CRYPTO-MINING AND ELECTRICITY MARKET NEXUS: ASSESSING THE EVIDENCE FROM THE NORDIC ELECTRICITY PRICES

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1. Introduction

The significant surge in Bitcoin (BTC) trading volume has garnered widespread attention from the media, financial sector, and government. Notably, the cryptocurrency market experienced explosive growth in 2017, with a market capitalization of $100.1 billion on October 21, 2017, soaring to $1.162 trillion by 2023, predominantly driven by BTC, which held approximately 50% of the market share. Ethereum (ETH), established in 2015, stands as the second-largest market player after BTC, comprising 18.5% of the market.

Crypto-mining is the process of creating new cryptocurrencies by solving a computational puzzle. Recent papers confirm that crypto-mining consumes a huge amount of energy, particularly electricity, in order to create virtual currencies in a proof-of-work (POW) scheme.[1] Studies by M. Krause and T. Tolaymat, A. Hern, and C. Stoll et al. have found that generating just one dollar's worth of Bitcoin

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consumes more energy than mining an equivalent value of many traditional metals, including aluminium, copper, gold, platinum, and rare earth oxides.[2]

Cryptocurrencies exhibit an imbalance between their technical performance and electrical energy consumption.[3] One of the primary issues surrounding Bitcoin mining revolves around its usage of electricity. According to M. Rauchs et al. Bitcoin mining currently uses about 0.53% of the world's annual electricity consumption, which exceeds the total electricity usage of medium-sized countries such as Sweden, Ukraine, and Argentina.[4] Moreover, this high energy consumption contributes to global warming due to its substantial carbon footprint.[5] It is estimated that Bitcoin alone could raise global temperatures by 2° Celsius in the next three decades.[6]

Furthermore, crypto-mining is the process that enables cryptocurrencies to function as a decentralized, peer-to-peer network while also enhancing the security of the blockchain. This task is carried out by miners who operate multiple computers and utilize significant processing power to validate transactions and secure the network. In fact, the amount of energy required reached 77.78 terawatt-hours (TWh) on May 2020 for Bitcoin mining and 12.7 TWh for Ethereum mining.[7] Recently, the amount of energy consumption by the whole network estimated was higher than some relatively medium-sized energy consuming nations such as Austria and Czech Republic. The estimated energy consumption for a single Bitcoin transaction is approximately 684.13 kWh, which is comparable to the electricity usage of an average U.S. household over 23.45 days. This is also equivalent to the energy required for 720,228 VISA transactions or for streaming 54,160 hours of YouTube. In comparison, an Ethereum transaction consumes about 32.43 kWh, which is equivalent to the electricity usage of an average U.S. household over 1.1 days.

Research indicates that crypto-mining presents a dual challenge. On one side, the substantial electricity consumption associated with cryptocurrency mining raises serious environmental concerns, including global warming.[8] C. Mora et al. warns of the consequences of rising temperatures within the coming decades due to crypto-driven energy demands.[9] M. Thum argues that Bitcoin mining wastes time, energy, and natural resources.[10] Furthermore, S. Corbet et al., in multiple articles, highlight that the environmental consequences of cryptocurrency growth are substantial and difficult to fully assess.[11] On the other hand, L. Cocco et al. emphasize that Bitcoin acts as a "safe haven," offering resilience against modern environmental challenges, outperforming traditional assets like gold.[12]

These foundational studies establish a link between cryptocurrency and its mining costs. Within this framework, an indirect relationship exists between cryptocurrency prices and electricity costs. To examine the balance between Bitcoin and its mining expenses, L. Kristoufek investigates the energy efficiency of miners.[13] This research reveals that higher energy consumption correlates to lower mining efficiency. Additionally, the author illustrates the dynamic interaction between key mining factors, such as Hashrate and electricity prices, and how fluctuations in these variables impact mining profitability, driving miners' operational decisions and affecting the broader sustainability and energy consumption of the Bitcoin network. This indicates that mining costs are influenced by several variables, including electricity prices, mining power consumption, and mining efficiency. Using cointegration models and causality tests, the analysis reveals that Bitcoin prices have an impact on mining costs.

Additionally, K. O'Dwyer and D. Malone investigate the profitability of Bitcoin mining alongside its energy consumption issues.[14] Their research shows a correlation between Bitcoin prices and electricity costs, highlighting how the competitive nature of mining has spurred the development of faster and more energy-efficient hardware to maintain financial viability in the industry.

Indeed, research by O. Delgado-Mohatar et al. and D. Das and A. Dutta highlights that increasing electricity costs and energy consumption imply reduced miner revenues.[15] As a result, profitability in Bitcoin mining is mainly observed among professional miners situated in regions with the lowest electricity prices.

S. Corbet et al. turned their attention to the connection between cryptocurrency and electricity prices.[16] Their research delved into how Bitcoin's price volatility affects energy markets, utility companies, and environmentally friendly Ethereum initiatives. Employing the dynamic conditional correlation (DCC-GARCH) approach, they analyzed the interactions between Bitcoin and selected energy sectors, constructing energy indices for countries like China, Japan, and Russia. Their findings reveal that the pricing behavior of Bitcoin correlates with major international electricity and utility commodities. In a subsequent paper, S. Corbet et al. examined how Bitcoin's price volatility and the underlying dynamics of cryptocurrency mining characteristics impact energy markets and utility companies.[17]

The existing body of research has primarily concentrated on Bitcoin as a virtual currency and its relationship with the energy market. This paper contributes to the literature by expanding the analysis to include Ethereum, exploring whether the cryptocurrency mining of this asset exerts significant energy consumption and influences electricity prices. Furthermore, recent research by S. Corbet et al. has focused on China, the largest mining pool, which accounts for 81% of mining pool concentration.[18] Interestingly, Nordic countries, comprising Scandinavian and Baltic nations, also emerge as significant players in the mining industry. However, a gap in the literature persists, as no studies have yet explored the dynamic correlations between the energy markets of these regions and cryptocurrencies.

This paper aims to explore the evolving connection between the cryptocurrency market, featuring Ethereum and Bitcoin, and the Nordic electricity market. Specifically, it examines how Bitcoin and Ethereum price volatility affects the Nordic electricity prices over the period 2015 to 2020.

The remainder of the paper is organized as follows: Section 2 outlines the data and the corresponding descriptive statistics. The methodology used is detailed in Section 3. Section 4 reports the obtained results and discusses the main findings, while Section 5 offers the paper's conclusions.

2. Data

Data Presentation: This research relies on daily data from August 8, 2015, to June 16, 2020. The primary variables used in the model include cryptocurrencies (Bitcoin and Ethereum), mining characteristics, and electricity spot prices.

Table 1 presents a description of the variables, highlighting that the dynamics of cryptocurrency mining characteristics are represented by factors such as Hashrate, the number of daily transactions, mining difficulty, block size, and the number of unique cryptocurrency mining addresses. The Hashrate refers to the speed at which a computer completes operations within the Bitcoin or Ethereum network, serving as an indicator of the network's power consumption, measured in hashes per second. Furthermore, increasing mining difficulty is directly linked to higher energy demands, especially electricity, for cryptocurrency mining.

Table 2 presents daily electricity spot prices (EUR/MWh) from various companies across the Nordic countries, including Sweden (SE), Estonia (EE), Lithuania (LT), Finland (FI), and Norway (NO), which are recognized as key players in the cryptocurrency mining industry.

Trends of the Series: Figure 1 shows the daily price evolution for the two cryptocurrencies in our study, Bitcoin and Ethereum, while Figure 2 illustrates the daily prices of electricity in some of the Nordic countries.

Table 1
VARIABLES' DESCRIPTION

Variables	Type	Observations	Period
Cryptocurrencies: ➢ Bitcoin (BTC) ➢ Ethereum (ETH)	• Primary variables • Daily closing prices	1,777 for each variable	August 8, 2015 to June 16, 2020
Source: https://coinmarketcap.com/fr/			
Cryptocurrencies' mining characteristics ➢ Hashrate ➢ Daily transactions ➢ Difficulty ➢ Block size ➢ Number of unique addresses	• Secondary variables • Daily series	1,777 for each variable	August 8, 2015 to June 16, 2020
Source: For Bitcoin Network: https://www.blockchain.com/ Source For Ethereum Network: https://etherscan.io/			
Electricity spot prices: Estonia (EE), Lithuania (LT), Finland (FI), Norway (NO), Sweden (SE)	• Primary variables • Daily electricity spot prices.	1,777 for each variable	August 8, 2015 to June 16, 2020
Source: https://www.nordpoolgroup.com/			

Figure 1
DAILY PRICES EVOLUTION OF BITCOIN AND ETHEREUM

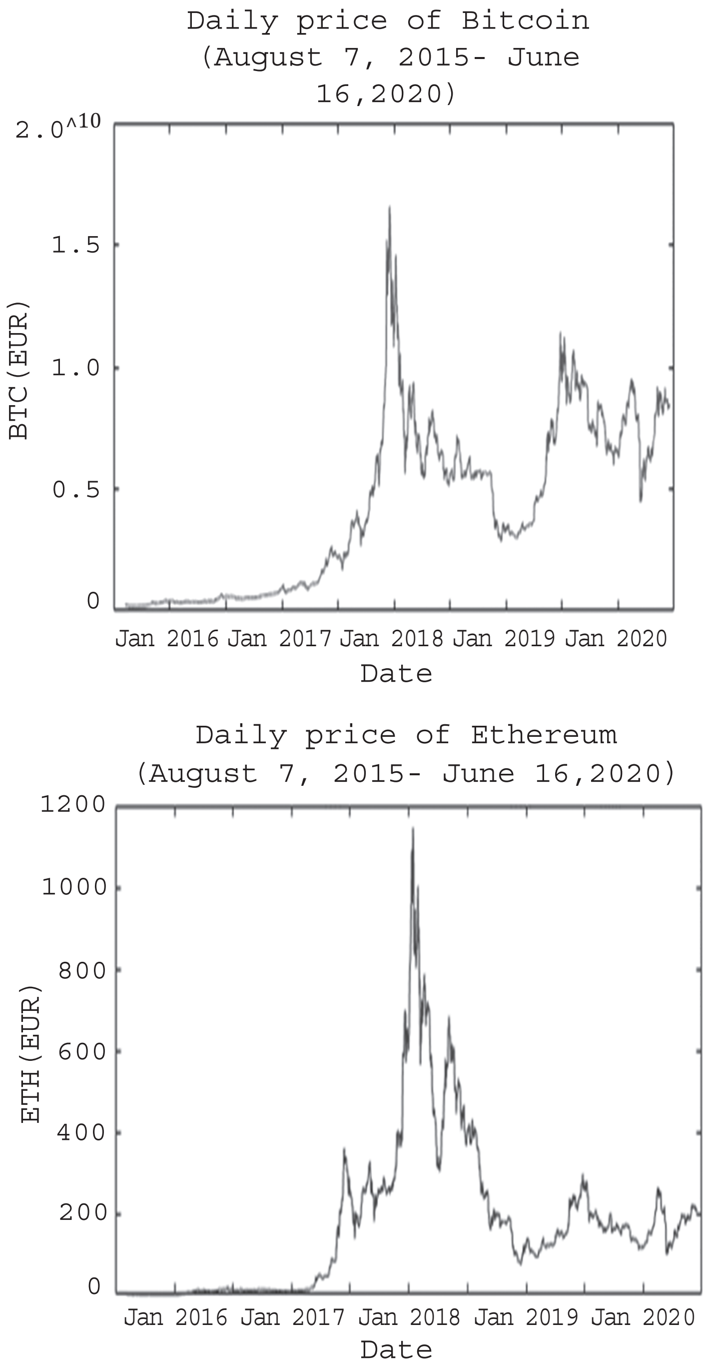
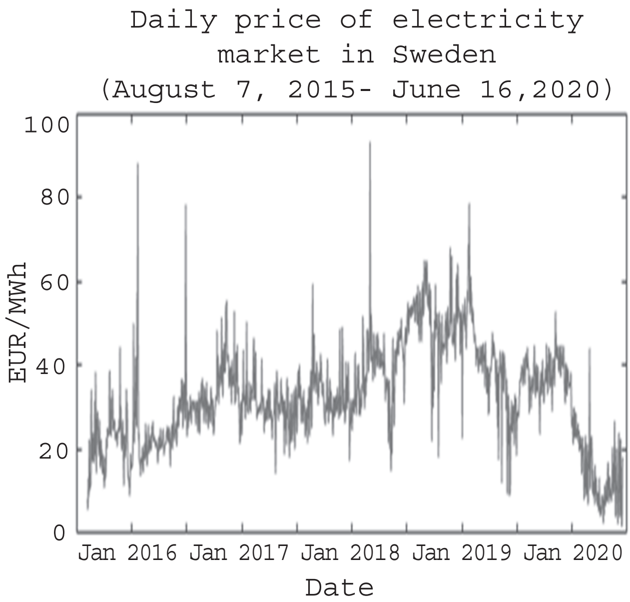


Figure 2
DAILY PRICES OF ELECTRICITY MARKET IN SOME NORDIC COUNTRIES



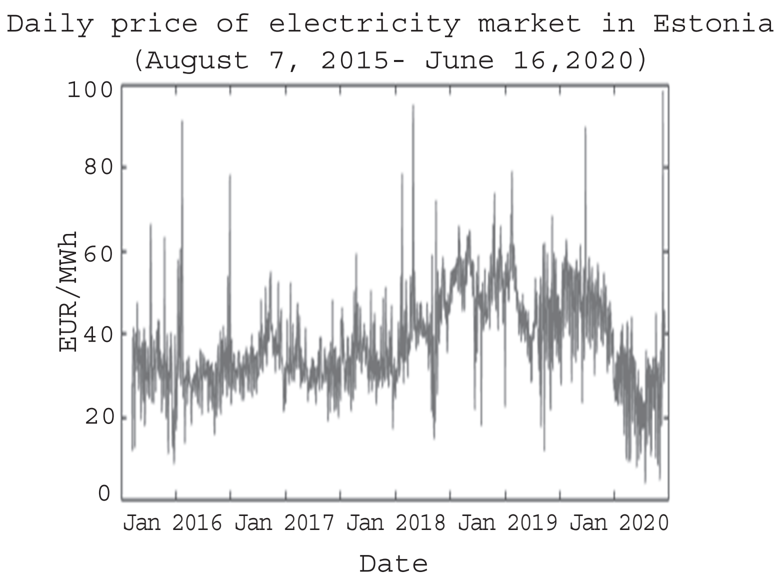


Figure 2 (continued)
DAILY PRICES OF ELECTRICITY MARKET IN SOME NORDIC COUNTRIES

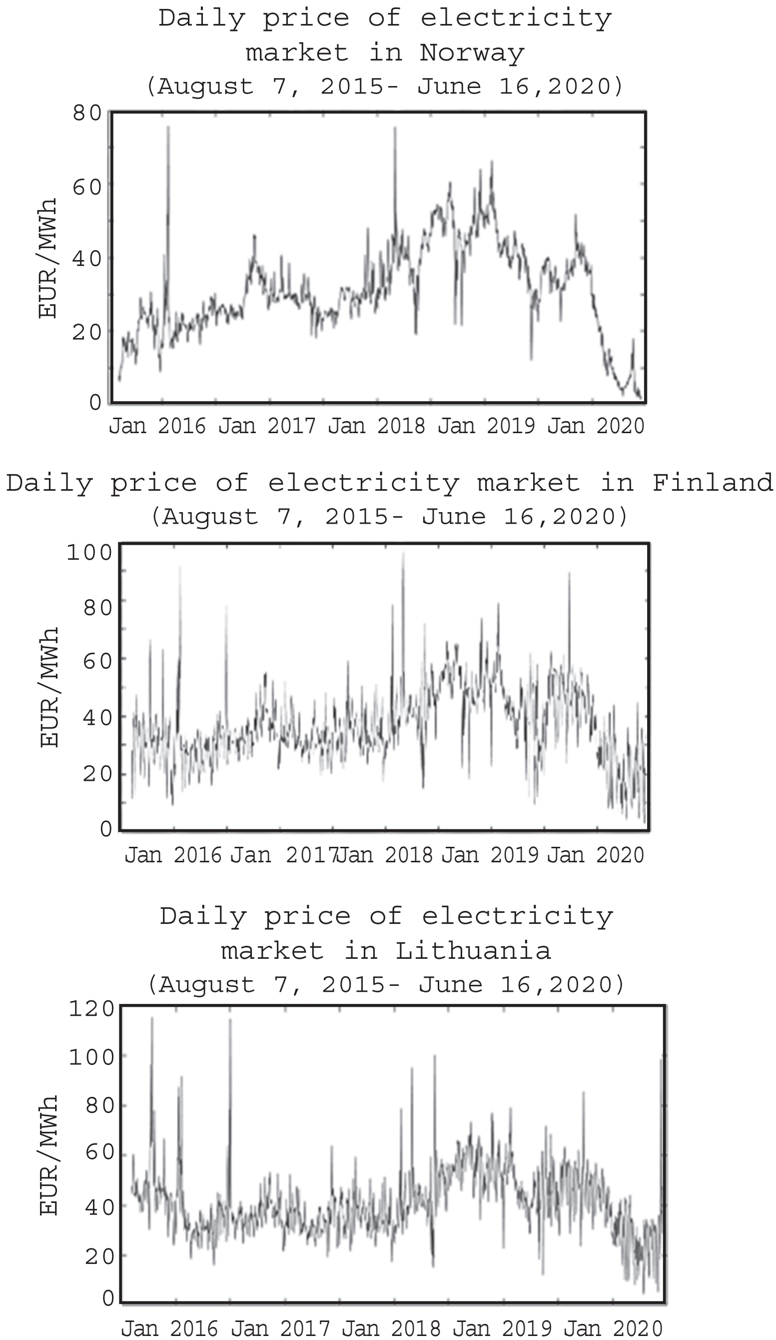


Figure 1 illustrates the daily prices of Bitcoin and Ethereum from August 7, 2015, to June 16, 2020. The data show that both Bitcoin and Ethereum experienced relatively stable price movements from 2015 through the first quarter of 2016. During this period, Bitcoin's price fluctuated between 250 EUR and 360 EUR, while Ethereum's price ranged between 2 EUR and 5 EUR, indicating no significant upward or downward trend.

Starting in the second quarter of 2016, Bitcoin's price began to climb steadily, rising from around 400 EUR to 1,100 EUR. In contrast, Ethereum's price remained relatively stable until early 2017, when it experienced a more dramatic rise. Initially, Ethereum's growth was slow, reaching 10 EUR by February 2, 2017, but soon surged to 115.6 EUR by May 5, 2017. By the end of 2017, both cryptocurrencies saw substantial price increases, reflecting heightened investor interest—particularly in Bitcoin—and growing momentum in the cryptocurrency trading markets.

According to S. Corbet et al., both Bitcoin and Ethereum entered a bubble phase.[19] However, in 2018, both cryptocurrencies underwent a significant price collapse, followed by a prolonged period of decline. Since then, their prices have remained in a downward trend.

Figure 2 presents the daily prices of electricity market in some Nordic countries. Several technical factors, including mining difficulty, Hashrate, daily transaction volume, number of unique addresses, and block size, play a crucial role in cryptocurrency mining and directly influence the electricity demand for both Bitcoin and Ethereum mining. Figure 2 displays that for Ethereum, the trends in mining difficulty and Hashrate appear to follow similar patterns. Notably, in the second half of 2018, both metrics reached their peak, coinciding with Ethereum's highest recorded price. Simultaneously, electricity prices in Nordic regions, such as Sweden, surged significantly, reaching 63 EUR per megawatt-hour (EUR/MWh). This suggests a potential relationship between these trends.

S. Corbet et al. note that the increased difficulty in mining has led to a need for more powerful technology and increased energy usage to mine cryptocurrency, indicating that mining difficulty is a key driver of the energy requirements for cryptocurrency mining.[20]

In the first half of 2020, both the cryptocurrency and electricity markets experienced significant price declines, primarily due to the global COVID-19 pandemic. Often referred to as a "third world war" because of its widespread and profound impact, the pandemic disrupted social, financial, and economic systems globally, with the crypto-mining sector being particularly affected. Strict quarantine measures and restrictions on movement limited access to mining farms, contributing to a decrease in cryptocurrency prices, which fell by approximately 15% by the end of March 2020.

Figure 1 illustrates the variability in the series, highlighting the non-constancy of variances, which indicates instability in the magnitude of fluctuations. The series also shows instability in their means, indicating non-linear behavior. This non-stationarity is confirmed by the autocorrelation function. Then, we consider the logarithmic return of the daily prices provided in equation (1):

$$R_t = \ln\,(P_t) - \ln\,(P_{t-1}) \tag{1}$$

where R_t = the return of the price, P_t = the price at day t, and P_{t-1} = the price at day $t-1$.

Graphically, the return series appear to be stationary, with the upward trend removed. Figure 3 clearly demonstrates the volatility clustering phenomenon, where periods of heightened volatility are followed by similar periods of high volatility, while low-volatility phases tend to persist. This behavior points to the presence of heteroscedasticity.

Descriptive Statistics: Table 2 displays the descriptive statistics of our data returns: cryptocurrencies, their mining characteristics and the electricity spot prices of the Nordic countries included in our study.

According to the results presented in Table 2, the means for all daily returns are positive but very small, close to zero. Notably, the average electricity price in Norway is the lowest, at nearly zero (−7.2458e-4). In contrast, Bitcoin's Hashrate shows the highest average return (0.0096), indicating that the two digital assets have higher mean returns than the electricity market. The Nordic electricity returns exhibit the highest standard deviations, ranging from 0.1065 to 0.2792, whereas Bitcoin and Ethereum show the lowest standard deviations, at 0.0405 and 0.0741, respectively.

For cryptocurrency mining characteristics, the measure of risk remains relatively low, with standard deviations ranging from 0.0067 to 0.1789. This indicates that the electricity markets in the Nordic countries demonstrate a much higher degree of risk and volatility compared to cryptocurrencies. Additionally, the maximum daily return varies between 0.2278 for Bitcoin and 2.3363 for FI returns, the latter being the highest value observed. Conversely, Bitcoin's minimum daily return (−0.4578) is higher than that of Ethereum (−1.3029) and the Nordic electricity markets, which range from −0.8108 to −1.9962.

Furthermore, we observe that the cryptocurrency series exhibit negative skewness, indicating that negative shocks have a greater impact than positive shocks, resulting in left-skewed, asymmetric distributions. In contrast, the electricity return series show positive skewness, with distributions that are asymmetric and right skewed.

The kurtosis values for both cryptocurrency and electricity return series are above 3, indicating leptokurtic distributions with fat tails and an increased probability of extreme values.

3. *Methodology*

Methodology Steps: To evaluate the strength of the dependency between the cryptocurrency market and the Nordic electricity market, we begin by estimating

Figure 3
DAILY RETURNS: ETHEREUM AND ELECTRICITY PRICES IN SWEDEN (SE)

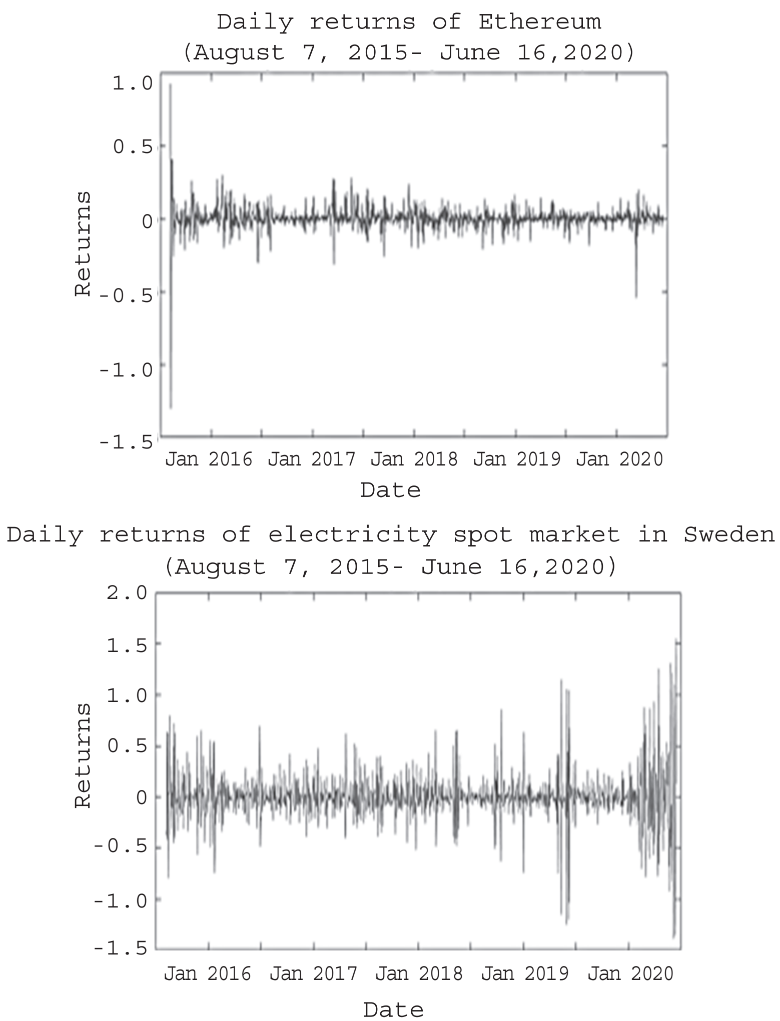


Table 2
DESCRIPTIVE STATISTICS FOR CRYPTOCURRENCIES, THEIR MINING CHARACTERISTICS, AND ELECTRICITY SPOT PRICES OF NORDIC COUNTRIES[a]

Description	Mean	St. Dev.	Max	Min	Kurtosis	Skewness
BITCOIN						
Bitcoin	0.002	0.0405	0.2278	−0.4578	15.8992	−0.9032
Difficulty	0.0032	0.0294	0.5731	−0.1731	11.7834	11.7834
Hashrate	0.0096	0.14	0.47	−0.6506	3.9349	−0.2272
Average Block Size	0.0006	0.1789	0.7865	−0.8268	5.3948	0.0094
Daily Transactions	0.0013	0.1533	0.4372	−0.5085	2.7701	−0.0545
Numb of Unique Addresses	0.0018	0.1569	0.4289	−0.4516	2.8505	−0.0203
ETHEREUM						
Ethereum	0.003	0.0741	0.9269	−1.3029	73.8991	−1.9296
Difficulty	0.0042	0.0335	0.2348	−0.4325	37.1087	−2.332
Hashrate	0.0043	0.0304	0.2282	−0.249	12.8192	−0.0591
Average Block Size	0.0022	0.1214	1.155	−1.5276	27.7081	−0.5374
Daily Transactions	0.0034	0.129	0.8905	−0.891	11.7066	−0.1321
Numb of Unique Addresses	0.0052	0.0067	0.1505	0.00052	131.7922	7.4907
ELECTRICITY MARKETS						
EE	0.000285	0.2481	1.7084	−1.3325	10.2049	0.5844
SE	0.000240	0.2147	1.5555	−1.3872	13.2594	0.3681
LT	−9.95E-06	0.2301	1.7084	−1.3325	11.37	0.5228
FI	1.47E-04	0.2792	2.3363	−1.9962	13.4811	0.4368
NO	−7.25E-04	0.1065	0.6242	−0.8108	13.1783	−0.3115

[a]EE = Estonia, SE = Sweden, LT = Lithuania, FI = Finland, and NO = Norway.

the univariate standard GARCH (1,1) model for each residual series, which captures the individual volatility dynamics of each market. Next, the multivariate DCC-GARCH (1,1) model is employed to analyze the dynamic correlations between the two markets. By using the standardized residuals, the parameters of the DCC-GARCH model are effectively estimated, providing deeper insights into the time-varying dependencies. The methodological steps for this process are outlined in Figure 4.

Figure 4
METHODOLOGY STEPS

Multivariate DCC-GARCH Model: The Dynamic Conditional Correlation (DCC-GARCH) model, introduced by Engle and Sheppard in 2001, is an extension of Bollerslev's (1990) Constant Conditional Correlation (CCC-GARCH) model. Widely applied in multivariate time series analysis, this model is part of the multivariate GARCH family and provides a robust framework for examining interactions between financial series by analyzing dynamic correlations and volatility transmission over time. The DCC-GARCH model is particularly valuable for capturing evolving relationships between assets, offering deeper insights into how market volatility is interconnected. The DCC-GARCH model is presented in equation (2):

$$H_t = D_t R_t D_t \tag{2}$$

where H_t is an $n \times n$ matrix of conditional variances of ε_t at time t with $H_t = Cov[\varepsilon_t]$; D_t is an $n \times n$ diagonal matrix of conditional standard deviations of ε_t at time t; R_t is an $n \times n$ conditional correlation matrix of ε_t at time t.

The DCC-GARCH model is implemented in two stages. First, the conditional volatility for each series is estimated using a univariate GARCH model. In the second stage, the standardized residuals from the first step are used to estimate the parameters of the dynamic correlation matrix R_t. This two-step process efficiently captures both individual volatilities and the time-varying correlations between the series, offering a thorough understanding of their interdependencies. In this model, the matrix H_t is decomposed into two matrices, D_t and R_t, as shown in equation (2), where:

$$D_t = \begin{pmatrix} \sqrt{h_{1,t}} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sqrt{h_{n,t}} \end{pmatrix}; \quad R_t = \begin{pmatrix} 1 & \cdots & \rho_{1n,t} \\ \vdots & \ddots & \vdots \\ \rho_{n1,t} & \cdots & 1 \end{pmatrix}$$

The elements in the D_t matrix are generated according to a GARCH (p,q) process:

$$h_{i,t} = \omega_i + \sum_{k=1}^{q_i} \alpha_{ik} \varepsilon_{i,t-k}^2 + \sum_{k=1}^{p_i} \beta_{ik}\, h_{i,t-\mathrm{k}} \tag{3}$$

Where:

- $h_{i,t}$ is the conditional variance at time t for the i^{th} time series.
- ω_i is a constant, or long-term average variance for the i^{th} time series.
- $\sum_{k=1}^{qi} \alpha_{ik} \varepsilon_{i,t-k}^2$ is the ARCH term, which represents the sum of past squared innovations (shocks) up to lag q_i. Here, $\varepsilon_{i,t-k}^2$ is the squared residual or error term from the model at time $t-k$, and α_{ik} is the weight of each lagged squared innovation.

- $\sum_{k=1}^{pi} \beta_{ik}\, h_{i,t-\mathrm{k}}$ is the GARCH term, which represents the sum of past conditional variances up to lag p_i. Here, $h_{i,t-k}$ is the lagged conditional variance at time $t-k$, and β_{ik} is the coefficient that determines the weight of the lagged variance.

To determine R_t, two conditions must be satisfied: (1) The matrix must be positive definite, as it represents a covariance matrix (i.e., R_t must be positive definite to ensure this property). (2) All elements in the correlation matrix R_t must be less than or equal to one ($\rho_{ij,t} \leq 1$). To satisfy these conditions, R_t is decomposed as shown in equation (4):

$$R_t = Q_t^* Q_t Q_t^* \tag{4}$$

where:

- R_t is the correlation matrix at time t.
- Q_t^* is the standardized diagonal matrix, expressed as:

$$Q_t^* = diag(Q_t)^{-\frac{1}{2}}.$$

- Q_t is the unstandardized dynamic covariance matrix at time t, which can be expressed as:

$$Q_t = (1-\alpha-\beta)\overline{Q} + \alpha\varepsilon_{t-1}\varepsilon'_{t-1} + \beta Q_{t-1}$$

where:

- α and β are the parameters of the model.
- $\overline{Q}$ is the unconditional covariance matrix of the standardized residuals, obtained by the univariate GARCH model.
- $\varepsilon_{t-1}\varepsilon'_{t-1}$ represents the outer product of standardized residuals at time $t-1$.
- Q_{t-1} is the lagged covariance matrix.

$$Q_t = \begin{pmatrix} q_{11,t} & \cdots & \sqrt{q_{11,t}}\sqrt{q_{nn,t}} \\ \vdots & \ddots q_{22,t} & \vdots \\ \sqrt{q_{11,t}}\sqrt{q_{nn,t}} & \cdots & q_{nn,t} \end{pmatrix}$$

Therefore, the matrix Q_t must be positive semi-definite, to ensure that R_t is positive definite.

α and β are scalars and must satisfy equation (5):

$$\alpha \geq 0,\ \ \beta \geq 0 \text{ and } \alpha + \beta < 1 \tag{5}$$

Moreover, the coefficients of the dynamic correlation matrix are presented in the following equations:

$$\rho_{ij,t} = \frac{qij,_t}{\sqrt{qii,_t}\sqrt{qjj,_t}} \quad \text{for } i,j=1\ldots,\ n \text{ and } i \neq j \tag{6}$$

$$\rho_{12,t} = \frac{(1-\alpha-\beta)\overline{q}_{12} + \alpha\mu_{1,t-1}\mu_{2,t-1+\beta q_{12,t-1}}}{\sqrt{(1-\alpha-\beta)\overline{q}_{12} + \alpha\mu^2_{1,t-1} + \beta q_{11,t-1}}\sqrt{(1-\alpha-\beta)\overline{q}_{22} + \alpha\mu^2_{2,t-1} + \beta q_{22,t-1}}} \tag{7}$$

According to Engle and Engle and Sheppard, the DCC model is estimated using a two-stage approach to maximize the log-likelihood function.[21] Let θ represent the parameters in D_t, and Φ the parameters in R_t. The parameters of the DCC model are estimated using maximum likelihood through two steps. In the first step, the variances are maximized, and in the second step, the dynamic conditional correlations are estimated. The log-likelihood is defined through the following equation (8) (see Engle):[22]

$$L(\theta,\Phi) = -\frac{1}{2}\sum_{t=1}^{T}(nlog(2\pi) + log|D_t|^2 + r'_t D_t^{-2} r'_t) - \frac{1}{2}\sum_{t=1}^{T}(log|R_t| + \varepsilon'_t R_t^{-1}\varepsilon_t - \varepsilon'_t\varepsilon_t) \tag{8}$$

$$L(\theta,\Phi) = L_v(\theta) + L_c(\theta,\Phi)$$

$$L_v(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(nlog(2\pi) + log|D_t|^2 + r'_t D_t^{-2} r_t) \text{ is the volatility part, and}$$

$$L_c(\theta,\Phi) = -\frac{1}{2}\sum_{t=1}^{T}(log|R_t| + \varepsilon'_t R_t^{-1}\varepsilon_t - \varepsilon'_t\varepsilon_t) \text{ is the correlation part.}$$

The first part of the likelihood function in equation (8) represents volatility, which is the sum of individual GARCH likelihoods. In the first step, the log-likelihood function is maximized with respect to the parameters in D_t. Once these parameters are estimated, the second part, which relates to the correlation component of the likelihood function, is maximized to estimate the correlation coefficients.

We apply a multivariate Dynamic Conditional Correlation (DCC) model, which enables the analysis of cross-market linkages and the dynamic interactions between volatility and correlations. This approach is particularly effective in capturing the behavior of investors in response to market shocks. Furthermore, the

DCC-GARCH model estimates the correlation coefficients of the standardized residuals and directly accounts for heteroscedasticity.[23] These estimations also allow for the calculation of optimal portfolio measures, providing valuable insights into portfolio risk management.

4. *Results*

The GARCH (1,1) Estimations Under Normal Distribution: First, we estimate the parameters for GARCH (1,1) model for all series returns by the method of Maximum Likelihood under the normal distribution. The results of this estimation are shown in Table 3.

Table 3 presents two key equations: the mean equation, represented by the parameter μ, and the conditional variance equation, represented by the parameters α_0, α_1, and β_1. The significance of the parameter μ indicates a dependency relationship between data returns and their lagged returns over the observation period. On the other hand, the parameters α_0, α_1, and β_1 are part of the conditional variance equation, and the results show that these estimates are highly significant at the 5% confidence level, confirming the presence of heteroscedasticity in the data.

For all variables, the ARCH term (α_1) is positive but relatively small, while the GARCH term (β_1) is positive and relatively high. This suggests the presence of volatility clustering in the data returns. Additionally, the sum of α_1 and β_1 ($\alpha_1 + \beta_1$) approaches one for all variables, indicating a strong persistence of volatility. This persistence parameter is below 1, which satisfies the mean-reverting condition of the process, further confirming that volatility persists strongly across all series.

Table 3
ESTIMATION OF THE UNIVARIATE GARCH-N MODEL[a]

	Mean Equation	**Variance Equation**			
	μ	α_0	α_1	β_1	**Persistence**
BTC	0.002389*	8.0812e^{-5}*	0.16637*	0.80825*	0.97462
ETH	0.001576	0.00037184*	0.22499*	0.70794*	0.93293
SE	0.004096	0.000918*	0.16966*	0.82258*	0.99224
EE	0.003702	0.0010011*	0.15849*	0.83834*	0.99683
LT	0.003324	0.0012514*	0.17086*	0.81503*	0.98589
FI	0.003472	0.00077351*	0.13518*	0.86482*	1
NO	0.003606*	0.00054705*	0.35763*	0.64237*	1

[a]* = the parameter is significant at 5% confidence level; α_1 = lagged squared residuals; β_1 = lagged conditional variance; BTC = Bitcoin; ETH = Ethereum; EE = Estonia; SE = Sweden; LT = Lithuania; FI = Finland; and NO = Norway.

Moreover, the results also highlight that all return series exhibit a kurtosis value greater than 3, implying that the distributions of the variables are leptokurtic and not normally distributed. Normality tests confirm the non-normal distribution of the variables, indicating heavier tails than those of a normal distribution. Therefore, we proceed by investigating the univariate GARCH model under the assumption of a Student's t-distribution to better capture these characteristics.

To validate that the data returns in our sample follow a Student's t-distribution, we conducted the Kolmogorov-Smirnov test. As shown in Table 4, the results indicate that the null hypothesis is accepted for the Student's t-distribution, confirming its suitability for our data. Therefore, we conclude that the Student's t-distribution is appropriate for this study.

The GARCH (1,1) Estimation under the Student Distribution: T. Bollerslev[24] advocates for the use of the Student's t-distribution over the Gaussian distribution when applying the GARCH (1,1) model. Accordingly, we estimate the GARCH (1,1) model for all return series using the Student's t-distribution, employing Maximum Likelihood Estimation (MLE).

Table 5 presents the estimation results of the GARCH (1,1) model. The parameters α_1 and β_1, which correspond to the ARCH and GARCH terms, respectively, are statistically significant at the 5% confidence level for all variables. Additionally, the persistence parameter ($\alpha_1 + \beta_1$) is close to one, indicating strong volatility persistence across all return series. Moreover, the GARCH term for all variables is positive and relatively high, further confirming the presence of volatility clustering in the data.

In summary, our return data exhibit two types of volatility: volatility clustering and persistence of individual shocks. Additionally, previous tests confirm that the variance equation is well specified. These findings allow us to proceed with estimating the multivariate GARCH model, specifically the DCC-GARCH model.

Table 4
KOLMOGOROV-SMIRNOV (KS) TEST[a]

	Normal				Student		
	H	**P-Value**	**KS-stat**	**C-Value**	**H**	**KS-stat**	**P-Value**
Bitcoin	1	$3.1616e^{-308}$	0.4457	0.0321	0	0.0286	0.1067
Ethereum	1	$1.9613e^{-281}$	0.4259	0.0321	0	0.0300	0.0796
EE	1	$5.7491e^{-151}$	0.3117	0.0321	0	0.0295	0.0895
SE	1	$1.2632e^{-176}$	0.3372	0.0321	0	0.0211	0.4025
LT	1	$8.1204e^{-163}$	0.3237	0.0321	0	0.0240	0.2546
FI	1	$1.4023e^{-145}$	0.3061	0.0321	0	0.0270	0.1472
NO	1	$3.5035e^{-244}$	0.3966	0.0321	0	0.0192	0.5202

[a]EE = Estonia; SE = Sweden; LT = Lithuania; FI = Finland; and NO = Norway.

Table 5
ESTIMATION OF THE UNIVARIATE GARCH-T MODEL[a]

	Mean Equation	Variance Equation			
	μ	α_0	α_1	β_1	Persistence
BTC	0.002146*	$1.33e^{-5}$*	0.271058*	0.875061*	1
ETH	0.000190	0.000353*	0.348312*	0.710882*	1
SE	−0.002976	0.001675*	0.329703*	0.711280*	1
EE	−0.005683	0.001302*	0.156727*	0.852072*	1
LT	−0.004644	0.001432*	0.156807*	0.834130*	0.990937
FI	−0.006179	0.001099*	0.151672*	0.867138*	1
NO	0.000197	0.000532*	0.432673*	0.642594*	1

[a]* = the parameter is significant at 5% confidence level; α_1 = the lagged squared residuals; β_1 = the lagged conditional variance; BTC = Bitcoin; ETH = Ethereum; EE = Estonia; SE = Sweden; LT = Lithuania; FI = Finland; and NO = Norway.

Multivariate DCC-GARCH (1,1) Estimation: Table 6 presents the results of the DCC-GARCH (1,1) model, where both estimated coefficients, αDCC and βDCC, are highly significant at the 5% confidence level. This confirms the presence of dynamic conditional correlations between the cryptocurrency and Nordic electricity markets, demonstrating that the DCC-GARCH model is a suitable choice for analyzing these relationships.

The parameter αDCC captures the short-term transmission of information from the cryptocurrency market to the Nordic electricity market, with its significance indicating notable short-run volatility. Conversely, the significance of βDCC

Table 6
DCC-GARCH (1,1) ESTIMATION

	Coefficient	Std. Err	t-stat
$\rho_{BTC\text{-}ETH}$	0.7886662	0.0245626	32.11
$\rho_{BTC\text{-}EE}$	−0.0556703	0.0643579	−0.87
$\rho_{BTC\text{-}SE}$	−0.0572869	0.0635664	−0.90
$\rho_{BTC\text{-}LT}$	−0.049635	0.064592	−0.77
$\rho_{BTC\text{-}FI}$	−0.0612135	0.0642583	−0.95
$\rho_{BTC\text{-}NO}$	−0.0522541	0.0634307	−0.82
$\rho_{ETH\text{-}EE}$	−0.0258457	0.0656517	−0.39
$\rho_{ETH\text{-}SE}$	−0.0240582	0.0651355	−0.37
$\rho_{ETH\text{-}LT}$	−0.0297406	0.0658129	−0.45
$\rho_{ETH\text{-}FI}$	−0.094155	0.0655159	−0.45
$\rho_{ETH\text{-}NO}$	−0.0104151	0.0649729	−0.16
α_{DCC}	0.06826*	0.0028575	23.89
β_{DCC}	0.909149*	0.0035948	252.91
Persistence ($\alpha_{DCC}+\beta_{DCC}$)		0.977409	

reflects long-term information transmission between the two markets, underscoring the presence of sustained interactions over time. Additionally, the condition (αDCC + βDCC) $<$ 1 is satisfied, confirming strong persistence of volatility in the conditional variance. This further indicates that the conditional correlations are dynamic and evolve over time, following a mean-reverting process, rather than remaining constant.

Model Evaluation: To ensure that the model effectively captures the information in the time series, it is important to test for autocorrelation in the standardized residuals. These residuals from the estimated model should be independently and identically distributed (white noise).

To evaluate the model, we apply the Ljung-Box test to the standardized squared residuals of the estimated univariate GARCH (1,1) model. The results of this test are presented in Table 7. We observe that the p-values for the variables used in the DCC model are greater than 5% with 20 degrees of freedom. This lack of significant autocorrelation in the standardized squared residuals confirms that the model effectively captures and explains the variance over time.

Additionally, we conduct an ARCH test on the standardized residuals for all series to check for conditional heteroscedasticity (non-constant variance). As shown in Table 8, the p-values exceed the 5% confidence level, indicating the absence of ARCH effects in the residual series. Consequently, the residuals are independently and identically distributed for all series.

Following this key estimation, it is crucial to proceed to the next step, which involves a graphical analysis to further explore the dynamic conditional correlation between the two selected markets.

Dynamic Conditional Correlation Analysis (Graphic Approach): Furthermore, we conducted an ARCH test on the standardized residuals for all series to check for conditional heteroscedasticity (non-constant variance). As shown in Table 8, the p-values exceed the 5% confidence level, indicating the absence of

Table 7

LJUNG-BOX TESTS (5%) ON STANDARDIZED SQUARED RESIDUALS[a]

Sector	Description	H	C-value	Stat	P-Value
Cryptocurrency 1	Bitcoin	0	31.4104	2.91228	0.7734
Cryptocurrency 2	Ethereum	0	31.4104	2.476	0.8413
Electricity market	EE	0	31.4104	8.20	0.1621
	SE	0	31.4104	2.91226	0.7734
	LT	0	31.4104	7.31256	0.1893
	FI	0	31.4104	4.645	0.5069
	NO	0	31.4104	7.046	0.1953

[a]EE = Estonia; SE = Sweden; LT = Lithuania; FI = Finland; and NO = Norway.

Table 8
ARCH LM TEST (5%) ON THE STANDARDIZED RESIDUALS[a]

Sector	Description	Stat	Shape	Scale	P-Value
Cryptocurrency 1	Bitcoin	3.0056	2.315	1.543	0.5125
Cryptocurrency 2	Ethereum	1.0905	2.315	1.543	0.8984
Electricity market	EE	6.366	2.315	1.543	0.1245
	SE	6.464	2.315	1.543	0.1130
	LT	5.004	2.315	1.543	0.2650
	FI	7.021	2.315	1.543	0.0926
	NO	6.595	2.315	1.543	0.1060

[a]EE = Estonia; SE = Sweden; LT = Lithuania; FI = Finland; and NO = Norway.

ARCH effects in the residual series. This confirms that the residuals are independently and identically distributed across all series, validating the model's adequacy.

Dynamic Conditional Correlation between Bitcoin and Nordic Electricity Market: Figure 5 illustrates that the daily conditional correlation between Bitcoin and the Finnish electricity market fluctuates between −0.4 and 0.5. A peak correlation of 0.5 in mid-2018 suggests a moderate level of dependency between these two markets during that period. This increase aligns with a sharp rise in Bitcoin prices, which drew heightened interest from both investors and miners. The surge in mining activities significantly increased energy consumption, driving higher demand for electricity and contributing to elevated electricity prices.

Figure 5
DYNAMIC CONDITIONAL CORRELATION BETWEEN BITCOIN AND FINNISH (FI) ELECTRICITY MARKET

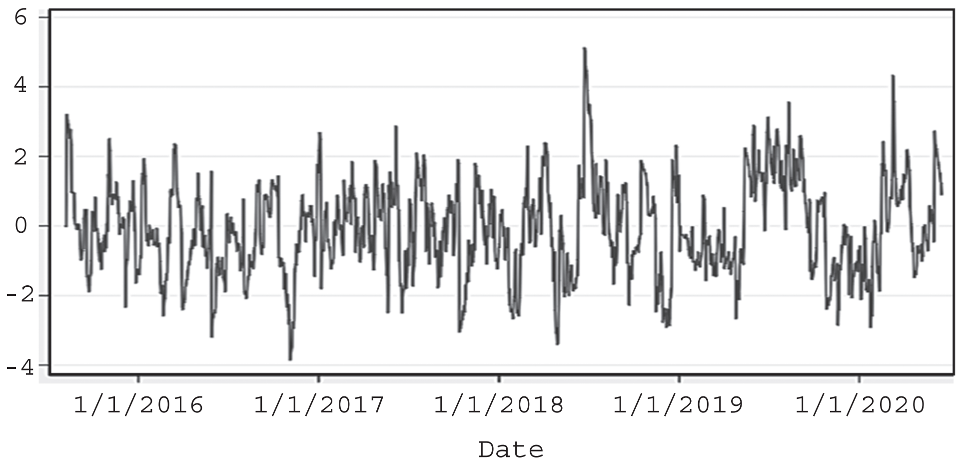


Figure 6 depicts the dynamic conditional correlation between the Swedish electricity market and Bitcoin returns, showing both positive and negative correlations over time. The correlation peaks at 0.49 in mid-2018, indicating a moderate relationship between Swedish electricity returns and Bitcoin returns during this period. Sweden plays a prominent role in the cryptocurrency mining industry, having invested heavily in its blockchain infrastructure and fostering a highly digitalized economy. Additionally, the Swedish government has demonstrated a commitment to integrating blockchain technology into mainstream governmental functions.

The conditional correlation analysis highlights a moderate interaction between Bitcoin and the Swedish electricity market in mid-2018, a time marked by a surge in Bitcoin transactions, record-high valuations, and increased market capitalization. This spike in activity attracted many investors and miners, driving up energy demand for cryptocurrency mining and pushing electricity prices to 63 EUR/MWh. The energy needs of mining farms across Sweden contributed to the growth of mining facilities throughout Europe. However, outside of this period, the relationship between the Swedish electricity market and Bitcoin returns remained relatively weak.

We can also observe the conditional correlation evolution of Bitcoin with Estonian electricity market (EE), Norwegian electricity market (NO) and Lithuanian electricity market (LT) through Figure 7. The correlation coefficients fluctuate between −0.39 and 0.42 for Estonia (EE) and Bitcoin (BTC), −0.49 and 0.39 for Norway (NO) and Bitcoin, and −0.39 and 0.41 for Lithuania (LT) and Bitcoin. These ranges indicate a moderate correlation at certain times, suggesting a degree of interaction

Figure 6
DYNAMIC CONDITIONAL CORRELATION BETWEEN BITCOIN AND SWEDISH (SE) ELECTRICITY MARKET

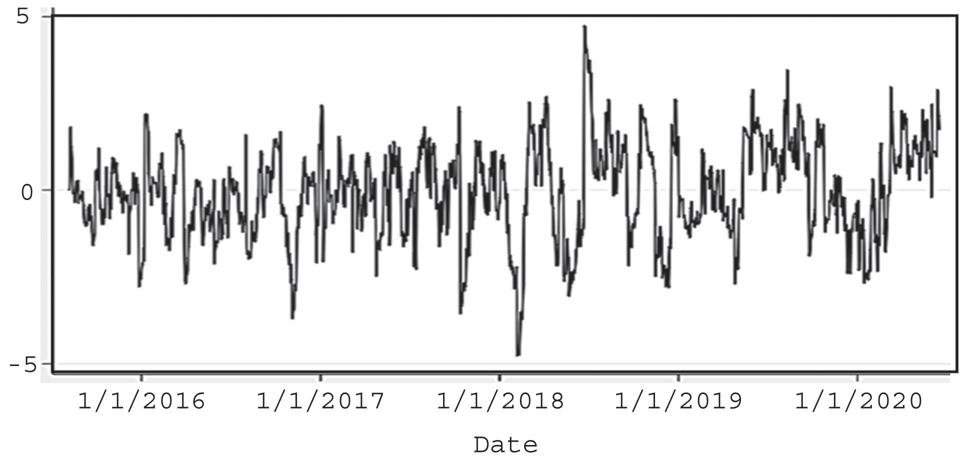
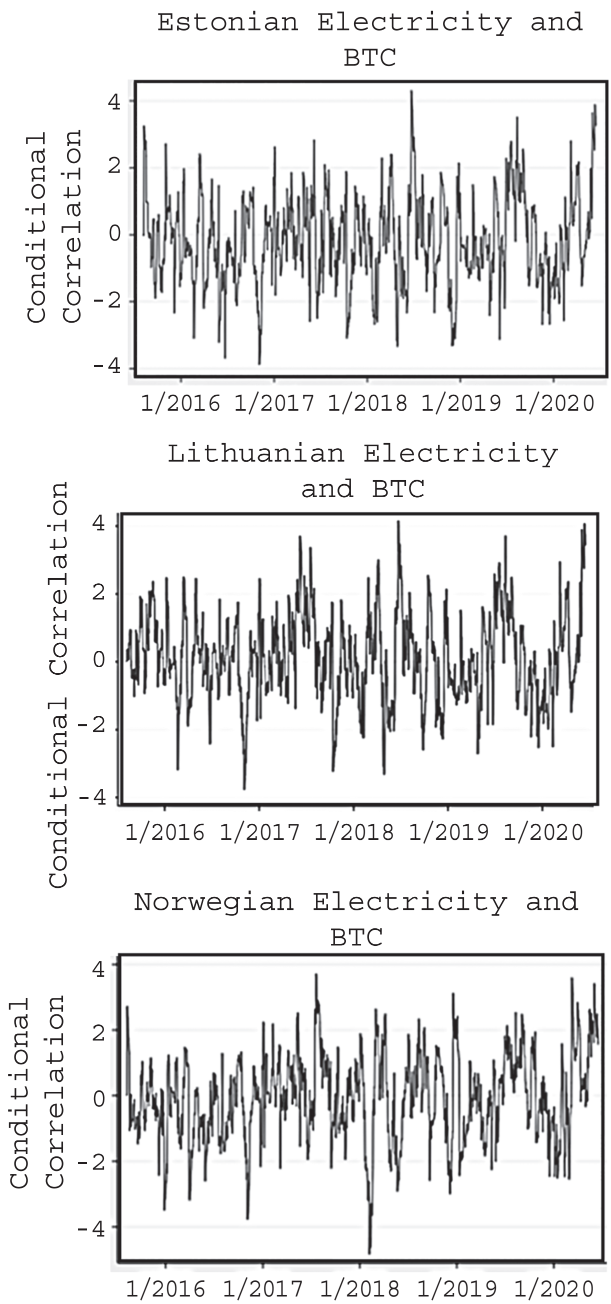


Figure 7
DYNAMIC CONDITIONAL CORRELATION BETWEEN BITCOIN AND NORDIC ELECTRICITY RETURNS



between Bitcoin and the respective electricity markets. However, during other periods, the correlation weakens, indicating minimal linkage between the two markets.

Dynamic Conditional Correlation between Ethereum and Nordic Electricity Market: We examine the dynamic conditional correlation between Ethereum and the Nordic electricity markets, with the following graphs illustrating the fluctuations in correlation across different periods.

Figure 8 depicts the dynamic conditional correlation between Ethereum volatility and the Norwegian electricity market, showing a moderate upward trend. Notable peaks are observed at 0.49 in mid-2016, and 0.40 at the beginning of both 2018 and 2019. In the second quarter of 2020, the correlation rises again to 0.46, remaining positive during this period. These findings suggest a moderate relationship between the two markets over time.

Figure 9 illustrates the dynamic conditional correlation between Ethereum and the Estonian electricity market, ranging from −0.39 to 0.49 over the observed period. In the first half of 2018, a moderate correlation is evident, as Ethereum reached its peak value and market capitalization, coinciding with elevated electricity prices in Estonia. This suggests that Ethereum's price likely impacted electricity prices, driven by the increased energy demand from miners seeking to capitalize on the rising cryptocurrency value.

Estonia is recognized as a digital pioneer, with its government operating a wide range of digital services, including e-governance, finance, tax administration, business, security, healthcare, education, mobility, and identity management. Blockchain technology plays a crucial role in strengthening the country's advanced digital infrastructure, and the Estonian government is actively deploying

Figure 8
DYNAMIC CONDITIONAL CORRELATION BETWEEN ETHEREUM AND THE NORWEGIAN (NO) ELECTRICITY MARKET

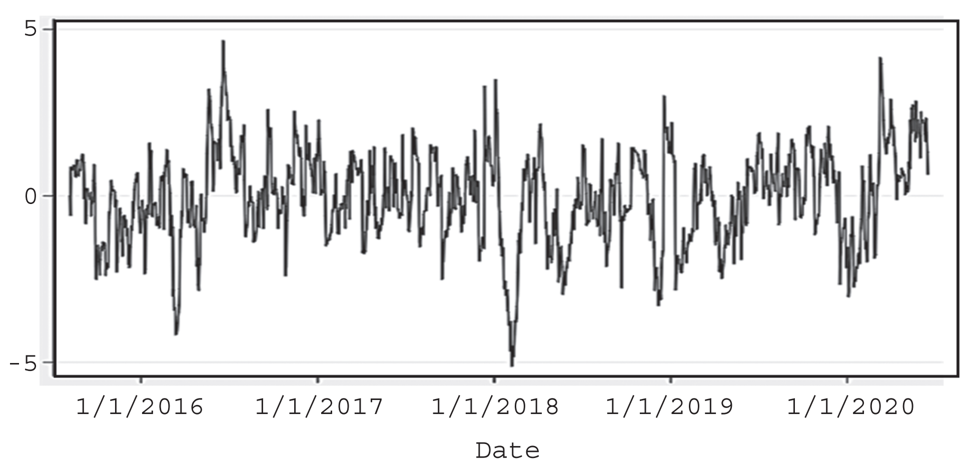
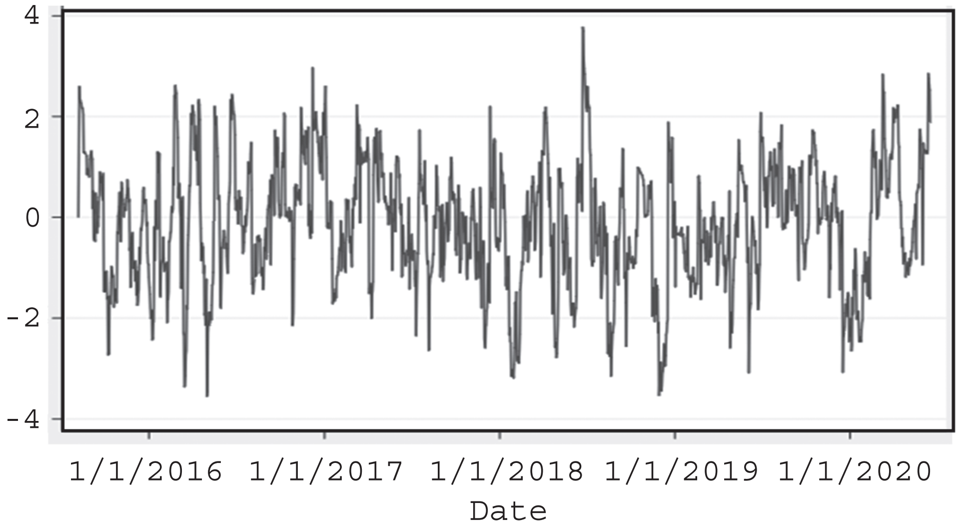


Figure 9
DYNAMIC CONDITIONAL CORRELATION BETWEEN ETHEREUM AND ESTONIAN (EE) ELECTRICITY MARKET



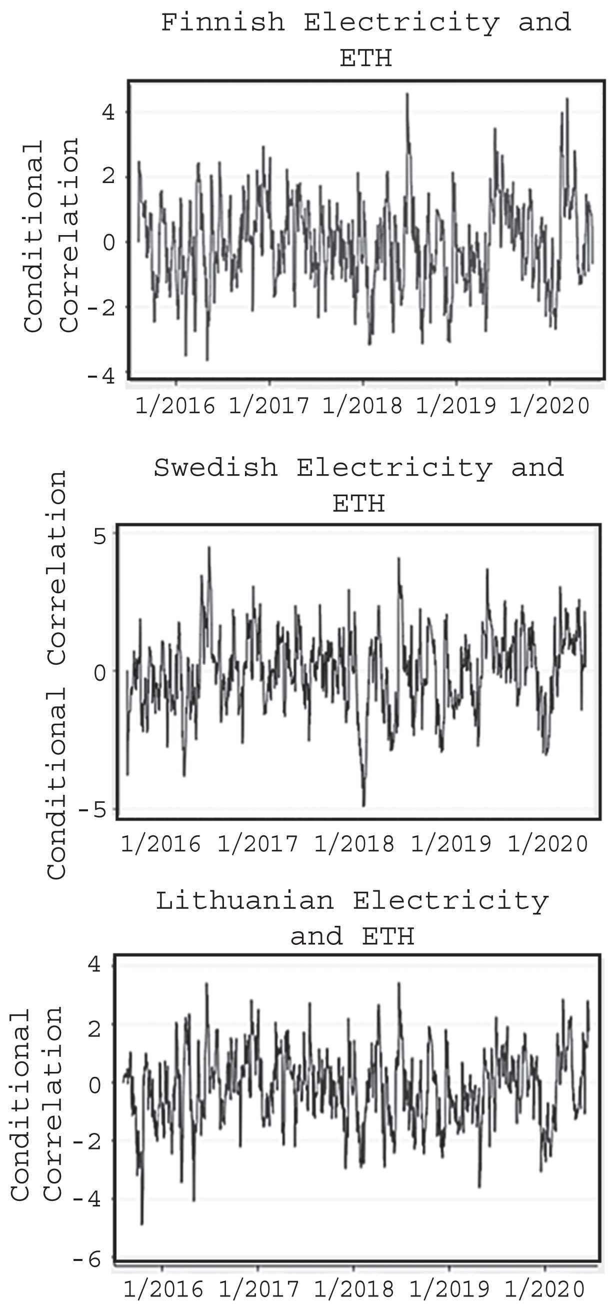
blockchain across various sectors of the economy. Moreover, Estonia is among the European countries that encourage cryptocurrency mining, owing to its highly digitalized environment. Consequently, mining farms in the region consume significant amounts of electricity, driving up energy costs.

Figure 10 presents the dynamic conditional correlation between Ethereum (ETH) and Nordic electricity returns, highlighting the relationship between Ethereum and the Swedish (SE), Finnish (FI), and Lithuanian (LT) electricity markets. The correlation patterns closely mirror those observed with Estonia (EE), suggesting a consistent interaction between cryptocurrency volatility and electricity market fluctuations in the region. Notably, during 2018, a significant correlation is evident, likely driven by the heightened demand for electricity due to increased cryptocurrency mining activities. This further reinforces the impact of cryptocurrency markets on regional electricity prices, particularly in highly digitalized economies that support blockchain and mining operations.

5. *Conclusion*

This paper seeks to analyze the evolving relationship between the cryptocurrency market—focusing on Bitcoin and Ethereum—and the Nordic electricity market. It specifically investigates the impact of Bitcoin and Ethereum price volatility

Figure 10
DYNAMIC CONDITIONAL CORRELATION BETWEEN ETHEREUM AND NORDIC ELECTRICITY RETURNS



on Nordic electricity prices over the period from 2015 to 2020. By examining this connection, the study aims to shed light on the extent to which fluctuations in cryptocurrency prices influence energy demand and electricity market dynamics in the Nordic region, particularly in the context of the growing energy consumption associated with cryptocurrency mining.

To assess the volatility dynamics, we first estimate the GARCH model under the normality assumption and later using the Student's t-distribution for improved robustness. Following this, we apply the DCC-GARCH model to capture the dynamic conditional correlations between cryptocurrencies and the Nordic electricity market. The findings reveal time-varying dynamic correlations between the Nordic electricity market and the two major cryptocurrencies, Bitcoin and Ethereum, over the period from August 2015 to June 2020. This suggests a shared volatility pattern, indicating a meaningful relationship between the cryptocurrency market and electricity prices in the Nordic region.

This research shows that, during the considered period (2015–2020), the pricing behaviors of Bitcoin (BTC) and Ethereum (ETH) correlate with the Nordic electricity market. Crypto-mining activity in the Nordic countries is highly electricity-demanding, leading to increased electricity prices, particularly during the winter months when energy consumption peaks. The legacy of cryptocurrencies further affects the time-varying correlations, as most Nordic countries have highly digitalized economies and actively encourage crypto-mining activities. These factors contribute to the observed interdependence between the cryptocurrency and energy markets.

The results demonstrate that fluctuations in Bitcoin and Ethereum prices have a direct impact on electricity prices in Nordic countries, reflecting the increasing energy demands associated with cryptocurrency mining activities. These findings align with previous research by S. Corbet et al.[25] who showed that Bitcoin price volatility influences electricity markets in regions like China, Japan, and Russia. Additionally, L. Kristoufek[26] supports this notion by confirming that Bitcoin price movements affect mining costs, with electricity prices being a central factor.

In conclusion, our study reinforces the growing evidence that cryptocurrency market dynamics, particularly price volatility, play a significant role in shaping electricity markets in various regions, including the Nordic countries. As cryptocurrency mining continues to expand, its influence on energy consumption and pricing will likely become even more pronounced. These insights are crucial for decision-makers in both the energy and financial sectors, as they offer valuable information for developing energy policies, market regulations, and investment strategies. Understanding these interdependencies will enable policymakers to anticipate market shifts and make informed decisions that balance energy demand with the evolving cryptocurrency landscape.

Looking forward, this domain offers exciting opportunities for further research. As both cryptocurrency technologies and energy infrastructures evolve, future studies could explore the impact of green energy solutions on cryptocurrency mining, the role of regulatory frameworks in managing energy consumption, and the potential for innovative blockchain technologies to optimize energy use. Additionally, as global energy challenges grow, integrating cryptocurrencies into broader sustainability strategies may pave the way for more resilient and efficient energy markets, opening new avenues for collaboration between the financial and energy sectors.

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APPENDIX

Appendix Table 1
VAR GRANGER CAUSALITY WALD TESTS' RESULTS

Equation	Excluded	Chi-square	Df	Prob
BTC	ETH	5.4085	4	0.248
	SE	6.7973	4	0.147
	EE	8.5535	4	0.043
	LT	12.745	4	0.012
	FI	1.8526	4	0.736
	NO	1.7663	4	0.779
	All	29.811	24	0.191
ETH	BTC	6.8777	4	0.142
	SE	0.77128	4	0.942
	EE	5.82199	4	0.210
	LT	11.348	4	0.023
	FI	0.6114	4	0.962
	NO	5.2199	4	0.265
	All	27.023	24	0.303
SE	BTC	2.5378	4	0.638
	ETH	4.9968	4	0.288
EE	BTC	5.5241	4	0.238
	ETH	1.7825	4	0.776

(continued)

Appendix Table 1 (continued)
VAR GRANGER CAUSALITY WALD TESTS' RESULTS

Equation	Excluded	Chi-square	Df	Prob
LT	BTC	4.1029	4	0.392
	ETH	3.9085	4	0.419
FI	BTC	4.5432	4	0.337
	ETH	4.3102	4	0.366
NO	BTC	1.3549	4	0.850
	ETH	0.63861	4	0.959

Appendix Table 2
GARCH ESTIMATION

	Parameters	Value	Std. Error	T-stat	P-Value
Bitcoin (BTC)					
	α_0	$8.0812e^{-05}$	$6.5196e^{-06}$	12.395	$2.7761e^{-35}$
	GARCH(1)	0.80825	0.010524	76.797	0
	ARCH(1)	0.16637	0.0089873	18.511	$1.6761e^{-76}$
Ethereum (ETH)					
	α_0	0.00037184	$3.4465e^{-05}$	10.789	$3.8827e^{-27}$
	GARCH(1)	0.70794	0.019129	37.008	$3.4864e^{-300}$
	ARCH(1)	0.22499	0.017536	12.83	$1.1094e^{-35}$
Estonian Electricity Market (EE)					
	α_0	0.0010011	0.00016103	6.2168	$5.0734e^{-10}$
	GARCH(1)	0.83834	0.012292	74.242	0
	ARCH(1)	0.15849	0.01348	11.757	$6.5342e^{-32}$
Swedish Electricity Market (SE)					
	α_0	0.000918	$7.1676e^{-5}$	12.808	$1.4851e^{-37}$
	GARCH(1)	0.82258	0.0064367	127.79	0
	ARCH(1)	0.16966	0.011846	14.322	$1.5988e^{-46}$
Lithuanian Electricity Market (LT)					
	α_0	0.0012514	0.0001764	6.9755	$3.0475e^{-12}$
	GARCH(1)	0.81503	0.01485	11.506	$1.2303e^{-30}$
	ARCH(1)	0.17086	0.01485	11.506	$1.2303e^{-30}$
Finnish Electricity Market (FI)					
	α_0	0.00077351	0.00013208	5.8563	$4.734e^{-9}$
	GARCH(1)	0.86482	0.0090863	95.179	0
	ARCH(1)	0.13518	0.011345	11.915	$9.9058e^{-33}$
Norwegian Electricity Market (NO)					
	α_0	0.00054705	$4.9246e^{-05}$	11.108	$1.1415e^{-28}$
	GARCH(1)	0.64237	0.014723	43.631	0
	ARCH(1)	0.35763	0.01711	20.902	$5.1173e^{-97}$