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Information flow dynamics between cryptocurrency returns and electricity consumption: A comparative analysis of Bitcoin and Ethereum

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ABSTRACT

Understanding energy consumption associated with cryptocurrency mining gained increasing attention, with the literature focusing mainly on Bitcoin. This study uses data from the two energy consumption indices, to estimate static and dynamic transfer entropies. The results provide a nuanced understanding of the bidirectional relationships and their implications. The dominant direction of information flow for Bitcoin is from electricity consumption to returns, while for Ethereum, it is from returns to electricity consumption, suggesting that Ethereum's returns significantly impact electricity consumption patterns. Results highlight the need for policies that integrate energy forecasting and environmental sustainability considerations and has significant implications for policymaking.

1. Introduction

There is a growing interest in understanding the energy and environmental footprint of cryptocurrencies, especially Bitcoin (BTC) and Ethereum (ETH) (Sai and Vranken, 2024). The mining process, though crucial to ensure the functionality and security of cryptocurrency networks, is electricity-intensive and harmful to the environment. This situation has led to debates around the BTC mining process, e.g., Li et al. (2019), Küfeoğlu and Özkuran (2019), and Maiti (2022). From an environmental perspective, depending upon the consensus mechanism, cryptocurrencies may augment electricity consumption and carbon emissions (Sai and Vranken, 2024). In response to this energy-intensive process, cryptocurrency projects were developed with reduced energy requirements, and others changed their mining protocol, as in the case of ETH.

BTC and ETH operate in geographically distributed networks of computing nodes, making it hard to measure their energy consumption accurately, consequently reducing the number of sources to obtain confinable energy consumption data. Initially, both employed the Proof-of-Work (PoW) consensus protocol, which led to similar issues concerning energy consumption and carbon emissions. However, ETH transitioned to ETH 2.0, adopting a Proof-of-Stake (PoS) mechanism (September 15, 2022) to address sustainability, scalability, and security concerns. Our findings indicate that a statistically significant predictive relationship exists between ETH returns and electricity consumption, which contrasts with BTC.

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The difference underscores the impact of consensus mechanisms on the environmental footprint and operational dynamics of cryptocurrencies. PoW-based cryptocurrencies generally require much more electricity than those using alternative consensus mechanisms like PoS (Drăgnoiu et al., 2023). Notably, the PoS consensus mechanism does not require miners to do intensive mathematical calculations to validate transactions, which offers potential energy savings over PoW (Asif and Hassan, 2023).

Understanding the relationship between cryptocurrency prices and electricity consumption is crucial to evaluate and accurately predict their future energy consumption, as stated, for example, by de Vries (2021) or Maiti (2022) for BTC. However, due to the asymmetric and nonlinear nature of this relationship, it is not easy (Maiti et al., 2023). While several studies, such as those by Bejan et al. (2023), Corbet et al. (2021), Huynh et al. (2022), Kumari et al. (2024), Li et al. (2019), Maiti (2022), and Sapra et al. (2024) have explored this relationship focusing on BTC, all, except for Maiti et al. (2023), utilized linear models, highlighting the need to apply approaches that consider the identified nonlinear relationship (Neto, 2022). Furthermore, most studies have focused on analyzing this relationship for BTC. The transfer entropy (TE) approach (Shannon and Rényi) was applied to overcome the identified gaps and quantify the asymmetric information flow between both two major cryptocurrencies' returns and total electricity consumption, amplifying the scope of the analysis made by Maiti et al. (2023). The TE approach, widely used in several research areas, is a directional measure of the dependence between two variables, e.g., Behrendt et al. (2019), and overcomes the low capability of conventional Granger tests to detect nonlinear causality.

The present study performed a dynamic evaluation of this relationship by applying a sliding windows approach. This assessment is useful as it allows us to identify how extraordinary events (such as the ETH's transition from PoW to PoS) affect the bidirectional relationship between variables. Our findings reveal that ETH returns have a statistically significant and predictive relationship with electricity consumption, while BTC returns do not show a significant relationship. Furthermore, the information flow dynamics indicate that ETH's transition from PoW to PoS substantially impacts the bidirectional relationship between returns and electricity consumption.

While our results concerning BTC align with the findings of Maiti et al. (2023), our study expands the literature by focusing on ETH. Unlike BTC, ETH is the backbone of decentralized finance (DeFi) and smart contracts. ETH distinguishes itself from BTC not only through its consensus mechanism—transitioning from PoW to PoS—but more critically through its diverse use cases in DeFi and smart contracts. Unlike BTC, which primarily functions as a store of value and medium of exchange, ETH supports a wide range of decentralized applications (dApps) that enable peer-to-peer financial transactions, automated contract execution, and the creation of new financial instruments. These functionalities make ETH a vital asset within the DeFi ecosystem, where the value of ETH is closely tied to the activity and demand for these applications. Consequently, the relationship between ETH returns and electricity consumption may differ markedly from BTC due to the distinct economic forces at play. Our study, therefore, contributes to the literature by not only comparing ETH and BTC but also by providing insights into how the unique features of ETH, particularly within the DeFi space, influence its energy dynamics and market behavior.

Moreover, our paper contributes to the extant literature on green finance by providing empirical evidence on how cryptocurrency trading activities, particularly for ETH, can influence energy consumption patterns and also cryptocurrency prices by empirically evaluating (statically and dynamically) the impact of electricity consumption on the BTC and ETH markets and vice versa. This study aims to address the following research questions: (i) How does the electricity consumption of BTC and ETH impact their financial performance? and (ii) How do the financial returns of BTC and ETH influence their electricity consumption patterns?

The remainder of the letter is structured as follows: Section 2 presents the data and methods, Section 3 presents and discusses the results, and Section 4 presents the conclusions.

2. Data and methods

2.1. Data

The study uses daily BTC and ETH closing prices from May 20, 2017, to June 2, 2024, obtained from https://www.investing.com/. The starting point of May 2017 was selected due to the availability of the Ethereum Energy Consumption Index data. Furthermore, the beginning of the data marks the period when both BTC and ETH experienced substantial growth in both market capitalization and energy consumption, providing a robust dataset for our analysis. The data for both cryptocurrency's energy consumption index was retrieved from https://digiconomist.net/. Both sites were accessed on June 3, 2024. BTC and ETH were selected due to their prominence in the cryptocurrency market, significant differences in their consensus mechanisms, and the availability of electricity consumption data.

2.2. Methods

The Shannon (STE) and Rényi (RTE) transfer entropies were applied. The STE, proposed by Schreiber (2000), is a non-parametric method that allows the measurement of the causal information transfer between systems in a bi-directional way. It is defined in Eq. (1) under the assumption of a Markovian process of k and l orders for Y and X, respectively.

$$STE_{Y\rightarrow X}(k,l) = \sum_{x,y} p\left(x_{t+1}, x_t^{(k)}, y_t^{(l)}\right) loglog \frac{p\left(x_t^{(k)}, y_t^{(l)}\right)}{p\left(x_t^{(k)}\right)} \tag{1}$$

The bootstrap method (particularly suited for dealing with non-stationarity and nonlinearity in the data) proposed by Dimpfl and Peter (2013) was used to evaluate the presence of information flow. Grounded in the existing literature that balances statistical reliability with computational efficiency, to estimate the standard errors and p-values of the TE measures, the bootstrapping process was performed with 300 replications [see, for example, Assaf et al. (2022), Banerjee et al. (2022), Behrendt et al. (2019) or Urdiales et al. (2021)]. This process provides a more reliable inference of the information flow between the variables. The Shannon Net TE was also utilized to identify which of the paired variables influence each other, as given by Eq. (2):

$$NET\ STE_{YX} = STE_{Y\rightarrow X} - STE_{X\rightarrow Y} \tag{2}$$

Thus, the dominant direction of the information flow could be (i) positive, i.e., from Y to X, if $STE_{Y\rightarrow X}(k, l) > STE_{X\rightarrow Y}(k, l)$; (ii) negative, i.e., from X to Y, if $STE_{Y\rightarrow X}(k, l) < STE_{X\rightarrow Y}(k, l)$; (iii) equal to zero, i.e., equal dominance of information flow in both directions, if $STE_{Y\rightarrow X}(k, l) = STE_{X\rightarrow Y}(k, l)$.

The STE was estimated considering sliding windows of 500 observations to dynamically analyze the information flow and evaluate how extraordinary events (such as the ETHs' PoW to PoS transition) can affect the bidirectional relationship between variables. This window size was chosen to provide enough data points for accurate TE estimation while effectively capturing temporal dynamics.

As the STE does not allow for considering the tail events, the RTE was also estimated as defined in Eq. (3). Similar to the $STE_{Y\rightarrow X}(k, l)$, the $RTE_{q;\,Y\rightarrow X}(k, l)$ measures the information flow (or TE) from Y to X. However, unlike in Shannon's case, $RTE_{q;\,Y\rightarrow X}(k, l)$ could also be negative (on account of nonlinear pricing). Moreover, if $RTE_{q;\,Y\rightarrow X}(k, l) = 0$, it does not imply the independence of both processes (Jizba et al., 2012).

$$RTE_{q;Y\rightarrow X}(k,l) = \frac{1}{1-q} log\left(\frac{\sum_x \varrho_q\left(x_t^{(k)}\right)p^q\left(x_t^{(k)}\right)}{\sum_{x,y}\varrho_q\left(x_t^{(k)}, y_t^{(l)}\right)p^q\left(x_t^{(k)}, y_t^{(l)}\right)}\right) \tag{3}$$

The escort distribution is represented by ϱ_q and the weighting parameters by q.

According to Jizba et al. (2012), the q parameter controls the measure's sensibility to different probability distributions. It allows for evaluating the tail events. For $0 < q < 1$, it gives high weight to extreme events of low probability. For $q \rightarrow 1$, the STE is regained. For $q > 1$, outcomes with higher initial probabilities are preferred.

All the TEs' estimates were made using the R package RTransferEntropy.

3. Results and discussion

The descriptive statistics reveal that both cryptocurrencies display (i) positive mean returns (the returns were calculated according to $r_t = lnln(P_t) - lnln(P_{t-1})$, where P_t and P_{t-1} represent the daily values of a given series on days t and $t-1$, respectively), which were higher for BTC and with a lower standard deviation, (ii) positive kurtosis (> 10.5), meaning fat-tailed distributions, and (iii) negative skewness (< -0.75), meaning a higher probability of negative returns than positive ones. The results of the Augmented Dickey–Fuller and Shapiro–Wilk tests allowed us to reject the null hypothesis in both.

Several studies reported the nonlinear relationship between BTC prices and returns, with its electricity consumption [see, for example, Huynh et al. (2022), Maiti (2022), and Maiti et al. (2023)]. Considering the cited studies, the TE approach was applied, given that it is a model-free and non-parametric technique that can deal with the identified nonlinearities. The STE and Net TE results for both cryptocurrencies are presented in Table 1.

Table 1
STE results.

BTC	Information flow	TE	ETE	S. Err	p-value	Net TE
	Returns–>Electricity	0.0042	0.0009	0.0013	0.1900	0.0003
	Electricity–>Returns	0.0039	0.0006	0.0012	0.3433	
	Bootstrapped TE (300 replications):					
	Quartiles	0	0.25	0.5	0.75	1
	Returns–>Electricity	0.0006	0.0022	0.003	0.004	0.0093
	Electricity–>Returns	0.0009	0.0028	0.0034	0.0043	0.0076
ETH	Information flow	TE	ETE	S. Err	p-value	Net TE
	Returns–>Electricity	0.0145	0.0108	0.0014	0.0000 ***	0.0095
	Electricity–>Returns	0.0050	0.0012	0.0013	0.1433	
	Bootstrapped TE (300 replications):					
	Quartiles	0	0.25	0.5	0.75	1
	Returns–>Electricity	0.0011	0.0029	0.0037	0.0047	0.0058
	Electricity–>Returns	0.0014	0.0026	0.0033	0.0043	0.0078

Notes: (i) "***" represents the significance level of 1 %; (ii) S.Err represents standard error estimates; (iii) Net TE corresponds to the Net STE, given by the difference between the STE (represented as TE on the table) from *Returns → Electricity* and *Electricity → Returns*; (iv) ETE is the effective transfer entropy, as defined by Marschinski and Kantz (2002). It is computed by comparing the original transfer entropy with that obtained from a shuffled version of the source time series. By randomizing the source series, spurious correlations are removed, *allowing ETE to isolate the true nonlinear transfer of information between variables; (v) the bootstrapped part of the table accounts for both the non-stationarity and nonlinearity in data; (vi) The quartiles represent the distribution of data points, highlighting the convergence of cryptocurrency returns with overall directional movement.*

Our results show that the information flow from Returns to Electricity is higher (0.08 and 1.9 times higher for BTC and ETH, respectively) than in the reverse case, which is consistent with previous work of Maiti et al. (2023). This finding indicates a strong directional relationship and, in a certain way, the predictive power of the Returns on Electricity. In this sense, both cryptocurrencies' returns can impact electricity consumption behavior. In the case of ETH, this relationship is even stronger and statistically significant (also supported by the results of the Net TE), meaning the changes in the ETH returns (and prices consequently) have a greater impact on its electricity consumption. These results and implications could also impact energy mix management and risk analysis.

For BTC, the bootstrapped TE estimates for *Returns* → *Electricity* range from 0.0006 at the 0th quartile to 0.0093 at the 100th quartile, while for *Electricity* → *Returns* range from 0.0009 to 0.0076 across the same quartiles. Although the TE values are generally low, there is a slight increase in the influence of Returns on Electricity at higher quartiles, indicating variability in the data's informational flow. For ETH, the bootstrapped TE estimates for *Returns* → *Electricity* show a more consistent and significant pattern, with values ranging from 0.0011 at the 0th quartile to 0.00583 at the 100th quartile and ranging from 0.0014 to 0.0078 for *Electricity* → *Returns*. These results highlight a stronger and statistically significant relationship between ETH returns and electricity consumption, reflecting a more pronounced and reliable informational flow than BTC. The bootstrapping provides a robust validation of these dynamic relationships by considering non-stationarity and nonlinearity.

ETH's integration into DeFi networks makes it a crucial asset for smart contracts and financial transactions beyond mere speculation. This unique role influences how ETH's price and returns are related to electricity consumption, as DeFi applications may demand continuous operation and significant computational resources. Indeed, our findings suggest that ETH's impact on energy use is tied to the mining process and the broader operational demands of maintaining DeFi systems.

The sliding windows approach was applied to evaluate these dynamic relationships and identify the time-varying dynamics of the TE and Net TE. Fig. 1 depicts the evolution of TE between each cryptocurrency and its electricity consumption, the reverse TE, and the Net TE for each pair.

Our results indicate a connectedness between energy consumption and both cryptocurrencies' returns, consistent with the findings of Sapra et al. (2024) for BTC. Most of the time, electricity consumption has a greater impact on BTC returns than the opposite. However, there are exceptions during certain periods. Conversely, ETH returns have a greater impact on electricity consumption than the opposite, with exceptions during specific periods. For instance, the highest values of information transmission from returns to electricity consumption and net transmission of information were observed near changes in its mining consensus protocol. Additionally, higher values of STE from *Returns* → *Electricity* and Net TE were noted during this period.

Since the STE does not consider tail events, the RTE was estimated, and the results are shown in Table 2. Once again, for ETH, there is a statistically significant flow of information from *Returns* → *Electricity* for most q values. This finding was not observed in the case of BTC, which may be explained by the theories of production and value investing (Sapra et al., 2024). In the opposite direction (*Electricity* → *Returns*), ETH, but not BTC, displays increased flow for higher q values. These results indicate that the impact of ETH's electricity consumption on its returns and, consequently, prices is not homogeneous and may vary with tail events. Furthermore, as

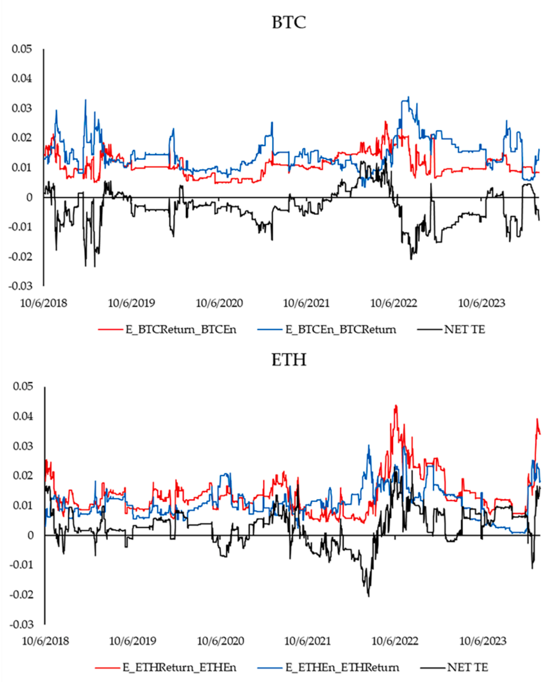

Fig. 1. Time evolution of the STE between BTC returns and electricity consumption (on the top) and between ETH returns and electricity consumption (on the bottom).

Table 2
Rényi TE results.

q	BTC		ETH	
	Returns → Electricity	*Electricity → Returns*	*Returns → Electricity*	*Electricity → Returns*
0.01	0.1076	0.1075	0.2904**	0.2267
0.10	0.0812	0.0783	0.2482**	0.1907
0.20	0.0591	0.0522	0.2063**	0.1591
0.30	0.0430	0.0329	0.1678***	0.1324
0.40	0.0312	0.0198	0.1321**	0.1077
0.50	0.0227	0.0119	0.1000**	0.0843*
0.60	0.0165	0.0076	0.0727**	0.0626**
0.70	0.0121	0.0056	0.0509***	0.0434***
0.80	0.0088	0.0047	0.0346***	0.0274**
0.90	0.0062	0.0043	0.0228***	0.0146***
0.99	0.0044	0.0039	0.0152***	0.0058*

Notes: (i) "***", "**" and "*" represents the significance level of 1 %, 5 % and 10 %, respectively; (ii) q denotes the weighting parameter.

shown in Fig. 2, the flow of information is greater in both directions for lower q values and decreases as $q \to 1$.

4. Conclusion

This paper assesses whether electricity usage of BTC and ETH impacts their financial performance and vice versa. The study provides insights for investors and users into the connection between cryptocurrency electricity consumption and utility usage.

For ETH, this study finds statistically significant information flow from *Returns → Electricity*, suggesting that energy companies can use this cryptocurrency's returns to better forecast and manage energy demand, potentially prioritizing renewable resources to meet this demand sustainably. Moreover, the variation in cryptocurrency prices, especially in what refers to extreme events, introduces risks to energy consumption stability and financial stability for energy companies, necessitating risk analysis and mitigation strategies such as hedging and diversification to ensure energy and economic resilience.

The STE and RTE results for *Electricity → Returns* for ETH are mixed, suggesting a complex influence of total ETH electricity consumption on returns. Additionally, substantial changes in the tail distribution of the ETH's electricity consumption behavior pattern may have a direct impact on its returns. For both cryptocurrencies, the RTE value converges with STE as $q \to 1$.

The present study's findings are highly relevant to policymakers in forecasting the future of both cryptocurrencies' total electricity consumption. They emphasize the bidirectional nature of the relationship between ETH returns and electricity consumption, a dynamic particularly relevant for the energy-intensive operations of DeFi platforms. This insight is crucial for developing strategies to manage the environmental impact of DeFi activities. Furthermore, this research reveals that ETH returns significantly impact

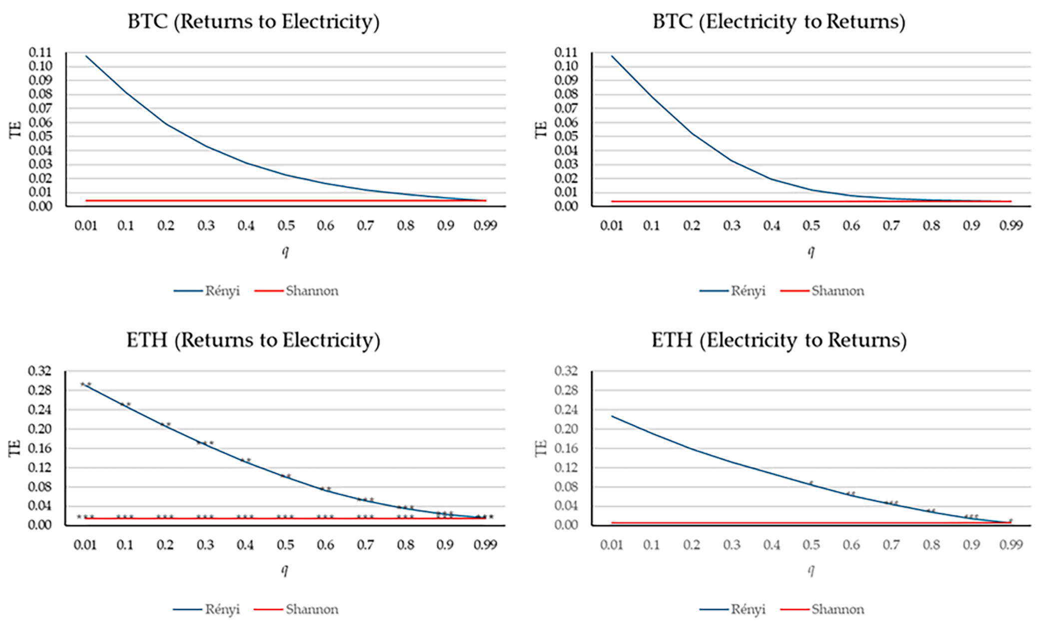

Fig. 2. Shannon and Rényi TE for different q values.
*Notes: (i) "***", "**" and "*" represents the significance level of 1 %, 5 % and 10 %, respectively; (ii) q denotes the weighting parameter.*

electricity consumption, indicating that market activities can influence energy usage. This work highlights the need for policies integrating energy forecasting and environmental sustainability considerations and has significant implications for policymaking, particularly as ETH transitions towards a PoS consensus mechanism. In this sense, policymakers could use this information to develop regulations that encourage more sustainable consensus mechanisms. Understanding these dynamics can aid in forecasting energy needs and planning for a more environmentally friendly energy mix.

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CRediT authorship contribution statement

Dora Almeida: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Andreia Dionísio:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Paulo Ferreira:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of interest

The authors have nothing to declare.

Data availability

Data will be made available on request.

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