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Bitcoin Price Volatility, Mining Load Instability, and Demand Response Implications for U.S. Grid Operators

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ABSTRACT

The rapid growth of Bitcoin mining has created a new class of large, financially driven electricity consumers whose demand responds to cryptocurrency markets rather than fixed production schedules, raising concerns for grid planning and demand response design. This study examines whether Bitcoin price volatility is associated with less stable mining incentives and whether mining-related instability reduces the predictability of aggregate electricity demand. Using monthly data from January 2021 to November 2025 for Texas, the analysis combines Bitcoin price, hash price, electricity demand, temperature, and heating degree day data in reduced-form ordinary least squares regressions. Bitcoin price volatility is measured as the absolute monthly percentage change in Bitcoin prices. Mining load instability is proxied by the absolute monthly percentage change in Bitcoin hash price, while grid instability is measured using monthly variability in a state-level electricity demand proxy. The results show that Bitcoin price volatility is significantly associated with mining load instability, with a one percentage point increase in price volatility corresponding to an increase of approximately 2.5 units in the mining instability proxy. In contrast, mining load instability is not statistically significant in explaining aggregate electricity demand variability at the monthly, system-wide planning horizon. These findings suggest that mining-related risks may be masked at coarse time scales and require higher-frequency operational data for direct reliability assessment.

Keywords: Bitcoin mining; electricity demand; grid reliability; demand response; ERCOT; cryptocurrency volatility; hash price; energy economics

INTRODUCTION

Bitcoin mining has introduced a large, electricity-intensive, and financially driven source of demand into modern power systems. Because proof-of-work mining relies on continuous computation, mining facilities can consume electricity at industrial scale while responding to economic incentives that differ from traditional production-based loads (1). This creates a direct connection between cryptocurrency markets and physical power-system planning (2, 3).

A consistent finding in prior research is that Bitcoin price dynamics help explain changes in mining activity and hashrate. Studies of price and hashrate dynamics suggest that price movements can lead mining behavior over time, meaning that market conditions may eventually affect the level of computational power devoted to

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mining (2, 4). Since electricity use is closely tied to the operation of mining hardware, this price-driven behavior makes mining loads different from traditional industrial electricity consumers whose demand is usually linked to physical production schedules.

At the same time, power-system studies show that mining facilities can act as flexible loads and may support grid operations when they participate in demand response programs (1, 5, 6). This creates a useful but also complicated situation for grid operators. Miners may be technically capable of curtailing quickly, but their willingness and timing may depend on profitability, electricity contracts, market prices, and network conditions. Therefore, the key issue is not only whether miners can be flexible, but whether their baseline demand is stable enough to be planned around.

The main gap motivating this paper is that existing research often treats mining load as a static or average quantity, while mining profitability is affected by volatile cryptocurrency prices. If mining incentives fluctuate sharply, mining-related electricity demand may become less stable and less reliable as a planned demand response resource. This matters especially for regions such as Texas, where large flexible loads are increasingly relevant to grid reliability and market design (5, 6).

This study examines two linked questions: first, whether Bitcoin price volatility is associated with instability in mining incentives; and second, whether that mining-related instability appears in aggregate electricity demand variability. The analysis uses monthly data from January 2021 to November 2025, combining Bitcoin prices, hash price, state-level electricity demand, temperature, and heating degree days.

The study contributes to the literature in three ways. First, it provides an empirical test connecting Bitcoin market volatility to mining-related incentive instability. Second, it evaluates whether this instability appears in monthly aggregate electricity demand. Third, it discusses how these results should be interpreted for demand response planning, while clearly separating monthly planning-level evidence from real-time operational reliability claims.

The findings show that Bitcoin price volatility is significantly associated with greater mining load instability, but mining instability is not statistically significantly associated with aggregate grid instability at the monthly system-wide level. Therefore, the paper does not conclude that mining has no operational grid impact; rather, it shows that such impacts are not clearly detected in monthly aggregate data.

LITERATURE REVIEW

Existing research connects Bitcoin mining, electricity consumption, and grid planning through three main themes. The first theme concerns the relationship between Bitcoin market conditions and mining activity. Fantazzini and Kolodin examine Bitcoin price and hashrate dynamics while accounting for mining equipment efficiency, halving, and structural breaks; importantly, they report that causality runs from Bitcoin price to hashrate or related proxies with time lags (2). Kubal and Kristoufek similarly describe Bitcoin pricing and hashrate as part of an endogenous system, emphasizing that the interaction between price and network activity translates into electricity demand and environmental implications (3). Rehman and Kang further show that the relationship between Bitcoin returns, hashrate, and energy commodities varies across time scales and market states (4). Together, these studies support the idea that mining activity is not fixed but responds to changing market and network incentives.

A related point is that hashrate is meaningful for both the Bitcoin system and electricity demand, but it may not always respond immediately to short-term profitability changes. Kim, Ryu, and Webb show that hashrate fluctuations are connected to Bitcoin network outcomes, reinforcing that hashrate is an active system variable rather than a passive background measure (7). However, because hashrate also reflects network-wide adjustments and difficulty mechanisms, profitability-based measures such as hash price may be more responsive to short-term changes in miner incentives when direct facility-level electricity data are unavailable.

The second theme treats miners as large flexible loads within power systems. Menati, Lee, and Xie simulate cryptocurrency mining in a synthetic ERCOT grid and show that the effects of new mining loads depend on load size, location, and demand response participation (5). Their work indicates that mining load is not simply a level increase in demand; it can affect prices and grid behavior in a non-uniform way. Menati and coauthors extend this work using high-resolution modeling and find that flexibility can mitigate shortages and market disruptions, but that the benefits depend strongly on how mining loads are managed and scheduled (6). Bruno, Weber, and Yates also show that Bitcoin mining can increase renewable capacity but may raise emissions unless miners provide grid management services through demand response (8). These studies support the policy relevance of mining flexibility while also showing that flexibility must be coordinated to be useful.

The third theme concerns volatility and predictability. Bakas, Magkonis, and Oh show that Bitcoin volatility is driven by attention and macro-financial variables, including Google Trends, total Bitcoin circulation, consumer confidence, and the S&P 500 (9). This matters for grid planning because mining incentives may shift due to financial or behavioral conditions outside the electricity system. Spatial evidence also shows that mining activity is geographically concentrated and dynamic, meaning that local grid exposure can differ from global mining trends (10). If mining loads are concentrated in specific regions, volatility in mining incentives may have localized operational relevance even when aggregate monthly effects are difficult to detect.

Across these studies, the literature establishes that Bitcoin price dynamics influence mining activity, that miners can be technically useful as flexible loads, and that grid impacts depend on management, location, and time scale. The remaining gap is that few studies directly connect Bitcoin price volatility to mining load instability and then evaluate whether this instability appears in planning-level electricity demand data. This paper addresses that gap using a transparent monthly empirical framework, while acknowledging that monthly data cannot capture all operational demand response dynamics.

METHODS AND MATERIALS

Data Sources and Sample

This study combines cryptocurrency market data, electricity consumption data for Texas, and weather data. Bitcoin price data are taken from CoinMarketCap and converted into end-of-month closing prices (11). The resulting Bitcoin price series is shown in Figure 1. Bitcoin hash price data are taken from Hashrate Index and averaged to the monthly level (12). The resulting monthly hash price series is shown in Figure 2. Hash price is reported in U.S. dollars per petahash per day (USD/PH/day); no unit conversion is applied beyond averaging daily observations within each month. The sample runs from January 2021 to November 2025.

Figure 3 shows the monthly percentage changes in Bitcoin price and hash price from January 2021 to November 2025. These changes are reported in percent (%) and are used because they focus on relative movements rather than long-run price levels. In the regression variables, the absolute values of these monthly percentage changes are used.

Electricity data are drawn from the U.S. Energy Information Administration State Energy Data System and are used as a Texas state-level electricity demand proxy (13). Because EIA state-level data do not perfectly align with ERCOT operating boundaries, the variable is not interpreted as a direct ERCOT operational-load measure. When source data are reported in energy units, the monthly average power equivalent is calculated by dividing monthly electricity consumption by the number of hours in the corresponding month. The resulting electricity demand proxy is shown in Figure 4 and is used only to examine monthly planning-level demand variability, not sub-hourly reliability conditions.

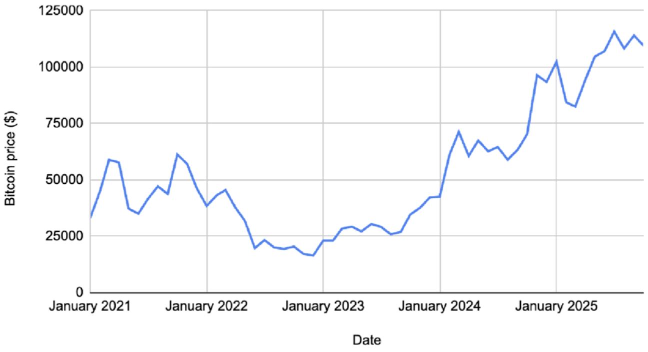

Figure 1. *Monthly end-of-month Bitcoin closing price in U.S. dollars from January 2021 to November 2025. This price series is used to compute monthly Bitcoin returns and the absolute monthly percentage change variable used as BTC_Volatility in the regression analysis.*

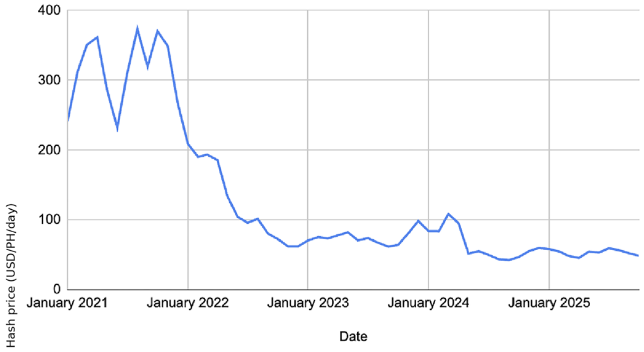

Figure 2. *Monthly average Bitcoin hash price from January 2021 to November 2025, reported in U.S. dollars per petahash per day (USD/PH/day). Daily hash price observations from Hashrate Index are averaged within each month, and the absolute monthly percentage change in this series is used as the Mining_Instability proxy.*

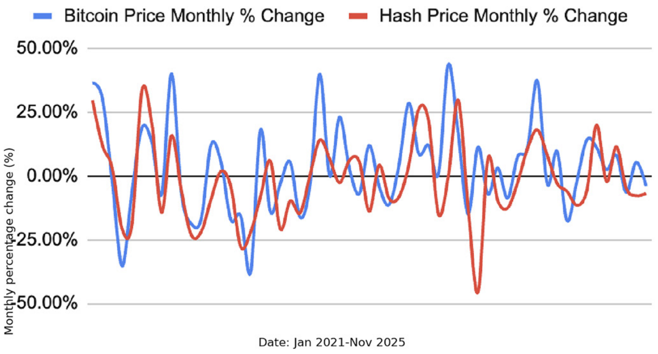

Figure 3. *Monthly percentage changes in Bitcoin price and Bitcoin hash price from January 2021 to November 2025. Values are reported in percent (%). The regression variables use the absolute values of these monthly changes, so negative values in the figure are converted to positive magnitudes when constructing BTC_Volatility and Mining_Instability.*

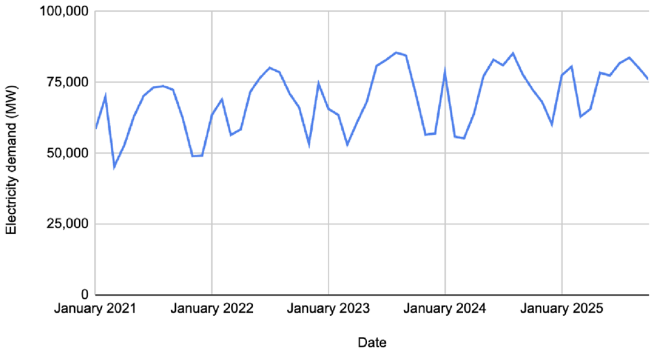

Figure 4. *Texas state-level electricity demand proxy from January 2021 to November 2025, expressed as monthly average power equivalent in megawatts (MW). The series is used to compute Grid_Instability and should be interpreted as a planning-level proxy rather than a direct ERCOT sub-hourly operational-load measure.*

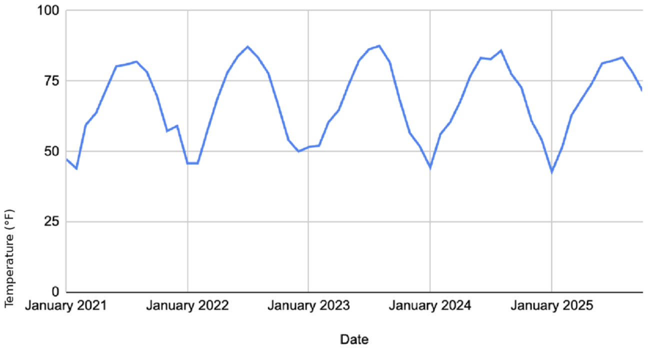

Figure 5. *Monthly average temperature in Texas from January 2021 to November 2025, measured in degrees Fahrenheit (°F). Temperature is included as a weather control to account for seasonal cooling- and weather-related electricity demand effects.*

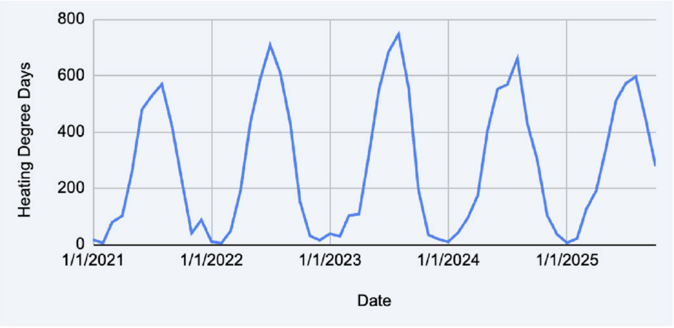

Figure 6. *Monthly Texas heating degree days (HDD) from January 2021 to November 2025. HDD measures colder-month heating pressure and is included as a weather control in the grid-instability regression.*

Weather controls include monthly average temperature and heating degree days (HDD) for Texas. Monthly average temperature is shown in Figure 5, and HDD is shown in Figure 6. These variables capture seasonal electricity demand conditions that may affect system demand independently of cryptocurrency mining.

Summary Statistics (Table 1)

Variable Construction

Bitcoin price volatility is constructed from monthly percentage changes in Bitcoin prices. To keep the variable definition consistent across the manuscript, the baseline measure used in the regressions is the absolute monthly percentage change in Bitcoin prices.

Let P_t denote the end-of-month Bitcoin price in month t. Monthly Bitcoin returns are computed as:

$$r_t = 100 \times (P_t - P_{t-1}) / P_{t-1} \qquad \text{(Eq.1)}$$

Bitcoin price volatility is then defined as the absolute value of this monthly return:

$$BTC\_Volatility_t = |r_t| \qquad \text{(Eq. 2)}$$

Mining load instability is proxied using changes in Bitcoin hash price. Hash price measures mining revenue per unit of computing power and incorporates Bitcoin

Table 1. *Summary statistics for the monthly variables used in the empirical analysis from January 2021 to November 2025. Bitcoin price is measured in U.S. dollars, hash price is measured in USD/PH/day, temperature is measured in degrees Fahrenheit, heating degree days are measured as monthly HDD totals, and the electricity demand proxy is expressed as monthly average power equivalent in MW.*

Variable	Mean	SD	Min	Max
Bitcoin price ($)	53,317.23	28,905.52	16,547.50	115,758.20
Hash price ($/PH/day)	144.92	136.40	48.47	241.37
Temperature (°F)	59.40	17.11	47.30	71.50
Heating degree days	147.50	184.55	17.00	278.00
Electricity demand (MW eq.)	67,725	10,707	45,380	85,508

Notes: Hash price is reported in U.S. dollars per petahash per day (USD/PH/day) and is averaged from daily observations to monthly observations. The electricity demand proxy is expressed as a monthly average power equivalent in MW; it is used as a state-level planning proxy and should not be interpreted as ERCOT sub-hourly operational load.

price, network difficulty, and transaction fees. Because electricity is a primary operating cost in Bitcoin mining, changes in expected mining revenue affect incentives to continue operating, curtail, or expand electricity consumption (1, 2, 5). However, hash price is not a direct measurement of facility-level power use. It is therefore interpreted as a profitability-based proxy for mining incentives rather than a metered electricity-consumption variable.

Let H_t denote monthly average Bitcoin hash price in month t, measured in USD/PH/day. Monthly percentage changes in hash price are defined as:

$$h_t = 100 \times (H_t - H_{t-1}) / H_{t-1} \quad \text{(Eq. 3)}$$

Mining load instability is proxied by the absolute monthly percentage change in hash price:

$$\text{Mining\_Instability}_t = |h_t| \quad \text{(Eq. 4)}$$

Let E_t denote the electricity demand proxy in month t. Monthly percentage changes in electricity demand are computed as:

$$e_t = 100 \times (E_t - E_{t-1}) / E_{t-1} \quad \text{(Eq. 5)}$$

Grid instability is measured as the absolute monthly percentage change in the electricity demand proxy:

$$\text{Grid\_Instability}_t = |e_t| \quad \text{(Eq. 6)}$$

Higher values of Grid_Instability indicate less predictable monthly electricity demand. This variable reflects planning-level demand variability and should not be interpreted as a direct measure of real-time operational reliability.

Econometric Strategy

The empirical analysis uses reduced-form ordinary least squares regressions. The first specification evaluates whether Bitcoin price volatility is associated with mining load instability. The second specification evaluates whether mining load instability is associated with aggregate grid instability at the monthly level. These models identify conditional associations rather than strict causal effects.

$$\text{Mining\_Instability}_t = \beta_0 + \beta_1\text{BTC\_Volatility}_t + \beta_2\text{Temperature}_t + \varepsilon_t \quad \text{(Eq. 7)}$$

The coefficient of interest is β_1. A positive value indicates that higher Bitcoin price volatility is associated with greater mining load instability.

$$\text{Grid\_Instability}_t = \alpha_0 + \alpha_1\text{Mining\_Instability}_t + \alpha_2\text{Temperature}_t + \alpha_3\text{HDD}_t + u_t \quad \text{(Eq. 8)}$$

The coefficient of interest is α_1. A positive value indicates that increased mining-related instability is associated with greater monthly grid instability. The interpretation is limited to monthly, system-wide variability and should not be generalized to sub-hourly operational reliability.

All regressions are estimated using monthly data with robust standard errors. The final regression sample contains 57 observations, so the relatively small sample size limits statistical power and may reduce coefficient precision, especially for detecting weak relationships in the second specification. Temperature and HDD may be correlated because both reflect seasonal weather conditions. Both controls are retained to capture broad weather-related demand patterns, but their coefficients are not interpreted as independent causal weather effects.

The use of monthly aggregation may attenuate short-term relationships because demand response operates at sub-hourly or hourly time scales. Facility-level curtailment data, ERCOT controllable-load records, and real-time demand response participation records are not available at sufficient resolution for this study. These data limitations are considered when interpreting the results.

RESULTS

This section reports estimated coefficients, statistical significance, and model fit from the regression analyses. Interpretation and policy implications are reserved for the Discussion section.

Bitcoin Price Volatility and Mining Load Instability

Table 2 reports the relationship between Bitcoin price volatility and mining load instability. Bitcoin price volatility is positively associated with mining load instability and is statistically significant at the 5% level. Temperature is not statistically significant in this specification. The model explains a modest share of variation in mining load instability, with an R^2 of 0.084.

The coefficient on Bitcoin price volatility is 2.469, with a standard error of 1.204. This means that a one percentage point increase in monthly Bitcoin price volatility is associated with a 2.469-unit increase in the mining instability proxy. Interpretation of this magnitude is discussed in the Discussion section.

Mining Load Instability and Grid Instability

Table 3 presents results from the regression of grid instability on mining load instability and weather controls. Mining load instability is not statistically significantly associated with grid instability at the monthly level. Temperature and HDD are also not statistically significant predictors in this specification.

The model reports an R^2 of 0.281. This indicates that the included variables explain approximately 28.1% of variation in monthly grid instability, but the absence of statistically significant individual predictors suggests that this explanatory power may reflect broad seasonal variation and aggregate demand patterns rather than a clearly identifiable mining-related effect.

DISCUSSION

This study investigates whether volatility in cryptocurrency markets affects mining load instability and whether such instability poses challenges for grid reliability and demand response planning. The results support the first part of the proposed mechanism, while

Table 2. *Ordinary least squares regression of Mining_Instability on Bitcoin price volatility and temperature using monthly observations from January 2021 to November 2025. The dependent variable, Mining_Instability, is the absolute monthly percentage change in Bitcoin hash price. Coefficients are shown with robust standard errors in parentheses. Notes: Standard errors are reported in parentheses. Bitcoin price volatility is measured as the absolute monthly percentage change in Bitcoin prices. Mining load instability is proxied by the absolute monthly percentage change in Bitcoin hash price. Monthly data from January 2021 to November 2025. **$p < 0.05$.*

Variable	Mining Load Instability
Bitcoin price volatility (%)	2.469** (1.204)
Temperature (°F)	-0.531 (1.036)
Constant	129.149 (76.312)
Observations	57
R^2	0.084
Adjusted R^2	0.050

Table 3. *Ordinary least squares regression of Grid_Instability on mining load instability, temperature, and heating degree days using monthly observations from January 2021 to November 2025. The dependent variable, Grid_Instability, is the absolute monthly percentage change in the Texas state-level electricity demand proxy. Coefficients are shown with robust standard errors in parentheses. Notes: Standard errors are reported in parentheses. Grid instability is measured as the absolute monthly percentage change in the state-level electricity demand proxy. Mining load instability is derived from the absolute monthly percentage change in hash price. Monthly data from January 2021 to November 2025. **$p < 0.05$.*

Variable	Grid Instability
Mining load instability	0.042 (0.125)
Temperature (°F)	-0.382 (0.294)
Heating degree days	-0.001 (0.017)
Constant	37.735** (15.878)
Observations	57
R^2	0.281
Adjusted R^2	0.240

the second part is not detected at the monthly, system-wide level.

Magnitude and Economic Significance

The first regression indicates that Bitcoin price volatility has a statistically significant association with mining load instability. The estimated coefficient suggests that a one percentage point increase in Bitcoin price volatility is associated with an increase of approximately 2.47 units in the mining instability proxy. This supports the idea that mining incentives become less predictable during volatile cryptocurrency market conditions.

In contrast, the second regression finds that increases in mining load instability do not produce statistically significant changes in aggregate grid instability at the monthly level. This null finding should not be interpreted as proof that mining has no operational grid impact. Rather, it shows that such effects are not detectable using monthly, system-wide data. The small sample size and monthly aggregation may also reduce the precision of the estimates and make weaker relationships harder to detect.

Implications for Grid Operations and Demand Response

These findings have several implications for grid operations and demand response planning, but these implications should be interpreted as policy-relevant extensions rather than direct causal findings. First, the sensitivity of mining incentives to Bitcoin price volatility suggests that mining loads may fluctuate more sharply during periods of financial market stress. Monthly, system-wide electricity data may mask localized and short-term effects that are most relevant for demand response activation and reserve management.

Second, the absence of a statistically significant monthly relationship suggests that aggregate planning metrics may understate the operational relevance of flexible loads. Mining-related variability may be absorbed by the broader system at the monthly level while still potentially affecting real-time prices, scarcity conditions, or operating reserves. ERCOT market documents show that scarcity-related price adders are tied to reserve conditions, so mechanisms such as the Operating Reserve Demand Curve should be interpreted here as relevant policy context rather than as outcomes directly tested by the regressions (14).

Third, mining facilities could be useful as controllable load resources if program design accounts for financial incentives and baseline uncertainty. ERCOT load resource participation rules require registration and telemetry for participating load resources, which highlights the importance of operational visibility and coordination when large flexible loads are used for grid services (15).

Limitations and Future Research

Several limitations qualify the interpretation of these results. The analysis uses aggregate monthly data, which limits causal identification and may obscure high-frequency operational dynamics. Demand response operates at sub-hourly or hourly intervals, and curtailment behavior may not appear in monthly averages. As a result, the null finding in the second regression may reflect attenuation from temporal aggregation rather than a true absence of operational impact.

Mining load instability is proxied using hash price rather than direct facility-level electricity consumption. This introduces measurement error because profitability does not always translate directly into facility-level power use, especially when miners have heterogeneous electricity contracts, fixed-price arrangements, or different equipment efficiencies. The electricity demand proxy is also based on state-level EIA data and does not perfectly align with ERCOT operational boundaries.

Future research could address these limitations by incorporating ERCOT 15-minute prices, facility-level telemetry, controllable load resource participation records, or high-frequency electricity market data. Event-study designs around extreme Bitcoin price movements may further clarify short-run impacts on prices, reserves, and curtailment behavior that are not visible in monthly aggregates.

Policy Implications

The results point to several policy-relevant considerations. Demand response programs that solicit pre-commitment bids from mining facilities could improve planning by clarifying curtailment availability during periods of market stress. Weather-adjusted baselines that account for cooling-related electricity use may also improve measurement of mining load response. Disclosure requirements and operational telemetry for large flexible loads could improve transparency and coordination between grid operators and mining facilities (15). These suggestions should be viewed as implications for program design rather than findings directly estimated by the regression models.

Overall, the findings suggest that Bitcoin price volatility materially affects mining load instability, but its implications for grid reliability depend on data resolution, program design, and how mining facilities are integrated into demand response frameworks.

CONCLUSION

This study examined how Bitcoin price volatility affects mining load instability and whether instability in mining-related incentives translates into reduced grid reliability. Using publicly available data and a transparent empirical framework, the analysis finds that higher Bitcoin price volatility is associated with greater mining load instability, indicating that cryptocurrency market dynamics introduce meaningful variability into mining incentives. However, this instability does not result in statistically significant deterioration in aggregate monthly grid instability once weather effects are taken into account.

For grid operators and planners, the main takeaway is that cryptocurrency mining behaves as a financially driven flexible load whose variability is closely linked to market conditions rather than traditional demand factors. The null result applies only to monthly, system-wide planning data and should not be generalized to real-time operational reliability. Future research incorporating higher-frequency ERCOT market data, controllable load records, and facility-level telemetry could further clarify the operational role of cryptocurrency mining in modern power systems.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest related to this work.

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