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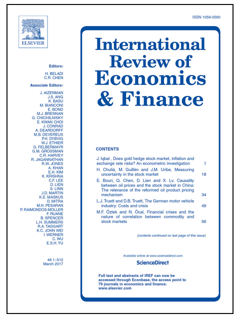

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Crypto currencies and Green Investment Impact on Global Environment: A Time Series Analysis

Abstract

Climate change has become a central theme in both national and international forums in recent decades. In this regard, the argument has quickly moved and centered on the role of crypto currencies, in addition to the fundamental culprits of ecological destruction, such as fossil fuels, agricultural, and industrial pollution. The aim of the present study is to assess the role of asymmetries in determining the relationship between blockchain and green investment with the environment using the Non-linear Autoregressive Distributive Lag (NARDL) technique. The data from the United States of America (USA) is used over the period from 2011 to 2020. The findings reveal that, contrary to common belief, there is asymmetric relation between crypto currencies and biofuel usage in both the short and long run. Similarly, asymmetry also exists between renewable energy use and consumption of biofuel. Further, there is a strong coherence among the concerned variables is also proved in this study. Therefore, the study implies that assuming symmetric and weak coherence relationships between blockchain technology and green investment in the global environment produce biased and misleading findings which are not a true representation of the real-world scenario. Based on this the study suggests that policymakers and environmentalists may strive to achieve low carbon emissions using environment-friendly technology and less energy use. Lastly, the negative nonlinear impacts of blockchain technology and green investment must be considered in the carbon emissions released in the USA economy.

Keywords: crypto currencies, USA, NARDL, Green Investment

1. Introduction

In the last decade, the public interest in crypto currencies has developed considerably since the emergence of this new mode of finance and investment. Bitcoin, the most prominent crypto currencies, began as an electronic cash transfer from one place to another without the participation of banking institutions. Crypto currencies were advocated as a medium to fulfill the purpose of inventorying transactions (Nakamoto, 2008). These new electronic currencies are considered to be reliable since their owners can only spend them once. They are marketed as a peer-to-peer version of electronic money transfers that use a database of nodes that operate together with minimum coordination(Davidson et al., 2016).

Despite of tremendous positive features of this new form of finance, concerns related to its environmental impact have arisen in the recent past. Environmentalists especially climate change experts have raised serious concerns related to mining and extensive technology usage in these currency trading. Nowadays, as crypto currencies' prominence has increased greatly, especially in developed countries, the concerns attached to the sustainability of the environment have become a hot topic of discussion. The argument for a sustainable environment advocates that crypto currencies relies on the utilization of a huge amount of electricity consumption for its extraction process thus causing an environmental hazard (Bendiksen et al., 2019; Köhler & Pizzol, 2019; Koomey, 2019; Li et al., 2019). The process of crypto currencies is such that holders compete with each other over the addition of the next block (extracted through the process called mining) of the currency to the chain thus creating environmental degradation.

Moreover, the competition for the next block also uses considerable processing power in an attempt to solve the complex puzzle of mining(Moll & Yigitbasioglu, 2019).As per Kokina et al. (2017), hashing is a complicated mathematical logic that is used to link the blocks together, these blocks are unchangeable due to a digital signature and a timestamp. An estimate is given by a website named: Blockchain.com. in 2018, the set mining value for a one-block addition roughly used 15-60 million Tera hashes per second which is extremely high and environmentally deteriorating. According to McGeeham (2021), a typical server that is involved in the mining of individual coins costs somewhat between $3224 to $9000.

Furthermore, according to Andoni et al. (2019), Gallersdörfer et al. (2020), and Reiff (2020), the quantity of energy consumed by crypto currencies, particularly of Bitcoin in ASIC algorithms is questionably large than the energy consumed in the market capitalization. These currencies have pluralistic promising technological advancement(Gallagher et al., 2019). Consequently, blockchain, in particular, is used in a number of industries, for example, supply chain management according to Wang et al. (2020), and cooperate operation and taxation as per Kimani et al. (2020). Also in the business and infrastructure sectors respectively(Bai et al., 2020; Shojaei et al., 2019). Similarly, in academia specifically in the management sector block chain technologies are widely used (Centobelli et al., 2021).According to Singh et al. (2019), the fourth industrial revolution demands the use of such innovative block chains. Given the importance of blockchain technologies, a rough estimate predicts that crypto currencies specifically Bitcoinemit more than 100 million tons of CO_2 emissions every year. Similarly, an empirical analysis conducted by Köhler and Pizzol (2019)estimated that the mining of Bitcoin alone produces 17.29 metric tons of CO_2.

At present, there are both positive as well as negative views regarding crypto currencies potential environmental impact. A study such as Krause and Tolaymat (2018)argued that the Bitcoin mining rate and consumption of energy contribute to an increase in CO_2in the atmosphere. To be more specific, according to Mora et al. (2018) and Howson (2019), Bitcoin alone among all crypto currencies may lead toa 2-degree Celsius rise in global temperature by 2050.On the other hand, Köhler and Pizzol (2019)concluded that increasing the hash rate of Bitcoin decreases both energy consumption as well as carbon footprint. Similarly, another study on carbon footprint by Yang and Hamori (2021)analyzed the carbon footprint network and found that the 95^{th}percentile fell at 8.04 and 10.37 billion Euros and the 99^{th} percentile sat 11.33 and 14.15 billion euro shortfall for atmospheric risk. Naeem and Karim (2021) further added that clean energy hedging ratio and effectiveness are greater for bitcoin, demonstrating its substantial diversification potential. According to Pham et al. (2022), green crypto currencies are not strongly connected to bitcoin and Ethereal indicating a need of more green financial assets including green crypto currencies. However, a strong policy assessment is necessary is this respect as green assets in USA are highly affected by the stock market volatilities (Naeem et al., 2022).

Considering these contracting views there is a need to explore in detail crypto currencies impact on the environment. Global warming is one of the human-generated environmental changes to the planet caused by the trapping of CO_2 emissions and other similar gases in the atmosphere. These trapped gases accumulate heat in the earth's system thereby raising its temperature (Hao et al., 2008). Global warming affects all aspects of human life. In particular, it causes flooding due to the melting of glaciers, changes in rain and weather patterns, urbanization, agricultural productivity losses, and serious threat to human health. In addition, it also poses constraints to economic growth and development, therefore, hindering the quality of life. So, considering the significance of the environment and the potential impact of crypto currencies on environmental quality motivate us to conduct this study. The existing literature on crypto currencies mostly highlights its positive attributes and features consequently ignoring mining and transacting aspects of crypto currencies on the environment.

Thus, motivated by this, we have assumed and explored asymmetries in crypto currencies and environment nexus. The findings of our study may be useful to environmentalists who have specific concerns related to climate change owing to rapidly growing blockchain technologies. Our study not only examines the impact of crypto currencies on the environment but also explores the optimal energy sources that are used in it extensively.

This study is one of its kinds since it adds to the present literature in several ways: To begin, this paper analyzes the impact of crypto currencies volume, prices, bitcoin energy use, biofuels use, renewable energy use, and coal consumption in the United States of America on CO_2 emissions. The selection of the USA is based on the reason the country is a developed economy and bitcoin is largely used in the country. As presently about 19.24 million bitcoin are in circulation in the USA with a total volume of 14312.274944 trillion. Along with this, the country has high carbon emissions. Therefore, it is important to explore whether bitcoin also plays any role in the carbon emissions of the country. If yes then what is the level of this effect? Second, this research uses the NARDL and NARDL bound tests, as well as CUSUM plots, to capture the long- and short-term relationships between variables. Thirdly, the study explores the effect of both bitcoin price and volume on carbon emission to highlight whether the pricing effect is greater or whether volume has a larger impact. Lastly, the findings of this study will help policymakers and environmentalists in defining concrete regulations for blockchain and crypto currencies functioning as it provides comparative findings on crypto energy algorithms and other energy-efficient alternatives so that efficient use of energy and environment conservation in blockchain technologies can be achieved throughout their lifecycle.

1.1. Research Question

This study intends to analyze blockchain versus green investment's impact on the environment by taking into consideration crypto currencies and investment in bitcoin's impacts on CO_2 emissions emitted in the US economy. The study attempts to explore the answer to the following questions:

1. What are the impact of crypto currencies, bitcoin energy use, and biofuel consumption on CO_2 emissions in the USA?

2. How one can evaluate the impact of crypto currencies on the environment and the optimal energy source in order to invest in crypto currencies for the reduction of its carbon footprints?
3. How do long-run and short-run relationships appear between crypto currencies and CO_2 emissions?

The remaining paper is arranged as: section 2 illustrates a brief literature review of the existing studies. Next is section 3 which provides information regarding the data sources and the econometric methodology employed in this study? Followed by it, section 4 presents the results and a detailed discussion of the findings. Lastly, there is section 5, which presents the conclusion of the study and provides policy suggestions in light of the obtained results.

2. Literature Review

Like the emergence of any other new technology, crypto currencies particularly bitcoin's impact on the environment ought to be investigated. The emerging literature explored the environment along with the impact on energy in the recent past. Roughly around 3 to 15 million tons of CO_2 emissions are generated through crypto currencies mining (Krause & Tolaymat, 2018).In addition, it is not simply crypto currencies-generated CO_2 emissions that have an impact on the environment. The attainment as well as the use of crypto currencies makes use of a variety of resources, the most important of which is the use of electricity. As a result, the consumption of energy and the generation of carbon dioxide are two major concerns about the environmental impact of crypto currencies.

The literature on the crypto currencies environment nexus evolved in late 2010 and early 2020. Several studies such as Jiang et al. (2021), Roeck and Drennen (2022), Badea and Mungiu-Pupăzan (2021)explored the electricity consumption of Bitcoin mining. However, other studies like Mora et al. (2018), Panah et al. (2022), Pham et al. (2022), and Erdogan (2022) investigated CO_2 emissions generated from the mining process of crypto currencies. Similarly, Scholtens (2009), Li and Jia, (2017), Ahmad et al. (2018), Ling et al. (2022), (Legotin et al., 2018); Thampanya et al. (2021), and Majeed et al. (2020)have explored the connection between social responsibility related to environment conservation and financial institution performance and finance respectively. Another strand such as Abu Bakar and Rosbi (2017), Lee et al. (2016), and Jadevicius and Huston (2015)predict the future impact of crypto currencies on environmental quality.

A study by Mora et al. (2018)is one of the pioneer studies that raise environmental concerns about bitcoin. The authors pointed out that approximately 0.033 percent of 314.2 billion cashless transactions done globally in 2017 were of bitcoin, which is significantly high. Therefore, there lies a need to explore the environmental impact of these transactions. The study predicted that like any other popular technology adaption by the masses, if bitcoin is adopted in a similar manner, then there would-be global warming of more than 2 degrees Celsius in the coming decades. Further, the study suggests that if bitcoin validation widens then its carbon footprint will increase many folds along with electricity consumption thereby deteriorating environmental quality greatly.

Focusing on the Bitcoin mining-generated carbon footprint, Köhler and Pizzol (2019), Shi et al. (2021), and Stoll et al. (2019)advocated similar findings. The study has employed the Life Cycle Assessment methodology in an attempt to explore the past, present, and future climatic effects of the bitcoin mining industry. The authors demonstrated that the geographical distribution of miners and their equipment had an impact on the ecosystem. Further, it is reported that in the year 2018, bitcoin generation consume 31.29 TWH of electricity and correspondingly generate 17.29 metric tons of CO_2 globally.

Another study in this realm has propagated exactly a similar environmental impact. Jiang and Liang (2017)investigated how China's bitcoin block chain process generates carbon emissions. For analysis, they used simulation-based modeling. The authors discovered that the country’s bitcoin usage emits around 130.05 million metric tons of CO_2 into the environment. Therefore, to control such a huge carbon footprint modification in the structure of energy consumption is needed. Using VAR and shortfall estimates for environmental risk, Yang and Hamori (2021)also analyzed the Bitcoin price impact on carbon emissions. The study found that the higher the percentile the greater the risk for climate degradation.

Another study on bitcoin by de Vries et al. (2022)incorporated its price element in the effect of the mining process on the environment. The study used the simple economic model and concluded that if the record-breaking price of bitcoin in early 2021 remains intact then its global data centers would use similar energy consumption and resultantly would generate the same carbon footprint as generated in London. Further, the rising popularity of bitcoin increases its demand due to which demand for electric chips globally increases thereby affecting the production of other electric appliances. Other than electric appliances demand, energy usage also increase sowing to wide bitcoin use. Badea and Mungiu-Pupăzan

(2021)pointed out that miners are primarily concerned about the profit obtained from crypto currencies trading rather than the efficient use of energy. This objective of miners enables a large number of other traders to enter the industry thereby exhausting energy at an alarming rate.

There are several studies conducted so far that report figures regarding the efficiency of mining, energy consumption, or health hazards caused by the mining process of crypto currencies. For instance, it has been reported that in 2010-13 when crypto currencies was relatively new, the average efficiency of mining across various mining networks was 0.40 Wat per GH/s (Hayes, 2017). Another paper written by Mohsin et al. (2020)on the energy use in the mining of crypto currencies reported that the consumption of crypto currencies particularly bitcoin in 2020 was around 63 TWh per year. Regarding health effects, Goodkind et al. (2020), reported that against each $1 bitcoin valued at $0.49 health and environmental damage is caused in the USA. Similarly, this figure is $0.37 for China. Therefore, it is substantially evident that the creation of crypto currencies is environmentally damaging.

Most recently, Erdogan et al. (2022)investigated the nexus using Toda-Yamamoto test. The study findings are in the favor of negative impact of crypto currencies on the environment. It advocated that as the demand for bitcoin increases, it increasingly deteriorates environmental quality by rising CO_2.Similarly, Badea and Mungiu-Pupăzan (2021)reported related findings. The authors incorporated the involvement of energy consumption in the analysis of bitcoin's effect on the environment and provide evidence of the established negative impact. The authors argued that though environmental consequences are there, the economic role of bitcoin cannot be ignored given its acceptance owing to the credibility gains of the currency.

Regarding the policy perspective, a handful number of other studies are also conducted in this strand of research. For example, a study by Panah et al. (2022)suggested that there is a need to induce integrated regulatory environmental policy within markets on a global scale. The study advocated investing in green hydrogen production and linking it with crypto currencies mining. The authors are of the view that crypto currencies miners can be taxed by requiring them to provide support for electrolyzes. Doing so would help control the emissions as well as the price of the crypto coin. The study further suggests that the mining of crypto currencies can be used to generate green hydrogen.

Employing Life Cycle Assessment (LCA) method, Roeck and Drennen (2022)conducted most recently gave practical suggestions to the policymakers. Apart from the emissions, the authors have also explored the formation of smog and acidification as a result of bitcoin mining in New York State the USA. The authors pointed out that the mining of bitcoin not only disturbs local environmental measures, but it also led to failing sustainable goals and national programs to combat environmental deterioration.

The most closely related to our analysis are Schinckus (2020) and Sarkodie et al. (2022). The study investigated the impact of crypto currencies trading volume on both short-run and long-run effects of energy consumption on the environment. The findings reveal that there is a positive effect of crypto trading on the environment irrespective of the short or long run.

This paper fills a gap in the literature by investigating the impacts of crypto currencies volume, pricing, bitcoin energy usage, biofuel use, renewable energy use, and coal use altogether in the United States of America on CO_2 emissions. Second, the NARDL bound testing approach, as well as CUSUM plots, are used in this study to find long- and short-term connections between variables. In the presence of non-linearities in the model, this approach provides the appropriate outcome. Thirdly, this study exploited the maximum available data for the analysis. Fourthly, a wide range of related control variables' effects on carbon emissions in the short run and long run are also studied in this paper. The selected investigation is a need of the hour due to the wide acceptance and usage of crypto currencies all over the world. Finally, the findings of this study will assist policymakers and environmentalists in defining specific regulations for the operation of block chain and crypto currencies by providing comparative findings on crypto energy algorithms and other energy-efficient alternatives to ensure that effective energy and environmental conservation in block chain technologies can be achieved throughout their lifecycle.

3. Data and Methodology

This study has attempted to find out the impact of blockchain technology and green investment on the global environment in terms of estimating the impact of crypto currencies volume, crypto energy use, and biofuels(as clean energy) on global warming (CO_2 emissions) by modeling with advanced techniques to analyze and understand the real scenario of blockchain versus green investment impact on the environment.

3.1. Data and Source

This study has used time series data for analyzing proposed relationships among variables for the USA in monthly frequency, its time duration will be from 2011 to 2020 based on the data availability. The data for most of the variables are collected from the website investing.com except the bitcoin energy use, which is collected from Cambridge Bitcoin. The description of the variables and data sources is given in Table 1.

Table 1. Time Series Variables and Their Descriptions

Variables	Abbreviation	Frequency	Data Source	Unit
CO2 emission	CO2_emi	Monthly	investing.com	Million Metric
Bitcoin volume in USD	BITCOIN_V	Monthly	investing.com	USD
Bitcoin market price	BITCOIN_MP	Monthly	investing.com	USD
Bitcoin energy use	BITCOIN_MP	Monthly	Cambridge Bitcoin	TWh
Biofuel production	BIOFUEL_P	Monthly	investing.com	Trillion Btu
Biofuel consumption	BIOFUEL_C	Monthly	investing.com	Trillion Btu
Renewable energy	RENEWABLE_EC	Monthly	investing.com	Trillion Btu
Coal Consumption	Coal_C	Monthly	investing.com	Thousand Short
Waste energy consumption	WEC	Monthly	investing.com	Trillion Btu

Source: Authors' Own Compilation

3.2. Basic Econometric Model

The study investigates the connection between bitcoin and green investment in order to determine how crypto currencies affects the global environment. Crypto currencies are regarded as a desirable and innovative approach to facilitating transactions. It has acquired widespread appeal over time, with a significant application in crypto currencies observed mostly in developed nations. With this, the environmental effects of crypto currencies are visible over time, as the mining process requires a large amount of energy, causing environmental damage. Based on this context and the preceding research, notably the study by Panah et al. (2022), the econometric model of the study is as follows:

$$CO2\_emi_t = \beta_0 + \beta_1 BCV_t + \beta_2 BCEU_t + \beta_3 BCMP_t + \beta_4 BioC_t + \beta_5 REC_t + \beta_6 CoalC_t + \varepsilon_t \dots\dots\dots eq\ (1)$$

Where CO2_emi is the CO2 emission, BCV is the bitcoin volume, BCEU is the bitcoin energy use, BCMP is the bitcoin market price, BioC is the biofuel consumption, REC renewable energy consumption, and CoalC is the coal consumption. β_0 is the intercept term measuring the impact of all other variables which are not included in the model in other words it shows the level of carbon emissions in the USA economy when BCV, BCEU, BCMP, BioC, REC, and CoalC are zero. The remaining coefficients are showing the impact of the associated variable on the carbon emission of the country. ε_t Is the error term while t in the subscript is showing the time period from 2011 to 2020.

3.3.Methods

Stationary checking is an important step in the time series data. Because a culmination of unit root, model misspecification, biased coefficients, and bogus estimation assumptions leads to unreliable results (Afandi, 2005; Campbell & Perron, 1991). The augmented Dickey-Fuller (ADF) test is utilized in this study to examine the stationary nature of variables used in the model. ADF is a common order of integration test that has three features: no intercept and trend, intercept and constant, and trend. The appropriate method is to use ARDL based on the varied order of integration of the variables. However, the study employs NARDL, an advanced econometric approach that takes into account the non-linearity of the data to investigate the asymmetric relationship between the variables of interest. Prior to this, the study used the Jarque-Bera test to assess the linearity of the data. If it is not near zero, it implies that the sample data does not have a normal distribution and is always positive. Then, the non-linearity test of rolling correlation plots, percentage change plots, and the BDS test are used to explore the non-linearity of the variables.

After confirming the non-linear relationship the NARDL bound test is applied for detecting the long relationship among the variables under consideration. This technique is better than traditional as it provides reliable findings and best fits in the presence of nonlinearity. The test is suggested by (Pesaran et al., 1999). The test hypothesis is, H_o: The coefficients of the long-run equations are all insignificant. If the F-statistics of the bound test is greater than the upper bound, the existence of long-term associations will be proven. After the long-run associations have been established, in the next step the asymmetric ARDL model together containing the long-run and constrained ECM is employed.

The NARDL model is one of the most common and well-established methods for analyzing the non-linear interactions among different time series variables. Because NARDL is the most straightforward technique for simulating both short-run and long-run non-linearities, it has a variety of advantages. If a time series vector is stationary, non-stationary, or both, it can be utilized to determine this. Bound testing is the method applied in this case to estimate the incidence of cointegrating relationships. Majeed et al. (2020) used the NARDL technique in their experiments to investigate the positive shocks and negative shock components independently. Equation 1 is written in the NARDL framework in the following manner:

$$\begin{aligned}\mathrm{Carbonemission}_t &= \gamma_o + \gamma_1\mathrm{Carbonemission}_t + \gamma_2^{+}\mathrm{bitcoinvolume}_t^{+} + \gamma_3^{-}\mathrm{bitcoinvolume}_t^{-} \\ &+ \gamma_4^{+}\mathrm{bitcoinenergyuse}_t^{+} + \gamma_5^{-}\mathrm{bitcoinenergyuse}_t^{-} + \gamma_6\mathrm{bitcoinmarketprice}_t \\ &+ \gamma_7\mathrm{biofuelproduction}_t + \gamma_8\mathrm{biofuelconsumption}_t \\ &+ \gamma_9\mathrm{renewableenergyconsumption}_t + \gamma_{10}\mathrm{CoalConsumption}_t \\ &+ \gamma_{11}\mathrm{wast\ energy\ consumption}_t + \varepsilon_t \ldots\ldots\ldots \mathrm{eq}\ (2)\end{aligned}$$

For bitcoin volume and bitcoin energy use two distinct components, comprising positive and negative shocks, are introduced. 's stand for parameters. The long-run parameter vectors are shown here as BCV_t = BCV_o +BCV_t^{+} + BCV_t^{-}. BCV_t^{+} and BCV_t^{-} display the partial total of positive and negative shocks to the bitcoin volume.

$$\begin{aligned}bitcoin\_V_t^{+} &= \sum_{i=1}^{n} \Delta\, bitcoin\_V_i^{+} = \sum_{i=1}^{n} maximum(\Delta bitcoin\_V_i, 0)\,, bitcoin\_V_t^{-} \\ &= \sum_{i=1}^{n} \Delta\, bitcoin\_V_i^{-} = \sum_{i=1}^{n} minimum(\Delta bitcoin\_V_i, 0) \ldots\ldots eq\ (3)\end{aligned}$$

This study adopted NARDL following Shin:

$$\Delta carbonemi_t = \gamma_o + \gamma_1 carbonemi_{t-1} + \gamma_2^{+} bitcoin\_V_{t-1}^{+} + \gamma_3^{-} bitcoin\_V_{t-1}^{-} + \gamma_4^{+} \mathrm{bitcoin\_EU} + \gamma_5^{-} bitcoin\_EU_{t-1}^{-} + \gamma_6 bitcoin\_MP_{\mathrm{t-1}} + \gamma_7 biofuel\_P_{\mathrm{t-1}} + \gamma_8 biofuel\_C_{t-1} + \gamma_9 renewabl\_EC_{t-1} + \gamma_{10} Coal\_C_{t-1} + \gamma_{11} waste\_EC_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta carbonemi_{t-i} + \sum_{i=0}^{p} (\gamma_i^{+} \Delta bitcoin\_V_{t-i}^{+} + \gamma_i^{-} \Delta bitcoin\_V_{t-i}^{-}) + \sum_{\mathrm{i=0}}^{\mathrm{p}} (\gamma_{\mathrm{i}}^{+} \Delta \mathrm{bitcoin\_EU}_{\mathrm{t-i}}^{+} + \gamma_{\mathrm{i}}^{-} \Delta \mathrm{bitcoin\_EU}_{\mathrm{t-i}}^{-}) + \sum_{\mathrm{i=0}}^{\mathrm{p}} \gamma_{\mathrm{i}} \Delta bitcoin\_MP + \sum_{\mathrm{i=0}}^{\mathrm{p}} \gamma_{\mathrm{i}} \Delta \mathrm{biofuel\_P}_{\mathrm{t-i}} + \sum_{\mathrm{i=0}}^{\mathrm{p}} \gamma_{\mathrm{i}} \Delta \mathrm{biofuel\_C}_{\mathrm{t-i}} + \sum_{\mathrm{i=0}}^{\mathrm{p}} \gamma \Delta \mathrm{renewable\_EC}_{\mathrm{t-i}} + \sum_{\mathrm{i=0}}^{\mathrm{p}} \gamma_{\mathrm{i}} \Delta \mathrm{Coal\_C}_{\mathrm{t-i}} + \sum_{\mathrm{i=0}}^{\mathrm{p}} \gamma_{\mathrm{i}} \Delta \mathrm{waste\_EC}_{\mathrm{t-i}} + \varepsilon_{\mathrm{t}} \ldots \ldots \mathrm{eq}\ (4)$$

Where p is lag orders, $\gamma_o =$ is the intercept. $\sum_{i=0}^{p} \gamma_i^{+} \Delta \mathrm{bitcoin\_V}_{t-i}^{+} =$ short-run impact of a rise in bitcoin volume on carbon, $\sum_{i=0}^{p} \gamma_i^{+} \mathrm{bitcoin\_V}_{t-i}^{-} =$ short-run effect of the fall in bitcoin volume on the emission of USA.

This study employed three tests for determining whether certain variables are nonlinear: percentage change plots over time, rolling correlation plots, and the BDS test. However, the normality will first be established by determining the descriptive statistics. After that, stationarity will be ensured using the ADF test. Making ensuring there are no I (2) series is crucial. Thirdly, since each of our variables is a mixture of I(1) and I, we observe a cointegrating relationship between them (0). The fourth step employs the NARDL methodology. The null hypothesis will be investigated using the Wald test.

Null Hypothesis: $\gamma_1 = \gamma_2^{+} = \gamma_3^{-} = \gamma_4^{+} = \gamma_5^{-} = \gamma_6 = \gamma_7 = \gamma_8 = \gamma_9 = \gamma_{10} = \gamma_{11} = 0$

Alternative Hypothesis: $\gamma_1 \neq \gamma_2^{+} \neq \gamma_3^{-} \neq \gamma_4^{+} \neq \gamma_5^{-} \neq \gamma_6 \neq \gamma_7 \neq \gamma_8 \neq \gamma_9 \neq \gamma_{10} \neq \gamma_{11} \neq 0$

Finally, it will be assessed whether there are short- and long-term nonlinear impacts of bitcoin V and bitcoin EU on carbon emissions. The unequal cumulative multiplier at 1 % disparity in $\mathrm{bitcoin_V}_{t-i}^{+}$and $\mathrm{bitcoin\_V}_{t-i}^{-}$ is written as:

$$\theta_x^+ = \sum_{i=0}^{x} \frac{\omega carbonemi_{t+i}}{\omega carbonemi_{t-1}^+}, \theta_x^- = \sum_{i=0}^{x} \frac{\omega carbonemi_{t+i}}{\omega carbonemi_{t-1}^-}, x = 1,2,3 \ldots \ldots eq\ (5)$$

Where x $\rightarrow\infty$,$\theta_x^+\rightarrow\gamma_1^+$,&$\theta_x^-\rightarrow\gamma_2^-$, the same steps will be followed for the other variables.

After this, analytical tests such as CUSUM plots, serial correlation tests, Heterosckedasticity tests, and dynamic multiplier plots to analyze the estimated NARDL model. For monitoring change detection, the CUSUM is frequently utilized. Later after a few years, Wald's SPRT approach was made public, and CUSUM was published in Biometrical in 1954. The NARDL model's stability is established by employing the CUSUM and CUSUM squared tests.

4. Results and Discussion

Simulating the impact of bitcoin volume, bitcoin energy use, bitcoin price, total biofuel production, biofuel consumption, renewable energy consumption, coal consumption, and waste energy consumption on the USA's carbon emissions, this study seeks to analyze the effects of block chain technology and crypto currencies mining on the environment of the country. Several advanced econometric techniques have been employed for analyzing and comprehending the real-world effects of bitcoin, blockchain technology use, and green investment.

a. ADF Test Results

Identifying whether the unit root process is present or not is the very first step in estimations. In this stage, the integration order of the variables must be decided. After the data series has been transformed into a log form, the ADF test is utilized. The findings demonstrate that the study's data series is a combination of I (1) and I (0). Table 2 displays the test results.

Table 2. ADF Critical Values

Scenarios	Critical values	Level of significance
With constant and trend(C,T)	-3.445	5%
With Intercept (C)	-2.883	5%
None	-1.943	5%

Source: Authors' Own Computation

Table 3 is explaining the ADF test results.

Table 3. Augmented Dicky Fuller (ADF) test

Variables	C,T	Lag	t-stat	P	Variables	Lags	t-stat	P	C, T
CO2_emi	C, T	4	-3.411	0.054	ΔCO2_emi	3	-13.635	0	None
BITCOIN_V	C, T	0	-6.128	0					
BITCOIN_MP	None	2	0.529	0.829	ΔBITCOIN_MP	1	-9.334	0	None
BITCOIN_MP	C,T	0	-1.998	0.596	ΔBITCOIN_MP	0	-9.895	0	None
BIOFUEL_P	C, T	0	-5.723	0					
BIOFUEL_C	C, T	4	-2.082	0.55	ΔBIOFUEL_C	3	-11.079	0	None
RENEWABLE_EC	C, T	5	-6.736	0					
Coal_C	C, T	1	-9.09	0					
WEC	C, T	3	-2.569	0.295	ΔWEC	3	-9.464	0	None

Source: Authors' Own Computation

According to the results, BITCOIN_V, BIOFUEL_P, RENEWABLE_EC, and Coal_C are I(0) at the 0.05 level of significance, while the other variables are I (1). In this scenario, the Schwarz Information Criteria offers suggestions for choosing the delays. The study then focused on estimating the initial model to derive the key conclusions. The ARDL model is the best fit but additional tests, including the Jarque-Bera test and descriptive statistics, are required before using the ARDL model to ensure that our data is normally distributed. The BDS test, percentage change plots, and rolling correlation graphs are then used to determine linearity.

b. Explanatory Summary

The test statistics for the Jarque Bera, skewness, and Kurtosis tests, as well as the summary statistics, are explained in Table 4.According to the results on average the emission in the USA economy is about 431.3 and reached a maximum of about 532.8 and a minimum of about 426.8. Similarly, the statistics for all other variables are given. The skewness, kurtosis, and JB test are explaining that the time series is normally distributed.

Table 4. Descriptive Statistics

	CO2_emi	BCV	BCP	BMP	BFC	BFP	Coal_C	REC	WEC
Mean	431.3407	8933909.	7753.419	2.429	185.19	185.86	62487.25	875.146	39.767
Median	426.8735	2130000.	720.6000	0.520	184.76	187.84	63038.84	869.941	39.979
Maximum	532.8910	1.54E+08	61309.60	10.56	208.33	223.97	99618.15	1106.24	46.745
Minimum	304.9500	85750.00	0.500000	0.000	161.30	120.62	26754.13	650.345	33.389
Std. Dev.	37.45292	19582366	14213.47	3.064	10.531	19.211	16140.02	104.776	3.0318
Skewness	-1.22E-01	4.407167	2.368600	1.1409	0.0942	-5.18 E-01	0.008161	0.13239	-5.16E-02
Kurtosis	3.895504	27.26706	7.660111	3.1322	2.5102	2.9979	2.247127	2.25368	2.1434
Jarque-Bera	4.810879	3721.752	246.5471	29.17	1.5375	5.9883	3.166217	3.50132	4.1553

Probability	0.090226	0.000000	0.000000	0.000	0.4635	0.0500	0.205336	0.17365	0.1252
Sum	57799.66	1.20E+09	1038958.	325.53	24815.72	24905.62	8373292.	117269.6	5328.847
Sum Sq. Dev.	186562.0	5.10E+16	2.69E+10	1248.73	14752.27	49085.45	3.46E+10	1460082.	1222.582
Observations	134	134	134	134	134	134	134	134	134

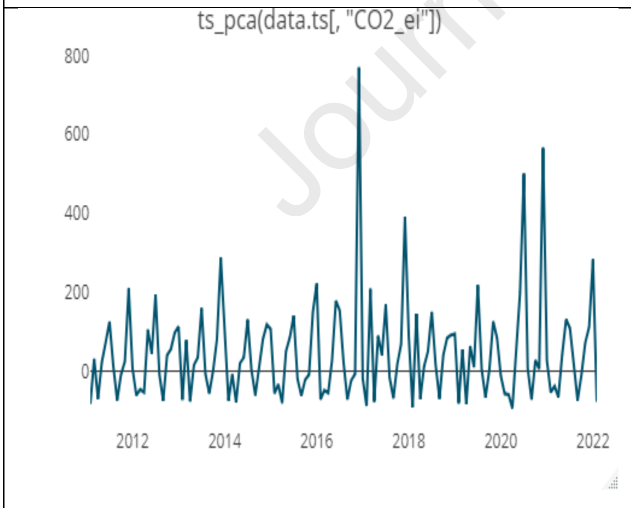
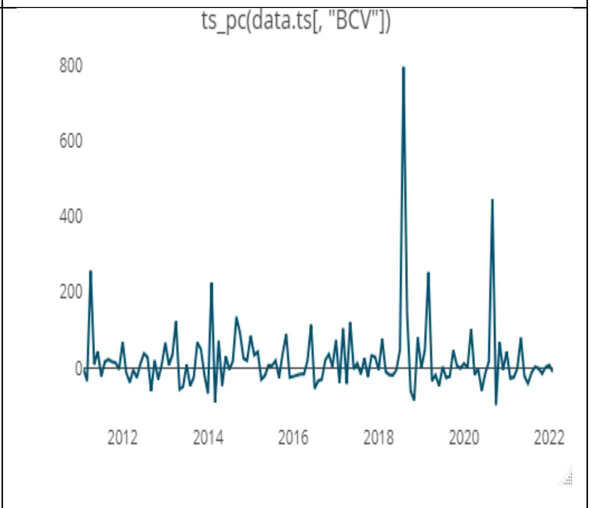
Source: Authors' Own Computation

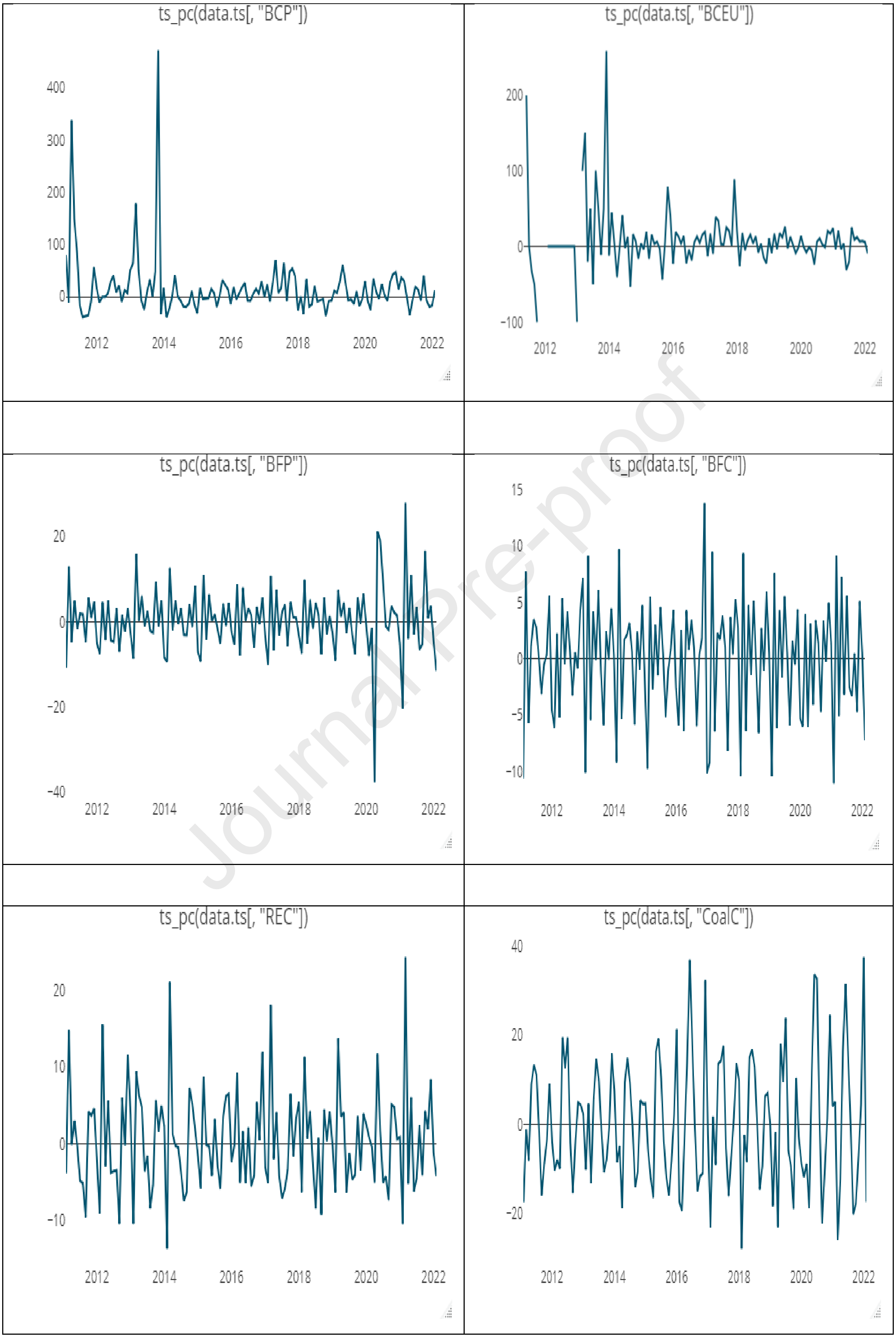
c. Linearity Test

Linearity test includes percentage change plots, rolling correlation plots, and BDS test stats. Which are the following:

i. Percentage Change Plots

Figure 1 is showing the nonlinear behavior of the time series, for further confirmation, we will move to a rolling correlation plot. Because the rate of percentage change between dependent and independent variables in the boom and recession phases is not similar, it is evident from these graphs that there are non-linear interactions.

Fossil fuels consumption	**Geo biomass consumption**
	
Renewable energy consumption	GDP per capita growth

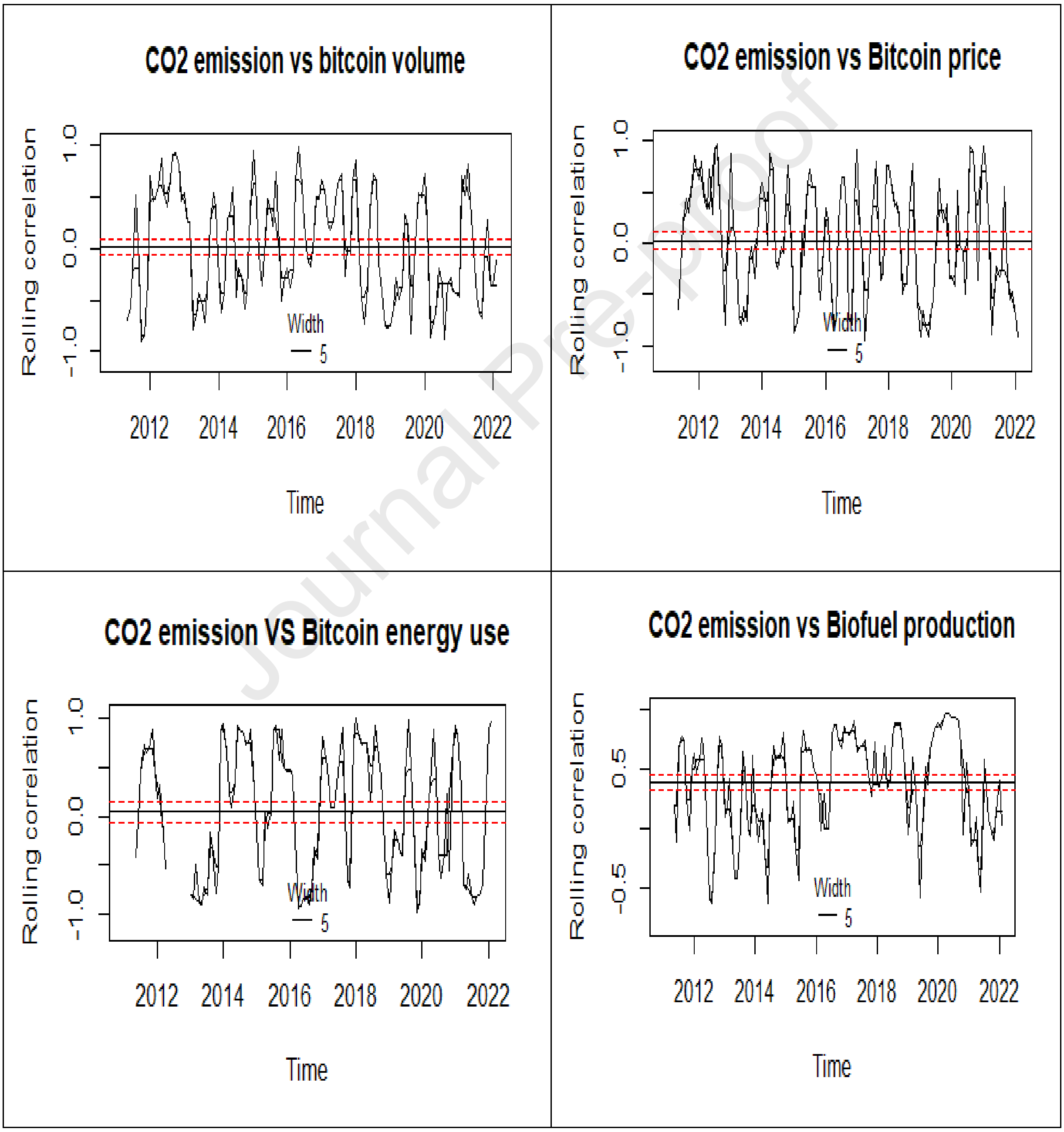


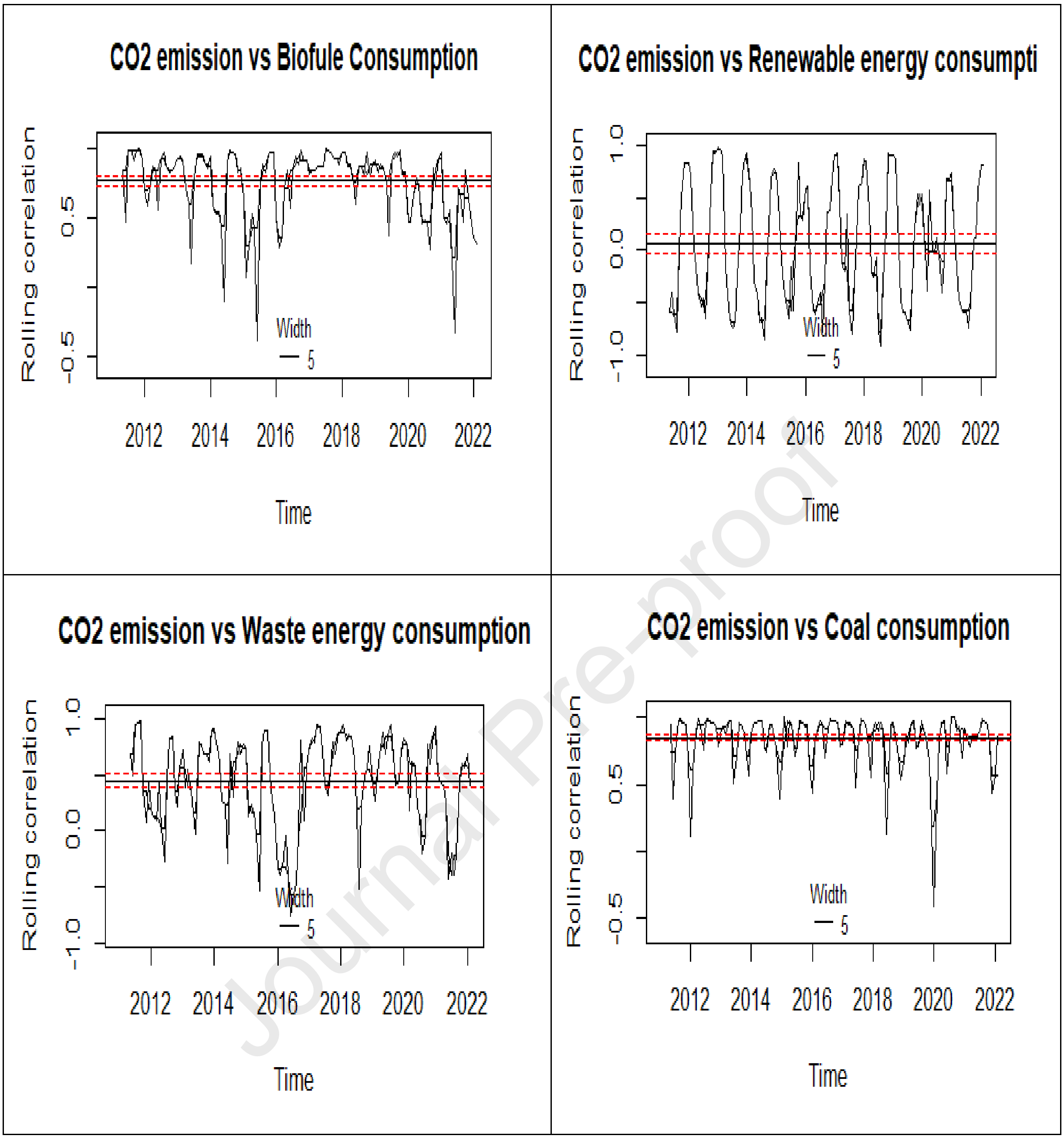
391 ***Figure 1 is showing the percentage change plots for all the time series in our study.***

(Source: Authors' Own Computation)

ii. Rolling correlation plots

The figures below demonstrate how a relationship's character develops over time. It indicates that some nonlinearity is present as up and down fluctuations are observed. Hence, it can be said the variable under consideration has the characteristics of non-linearity and therefore required a NARDL framework for further estimation.





398 ***Figure 2. Rolling Correlation Plots(Source: Authors' Own Computation)***

iii. BDS Examination

The BDS test was developed to determine whether the nonlinear dependency is likely to exist or not. The null hypothesis states that the distribution of the data in a time series is random, equal, independent, and uniform (iid).According to the test statistics (in Table 5), the linearity null hypothesis cannot be accepted in this case for all degrees of embedding dimension. The findings demonstrate that all of the data series exhibit nonlinear dependence.

Table 5. Results of the BDS Test

BDS Test for CO2_EI

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.019399	0.002443	7.941955	0.0000
3	0.022260	0.001630	13.65863	0.0000
4	0.018136	0.000816	22.22888	0.0000
5	0.011599	0.000358	32.42175	0.0000
6	0.008161	0.000145	56.19952	0.0000

BDS Test for BITCOIN_V

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.183825	0.014073	13.06258	0.0000
3	0.315427	0.021915	14.39349	0.0000
4	0.400683	0.025609	15.64606	0.0000
5	0.454708	0.026215	17.34541	0.0000
6	0.486269	0.024844	19.57284	0.0000

BDS Test for BCP

Dimension	BDS	Std. Error	z-Statistic	Prob.
2	0.186211	0.011738	15.86398	0.0000
3	0.299505	0.015616	19.17917	0.0000
4	0.361092	0.015598	23.15038	0.0000
5	0.391360	0.013650	28.67015	0.0000
6	0.403510	0.011062	36.47584	0.0000

BDS Test for BITCOIN_MP

Dimension	BDS	Std. Error	z-Statistic	Prob.
2	0.223598	0.008787	25.44584	0.0000
3	0.314508	0.008788	35.78723	0.0000
4	0.350019	0.006607	52.97761	0.0000
5	0.361658	0.004355	83.03578	0.0000
6	0.363130	0.002661	136.4882	0.0000

BDS Test for BIOFUEL_C

Dimension	BDS	Std. Error	z-Statistic	Prob.
2	0.011599	0.001551	7.479861	0.0000
3	0.013511	0.000946	14.28509	0.0000
4	0.010316	0.000433	23.85026	0.0000
5	0.008228	0.000173	47.50937	0.0000
6	0.005663	6.42E-05	88.22898	0.0000

BDS Test for BIOFUEL_P

Dimension	BDS	Std. Error	z-Statistic	Prob.
2	0.044898	0.001360	33.00594	0.0000
3	0.045088	0.000853	52.83557	0.0000
4	0.030409	0.000401	75.78539	0.0000
5	0.017909	0.000165	108.4306	0.0000
6	0.010910	6.29E-05	173.4117	0.0000

BDS Test for COAL_C

Dimension	BDS	Std. Error	z-Statistic	Prob.
2	0.056919	0.001143	49.78301	0.0000
3	0.043553	0.000694	62.75534	0.0000
4	0.024763	0.000316	78.43972	0.0000
5	0.015608	0.000126	124.1629	0.0000
6	0.010291	4.63E-05	222.2047	0.0000

BDS Test for RENEWABLE_EC

Dimension	BDS	Std. Error	z-Statistic	Prob.
2	0.059283	0.001201	49.38120	0.0000
3	0.045053	0.000716	62.89920	0.0000
4	0.027742	0.000320	86.61315	0.0000
5	0.014608	0.000125	116.5127	0.0000
6	0.008709	4.54E-05	191.7712	0.0000

BDS Test for WEC

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.028185	0.001027	27.44350	0.0000
3	0.023235	0.000627	37.06362	0.0000

4	0.014616	0.000287	50.97777	0.0000
5	0.008385	0.000115	73.05322	0.0000
6	0.004460	4.25E-05	104.9000	0.0000

Source: Authors' Own Computation

d. NARDL Approach

Based on all the tests and analysis, it is determined that the non-linear ARDL model is the best model for this time series analysis in both the long run and the short run. Here, in order to ascertain whether cointegrating linkages were present, we will estimate our results utilizing NARDL and NARDL bound tests.

Initially lag length is selected using the AIC method and then NARDL bound test is applied to explore the long-run relationship among the variables. The results are shown in Table 6. According to the study's findings, F statistics is more significant than the upper bound value at a 5% level of significance. Therefore, the null hypothesis is rejected. As can be observed in the table below, cointegration among the variables means that cointegration NARDL modeling is required.

Table 6. NARDL Bound Test

Bounds F-test (wald) for no cointegration			
Test, (K)	**Estimate**	**Lower bound I(0)**	**Upper bound I(1)**
F-stat, (10)	6.191	1.98	3.04
Alternative hypothesis: Possible cointegration			

Source: Authors' Own Computation

The results of NARDL long-run and short-run estimates are provided in table 7. In the long run, CO_2 emissions increased for the USA due to an increase in crypto currencies (bitcoin) volume, both positive and negative, crypto currencies (bitcoin) prices. This is because extensive use of bitcoin consumes a lot of energy and therefore increase emission into the atmosphere. This implies that bitcoin is not promoting green growth in the USA. This finding is in line with Mora et al. (2018) and Panah et al. (2022). Further, the impact of coal consumption is positive as coal is among the major fossil fuels that are harmful to the global environment. Here the results show that a 1% increase in coal leads to a 0.114 % increase in carbon emissions. These findings are in line with Pata (2018). Renewable is an environmentally friendly energy source and it greatly helps to reduce pollutants. According to the present findings with a 1 % increase in renewable energy consumption, carbon emission reduces by 0.362%. Wind energy is also clean and its 1 % increase is associated with a 0.077 % reduction in carbon emissions. These findings are supported by Bilgili et al. (2016) and Charfeddine and Kahia (2019).

The results for the short run are also shown in Table 7. The findings are diverse. In the findings, the large carbon emission carries a positive sign showing that a 1 % increase in carbon emissions is a previous increase in the CO_2 emission presently by 0.44 %. Likewise, the third lag of bitcoin is positive and significant implying that a stable increase in prices of bitcoin increases the use of bitcoin and energy use thereby increasing the carbon emissions. Similar results are seen for bitcoin volume. The impact of biofuel and its lags are positively significant along with renewable energy effects and wind energy effects. This is because of the overtime increases in the significance of these resources in economic activities. The estimated ECT is also negative, demonstrating that a shock to the USA's CO_2 emissions that occurs in one period as a result of crypto currencies and other independent variables of our model can be recovered by changes to the independent variables of our analysis by 46.3 percent in the following period.

Table 7. Long Run and ECM Part of the NARDL

ARDL Long Run Form and Bounds Test
Dependent Variable: D(LCO2_EI)
Selected Model: ARDL(2, 4, 1, 0, 3, 0, 0, 4, 3, 4, 4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Conditional Error Correction Regression				
C	1.946154***	0.648596	3.000566	0.0035
LCO2_EI(-1)*	-0.463902***	0.071946	-6.447877	0.0000
BITCOIN_MP_POS(-1)	-9.40E-05	0.003415	-0.027514	0.9781
BITCOIN_MP_NEG(-1)	-0.004929	0.004750	-1.037480	0.3022
LBITCOIN_V_POS**	0.004995**	0.002459	2.031534	0.0451
LBITCOIN_V_NEG(-1)	0.006072**	0.002771	2.190934	0.0310
LBCP**	0.006303*	0.003217	1.959378	0.0531
LBIOFUEL_C**	-0.126056*	0.070114	1.797870	0.0754
LBIOFUEL_P(-1)	-0.312353***	0.053954	5.789207	0.0000
LCOAL_C(-1)	0.114639***	0.036937	3.103653	0.0025
LRENEWABLE_EC(-1)	-0.362215***	0.077572	-4.669422	0.0000
LWEC(-1)	-0.077359	0.082962	-0.932457	0.3535
ARDL Error Correction Regression				
D(LCO2_EI(-1))	0.449344***	0.065896	6.818986	0.0000
D(BITCOIN_MP_POS)	-0.011019	0.006893	-1.598474	0.1133
D(BITCOIN_MP_POS(-1))	-0.008005	0.006439	-1.243317	0.2169
D(BITCOIN_MP_POS(-2))	-0.002935	0.006554	-0.447852	0.6553
D(BITCOIN_MP_POS(-3))	0.022878***	0.006531	3.503070	0.0007
D(BITCOIN_MP_NEG)	0.011029*	0.005880	1.875611	0.0638
D(LBITCOIN_V_NEG)	0.007187*	0.003898	1.843984	0.0684
D(LBITCOIN_V_NEG(-1))	0.004733	0.003982	1.188494	0.2377
D(LBITCOIN_V_NEG(-2))	-0.008925**	0.004021	-2.219513	0.0289
D(LBIOFUEL_P)	0.228460***	0.034919	6.542617	0.0000
D(LBIOFUEL_P(-1))	-0.219945***	0.044395	-4.954325	0.0000

D(LBIOFUEL_P(-2))	-0.119294***	0.041447	-2.878254	0.0050
D(LBIOFUEL_P(-3))	-0.103828***	0.038602	-2.689681	0.0085
D(LCOAL_C)	0.395196***	0.019208	20.57414	0.0000
D(LCOAL_C(-1))	-0.163372***	0.033544	-4.870396	0.0000
D(LCOAL_C(-2))	0.095303***	0.018086	5.269501	0.0000
D(LRENEWABLE_EC)	0.077881	0.048400	1.609120	0.1110
D(LRENEWABLE_EC(-1))	0.316690***	0.061553	5.145033	0.0000
D(LRENEWABLE_EC(-2))	0.193487***	0.061535	3.144366	0.0022
D(LRENEWABLE_EC(-3))	0.204884***	0.061544	3.329087	0.0012
D(LWEC)	0.254858***	0.057150	4.459498	0.0000
D(LWEC(-1))	0.041164	0.065877	0.624856	0.5336
D(LWEC(-2))	0.157047***	0.059401	2.643850	0.0096
D(LWEC(-3))	0.113740**	0.054171	2.099664	0.0385
CointEq(-1)*	-0.463902	0.050894	-9.115024	0.0000

Source: Authors' Own Computation

e. Analytical Test

CO_2 is mostly produced by burning fossil fuels. Contrary to fossil fuels, using geo biomass, and renewable energy as a fuel is additionally benign to the environment. After providing an explanation for both the short and long-term outcomes, we looked at serial correlation, the Heterosckedasticity test, cumulative sum, and CUSUM graphs to look at the stability of error terms. The findings are as follows:

i. Serial correlation and Heterosckedasticity Test

The results of the Breusch-Godfrey serial correlation LM test and Heterosckedasticity test Breusch-Pagan-Godfrey are presented in table 8. The test's F-statistics values are insignificant verifying that autocorrelation and Heterosckedasticity problems exist in the data.

Table 8. Diagnostic Test

Breusch-Godfrey Serial Correlation LM Test:			
F-statistic	1.948222	Prob. F(4,89)	0.1094
Obs*R-squared	10.38592	Prob. Chi-Square(4)	0.0344
Heterosckedasticity Test: Breusch-Pagan-Godfrey			
F-statistic	0.740740	Prob. F(35,93)	0.8409
Obs*R-squared	28.12205	Prob. Chi-Square(35)	0.7887
Scaled explained SS	11.41860	Prob. Chi-Square(35)	0.9999

Source: Authors' Own Computation

ii. CUSUM Plots

CUSUM plots are used to test the stability of the NARDL model in this study analysis. The results are shown in Figure 3 demonstrating the stability of the model. The confidence interval's bottom and upper limits indicated the mean and variance of the error term. Our results indicate that the estimates are constant in both long and short terms thereby accepting the null hypothesis.

The usage of renewable energy, the consumption and production of biofuels, waste energy, coal, and bitcoin volume, price, and energy use all have non-linear correlations with CO_2 emissions. Further, the non-linear correlation is proved between the variables thereby providing reliable estimates. The ECM demonstrates how by making changes to these sectors, we may gradually recover from shocks in the USA's CO_2 emissions.

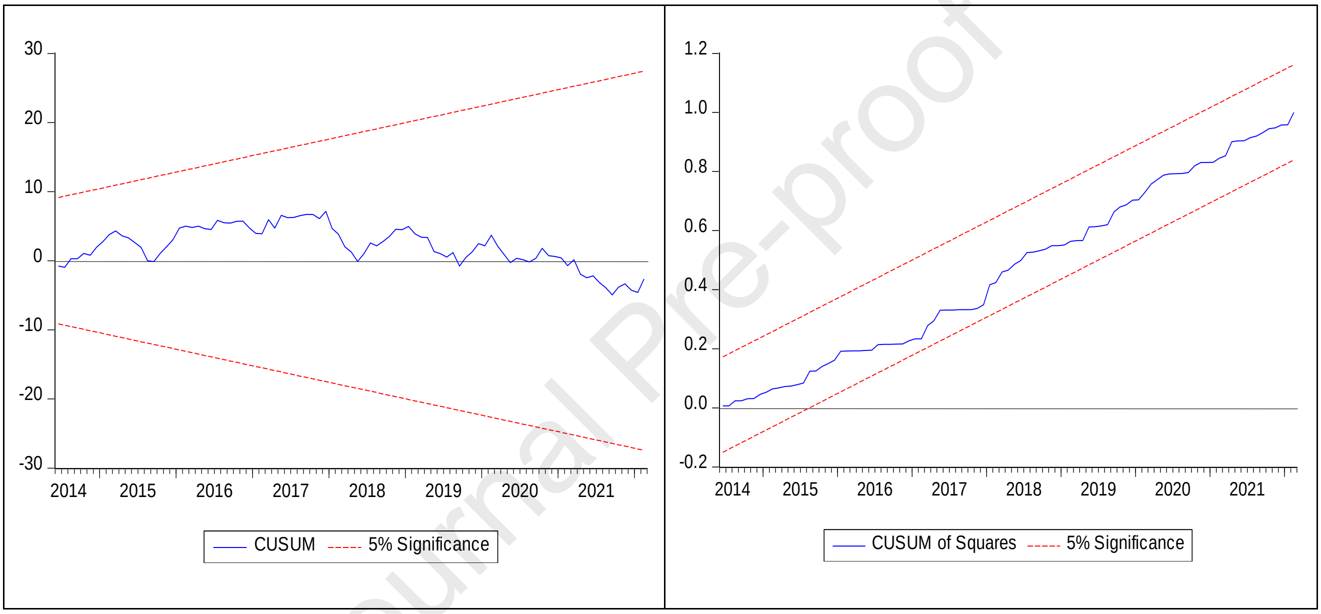


Figure 3. CUSUM Plots(Source: Authors' Own Computation)

iii. Dynamic Multiplier Plots

Dynamic multiplier graphs of NARDL check nonlinearity in the model. This graph tells the response of variable's pattern to its new long-run equilibrium owing to the unitary shocks in the regressors.The results are in Figure 4.The black nonstop line in the dynamicmultiplier charts represents the change in carbon emissions for the USA due to a positive shock to bitcoin volume and energy use. The black dotted line depicts a change in the emissions owing to a decline in bitcoin volume and energy consumption. The asymmetry plot is demonstrated by the three red dotted lines. Similarly, the 95 percent confidence interval is depicted through the sided red dotted line.

The relationship between the amount of bitcoin transactions and energy use demonstrates that positive shocks have a favorable impact on US carbon emissions, but negative shocks have the opposite effect. Short-term magnitude differences between positive and negative reactions are substantial, whereas long-term differences are quite marginal. In the short run, we can say that there is a sizable nonlinear relationship. The blatant mismatch between all plot variables is depicted by the line of asymmetry. Therefore, the short-term effects are enormously important.

To conclude, in the modern world, ecological devastation and climate change are major problems. As a result, nations all around the world are making great efforts to manage global warming and climate change. Blockchain technologies, crypto currencies mining, and green investments all play significant roles in this. This study looked into the effect of crypto currencies on the USA's CO_2 emissions and the best energy source for mining crypto currencies to minimize their carbon footprints.

With respect to methodology, the study results show that nonlinear, long-run, and short-run relationships exist between crypto currencies and CO_2 emissions. Results indicate that an increase in bitcoin volume, bitcoin energy use, and Coal consumption led to an increase in the emissions in the long run and short run, this may occur due to the heavy use of coal, and oil as fuel in crypto currencies mining. In conclusion, the block chain technology used in crypto currencies and energy used in crypto currencies mining caused to increase in CO_2 emissions in the USA and it is needed to convert from high carbon energy to low carbon energy such as biofuel consumption to save the environment of the USA as well as the global environment. To meet this goal, it is needed to do green investments such as investments in low carbon energy production for example biofuel production. As a result, the green investment will lead to saving the environment of the USA as well as theglobal environment.Overall, the results are showing a nonlinear relationship among variables and show that green investment will lead to saving the environment of the USA as well as the global environment.

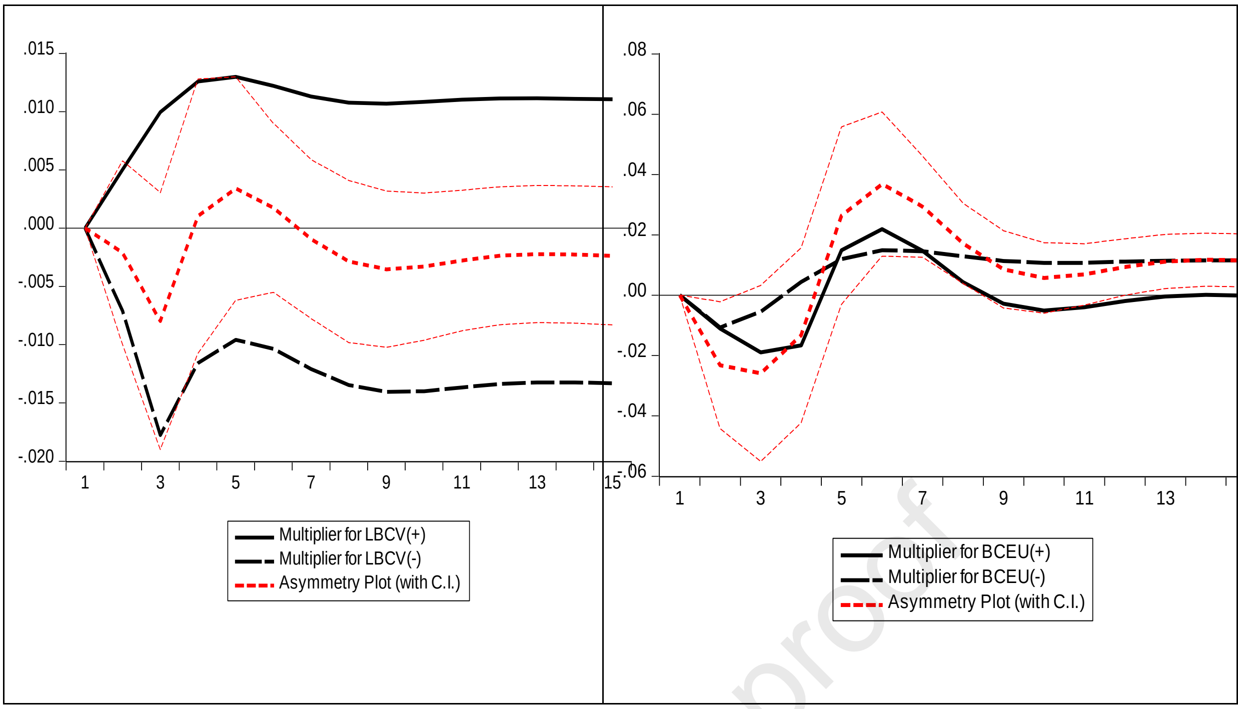


Figure 4. Dynamic Multiplier Graphs for NARDL (Source: Authors' Own Computation)

5. Conclusion and Policy Recommendations

This study investigates the association between crypto currencies, biofuel consumption, and CO_2emissions in the USA using monthly data. The study has employed non-linear ARDL and other preliminary methods over the data of the USA economy. The graphical analysis found that there exists an asymmetric relationship among the selected dependent and independent variables of the study. The results of the unit root analysis haveshown that the observed variables are mixed (integrated of order 0 and 1) integrated. Furthermore, the findings of Wavelet Coherence suggest that bitcoin, biofuel consumption, and other concerned control variables have a strong correlation with CO_2 emissions in the USA.The long run and ECM of NARDL confirm that carbon emissions in the USA economy increase as a result of both positive and negative shocks in crypto currencies volume. On contrary, a rise in biofuel consumption reduces the emissions in the atmosphere. FurtherCUSUM plotsindicate that the mean and variance of error terms are witnessed between the lower and upper limit of the confidence interval and inside lower and upper critical limits thereby indicating the stability of the estimates. Dynamic multiplier graphs of the ARDL model also confirm the strong non-linear relationship among variables in the long run.

Based on the findings, this study concludes that crypto currencies trading in the USA leads to high CO_2 emissions in the country. Therefore, our study recommends controlling crypto currencies volume or making it environment-friendly by adopting renewable energy sources forits mining process. Our study also suggests taking into account the non-linearity among carbon emissions and crypto currencies so that realistic environmental protection policies can be made and successfully implemented. Overall, the study is limited to only US and provide important implications regarding bitcoin price, volume, and carbon emissionsFuture study can capture the influence of bitcoin's impact on other environmental variables to further aid authorities in determining which areas require further regulation. In addition, a spatial analysis of USA states can be performed.

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References

Abu Bakar, N., & Rosbi, S. (2017). Autoregressive integrated moving average (ARIMA) model for forecasting cryptocurrency exchange rate in high volatility environment: A new insight of bitcoin transaction. *International Journal of Advanced Engineering Research and Science*, *4*(11), 130-137.

Afandi, A. (2005). Monetary policy transmission mechanism and structural breaks in Indonesia.

Ahmad, M., Khan, Z., Ur Rahman, Z., & Khan, S. (2018). Does financial development asymmetrically affect CO2 emissions in China? An application of the nonlinear autoregressive distributed lag (NARDL) model. *Carbon Management*, *9*(6), 631-644.

Andoni, M., Robu, V., Flynn, D., Abram, S., Geach, D., Jenkins, D., McCallum, P., & Peacock, A. (2019). Blockchain technology in the energy sector: A systematic review of challenges and opportunities. *Renewable and sustainable energy reviews*, *100*, 143-174.

Badea, L., & Mungiu-Pupăzan, M. C. (2021). The economic and environmental impact of bitcoin. *IEEE Access*, *9*, 48091-48104.

Bai, C. A., Cordeiro, J., & Sarkis, J. (2020). Blockchain technology: Business, strategy, the environment, and sustainability. *Business Strategy and the Environment*, *29*(1), 321-322.

Bendiksen, C., Gibbons, S., & Lim, E. (2019). The bitcoin mining network-trends, composition, average creation cost, electricity consumption & sources. *CoinShares Research, Whitepaper*.

Bilgili, F., Koçak, E., & Bulut, Ü. (2016). The dynamic impact of renewable energy consumption on CO2 emissions: a revisited Environmental Kuznets Curve approach. *Renewable and Sustainable Energy Reviews*, *54*, 838-845.

Campbell, J. Y., & Perron, P. (1991). Pitfalls and opportunities: what macroeconomists should know about unit roots. *NBER macroeconomics annual*, *6*, 141-201.

Centobelli, P., Cerchione, R., Esposito, E., & Oropallo, E. (2021). Surfing blockchain wave, or drowning? Shaping the future of distributed ledgers and decentralized technologies. *Technological Forecasting and Social Change*, *165*, 120463.

Charfeddine, L., & Kahia, M. (2019). Impact of renewable energy consumption and financial development on CO2 emissions and economic growth in the MENA region: a panel vector autoregressive (PVAR) analysis. *Renewable energy*, *139*, 198-213.

Davidson, S., De Filippi, P., & Potts, J. (2016). Economics of blockchain. *Available at SSRN 2744751*.

de Vries, A., Gallersdörfer, U., Klaaßen, L., & Stoll, C. (2022). Revisiting Bitcoin’s carbon footprint. *Joule*, *6*(3), 498-502.

Erdogan, S., Ahmed, M. Y., & Sarkodie, S. A. (2022). Analyzing asymmetric effects of cryptocurrency demand on environmental sustainability. *Environmental Science and Pollution Research*, *29*(21), 31723-31733.

Gallagher, S., Greene, R., Baker, J., & Wiegmann, B. (2019). 2019 Cato Institute Surveillance Conference—PANEL–"Return of the Crypto Wars".

Gallersdörfer, U., Klaaßen, L., & Stoll, C. (2020). Energy consumption of crypto currencies beyond bitcoin. *Joule*, *4*(9), 1843-1846.

Goodkind, A. L., Jones, B. A., & Berrens, R. P. (2020). Cryptodamages: Monetary value estimates of the air pollution and human health impacts of cryptocurrency mining. *Energy Research & Social Science*, *59*, 101281.

Hao, X., Chen, Y., Xu, C., & Li, W. (2008). Impacts of climate change and human activities on the surface runoff in the Tarim River Basin over the last fifty years. *Water resources management*, *22*(9), 1159-1171.

Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and informatics*, *34*(7), 1308-1321.

Howson, P. (2019). Tackling climate change with blockchain. *Nature Climate Change*, *9*(9), 644-645.

Jadevicius, A., & Huston, S. (2015). ARIMA modelling of Lithuanian house price index. *International Journal of Housing Markets and Analysis*.

Jiang, Y., Wu, L., Tian, G., & Nie, H. (2021). Do crypto currencies hedge against EPU and the equity market volatility during COVID-19?–New evidence from quantile coherency analysis. *Journal of International Financial Markets, Institutions and Money*, *72*, 101324.

Jiang, Z., & Liang, J. (2017). Cryptocurrency portfolio management with deep reinforcement learning. 2017 Intelligent Systems Conference (IntelliSys),

Kimani, D., Adams, K., Attah-Boakye, R., Ullah, S., Frecknall-Hughes, J., & Kim, J. (2020). Blockchain, business and the fourth industrial revolution: Whence, whither, wherefore and how? *Technological Forecasting and Social Change*, *161*, 120254.

Köhler, S., & Pizzol, M. (2019). Life cycle assessment of bitcoin mining. *Environmental science & technology*, *53*(23), 13598-13606.

Kokina, J., Mancha, R., & Pachamanova, D. (2017). Blockchain: Emergent industry adoption and implications for accounting. *Journal of Emerging Technologies in Accounting*, *14*(2), 91-100.

Koomey, J. (2019). Estimating bitcoin electricity use: A beginner's guide. *May, Coin Center report: https://www. coincenter. org/app/uploads/2020/05/estimating-bitcoin-electricity-use. pdf*.

Krause, M. J., & Tolaymat, T. (2018). Quantification of energy and carbon costs for mining crypto currencies. *Nature Sustainability*, *1*(11), 711-718.

Lee, H.-S., Ng, D. C.-Y., Lau, T.-C., & Ng, C.-H. (2016). Forecasting stock market volatility on Bursa Malaysia plantation index. *International Journal of Finance and Accounting, 5 (1)*, 54-61.

Legotin, F. Y., Kocherbaeva, A. A., & Savin, V. E. (2018). Prospects for crypto-currency and blockchain technologies in financial markets. *Revista Espacios*, *39*(19).

Li, J., Li, N., Peng, J., Cui, H., & Wu, Z. (2019). Energy consumption of cryptocurrency mining: A study of electricity consumption in mining crypto currencies. *Energy*, *168*, 160-168.

Ling, G., Razzaq, A., Guo, Y., Fatima, T., & Shahzad, F. (2022). Asymmetric and time-varying linkages between carbon emissions, globalization, natural resources and financial development in China. *Environment, Development and Sustainability*, *24*(5), 6702-6730.

Majeed, M. T., Samreen, I., Tauqir, A., & Mazhar, M. (2020). The asymmetric relationship between financial development and CO2 emissions: the case of Pakistan. *SN Applied Sciences*, *2*(5), 1-11.

McGeeham, P. (2021). Bitcoin miners flock to New York's remote corners, but get chilly reception. *The New York Times*, *19*.

Mohsin, M., Naseem, S., Zia-ur-Rehman, M., Baig, S. A., & Salamat, S. (2020). The crypto-trade volume, GDP, energy use, and environmental degradation sustainability: An analysis of the top 20 crypto-trader countries. *International Journal of Finance & Economics*.

Moll, J., & Yigitbasioglu, O. (2019). The role of internet-related technologies in shaping the work of accountants: New directions for accounting research. *The British Accounting Review*, *51*(6), 100833.

Mora, C., Rollins, R. L., Taladay, K., Kantar, M. B., Chock, M. K., Shimada, M., & Franklin, E. C. (2018). Bitcoin emissions alone could push global warming above 2 C. *Nature Climate Change*, *8*(11), 931-933.

Naeem, M. A., & Karim, S. (2021). Tail dependence between bitcoin and green financial assets. *Economics Letters*, *208*, 110068.

Naeem, M. A., Karim, S., Uddin, G. S., & Junttila, J. (2022). Small fish in big ponds: connections of green finance assets to commodity and sectoral stock markets. *International Review of Financial Analysis*, *83*, 102283.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system. *Decentralized Business Review*, 21260.

Panah, P. G., Bornapour, M., Cui, X., & Guerrero, J. M. (2022). Investment opportunities: Hydrogen production or BTC mining? *International Journal of Hydrogen Energy*, *47*(9), 5733-5744.

Pata, U. K. (2018). The influence of coal and noncarbohydrate energy consumption on CO2 emissions: revisiting the environmental Kuznets curve hypothesis for Turkey. *Energy*, *160*, 1115-1123.

Pham, L., Karim, S., Naeem, M. A., & Long, C. (2022). A tale of two tails among carbon prices, green and non-green crypto currencies. *International Review of Financial Analysis*, *82*, 102139.

Reiff, N. (2020). Blockchain explained. *Investopedia, Available at https://www. investopedia. com/terms/b/blockchain. asp (Accessed 05 April, 2021)*.

Roeck, M., & Drennen, T. (2022). Life cycle assessment of behind-the-meter Bitcoin mining at US power plant. *The international journal of life cycle assessment*, *27*(3), 355-365.

Sarkodie, S. A., Ahmed, M. Y., & Leirvik, T. (2022). Trade volume affects bitcoin energy consumption and carbon footprint. *Finance Research Letters*, 102977.

Schinckus, C. (2020). Crypto-currencies trading and energy consumption. *670216917*.

Scholtens, B. (2009). Corporate social responsibility in the international banking industry. *Journal of Business Ethics*, *86*(2), 159-175.

Shi, X., Xiao, H., Liu, W., Chen, X., Lackner, K., Buterin, V., & Stocker, T. F. (2021). Confronting the Carbon-footprint Challenge of Blockchain. *arXiv preprint arXiv:2201.06929*.

Shin, Y., Yu, B., & Greenwood-Nimmo, M. (2014). Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework. In *Festschrift in honor of Peter Schmidt* (pp. 281-314). Springer.

Shojaei, A., Wang, J., & Fenner, A. (2019). Exploring the feasibility of blockchain technology as an infrastructure for improving built asset sustainability. *Built environment project and asset management*.

Singh, H., Jain, G., Munjal, A., & Rakesh, S. (2019). Blockchain technology in corporate governance: disrupting chain reaction or not? *Corporate Governance: The International Journal of Business in Society*.

Stoll, C., Klaaßen, L., & Gallersdörfer, U. (2019). The carbon footprint of bitcoin. *Joule*, *3*(7), 1647-1661.

Thampanya, N., Wu, J., & Cowton, C. (2021). Carbon neutrality targets, optimal environmental management strategies & the role of financial development: New evidence incorporating non-linear effects and different income levels. *Journal of Environmental Management*, *297*, 113352.

Wang, M., Wang, B., & Abareshi, A. (2020). Blockchain technology and its role in enhancing supply chain integration capability and reducing carbon emission: A conceptual framework. *Sustainability*, *12*(24), 10550.

Yang, L., & Hamori, S. (2021). The role of the carbon market in relation to the cryptocurrency market: Only diversification or more? *International Review of Financial Analysis*, *77*, 101864.

Author Statement

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Dear Sir,

We have revised manuscript titled **Crypto Currency and Green Investment Impact on Global Environment: A Time Series Analysis.** There is no author's conflict among authors in this research. The plagiarism of this manuscript is not greater than 15%. So, this will be a good edition in existing literature.

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