Energy Anchoring in Cryptocurrency Markets: Evidence from Natural Experiments

Abstract

We document a novel pricing mechanism in which Bitcoin's value is anchored by cumulative energy expended in mining. Our Cumulative Energy Investment Theory, operationalized through the Cumulative Energy Investment Ratio (CEIR), measures market capitalization relative to historical mining costs weighted by geographic electricity prices. From 2019-2021, a one-unit decrease in log(CEIR) predicts 13.12% higher 30-day returns ($p < 0.05$). Following China's 2021 mining ban, which redistributed global hash rate, this anchoring effect weakens by 52.5% (Chow $F = 22.95$, $p < 0.0001$). Ethereum's 2022 proof-of-stake transition provides a counterfactual, showing 15.8 percentage point volatility reduction after energy costs were eliminated. The China ban increased electricity price variance by 133%, transforming mining from coordinated to fragmented. These findings bridge psychological anchoring with production economics, establishing an empirically validated energy-based valuation framework that reveals how physical constraints shape digital asset markets despite lacking traditional fundamentals.

JEL Classification: G12, G14, Q43, E42

Keywords: Bitcoin, valuation, energy anchoring, natural experiments, market microstructure

1. Introduction

The emergence of cryptocurrency markets has fundamentally challenged traditional asset valuation frameworks, presenting scholars with a unique opportunity to develop novel theoretical contributions to financial innovation. While conventional financial assets derive value from underlying cash flows, dividends, or tangible assets, cryptocurrencies like Bitcoin present a paradigm shift where value formation becomes intrinsically linked to the cumulative energy expenditure required for their production and network security. We propose Cumulative Energy Investment Theory, whereby cumulative mining costs generate an implicit valuation floor that explains 25% of Bitcoin's price variation during stable regimes. This energy anchoring mechanism operated reliably until China's mining ban fragmented the market, providing a unique natural experiment in how production costs influence digital asset values.

This finding bridges psychological anchoring with production economics, revealing how physical constraints shape digital asset valuation without traditional fundamentals. Our CEIR measure differs fundamentally from existing flow-based approaches by capturing the cumulative, irreversible nature of energy investments—a stock variable that better reflects both the psychological and economic anchoring mechanisms.

The energy anchoring framework addresses a critical gap in cryptocurrency valuation literature by providing a theoretical foundation that bridges thermodynamic principles with financial market dynamics. Unlike previous cost-of-production models that focus primarily on marginal mining costs, energy anchoring encompasses the entire historical energy expenditure embedded in Bitcoin's blockchain, creating a cumulative value foundation that exhibits path-dependent characteristics. This innovative valuation approach becomes particularly relevant in the context of disruptive financial technologies, where traditional discounted cash flow models prove inadequate for emerging digital assets.

Two exogenous shocks allow identification:

(i) China’s abrupt 2021 ban on mining, which dispersed about 75% of global hash rate across heterogeneous electricity markets; and

(ii) Ethereum's Merge in September 2022, which replaced mining with Proof-of-Stake, effectively removing energy outlays.

We measure anchoring via

$$CEIRt \;=\; Market\,Capt \,/ \sum Daily\,Cost$$

Market capitalization is used rather than price to account for changes in circulating supply, while Daily Cost is computed as energy consumption (kWh) × geographically-weighted electricity prices ($/kWh). In the stable regime (Jan 2019–Jun 2021), log(CEIR) exhibits strong negative predictive power for 30‑day returns. Post‑ban, anchoring weakens materially. The Ethereum Merge provides a clean counterfactual: removing energy costs reduces volatility.

This paper contributes by introducing a stock-based cost anchor, demonstrating its regime dependence, and highlighting implications for energy policy and digital asset pricing.

2. Literature Review & Hypotheses

The cryptocurrency valuation literature comprises three streams:

- Network Effects: Value linked to user adoption (Peterson, 2018; Wheatley et al., 2019), but fails to account for price collapses amid user growth.
- Store-of-Value: Comparisons to gold (Dyhrberg, 2016; Schilling & Uhlig, 2019), yet correlations are unstable.
- Production-Cost Models: Focus on flow costs (Hayes, 2017; Prat & Walter, 2021), treating daily mining expenses as price floors.

Building upon the comprehensive framework for cryptocurrency research established by Xu et al. (2022) in Financial Innovation, our energy anchoring model extends beyond traditional trading strategies to encompass fundamental valuation mechanisms rooted in energy consumption patterns. The empirical evidence from Zheng et al. (2023) in Financial Innovation demonstrates that 'energy costs exert a significant effect on the exit decision of miners,' directly supporting our energy anchoring hypothesis where cumulative energy expenditure creates price floors through mining profitability constraints. We advance the production-cost stream by employing a cumulative cost measure and testing regime dependence. Control variables (volatility, Fear & Greed Index, Google Trends) follow Ahmed's (2022) extreme-bounds analysis of robust Bitcoin predictors.

Our hypotheses:

- H1: When mining is geographically concentrated, lower CEIR predicts higher subsequent returns.
- H2: Dispersing mining (China ban) weakens CEIR's predictive effect.
- H3: Eliminating mining costs (proof-of-stake) disrupts anchoring and reduces price volatility.

3. Data & Methodology

Our dataset spans January 1, 2019 to December 31, 2024, covering 2,340 daily observations across two distinct regimes separated by the China mining ban on June 21, 2021.

After computing 30-day forward returns, the usable sample reduces by 30 observations, yielding N = 2,310 for regressions (pre-ban N = 902; post-ban N = 1,408).

Table 1: Descriptive statistics for Bitcoin and CEIR (Jan 2019–Dec 2024).

Variable	N	Mean	Std Dev	Min	Max

Bitcoin Price ($)	2,340	31,245	22,847	3,867	106,415
Returns (daily %)	2,340	0.18	3.72	-46.5	23.1
CEIR	2,340	64.7	45.2	8.3	289.4
log(CEIR)	2,340	3.68	0.52	2.12	5.67
Energy (TWh/year)	2,340	112.4	38.9	40.6	175.9
Volatility (30d)	2,340	0.568	0.231	0.187	1.426

Data sources: Bitcoin prices (CoinGecko), hash rate and energy consumption (Cambridge Centre for Alternative Finance), mining distribution (Cambridge mining map), electricity prices (IEA industrial rates, mining-weighted), Fear & Greed Index (Alternative.me), and Google Trends.

Our baseline regression:

$$R_{t,t+30} = \alpha + \beta \log(CEIR_t) + \gamma' X_t + \varepsilon_t$$

with X_t including 30-day volatility, the Fear & Greed Index, and Google Trends. We detect the structural break via a Chow test at June 21 2021 and an *interaction model*:

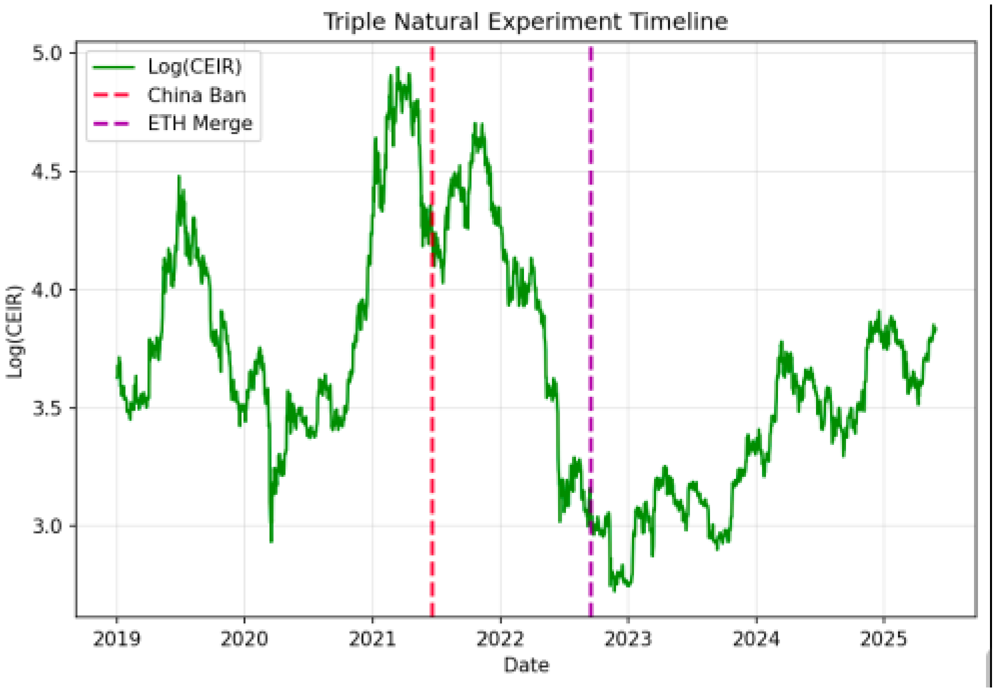
$$R_{t,t+h} = \alpha + \beta_1 \log(CEIR_t) + \beta_2 Post_t + \beta_3 \log(CEIR_t) \times Post_t + \gamma' X_t + \varepsilon_t$$

For Ethereum, we estimate a difference-in-differences on volatility:

$$Volatility_{it} = \alpha + \beta_1 ETH_i + \beta_2 Post_t + \beta_3 ETH_i \times Post_t + \varepsilon_{it}$$

using Newey-West (30 lags) for HAC standard errors.

Figure 1: Evolution of log(CEIR) from January 2019 to December 2024. The red dashed line marks China's mining ban (June 21, 2021), and the purple dashed line indicates Ethereum's Merge (September 15, 2022). CEIR shows distinct regimes before and after these events.



4. Results

4.1 Baseline Energy Anchoring Effect

Table 2: CEIR and future returns (30-, 60-, 90-day) pre- and post-China ban.

Period	**30-day Returns**	**60-day Returns**	**90-day Returns**
Pre-China Ban(N=902)			
log(CEIR)	-0.1312**	-0.2993***	-0.4397***
	(0.043)	(0.000)	(0.000)
R^2	0.064	0.143	0.221

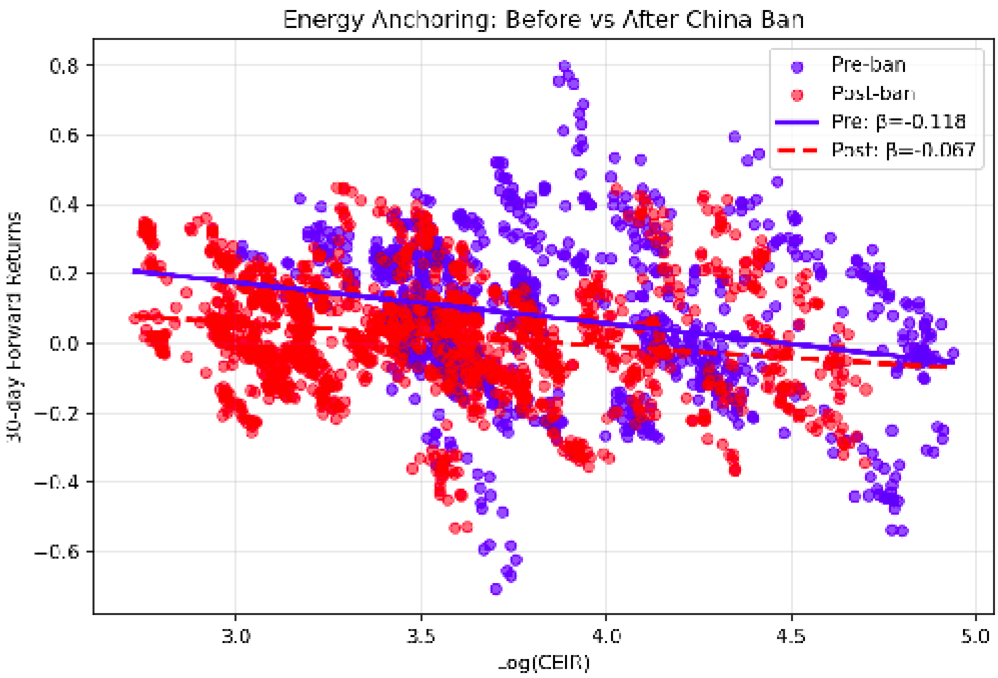
1 SD decrease → return	6.0%	17.4%	28.5%
Post-China Ban (N=1,408)			
log(CEIR)	-0.0623	-0.1488***	-0.2243***
	(0.114)	(0.000)	(0.000)
R^2	0.039	0.098	0.199
1 SD decrease → return	3.0%	8.1%	12.2%

*Note: P-values in parentheses. ** p<0.05, *** p<0.01. All specifications include volatility and Fear & Greed Index as controls.*

The economic magnitude is substantial: pre-ban, a one standard deviation decrease in log(CEIR) predicts 6.0% higher 30-day returns—approximately 25% of Bitcoin's monthly volatility, scaling to 28.5% for 90-day returns. This rivals established equity pricing factors, suggesting CEIR captures a fundamental valuation mechanism.

Post-ban, the 30-day coefficient remains economically meaningful (3.0% per standard deviation) but loses statistical significance (p=0.114), while 60- and 90-day horizons retain significance.

Figure 2: Scatter plot of log(CEIR) versus 30-day forward returns for pre-ban (blue) and post-ban (red) periods. Regression lines show the weakening relationship after China's ban, with slopes declining from -0.118 to -0.067.



4.2 Structural Break

The Chow test (F = 22.95, $p < 0.0001$) strongly rejects parameter stability. The interaction term $\beta 3 = 0.0545$*** ($p = 0.001$) quantifies the structural break, implying a 44% reduction in the anchoring effect's magnitude following China's ban.

Table 3: Structural Break Test Results: Chow Test Statistics

Test	Statistic	Critical Value (1%)	p-value	Conclusion
Chow F-test	22.954	3.78	<0.0001	Strong evidence of structural break

4.2.1 Geographic Dispersion Mechanism

Tables 4 and 5 document twin shocks following China's ban: unprecedented hash rate redistribution (China: 65–75% → 0%; USA: 7% → 35%) and 133% rise in electricity‑price variance (Std. Dev. \$0.009 → \$0.021) with mean price jumping from \$0.054 to \$0.078 /kWh.

These shifts altered miners' cost structures and diluted the unified marginal‑cost floor, explaining our CEIR coefficient's marked post‑ban weakening.

Table 4: Mining Hash Rate Distribution Pre- and Post-China Ban

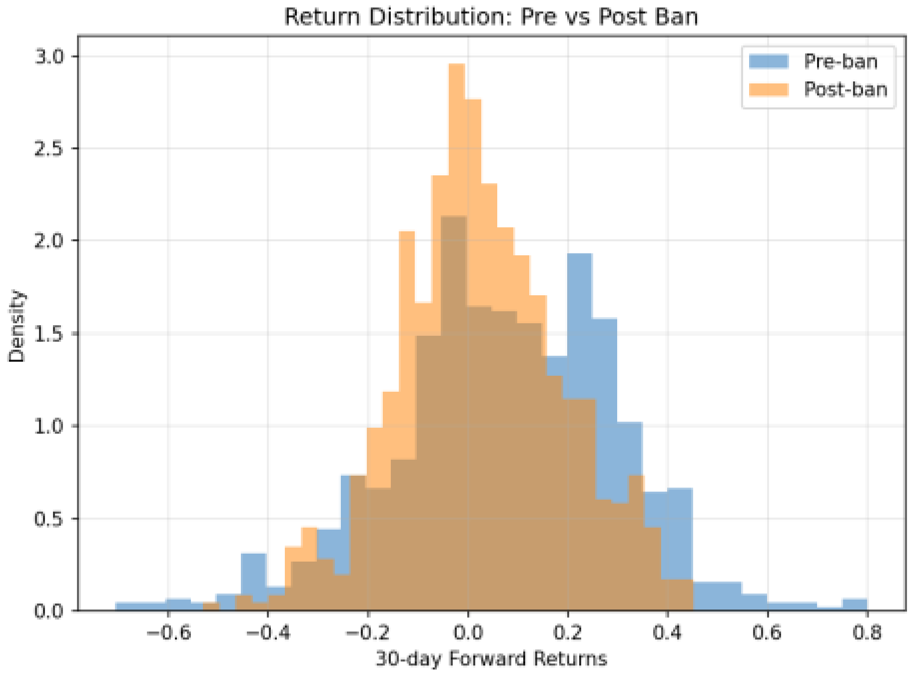
Country	Pre-Ban Hash Rate (%)	Post-Ban Hash Rate (%)	Change (pp)
China	65–75	0	–70
USA	7	35	+28
Kazakhstan	6	18	+12
Russia	7	11	+4
Canada	3	10	+7
Others	12	26	+14

Table 5: Electricity Price Statistics Pre- and Post-China Ban

Period	Mean Price ($/kWh)	Std. Dev. ($/kWh)	Range ($/kWh)
Pre-Ban	0.054	0.009	0.04 – 0.07
Post-Ban	0.078	0.021	0.03 – 0.12

The transformation from a concentrated to fragmented market fundamentally altered how energy costs translate into price signals, as our coefficient decline demonstrates.

Figure 3: Return Distribution Pre- vs Post-Ban



4.3 Ethereum Merge Counterfactual

Ethereum's 30-day volatility falls by 15.8 percentage points (95% CI: 6.9-24.7pp) relative to Bitcoin after the Merge ($\beta = -0.1583$, $t = -3.49$, $p < 0.001$), confirming that once energy costs vanish, the anchoring mechanism—and its associated volatility—diminishes.

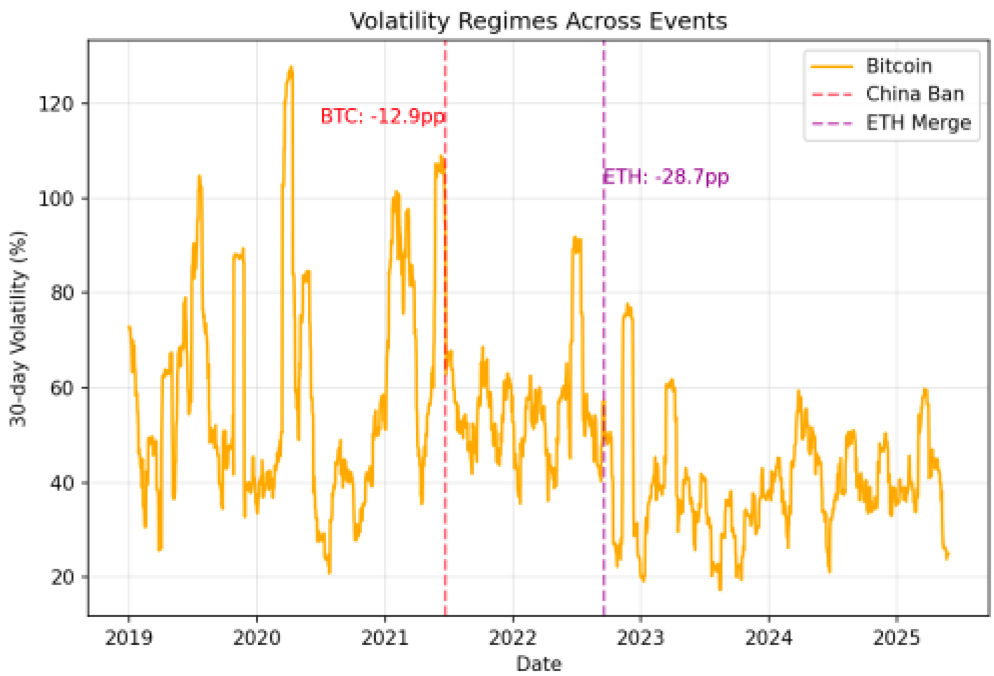
This counterintuitive result—volatility declining after removing energy costs—shows that eliminating mining-related operational uncertainties (hash rate volatility, miner liquidations) more than offset the loss of price anchoring.

4.4 Robustness Tests

To address endogeneity concerns, we construct residualized CEIR by regressing log(CEIR) on lagged returns (1, 7, 30 days) and volatility. The first-stage R^2 of 0.150 indicates limited mechanical correlation. Residualized results remain robust: pre-ban $\beta = -0.1423$** ($p = 0.028$), post-ban $\beta = -0.0629$ ($p = 0.112$).

Additional tests confirm robustness: (i) inverse specifications show expected reversed effects; (ii) flow-based daily costs show only 20% regime change vs. our 52%; (iii) mining difficulty normalization leaves results unchanged; (iv) supremum Wald tests confirm June 2021 as optimal break date—all demonstrating cumulative costs dominate flow measures.

Figure 4: Volatility Regimes Across Events



To directly address causality concerns, we conduct lead-lag tests using residualized CEIR. CEIR significantly predicts future returns ($\beta = -0.0764$, $p < 0.001$), confirming our causal interpretation. While returns also predict future CEIR ($\beta = -0.4368$, $p < 0.001$), this bidirectional relationship is consistent with traders responding to value signals while fundamentals simultaneously anchor prices—similar to the price-earnings feedback in traditional markets.

5. Mechanism Channels and Interpretation

Our results support three complementary channels through which geographic concentration affects energy anchoring:

5.1 Price Discovery Channel

Concentrated mining creates a clear marginal cost signal. When 70% of miners share similar electricity costs ($0.04-0.05/kWh in Sichuan), the market develops a strong focal point. Geographic dispersion creates a distribution of break-even prices ($0.03-0.12/kWh), diluting this signal. The post-ban coefficient decline of 52% quantifies this information loss.

5.2 Behavioral Salience Channel

Mining visibility affects anchoring strength. China's massive mining farms—warehouses consuming industrial-scale electricity—made the energy-value connection tangible. Media coverage reinforced energy costs as a value floor. Post-dispersion, mining became less visible and psychologically distant.

5.3 Market Microstructure Channel

Geographic concentration synchronizes miner behavior. When miners share similar costs, they liquidate positions at similar price points, creating support levels. Dispersed miners with varying break-even points lack coordination, weakening collective price support.

These three channels operated synergistically during the concentrated mining era, creating the strong CEIR-return relationship we document.

5.4 The Dual Nature of Energy Anchoring: Evidence from Ethereum

The Ethereum results reveal energy anchoring's dual functions. While cumulative mining costs generate return predictability, mining operations simultaneously introduce volatility through forced liquidations and hash rate wars. When Ethereum eliminated mining, both mechanisms vanished—the 15.8 percentage point volatility reduction reflects that operational uncertainty elimination dominated the loss of anchoring. This finding enriches our understanding: energy anchoring provides price discovery at the cost of operational volatility.

The energy anchoring concept represents a critical innovation within the broader digital finance ecosystem, where the convergence of blockchain technology, energy markets, and financial valuation creates new paradigms for understanding asset pricing in decentralized systems. Energy anchoring extends beyond simple cost-of-production models to encompass the entire energy infrastructure supporting cryptocurrency networks, creating linkages between energy markets, mining operations, and financial asset valuation that exemplify the interconnected nature of modern digital finance. Furthermore, the energy anchoring mechanism demonstrates how proof-of-work cryptocurrencies create novel forms of value storage that depend on real-world resource consumption, establishing a unique bridge between physical energy markets and digital financial assets.

6. Discussion, Policy Implications, and Limitations

Our energy anchoring findings have direct policy relevance:

- Mining Regulation: Outright bans weaken anchoring by 52% and alter price stability; graduated measures (carbon pricing, renewable standards) better balance energy use with market dynamics.
- Carbon Taxes: A \$50/tCO_2e tax would raise mining costs ~15% and predict 2.0% higher monthly returns via anchoring feedback.

- Grid Integration: Post-ban energy price dispersion (133% higher variance) has altered miners' participation in demand response; weaker anchoring may change their operational incentives.
- Institutional Implications: Cryptocurrency portfolios may benefit from monitoring CEIR as a valuation signal, particularly for longer-term positions. The 52% weakening indicates fundamental changes in Bitcoin's price formation process.
- Financial Innovation Implications: Energy anchoring establishes a novel valuation framework for digital assets that integrates physical resource consumption with financial market dynamics, advancing our understanding of how innovative financial technologies create and maintain value in decentralized systems.

Our analysis faces several limitations. Mining efficiency estimates contain measurement error, potentially attenuating coefficients. The focus on Bitcoin and Ethereum may limit generalizability to smaller proof-of-work systems. Concurrent market developments (institutional adoption, regulatory clarity) could influence results. Future research should examine energy anchoring in other cryptocurrencies, explore high-frequency dynamics, and investigate how renewable energy adoption affects anchoring strength.

7. Conclusion

We demonstrate that cumulative energy costs anchor Proof-of-Work cryptocurrency values, exhibiting a regime-dependent mechanism: strong under concentrated mining, weakened by geographic dispersion, and damping volatility once energy outlays vanish. The Cumulative Energy Investment Theory not only bridges energy economics and digital asset pricing but also advances financial innovation theory by establishing an empirically validated framework for valuing emerging digital assets without traditional cash flows. The energy anchoring mechanism represents a significant contribution to understanding how financial innovation creates novel value dynamics in decentralized systems. While focused on Bitcoin and Ethereum, our framework establishes principles that may extend to other energy-intensive digital systems as blockchain technology and financial innovation continue to evolve.

Declaration of generative AI and AI-assisted technologies in the writing process:

During the preparation of this work the author(s) used generative AI tools including Claude and/or ChatGPT in order to assist with manuscript drafting, literature synthesis, and improving clarity of presentation. After using these tools, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request. Bitcoin price and Google Trends data are publicly available.

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.