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*Article*

# Decentralization Under Energy Growth: Geographic Reallocation and Convergence in Bitcoin Mining

**Angeliki Papana * and Konstantinos Katrakilidis**

Department of Economics, Aristotle University of Thessaloniki, Greece
* Correspondence: agpapana@econ.auth.gr

**Abstract**

Understanding how Bitcoin mining is distributed across countries is important for evaluating both the sustainability and resilience of the network. In this study, we examine the evolution of total Bitcoin electricity consumption alongside the geographic distribution of Bitcoin mining. Data are provided by the Cambridge Centre for Alternative Finance (Licensed under CC BY–NC–SA 4.0): Annual data from the Cambridge Bitcoin Electricity Consumption Index (2010–2025) and a monthly panel of country-level Bitcoin hashrate shares for 105 countries (Sept. 2019–Jan. 2022). To assess the degree of decentralization in the global mining network, we employ entropy-based measures, inequality indices and panel convergence tests. The results indicate that total electricity consumption grew exponentially during the early years of Bitcoin, but later transitioned to a more stable, approximately linear path. Country-level permutation entropy reveals highly volatile and dynamic mining trajectories. The Theil index shows that cross-sectional inequality declines over time, while increasing symbolic entropy reflects a progressively more even cross-country distribution of mining activity. Further evidence from $\sigma$-convergence supports a statistically significant reduction in cross-country dispersion of mining shares. Dynamic panel fixed-effects estimates reveal mean-reverting behavior in relative country shares, consistent with stochastic convergence. Finally, Phillips–Sul analysis points to heterogeneous early transition paths but ultimately supports convergence toward a single global club. The gradual geographical decentralization occurs alongside persistent core–periphery asymmetries in long-run mining shares. Overall, our findings suggest that Bitcoin mining behaves as a globally integrated industry in which computational capacity reallocates rapidly across countries in response to economic and regulatory conditions.

**Keywords:** Bitcoin mining; electricity consumption; decentralization; geographic reallocation; inequality measures; club convergence; stochastic convergence; $\sigma$-convergence

## 1. Introduction

Bitcoin mining has evolved into an increasingly energy-intensive activity with important environmental and policy implications. However, empirical evidence on the evolution of total electricity consumption and its distribution across countries remains limited. Recent studies report large and uncertain estimates of Bitcoin's power demand and highlight serious climate and pollution concerns [1,2]. Most existing studies focus on aggregate consumption or provide static snapshots of mining locations, without examining global energy demand trends alongside the geographical distribution of mining [3,4]. As a result, concerns have been raised about the sustainability of the computational mining protocol, the risk of mining becoming too centralized, and the unequal environmental and regulatory impacts across countries.

Bitcoin's energy and environmental impacts have recently attracted considerable attention, and a growing literature on this subject has emerged. Many studies examine Bitcoin mining's energy use by relating the network's total computing power to assumptions about the efficiency of mining hardware [3,5,6]. Recent studies quantify global and country-level carbon footprints, while analysis

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is increasingly extended to water and land use impacts [1,7,8]. Life-cycle emissions and renewable integration potential are examined in [9,10]. In [11], the effect of Bitcoin emissions on the climate and the global warming is discussed and a potential increased warming of more than 2°C due to Bitcoin emissions is noted. Geospatial studies show a strong concentration of Bitcoin mining in regions with abundant electricity. That is particularly evident after China's 2021 ban [4,12].

Beyond environmental impacts, several studies examine the relationship between crypto-currency activity, energy use, and policy. A positive cointegrating relationship between crypto-currency hashrate and energy consumption has been identified using vector error-correction models [13]. Policy-focused studies examine how environmental and energy regulations affect the mining landscape [14]. Comparisons of energy use and environmental footprints across nine different crypto-currency projects reveal large differences in electricity consumption, mainly driven by their consensus mechanisms [15], i.e. by the underlying protocols that govern how transactions are verified. Aramonte et al. [16] analyze concentration in crypto-currency markets using inequality metrics, such as Gini coefficient and Nakamoto index. A more recent study suggests that the global carbon footprint of Bitcoin mining is rising rapidly, due to electricity use during mining but also by emissions associated with the production of mining hardware [17]. Despite the growing interest in the geographical spread of Bitcoin mining, formal econometric evidence on its dynamic evolution and long-run convergence across countries remains relatively limited.

Most existing studies either analyze Bitcoin electricity consumption without considering geographic information [6,13], while others map mining locations using cross-sectional geospatial data [4]. The majority of hashrate distribution analyses rely on static snapshots that do not capture how mining activity evolves over time. In this study, we examine both the long-run trend in aggregate Bitcoin electricity consumption and the cross-country dynamics of mining activity. Annual electricity estimates from 2010 to 2025 are used to quantify the overall mining demand. Additionally, monthly country-level hashrate shares (Sept. 2019 – Jan. 2022) help us understand the changing geography of mining activity. Both sample periods include two major shocks: the 2020 Bitcoin halving and the 2021 China mining ban, allowing us to evaluate how the mining landscape adjusted after these events.

A trend analysis is employed for total electricity consumption, assessing its long-run growth. Country-level hashrate shares are then studied using different complementary methods. Country-level permutation entropy captures temporal complexity. Cross-sectional Theil index and cross-sectional symbolic entropy quantify heterogeneity and decentralization in the global mining network. Further, we investigate the evolution of cross-country dispersion in mining intensity over time using $\sigma$-convergence analysis. Finally, stochastic convergence is examined based on panel unit root tests, while the Phillips–Sul methodology is utilized to explore potential common transition paths.

Decentralization can be understood as the absence of pronounced geographic concentration in a small number of countries and reduced vulnerability to coordinated country-level shocks. Therefore, we examine decentralization through complementary dimensions: temporal stability via predictability of country-level mining trajectories, spatial concentration quantifying monthly inequality across countries and convergence trends that reflect the evolution toward equal relative shares. On the other hand, Bitcoin mining can be understood as a form of highly mobile digital capital that relocates geographically in response to changes in electricity prices, regulatory conditions, and infrastructure availability. Within this framework, convergence in mining shares reflects the gradual adjustment of mining capacity across locations as miners respond to differences in energy costs and or other policy decisions regarding institutional conditions. Mining decentralization can therefore be interpreted as the outcome of economic forces shaping the global allocation of energy-intensive computing activity.

Bitcoin mining is analyzed both in terms of its demanding energy use and its global geographic spread. Our aim is to examine the geographic distribution of Bitcoin mining and its evolution over time, bridging the gap between estimates of total energy use and the distribution of mining power across countries. Methodologically, we employ trend analysis, estimate heterogeneity indicators and apply convergence techniques to explore how mining activity is distributed across countries over time. This approach provides new evidence on mining decentralization, the resilience of the network's spatial structure, and countries' relative long-run positions in the global mining network. In particular, results suggest transitional decentralization characterized by mean-reverting dynamics and declining dispersion, although persistent core–periphery asymmetries in long-run mining shares remain.

Section 2 presents the data and the methodology used. The empirical findings are presented in Section 3. We discuss the findings and the implications in Section 4. Finally, Section 5 summarizes the study and gives directions for future research.

## 2. Data and Methodology

The Data and Methodology section describes the sample data and the econometric methods used in our study. The datasets were provided by the Cambridge Centre for Alternative Finance. The applied methodologies include trend analysis, heterogeneity measures, and convergence tests.

### *2.1. Data*

Two datasets are obtained from the Cambridge Centre for Alternative Finance (CCAF) and are licensed under CC BY-NC-SA 4.0, providing complementary perspectives on the evolution of the mining network.

Annual total electricity consumption estimates are sourced from the Cambridge Bitcoin Electricity Consumption Index (CBECI) for the period 2010 to 2025 (up to 14-10-2025). The daily annualized TWh values are provided under three hardware efficiency scenarios: central (GUESS), lower-bound (MIN), and upper-bound (MAX). These data reflect the overall growth of global mining demand.

A monthly panel of global Bitcoin hashrate shares for 105 countries covers the period Sept. 2019 – Jan. 2022 (29 months, 3045 observations). Country-level hashrate shares capture the geographic distribution of mining activity. Due to data availability, this panel does not fully cover the sample period of the electricity consumption series. However, after 2022, data availability and reporting methodologies changed substantially, while the increasing use of VPNs and intermediary mining pools has made country-level attribution less reliable.

### *2.2. Methodology*

The methodology used in our analysis is described below. First, we examine electricity consumption trends and then analyze the dynamics of hashrate distribution using entropy-based measures and convergence tests.

#### 2.2.1. Electricity Trends

We analyze the long-run evolution of Bitcoin's electricity consumption using annual estimates from CBECI covering the period 2010–2025, where 2025 is only partially observed (up to 14 October 2025). Annual electricity consumption is constructed by converting daily annualized values into daily energy use and aggregating over each calendar year:

$$E_y = \sum_{d \in y} \frac{A_d}{365},$$

where $A_d$ denotes the daily annualized CBECI estimate. For 2025, observed daily consumption is summed through the last available date, and the remaining days are projected using the mean observed daily rate. The central analysis is based on the CBECI 'GUESS' scenario, while the corresponding MIN and MAX scenarios are used to construct uncertainty bounds, where MIN assumes highest hardware efficiency and MAX assumes lowest hardware efficiency.

In the early years of the sample, electricity consumption is close to zero, while later, its rapid expansion is observed. We estimate a log-linear time-trend model to capture proportional growth dynamics:

$$\log(y_t) = \beta_0 + \beta_1 t + \varepsilon_t,$$

where $y_t$ denotes annual electricity consumption and $t$ is a linear time index. To capture more flexible long-run dynamics and possible persistence in deviations from trend, we also estimate a linear time-trend model with autoregressive disturbances:

$$y_t = \alpha_0 + \alpha_1 t + u_t, \quad u_t = \rho u_{t-1} + \eta_t.$$

Both specifications are estimated using ordinary least squares and standard diagnostic tests are performed to assess model fit and residual behavior. We also produce simple projections for 2026 based on each trend specification.

The data series comprises 16 annual observations, which is relatively small for econometric analysis. However, it spans the full history of Bitcoin mining activity. Although the small sample size may limit the statistical power of the tests, the analysis still provides an informative and reliable picture of the growth path of mining.

#### 2.2.2. Heterogeneity Measures

We employ several heterogeneity measures to capture different dimensions of complexity and inequality in the global Bitcoin mining network. These measures quantify both the uneven geographic distribution of mining activity and the temporal volatility of national mining shares. Specifically, we quantify the country-level temporal complexity using permutation entropy, cross-sectional concentration using the Theil index, and cross-sectional decentralization using a symbolic entropy measure. Together, they provide a comprehensive view of decentralization and structural change in global hashrate distribution.

The inequality and entropy measures are computed directly on the original hashrate shares. These metrics are scale-invariant by construction and properly handle zero and near-zero mining activity.

##### Permutation Entropy

Permutation Entropy (PE) is an information measure estimated on the relative frequencies of ordinal patterns in the time series [18]. PE is fundamentally a time series complexity measure, therefore, it is used to quantify the temporal complexity of mining activity for each country. We compute PE for each national hashrate series. Given an embedding dimension $m$ and time delay $\tau$, each series is mapped into sequences of ranked values, and the associated probability distribution over the $m!$ possible orderings is constructed. Permutation entropy is defined as

$$H = -\sum_{i=1}^{m!} p_i \log p_i,$$

where $p_i$ denotes the relative frequency of a given ordinal pattern (permutation) in the time series. We normalize PE in order to be within the $[0, 1]$ interval, by dividing $H$ with $\log(m!)$. Higher PE values indicate greater temporal irregularity and lower predictability in a country's mining activity over time.

To handle ties, we add a small Gaussian perturbation ($10^{-10}$) to each observation before computing ordinal patterns. This ensures that all values are unique. This is a standard procedure in ordinal analysis that prevents the occurrence of undefined patterns [18].

##### Theil Index

To measure the degree of cross-country concentration in Bitcoin mining activity, we utilize the Theil index, a widely used inequality metric derived from information theory [19]. Let $s_{i,t}$ denote country $i$'s share of global hashrate at time $t$, with $\sum_i s_{i,t} = 1$ and $N$ countries. The Theil index is defined as

$$T_t = \sum_{i=1}^{N} s_{i,t} \log\left(\frac{s_{i,t}}{1/N}\right).$$

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It is equal to zero under perfect equality and increases with concentration. It is scale-invariant and decomposable, and therefore provides a transparent measure of mining centralization at each point in time. In this context, it summarizes the extent to which global hashrate share is disproportionately concentrated in a small number of countries, complementing convergence tests that focus on dynamic adjustment.

Cross-Sectional Symbolic Entropy

A normalized Shannon entropy [20] over three hashrate categories is proposed as a simple cross-sectional decentralization indicator for Bitcoin mining. The resulting cross-sectional symbolic entropy (CSE) is designed to quantify the cross-sectional concentration of Bitcoin mining activity based on discrete hashrate categories. At each time $t$, countries are classified into three groups according to their share of global hashrate: high (hashrate share at least 5% of the global total), medium (between 1% and 5% of global capacity), and low (below 1%). These thresholds are selected to provide an economically meaningful partition of mining activity and are motivated by concentration concepts used in industry reporting (e.g. CCAF) and in the decentralization literature [21].

The three categories are encoded as symbols $N$, $M$, and $L$ and provide a symbolic representation of the cross-sectional distribution in each month. Let $p_{N,t}$, $p_{M,t}$, and $p_{L,t}$ denote the fractions of countries in each category at time $t$. The symbolic entropy is defined as

$$SE_t = -\sum_{k\in\{N,M,L\}} p_{k,t}\log_2 p_{k,t},$$

where the sum runs over the three symbols $N, M, L$ and we normalize it by its maximum value $\log_2 3$ to obtain

$$CSE_t = \frac{SE}{\log_2 3}$$

so that $CSE_t \in [0,1]$. We use base-2 logarithms so that entropy is measured in bits, although the normalization by $\log_2 3$ makes CSE invariant to the log base choice. High CSE values imply a more even distribution of hashrate across the three groups, whereas lower values reflect stronger concentration in the high-share category. CSE summarizes how evenly countries are distributed across the high, medium, and low hashrate categories and therefore provides a simple and robust measure of cross-sectional decentralization.

2.2.3. Convergence

The evolution of cross-country differences in Bitcoin mining activity is examined using three complementary convergence approaches. To avoid zero values of the share data $s_{it}$, we construct adjusted shares as

$$\tilde{s}_{it} = s_{it} + 0.0001.$$

This adjustment is negligible and does not affect the underlying dynamics, but improves numerical stability in subsequent logarithmic transformations and convergence estimation [22,23]. The cross-sectional mean share is approximately $1/N \approx 0.0095$, therefore the offset represents roughly 1% of the average magnitude and is much smaller than the typical variation among non-zero shares. Because the same constant is applied uniformly across countries and over time, it does not distort relative dynamics but instead regularizes observations that are zero or extremely close to zero.

Country hashrate shares are compositional ($\sum_i s_{it} = 1$), so part of the observed dispersion dynamics could in principle reflect the adding-up constraint. This concern is mitigated in our framework because stochastic convergence is evaluated using relative log deviations, inequality and entropy measures display consistent decentralization patterns, and the Phillips–Sul transition paths exhibit substantial early heterogeneity prior to gradual compression.

First, we assess $\sigma$-convergence by examining the evolution of cross-sectional dispersion in hashrate shares, and thereby quantify the overall reduction in inequality among countries.

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Before estimating stochastic convergence, we test for cross-sectional dependence using Pesaran's CD test [24]. To account for common global shocks, we employ a two-way fixed-effects model, based on the rationale of stochastic convergence literature [25,26].

While stochastic convergence captures average mean-reverting dynamics, it does not preclude heterogeneous long-run paths across countries. Therefore, we implement the Phillips–Sul club convergence test [27], which groups countries following similar long-run paths and tests for common equilibria, capturing heterogeneous convergence dynamics and potential formation of convergence clubs.

$\sigma$-Convergence

To assess whether cross-country dispersion in mining activity declines over time, we employ $\sigma$-convergence. Specifically, we study the evolution of cross-sectional standard deviation of adjusted hashrate shares $\tilde{s}_{it}$. To test for $\sigma$-convergence, we estimate the linear trend :

$$\sigma_t = \alpha + \beta t + \varepsilon_t.$$

A negative and statistically significant $\beta$ indicates convergence in hashrate shares across countries.

As a complementary robustness check, we also compute the coefficient of variation at each time $t$:

$$CV_t = \frac{\sigma_t}{\mu_t},$$

where $\mu_t$ denotes the cross-sectional mean of the shares. The coefficient of variation provides a scale-adjusted measure of dispersion, ensuring that the assessment of convergence is not mechanically influenced by changes in the overall scale of the Bitcoin network. A negative time trend of $CV_t$ can offer additional evidence of relative convergence.

Stochastic Convergence

To examine whether cross-country differences in Bitcoin mining shares are mean-reverting, a stochastic convergence framework based on country-specific relative deviations is employed. We construct relative log deviations from adjusted shares $\tilde{s}_{it}$:

$$z_{it} = \log(\tilde{s}_{it}) - \log(\bar{s}_t),$$

where $\bar{s}_t$ is the cross-sectional mean of adjusted shares at time $t$. Under stochastic convergence, the relative deviations $z_{it}$ should be stationary.

Before estimating the dynamic specification, we test for cross-sectional dependence using Pesaran's CD test [24]. The test is applied to the residuals from the auxiliary pooled regression:

$$z_{it} = \phi z_{i,t-1} + u_{it},$$

where $u_{it}$ denotes the disturbance term. The null hypothesis is $H_0 : \mathrm{Cov}(u_{it}, u_{jt}) = 0 \quad \forall i \neq j$, against the alternative of cross-sectional dependence. Rejection of $H_0$ indicates the presence of common shocks affecting multiple countries simultaneously.

To account for both country-specific heterogeneity and common global shocks, we estimate the two-way fixed-effects model:

$$z_{it} = \rho z_{i,t-1} + \alpha_i + \gamma_t + \varepsilon_{it},$$

where $\alpha_i$ captures country fixed-effects, $\gamma_t$ captures time fixed-effects, and $\varepsilon_{it}$ is an idiosyncratic error term. The inclusion of time fixed-effects is essential, as global developments in the Bitcoin network may induce common shocks across countries. Stochastic convergence is evaluated by testing the null hypothesis ($H_0$) of a unit root ($\rho = 1$) against the alternative of mean reversion ($\rho < 1$). A value of $\rho < 1$ implies that shocks to mining shares are transitory, indicating long-run convergence in the geographic distribution of Bitcoin mining activity. Given that the time dimension of our panel is $T = 29$, the within-group estimator is expected to be subject to a small downward bias. However, as $T > 25$, this bias becomes sufficiently small, and the estimator provides a reliable assessment of convergence dynamics. To ensure the validity of our inferences, we employ Driscoll–Kraay robust standard errors [28], which are resilient to cross-sectional dependence and temporal autocorrelation.

In contrast to classical fixed-T panel unit root tests such as Harris–Tzavalis and Karavias-Tzavalis [25,26], our dynamic two-way fixed-effect model explicitly accommodates the strong cross-sectional dependence inherent in global Bitcoin mining shares through the inclusion of time fixed-effects and Driscoll–Kraay robust inference. Given the highly interconnected nature of mining activity across countries, this framework provides a more flexible and economically interpretable assessment of stochastic convergence dynamics. Although dynamic fixed-effects models may exhibit Nickell bias in short panels, the length of our sample ($T = 28$) and the relatively large cross-sectional dimension likely mitigate this concern, so the estimated persistence parameter can be interpreted as a reasonable approximation of the underlying adjustment dynamics.

Club Convergence

To study heterogeneous long-run patterns in country-level Bitcoin mining, we use the Phillips–Sul (PS) log-t and club convergence methodology [27]. Due to the high concentration and right-skewness of Bitcoin hashrate shares, we employ log-adjusted shares in the analysis. This transformation reduces the sensitivity of the PS test to extreme values and improves the stability of the cross-sectional variance, thereby better capturing relative transition dynamics across countries. Without this adjustment, the strong influence of major mining hubs may mask more subtle heterogeneity and potentially the presence of convergence clubs.

For each country, we define the relative transition parameter based on the log-adjusted shares $\log(\tilde{s}_{it})$:

$$h_{it}^{\text{rel}} = \frac{\log(\tilde{s}_{it})}{\frac{1}{N}\sum_{i=1}^{N}\log(\tilde{s}_{it})}.$$

The parameter $h_{it}^{\text{rel}}$ captures how a country's mining power deviates from the global cross-sectional average at any given time. Convergence is assessed by the log-t regression

$$\log\left(\frac{H_1}{H_t}\right) - 2\log\log t = \hat{a} + \hat{b}\log t + u_t,$$

where

$$H_t = \frac{1}{N}\sum_{i=1}^{N}(h_{it}^{\text{rel}} - 1)^2,$$

is the cross-sectional variance of the relative transition parameter and $H_1$ is the variance in the initial period.

The null hypothesis of overall convergence is $H_0 : b \geq 0$, which implies that all units in the panel converge to a common steady-state, with alternative the case of divergence ($H_1 : \hat{b} < 0$). We reject $H_0$ if the calculated statistic $t_{\hat{b}}$ is less than the critical value of $-1.65$.

Rejection of the null motivates the search for convergence clubs. The PS club convergence algorithm then groups countries with similar long-run transition paths. Within this framework, each identified club satisfies the $t_{\hat{b}} \geq -1.65$ criterion. The point estimate of the speed of convergence, $\hat{b}$, provides further insights into the nature of the transition. Positive values indicate strong or 'absolute' convergence, where units within the club are moving closer together at a rapid pace. Negative $\hat{b}$ values ($-1 < \hat{b} < 0$) do not necessarily imply divergence if the $t$-statistic remains above the $-1.65$ threshold. Instead, it signifies weak or relative convergence, where the units follow a similar path but at a slower pace, or their relative transition paths are narrowing asymptotically but with limited speed.

Furthermore, following the refinement suggested by [29], we apply a club merging algorithm to prevent over-specification. The initial clustering procedure may partition the data into an excessive

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number of groups. The merging process iteratively tests whether adjacent clubs can be combined into a single group without violating the convergence criterion ($t_{\hat{b}} \geq -1.65$). This ensures that the final club structure is both statistically robust and economically parsimonious. The alternative merging method of [30] is further used as a robustness check. In our implementation, we take the final period as the reference date and trim the first 20% of observations ($r_T = 0.20$) to reduce the influence of early-period volatility and focus on the long-run transition dynamics.

To characterize heterogeneity within each converging group, we compute country-specific long-run relative positions as

$$\mu_i = \frac{1}{T'} \sum_{t \in \text{last 20\% of periods}} h_{it}^{\text{rel}},$$

where $T'$ is the number of periods in the final subsample. The estimated $\mu_i$ represents each country's equilibrium position within the converging panel.

## 3. Empirical Findings

This section presents the main results from electricity trend analysis and hashrate distribution dynamics across 105 countries.

### 3.1. Aggregate Electricity Trends

We first construct annual totals of Bitcoin electricity consumption using the CBECI daily 'annualised GUESS' series. Each daily value (TWh/year) is converted to TWh/day, summed over observed days in 2025, and extrapolated to the full year using the mean daily consumption, yielding an annual total of about 186.6 TWh. To characterize uncertainty, we repeat the same calculation for the CBECI MIN and MAX series, which assume very efficient and very inefficient mining hardware, respectively. The resulting 2025 estimate shows wide uncertainty taking values between roughly 94 and 391 TWh due to the structural uncertainty about the global composition of mining hardware. This uncertainty interval is very broad, providing a reliable indication of the range of potential annual electricity consumption, while also reflecting seasonal or short-term fluctuations that our estimate from partial-year data may have ignored. Therefore, the mean-daily extrapolation for 2025 should be viewed as a conditional projection rather than a precise point estimate.

Figure 1 displays the annual consumption series for 2010–2025. Annual Bitcoin electricity consumption shows a shift in growth patterns over time. Early years appear to exhibit exponential growth, while this growth has slowed in more recent years, with annual increases becoming more moderate.

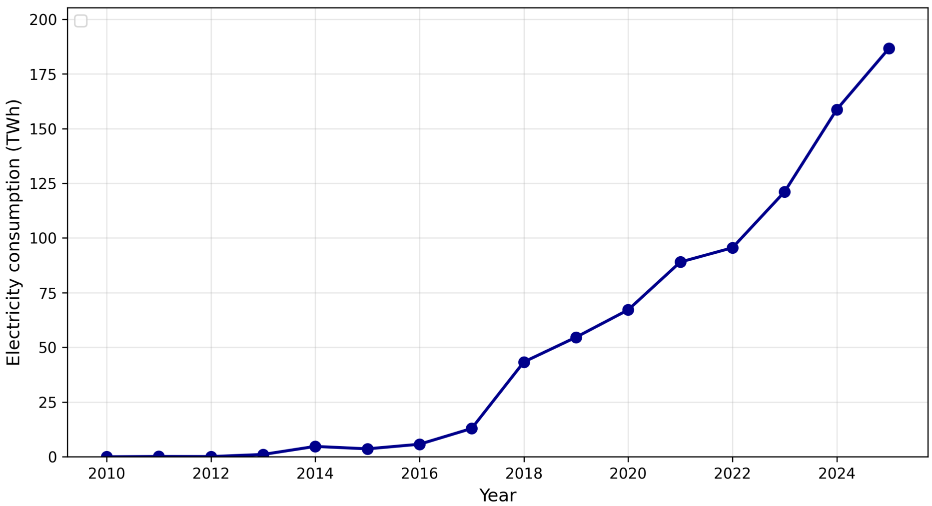


**Figure 1.** Annual Bitcoin electricity consumption (TWh) for the period 2010–2025. The 2025 value is an estimate based on CBECI's GUESS series.

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Table 1 reports estimates from both a log-linear (exponential) trend and a linear trend with AR(1) errors. The log-linear model gives a large and highly significant time coefficient (0.637, $p < 0.01$). It explains about 82% of the variation and reflects the strong proportional growth observed over the full sample. Although this model describes Bitcoin's early development well, it would imply unrealistically large predictions for future consumption (around 1685 TWh).

On the other hand, the linear AR(1) specification describes better the later part of the sample. The estimated trend of about 12.38 TWh per year is positive and significant ($p < 0.01$). The estimated AR(1) coefficient is around 0.9 and indicates strong persistence in deviations from trend. This model achieves a slightly better fit ($R^2 \approx 0.86$) and implies a simple extrapolation for 2026 of about 180 TWh, which is consistent with recent observations. This global expansion of electricity consumption for mining provides the economic background for changes in the geographic distribution of mining activity.

**Table 1.** Estimated trends in total electricity consumption, 2010–2025 (CBECI data).

| | Log-linear (Exponential) | | Linear AR(1) | |
|---|---|---|---|---|
| | Estimate | t-stat | Estimate | t-stat |
| Intercept | -1282 | -7.99*** | -24.9 | -4.98*** |
| Time trend | 0.637 | 8.00*** | 12.38 | 4.99*** |

*** p<0.01. Linear specification estimated with AR(1) errors; estimated AR(1) coefficient $\rho \approx 0.90$.

### 3.2. Cross-Country Hashrate Distribution

After documenting the rapid rise of global electricity demand, the spatial distribution of mining activity is assessed. Table 2 presents the summary statistics for monthly (raw) Bitcoin hashrate shares for 105 countries (Sept. 2019 - Jan. 2022). The mean share stayed constant at approximately 0.0095, as expected from normalization ($1/105 \approx 0.00952$). Cross-sectional standard deviation ($\sigma$) systematically decreased from 0.074 to 0.044 during this period. Max shares significantly decreased from 0.755 to 0.378 by the end of the period, while the min shares remained near zero. Dominant mining regions seem to have lost relative power. The distribution of hashrate shares remains strongly right-skewed and leptokurtic (heavy-tailed) over time. Skewness declines from approximately 10 to slightly above 6 and kurtosis declined from above 100 to slightly over 51. Therefore, a mild decentralization over time is implied. A few countries still dominate, but the intensity of this concentration has eased.

**Table 2.** Cross-country Bitcoin hashrate share statistics across 105 countries.

| Statistic | Sept 2019 | March 2021 | Jan 2022 | Pattern |
|---|---|---|---|---|
| Mean Share | 0.0095 | 0.0095 | 0.0095 | Stable (normalization) |
| Std. Dev. | 0.074 | 0.051 | 0.044 | Decentralization |
| Min Share | $\approx 0$ | $\approx 0$ | $\approx 0$ | Near zero |
| Max Share | 0.755 | 0.491 | 0.378 | Reduced dominance |
| Skewness | 9.93 | 8.31 | 6.68 | Less skewed |
| Kurtosis | 100.6 | 76.6 | 51.1 | Lighter tails |

Figure 2 displays the mean country Bitcoin hashrate share (black line) with its $\pm 1$ standard deviation band (blue shading) for 105 countries from September 2019 to January 2022. The mean stays close to $\approx 0.0095$ due to normalization (global total = 1). The standard deviation band narrows visibly from 0.074 (Sept. 2019) to 0.044 (Jan. 2022), suggesting declining cross-country inequality.

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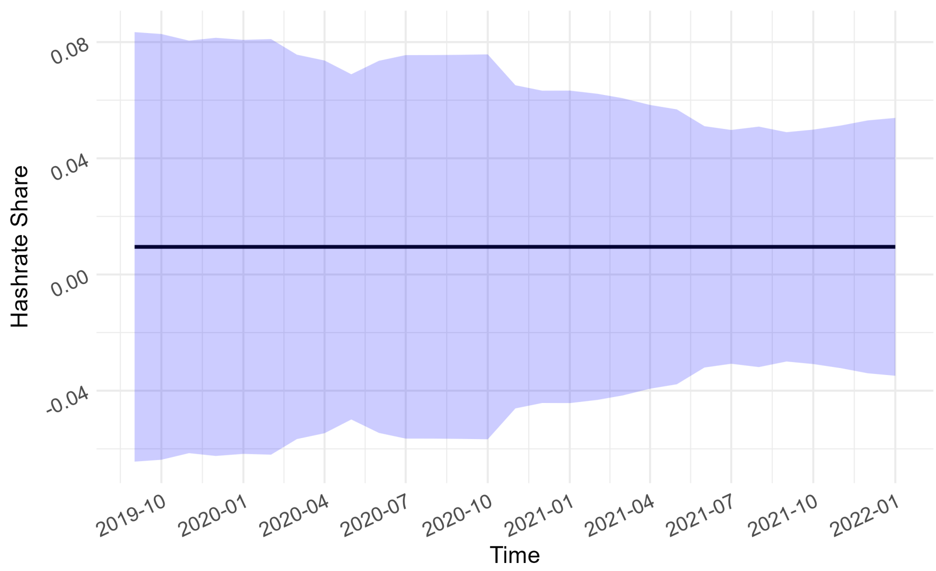


**Figure 2.** Mean country Bitcoin hashrate shares (black) with ±1 standard deviation (light blue band), Sept 2019–Jan 2022. Shrinking band shows declining dispersion.

*3.3. Heterogeneity Indices Results*

Below, the heterogeneity indices results are presented. These quantify temporal complexity for each country and inequality patterns across the global mining distribution.

3.3.1. Country-Level Permutation Entropy

Permutation entropy (PE) provides a compact summary of how stable or erratic each country's Bitcoin mining share is over time. For 105 countries over 29 months, we estimate the normalized PE setting the embedding dimension $m = 3$ and the delay $\tau = 1$. The parameters are selected in order to balance reliable pattern estimation (3! = 6 ordinal patterns) with the short length of the monthly series (29 observations), avoiding sparsity that would arise with higher values of $m$. The choice of $\tau = 1$ focuses on consecutive monthly changes, which is natural for mining activity and consistent with common applications of permutation entropy in financial and crypto-currency time series.

Given the relatively short length of the monthly series, permutation entropy estimates may be affected by finite-sample bias, potentially biasing the estimates upward toward higher apparent disorder. Results should therefore be interpreted as qualitative indicators of instability rather than precise entropy levels. However, the consistently high entropy values across all countries provide robust evidence of substantial temporal instability in the geographic distribution of mining activity.

Results indicate that the distribution of the series is heavily skewed toward high disorder. The majority of the countries (68 countries, 65%) exhibit very high disorder (PE $\geq$ 0.9), indicating highly unpredictable mining dynamics. High disorder is observed in 33 countries (31%), with estimated PE between 0.8 and 0.9. These countries have a stochastic behavior with some temporal patterns. Only 4 countries have PE between 0.7 and 0.8 (Kuwait 0.702, USA 0.718, Italy 0.777, Hungary 0.754), displaying a moderate disorder. All country-level PE estimated are higher than 0.7, suggesting unstable and unpredictable mining dynamics.

The high temporal disorder in country-level shares points to a highly dynamic mining landscape. Mining activity appears to shift frequently across countries rather than remaining concentrated in a small number of locations. Recent studies show that miners tend to move in areas with abundant and cheap energy, but the mining distribution can easily change due to economic and regulatory shocks, such as China's 2021 mining ban [4].

PE values should be interpreted primarily as relative indicators of temporal instability rather than as precise estimated entropy values. Therefore, our findings imply partial decentralization since countries do not maintain their positions permanently. Countries exhibiting high disorder

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may experience frequent hashrate shifts and sensitivity to economic or regulatory shocks, whereas moderately disordered countries contribute more steadily and act as anchors in the global network. This interpretation is consistent with [21], who documents that mining activity responds strongly to policy and economic changes that affect profitability and network stability.

#### 3.3.2. Cross-Sectional Theil Index

The Theil index is estimated cross-sectionally in order to capture inequality in global hashrate shares. Its average is 2.93, which suggests substantial concentration, while a significant shift in how mining power is distributed is revealed. The Theil index is above 3 at the beginning of the examined period, but declines and takes values around 2.5 at the beginning of 2022 (Figure 3). This decrease suggests that Bitcoin mining has spread to more countries during these 29 months. This geographic spread is further supported by the raw standard deviation, which also decreases from 0.074 to 0.044. Although this reflects partial decentralization in regard to China's dominance, a Theil value of 2.5 shows that mining is still concentrated in a few key regions. In other words, even though dominant countries may have lost part of their share, most countries contribute little or only modestly to the global hashrate.

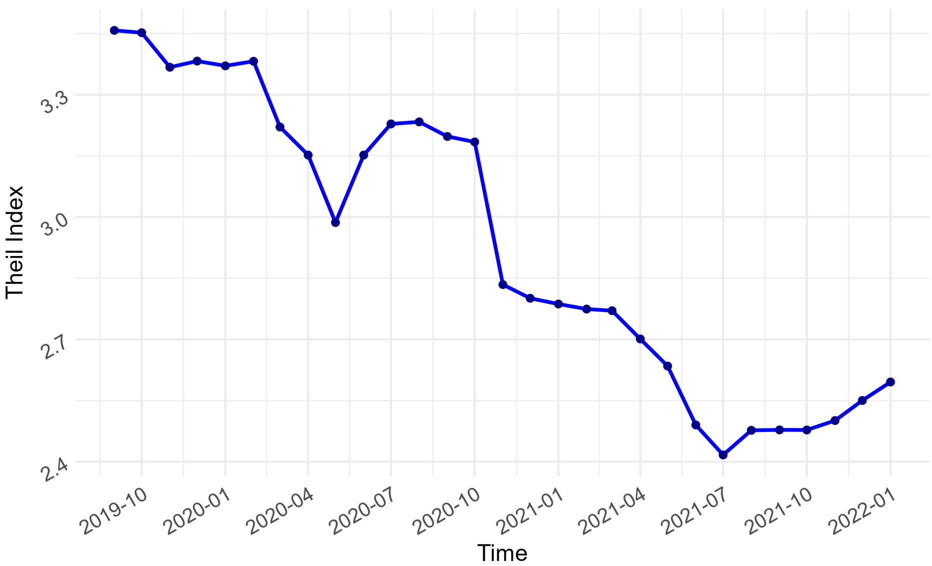


**Figure 3.** Bitcoin hashrate spatial inequality based on Theil index. Higher values denote greater concentration.

#### 3.3.3. Cross-Sectional Symbolic Entropy

Cross-sectional symbolic entropy (CSE) is also used to quantify decentralization patterns. Each month, countries are classified according to their hashrate share as high ($\geq$ 5% of global share), medium (1–5%), or low ($<$ 1%) and the proportion of countries in each category is used for the computation of CSE. Higher values correspond to a more even distribution across groups, while lower ones indicate stronger concentration in a few countries.

The estimated CSE values range from 0.23 to 0.37 over time. Entropy rises when inequality declines and falls when concentration intensifies. The inverse relationship reflects the fact that entropy increases as mining shares become more evenly distributed and decreases when activity becomes more concentrated. This symbolic approach confirms our previous findings. Although there has been a partial shift in mining power, participation is still far from uniform across the globe.

### *3.4. Convergence Analysis*

To test whether cross-country differences in Bitcoin mining shares are narrowing over time, we apply three complementary approaches: $\sigma$-convergence, stochastic convergence, and Phillips–Sul club convergence analysis.

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3.4.1. $\sigma$-Convergence Results

We test $\sigma$-convergence in Bitcoin mining activity using the dispersion of adjusted shares ($\tilde{s}_{it}$). The estimated time trend for the cross-sectional standard deviation (dispersion) is negative and statistically significant. Specifically, the coefficient of the time trend is $-0.0013$ ($t = -16.45$, $p < 0.001$), with a high $R^2$ of (0.909), indicating a pronounced and systematic decline in the dispersion across countries. Although the magnitude of the coefficient is small, it provides clear evidence of $\sigma$-convergence, as cross-country differences in mining shares declined steadily over the sample (Figure 4).

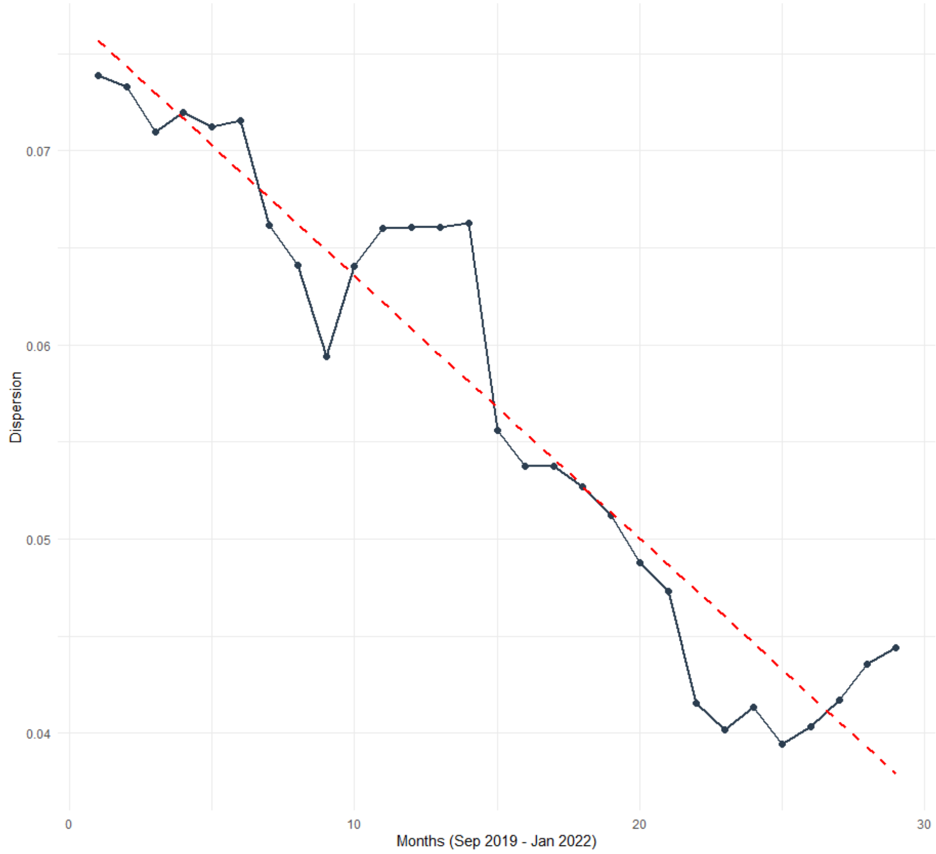


**Figure 4.** Dispersion ($\sigma$) of adjusted Bitcoin mining hashrate shares across countries over time.

This finding is further confirmed when using the coefficient of variation (CV) as a scale-invariant measure of relative dispersion. A negative ($-0.141$) and statistically significant ($p < 0.001$) time trend is again obtained, and a high goodness-of-fit too ($R^2 = 0.910$). Overall, the results suggest that the geographic distribution of mining activity became progressively more decentralized and balanced over the sample period, even though significant heterogeneity across countries remains.

3.4.2. Stochastic Convergence Results

We begin our analysis by testing for cross-sectional dependence (CD) in our panel. Given that mining shares are inherently linked, we expect significant cross-sectional correlation across nations. The Pesaran CD test strongly rejects the null hypothesis of cross-sectional independence ($z = 23.75$, $p < 0.001$).

To account for this dependence and ensure reliable inference, we estimate a two-way fixed-effects model with Driscoll–Kraay robust standard errors. The estimated persistence parameter on the lagged relative share ($z_{i,t-1}$) is $\hat{\rho} = 0.7959$ (SE = 0.0539). The coefficient is highly statistically significant ($t = 14.757$, $p < 0.0001$), indicating clear evidence of mean reversion and rejecting the hypothesis of divergence.

The model has a high explanatory power (within $R^2 = 0.639$). The estimated magnitude of $\hat{\rho}$ implies that deviations of a country's mining share from the global mean are transitory, with a speed of adjustment of approximately $1 - \hat{\rho}$ =20.4% per month. To further quantify the adjustment process, we compute the half-life of shocks, defined as the time required for a deviation to decline by 50%: ($HL = \log(0.5)/\log(\hat{\rho})$). Half of any idiosyncratic shock to a country's hashrate share is absorbed by the global market within approximately 3 months ($HL = 3.04$ months), suggesting a rapid adjustment process.

Mean-reverting dynamics in countries' relative mining shares are found by the stochastic convergence analysis. This does not necessarily imply uniform adjustment across all nations. In practice, structural factors such as electricity costs, regulatory environments, and infrastructure differences may lead to heterogeneous transition paths. Consequently, even in the presence of overall mean reversion, countries may converge toward different steady-state levels rather than a single common equilibrium. To account for this, we apply the Phillips–Sul club convergence analysis to look for groups of countries that move toward their own long-run targets.

At this point, we should note that the stochastic convergence specification is based on relative log deviations, which removes the common adding-up constraint of shares. Therefore, these findings mitigate concerns that the observed convergence is purely mechanical.

### 3.4.3. Club Convergence Results

The Phillips–Sul (PS) club convergence test is applied to the adjusted shares ($\tilde{s_{it}}$) in order to further investigate the convergence dynamics within our panel of 105 countries. The PS clustering algorithm is implemented across the recommended range of trimming parameters $r_T \in [0.2, 0.3]$.

The results are consistent with global convergence. Specifically, the PS test identifies a single convergence club for all examined trimming values (see Table 3). The null hypothesis of overall convergence cannot be rejected, as the computed $t$-statistic exceeds the critical value of $-1.65$ at the 5% significance level. The results are consistent with convergence of the full country panel toward a common long-run path.

**Table 3.** Estimated $\hat{b}$, Std.Err, $t_{\hat{b}}$ from Phillips–Sul global club convergence test with adjusted shares for different trimming parameters $r_T$.

| $r_T$ | $\hat{b}$ | Std.Err | $t_{\hat{b}}$ |
|---|---|---|---|
| 0.20 | 0.0743 | 0.147 | 0.506 |
| 0.25 | 0.157 | 0.151 | 1.041 |
| 0.30 | 0.39 | 0.126 | 3.086 |

In addition, the estimated convergence coefficient ($\hat{b}$) is positive across all trimming specifications and becomes statistically stronger as the trimming parameter increases. Although the magnitude of $\hat{b}$ varies with $r_T$, it consistently lies within the interval $[0, 2)$, implying slow but stable convergence in relative mining shares. Given the relatively short time dimension ($T = 29$), we further examine the small-sample stability of the Phillips–Sul procedure over a wider range of trimming parameters (trims between 0.16 and 0.35), obtaining consistent convergence results.

The plot of the relative transition paths ($h_{it}$) illustrates the statistical evidence of convergence in a single club (Figure 5). The sample initially exhibits substantial heterogeneity, with several countries located far from the panel average. Over time, however, relative positions seem to converge toward the unity line. The remaining fluctuations toward the end of the sample are consistent with short-run volatility and idiosyncratic shocks and with the moderate estimated speed of convergence.

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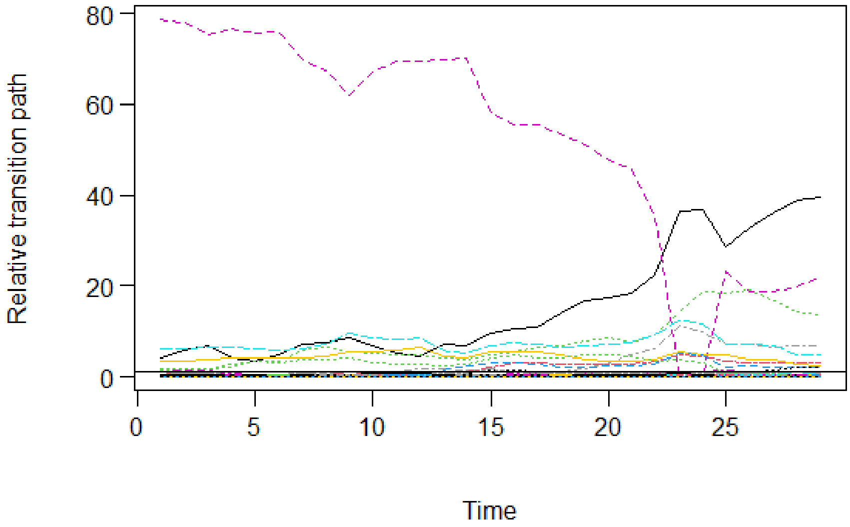


**Figure 5.** Relative transition paths from Phillips–Sul club convergence test on adjusted shares from Sept. 2019 to Jan. 2022 (trim = 0.2).

The Phillips–Sul transition parameter is defined in terms of positive relative levels. Accordingly, we avoid applying a logarithmic transformation within the ratio, as this may distort transition paths when the data are bounded shares. The convergence results remain robust to alternative positive rescalings of the shares, such as $s_{it} + 1$ or mapping the shares to the interval $(1, 100]$.

### *3.5. Heterogeneity in Long-Run Mining Positions*

Although the PS test indicates a single global convergence club, the estimated long-run relative positions ($\mu_i$) reveal meaningful heterogeneity within the converging panel. The distribution of $\mu_i$ is strongly right-skewed, implying an asymmetric convergence process. Convergence above the club average is suggested for values of $\mu_i > 1$, whereas $\mu_i < 1$ below it. A small number of countries seem to account for a disproportionately large share of global hashrate capacity, while most countries remain near the lower tail.

Considering only the 6 first months of the sample, 5.7% of countries are above the panel average ($\mu_i > 1$), highlighting the high concentration of mining activity in a few hubs. At the end of the sample period (6 last months), 10.5% of the countries exhibit $\mu_i > 1$. Thus, a limited number of countries move toward the leading group. The dominance of few major mining hubs is supported by the fact that nearly 90% of the countries remain below the panel average. These results help explain the relatively slow convergence speed.

The obtained leading mining countries from the end of the sample period remain unchanged under different specifications (15% and 20% of the sample), supporting the robustness of the findings and pointing to a persistent structural reallocation rather than a temporary fluctuation. Table 4 reports the ten dominant mining countries at the start and end of the sample period, the long-run relative positions and the corresponding standard deviation.

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**Table 4.** The ten dominant Bitcoin mining countries at the start (first 6 months) and end (last 6 months) of the sample period (Sept 2019–Jan 2022), based on long-run relative positions $\mu_i$. Convergence stability is denoted by $\sigma_{\mu_i}$.

| | First 6 months | | | | Last 6 months | | |
|---|---|---|---|---|---|---|---|
| Rank | Country | $\mu_i$ | $\sigma_{\mu_i}$ | Rank | Country | $\mu_i$ | $\sigma_{\mu_i}$ |
| 1 | Mainland China | 76.7 | 1.32 | 1 | United States | 35.5 | 4.03 |
| 2 | Russian Federation | 6.24 | 0.266 | 2 | Mainland China | 17.1 | 8.56 |
| 3 | United States | 4.88 | 1.24 | 3 | Kazakhstan | 16.9 | 2.29 |
| 4 | Malaysia | 3.86 | 0.385 | 4 | Canada | 7.45 | 1.24 |
| 5 | Iran, Islamic Rep. | 2.44 | 0.744 | 5 | Russian Federation | 7.06 | 2.48 |
| 6 | Kazakhstan | 2.34 | 0.967 | 6 | Malaysia | 3.81 | 0.931 |
| 7 | Norway | 0.983 | 0.076 | 7 | Germany | 3.51 | 0.587 |
| 8 | Canada | 0.979 | 0.166 | 8 | Ireland | 2.67 | 1.09 |
| 9 | Libya | 0.806 | 0.632 | 9 | Singapore | 1.51 | 0.487 |
| 10 | Germany | 0.503 | 0.222 | 10 | Thailand | 1.18 | 0.161 |

## 4. Discussion

The growth in total Bitcoin electricity consumption over the past decade is important for explaining the observed geographic reallocation of mining activity. During the examined period, mining hardware improved substantially and China's 2021 ban triggered a large-scale relocation of miners, with the United States emerging as the leading mining country, followed by China and Kazakhstan. The resulting large-scale redistribution of hashrate can be viewed as a natural experiment illustrating the highly adaptive and geographically mobile nature of the Bitcoin mining industry, as mining capacity rapidly relocated across countries. Although China's mining ban triggered a large-scale relocation of global mining capacity and accelerated the geographic redistribution of mining activity, the gradual decline in dispersion and the persistence of mean-reverting dynamics suggest that relocation forces were already present in the mining network.

The declining Theil index, as well as the $\sigma$-convergence analysis, clearly shows the gradual reduction in mining dispersion. In addition, stochastic convergence points to mean-reverting dynamics in relative mining shares. Finally, a single convergence club is identified by the Phillips–Sul analysis. Therefore, our empirical findings suggest common transition dynamics across countries, although convergence toward identical shares is not observed. The identification of a single convergence club indicates that the Bitcoin mining network operates under a common global adjustment process. Despite national differences, mining activity across countries appears to evolve along comparable dynamic trajectories. This is consistent with the high mobility of mining capital, as reflected in the short estimated half-life ($HL = 3.04$ months). These results point to a dynamic market structure in which emerging mining hubs partially narrow the gap with established leaders. The consistently high permutation entropy values across all countries further indicate that Bitcoin mining activity is highly dynamic and subject to frequent geographic shifts.

Although there is geographic dispersion of mining, it still remains concentrated in a small group of dominant countries. This persistent concentration is due to the tendency of miners to locate in regions with abundant and low-cost energy resources [4,31]. Energy availability, pricing, and infrastructure affect the long-run position of each location and explain the differences between dominant and peripheral hubs [32]. In this sense, Bitcoin mining illustrates the geography of digital infrastructure, where computational activity relocates globally in response to energy market conditions.

The dominance of few major hubs is reflected in the estimated long-run positions of the countries. Table 4 further illustrates that that leadership of China has transitioned to United States. After the 2021 regulatory shock of the mining ban, China remains a dominant hub but exhibits large fluctuations ($\sigma_{\mu_i} = 8.56$) in response to policy shocks [33], while most peripheral countries contribute very little to the global hashrate capacity. Our results are consistent with the geographic patterns reported by CCAF [34].

Convergence occurs alongside persistent core–periphery differences, reflecting the advantages of countries with stronger infrastructure. Recent studies also show that mining profitability depends on reliable infrastructure and economies of scale [35,36]. The convergence dynamics suggest that restrictive national policies may redirect mining activity to new locations rather than reduce it globally. This relocation of mining capacity across countries implies that policies based solely on prohibitions may have limited long-term effectiveness. More effective policy approaches may involve energy-market mechanisms, including electricity market design, carbon pricing, and incentives that encourage the use of renewable and low-carbon energy sources in major mining hubs. Continued monitoring is important in peripheral locations, where regulatory or cost shocks could trigger sudden reallocations of hashrate. Moreover, Bitcoin mining activity remains highly volatile. This indicates that the global mining network combines convergence dynamics with considerable short-run instability. As a result, electricity systems that host large mining operations may face sudden changes in demand, creating challenges for grid management and longer-term energy planning. At the same time, the concentration of mining activity in a few countries can also impose significant local costs. Evidence from Upstate New York shows that crypto-mining increased annual electricity bills by about $88 for the average household and $168 for small businesses [37].

## 5. Conclusions

Over the past years, global mining demand has increased and continues to grow, although at a more moderate pace. In addition, the distribution of mining evolves and the leading mining capacity of China is gradually redistributed across countries. This is reflected in the estimated heterogeneity measures and our convergence analyses, where short-run fluctuations remain substantial. Permutation entropy shows a high temporal volatility, with PE values above 0.7 for all countries. Stochastic convergence supports mean-reversion and is consistent with the evidence of declining dispersion from the $\sigma$-convergence analysis. Further, the Phillips–Sul methodology identifies a single converging club. We should note here that given the relatively short sample period (Sept. 2019–Jan. 2022), these findings should be interpreted as evidence of transitional dynamics rather than full long-run equilibrium convergence.

We employ various methodologies in this study since we aim to examine the distribution and evolution of the global Bitcoin mining network. The Theil index measures the monthly cross-sectional inequality in the distribution of mining shares. Another intuitive measure of distributional dynamics is the proposed cross-sectional symbolic entropy (CSE). The $\sigma$-convergence analysis captures the evolution of dispersion over time, while the Phillips–Sul framework assesses the dynamic convergence of transition paths. Our results consistently point to increasing decentralization, although important structural differences across countries persist.

Two major events are included within our sample period: the 2020 Bitcoin halving and China's ban. Our analysis does not require detection or formal modeling of structural breaks, but knowing these events helps explain the economic shocks that lead to persistent country-specific changes. The Bitcoin halving changed profitability conditions across countries, creating persistent local differences. China's ban triggered a large-scale hashrate relocation, in which a few hubs absorbed most of the capacity, while peripheral economies remained more volatile. For policymakers, understanding the pace of adjustment and the effects of such structural shocks is crucial for anticipating future reallocations of global hash power.

Our study provides a comprehensive empirical assessment of the evolution of global Bitcoin mining using two complementary datasets. First, we analyze the long-run growth trend of total Bitcoin electricity consumption. Then, we examine the cross-country dynamics of mining activity through entropy-based measures and panel convergence tests. Our results offer new evidence on the extent and speed of geographic decentralization in the mining landscape. The complementary methods provide a dynamic view of the evolving geographic distribution. Gradual but partial decentralization is found: mining activity is becoming more geographically dispersed, but a group of dominant hubs remains.

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Importantly, this panel provides a particularly useful reference point for the analysis, as it captures the geographic distribution of mining activity before the growing use of VPNs and intermediary pools made country-level attribution less reliable.

The limitations of this study are noted here. Although both datasets are relatively small, the electricity consumption series covers the full history of Bitcoin mining. Entropy-based measures are sensitive to short $T$; therefore, careful interpretation is adopted, that does not rely on the exact estimated values. The Phillips–Sul log-t regression is potentially the method most affected by the limited sample size, but all robustness checks support the single-club identification. Further, hashrate shares are bounded in the interval $[0,1]$ and are inherently interdependent, i.e., a decline in one country's share implies a gain elsewhere. Possible concerns related to the adding-up constraint are mitigated by the mean-reverting results based on relative log-deviations.

Future research could investigate causal determinants of long-run positions ($\mu_i$) for example using a multinomial probit framework with country-level fundamentals, such as electricity prices, GDP, internet penetration, and renewable capacity. Extending the convergence analysis beyond 2022 would also be valuable, particularly in light of the growing dominance of few hubs, such as the United States, which now account for roughly 40% of global hash rate [38].

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