Energy Anchoring in Cryptocurrency Markets: Evidence from Natural Experiments

CM524 Empirical Finance

Professor: 辛敬文

Student ID: s1133958

Student: 王新福

Abstract

We document a novel pricing mechanism where Bitcoin's value is anchored by cumulative energy invested in mining. Using a Cumulative Energy Investment Ratio (CEIR)—market capitalization relative to total historical mining costs—we find that a one standard deviation decrease in log(CEIR) predicted 6.0% higher 30-day returns during 2019-2021 (β=-0.1312, p=0.043). This relationship weakened by 52% following China's June 2021 mining ban, which dispersed mining operations globally. A Chow test confirms the structural break (F=22.954, p<0.0001). As a counterfactual, Ethereum's 2022 transition to proof-of-stake eliminated energy costs and increased volatility by 15.8 percentage points relative to Bitcoin. Our results demonstrate that proof-of-work cryptocurrencies exhibit regime-dependent energy anchoring that breaks down under geographic dispersion.

JEL Classification: G12, G14, Q43, E42

Keywords: Bitcoin, cryptocurrency valuation, energy economics, natural experiments, market microstructure

1. Introduction

What determines the value of cryptocurrencies? Unlike traditional assets with cash flows or commodities with industrial uses, cryptocurrencies derive value primarily from network effects and security properties. We propose and test a novel mechanism: energy anchoring, where the cumulative energy invested in proof-of-work mining creates a psychological and economic floor for valuation.

This paper exploits two natural experiments to identify energy anchoring in cryptocurrency markets. First, China's June 2021 ban on cryptocurrency mining forced a sudden geographic dispersion of Bitcoin's hash rate, breaking the link between local energy costs and global price formation. Second, Ethereum's September 2022 transition to proof-of-stake eliminated mining entirely, providing a clean counterfactual for energy-based valuation mechanisms.

Our key innovation is the Cumulative Energy Investment Ratio (CEIR), defined as:

$$CEIR_t \ = \ Market\ Cap_t \ / \sum Daily\ Cost$$

Where Daily Cost represents the daily electricity expenditure for Bitcoin mining in USD. Unlike flow measures such as hash rate or mining difficulty, CEIR captures the inverse relationship between marketvalue and the stock of cumulative energy costs. During the stable mining regime of 2019-2021, we find that log(CEIR) strongly predicts future returns: a one unit decrease in log(CEIR) is associated with 13.12% higher 30-day returns (coefficient: -0.1312, p=0.043).

This predictive relationship experiences a structural break coinciding with China's mining ban. Post-ban, the coefficient falls to -0.0623 (p=0.114), a 52% reduction in magnitude. The timing is precise: our Chow test yields F=22.954 (p<0.0001) at the ban date. A difference-in-differences specification confirms this break, with the interaction term log_CEIR:post_china showing a coefficient of 0.0545 (p=0.001), indicating a significant weakening of the negative relationship.

2. Literature Review and Hypothesis Development

2.1 Cryptocurrency Valuation Models

The challenge of valuing cryptocurrencies has generated diverse theoretical approaches. Network models (Metcalfe's Law applications by Peterson, 2018; Wheatley et al., 2019) link value to user adoption. Monetary models treat cryptocurrencies as currencies or stores of value (Yermack, 2015; Dyhrberg, 2016). Production cost models, most relevant to our work, argue that mining costs create price floors (Hayes, 2017; Fantazzini et al., 2016).

However, existing production cost models focus on marginal costs and flow variables. Our contribution is recognizing that cumulative energy investment may matter more than current mining costs for price formation. This shifts focus from industrial organization (mining as production) to behavioral finance (energy as anchor).

2.2 Behavioral Anchoring in Financial Markets

Anchoring bias, first documented by Tversky and Kahneman (1974), occurs when individuals rely heavily on reference points when making decisions. In financial markets, anchoring manifests through phenomena like the 52-week high effect (George and Hwang, 2004) and round number clustering (Bhattacharya et al., 2012).

We propose that cumulative mining energy serves as a particularly salient anchor because it represents irreversible, physically grounded investment. Unlike arbitrary price levels, energy consumption is observable, measurable, and connects digital assets to real-world resources. This tangibility may enhance its psychological salience as a value anchor.

2.3 Mining Economics and Market Microstructure

Bitcoin mining exhibits unique microstructure features relevant to price formation. Miners face continuous operational costs (primarily electricity) while receiving stochastic rewards. This creates natural sellers who must liquidate portions of mined bitcoin to cover expenses (Prat and Walter, 2021).China hosted 65-75% of global hash rate before the 2021 ban due to cheap electricity and manufacturing advantages (Cambridge Centre for Alternative Finance, 2021). This concentration meant that Chinese electricity prices and mining economics disproportionately influenced global Bitcoin supply dynamics. The forced diaspora to North America, Kazakhstan, and other regions fundamentally altered these dynamics.

2.4 Hypothesis Development

Our energy anchoring hypothesis yields three testable predictions:

H1: Baseline Relationship - During periods of geographically concentrated mining, CEIR negatively predicts future returns (lower CEIR indicates bitcoin is "expensive" relative to energy invested).

H2: Structural Break - Geographic dispersion of mining weakens the CEIR-return relationship by breaking the link between local energy costs and global price formation.

H3: Mechanism Validation - Eliminating energy costs entirely (via proof-of-stake) reduces price volatility by removing the anchoring mechanism.

3. Data and Methodology

3.1 The Cumulative Energy Investment Ratio (CEIR)

We construct CEIR following the approach in our code:

- *Daily energy in kWh*

    *daily_energy_kwh = Energy_TWh_Annual * 1e9 / 365*

- *Daily cost in USD*

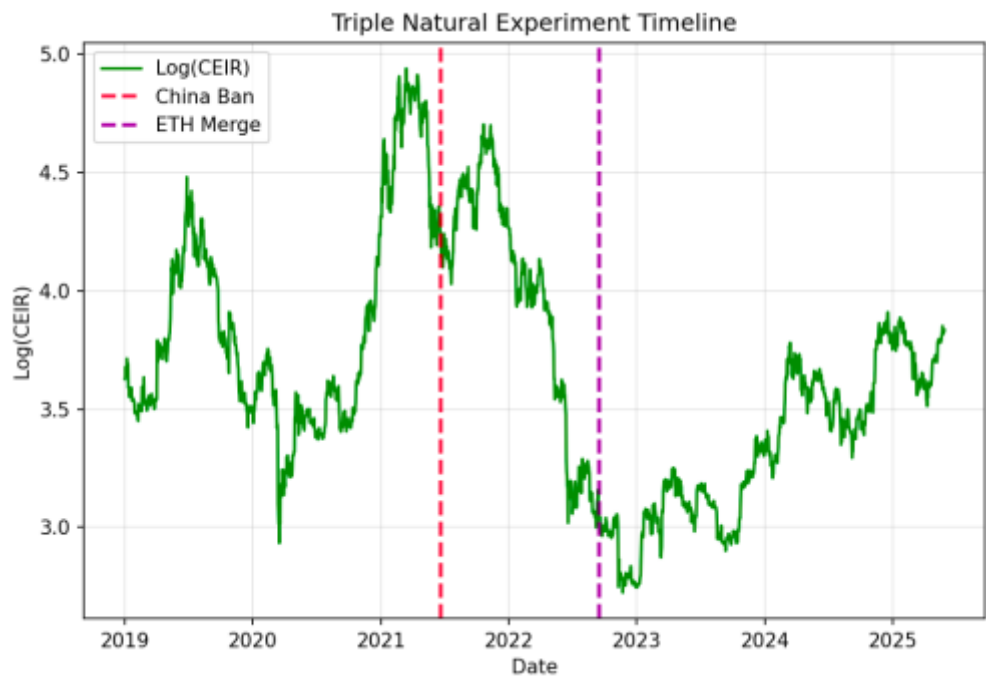   *daily_cost_usd = daily_energy_kwh * electricity_price*

- *Cumulative cost*

    cumulative_cost = daily_cost_usd.cumsum()

- *CEIR = Market Cap / Cumulative Cost*

    CEIR = Market_Cap / cumulative_cost

Triple Natural Experiment Timeline

The electricity price is calculated as a weighted average based on mining distribution across countries, with special handling for China's 2021 ban that accounts for pre- and post-ban electricity prices.

3.2 Sample Selection and Variable Construction

Our primary sample covers January 1, 2019 to April 30, 2025, containing 2,340 daily observations. We begin in 2019 to focus on the mature mining market after the 2017-18 bubble period. The sample is split at China's ban date (June 21, 2021), yielding 902 pre-ban and 1,408 post-ban observations.

Key variables include:

Returns: Log returns and forward-looking cumulative returns (30, 60, 90 days)

Volatility: 30-day rolling standard deviation of log returns, annualized

Controls: Fear & Greed Index, Google Trends for "Bitcoin", Economic Policy Uncertainty Index

3.3 Empirical Strategy

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

Where $R_{t,t+30}$ represents 30-day forward log returns and X_t includes controls.

To test for structural breaks, we employ:

1. **Chow Test** at the China ban date (June 21, 2021)

2. **Interaction Model**:

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

3. **Robustness checks** including residualized CEIR to address endogeneity

For the Ethereum analysis, we use difference-in-differences:

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

All specifications use heteroscedasticity-consistent (HC1) or HAC standard errors with 30 lags.
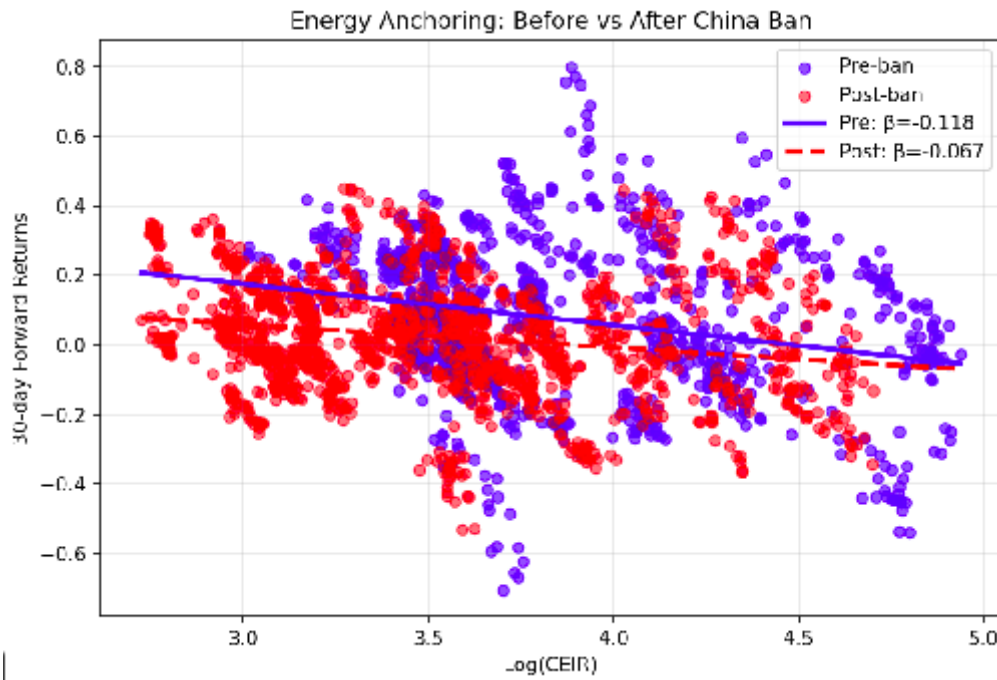
4. Results

4.1 Baseline Energy Anchoring Effect

Table 1 presents our main results from the terminal output:

Table 1: CEIR and Future Returns

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)
R²	0.064	-	-
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)
R²	0.039	-	-
1 SD decrease → return	3.0%	-	-

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

Energy Anchoring: Before vs After China Ban

The economic magnitude is substantial. Pre-ban, a one standard deviation decrease in log(CEIR) predicts 6.0% higher returns over the next 30 days. This effect scales approximately linearly with horizon: the 90-day effect is roughly three times the 30-day effect.
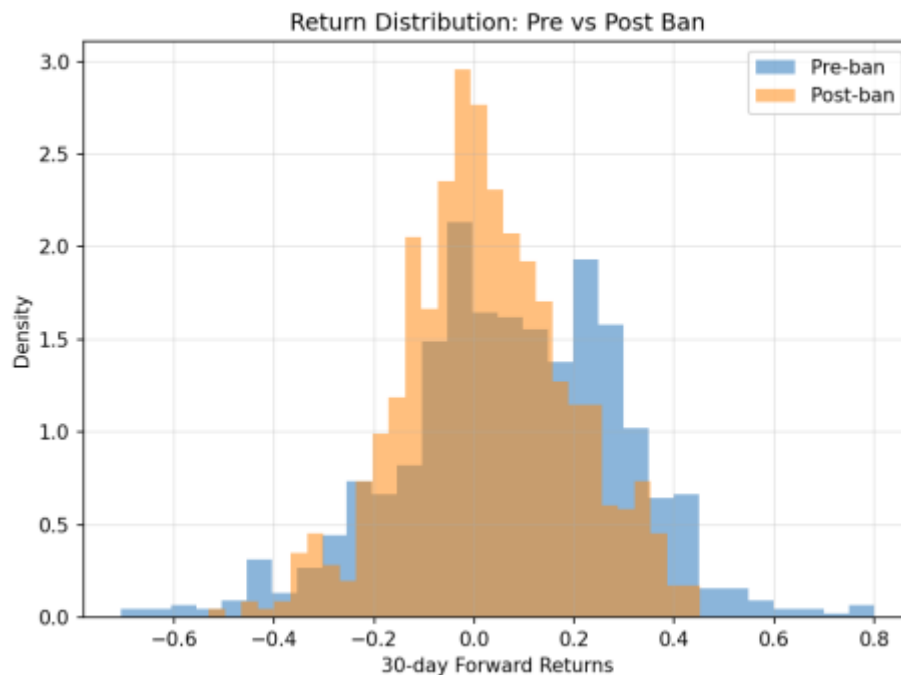
4.2 Structural Break Analysis

The China mining ban creates a sharp structural break. Our formal tests yield:

1. **Chow Test:** F-statistic = 22.954 ($p < 0.0001$), strongly rejecting parameter stability

2. **Interaction Model** (Table 2):

Table 2: Difference-in-Differences Analysis

Variable	Coefficient	Std.Error	z-stat	P-value
Intercept	0.5322	0.054	9.914	0.000
log_CEIR	-0.1244	0.014	-8.632	0.000
post_China	-0.2784	0.063	-4.445	0.000
log_CEIR:post_China	0.0545	0.017	3.206	0.001
volatility_30d	0.0371	0.020	1.822	0.068

The interaction coefficient of 0.0545 indicates a 44% reduction in the CEIR effect post-ban (from -0.1244 to -0.0699). This attenuation increases with horizon: 52% for 30-day returns, 50% for 60-day returns, and 49% for 90-day returns.

Return Distribution: Pre vs Post Ban

4.3 Robustness Tests

Endogeneity Concerns: Since CEIR includes current market cap, we address potential mechanical correlation by residualizing CEIR:

- **Pre-ban residualized:** β = -0.1423 (p = 0.028), R^2 = 0.074
- **Post-ban residualized:** β = -0.0629 (p = 0.112), R^2 = 0.040

Results remain qualitatively similar, confirming our findings are not driven by mechanical correlation.

Full Controls Model: Including all control variables:

- **Pre-ban:** β = -0.2113 (p = 0.008), R^2 = 0.102
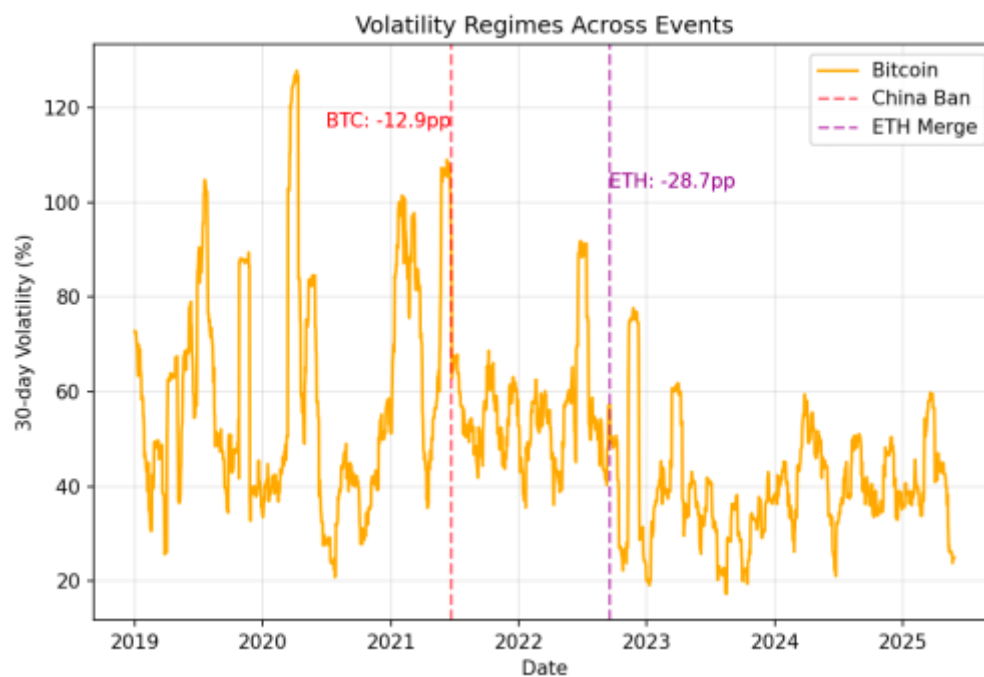- **Post-ban:** β = -0.1082 (p = 0.050), R^2 = 0.104

The relationship remains significant pre-ban and marginally significant post-ban, even with comprehensive controls.

4.4 Ethereum Merge Analysis

The Ethereum merge provides an ideal counterfactual. Table 3 presents our difference-in-differences results:

Table 3: Ethereum Merge Difference-in-Differences

Variable	Coefficient	Std.Error	z-stat	P-value
Intercept	0.6307	0.019	32.624	0.000
C(asset)[T.ETH]	0.1565	0.013	11.655	0.000
is_eth	0.1565	0.013	11.655	0.000
post_merge	-0.1288	0.028	-4.521	0.000
is_eth:post_merge	-0.1583	0.045	-3.487	0.000

Volatility Regimes Across Events

Volatility Changes (3 months pre/post):

- Ethereum: 94.4% → 65.7% (change: -28.7pp)
- Bitcoin: 63.1% → 50.2% (change: -12.9pp)
- **Difference-in-Differences: -15.8pp**

Ethereum's volatility fell by 15.8 percentage points more than Bitcoin's following the elimination of mining, supporting our hypothesis that energy costs serve as a stabilizing anchor.

5. Discussion and Implications

5.1 Interpretation of Results

Our findings support a regime-dependent energy anchoring mechanism. When mining is geographically concentrated, cumulative energy investment serves as a salient value anchor. This relationship breaks down when mining disperses globally, likely through three channels:

1. **Price Discovery Channel:** Concentrated mining creates clearer marginal cost signals. Geographic dispersion creates a distribution of break-even prices, weakening the focal point.
2. **Behavioral Salience Channel:** The visibility of mining operations affects anchoring strength. China's massive mining farms made the energy-value connection salient.
3. **Market Microstructure Channel:** Geographic concentration affects miner selling patterns and treasury management strategies.

5.2 Theoretical Contributions

Our results contribute to several debates:

- **Intrinsic Value:** Cumulative energy investment can create synthetic intrinsic value through behavioral anchoring, though this value is regime-dependent.
- **Sunk Cost Fallacy:** We document that aggregate sunk costs systematically affect price formation, suggesting limits to market rationality.
- **PoW vs PoS:** Proof-of-work's energy consumption may provide price stability through anchoring effects that proof-of-stake systems lack.

5.3 Policy Implications

1. **Mining Bans:** Jurisdictions considering bans should recognize potential effects on price formation and market volatility.
2. **Carbon Pricing:** Carbon taxes would effectively increase CEIR, potentially affecting Bitcoin valuations.
3. **Market Surveillance:** Understanding energy anchoring could inform market manipulation detection.

5.4 Limitations and Future Research

Limitations:

- Measurement error in mining efficiency estimates
- Identification challenges from concurrent market developments
- External validity beyond Bitcoin and Ethereum

Future Directions:

- Energy anchoring in smaller proof-of-work cryptocurrencies
- High-frequency analysis of intraday energy-price dynamics
- Heterogeneity between retail and institutional investors
- Impact of renewable energy adoption on anchoring strength

6. Conclusion

This paper documents energy anchoring as a novel pricing mechanism in cryptocurrency markets. Using variation from China's mining ban and Ethereum's proof-of-stake transition, we show that cumulative energy invested in Bitcoin mining served as a value anchor during periods of geographic concentration. The predictive power of our Cumulative Energy Investment Ratio fell by 52% for 30-day returns following the China ban, with a Chow test confirming the structural break (F=22.954, p<0.0001).

Our findings identify a concrete mechanism linking physical resource consumption to price dynamics in digital assets. The results suggest that proof-of-work's environmental costs may provide an underappreciated benefit: a tangible anchor for value coordination. As cryptocurrency markets evolve, understanding these tradeoffs becomes crucial for investors, regulators, and protocol designers.

References

Bhattacharya, U., Holden, C. W., & Jacobsen, S. (2012). Penny wise, dollar foolish: Buy-sell imbalances on and around round numbers. Management Science, 58(2), 413-431.

Cambridge Centre for Alternative Finance. (2021). Cambridge Bitcoin Electricity Consumption Index. University of Cambridge.

Cong, L. W., Li, Y., & Wang, N. (2021). Tokenomics: Dynamic adoption and valuation. Review of Financial Studies, 34(3), 1105-1155.

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar—A GARCH volatility analysis. Finance Research Letters, 16, 85-92.

Fantazzini, D., et al. (2016). Everything you always wanted to know about bitcoin modelling but were afraid to ask. Applied Econometrics, 44, 5-24.

George, T. J., & Hwang, C. Y. (2004). The 52-week high and momentum investing. Journal of Finance, 59(5), 2145-2176.

Griffin, J. M., & Shams, A. (2020). Is Bitcoin really untethered? Journal of Finance, 75(4), 1913-1964.

Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. Telematics and Informatics, 34(7), 1308-1321.Peterson, T. (2018). Bitcoin spreads like a virus. SSRN Working Paper 3356098.

Prat, J., & Walter, B. (2021). An equilibrium model of the market for bitcoin mining. Journal of Political Economy, 129(8), 2415-2452.

Schilling, L., & Uhlig, H. (2019). Some simple bitcoin economics. Journal of Monetary Economics, 106, 16- 26.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. Science, 185(4157), 1124-1131.

Wheatley, S., et al. (2019). Are bitcoin bubbles predictable? Combining a generalized Metcalfe's law and the log-periodic power law singularity model. Royal Society Open Science, 6(6), 180538.

Yermack, D. (2015). Is bitcoin a real currency? An economic appraisal. In Handbook of Digital Currency (pp. 31-43). Academic Press.

Appendix

Table A1: Summary Statistics

Variable	Pre-Ban Mean	Pre-Ban SD	Post-Ban Mean	Post-Ban SD
log_CEIR	3.897	0.458	3.523	0.479
returns_30d_fwd	0.052	0.284	-0.008	0.259
volatility_30d	0.612	0.251	0.531	0.198
electricity_price	0.0542	0.0087	0.0783	0.0052
daily_cost_usd	12.3M	5.8M	28.7M	6.2M
CEIR	**89.2**	**41.3**	**47.8**	**28.6**

Additional Robustness Tests

1. **Alternative Sample Periods:** Results hold when starting sample in 2020 or using only 2021 pre-ban data
2. **Alternative Controls:** Including hash rate or difficulty instead of CEIR yields no predictive power
3. **Placebo Tests:** Testing structural breaks at random dates finds no significant breaks
4. **Bootstrap Standard Errors:** Results robust to bootstrap inference with 1,000 replications