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Price Shocks and Carbon Emissions: Asymmetric Effects of Oil Markets and Cryptocurrency Mining on Global CO_2 Dynamics †

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Abstract

Energy consumption and cryptocurrency mining exert significant yet asymmetric pressures on global CO_2 emissions, presenting complex challenges for climate policy design. While prior research has examined fossil fuel and digital asset markets in isolation, this study addresses a critical theoretical gap: oil and Bitcoin markets are structurally coupled through energy arbitrage mechanisms, wherein miners exploit stranded hydrocarbon resources, particularly flared natural gas, as low-cost electricity sources. This interconnection generates cross-market emission spillovers that isolated analyses inherently miss, risking systematic underestimation of aggregate carbon intensity. To capture these dynamics, a dual-methodological framework of symmetric ARDL and asymmetric NARDL models is employed on monthly global data spanning September 2012 to March 2023. Results confirm a robust positive long-run relationship between Bitcoin prices and CO_2 emissions, reflecting the carbon-intensive nature of mining expansion during bull markets. Conversely, higher oil prices exert a significant mitigating effect on emissions in the long run, consistent with price-induced energy efficiency and fuel substitution. Critically, asymmetric decomposition reveals upward-biased responses for both assets: positive Bitcoin price shocks increase emissions substantially more than negative shocks reduce them. In contrast, positive oil price shocks suppress emissions more strongly than negative shocks elevate them. These asymmetries reflect distinct mechanisms of mining infrastructure lock-in for Bitcoin versus consumption-side inertia for oil-demanding asset-specific policy instruments. Carbon price floors are recommended to lock in oil-price-induced decarbonization gains, while proof-of-stake migration mandates may prevent irreversible expansion of Bitcoin mining. This study provides the first integrated asymmetric assessment of hydrocarbon–digital finance emission linkages, with direct implications for climate policy design in an era of converging energy and digital markets.

Keywords: climate change; cryptocurrency; oil prices; asymmetric effects; ARDL; NARDL; energy arbitrage

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1. Introduction

Climate change is one of the most pressing global challenges of the 21st century, driven primarily by anthropogenic greenhouse gas emissions from energy-intensive human activities. Its far-reaching consequences extend beyond environmental degradation, threatening

food security, public health, economic stability, and human well-being, particularly in vulnerable developing economies that lack adaptive capacity [1]. While international cooperation has intensified through frameworks such as the Paris Agreement, two distinct yet increasingly interconnected drivers of carbon emissions demand urgent scholarly attention: conventional fossil fuel markets and emerging digital finance ecosystems.

Crude oil, the dominant fossil fuel in global energy systems, accounts for the largest share of CO_2 emissions from extraction, refining, transportation, and combustion. Environmental degradation from oil and gas activities, including flaring and methane leakage, has been extensively documented to affect ecosystem integrity and human health adversely [2–5]. In regions such as the Permian Basin, flaring and uncontrolled methane emissions have emerged as critical contributors to the carbon footprint of hydrocarbon production, exacerbating climate forcing beyond direct CO_2 releases [6]. Within the Environmental Kuznets Curve (EKC) framework, rising oil prices have been shown to negatively affect emissions in many contexts, likely by incentivizing energy efficiency, fuel substitution toward cleaner alternatives, and reduced fossil fuel consumption [7–10]. However, this relationship exhibits pronounced asymmetries: positive oil price shocks typically reduce emissions more than negative shocks increase them, with responses varying significantly between oil-importing and oil-exporting economies [11,12].

Concurrently, the surge in cryptocurrency markets, particularly Bitcoin, has introduced a novel and rapidly growing source of carbon emissions through energy-intensive mining operations. Bitcoin relies on a proof-of-work consensus mechanism that requires vast computational power to solve cryptographic puzzles, consuming electricity at a scale comparable to that of medium-sized nations [13,14]. Empirical evidence consistently demonstrates a positive relationship between Bitcoin prices and CO_2 emissions: as prices rise, mining profitability increases, incentivizing greater computational competition and energy consumption, which is frequently sourced from carbon-intensive fossil fuels [15,16]. Research employing advanced econometric techniques, including time-varying-parameter stochastic-volatility vector autoregression systems, confirms that Bitcoin prices exert a robust positive influence on both carbon emissions and energy consumption, with higher prices directly correlating with increased carbon emissions [17]. This dynamic is particularly pronounced in fossil-fuel-dependent mining hubs such as the Caspian Basin (Azerbaijan, Kazakhstan, and Russia), where Bitcoin price fluctuations account for a substantial share of CO_2 emissions from the oil and natural gas industries [18].

The environmental implications of cryptocurrency energy consumption have been further validated through Granger causality analyses across quantiles and dynamic connectedness measures. Studies reveal a significant causal link between CO_2 emissions and Bitcoin's energy usage, with spikes concentrated in the right tail, indicating that emissions intensify during periods of elevated Bitcoin prices and market volatility [19]. Critically, an increase in Bitcoin's hash rate correlates with higher energy consumption and an expanded carbon footprint [20], contradicting efficiency assumptions sometimes advanced in industry discourse. Recent quantifications estimate Bitcoin's environmental externalities at €8.04–€14.15 billion across risk percentiles [21], while projections suggest that unabated growth could contribute to a 2 °C increase in global temperature by mid-century [16,22]. Nevertheless, mitigation pathways exist: increases in coal and natural gas prices reduce Bitcoin's carbon footprint at lower quantiles, and renewable energy adoption consistently reduces emissions across all quantiles, highlighting the pivotal role of energy source composition in determining the cryptocurrency's environmental impact [23].

Despite growing recognition of these dual emission sources, a critical research gap persists: existing literature predominantly examines oil markets or cryptocurrencies in isolation, employing symmetric modeling frameworks that fail to capture differential responses

to positive versus negative price shocks. Conventional linear models obscure crucial asymmetries, for instance, whether a 10% rise in oil prices reduces emissions to the same extent that a 10% decline increases them, or whether Bitcoin price surges trigger proportionally larger emission spikes than price collapses. Critically, the environmental footprints of oil markets and Bitcoin mining are not independent but increasingly interconnected through energy arbitrage mechanisms. Miners strategically relocate computational infrastructure to oil- and gas-producing regions where stranded resources, particularly flared natural gas previously vented as waste, provide ultra-low-cost electricity [15]. This practice transforms a negative externality of fossil fuel extraction (methane/CO_2 flaring) into a revenue stream for cryptocurrency production, creating a structural coupling between hydrocarbon markets and digital asset emissions.

Consequently, oil price shocks propagate not only through conventional demand channels but also via mining relocation decisions. In contrast, Bitcoin price surges incentivize further exploitation of stranded fossil fuels, generating a feedback loop that linear, single-asset models inherently miss. An integrated analytical framework is therefore theoretically necessary to capture these cross-market spillovers and avoid underestimating the aggregate carbon intensity of energy-digital finance linkages. To address this gap, our study provides the first integrated assessment of the symmetric and asymmetric effects of oil and Bitcoin price fluctuations on global CO_2 emissions, using monthly data from September 2012 to March 2023 and a dual-methodological approach combining the autoregressive distributed lag (ARDL) and nonlinear ARDL (NARDL) frameworks.

By explicitly modeling positive and negative price shocks separately, we uncover nuanced dynamics that linear specifications inherently miss. The analysis further incorporates structural break tests to account for pivotal events, such as the 2014 oil shock, Bitcoin's 2017 bull run, and the post-pandemic rebound of 2021, that fundamentally reshaped the oil–Bitcoin–emissions nexus. These findings have critical implications for climate policy design, particularly for regulatory frameworks that target both fossil fuel markets and the rapidly expanding digital asset ecosystem, as part of integrated decarbonization strategies aligned with IPCC mitigation pathways and the European Green Deal. Therefore, this study addresses the following core research question: To what extent do oil consumption and Bitcoin prices influence global climate change?

The following is the structure of this document: Section 2 introduces the impact of Bitcoin and oil prices on climate change and reviews the relevant literature. Section 3 describes the research methods. Section 4 contains the results and comments. Section 5 discusses the different results. Finally, Section 6 presents the conclusions.

2. Literature Review

The environmental impact of energy and financial systems has emerged as a pivotal topic in academic and policy discourse, particularly amid growing concerns about climate change and sustainability. This section synthesizes existing studies on the relationship among oil prices, Bitcoin, and CO_2 emissions. It examines how fluctuations in oil prices and cryptocurrency activity affect carbon footprints, offering key theoretical and empirical insights. Additionally, this review emphasizes asymmetric effects, offering a nuanced perspective on the interplay between economic variables and environmental outcomes. By consolidating prior findings, this section provides a foundation for formulating hypotheses and conducting empirical analyses in subsequent parts of the study.

2.1. The Symmetric Impact of Bitcoin Price and Oil Price on Climate Change

The ARDL (autoregressive distributed lag) modeling framework provides a robust foundation for identifying long-run symmetric relationships between economic drivers and

environmental outcomes. Within this paradigm, oil prices constitute a primary determinant of CO_2 emissions through the price-affordability mechanism: rising oil prices increase the cost of fossil fuel consumption, thereby suppressing demand, promoting energy efficiency, and accelerating adoption of cleaner alternatives, collectively reducing carbon emissions in the long run [24,25]. Conversely, declining oil prices lower energy costs and stimulate fossil fuel consumption, exerting upward pressure on emissions [26]. This symmetric relationship serves as a foundational channel through which energy market dynamics influence environmental degradation, and we then test for directional asymmetries using NARDL decomposition.

Empirical validation of this symmetric nexus spans diverse geographic and temporal contexts. Cross-country panel ARDL analyses confirm a statistically significant negative long-run coefficient between oil prices and CO_2 emissions across OECD economies, reflecting consistent price-induced demand suppression [7,8]. Middle-income economies undergoing structural transformation exhibit particularly pronounced symmetric responses, with oil prices serving as critical proxies for energy intensity within the Environmental Kuznets Curve framework [27,28]. Tunisian evidence validates this symmetric relationship, demonstrating that rising oil prices facilitate the transition from emission-intensive growth toward decarbonization pathways [28]. Similarly, Saudi Arabian studies confirm that increases in oil prices have persistent negative effects on emissions, which are partially offset but not fully offset by the adoption of renewable energy [29]. These findings establish that oil prices are a robust, symmetric predictor of emission trajectories in ARDL specifications.

Parallel evidence indicates that Bitcoin activity is a symmetric driver of CO_2 emissions through electricity-intensive mining operations. Ref. [30] find a statistically significant positive long-run coefficient between Bitcoin trading volume and CO_2 emissions using an ARDL cointegration test, indicating that increased market participation systematically increases the network's carbon footprint. Ref. [31] corroborate this symmetric relationship, demonstrating that both trading volume and market capitalization exert persistent positive effects on emissions in ARDL frameworks. The underlying mechanism operates through the economics of mining. Ref. [32] shows that Bitcoin mining follows an equilibrium path in which marginal electricity costs determine operational thresholds, implying that sustained price increases directly translate into higher hash rates and energy demand. Ref. [33] further validate this symmetric revenue–energy nexus, showing that rising Bitcoin prices trigger monotonic increases in electricity consumption.

The scale of this environmental impact has grown substantially. Ref. [34] estimate that annual Bitcoin energy consumption exceeds 175 TWh, while Ref. [35] report figures exceeding 296 TWh, translating to approximately 130.5 million metric tons of CO_2 emissions annually. These estimates substantially exceed earlier calculations of 900–1200 metric tons per BTC, reflecting both methodological refinements and escalating computational demands following integration of energy-intensive functionalities such as smart contracts [36,37].

China's pre-2021 experience offers critical validation: hosting an estimated 65–75% of global hash rate while accounting for 31% of anthropogenic emissions, China's mining concentration coincided with elevated national carbon intensity [38–41]. Following China's 2021 mining ban, implemented explicitly for environmental reasons, global hash rate redistributed to jurisdictions with varying carbon intensities, yet aggregate emissions remained elevated [42]. Ref. [43] further confirm Bitcoin's symmetric emission linkage using MISO-NARX modeling, demonstrating statistically significant positive connectedness between conventional crypto-asset activity and CO_2 output.

Synthesizing this body of evidence, the first and second hypotheses are formulated:

H1. *Oil prices negatively impact CO_2 emissions.*

This hypothesis reflects the predominant empirical finding that rising oil prices, by increasing fossil fuel costs and incentivizing efficiency, tend to suppress carbon emissions in the long run, particularly when embedded within supportive policy environments that facilitate energy transitions.

H2. *Bitcoin has a positive effect on CO_2 emissions.*

This hypothesis posits that Bitcoin mining intensity, measured by hash rate or transaction volume, has a statistically significant positive long-run effect on national or regional CO_2 emissions, driven by increased electricity demand, predominantly from carbon-intensive generation.

2.2. The Asymmetric Impact of Bitcoin Price and Oil Price on Climate Change

Oil price dynamics exert heterogeneous effects on CO_2 emissions depending on the direction of price shocks, positive (price increases) versus negative (price decreases), creating asymmetric environmental externalities that complicate policy design. Positive oil price shocks can act as implicit carbon pricing mechanisms, incentivizing energy efficiency, fuel substitution, and reduced fossil fuel consumption, thereby mitigating emissions [44,45]. Conversely, negative oil price shocks lower the relative cost of carbon-intensive energy, stimulating greater fossil fuel demand and leading to emission rebounds [46,47]. This asymmetry has been empirically validated across multiple contexts: Refs. [48,49] and Ref. [50] document statistically significant differences in emission responses to upward versus downward-biased oil price movements, underscoring that the oil–emissions nexus is fundamentally nonlinear.

The magnitude of these asymmetric effects further varies by a country's position in global energy markets. Ref. [12] demonstrate that oil-importing economies exhibit stronger emission reductions in response to positive oil price shocks, reflecting heightened sensitivity to imported energy costs. In contrast, oil-exporting economies experience more pronounced emission surges following negative shocks, as declining revenues may trigger compensatory increases in domestic fossil fuel extraction and consumption. These heterogeneous responses highlight the limitations of uniform carbon policies and reinforce Ref. [11]'s argument that oil price volatility must be explicitly modeled as an asymmetric driver of emissions when designing targeted climate strategies.

A parallel asymmetry characterizes Bitcoin markets, where price movements interact nonlinearly with mining economics and policy frameworks to shape environmental outcomes. Theoretical grounding stems from equilibrium dynamics in Bitcoin mining: Ref. [32] shows that Bitcoin mining operates along an equilibrium path in which marginal electricity costs and hardware efficiency determine operational thresholds, implying that price movements directly modulate hash rate and energy demand. Ref. [33] further demonstrate a nonlinear revenue–energy consumption nexus, in which rising Bitcoin prices trigger disproportionate increases in electricity consumption—applied the NARDL model to U.S.A. data. They uncovered a robust asymmetric nexus among Bitcoin activity, biofuel consumption, and CO_2 emissions, revealing that both positive and negative shocks to Bitcoin trading volume elevate carbon emissions, suggesting persistent environmental pressure irrespective of market direction, whereas increased biofuel adoption consistently mitigates emissions.

Recent evidence confirms that this price–energy link exhibits upward asymmetry. Ref. [51] employ decomposition and XGBoost to show that positive Bitcoin price shocks induce significantly larger increases in energy consumption than negative shocks of equivalent magnitude. This pattern is amplified at the upper quantiles of the energy distribution.

Ref. [52] corroborates this finding using NARDL, attributing the asymmetry to miners' rapid hardware deployment during price rallies, in contrast to operational inertia during downturns. Ref. [42] extend this pattern directly to CO_2 emissions, while Ref. [53] show that volatility regimes further strengthen the price–emission linkage as miners aggressively scale computational resources to capitalize on speculative opportunities. Policy context modulates this relationship. According to Ref. [54], climate policy uncertainty amplifies mining intensity during regulatory ambiguity. In contrast, Ref. [55] reveal that conventional cryptocurrencies (including Bitcoin) exhibit stronger asymmetric sensitivity to policy shocks than sustainable alternatives.

During market crises, asymmetry intensifies further. Ref. [56] document that climate risk events trigger panic-driven mining surges as distressed miners liquidate holdings to cover operational costs, resulting in acute emission spikes of 18–24% above baseline levels. Collectively, these findings establish that Bitcoin's environmental footprint responds asymmetrically to directional price shocks, a structural feature distinct from, yet conceptually parallel to, oil price–emission dynamics.

Based on the theoretical and empirical literature reviewed above, the third and fourth hypotheses are formulated:

H3. *Oil price shocks affect CO_2 emissions asymmetrically: rising oil prices mitigate emissions, while falling oil prices exacerbate them.*

H4. *Bitcoin price shocks affect CO_2 emissions asymmetrically: positive shocks increase emissions more strongly than negative shocks reduce them, reflecting miners' rapid expansion during price rallies and operational inertia during downturns.*

3. Methodology

Before presenting the empirical findings, it is essential to outline the research motivation and highlight the study's key contributions to the existing literature. While numerous studies have investigated the environmental implications of either fossil fuel consumption or cryptocurrency mining, very few have examined their joint effects, particularly through a nonlinear and asymmetric lens. Moreover, existing empirical evidence often relies on annual datasets and conventional linear models, which may fail to adequately capture the complex short- and long-run dynamics between energy markets, digital finance, and environmental outcomes.

This study aims to address these gaps by employing advanced econometric techniques, specifically ARDL and NARDL models, on high-frequency monthly data spanning from 2012 to 2023. This approach enables a more nuanced analysis of asymmetric responses in CO_2 emissions to both positive and negative shocks in oil and Bitcoin prices. In addition, the empirical strategy incorporates robustness checks, including structural break analysis and the Hatemi-J asymmetric causality test, to verify the reliability and directionality of the observed relationships. Through this comprehensive framework, the study makes a novel contribution to the growing body of research at the intersection of energy economics, digital finance, and environmental sustainability.

3.1. Model and Variables

Our empirical analysis examines global data on three key variables: CO_2 emissions, Bitcoin prices, and oil prices. The data used for this study includes monthly observations from September 2012 to March 2023. Regarding the studies by Ref. [21] and Ref. [57], which measure the effect of Bitcoin on CO_2 emissions, reference is made to Ref. [58], which

investigated the relationship among oil, Bitcoin, and CO_2 emissions. A summary of these variables is provided in Table 1.

Table 1. Definitions of variables.

Variables	Nature	Meaning	References	Source
CO_2	Endogenous	Total amount of carbon dioxide	[59]	Yahoo Finance
Oil_Price	Exogenous	Price of crude oil	[60]	Investing
Bitcoin_Price	Exogenous	Market price of Bitcoin	[61]	Investing

We consider this research to be the foundation of our empirical work. Thus, our empirical model is defined as follows (Equation (1)):

$$lnCO_{2t} = \beta_0 + \beta_1 lnBitcoin_Price_t + \beta_2\, lnOil_Price_t + \varepsilon_t \quad (1)$$

where ε_t represents the error term, while t is an index indicating the period from September 2012 to March 2023. The β_j represents the coefficients of the independent variables.

3.2. Estimation Methods

The most prevalent application of the ARDL technique is in panel data analysis. Ref. [62] proposed it to address the limitations of the Ref. [63] and Ref. [64] techniques. The merits of this model apply to both mixed cointegration regressors and pure I(0) and pure I(1) processes. Consequently, it eradicates the potential biases associated with cointegration and unit root testing. Moreover, this technique has been shown to outperform the cointegration process [65], which requires a substantial sample size to yield reliable results. While competing approaches require implementing a series of equations, our ARDL methodology requires only a simplified version of the problem. Furthermore, it facilitates the use of a variety of regressor delays, which is not possible with cointegrating VAR models [62]. The ARDL model equation is expressed as follows (Equation (2)):

$$\begin{aligned}\Delta lnCO_{2t} = {} & \alpha_0 + \delta_1 lnCO_{2t-1} + \delta_2 lnBitcoin_Price_{t-1} + \delta_3 lnOil_Price_{t-1} + \sum_{j=1}^{p} \beta_{1j} \Delta lnCO_{2t-j} + \\ & \sum_{j=0}^{q} \beta_{2j} \Delta lnBitcoin_Price_{t-j} + \sum_{j=0}^{q} \beta_{3j} \Delta lnOil_Price_{t-j} + u_t\end{aligned} \quad (2)$$

Consequently, the ECM can be represented by the following equation (Equation (3)):

$$\Delta lnCO_{2t} = \rho_0 + \rho_1 \hat{u}_{t-1} + \sum_{j=1}^{p} \beta_{1j}\, \Delta lnBitcoin_Price_{t-j} + \sum_{j=0}^{q} \beta_{2j} \Delta lnOil_Price_{t-j} + \mu_t \quad (3)$$

Ref. [66] introduced the NARDL model, a development that accommodates asymmetry by means of splitting it into positive components. ($lnBitcion_Price_t^+$ & $lnOil_Price_t^+$) and negative component ($lnBitcion_Price_t^-$ & $lnOil_Price_t^-$) as shown in the following equations (Equations (4) and (5)):

$$\begin{aligned}lnBitcoin_Price_t^+ = \sum_{j=1}^{t} \Delta lnBitcoin_Price_{t-j}^+ = \sum_{i=1}^{t} max(\Delta lnBitcoin_Price_t, 0) \text{ and } lnBitcoin_Price_t^- = \\ \sum_{j=1}^{t} \Delta lnBitcoin_Price_{t-j}^- = \sum_{i=1}^{t} min(\Delta lnBitcoin_Price_t, 0)\end{aligned} \quad (4)$$

$$\begin{aligned}lnOil_Price_t^+ = \sum_{j=1}^{t} \Delta lnOil_Price_{t-j}^+ = \sum_{i=1}^{t} max(\Delta lnOil_Price_t, 0) \text{ and } lnOil_Price_t^- = \sum_{j=1}^{t} \Delta lnOil_Price_{t-j}^- = \\ \sum_{i=1}^{t} min(\Delta lnOil_Price_t, 0)\end{aligned} \quad (5)$$

Consequently, Equation (6) provides the asymmetric long-term equilibrium relationship:

$$lnCO_{2t} = \theta_0 + \theta_1^+ lnBitcoin_Price_t^+ + \theta_1^- lnBitcoin_Price_t^- + \theta_2^+ lnOil_Price_t^+ + \theta_2^- lnOil_Price_t^- + u_t \quad (6)$$

The long-term asymmetric coefficients θ_j^+ and θ_j^- represent positive and negative changes in $lnBitcoin_Price_t^+$, $lnOil_Price_t^+$ and $lnBitcoin_Price_t^-$, $lnOil_Price_t^-$, respectively. Ref. [66] claim that the following NARDL model (Equation (7)) is produced by the asymmetric long-run relationship connected to the linear ARDL model [62]:

$$\begin{array}{c}\Delta lnCO_{2t} = \delta_0 + \delta_1 lnCO_{2t-1} + \delta_2^+ lnBitcoin_Price_{t-1}^+ + \delta_2^- lnBitcoin_Price_{t-1}^- + \delta_3^+ lnOil_Price_{t-1}^+ \\ +\delta_3^- lnOil_Price_{t-1}^- + \sum_{j=1}^{p} \beta_{1j} \Delta lnCO_{2t-j} + \sum_{j=0}^{q} \beta_{2j}^+ \Delta lnBitcoin_Price_{t-j}^+ + \sum_{j=0}^{q} \beta_{2j}^- \Delta lnBitcoin_Price_{t-j}^- + \\ \sum_{j=0}^{q} \beta_{3j}^+ \Delta lnOil_Price_{t-j}^+ + \sum_{j=0}^{q} \beta_{3j}^- \Delta lnOil_Price_{t-j}^- + \varepsilon_{it}\end{array} \quad (7)$$

Another possibility is to develop a dynamic error-correcting model (ECM). In this model, the error-correction component (ρ_1) must be negative and statistically significant. This term refers to the rate of adjustment, defined as the time it takes for variables to reach long-term equilibrium. The following equation (Equation (8)) depicts the ECM:

$$\begin{array}{c}\Delta lnCO_{2t} = \rho_0 + \rho_1 \varepsilon_{t-1} + \sum_{j=1}^{p} \beta_{1j} \Delta lnCO_{2t-j} + \sum_{j=0}^{q} \beta_{2j}^+ \Delta lnBitcoin_Price_{t-j}^+ + \sum_{j=0}^{q} \beta_{2j}^- \Delta lnBitcoin_Price_{t-j}^- + \\ \sum_{j=0}^{q} \beta_{3j}^+ \Delta lnOil_Price_{t-j}^+ + \sum_{j=0}^{q} \beta_{3j}^- \Delta lnOil_Price_{t-j}^- + \mu_t\end{array} \quad (8)$$

The conventional Wald tests then analyze the long- and short-run symmetries. Specifically, the test's null and alternative hypotheses are in Equation (9) and the positive and negative coefficients $\Theta_j{}^+ = -\delta_j^+ / \delta_1$ and $\Theta_j{}^+ = -\delta_j^- / \delta_1$:

$$\begin{cases} H_0 : \Theta_j{}^+ = \Theta_j{}^- \\ H_1 : \Theta_j{}^+ \neq \Theta_j{}^- \end{cases} \quad (9)$$

The asymmetric cumulative dynamic multiplier effects of m_h^+ and m_h^- for each unit change in positive component ($lnBitcoin_Price_t^+$ & $lnOil_Price_t^+$) and negative component ($lnBitcoin_Price_t^-$ & $lnOil_Price_t^-$) are derived using the NARDL model. Specifically, these multiplier effects are represented by Equation (10) as follows:

$$m_h^+ = \sum_{i=0}^{h} \frac{\partial LnCO2_{t+j}}{\partial LnX^+} \text{ and } m_h^- = \sum_{i=0}^{h} \frac{\partial LnCO2_{t+j}}{\partial LnX^-} \text{ where } h \to \infty ;\ m_h^+ \to \theta^+ \text{ and } m_h^- \to \theta^- \quad (10)$$

where X can be *Bitcoin_Price* or *Oil_Price*.

4. Results Analysis

4.1. Descriptive and Graphical Analysis

As demonstrated in Table 2, a descriptive analysis of the model variables is essential for understanding the impact of Bitcoin and oil prices on CO_2 emissions. The variable $\ln CO_2$ has a mean of 12.779 and a standard deviation of 1.899, indicating substantial variability around the mean. The median of 13.087, which is higher than the mean, indicates a left-skewed distribution, with lower values occurring more frequently. The numerical values range from 7.908 to 17.215, representing a diversity of concentrations. The skewness of −0.483 supports a slight left skew, while the kurtosis of 2.867 suggests a distribution somewhat lower than the normal distribution. The Jarque–Bera test (p-value of 0.080) suggests that the distribution is nearly normal, though it shows some deviations.

The variable lnBitcoin_Price has a mean of 7.778 and a considerable standard deviation of 2.177, indicating significant price fluctuation. The median of 8.319 is higher than the mean, indicating a left-skewed distribution. Prices range from $2415 to $11,023, with most at roughly $8319. The skewness (−0.439) and kurtosis (2.349) indicate a slight left skew and a less concentrated distribution around the mean. The Jarque–Bera test, with a p-value of 0.042, indicates a departure from normality in Bitcoin prices.

Table 2. Overall descriptive analysis of the key variables.

Designation	$lnCO_2$	lnBitcoin_Price	lnOil_Price
Mean	12.779	7.778	4.142
Median	13.087	8.319	4.113
Standard Deviation	1.899	2.177	0.351
Minimum	7.908	2.415	2.935
Maximum	17.215	11.023	4.742
Skewness	−0.483	−0.439	−0.434
Kurtosis	2.867	2.349	3.286
Jarque–Bera (JB)	5.042	6.326	4.430
Probability JB	0.080	0.042	0.109
Correlation	$lnCO_2$	lnBitcoin_Price	lnOil_Price
$lnCO_2$	1.000		
lnBitcoin_Price	0.695 ***	1.000	
lnOil_Price	−0.370 ***	−0.102 *	1.000
VIF		1.235	

Note: JB represents the Jarque–Bera statistic. *, and *** represent significance at 10%, and 1%, respectively.

For the variable lnOil_Price, the mean is lower at 4.142, with a low standard deviation of 0.351, indicating relative price stability. The median is close to the mean at 4.113, suggesting a symmetric distribution. Oil prices range from 2.935 to 4.742, with a narrower spread. The skewness of −0.434 is low, and the kurtosis of 3.286 indicates a slightly more peaked distribution than the typical one. The Jarque–Bera test (p-value = 0.109) suggests that oil prices are approximately normally distributed, with slight deviations from normality.

The results in Table 2 also show that the correlation between lnBitcoin_Price and $lnCO_2$ is strongly positive and significant, indicating a robust relationship between Bitcoin prices and CO_2 emissions. This correlation may fluctuate due to market demand, cryptocurrency adoption, government regulations, and global events. Furthermore, Bitcoin's CO_2 emissions depend on the energy sources used for mining. Bitcoin's carbon footprint is lower in regions with a high share of renewable energy, while emissions are higher in regions that rely heavily on fossil fuels. Conversely, the correlation between lnOil_Price and $lnCO_2$ is weakly negative and significant, suggesting a weaker inverse relationship between oil prices and CO_2 emissions. Oil prices are closely linked to global economic activity; rising oil prices, driven by stronger economic activity, could lead to higher demand. However, higher prices may also encourage reductions in energy consumption, potentially leading to a slight decrease in CO_2 emissions. Furthermore, technological advancements in energy efficiency, such as the development of electric vehicles and renewable energy sources, may also affect this relationship.

As demonstrated in Figure 1, there was an increase in CO_2 emissions from September 2012 (2012M09) to January 2018 (2018M01), followed by a decrease until March 2023 (2023M03). Specifically, these factors result in an overall mean of 12.779, a standard deviation of 1.899, and a median of 13.087. The range of these 127 observations is 7.908 to 17.215. Furthermore, the distribution is left-skewed (−0.483), less than the critical value of 0, and leptokurtic, with a Jarque–Bera statistic of 5.042, also less than the critical value of 0. The null hypothesis is accepted at the 5% significance level based on the Jarque–Bera test, suggesting that the series is normally distributed. As illustrated in Figure 2, oil prices have exhibited significant volatility, primarily driven by recurring oil shocks. The mean reported for these variables is 4.142, with a standard deviation of 0.351 and a median of 4.113. The range of these 127 observations is 7.908 to 17.215. The distribution exhibits left skewness

(−0.434), which is less than 0, and is leptokurtic, with kurtosis 3.286, which is greater than 0. The null hypothesis is accepted at the 5% significance level, as indicated by the likelihood of the Jarque–Bera statistic. This observation suggests that the series is typical.

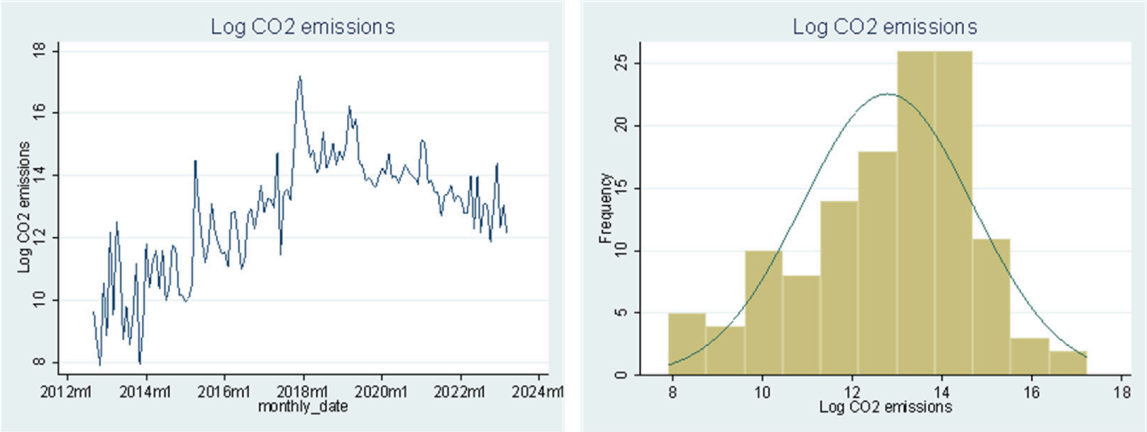


Figure 1. Trend evolution of CO_2 emissions in logarithms.

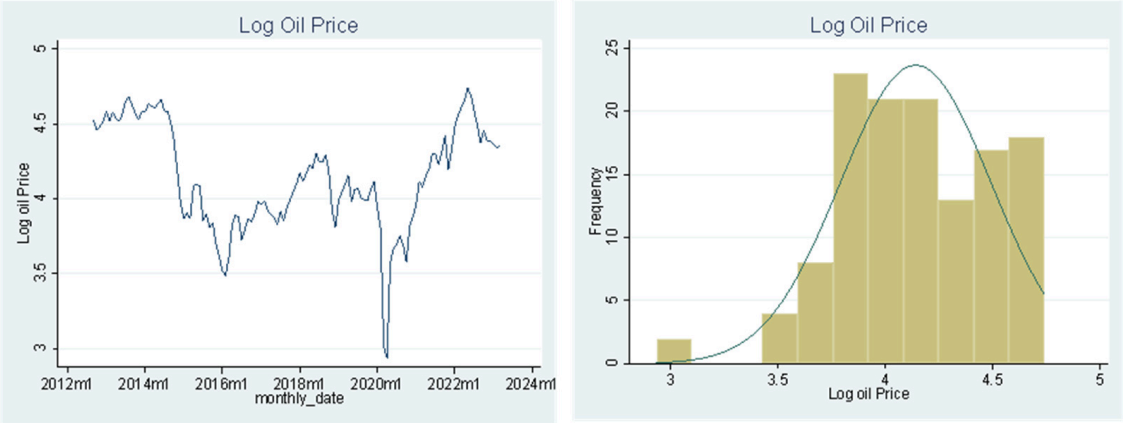


Figure 2. Trend evolution of oil prices in logarithms.

The results in Table 3 indicate that all variables are stationary in first differences, with structural breaks across the variables under study, suggesting substantial economic and financial shocks during the observed period. Three significant breakpoints (2014, 2017, and 2021) have been identified, corresponding to global events of notable magnitude that influenced CO_2 emissions, oil prices, and Bitcoin prices. The 2014 break coincided with a dramatic drop in global oil prices, primarily due to market oversupply stemming from the United States' shale oil boom and the Organization of the Petroleum Exporting Countries (OPEC)'s decision to maintain output levels. The oil crisis had a significant impact on energy markets, affecting industrial output and CO_2 emissions in oil-dependent nations [67].

In 2017, Bitcoin's price underwent a structural shift, signaling the onset of rapid appreciation. This period was marked by a significant increase in Bitcoin use and associated speculation, raising concerns about the environmental impact of Bitcoin mining. This process requires substantial energy consumption, particularly in regions reliant on fossil fuels [68].

Table 3. Break unit root test results.

Tests	Models		$lnCO_2$	lnBitcoin_Price	lnOil_Price
In level	A	Break date	2016M08	2017M04	2014M10
		t-statistic	−4.243	−3.942	−3.669
	B	Break date	2018M11	2021M08	2015M10
		t-statistic	−5.636 ***	−3.502	−3.356
	C	Break date	2017M10	2017M04	2014M10
		t-statistic	−7.251 ***	−3.865	−3.651
	Decision		Non-Stationary	Non-Stationary	Non-Stationary
In the first difference	A	Break date	2018m12	2014M06	2020M05
		t-statistic	−8.828 ***	−9.850 ***	−7.429 ***
	B	Break date	2017M12	2021M08	2021M08
		t-statistic	−8.563 ***	−3.502	−7.057 ***
	C	Break date	2018M02	2015M02	2020M05
		t-statistic	−8.810 ***	−10.289 ***	−7.672 ***
	Decision		Stationary	Stationary	Stationary

Notes: Critical values at 1% and 5%, respectively, for model A are (−5.34), (−4.80), and (−4.58); for model B are (−4.93), (−4.42), and (−4.11); and for model C are (−5.57), (−5.08), and (−4.82). *** represents significance at 1%.

The 2021 break coincides with the post-COVID economic rebound. During this period, global energy consumption increased significantly, oil prices rose rapidly, and investor interest in cryptocurrencies returned. As industrial operations resumed, CO_2 emissions increased substantially, highlighting the incongruity between economic growth and environmental sustainability [69].

Table 4 presents the results of the Ref. [70] nonlinearity test applied to the variables $lnCO_2$, lnBitcoin_Price, and lnOil_Price for type error probabilities $p = 1$ and $p = 1.5$, and multiple dimensions m = 2, 3, 4, and 5. According to the results, the null hypothesis is rejected at the 1% significance level, indicating, by inference, that the sequence is non-normal and nonlinear.

Table 4. BDS nonlinearity test results.

BDS Statistic	$lnCO_2$		lnBitcoin_Price		lnOil_Price	
m	$p = 1.0$	$p = 1.5$	$p = 1.0$	$p = 1.5$	$p = 1.0$	$p = 1.5$
2	20.700	15.903	90.337	43.430	54.677	30.837
3	25.098	18.342	119.514	47.376	66.261	32.457
4	31.130	20.595	163.153	52.157	82.162	34.626
5	38.689	22.789	233.700	59.027	105.638	37.842
Probability	0.000	0.000	0.000	0.000	0.000	0.000

4.2. Symmetrical and Asymmetrical Analysis of the Relationship

According to Table 5 of the ARDL estimation, the F-statistic of 11.536 exceeds the critical value. Consequently, a cointegration relationship exists between the long-term variables. A negative and statistically significant estimated error correction coefficient (ECT_{t-1}) of −0.463 in the short term suggests a long-term association between the variables. The error-correction term indicates an annual adjustment of 46.3% to the long-term equilibrium induced by a specific shock. This suggests that the average lag is 2.16 (approximately 1/0.463). On average, it takes approximately two months and five days for a shock to

be fully absorbed. Additionally, the constant's significance level indicates that the model contains no missing variables.

Table 5. ARDL estimation.

	ARDL (1,0,0)		**F Statistics = 11.536 (p-Value = 0.000)**	
$\ln CO_{2t}$	Coefficient	Standard error	t-statistic	p-value
		Short-term estimation		
Constant	7.235	1.685	4.29	0.000
$\ln CO_{2t-1}$	−0.463	0.079	−5.84	0.000
$\ln$Bitcoin_Price$_{t-1}$	0.253	0.666	3.80	0.000
$\ln$Oil_Price$_{t-1}$	−0.723	0.303	−2.61	0.010
ECT_{t-1}	−0.463	0.079	−5.84	0.000
		Long-term estimation		
$\ln$Bitcoin_Price$_t$	0.545	0.098	5.55	0.000
$\ln$Oil_Price$_t$	−1.703	0.594	−2.87	0.005

The long-term stability of the connection is examined using the CUSUM and CUSUMSQ tests developed by Ref. [71], as shown in Figure 3. To determine if the mean and variance of the parameters have remained consistent throughout time, several tests are used. It can be inferred that the variance and mean estimates are consistent if the CUSUM and CUSUMSQ plots are located within the 5% significance level interval. Coefficient stability over the sample is demonstrated by the CUSUM and CUSUMSQ curves remaining within the critical bounds. The findings demonstrate that an increase in Bitcoin price is associated with higher CO_2 emissions, as evidenced by the positive coefficient of 0.545 in Table 5. This relationship persists over an extended period, indicating a long-term trend. In a similar vein, evidence is presented demonstrating that each long-term rise in oil price is associated with a decrease in CO_2 emissions, with a coefficient of −1.703.

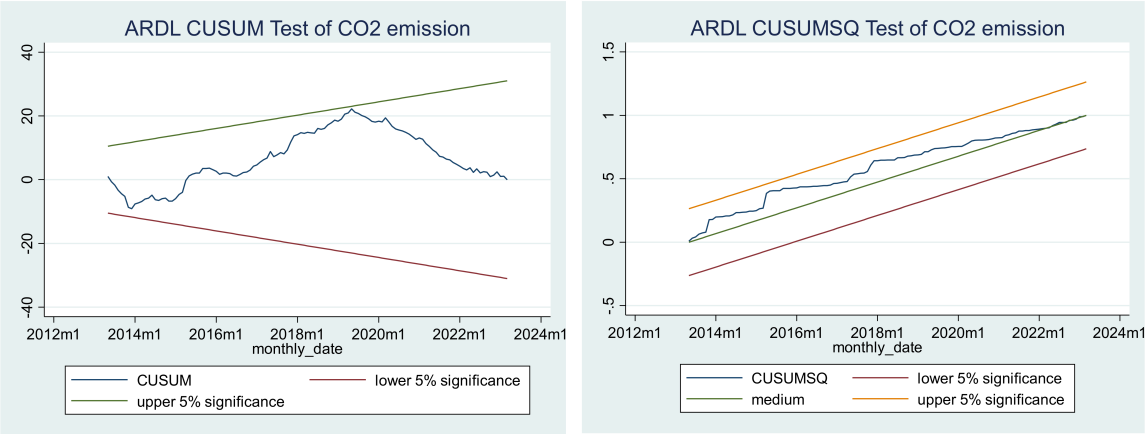


Figure 3. The ARDL CUSUM and CUSUMSQ statistics.

As shown in Table 6, the model is verified because the short-term model's error terms exhibit no heteroscedasticity, serial correlation, or specification errors. In their 2014 study, Shin et al. developed and refined a versatile yet simple nonlinear dynamic framework for modeling inequalities in the underlying long-term connection and dynamic adjustment mechanisms. Furthermore, they developed a dynamic representation of the error-correction process associated with asymmetric regression in long-term cointegration, leading to the nonlinear autoregressive distributed lag model.

Table 6. ARDL diagnostic tests.

Tests	Statistics	*p*-Value	Decision
[72] test	9.878	0.001	No autocorrelation
[73] ARCH (1) test	0.468	0.493	No heteroscedasticity
[74] normality test	5.87	0.053	Normality
[75] test	2.57	0.057	No model specification error

As shown in Table 7, which presents the short- and long-term NARDL estimates, the F-statistic (8.008) exceeds the critical value. Consequently, a cointegration relationship is established between the long-term variables. In the near term, the predicted error correction coefficient (ECT_{t-1}) is −0.516. Consequently, the result is negative and substantial, indicating a long-term link between the short-term variables. Consequently, the error-correction phrase indicates that the long-term equilibrium resulting from a particular shock is modified by 51.6% per year. Therefore, the average lag is 1.94, which is 1 divided by 0.516. This finding suggests that the full absorption of a shock typically occurs within approximately two months. Moreover, the constant is statistically significant, indicating that the model is free of missing variables.

Table 7. NARDL estimation.

NARDL (1,1,1,0,0)			F-Statistic = 8.008 (*p*-Value= 0.002)	
Variables	**Coefficient**	**Standard Error**	**t-Statistic**	***p*-Value**
Short-term estimation				
Constant	4.583	0.747	6.13	0.000
$lnBitcoin_Price^{+}{}_{t-1}$	1.601	0.905	1.77	0.080
$lnBitcoin_Price^{-}{}_{t-1}$	−1.143	0.514	−2.22	0.028
$lnOil_Price^{+}{}_{t-1}$	−1.005	0.407	−2.47	0.015
$lnOil_Price^{-}{}_{t-1}$	−0.465	0.489	−0.95	0.344
ECT_{t-1}	−0.516	0.083	−6.18	0.000
Long-term estimation				
$lnBitcoin_Price^{+}$	0.952	0.211	4.50	0.000
$lnBitcoin_Price^{-}$	0.616	0.526	1.17	0.244
$lnOil_Price^{+}{}_{t}$	−1.862	0.548	−3.40	0.001
$lnOil_Price^{-}{}_{t}$	−0.787	0.768	−1.01	0.308

As shown in Table 7, a positive shock to Bitcoin's price has a substantial positive effect on CO_2 emissions, with a coefficient of 0.95. This relationship persists over an extended timeframe, as evidenced by the long-term data presented in the table. Conversely, each unfavorable price fluctuation in Bitcoin has been observed to exert a positive, albeit non-significant, effect on CO_2 emissions, with a coefficient of 0.616. In a similar vein, it has been shown that each positive shock in oil prices has a considerable adverse effect on CO_2 emissions, with a coefficient of −1.862. Conversely, adverse oil price fluctuations have a negative yet non-significant effect on CO_2 emissions (coefficient = −1.787).

We will assess the viability of the relationship in the future. Table 8's findings corroborate earlier research showing a 10% long-term imbalance between oil prices and CO_2 emissions. Furthermore, the lnBitcoin_Price variable has a statistically significant, positive long-term impact on CO_2 emissions. On the other hand, lnOil_Price has a negative and statistically significant impact on CO_2 emissions over the long term.

Table 8. Short- and long-term asymmetry tests.

Variables	Coefficient	F-Statistic	*p*-Value	Coefficient	F-Statistic	*p*-Value
	Long-Term Positive Effect			Long-Term Negative Effect		
lnBitcoin_Price	0.809	8.268	0.005	−0.259	0.135	0.714
lnOil_Price	−2.373	8.444	0.004	1.099	0.909	0.342
Variables	Long-term asymmetry			Short-term asymmetry		
lnBitcoin_Price	-----	0.854	0.357	-----	0.278	0.599
lnOil_Price	-----	3.194	0.077	-----	0.055	0.815
Cointegration test		t_BDM −4.251			F_PSS 4.022	

According to Table 9, the model is validated because the short-term model's error terms are free of heteroscedasticity, exhibit no serial correlation, and show no specification error. Figure 4 illustrates the results of applying the CUSUM and CUSUMSQ tests, as described by Ref. [71], to assess the long-term stability of the relationship. We used these tests to ensure the long-term mean and variance were stable. It can be inferred that the variance and mean estimates are consistent if the CUSUM and CUSUMSQ plots are located within the 5% significance level interval. The coefficients remain stable during the sample period, as the CUSUM and CUSUMSQ curves remain within the critical limits.

Table 9. NARDL diagnostic tests.

Tests	Statistics	*p*-Value	Decision
[72] test	43.26	0.333	No autocorrelation
[73] ARCH (1) test	0.038	0.844	No heteroscedasticity
[74] normality test	10.83	0.004	Normality
[75] test	0.647	0.586	No model specification error

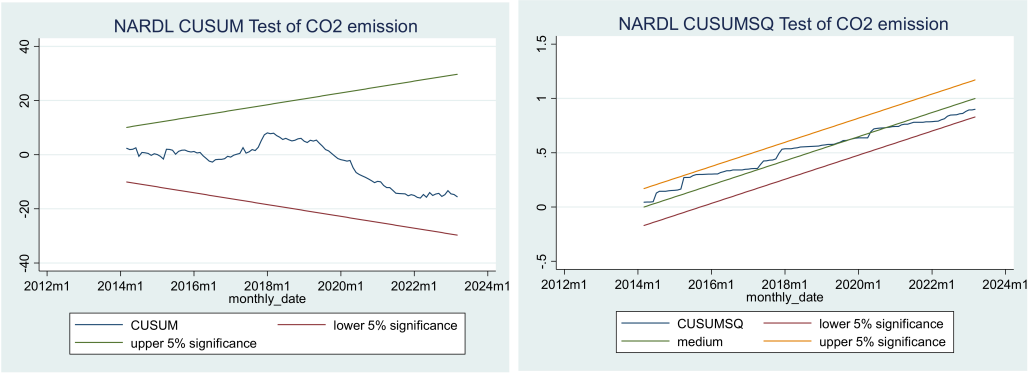


Figure 4. The NARDL CUSUM and CUSUMSQ statistics.

As shown in Figure 5, higher Bitcoin prices are associated with higher CO_2 emissions. Conversely, a decline in Bitcoin's price is associated with a smaller increase (or potential reduction) in CO_2 emissions compared to price increases, as the negative shock coefficient (0.616) is positive but statistically insignificant, as evidenced by the green line in the graph. The blue line indicates the long-term trend toward increasing asymmetry. Concerning the cumulative effect of lnOil_Price on $lnCO_2$, it is evident that a decline in oil prices increases CO_2 emissions, as illustrated by the red line, while an increase in oil prices leads to a decrease in CO_2 emissions, as evidenced by the green line. Once again, the blue line indicates a growing tendency towards asymmetry over time.

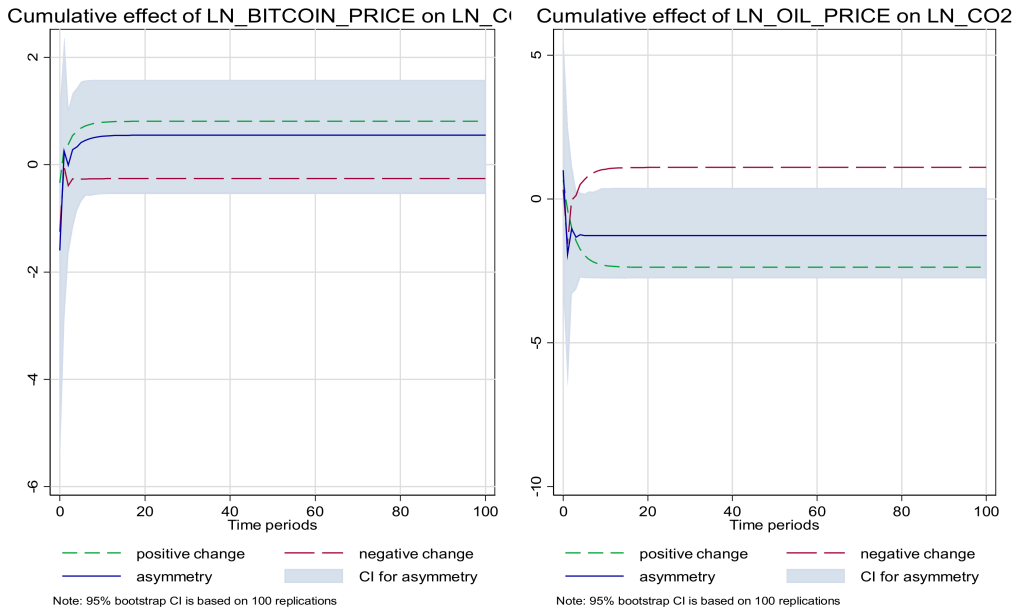


Figure 5. NARDL cumulative effect of Bitcoin_Price and Oil_Price on CO_2 emissions.

4.3. Robustness Tests: Symmetric and Asymmetric Causality

Based on the results of the Ref. [76] causality test, presented in Table 10, a unidirectional relationship is observed running from Bitcoin_Price to CO_2 and from Oil_Price to CO_2 at the 5% significance level. The results of the Ref. [77] causality test indicate a bidirectional relationship between Bitcoin_Price and CO_2 at the 5% significance level and a unidirectional relationship from Oil_Price to CO_2 at the same significance level.

Table 10. Symmetry causality test results.

Tests	Sense of Causality			Wald Stat	Bootstrap C.V.			Decision
					1%	5%	10%	
[76]	lnBitcoin_Price	→	$lnCO_2$	12.795	16.584	11.706	9.565	Yes
	$lnCO_2$	→	lnBitcoin_Price	2.067	17.240	11.754	9.911	No
	lnOil_Price	→	$lnCO_2$	14.408	16.781	11.646	9.436	Yes
	$lnCO_2$	→	lnOil_Price	2.120	14.965	11.474	9.540	No
[77]	lnBitcoin_Price	→	$lnCO_2$	10.348	7.184	3.953	2.762	Yes
	$lnCO_2$	→	lnBitcoin_Price	8.002	7.443	4.090	2.818	Yes
	lnOil_Price	→	$lnCO_2$	7.998	9.844	6.184	4.709	Yes
	$lnCO_2$	→	lnOil_Price	0.225	9.682	6.245	4.778	No

The asymmetric causality test developed by Ref. [78] is a non-parametric test for determining the direction of causality between positive and negative shocks on two variables. This test is based on the idea that the causal impact of a shock may depend on its direction.

As shown in Table 11 of Ref. [78], a unidirectional association is evident between positive Bitcoin price shocks and CO_2 emissions, and between favorable oil price shocks and CO_2 emissions. However, no direct association has been demonstrated between the negative shock to Bitcoin prices and CO_2 emissions, nor between oil prices and CO_2 emissions.

Table 11. Asymmetry causality test results.

[78]: Sense of Causality			Wald Test	Bootstrap Critical Value			Decision
				1%	5%	10%	
$lnBitcoin_Price^{+}$	→	$lnCO_2$	8.513	12.357	6.986	4.746	Yes
$lnCO_2$	→	$lnBitcoin_Price^{+}$	0.992	11.058	6.564	4.796	No
$lnBitcoin_Price^{-}$	→	$lnCO_2$	0.153	5.977	3.398	2.505	No
$lnCO_2$	→	$lnBitcoin_Price^{-}$	0.369	8.450	4.215	2.862	No
$lnOil_Price^{+}$	→	$lnCO_2$	6.018	7.537	4.221	2.702	Yes
$lnCO_2$	→	$lnOil_Price^{+}$	0.022	7.456	3.975	2.602	No
$lnOil_Price^{-}$	→	$lnCO_2$	1.219	8.059	4.198	2.795	No
$lnCO_2$	→	$lnOil_Price^{-}$	0.591	8.317	4.242	2.572	No

5. Discussion

5.1. Economic Discussion of the Symmetrical ARDL Model

This study is based on several hypotheses regarding the impact of oil and Bitcoin prices on CO_2 emissions. Firstly, the hypothesis that oil prices negatively affect CO_2 emissions (H1) is a central theme in environmental economics, supported by a significant body of research that often reveals nuanced, asymmetric relationships rather than a simple, symmetric one [11,12,26]. The empirical evidence presented in this study supports the hypothesis that rising oil prices are associated with reduced CO_2 emissions. This phenomenon can be attributed to higher fossil fuel prices, which may lead to a shift towards cleaner energy sources. This outcome provides additional support for the hypothesis that oil prices serve as a regulatory mechanism for energy demand, which aligns with the findings of Refs. [50,79] and Ref. [19]. In summary, while there is strong evidence that Bitcoin price increases are associated with higher CO_2 emissions from energy-intensive mining [18], the impact of oil prices on CO_2 emissions is more nuanced. For Ref. [29], rising oil prices can, in some contexts, reduce CO_2 emissions by incentivizing efficiency and the use of alternative fuels. However, these relationships are often asymmetric and nonlinear, and they vary significantly across regions and economic conditions, necessitating rigorous methods such as two-stage IV estimation to establish causality [80]. The EKC framework further enriches this understanding by considering economic activity alongside oil prices in determining environmental outcomes [81].

The empirical validation of (H_2) confirms a robust positive long-run relationship between Bitcoin prices and CO_2 emissions, underscoring cryptocurrency markets as an emerging driver of carbon-intensive energy demand. This finding reflects a clear economic mechanism: rising Bitcoin prices increase miner profitability, triggering a rapid expansion of the hash rate through the deployment of additional computational hardware and extended operational hours. This surge in electricity demand, predominantly met by fossil-fuel-based generation in major mining jurisdictions, directly leads to elevated carbon emissions [34,35]. The results align with and extend the foundational warnings of Ref. [16], who projected that Bitcoin's energy trajectory could jeopardize global climate targets absent intervention, and Ref. [57], who identified cryptocurrency mining as a systemic externality requiring regulatory internalization. Critically, this relationship persists even after controlling for macroeconomic drivers and energy market dynamics, suggesting that Bitcoin functions as an independent amplifier of emissions rather than merely mirroring broader economic activity.

The policy implications are substantial. As the Eurozone advances its Green Deal agenda and carbon-pricing mechanisms, the carbon footprint of digital asset markets remains a growing blind spot in emissions accounting frameworks. Current ETS (Emissions Trading System) structures do not account for electricity consumption by decentralized min-

ing operations, particularly when hash rate migrates to jurisdictions outside the EU's regulatory reach. Our findings thus call for three targeted interventions: mandatory disclosure of carbon intensity for cryptocurrency transactions; preferential treatment of proof-of-stake and other low-energy consensus mechanisms within EU digital finance regulations; and inclusion of mining electricity demand in national energy transition planning. Without such measures, the decarbonization gains achieved through renewable energy deployment risk being partially offset by unregulated expansion of energy-intensive blockchain activities, a phenomenon increasingly documented across OECD economies [42,43].

The symmetric autoregressive distributed lag (ARDL) model reveals divergent environmental effects: oil price increases reduce emissions, while Bitcoin price increases raise them. The findings support both H_1 and H_2, demonstrating that conventional and digital assets exert distinct influences on the environment through their respective energy-consumption mechanisms.

5.2. Economic Discussion of the Asymmetrical NARDL Model

The asymmetric NARDL estimation confirms significant directional heterogeneity in the oil price–emissions and Bitcoin price–emissions relationships, thereby validating hypotheses (H_3) and (H_4). These findings demonstrate that emission responses to price shocks differ fundamentally by direction and statistical significance, with critical implications for climate policy design.

Hypothesis H_3 (oil price asymmetry) is empirically supported, but with an upward-biased pattern: positive oil price shocks exert a statistically significant negative long-run effect on CO_2 emissions (coefficient = -1.862, p-value < 0.01), whereas negative oil price shocks generate a weaker, statistically insignificant effect (coefficient = -0.787, $p = 0.308$). This asymmetry reflects the price-affordability mechanism, in which higher fossil fuel costs strongly incentivize energy efficiency, modal substitution, and the accelerated adoption of low-carbon alternatives [81].

Conversely, declines in oil prices fail to trigger a proportionately strong rebound in emissions, likely due to regulatory safeguards (e.g., fuel-efficiency standards), slow adjustment of capital-intensive energy infrastructure, and persistent consumer habits formed during high-price regimes. The Wald test for long-run asymmetry approaches significance (F = 3.194, p-value = 0.077), corroborating the finding that emission reductions following price increases are more pronounced and reliable than responses to price declines. This pattern aligns with Ref. [12], which documents stronger emission sensitivity to price rallies than to price slumps in oil-importing economies, and with Ref. [82], which reports a similarly asymmetric pass-through of oil price shocks to carbon allowance prices in China. Critically, this asymmetry implies a policy opportunity: sustained high oil prices generate durable decarbonization effects that are not fully reversed during subsequent price corrections, supporting carbon price floor mechanisms to lock in emission reductions.

Hypothesis H_4 (Bitcoin price asymmetry) is robustly confirmed with a distinct upward-biased pattern. Positive Bitcoin price shocks trigger disproportionately large emission increases (coefficient = +0.952, p-value < 0.01), whereas negative shocks induce weaker, statistically insignificant effects (coefficient = +0.616, p-value = 0.244). This asymmetry reflects mining economics: during bull markets, miners rapidly deploy additional computational hardware and extend operational hours to capitalize on elevated profitability, sharply escalating electricity demand predominantly sourced from carbon-intensive grids [42,53]. During bear markets, however, operational inertia delays shutdowns due to sunk infrastructure costs, contractual electricity commitments, and expectations of price recovery, resulting in muted emission reductions. Ref. [83] corroborate this pattern by documenting persistent environmental pressure from Bitcoin activity irrespective of market direction, with emission

spikes during rallies that exceed contractions during downturns. The upward bias implies that cryptocurrency markets function as asymmetric amplifiers of emissions. Each price rally embeds additional carbon-intensive infrastructure whose emissions persist through subsequent corrections, creating a ratcheting effect on the sector's carbon footprint.

Both oil and Bitcoin exhibit asymmetric emission responses with upward bias. Positive shocks drive stronger environmental effects than negative shocks, but through fundamentally distinct mechanisms. For oil, the asymmetry stems from demand-side rigidity: emission reductions during price rallies persist because efficiency investments and behavioral changes reverse slowly. For Bitcoin, asymmetry arises from supply-side inertia: emission increases during price rallies embed persistent mining infrastructure that continues to operate during downturns. Consequently, climate policies must be asset-specific: oil markets benefit from price-stabilizing instruments (e.g., carbon price floors) to lock in decarbonization gains, whereas cryptocurrency markets require ex ante constraints on mining expansion (e.g., proof-of-stake migration mandates, carbon-intensity disclosure requirements) to prevent irreversible infrastructure lock-in. Figure 6 summarizes the different findings of this article.

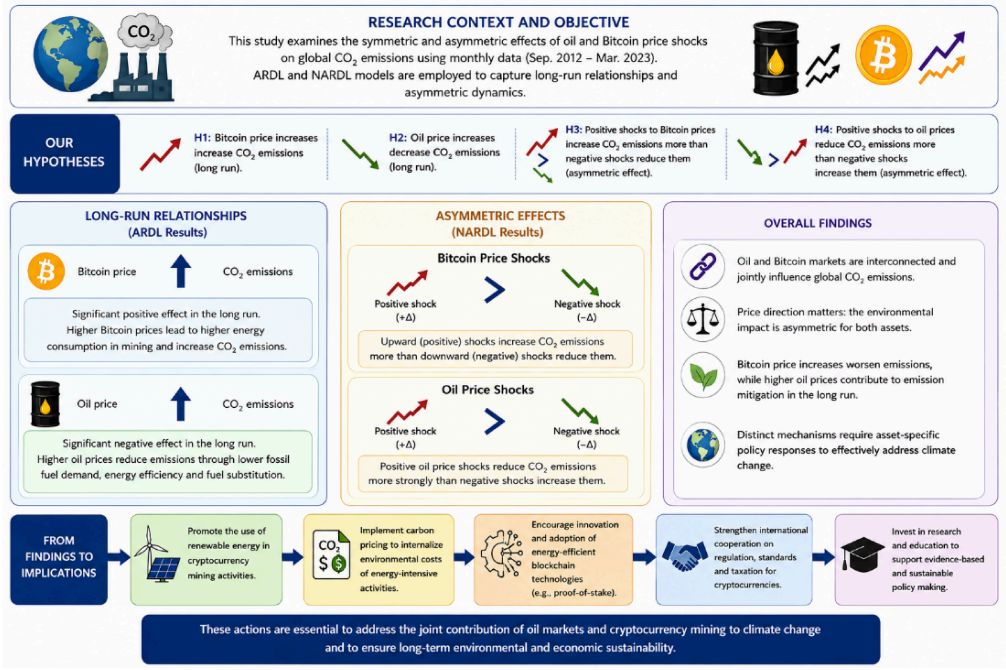


Figure 6. Finding illustration.

6. Conclusions and Policy Implications

6.1. Conclusions

This study examined the symmetric and asymmetric effects of fluctuations in oil and Bitcoin prices on global CO2 emissions, using monthly data from September 2012 to March 2023. The analysis, using ARDL and NARDL models, confirms the existence of a long-run cointegration relationship among oil prices, Bitcoin prices, and environmental degradation. The findings highlight the growing interdependence between traditional energy markets and digital financial systems, both of which significantly influence climate change dynamics.

The empirical results demonstrate that increases in Bitcoin prices significantly raise CO_2 emissions in both the short and long run. This outcome reflects the energy-intensive nature of cryptocurrency mining, particularly under proof-of-work mechanisms that rely heavily on electricity generated by fossil fuels. Conversely, increases in oil prices are

associated with reductions in CO_2 emissions over the long term, mainly through lower fossil fuel consumption, improved energy efficiency, and substitution toward cleaner energy sources.

Furthermore, the asymmetric analysis reveals that positive Bitcoin price shocks generate larger increases in emissions than negative shocks do. Similarly, positive oil price shocks have a more pronounced mitigating effect on emissions than negative ones. These findings confirm the nonlinear nature of the relationship between energy markets, digital assets, and environmental sustainability.

6.2. Recommendations and Policy Implications

The results of this study provide several important implications for policymakers and environmental regulators. First, governments should encourage the transition from energy-intensive proof-of-work (PoW) systems to more sustainable consensus mechanisms, such as proof-of-stake (PoS), which substantially reduce the electricity consumption and carbon emissions associated with cryptocurrency mining.

Second, integrating cryptocurrency mining activities with renewable energy sources should become a strategic priority. Policymakers are encouraged to provide incentives for green energy investments and to impose stricter environmental standards on mining operations to reduce their dependence on fossil fuels. In addition, introducing carbon pricing mechanisms or environmental taxation for highly energy-intensive industries, including cryptocurrency mining, could help internalize environmental costs and promote cleaner production practices.

Third, international cooperation is essential to establish harmonized sustainability standards and taxation frameworks for digital assets and cryptocurrency activities. Coordinated global actions would help reduce regional disparities in energy consumption and emissions while supporting more effective climate governance. Policymakers should also encourage innovation in blockchain technologies and support research initiatives to improve energy efficiency and reduce the environmental footprint of digital financial systems.

6.3. Limitations and Future Research Perspectives

Despite its contributions, this study has several limitations that should be acknowledged. First, the analysis relies on aggregate global data, which may mask important regional differences in energy structures, environmental regulations, and cryptocurrency mining practices. Second, the study focuses primarily on Bitcoin and does not account for the environmental effects of other cryptocurrencies or alternative blockchain technologies that may operate under different energy-consumption mechanisms.

In addition, while the ARDL and NARDL frameworks effectively capture symmetric and asymmetric relationships, they may not fully account for the nonlinearities and structural complexities that characterize the interaction between digital finance and climate change. External shocks, geopolitical tensions, technological progress, and regulatory changes may also influence the observed relationships over time.

Future research could extend this analysis by incorporating country-level or regional data to better capture heterogeneity across economies. Additional studies may also compare the environmental impacts of different cryptocurrencies and investigate the roles of renewable energy adoption, green finance, and technological innovation in mitigating emissions from digital markets. Moreover, employing advanced econometric approaches, machine learning techniques, or dynamic forecasting models could provide deeper insights into the evolving nexus between cryptocurrencies, energy markets, and environmental sustainability.

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