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Revisiting the carbon footprint of cryptocurrency trading: A granger causality approach

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ABSTRACT

The environmental impact of cryptocurrencies has attracted increasing scrutiny, largely due to the high energy consumption of blockchain networks. However, empirical research on the causal relationship between cryptocurrency trading activity and carbon emissions remains scarce. This study addresses this gap by analysing the dynamic interplay between cryptocurrency trading and CO_2 emissions for Bitcoin, Ethereum, and Binance Coin, using monthly data from January 2015 to September 2024. Employing the Toda-Yamamoto augmented Granger causality approach, we apply logarithmic transformations to ensure data stationarity and address integration and endogeneity concerns. Our results reveal a bidirectional Granger causality between Bitcoin trading and CO_2 emissions, suggesting a feedback loop between market activity and environmental impact. For Ethereum, we find a similar albeit weaker bidirectional causality from trading to emissions, while no significant causal link is detected for Binance Coin, likely reflecting its more energy-efficient consensus mechanism. These findings highlight the disproportionate environmental burden of proof-of-work cryptocurrencies and underscore the need for targeted regulatory responses. We recommend the adoption of carbon-sensitive crypto policies, such as mandatory energy usage disclosures and incentives for transitioning to sustainable consensus mechanisms. This study advances the environmental finance literature by providing robust empirical evidence on the links between digital asset markets and carbon emissions.

1. Introduction

Blockchain technology, introduced by Satoshi Nakamoto in 2008 with the advent of Bitcoin, has been widely recognized as a transformative innovation in the digital era. By enabling decentralized, peer-to-peer transactions without the need for traditional financial intermediaries, blockchain has laid the foundation for a rapidly expanding ecosystem of cryptocurrencies [1]. Since Bitcoin's inception, the cryptocurrency landscape has evolved dramatically, with thousands of alternative digital assets emerging, each offering unique functionalities and use cases. Notably, the adoption of Bitcoin as legal tender by El Salvador [2] and the proliferation of platforms such as Ethereum, Binance Coin, Solana, Cardano, and Ripple have underscored the growing significance of cryptocurrencies in global finance. As of October 17, 2024, the total market capitalization of cryptocurrencies is estimated at $2.25 trillion, with over 2850 distinct cryptocurrencies in circulation, most of which utilise blockchain technology [3].

The rapid expansion and mainstreaming of cryptocurrencies have sparked intense debate and scrutiny, particularly regarding their environmental impact [4,5]. A central concern is the substantial energy consumption associated with blockchain operations, especially those employing proof-of-work (PoW) consensus mechanisms. The process of mining whereby miners solve complex cryptographic puzzles to validate transactions and secure the network demands significant computational power and, consequently, vast amounts of electricity [1,6]. This energy is often sourced from fossil fuels, leading to considerable carbon emissions and raising alarms about the sector's contribution to global warming [7,8]. The environmental implications are further exacerbated by the geographic concentration of mining activities in regions with abundant but carbon-intensive energy sources, such as China, Kazakhstan, and certain parts of the United States [9]. Recent studies estimate that Bitcoin mining alone consumes as much energy as entire countries, including Mexico, Italy, Ireland, Argentina, and Austria, highlighting the scale of the issue [10,11].

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While the environmental impact of mining has been widely discussed, the role of cryptocurrency trading in contributing to carbon emissions is less frequently examined but equally important. Trading activities, which involve the operation of data centers, servers, and network infrastructure, also require substantial energy inputs [12,13]. As trading volumes surge, particularly during periods of heightened market activity, there is a corresponding increase in the demand for mining, as more transactions require validation and inclusion in the blockchain. This creates a feedback loop whereby increased trading stimulates more mining, which in turn amplifies energy consumption and carbon emissions. Moreover, the migration of mining operations to jurisdictions with lax environmental regulations or cheaper, dirtier energy sources further compounds the sector's carbon footprint [10,14].

Despite the growing body of research on the environmental consequences of cryptocurrencies, several critical gaps remain. Much of the existing literature has focused on the aggregate energy consumption and carbon footprint of entire cryptocurrency networks, with a predominant emphasis on Bitcoin [2,7,10,15]. Studies that specifically investigate the causal relationship between cryptocurrency trading activities and carbon emissions are rare, and even fewer consider the potential for bidirectional causality or feedback effects. Furthermore, research has often relied on aggregated or outdated data, limiting the ability to capture recent technological and market developments such as Ethereum's transition from proof-of-work to the more energy-efficient proof-of-stake (PoS) consensus mechanism, which is expected to drastically reduce its energy consumption.

Methodologically, attributing carbon emissions to specific cryptocurrency activities presents significant challenges. Many studies conflate the energy demands of mining, trading, and general network maintenance, making it difficult to isolate the environmental impact of trading alone [13,16]. The use of aggregated data and broad assumptions about the energy mix and network activity introduces further uncertainty. For example, estimates often rely on average energy consumption figures or assume a uniform distribution of mining activity, despite significant geographic and operational variation. Additionally, both top-down and bottom-up approaches to estimating emissions have inherent limitations, such as the reliance on proxies for energy use or the lack of granularity in tracking the energy consumption of individual trading platforms.

The cryptocurrency sector is also characterized by rapid technological change, which can quickly render previous findings obsolete. Ethereum's recent shift to PoS, for instance, represents a fundamental change in the energy profile of one of the world's largest cryptocurrencies. As such, there is a pressing need for studies that incorporate the most recent data and account for ongoing market and technological developments. By doing so, research can provide more accurate and policy-relevant insights into the environmental impacts of digital assets.

This study seeks to address these gaps by employing a robust causality framework to examine the dynamic relationship between cryptocurrency trading activities and carbon emissions. Focusing on three major cryptocurrencies—Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB)—and utilizing monthly data from January 2015 to September 2024, this research utilises the Toda-Yamamoto augmented Granger causality approach to explore both the direction and strength of causal links. Importantly, the study considers not only the impact of trading on emissions but also the potential for feedback effects, drawing on systems theory to conceptualize the cyclical nature of these interactions. By including Ethereum's recent transition to PoS and considering Binance Coin's more energy-efficient consensus mechanism, the analysis provides a nuanced understanding of how different technological architectures influence the environmental footprint of cryptocurrency trading.

The core research questions guiding this study are as follows:

1. Does trading activity in major cryptocurrencies—specifically Bitcoin, Ethereum, and Binance Coin—Granger-cause carbon emissions?
2. Does carbon emission, as an environmental indicator, exert a causal influence on cryptocurrency trading behaviour?
3. To what extent are the findings robust across alternative Granger-type causality frameworks?

By addressing these questions, this study aims to contribute to both the academic literature and policy debates on the environmental sustainability of digital assets. The findings are expected to inform the development of targeted regulatory measures and industry best practices, with the ultimate goal of mitigating the environmental impact of cryptocurrency trading and supporting a more sustainable future for the digital asset ecosystem.

The remainder of this paper is structured as follows: Section 2 reviews the relevant literature; Section 3 details the research methodology and data; Section 4 presents and discusses the empirical results; and Section 5 concludes the study and discusses relevant policy implications.

2. Literature review

The intersection of cryptocurrency and environmental sustainability has become a focal point of academic inquiry, reflecting mounting concerns over the ecological consequences of digital currencies [2,12,17]. The surge in cryptocurrency adoption has been paralleled by a significant increase in greenhouse gas emissions and energy consumption, largely attributable to the energy-intensive nature of blockchain operations [4,18,19]. However, while the literature has grown rapidly, it remains fragmented, with notable methodological and conceptual limitations.

A substantial body of research has examined the environmental impact of cryptocurrency mining, particularly Bitcoin, which relies on the proof-of-work (PoW) consensus mechanism. Zhang et al. [13] demonstrated that Bitcoin's energy usage is influenced by factors such as hash rate, blockchain size, and market returns, but these relationships are not uniform across time or market conditions. This variability underscores the complexity of modelling the environmental footprint of cryptocurrencies and highlights the limitations of studies that rely on static or overly simplified models. Kohli et al. [20] further highlight the tension between the innovative potential of digital currencies and the urgent need to mitigate carbon emissions, emphasizing the disparities in energy usage among different cryptocurrencies. Bitcoin, in particular, stands out as especially energy-intensive due to its PoW protocol, yet many studies generalize findings from Bitcoin to the entire crypto sector, potentially overstating the environmental impact of less energy-intensive coins.

Life-cycle assessment frameworks have provided granular insights into the carbon emissions associated with cryptocurrency transactions. Onat et al. [21] quantified Bitcoin's carbon emissions at both the transaction and supply chain levels, revealing that a single transaction can emit greenhouse gases equivalent to driving a mid-sized sedan 1600–2600 km. Notably, about half of mining emissions are localized in the USA, with significant upstream emissions traced to China, highlighting the importance of considering supply-chain embedded emissions when assessing the environmental impact of trading activity. However, such studies often face data limitations, particularly regarding the transparency and granularity of energy sourcing, and may not fully capture the dynamic relocation of mining operations in response to regulatory or market changes.

The sustainability of Bitcoin mining has also been questioned in light of network events such as halvings, which reduce mining rewards and can increase the energy intensity of mining operations [22]. Yet, the long-term effects of such events remain underexplored, with most analyses focusing on short-term impacts. The geographic distribution of miners and their reliance on fossil fuels, particularly coal, further exacerbate the sector's carbon footprint [23,24]. Siddik et al. [25] compared the environmental impact of crypto mining to conventional financial systems, finding that in 2021, crypto mining consumed more than double the water footprint and generated 139 million tons of CO_2 equivalent, underscoring the broader systemic implications and the role of regulatory interventions such as China's 2021 mining ban. However, these comparisons often overlook the evolving energy mix and technological innovations within the crypto sector, such as the increasing adoption of renewable energy sources and the shift to less energy-intensive consensus mechanisms.

Beyond energy consumption, the literature has explored the responsiveness of mining activity to market incentives. Dogan et al. [26] and Papp et al. [27] found that Bitcoin mining is highly elastic to price changes, with even modest price increases leading to significant rises in carbon emissions. De Vries et al. [28] estimated that Bitcoin mining is responsible for millions of tons of carbon emissions annually, primarily due to the use of coal-fired power in major mining regions. These findings raise critical questions about the long-term sustainability of cryptocurrencies in the context of global climate change. However, the focus on mining incentives often neglects the broader market dynamics, including the role of trading activity in driving network demand and, by extension, energy use.

While the environmental impact of mining is well-documented, the role of cryptocurrency trading in driving energy demand and emissions has received comparatively less attention. Islam et al. [29] suggest a complex interplay between trading activities and environmental outcomes, but empirical studies isolating the impact of trading are scarce. Sarkodie et al. [16] employed dynamic ARDL simulations and VAR models to show that a 1 % increase in Bitcoin trade volume can raise long-run energy and carbon footprints by 24 %, with impulse shocks amplifying these effects. This provides a methodological precedent for estimating causal effects in Granger-type frameworks. However, the reliance on aggregate data and the lack of granularity in distinguishing between mining and trading activities limit the conclusiveness of such findings. Some scholars, such as Ibañez & Freier [30], have proposed that PoW mining could serve as a flexible demand-response resource, potentially facilitating grid decarbonization if coupled with renewable energy, suggesting that the environmental impact of trading may vary depending on mining practices and energy sources. Yet, these potential benefits remain largely theoretical and are not yet substantiated by empirical evidence.

Chamanara et al. [31] provided the first global estimates of Bitcoin mining's carbon, water, and land footprints, highlighting the immense scale of these impacts and the persistent data gaps. Such baseline metrics are essential for causality analyses linking trading intensity to environmental outcomes. However, most studies continue to focus on Bitcoin, often neglecting altcoins, which collectively account for a majority of the cryptocurrency market [6]. Stamoulis [32] and others have emphasized that different cryptocurrencies employ distinct consensus mechanisms, resulting in varying environmental footprints. Incorporating altcoins into analyses is therefore crucial for a comprehensive understanding of the sector's environmental impact. The lack of comparative studies on altcoins represents a significant gap, as it limits the ability to generalize findings and inform policy across the broader digital asset landscape.

Another emerging area of interest is the potential influence of environmental factors, such as carbon emissions, on cryptocurrency market behavior. Clark et al. [33] found that carbon emissions can significantly affect the returns of volatile cryptocurrencies like Bitcoin and Ethereum, suggesting that environmental degradation and climate change concerns may increasingly shape market dynamics. However, studies explicitly examining the causal impact of carbon emissions on cryptocurrency trading remain rare, and the directionality of this relationship is still poorly understood. This gap is particularly salient given the increasing integration of environmental, social, and governance (ESG) considerations into investment decisions.

To address these empirical and conceptual gaps, systems theory offers a compelling framework for understanding the complex, reciprocal relationship between cryptocurrency activity and environmental outcomes [34]. At its core, systems theory posits that economic, technological, and ecological subsystems are deeply interdependent, with actions in one domain provoking feedback responses in others. In the context of cryptocurrencies, rising asset valuations and trading intensity can incentivize increased mining, particularly for PoW currencies, leading to higher energy use and emissions [20,26]. These environmental impacts may, in turn, influence regulatory responses, investor behaviour, and market trends, creating feedback loops that reinforce the bidirectional linkage between trading and environmental degradation [28,33].

Despite its relevance, systems theory has been underutilized in empirical studies of cryptocurrency and the environment. Most existing research adopts a linear, unidirectional perspective, typically from mining or trading to emissions, without adequately considering the possibility of reverse causality or dynamic feedback. This theoretical limitation constrains our understanding of how environmental outcomes may themselves shape market behaviour, regulatory interventions, or technological innovation within the crypto sector. By explicitly incorporating systems theory, future research can move beyond static models to capture the cyclical, evolving nature of the crypto-environment nexus, providing a more holistic and policy-relevant analysis.

In summary, the literature underscores the significant environmental impact of cryptocurrency mining, particularly in terms of energy consumption and carbon emissions. However, there is a notable gap regarding the impact of trading activities on emissions, as well as the potential for carbon emissions to influence trading behaviour. Most studies focus on Bitcoin, often overlooking the broader cryptocurrency ecosystem and the diversity of consensus mechanisms. Methodological limitations, such as reliance on aggregate data and static models, further constrain the field. This study seeks to address these gaps by investigating the bidirectional relationship between trading activity and carbon emissions across major cryptocurrencies, employing a systems theory perspective and robust causality testing. In doing so, it aims to contribute to a more comprehensive and dynamic understanding of the environmental implications of digital asset markets.

3. Methodology

3.1. Data

This study investigates the causal relationship between global cryptocurrency trading and carbon emissions using the Toda and Yamamoto [35] methodology. Monthly global carbon emissions (measured in parts per million) data was collected from February 2015 (M2) to September 2024 (M9) along with cryptocurrency market data focused on the three largest cryptocurrencies by market capitalization: Bitcoin (BTC), Ethereum (ETH), and Binance Coin (BNB). The sample periods for each asset reflect their respective market histories: BTC from February 2015 to September 2024, ETH from April 2016 to September 2024, and BNB from December 2017 to April 2024. These three cryptocurrencies were selected because they collectively account for over 70 % of the global cryptocurrency market [36] which is valued at approximately $2.26 trillion [3]. This market dominance supports their

Table 1
Top 3 Cryptocurrencies by market capitalizations.

Cryptocurrency	Market cap.	Price	Year-over-year return
Bitcoin (BTC)	$1.2 trillion	$62,572.01	128 %
Ethereum (ETH)	$293.5 billion	$2437.72	53 %
BNB (BNB)	$81.8 billion	$575.94	178 %

Source: USAtoday [3].

use as representations for broader cryptocurrency market dynamics Table 1.

Carbon emissions data was sourced from the NOAA (National Oceanic and Atmospheric Administration) Earth System Research Laboratories (ESRL), which provides monthly global averages based on CO2 measurements. Cryptocurrency price data were obtained from USAtoday [3]. All variables were logarithmically transformed to enhance understanding, interpretation, and the statistical properties of the dataset. This transformation is standard in time series analysis, particularly when dealing with variables that exhibit exponential growth or volatility. Fig. 1 presents logarithmic line graphs that illustrate upward trends, indicating a consistent increase in carbon emissions as well as the prices of BTC, ETH, and BNB throughout this timeframe.

3.2. Estimation technique

The study utilizes the Toda and Yamamoto [35] causality test to examine the predictive relationships between cryptocurrency prices and carbon emissions. The use of this approach addresses challenges associated with the Granger causality test by effectively managing integrated series of different orders, allowing for the examination of causal relationships among these series. Likewise, the traditional VAR-based Granger causality tests require that all series be stationary, or that one first establish cointegration and then estimate a Vector Error-Correction Model (VECM) to avoid spurious inference [37,38]. However, environmental and financial time series, such as cryptocurrency trading volumes and carbon emissions, are often integrated of order one (I(1)) and may exhibit uncertain integration orders or structural breaks, making pre-testing both cumbersome and prone to size distortions [39].

The Toda–Yamamoto [35] approach circumvents these issues by estimating an "over-parameterized" VAR in levels, augmented with extra lags equal to the maximum integration order (d_{max}) of the variables. A standard Wald test on the coefficients of the first p lags then delivers valid χ^2 inference, irrespective of whether the underlying series are I(0), I(1), or cointegrated [35]. This ensures that the Granger causality tests maintain correct size and power without requiring pre-testing for unit roots or cointegration, which can yield misleading decisions [40]. Based on all these key advantages, the Toda-Yamamoto test is often performed without needing to assess the integration and cointegration properties of the data. In this study's context, this property is especially valuable as it allows for modelling the dynamic interdependencies between trading activity and emissions in a unified level-VAR framework, thereby avoiding potential bias associated with pre-filtering non-stationary data or misspecifying cointegration relationships. Furthermore, the Toda–Yamamoto procedure's robustness to uncertain integration orders and structural breaks aligns with the empirical realities of rapid shifts in mining technology, policy interventions, and market sentiment, all of which can induce non-stationarity in both trade volume and emissions series [41]. In contrast to cointegration-dependent frameworks like ARDL or NARDL, which focus on estimating long-run and short-run dynamics within a single-equation setup, the Toda-Yamamoto procedure permits unrestricted system-level causal exploration, which aligns more closely with the central objective of this study. Hence, the consideration of Granger causality approach rests on a sound theoretical foundation that balances rigor with practical tractability.

To assess the significance of parameters within a vector autoregressive (VAR$_{(k)}$) model, the Modified Wald statistic serves as a useful tool, involving several sequential steps. First, the maximum order of integration (referred to as d_{max}) for the time series is determined, followed by identifying the optimal lag length (k) for the VAR model. Once these values are established, a VAR model of order ($k + d_{max}$) is estimated, ensuring that the Wald statistic adheres to an asymptotic Chi-square distribution. Finally, hypothesis testing is carried out using a standard Wald statistic test, which follows a chi-square distribution with m degrees of freedom. The formulas for the Toda and Yamamoto [35]

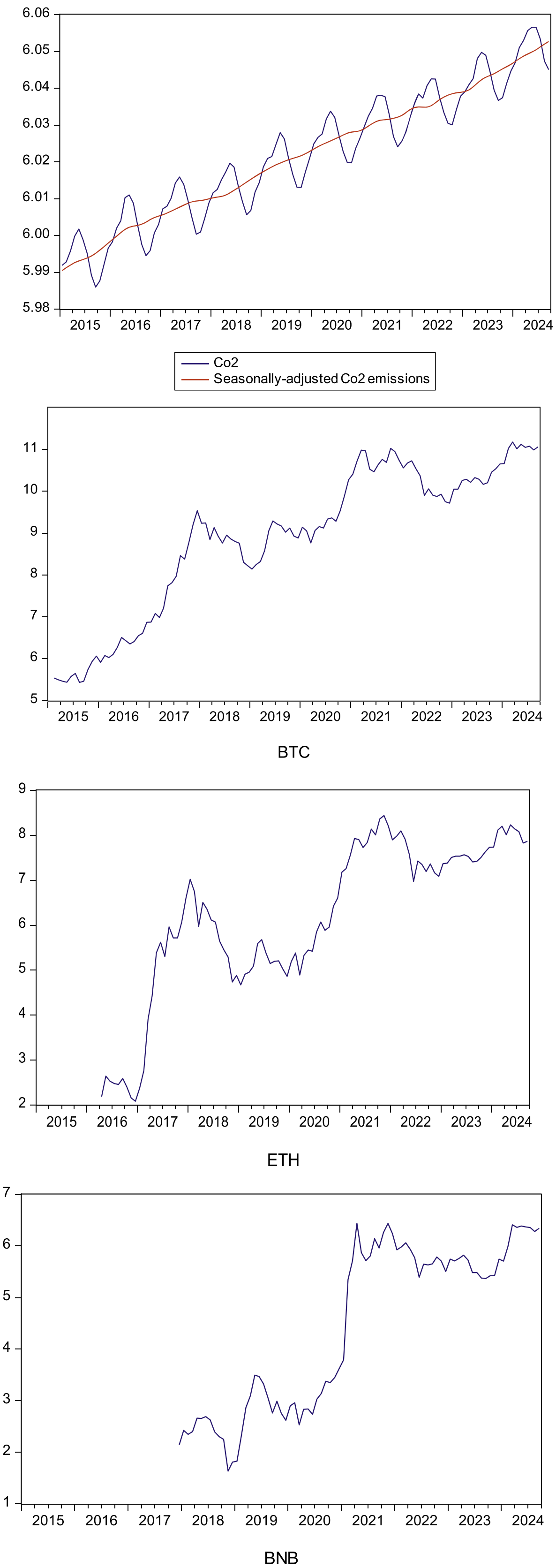

Fig. 1. Trends of carbon emission and cryptocurrency prices between 2015 (M2) to 2024 (M9).

causality test are presented as follows:

$$LnYt = \alpha_0 + \sum\nolimits_{i-1}^{k} \alpha i\, LnYt - 1 + \sum\nolimits_{j-k+1}^{dmax} \alpha j\, LnYt - j + \sum\nolimits_{i-1}^{k} \phi_i\, LnX_{t-1} + \sum\nolimits_{j-k+1}^{dmax} \phi_j\, LnX_{t-1} + v_{1t} \tag{1}$$

$$LnXt = \beta_0 + \sum\nolimits_{i-1}^{k} \beta i\, LnXt - 1 + \sum\nolimits_{j-k+1}^{dmax} \beta j\, LnXt - j + \sum\nolimits_{i-1}^{k} \infty_i\, LnY_{t-1} + \sum\nolimits_{j-k+1}^{dmax} \infty_j\, LnY_{t-j} + v_{2t} \tag{2}$$

LnY and LnX signify the logarithmically transformed variables representing Co2, BTC, ETH, and BNB respectively. The parameter k indicates the optimal lag order, whereas d means the highest or maximum integration order within the sequence. Additionally, v_{1t} and v_{2t} represent the error terms unified in the equations. To further ensure robustness and mitigate concerns around methodological limitations, standard pairwise Granger causality tests were also performed as a supplementary check, and the consistency of results between the two approaches strengthens confidence in the findings.

4. Results

4.1. Descriptive analysis

To begin, as presented in Fig. 1, the study applied X-11 seasonal adjustment to the monthly data, utilizing automatic ARIMA selection through X-11 auto to produce seasonally adjusted and trend values. As anticipated, the trend in carbon emissions exhibited seasonality, while all other variables were also converted into logarithmic values.

Table 2 presents the descriptive statistics for each variable. The results reveal that while the carbon emission values are stable with low variation, BTC, ETH, and BNB show higher variability, particularly BTC and ETH, indicating more fluctuation in those values. The close alignment of the mean and median for CO_2, along with a small standard deviation, suggests a symmetric distribution and low variability, with data clustered around the mean. In contrast, the larger standard deviations and greater differences between mean and median for BTC, ETH, and BNB indicate less symmetry and more dispersion, reflecting the volatile nature of cryptocurrency prices.

4.2. Main analysis

Assessing causal relationships among variables is crucial in econometric analyses, requiring the use of various methodologies to reduce the risk of misleading results. A critical step in conducting a causality test is determining the order of integration of the series (d_{max}) and identifying the appropriate lag length ($k+d_{max}$).

We began with the ADF Dickey-Fuller unit root test, followed by a confirmatory test using the Phillips and Perron method to establish the highest order of integration. As presented in Table 3 both unit root tests showed non-stationarity in both the intercept and trend-and-intercept forms at the level but exhibited stationarity at the first difference. This state of stationarity indicates that the variables are integrated to the first order, denoted as $I(1)$. As a result, the maximum order of integration for the variables in the system is one, or $d_{max} = 1$.

The next step is selecting the lag order, which focuses on identifying the ideal lag length. A VAR model was created using all endogenous variables and a randomly chosen lag interval. Afterward, a test was conducted on the residuals to determine the best lag length based on several criteria, including LogL (Log-Likelihood), LR (Likelihood Ratio), FPE (Final Prediction Error), AIC (Akaike Information Criterion), SC (Schwarz Criterion), and HQ (Hannan-Quinn Criterion). Each criterion has its own advantages and drawbacks, influencing the chosen lag order. An asterisk (*) indicates the statistic or coefficient with the lowest value in each category, signifying the optimal lag for that specific criterion.

Table 4 shows the optimal delay lengths, marked with an asterisk (*). The Schwarz information criterion (SC) indicates a lag length of 2, while the sequentially modified LR test statistic, Hannan-Quinn information criterion (HQ), final prediction error (FPE), and Akaike information criterion (AIC) all suggest a lag length of 12. Since the information delay with the most asterisks (*) indicates the best lag length, the study thus adopted a lag length of 12.

Additionally, Fig. 2 illustrates the stability condition for an autoregressive (AR) model revealing nil roots outside the unit circle., which is crucial in time series analysis for ensuring model stability. The model is confirmed stable as all inverse roots of the AR characteristic polynomial fall within the unit circle, highlighting the significance of this condition for a valid analysis of the model's results.

Table 5 presents the results of the Toda and Yamamoto causality test, showing a chi-squared statistic of 21.4 with a p-value of 0.0448. This indicates that bitcoin trading granger-causes carbon emissions at the 5 % significance level. For Ethereum, the chi-squared statistic is 24.13 with a p-value of 0.0195, suggesting that Ethereum also granger-causes carbon emissions. This supports the view that both Bitcoin and Ethereum trading contributes to carbon emissions. However, the result for BNB (14.73, $p = 0.2567$) shows no evidence of granger causality, indicating that BNB trading does not have a significant impact on carbon emissions.

From the inverse outlook, the result (21.29, $p = 0.0463$) shows that carbon emissions granger-cause bitcoin trading. This suggests that environmental concerns or regulatory measures related to carbon emissions may influence Bitcoin trading behaviours. The test further shows a coefficient of 19.298 for Ethereum with a p-value of 0.0816 is significant at the 10 % level which suggests a possible weak relationship. While no significant relationship is observed in the case of BNB as indicated by the chi-squared statistic of 8.83 and p-value of 0.7172. Furthermore, the joint causality test results show that when all variables

Table 2
Descriptive analysis of variables.

	Co2	BTC	ETH	BNB
Mean	6.0220	8.8914	6.1681	4.4347
Median	6.0215	9.1616	6.3912	5.3847
Minimum	5.9860	5.4359	2.0794	1.6332
Maximum	6.0566	11.1751	8.4401	6.4351
Std. Dev	0.0178	1.7430	1.7343	1.6082
Obs	117	116	102	82

Table 3
Result of unit root tests.

Augmented Dickey-Fuller (ADF)				
Level				
Levels	Co2	BTC	ETH	BNB
t-statistic	−0.25052	−1.513803	−2.152933	−1.006044
Prob.	0.9272	0.5232	0.2249	0.7478
At first difference				
Levels	Co2	BTC	ETH	BNB
t-statistic	−3.870607	−9.246999	−8.56047	−7.744716
Prob.	0.0032***	0.000***	0.000***	0.000***
Phillips-Perron (PP)				
Level				
Levels	Co2	BTC	ETH	BNB
t-statistic	−1.236424	−1.486562	−2.115993	−1.114589
Prob.	0.6569	0.537	0.239	0.7067
At first difference				
Levels	Co2	BTC	ETH	BNB
t-statistic	−3.337438	−9.328177	−8.656877	−7.737061
Prob.	0.0154**	0.000***	0.000***	0.000***

** Significant at the 5 %.
*** Significant at the 1 %. and (no) Not Significant.

Table 4
VAR lag order selection.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	112.1538	NA	5.35E-07	−3.09011	−2.96162	−3.03907
1	378.0606	493.8269	4.24E-10	−10.2303	−9.58788	−9.97512
2	415.241	64.80015	2.33E-10	−10.8355	−9.679088*	−10.3761
3	430.1056	24.20803	2.43E-10	−10.803	−9.13271	−10.1396
4	446.6238	25.01325	2.45E-10	−10.8178	−8.63357	−9.95021
5	457.7587	15.58886	2.92E-10	−10.6788	−7.98063	−9.60706
6	477.6084	25.52106	2.77E-10	−10.7888	−7.57668	−9.51291
7	506.0434	33.30958	2.10E-10	−11.1441	−7.41802	−9.66405
8	521.5942	16.43938	2.38E-10	−11.1313	−6.89124	−9.44707
9	553.5551	30.13462	1.76E-10	−11.5873	−6.83333	−9.69896
10	587.0064	27.71675	1.31E-10	−12.0859	−6.81799	−9.99342
11	610.7243	16.94137	1.39E-10	−12.3064	−6.52456	−10.0098
12	670.9173	36.11577*	5.73e-11*	−13.56906*	−7.27328	−11.06830*

* indicates lag order selection by the criterion.

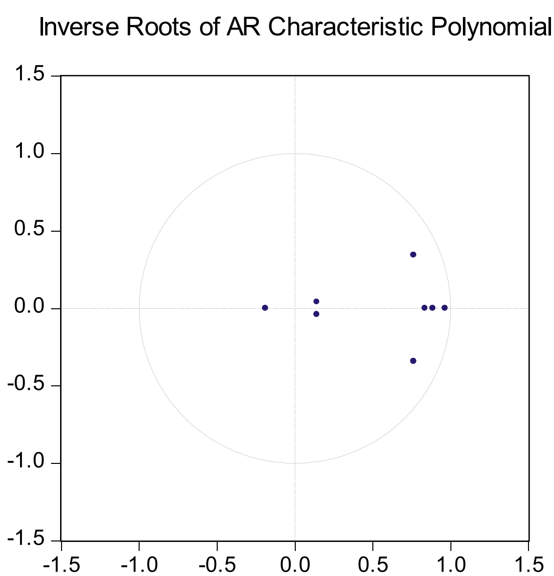

Fig. 2. Inverse roots of AR characteristic polynomial.

are included, there is a significant overall causality from all cryptocurrencies to carbon emissions (77.61, $p = 0.0001$), emphasizing the collective impact of cryptocurrency trading on carbon emissions. Conversely, the overall causality from carbon emissions to all cryptocurrencies shows weak significance at the 10 % level (49.53, $p = 0.066$), suggesting that while carbon emissions influence bitcoin to some extent, this effect does not extend significantly to Ethereum and BNB.

4.3. Robustness test

To reinforce the robustness of the Toda and Yamamoto results the study further conducted the standard pairwise Granger causality test in line with Ahmed et al. [42]. The results as presented in Table 6 largely corroborate the earlier findings. Specifically, the test reveals that Bitcoin Granger-causes carbon emissions, confirming the directional influence of BTC trading on carbon emissions. The absence of reverse causality from CO_2 to Bitcoin reinforces the dominance of Bitcoin's impact on the environment rather than the reverse.

Likewise, Ethereum Granger-causes carbon emissions at the 5 % level in line with the earlier results. This consistency further strengthens the claim that pre-Merge Ethereum trading activity had a significant

Table 6
Pairwise granger causality tests.

Null Hypothesis:	F-Statistic	Prob.	Decision
LNBTC $\nrightarrow$ LNCO2	2.48245	0.0082	LNBTC → LNCO2
LNCO2 $\nrightarrow$ LNBTC	1.02769	0.4325	
LNETH $\nrightarrow$ LNCO2	3.96277	0.0222	LNETH → LNCO2
LNCO2 $\nrightarrow$ LNETH	2.19643	0.1168	
LNCO2 $\nrightarrow$ LNBNB	1.77447	0.1867	LNBNB $\nrightarrow$ LNCO2
LNBNB $\nrightarrow$ LNCO2	0.96913	0.3279	

Table 5
Toda-yamamoto granger causality test results.

Dependent variable: CO2				Dependent variable: BTC			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
BTC	21.40093	12	0.0448**	CO2	21.28885	12	0.0463*
ETH	24.12867	12	0.0195**	ETH	16.75371	12	0.1591
BNB	14.72739	12	0.2567	LNBNB	16.20813	12	0.1819
All	77.61026	36	0.0001***	All	49.53163	36	0.066
Dependent variable: ETH				Dependent variable: BNB			
Excluded	Chi-sq	df	Prob.	Excluded	Chi-sq	df	Prob.
CO2	19.29816	12	0.0816*	CO2	8.832358	12	0.7172
BTC	17.85092	12	0.1203	BTC	4.09471	12	0.9817
BNB	15.85967	12	0.1977	ETH	11.80022	12	0.4619
All	45.03457	36	0.1437	All	41.33973	36	0.2488
d_{max}	1						
Lag	12						
$K+d_{max}$	13						

* Statistical significance at the 10 % level.
** Statistical significance at the 5 % level.
*** Statistical significance at the 1 % level.

environmental footprint. Similarly, reverse causality is not observed, contrasting with the marginal 10 % significance level observed previously. The robustness result thus narrows the bidirectional influence to a unidirectional causality from Ethereum to carbon emissions, suggesting that environmental factors have a limited immediate effect on Ethereum trading behaviour in the sample period. For BNB, the robustness test also confirms the earlier of no significant causality in either direction. This confirms BNB's comparatively negligible environmental effect, in line with the coin's low-energy delegated proof-of-stake (DPoS) infrastructure used in Binance Smart Chain. Overall, these robustness tests affirm that the environmental burden of cryptocurrency trading is not uniform. The results support the view that Bitcoin and Ethereum have a statistically significant and direct impact on carbon emissions. The absence of causality from carbon emissions to cryptocurrency trading across most pairs further emphasizes that crypto markets may remain relatively insensitive to environmental signals, at least in the short term.

5. Discussion

The causality analysis reveals a statistically significant unidirectional Granger causality running from Bitcoin trading to carbon emissions. This implies that increases in bitcoin trading are linked to higher carbon emissions, likely due to the energy-intensive nature of bitcoin mining and transactions. This relationship persists across both the Toda-Yamamoto approach and the robustness checks using pairwise Granger tests suggesting that trading volumes of these digital assets may proxy underlying mining activity or investor responses to blockchain activity, both of which have direct energy implications. This finding corroborates the findings from the studies of Khosravi and Säämäki, [18]; Kohli at al [20] and Winotoatmojo et al. [4], which highlighted Bitcoin's high energy intensity due to proof-of-work (PoW) mining mechanisms that demand vast computational resources, largely powered by fossil fuels and consequently result in substantial carbon footprints. The result suggests that fluctuations in BTC trading activity, likely associated with mining incentives, directly influence carbon emissions.

Similarly, Ethereum trading is found to Granger-cause carbon emissions, reinforcing the claim that Ethereum, at least prior to its full transition to proof-of-stake (PoS) via the Merge, also contributed significantly to environmental externalities. This echoes the work of Kohli at al [20] and Zhou and Wang [14], who identified Ethereum as the second-largest emitter among cryptocurrencies before its protocol switch. Despite Ethereum's recent greening through PoS, the legacy impact of its energy consumption continues to be evident in the time series data. These findings also align with broader debates on the environmental sustainability of blockchain technologies and support calls for regulating crypto markets to internalize their carbon footprints.

In contrast, the causality test for Binance Coin (BNB) reveals no statistically significant influence on carbon emissions. This divergence is consistent with the fact that BNB does not use PoW mining and relies on the Binance Smart Chain (BSC), which operates under a delegated proof-of-stake (DPoS) consensus algorithm. As highlighted by Wüst and Gervais [43], such consensus mechanisms are considerably less energy-intensive, resulting in a weaker or negligible carbon impact. This implies that not all cryptocurrencies contribute equally to environmental degradation, and the technological underpinnings of different coins play a crucial role in determining their ecological footprints.

The reverse causality analysis reveals that carbon emissions Granger-cause Bitcoin trading, implying a possible feedback loop as systems theory suggests [34], whereby not only does trading activity exacerbate carbon output, but growing emissions, or the regulations they prompt may also influence market sentiment and transactional behaviour. This implies that current developments in global cryptocurrency policy, where climate-based scrutiny and ESG considerations are beginning to affect institutional investment flows and mining operations. This may also reflect the influence of environmental regulations, climate news, or social pressures on investor behaviour and market sentiment. For example, announcements regarding carbon taxes, ESG concerns, or bans on crypto mining in countries like China and Kazakhstan could affect Bitcoin market dynamics, as also suggested by Bouri et al. [44]. These results add empirical depth to the claim that digital financial innovations are not environmentally neutral and that their sustainability implications must be critically appraised.

For Ethereum, a weaker form of reverse causality exists at the 10 % level, while BNB again exhibits no significant linkage, reinforcing the notion that environmental responsiveness varies across different cryptocurrencies. However, the joint causality results offer an inclusive perception. While combined cryptocurrency trading activities significantly Granger-cause carbon emissions, the reverse joint causality from carbon emissions to cryptocurrencies is weaker and only statistically significant at the 10 % level. This asymmetry emphasizes the dominant environmental impact of aggregate crypto trading activities and supports recent policy discussions around the introduction of sustainability frameworks for digital assets.

Overall, the findings reveal a pressing need to distinguish between crypto assets based on their environmental intensity and to explore adaptive strategies for decarbonizing the sector. The evidence of directionality and asymmetry in the environmental impact across cryptocurrencies provides an empirical foundation for tiered regulatory interventions, where high-emission cryptocurrencies face stricter environmental reporting and compliance requirements, while cleaner tokens are incentivized. Thus, this study offers a valuable lens for understanding the real-world environmental implications of crypto-financial systems, bridging an important gap between energy economics, environmental policy, and digital finance.

6. Conclusion and recommendations

This study examined the relationship between cryptocurrency trading and carbon emissions using the Toda-Yamamoto Granger causality test to analyse monthly data between 2015 (M2) and 2024 (M9). The results indicate a strong bidirectional causal relationship between BTC and carbon emissions implying that trading and price movements of BTC results in increased carbon emissions vice versa. This causal impact is consistent with existing literature on the energy-intensive nature of these cryptocurrencies and underscores the energy-intensive nature of Bitcoin's proof-of-work (PoW) mechanism, where heightened trading activity likely stimulates mining incentives, leading to increased energy consumption and carbon output. Conversely, periods of elevated carbon emissions, often linked to intensified mining, may also influence BTC trading and pricing, highlighting a feedback loop consistent with systems theory.

A similar, though somewhat weaker, bidirectional granger causality for Ethereum trading to was also found. While ETH trading Granger-causes carbon emissions, the reverse effect is less pronounced, potentially due to the significantly lower trading volume of ETH relative to BTC which implies a smaller scale of operation or the switch of ETH to proof-of-stake verification mechanism in 2022 which is believed to be much less energy consuming relative to the proof-of-work mechanism. Nevertheless, our results highlights, in agreement with existing literature, the environmental impact and the energy-intensive nature of these cryptocurrencies. In contrast, BNB did not exhibit a significant causal relationship with carbon emissions, suggesting that BNB operates more sustainably and with minimal contributions to carbon emissions. We attribute this to BNB being based on the delegated proof-of-stake verification for trading which has been suggested to be more energy efficient and environmentally sustainable.

The policy implications of this study are particularly salient as governments and regulatory bodies are seeking to balance fostering financial innovation and mitigating climate risks. While previous research has often concentrated on the technical underpinnings or market dynamics of cryptocurrencies, this study contributes a distinct perspective by empirically interrogating their environmental ramifications. By empirically demonstrating the causal links between cryptocurrency trading and carbon emissions, this study contributes to ongoing policy debates on climate-aligned financial regulation, carbon taxation of digital assets, and the inclusion of cryptocurrency mining in national emissions inventories. The differentiated results—where Bitcoin and Ethereum show significant environmental impacts, but BNB does not—suggest that technology-specific regulatory interventions are warranted.

In particular, the identification of bi-directional causality between Bitcoin trading and carbon emissions suggests feedback loops that might be amplified by market volatility or changing energy markets. Regulatory strategies could therefore target consensus mechanisms, energy sourcing, and carbon disclosure requirements for blockchain operations. For instance, differentiated transaction taxes or carbon levies could be imposed on high-emission cryptocurrencies, dynamically adjusted based on mining practices and energy sources. Exchanges listing PoW assets might be required to publish regular reports on mining energy sources and emissions intensity, similar to ESG reporting standards in traditional finance. Such measures would enhance transparency and accountability, especially in jurisdictions pursuing net-zero targets, such as the EU under its MiCA framework and the U.S. through recent SEC climate disclosure rules.

In parallel, financial and environmental authorities should incentivize the adoption and development of energy-efficient consensus mechanisms, such as proof-of-stake and delegated proof-of-stake, by offering regulatory sandboxes, tax incentives, or green certification labels for low-emission cryptocurrencies and blockchain networks. Ethereum's recent shift to PoS (Ethereum 2.0) and BNB's already efficient model present viable benchmarks. Policymakers should also collaborate with grid operators to pilot smart load balancing projects that integrate PoS mining with surplus renewable energy, especially in countries facing energy curtailment or grid instability. This policy alignment would not only mitigate crypto's environmental risks but also transform blockchain technologies into instruments for decarbonization and energy optimization, reframing them as part of the climate solution rather than the problem.

Methodologically, this study's focus on Toda-Yamamoto causality, reinforced by robustness checks, provides a time-sensitive understanding of dynamic interactions. This temporal dimension allows for more adaptive policy tools that respond to fluctuations in trading intensity and energy demand. Future-oriented regulation, especially in the context of emerging global frameworks such as the EU's MiCA (Markets in Crypto-Assets) Regulation and international carbon accounting protocols, would benefit from a firmer grounding in such empirical evidence. Ultimately, these findings call for a calibrated approach that balances the environmental externalities of cryptocurrencies with their economic and technological promises.

Whilst the study has sought to minimise any limitations, further remaining limitations present opportunities for future studies to build on. This study focuses on the three largest cryptocurrencies excluding other emerging cryptocurrencies and decentralized finance (DeFi) tokens. Future research should expand the analysis to include a wider range of cryptocurrencies, particularly those using different consensus mechanisms. Furthermore, future studies may benefit from examining the impact of a switch from proof-of-work mechanism to proof-of-stake as has been seen with ETH. This may further demonstrate the positive impact of adopting the latter framework. Future research could explore the long-run and asymmetric effects of cryptocurrency trading on carbon emissions using frameworks such as the ARDL and NARDL models. These approaches would enable deeper analysis of both equilibrium relationships and potential non-linearities between cryptocurrency activity and environmental impact—especially in the context of evolving consensus mechanisms and regulatory landscapes. Additionally, future studies could incorporate panel data techniques to account for cross-country heterogeneity and investigate the differentiated environmental effects of crypto adoption across developed and developing economies. Finally, the evolving geopolitical landscape including developments in the U.S., the Russia-Ukraine conflict, and the growing influence of high-profile figures such as Elon Musk in the crypto space may further shape the relationship between cryptocurrencies and carbon emissions, warranting continued empirical attention.

In summary, this study provides robust evidence of the environmental consequences of cryptocurrency trading, particularly for PoW-based assets, and offers actionable insights for policymakers seeking to align digital finance with climate action. A calibrated, technology-specific regulatory approach balancing innovation with sustainability will be essential as the digital asset ecosystem continues to evolve.

CRediT authorship contribution statement

Abdulkadri Toyin Alabi: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Abdullahi Omogbolahan Ishola:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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