2)	0.002462	0.04814
D(LNX3(-2),2)	-0.009975	-0.16644
D(LNX3(-3),2)	0.011797	0.18523
D(LNX3(-4),2)	0.084358	1.62086
D(LNX3(-5),2)	0.072468	2.31127
D(LNX4(-1),2)	-0.046968	-2.20381
D(LNX4(-2),2)	-0.043444	-1.61754
D(LNX4(-3),2)	-0.056768	-1.76192
D(LNX4(-4),2)	-0.076573	-2.62081
D(LNX4(-5),2)	-0.042481	-2.25089
D(LNX5(-1),2)	-0.105151	-0.38074
D(LNX5(-2),2)	-0.444074	-1.48251
D(LNX5(-3),2)	-0.473842	-1.60891
D(LNX5(-4),2)	-0.473842	-1.60891
D(LNX5(-5),2)	-0.431563	-1.96927

Based on Table 8, the short-term VECM test results show that only one variable, besides the error correction term, is significant. The parameter CointEq1 has a coefficient of -0.022678 with a t-statistic of -0.28128, indicating no significant relationship between the short and long term. The global primary electricity consumption (LNY) shows significant negative relationships at Lag 1, Lag 3, and Lag 4, with coefficients of -0.662858, -0.886715, and -0.928827, and t-statistics of -3.05682, -5.87835, and -3.58304, respectively. Bitcoin market value (LNX2) and mining difficulty (LNX3) have significant positive relationships at Lag 2 and Lag 5, with coefficients of 0.160753 and 0.072468, and t-statistics of 2.39738 and 2.31127. Adjusted transaction value (LNX4) shows significant negative relationships at Lag 1 and Lag 4, with coefficients of -0.046968 and -0.076573, and t-statistics of -2.20381 and -2.62081.

The VECM results, both long-term and short-term, align with research indicating that Bitcoin mining requires substantial energy due to the complex hashing calculations involved in processing transactions without intermediaries (De Vries, 2018). Bitcoin's hashrate, which influences energy consumption, is identified as a key factor in these studies (De Vries, 2020), Yuan supports this view by noting that "the high hashrate and electricity demand within the Bitcoin network is a systematic risk in the Bitcoin market" (Yuan et al., 2022). Research shows that fluctuations in energy sector commodity prices significantly impact Bitcoin prices (Wahyudi et al., 2024). Specifically, global commodity prices in the energy sector, including crude oil and natural gas, have a positive effect on Bitcoin prices (Rakhmat et al., 2022). Mining one Bitcoin requires approximately 1,820 kWh, which is equivalent to the electricity consumption of a U.S. household for 62 days. his process is intentionally made inefficient to prevent monopolies and to increase mining difficulty, thus requiring substantial energy. The relationship between mining difficulty and energy consumption can be either positive or negative, depending on factors such as technology and energy sources. Additionally, Bitcoin transaction volume does not significantly affect energy consumption, as it is influenced by other factors like transaction fees and block capacity.

Impulse Response Function (IRF) Analysis

Impulse Response Function (IRF) analysis is employed to understand the response of endogenous variables to shocks in a VAR model. The IRF tracks the response of endogenous variables to disturbances, as individual coefficients in the VAR model are difficult to interpret directly. The IRF can be analyzed through tables or graphs using applications such as EViews. The IRF graph shows the magnitude of the response (vertical axis) and the duration of the response (horizontal axis). If the graph approaches the equilibrium line, the response to the shock diminishes over time; if it deviates from the equilibrium line, the response becomes more pronounced.

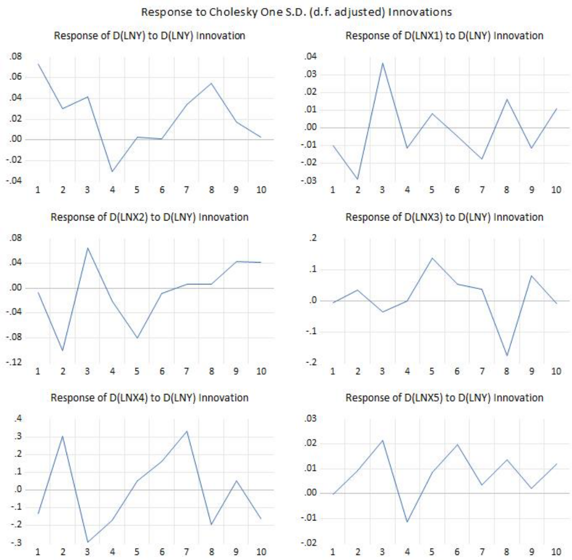

Figure 1. Impulse Response Function

This study uses Impulse Response Function (IRF) analysis to explore how global primary electricity consumption responds to various variables within the cryptocurrency ecosystem. The analysis reveals varying response patterns to each variable. For global primary electricity consumption itself, there is a dominant negative response in the early periods (1-4) and a positive response in the subsequent periods (6-8), with the highest peak occurring in period 8. In terms of Bitcoin's hash rate, electricity consumption shows a positive response in periods 3, 5, 8, and 10, but also a negative response in periods 1, 2, 4, 6, 7, and 9, indicating a variable relationship depending on the time. Bitcoin's market value shows a significant positive response in periods 3, 7, 8, 9, and 10, while there is a negative response in the early periods (1, 2, and 4-6). For mining difficulty, there is a positive response observed in periods 2, 5, 6, 7, and 9, with the highest peak in period 5. However, there is also a negative response in periods 1, 3, 4, 8, and 10. Adjusted transaction value shows a positive response in periods 2, 5, 6, 7, and 9, and a negative response in the early periods as well as periods 8 and 10, with the highest peak in period 7. Finally, the number of Bitcoin transactions shows a positive response in periods 2, 3, and 5-10, with the highest peak in period 6, while there is a negative response in the early periods (1 and 4). Overall, the IRF reveals a complex and inconsistent relationship between global primary electricity consumption and the related variables, which fluctuates over time and market conditions.

Variance Decomposition Analysis

Variance Decomposition (VD) analysis in VECM helps to understand the contribution of each variable to the changes in other variables in the future periods. VD shows the percentage contribution of each variable to the variance of other variables in the VAR system.

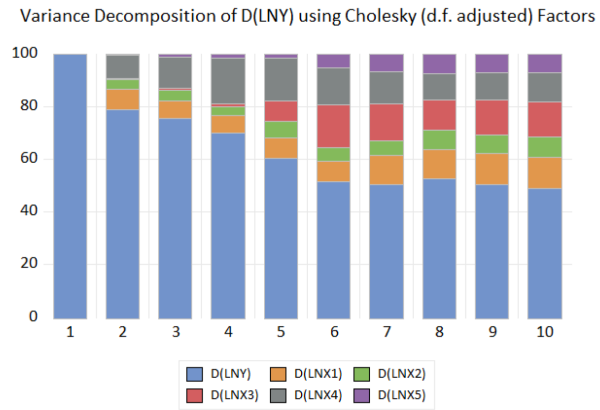

Figure 2. Variance Decomposition

The Variance Decomposition analysis in Figure II shows that over a 10-period horizon, the global primary electricity consumption variable has a dominant influence. By the end of the 10th period, its largest contribution is to its own influence. Additionally, Bitcoin’s hashrate also shows significant impact with a continuous increase in each period.

CONCLUSION

This study demonstrates that various variables within the Bitcoin mining ecosystem have different impacts on global primary electricity consumption. In the long term, Bitcoin's hashrate has been shown to have a positive and significant effect, meaning that an increase in hashrate will lead to higher primary energy consumption. Conversely, in the short term, hashrate has a negative and insignificant effect. The market value of Bitcoin has a positive and significant impact on global primary electricity consumption both in the long and short terms, indicating that an increase in market value will consistently lead to higher energy consumption. Mining difficulty has a negative and insignificant effect in the long term, but a positive and significant effect in the short term, suggesting that increased mining difficulty will boost energy consumption in the short run. Adjusted transaction value has a negative and insignificant effect in the long term, but a negative and significant effect in the short term, indicating that a decrease in adjusted transaction value will reduce energy consumption in the short term. Finally, the number of Bitcoin transactions does not have a significant impact on global primary electricity consumption in either the long or short term. This study highlights the complexity of the relationship between Bitcoin mining ecosystem variables and global primary electricity consumption, and the importance of considering various factors in the energy impact analysis of Bitcoin mining.

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