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Research Article

A Threshold Approach to Investigating Bitcoin's Environmental Impact

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Abstract. The rapid growth of Bitcoin trading has created tension between financial innovation and environmental sustainability. While existing research has focused on mining energy consumption, the environmental consequences of trading activity – a primary economic driver – remain underexplored, particularly across different developmental contexts. This study examines whether Bitcoin trading volume affects progress toward Sustainable Development Goal 7 (SDG7), which mandates affordable and clean energy, and whether this relationship varies by developmental status and trading intensity. Utilising a balanced panel of 21 developed and developing countries from 2014 to 2023, we employ fixed-effects models, two-stage least squares instrumental variable regression, and threshold regression to analyse the relationship between Bitcoin trading activity and energy sustainability outcomes. The results reveal significant developmental asymmetry. In developing economies, high-volume Bitcoin trading regimes—exceeding a critical threshold of approximately $28.4 trillion in annual volume—are associated with a statistically significant deterioration in SDG7 progress (coefficient = -0.0153, p = 0.031). This effect operates through increased reliance on carbon-intensive electricity generation rather than aggregate energy consumption. No significant impact is observed in developed economies. The allocation of trading volume by exchange denomination may introduce measurement bias, and the analysis does not capture subnational variation in mining concentration. Subsequent studies should employ subnational data, extend analysis to other cryptocurrencies, and investigate which specific institutional characteristics most effectively mitigate environmental damage. Bitcoin's environmental impact is neither uniform nor linear but conditional on institutional context and trading intensity, underscoring the need for context-sensitive, volume-dependent regulatory interventions.

Keywords: Bitcoin trading, SDG7, developmental asymmetry, threshold regression, energy sustainability, cryptocurrency regulation.

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1. Introduction

The emergence of Bitcoin as the world's largest cryptocurrency has created a fundamental tension between financial innovation and environmental sustainability. As a decentralized digital asset, Bitcoin offers economic benefits including financial inclusion, remittance efficiency, and portfolio diversification. However, its proof-of-work consensus mechanism demands substantial electricity consumption, raising critical questions about its compatibility with global climate objectives, particularly Sustainable Development Goal 7 (SDG7), which mandates affordable and clean energy for all [1,2].

The existing economic literature has predominantly focused on two distinct dimensions: the price dynamics and market efficiency of cryptocurrencies, and the direct energy consumption of mining activities [3,4]. Yet surprisingly, the environmental consequences of *trading activity* – a primary economic driver of market demand and subsequent mining intensity – remain underexplored. Furthermore, studies have largely treated Bitcoin's environmental impact as homogeneous across countries, failing to account for how institutional capacity, regulatory quality, and energy infrastructure mediate this relationship [5]. This oversight is economically significant because it obscures whether the externalities of cryptocurrency markets are distributed equitably across developed and developing economies.

This paper addresses these gaps by providing a systematic empirical investigation into how Bitcoin trading volume affects SDG7 progress across different developmental contexts. Specifically, we ask three research questions: (1) Does Bitcoin trading volume significantly affect SDG7 progress? (2) Does this relationship differ between developed and developing economies? (3) Does the effect exhibit nonlinear threshold behavior, materializing only beyond a critical trading intensity?

Using a balanced panel of 21 countries from 2014 to 2023, we employ fixed-effects models, two-stage least squares instrumental variable regression, and threshold regression to test whether the relationship is conditional on trading intensity and national institutional capacity.

This study makes three key contributions to the economic literature. First, we isolate the effect of trading volume from mining activity, demonstrating that market-driven demand functions as a distinct economic channel affecting energy systems. Second, we identify a novel *developmental asymmetry*: Bitcoin trading imposes significant environmental costs in developing economies while exhibiting no measurable effect in developed nations, challenging assumptions of uniform economic externalities. Third, we establish that the transmission mechanism operates through the electricity generation mix rather than aggregate consumption, providing empirical evidence for context-sensitive policy design [6].

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and develops the theoretical framework. Section 3 describes the data and econometric methodology. Section 4 presents empirical results. Section 5 discusses findings and limitations, and Section 6 concludes with policy implications and future directions.

2. Literature Review

This section synthesizes the existing literature on cryptocurrency markets and environmental sustainability across four interconnected dimensions: the energy economics of Bitcoin mining, environmental externalities of cryptocurrency activity, the role of developmental context, and the theoretical framework of the Environmental Kuznets Curve.

2.1. Bitcoin and Energy Economics

The energy-intensive nature of Bitcoin's proof-of-work consensus mechanism is well-documented. De Vries [3] estimated that Bitcoin's annual energy consumption rivals that of entire nations, framing cryptocurrency as an energy-economic phenomenon. Krause and Tolaymat [4] quantified that Bitcoin requires substantially more energy per transaction than conventional financial systems, with miners responding to price signals by deploying increasingly powerful hardware, creating escalating energy demand.

Gallersdörfer, Klaaßen, and Stoll [7] extended this analysis beyond Bitcoin, estimating that while Bitcoin accounts for approximately 66% of total cryptocurrency energy demand, the other 19 mineable cryptocurrencies collectively contribute an additional third, making the sector's aggregate energy footprint roughly 50% larger than Bitcoin alone. Schinckus et al. [8] found that the relationship between cryptocurrency trading and energy consumption varies with national income levels, highlighting the importance of developmental context. Together, these studies establish that cryptocurrency energy demand is substantial, growing, and context-dependent – yet they do not isolate trading activity as a distinct driver.

2.2. Environmental Consequences and Economic Externalities

Sarkodie, Ahmed, and Owusu [9] employed wavelet analysis and machine learning methods to examine Bitcoin's carbon footprint, finding that a one percent increase in trading volume increases the carbon footprint by approximately $24. Market capitalization emerged as the primary emissions driver, while block size served as the only mitigating factor. Truby [10] argued that blockchain's energy intensity undermines global climate initiatives, proposing fiscal policies including energy consumption taxes and carbon levies calibrated to the social cost of emissions.

Kohli et al. [11] found that Bitcoin alone produces annual emissions comparable to countries like Jordan or Sri Lanka, identifying proof-of-stake transition and renewable energy sourcing as promising mitigation strategies. Mustafa, Mordi, and Elamer [12] extended analysis to water resources, finding that a one percent increase in trading volume increases water usage intensity by approximately 0.08 percent. Zhang et al. [13] noted that mining operations often locate in jurisdictions with weak environmental enforcement, creating regulatory arbitrage opportunities. Despite these contributions, the literature has not systematically examined how the environmental effects of *trading* – as distinct from mining – vary across developmental contexts.

2.3. Trading Activity versus Mining

While much literature focuses on mining consumption, several studies examine trading activity's distinct role. Miśkiewicz, Matan, and Karnowski [14] found that trading volume, independent of mining location, exerts measurable effects on energy consumption patterns, functioning as a demand-side driver signaling market conditions to miners. Huynh et al. [15] identified bidirectional causality between trading activity and energy use, with intense trading periods preceding increased energy consumption. Corbet et al. [16] documented Bitcoin market maturation from 2014 to 2023, encompassing multiple cycles shaping the trading-environment relationship.

Emerging evidence suggests cryptocurrency's environmental impact varies significantly across institutional contexts. Attarzadeh and Balcılar [17] found heterogeneous transmission patterns across developed and emerging markets. Huynh et al. [15] attributed these differences to variation in regulatory quality, energy infrastructure resilience, and institutional capacity to absorb demand shocks. Bublyk, Borzenko, and Hlazova [18] demonstrated that environmental intensity varies by approximately 400 percent depending on the electricity generation mix of mining locations. Yan, Mirza, and Umar [19] found that mining profitability during price surges attracts investment away from renewable energy projects, suggesting a crowding-out mechanism. Oğuz [20] demonstrated that the marginal environmental impact of trading is substantially larger in lower-income countries. Qin et al. [21] characterized Bitcoin as shifting between carbon asset and environmental shelter depending on market conditions.

2.4. Theoretical Framework: Environmental Kuznets Curve

The Environmental Kuznets Curve (EKC) provides theoretical grounding for understanding heterogeneous environmental effects across developmental contexts. Dinda [22] documented the inverted U-shaped relationship between economic development and environmental degradation, where conditions initially worsen before improving beyond a development threshold. Stern [23] noted that validity depends on pollution type and institutional context.

Applying EKC to cryptocurrency markets suggests developing economies are more vulnerable to Bitcoin-related degradation due to weaker institutions, less resilient infrastructure, and greater reliance on carbon-intensive generation. Miśkiewicz et al. [14] connected EKC theory to cryptocurrency, finding that trading introduces complex dynamics, simultaneously contributing to economic growth while generating environmental degradation. This framework implies that the environmental impact of Bitcoin trading should not be assumed constant across countries but should instead vary with developmental stage and institutional capacity.

2.5. Research Gap and Hypothesis Development

Despite substantial contributions, significant gaps remain. First, no study has systematically isolated Bitcoin trading volume's effect from mining activity on SDG7 outcomes across developmental contexts. Second, existing research has not tested for nonlinear threshold effects in the trading – environment relationship, despite theoretical reasons to expect disproportionately larger impacts during high-volume regimes. Third, the transmission mechanism – whether trading affects energy systems through aggregate consumption, efficiency, or generation mix—remains undertheorized and empirically untested.

Addressing these gaps, this study tests five hypotheses grounded in EKC theory [22,23] and institutional theory [15]:

H1 (Developmental Asymmetry): The effect of Bitcoin trading volume on SDG7 progress differs significantly between developed and developing economies, with negative effects concentrated in developing economies.

H2 (Nonlinear Threshold Effects): The relationship between Bitcoin trading volume and environmental outcomes is nonlinear, with deterioration occurring only beyond a critical trading volume threshold.

H3a-c (Transmission Channels): Bitcoin trading affects SDG7 progress through (a) aggregate energy consumption, (b) energy intensity, or (c) electricity generation mix, with the latter hypothesized as the primary mechanism.

H4 (Institutional Moderation): Regulatory quality mitigates the negative environmental impact of Bitcoin trading in developing economies.

H5 (Primary Hypothesis): Bitcoin trading volume significantly impedes SDG7 progress in developing economies.

3. Data and Methods

This section describes the data sources, variable definitions, econometric models, and estimation strategies employed to investigate the impact of Bitcoin trading volume on SDG7 progress across developed and developing economies.

3.1. Data Sources and Sample Selection

This study employs a balanced panel dataset comprising 21 countries spanning ten years from 2014 to 2023, yielding 210 observations. The sample period captures Bitcoin's maturation from early establishment through multiple market cycles, technological advancements, and regulatory developments [16]. Countries were selected based on data availability and representation across geographic regions and development levels. Classification into developed and developing groups follows the World Bank's income classification and the United Nations Development Programme's Human Development Index [24]. Appendix (Table A) presents the sample composition. Data are drawn from multiple sources: Bitcoin trading volumes from Coindance and Blockchain.com; energy and emissions indicators from the International Energy Agency's World Energy Balances database [25]; macroeconomic variables from the World Bank Development Indicators [26]; and institutional quality measures from the Worldwide Governance Indicators [27]. Missing values for two observations (Nigeria 2014 and Ukraine 2022) were addressed using linear interpolation following Rubin [28].

3.2. Variable Definitions

Consistent with SDG7 targets, this study employs four dependent variables capturing different dimensions of energy sustainability. Table 1 summarises all variable definitions and sources.

Table 1. Variable Definitions and Data Sources.

Variable	Symbol	Definition	Source
Dependent Variables			
SDG7 Composite Index	SDG7	Standardized index integrating energy access, renewable share, efficiency, and cooperation	Author calculation using IEA data
Energy Use	Euse	Kilograms of oil equivalent per capita	IEA World Energy Balances
Energy Intensity	Eintensity	Megajoules per constant GDP (2017 PPP)	IEA / World Bank
CO_2 Emissions	lco2	Logarithm of metric tons CO_2 from energy consumption	IEA
Independent Variable			
Bitcoin Trading Volume	lBitcoin	Logarithm of annual transaction value (constant 2014 $)	Coindance, Blockchain.com
Control Variables			
Real GDP	lRGDP	Logarithm real GDP (constant 2015 $)	World Bank WDI
GDP Squared	$(lnGDP)^2$	Square of log real GDP	Author calculation
Population	lPop	Logarithm of total population	World Bank WDI
Bank Branches	FB	Commercial bank branches per 100,000 adults	
Market Capitalization	MCAP	Market capitalization of listed companies (% GDP)	
Domestic Credit	DOMC	Domestic credit to private sector (% GDP)	
Inflation	INF	Annual consumer price inflation (%)	
Unemployment	UNEMP	Unemployment (% of total labor force)	
Internet Users	IUI	Internet users (% of population)	
Electricity Access	ELEC	Access to electricity (% of population)	
Regulatory Quality	RQ	Regulatory quality index (-2.5 to 2.5)	Worldwide Governance Indicators

Source: developed by the authors.

3.2.1. Independent Variable

The primary independent variable is the natural logarithm of annual Bitcoin transaction value in constant 2014 US dollars, adjusted for inflation using World Bank GDP deflators. Trading volume is assigned to countries based on exchange platform currency denominations (e.g., USD for US-based exchanges, EUR for European) and validated against reported volumes with correlation exceeding 0.85 across platforms. We acknowledge that this assignment method may not fully capture peer-to-peer or decentralized exchange activity, particularly in developing economies where such channels may be more prevalent. The logarithmic transformation

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addresses extreme right-skewness (skewness coefficient = 5.23) and enables elasticity interpretation [29].

3.2.2. Control Variables

Following the literature, a comprehensive set of control variables accounts for factors potentially confounding the relationship between Bitcoin trading and energy outcomes. These include economic development indicators (lRGDP, $(\ln GDP)^2$, lPop), financial development measures (MCAP, DOMC, FB), macroeconomic stability indicators (INF, UNEMP), technological infrastructure variables (IUI, ELEC), and institutional quality (RQ).

3.3. Descriptive Statistics

Table 2 presents descriptive statistics for the full sample and subsamples, highlighting significant heterogeneity across country groups.

Table 2. Descriptive Statistics.

Variable	Full Sample Mean	Full Sample Std. Dev.	Developed Mean	Developing Mean
Bitcoin (USD)	2.77×10^{13}	1.64×10^{14}	7.23×10^{8}	5.82×10^{13}
sdg7 (Index)	0.000	1.087	0.542	-0.623
Euse (kg oil eq.)	3,112	1,845	4,187	2,035
Eintensity (MJ/$)	4.154	1.876	3.393	4.915
CO_2 (Mt)	734	1,256	954	513
FB (branches)	24.486	14.782	35.214	13.758
RGDP ($ billion)	2,615	4,925	4,823	408
MCAP (% GDP)	157.645	257.267	234.156	81.134
INF (%)	3.935	5.112	2.184	5.686
UNEMP (%)	6.081	5.843	5.234	6.928
ELEC (%)	96.670	9.610	99.845	93.495
POP (million)	160.4	295.5	45.2	275.6
IUI (%)	76.511	22.221	91.234	71.788
DOMC (% GDP)	118.522	62.853	148.567	88.477
RQ (estimate)	0.874	0.995	1.747	0.090
Observations	210	210	110	100

Source: developed by the authors.

Bitcoin trading volume shows extreme volatility and skewness across years and countries. Notably, developing countries exhibit substantially higher mean Bitcoin trading volume compared to developed countries, suggesting Bitcoin activities may serve as alternatives to formal financial channels in less stable environments. Developing economies also display higher energy intensity (4.915 vs. 3.393 MJ/$), indicating lower energy efficiency per unit output.

Table 3 presents the correlation matrix for key variables, providing initial insights into relationships.

Table 3. Correlation Matrix.

Variable	Bitcoin	SDG7	Euse	lco2	FB	RGDP	MCAP	RQ
Bitcoin	1.000							
sdg7	-0.111	1.000						
Euse	-0.157*	0.488*	1.000					
lco2	-0.061	0.188*	0.345*	1.000				
FB	-0.104	0.031	0.412*	0.053	1.000			
RGDP	-0.079	0.170*	0.245*	0.925*	0.254*	1.000		
MCAP	-0.072	-0.276*	-0.134	-0.098	0.257*	-0.073	1.000	
RQ	-0.212*	0.088	0.456*	0.077	0.860*	0.237*	0.329*	1.000

Note: * indicates statistical significance at $p < 0.05$.
Source: developed by the authors.

Bitcoin trading volume shows statistically significant negative correlations with energy use (-0.157) and regulatory quality (-0.212). CO_2 emissions are highly correlated with real GDP (0.925), confirming economic scale as the primary emissions driver. The strong correlation between RGDP and CO_2 emissions raises multicollinearity concerns, addressed through VIF testing (mean VIF = 3.42, indicating no severe issues).

3.4. Panel Unit Root Tests

Table 4. Panel Unit Root Test Results.

Variable	Fisher-ADF (p)	IPS (p)	LLC (p)	Breitung (p)	Conclusion
lBitcoin	0.007	0.006	0.000	0.004	I(0) Stationary
sdg7	0.839	0.795	0.000	0.982	Mixed → I(1)
lco2	0.986	0.998	0.174	0.981	I(1) Non-stationary
Euse	0.876	0.892	0.234	0.945	I(1) Non-stationary
Eintensity	0.654	0.712	0.045	0.867	Mixed → I(1)
FB	0.000	0.285	0.000	1.000	I(0) Stationary
lRGDP	0.998	0.999	0.444	1.000	I(1) Non-stationary
MCAP	0.000	0.015	0.000	0.076	I(0) Stationary
INF	0.000	0.009	0.000	0.000	I(0) Stationary
UNEMP	0.000	0.025	0.000	0.444	I(0) Stationary
ELEC	0.001	N/A	0.002	0.810	I(0) Stationary
lPop	0.922	1.000	0.000	1.000	Mixed → I(1)
IUI	0.000	0.579	0.000	1.000	I(0) Stationary
DOMC	0.501	0.340	0.000	0.795	Mixed → I(1)
RQ	0.000	0.005	0.000	0.318	I(0) Stationary

Source: developed by the authors.

Table 4 presents panel unit root test results across four specifications to determine variable stationarity.

The main independent variable, Bitcoin trading volume, proves stationary across all four tests, so it will be treated as I(0). This indicates a significant theoretical implication: Bitcoin market activities show evidence of mean-reverting behavior, suggesting that shocks in the market diminish over time without requiring permanent shifts.

Control variables of financial market development (MCAP, FB), macroeconomic stability (INF, UNEMP), technological infrastructure (ELEC, IUI), and institutional quality (RQ) are stationary, providing a stable basis for regression analysis. CO_2 emissions and energy variables are non-stationary (I(1)), consistent with their trending nature over the sample period.

3.5. Econometric Models

3.5.1. Baseline Fixed Effects Model

The Hausman specification test determines whether fixed effects (FE) or random effects (RE) is appropriate (Table 5).

$$Yit=\beta 0+\beta 1\text{lBitcoin}it+\mathbf{X}it'\gamma+\alpha i+\lambda t+\varepsilon it \quad (1)$$

where *Yit* is dependent variable (SDG7, lco2, Euse, or Eintensity) for country i*i* in year t*t*; lBitcoin*it* is log of Bitcoin trading volume (endogenous regressor); **X***it* is vector of exogenous control variables (FB, lRGDP, MCAP, INF, UNEMP, ELEC, lPop, IUI, DOMC); *αi* is country fixed effects (capturing time-invariant unobserved heterogeneity); *λt* is year fixed effects (controlling for global time trends); *εit* is idiosyncratic error term.

Table 5. Hausman Specification Test.

Test	Chi-square Statistic	P-value	Conclusion
Hausman Test (FE vs. RE)	17.306	0.044**	Reject RE in favor of FE

Note: H_0: Random Effects model is consistent. ** $p < 0.05$.
Source: developed by the authors.

The Hausman test rejects the null hypothesis ($\chi^2 = 17.306$, $p = 0.044$), indicating that FE is preferred over RE. The FE specification accounts for time-invariant country-specific unobserved heterogeneity, such as geographic and cultural factors that may influence both cryptocurrency adoption and energy outcomes.

3.5.2. Instrumental Variable Estimation

To address potential endogeneity concerns – including reverse causality where energy constraints might affect trading activity and omitted variable bias – we employ two-stage least squares (2SLS) estimation. Following the literature [15,20], we instrument Bitcoin trading volume using its lagged value and regulatory quality. The lagged instrument captures persistence in trading behavior while being predetermined relative to current emissions.

Regulatory quality is plausibly exogenous to short-term trading fluctuations but affects the institutional environment shaping mining location decisions.
First Stage Equation:

$$lBitcoin_{it}=\pi 0+\pi 1\cdot L\_lBitcoin_{it}+\pi 2\cdot RQ_{it}+X_{it}'\pi 3+v_{it} \tag{2}$$

Second Stage Equation:

$$Yit=\beta 0+\beta 1\cdot l\widehat{Bitcoin}_{it}+Xit'\gamma+\alpha i+\varepsilon it \tag{3}$$

where i indexes countries and $t$indexes years; $Y_{it}$is the dependent variable (e.g., lco2, lEuse, Eintensity, sdg7); $\mathrm{lBitcoin}_{it}$is the log of Bitcoin trading volume (endogenous regressor); $\mathrm{L_lBitcoin}_{it}$is the lagged log of Bitcoin trading volume; $\mathrm{RQ}_{it}$is the Regulatory Quality index; $\mathbf{X}_{it}$is a vector of exogenous control variables: FB, lRGDP, MCAP, INF, UNEMP, ELEC, lPop, IUI, DOMC; $\mathrm{l\widehat{Bitcoin}}_{it}$is the predicted value from the first stage; $\alpha_i$represents country fixed effects; $\varepsilon_{it}$is the idiosyncratic error term.

3.5.3. Threshold Regression Model

To test for potential non-linearities where the effect of Bitcoin trading on emissions may change at different levels of trading activity, we estimate a panel threshold model following Hansen [30]. This approach allows the coefficient on Bitcoin trading volume to differ across regimes defined by the level of trading activity itself.

The threshold model is specified as:

$$Yit= \{ \beta 1L\cdot lBitcoinit+\gamma LXit+\mu i+\lambda t+\varepsilon it, \text{ if } lBitcoinit \leq \tau\} \tag{4}$$

$$\{ \beta 1H\cdot lBitcoinit+\gamma HXit+\mu i+\lambda t+\varepsilon it, \text{ if } lBitcoinit > \tau\} \tag{5}$$

Where $\beta 1L$ and $\beta 1H$ are the regime-specific coefficients on Bitcoin trading volume; τ is the threshold parameter estimated from the data; μi denotes country fixed effects; λt denotes year fixed effects (controlling for global time trends such as crypto market cycles and energy price volatility); εit is the idiosyncratic error term. The significance of the threshold effect is assessed using bootstrap methods with 1,000 replications.

For CO_2 model:

$$lnCO_2,it= \{\beta 1LlnBitcoinit+\gamma L\mathbf{X}it+\mu i+\lambda t+\varepsilon it, \text{ if } lnBitcoinit\leq\tau i\} \tag{6}$$

$$lnCO_2,it= \{\beta 1HlnBitcoinit+\gamma H\mathbf{X}it+\mu i+\lambda t+\varepsilon it, \text{ if } lnBitcoinit>\tau\} \tag{7}$$

where $\beta_{1L}$and $\beta_{1H}$are the regime-specific coefficients on Bitcoin trading volume, $\mathbf{X}_{it}$is a vector of time-varying control variables: lnGDPit, (lnGDPit)2, broadband, market cap, inflation, unemployment, internet users, domestic credit, and regulatory quality; μi denotes country fixed effects (capturing time-invariant unobserved heterogeneity); $\lambda_t$denotes year fixed effects (controlling for global time trends such as crypto market cycles, pandemic shocks, and energy price volatility); $\varepsilon_{it}$is the idiosyncratic error term, assumed to be independently distributed with mean zero and finite variance.

4. Results

This section presents the empirical results, proceeding from baseline fixed effects estimations through instrumental variable robustness checks to threshold regression findings, with particular attention to developmental asymmetry and nonlinear effects.

4.1. Baseline Fixed Effects Results

Table 6 presents the fixed effects estimation results for the full sample and split samples by development status.

Table 6. Fixed Effects Results – SDG7 Composite Index.

Variable	Full Sample	Developing Economies	Developed Economies
lBitcoin	-0.0153**	-0.0153**	0.00951
	(0.00698)	(0.00698)	(0.0134)
FB	-0.0297***	-0.0297***	-0.0345***
	(0.00402)	(0.00402)	(0.00939)
lRGDP	0.320	0.320	0.579
	(0.237)	(0.237)	(0.479)
MCAP	0.00175***	0.00175***	-0.000179
	(0.000591)	(0.000591)	(0.000155)
INF	0.00352	0.00352	-0.0136
	(0.00273)	(0.00273)	(0.00865)
UNEMP	-0.00166	-0.00166	0.000318
	(0.00839)	(0.00839)	(0.0185)
ELEC	-0.0228***	-0.0228***	4.250***
	(0.00769)	(0.00769)	(0.928)
lPop	1.081**	1.081**	-1.735**
	(0.479)	(0.479)	(0.735)
IUI	0.000322	0.000322	-0.000901
	(0.00144)	(0.00144)	(0.00404)
DOMC	0.00519***	0.00519***	0.000356
	(0.00144)	(0.00144)	(0.00166)
RQ	0.00253	0.00253	0.000365
	(0.120)	(0.120)	(0.0964)
Observations	210	210	210
R^2 (within)	0.584	0.584	0.612

Note: Standard errors in parentheses: *** $p < 0.01$, ** $p < 0.05$. Country and year fixed effects included. Robust standard errors reported.
Source: developed by the authors.

The results reveal notable developmental asymmetry. In developing economies, a one percent increase in Bitcoin trading volume is associated with a 0.0153 percent decrease in the SDG7 composite index, statistically significant at conventional levels ($p < 0.05$). This finding supports H1 and H5, confirming that Bitcoin trading activity significantly impedes progress toward affordable and clean energy goals in developing countries. Conversely, the coefficient for developed economies is positive but statistically insignificant, indicating no measurable impact. This finding challenges the homogeneous treatment of cryptocurrency's environmental impact prevalent in existing literature [9,12], demonstrating that institutional context fundamentally mediates the relationship between digital finance and sustainability outcomes. It also provides empirical support for extending Environmental Kuznets Curve theory to cryptocurrency markets, confirming that developmental thresholds condition environmental vulnerability [22,14].

4.2. Transmission Mechanism Analysis

To understand how Bitcoin trading affects SDG7 progress, Table 7 presents fixed effects results for the component indicators: energy use (Euse), energy intensity (Eintensity), and CO_2 emissions (lco2) for developing economies.

Table 7. Transmission Mechanism Results – Developing Economies.

Variable	Energy Use (Euse)	Energy Intensity (Eintensity)	CO_2 Emissions (lco2)
lBitcoin	0.00842	0.0113	0.0247***
	(0.00921)	(0.00894)	(0.00583)
Controls	Yes	Yes	Yes
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	100	100	100
R^2 (within)	0.512	0.487	0.643

Note: Standard errors in parentheses: *** $p < 0.01$.
Source: developed by the authors.

The results provide evidence regarding transmission channels. Bitcoin trading volume has no statistically significant effect on aggregate energy use or energy intensity in developing economies. However, it exhibits a strong positive and significant effect on CO_2 emissions (coefficient = 0.0247, $p < 0.01$), indicating that a one percent increase in trading volume is associated with approximately a 2.47 percent increase in carbon emissions.

This pattern supports H3c while rejecting H3a and H3b. The transmission mechanism operates through the electricity generation mix rather than through aggregate consumption or efficiency changes. When trading volume surges during periods of intense market activity, mining demand increases pressure on electricity grids. In developing economies with carbon-intensive generation portfolios, this demand is met by activating fossil fuel power plants, particularly coal and natural gas peaker plants, which increases emissions per unit of electricity generated. The finding that energy use and intensity remain unchanged while emissions rise indicates a compositional shift toward more carbon-intensive sources.

4.3. Instrumental Variable Results

To address potential endogeneity concerns, Table 8 presents two-stage least squares (2SLS) estimation results using lagged Bitcoin volume and regulatory quality as instruments.

Table 8. 2SLS Second Stage Results – Developing Economies.

Variable	SDG7 Index	CO_2 Emissions
lBitcoin (instrumented)	0.0122	0.0144
	(0.00818)	(0.00877)
Controls	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes
Observations	90	90
First-stage F-statistic	24.63***	24.63***

Note: Standard errors in parentheses: *** $p < 0.01$. Instruments: lagged Bitcoin volume and regulatory quality.
Source: developed by the authors.

The first-stage F-statistic (24.63) exceeds the Stock and Yogo [31] critical value, confirming instrument relevance. Notably, the second-stage coefficients for instrumented Bitcoin volume are statistically insignificant, contrasting with the significant fixed effects results. This apparent discrepancy suggests that the relationship identified in fixed effects estimation may be heterogeneous. A plausible interpretation – and the one supported by subsequent threshold analysis – is that the 2SLS estimator averages over heterogeneous effects, obscuring nonlinearities. Linear instrumental variable estimation imposes a constant treatment effect, but if Bitcoin's environmental impact materializes only during high-volume regimes, averaging across low- and high-volume periods will attenuate estimates toward zero.

4.4. Threshold Regression Results

Table 9. Threshold Regression Results.

Variable	Full Sample SDG7	Developing SDG7	Developed SDG7
bit_low	0.000	0.000	0.000
	(0.092)	(0.630)	(0.176)
bit_high	0.000	-0.015**	0.000
	(0.152)	(0.031)	(0.275)
Threshold τ	28.4 trillion USD	28.4 trillion USD	28.4 trillion USD
Bootstrap p-value	0.043**	0.038**	0.421

Note: P-values in parentheses. ** $p < 0.05$.
Source: developed by the authors.

Table 9 presents threshold regression results testing for nonlinear effects in the relationship between Bitcoin trading volume and environmental outcomes.

The threshold regression reveals that the negative impact of Bitcoin trading on SDG7 progress in developing economies is concentrated exclusively in high-volume regimes exceeding approximately $28.4 trillion in annual trading volume. In low-volume regimes, the coefficient is statistically indistinguishable from zero. For developed economies, neither regime exhibits significant effects. This finding provides strong support for H2 (nonlinear threshold effects). It explains the apparent discrepancy between fixed effects and 2SLS results: linear models average over low-volume periods with no effect and high-volume periods with substantial effects, diluting the true impact to statistical insignificance. The identification of a critical threshold provides policymakers with an actionable target for intervention.

4.5. Robustness Checks

The threshold finding remains significant after clustering standard errors at the country level ($t = 12.43$, $p < 0.001$), confirming robustness to within-country correlation. Variance inflation factors (mean VIF = 3.42, maximum VIF = 4.87) indicate no severe multicollinearity. Alternative lag structures for instrumental variables (one-year and two-year lags) produce consistent first-stage F-statistics above critical values.

5. Discussion and Limitations

This section interprets and contextualizes the results in relation to the research question and previous studies, explaining the meaning and implications of the findings while acknowledging study limitations.

5.1. Interpretation of Findings

The results of this study demonstrate that Bitcoin's environmental impact is neither uniform nor linear but conditional on developmental context and trading intensity. This finding challenges the homogeneous treatment prevalent in existing studies [9,12] and extends the Environmental Kuznets Curve framework to digital finance, showing that institutional capacity mediates the relationship between financial innovation and environmental outcomes [22,23].

The identification of the electricity generation mix as the primary transmission channel resolves a key ambiguity in the literature. Previous studies debated whether cryptocurrency affects energy systems through aggregate consumption [3], efficiency [14], or generation composition [18]. Our results are consistent with the generation mix channel, with important policy implications: interventions should target the carbon intensity of mining energy sources rather than attempting to cap aggregate consumption or mandate efficiency improvements.

The establishment of a critical trading volume threshold (approximately $28.4 trillion annually) beyond which environmental damage accelerates provides a scientific basis for volume-dependent policy interventions. This nonlinearity explains why previous linear estimates produced inconsistent results [8,20] and corresponds to observable market conditions where marginal mining operations become profitable during speculative bubbles, triggering the environmental damage cascade.

5.2. Comparison with Previous Studies

Our findings align with Huynh et al. [15] who attributed cross-country differences in cryptocurrency impacts to variation in regulatory quality and institutional capacity. They also support Bublyk, Borzenko, and Hlazova [18] who demonstrated that environmental intensity varies substantially depending on the electricity generation mix of mining locations.
The developmental asymmetry documented in this study is consistent with Oğuz [20] who found that the marginal environmental impact of trading is substantially larger in lower-income countries. However, our results extend this literature by identifying the specific mechanism (generation mix) and nonlinear threshold at which damage materializes, providing more precise guidance for policy design.

The insignificant effects in developed economies contrast with some studies that predicted universal environmental impacts [10,11]. This divergence suggests that resilient energy infrastructure, robust regulatory frameworks, and cleaner generation portfolios in developed economies may effectively absorb demand fluctuations without compromising sustainability goals.

5.3. Limitations

This study has several limitations that should be acknowledged. First, the analysis aggregates Bitcoin trading volume at the country level, potentially obscuring subnational variation. Mining operations often concentrate in specific regions with cheap electricity, and subnational data could reveal localized environmental impacts not captured in national averages.

Second, the allocation of trading volume based on exchange denomination may introduce measurement bias, particularly in developing economies where peer-to-peer and decentralized exchange activity may be more prevalent. While we validated volumes against multiple sources, this remains a limitation.

Third, the sample period ends in 2023, predating potential effects of Ethereum's transition to proof-of-stake and emerging regulatory frameworks. Future research should examine whether alternative consensus mechanisms reduce environmental vulnerability.

Fourth, the study focuses exclusively on Bitcoin, leaving open questions about other cryptocurrencies. Given that Gallersdörfer et al. [7] found the cryptocurrency sector's energy footprint is 50% larger than Bitcoin alone, extending analysis to other coins is essential.

Fifth, while this study identifies the generation mix as the transmission mechanism, data limitations prevent direct observation of mining electricity sourcing. Future research could employ granular grid emissions data to trace the causal chain from trading volume to mining activity to generation composition to emissions.

Sixth, the institutional mediation findings suggest the need for deeper investigation into which specific institutional characteristics—regulatory quality, enforcement capacity, grid resilience, renewable energy penetration—are most important for mitigating environmental damage.

5.4. Implications

The findings carry significant implications for policy design. First, the developmental asymmetry documented in this study indicates that blanket regulations applied uniformly across countries are likely to be ineffective. Developing economies require targeted interventions addressing their specific vulnerabilities, while developed economies may need minimal additional regulation.

Second, the identification of the electricity generation mix as the primary transmission channel suggests that policies should focus on the carbon intensity of mining energy sources rather than aggregate consumption caps or efficiency mandates. Requiring mining operations to source renewable energy, either through direct procurement or renewable energy certificates, would directly address the mechanism driving environmental damage.

Third, the nonlinear threshold effect supports implementation of volume-dependent dynamic policies. Carbon pricing mechanisms could be calibrated to trading activity, with rates increasing when volume exceeds the $28.4 trillion threshold. This approach would internalize environmental externalities during precisely the periods when they materialize, without imposing unnecessary costs during low-volume regimes.

Fourth, mandatory mining registries requiring operators to disclose electricity consumption, energy sources, and estimated emissions would provide the transparency necessary for effective regulation. Noncompliance penalties should be sufficiently stringent to ensure participation.

Fifth, international coordination is essential to prevent regulatory arbitrage. Without coordinated action, mining operations may relocate to jurisdictions with weakest environmental enforcement, concentrating environmental damage in precisely those developing economies least equipped to manage it.

6. Conclusions and Future Directions

This study investigated the impact of Bitcoin trading volume on progress toward Sustainable Development Goal 7 (affordable and clean energy) across developed and developing economies from 2014 to 2023. Employing fixed-effects models, instrumental variable estimation, and threshold regression on a balanced panel of 21 countries, the research yields several novel findings with significant implications for economic theory, policy design, and future research.

6.1. Principal Findings

The empirical analysis reveals four main conclusions. First, Bitcoin trading volume significantly impedes SDG7 progress in developing economies, with a one percent increase in trading volume associated with a 0.0153 percent reduction in the SDG7 composite index. No significant effect is observed in developed economies, confirming developmental asymmetry (H1, H5).

Second, the transmission mechanism operates through the electricity generation mix rather than aggregate energy consumption or efficiency improvements. Bitcoin trading is associated with increased CO_2 emissions in developing economies while leaving energy use and energy intensity unchanged, indicating a shift toward more carbon-intensive generation sources to meet mining demand (H3c).

Third, the relationship exhibits nonlinear threshold effects, with environmental deterioration concentrated exclusively in high-volume regimes exceeding approximately $28.4 trillion in annual trading volume. In low-volume regimes, no significant effects are detected (H2).

Fourth, institutional quality appears to mediate these effects, with developed economies' resilient infrastructure and strong regulatory frameworks potentially insulating them from Bitcoin-related environmental damage (H4).

6.2. Contributions to the Literature

This study makes several contributions to the economic literature. First, it provides a systematic empirical test of developmental asymmetry in cryptocurrency's environmental impact, extending Environmental Kuznets Curve theory to digital finance [22,23]. Second, it identifies and empirically validates the transmission mechanism, resolving ambiguity in previous research about how trading activity translates into environmental outcomes [3,14,18]. Third, it establishes the existence of nonlinear threshold effects, explaining discrepancies in previous linear estimates and providing a scientific basis for volume-dependent policy interventions [8,20]. Fourth, it demonstrates the importance of institutional context in conditioning environmental vulnerability, supporting institutional mediation theory [15].

6.3. Policy Implications

The findings support implementation of context-sensitive, dynamically calibrated policy interventions. Developing economies should consider volume-dependent carbon pricing mechanisms that activate when trading exceeds critical thresholds, mandatory renewable energy sourcing requirements for mining operations, and mining registries ensuring transparency. International coordination is essential to prevent regulatory arbitrage and ensure that the pursuit of digital financial progress does not come at the expense of environmental justice and climate stability.

6.4. Future Research Directions

Future research should employ subnational data to examine localized environmental impacts of mining concentrations. Extended analysis beyond Bitcoin to include other cryptocurrencies is essential given the sector's aggregate energy footprint. Granular grid emissions data could trace the causal chain from trading volume to mining activity to generation composition to emissions more precisely. Deeper investigation into which specific institutional characteristics are most important for mitigating environmental damage would inform targeted institutional reforms.

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Finally, as Ethereum and other cryptocurrencies transition to proof-of-stake, examining whether alternative consensus mechanisms reduce environmental vulnerability represents a critical research frontier.

6.5. Concluding Remarks

This study demonstrates that Bitcoin's environmental impact is neither uniform nor inevitable but conditional on developmental context and trading intensity. The same technology that leaves developed economies unscathed is associated with significant environmental costs in developing countries during periods of intense market activity, operating through carbon-intensive electricity generation. These findings challenge assumptions of homogeneous externalities in digital finance and underscore the need for context-sensitive, dynamically calibrated policy interventions. As cryptocurrency markets continue to evolve and expand, aligning financial innovation with global sustainability objectives requires rigorous evidence, targeted regulation, and international cooperation.

Statements and Declarations

Author Contributions: Conceptualisation: D.M.S., S.M., and I.A.; Methodology: D.M.S. and I.A.; Software: S.M.; Validation: D.M.S., S.M., and I.A.; Formal analysis: I.A.; Investigation: S.M.; Resources: D.M.S.; Data curation: S.M.; Writing – original draft preparation: S.M.; Writing – review and editing: D.M.S. and I.A.; Visualization: S.M.; Supervision: D.M.S.; Project administration: D.M.S. All authors have read and approved the final version of the manuscript.

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Appendix A.

Table A. Sample Composition by Development Status.

Developed Economies (11)	Developing Economies (10)
Switzerland	Brazil
United States	Philippines
Hong Kong SAR (China)	Mexico
Australia	Nigeria
Japan	United Arab Emirates
New Zealand	Thailand
Singapore	India

Denmark	South Africa
United Kingdom	Vietnam
Canada	Ukraine
European Union (aggregated)	

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