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Are Sustainable Cryptocurrencies Immune to Policy Uncertainties? Unveiling the Asymmetric Implications of Climate and Global Economic Policy Uncertainty for Green Cryptocurrencies

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Abstract

Advanced blockchain technologies and growing environmental and economic uncertainties have motivated us to investigate the impact of climate policy uncertainty (CPU) and global economic policy uncertainty (GEPU) on five green cryptocurrencies—ADA, EOS, IOTA, XLM, XTZ—selected based on energy efficiency and mining processes. We examined the short- and long-run impacts of alternative assets on these cryptocurrencies using a non-linear autoregressive distributed lag model. In the long run, these cryptocurrencies are negatively affected by CPU and GEPU, questioning their safe-haven potential. In the short run, ADA, EOS, and XLM share a positive asymmetric relationship with CPU, whereas all cryptocurrencies have a negative asymmetric relationship with GEPU. Therefore, they can be considered a safe haven. In the short and long term, green bonds exert a positive impact, whereas interest rates, the S&P 500, and the gold index negatively impact these cryptocurrencies. In the short run, Bitcoin shows a negative relationship with EOS, IOTA, and XTZ and a positive relationship with ADA and XLM. Over the long term, Bitcoin exhibits a positive correlation with all cryptocurrencies. USD exhibits a positive relationship in the short run and a negative relationship in the long run with all cryptocurrencies. The findings offer practical implications for portfolio construction and investors dealing in the green cryptocurrency market.

Keywords: green cryptocurrencies; climate policy uncertainty; global economic policy uncertainty; Bitcoin; non-linear autoregressive distributed lag (NARDL)

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¿Las criptomonedas sostenibles son inmunes a la incertidumbre política? Revelando las implicaciones asimétricas de la incertidumbre climática y de la política económica global para las criptomonedas verdes

Resumen

Los avances en tecnologías *blockchain* y las crecientes incertidumbres ambientales y económicas nos llevaron a investigar el impacto de la incertidumbre de la política climática (IPC) y la incertidumbre de la política económica global (IPEG) en cinco criptomonedas verdes —ADA, EOS, IOTA, XLM, XTZ— seleccionadas en función de la eficiencia energética y los procesos de minería. Se examinó el impacto a corto y largo plazo de activos alternativos en estas criptomonedas mediante un modelo autorregresivo con rezagos distribuidos no lineal. A largo plazo, estas criptomonedas se ven afectadas negativamente por la IPC y la IPEG, lo que cuestiona su potencial de refugio seguro. A corto plazo, ADA, EOS y XLM comparten una relación asimétrica positiva con la IPC, mientras que todas las criptomonedas tienen una relación asimétrica negativa con la IPEG. Por lo tanto, a corto plazo, ADA, EOS y XLM pueden considerarse un refugio seguro. Tanto a corto como a largo plazo, los bonos verdes ejercen un impacto positivo, mientras que las tasas de interés, el S&P 500 y el índice del oro tienen un impacto negativo en estas criptomonedas. A corto plazo, el bitcoin comparte una relación negativa con EOS, IOTA y XTZ y una relación positiva con ADA y XLM. A largo plazo, exhibe una correlación positiva con todas las criptomonedas verdes. El USD comparte una relación positiva a corto plazo y una relación negativa a largo plazo con todas las criptomonedas verdes. Los hallazgos tienen implicaciones prácticas para la construcción de carteras y las transacciones de los inversores en el mercado de criptomonedas verdes.

Palabras clave: criptomonedas verdes; incertidumbre de la política climática; incertidumbre de la política económica global; bitcoin; modelo autorregresivo con rezagos distribuidos no lineal (NARDL)

INTRODUCTION

The advent of the Fourth Industrial Revolution has witnessed numerous changes in various facets of human life and society, with the financial sector being no exception. The emergence of digital assets in the realm of available financial assets is one of the remarkable contributions of the Fourth Industrial Revolution. Existing literature claims that the emergence of digital assets, driven by technological advancement, has provided investors with a new alternative to conventional assets for portfolio diversification and risk mitigation (Syed et al., 2022). Among the prevalent digital assets, cryptocurrencies, specifically Bitcoin, have emerged as a prime example of the growing inclination of investors toward digital assets. Bitcoin, a transformative virtual currency introduced by Nakamoto in 2008, gained significant attention among investors owing to its potential for higher returns and weak correlation with other conventional financial assets. Due to its potential as an alternative financial asset and its speculative characteristics, the price of Bitcoin recorded a tremendous growth from $0.20 in October 2010 to a peak of $103,332.30 in December 2024. Over the years, the substantial returns linked to Bitcoin and advancements in blockchain technologies have led to an exploration of alternative cryptocurrencies, which resulted in an exponential increase in the number of cryptocurrencies, surpassing 19,850, with 70 per cent of these cryptocurrencies achieving a market valuation exceeding $1 billion (Yousaf et al., 2023).

The investigation of alternative cryptocurrencies, which aim to optimise cryptocurrency portfolios, and the growing environmental concerns associated with traditional cryptocurrency mining mechanisms have also led to the emergence of green cryptocurrencies. Existing literature identifies two primary mechanisms—proof-of-work and proof-of-stake —that cryptocurrencies employ to create new tokens, process transactions, and add these to the blockchain. Among these mechanisms, proof-of-work is the oldest technique used by traditional cryptocurrencies, such as Bitcoin, Ethereum, and Tether (Haq et al., 2023). This mechanism is intricately connected to mining, utilising a substantial amount of processing power. The literature also indicates that the annual energy consumption of Bitcoin is estimated to be around 204.50 TWh, which is equivalent to Thailand's electricity consumption (Gallersdörfer et al., 2020). The consumption of a substantial amount of processing power makes the process energy-intensive and significantly increases the carbon footprint, especially since electricity generation frequently relies on fossil fuels. Conversely, proof-of-stake mechanisms use significantly less energy due to their implementation of block-lattice technology, which eliminates the need for mining

(Patel et al., 2024). Therefore, cryptocurrencies that run on proof-of-stake mechanisms are considered green, as they are more environmentally sustainable than traditional cryptocurrencies.

The evolving dynamics of environmental sustainability, coupled with technological advances and globalisation, have made climate change another significant challenge confronting humanity. Unlike other crises, such as the COVID-19 pandemic, climate change is a topic that is becoming increasingly complex over time. Several regional and global efforts are undertaken worldwide to mitigate the adverse consequences of climate change. The 2015 Paris Conference on Climate Change was the first such event to provide a common platform for 196 countries to understand and agree on joint initiatives to mitigate global climate change. These global events have clarified that climate change is a critical issue gripping the whole world, and dedicated efforts are required from all segments of society; the financial sector is no exception (Naeem & Karim, 2021). Initiatives such as transitioning from traditional energy-intensive mechanisms to cleaner fuels and energy-efficient solutions are urgently needed. As already discussed in the context of the financial market, the growing cryptocurrency market is becoming a bigger environmental problem because it uses a lot of energy and leaves behind a big carbon footprint (Ren & Lucey, 2022). Therefore, the increasing environmental concerns have also adversely affected the prices of traditional cryptocurrencies. For example, the recent announcement by Elon Musk that Tesla would no longer accept Bitcoin as a payment method due to its negative environmental impact has created significant price volatility in Bitcoin prices (Patel et al., 2024). To sum up, the growing concern about climate change and the consequences of high-energy-intensive cryptocurrencies have recently shifted investors' attention toward green cryptocurrencies.

The increasing shift of investors toward green cryptocurrencies, similar to sustainable investment alternatives, has led to the development of a green cryptocurrency market encompassing several green cryptocurrencies. Some of the prominent examples include ADA (Cardano), XLM (Stellar), EOS (EOSIO), IOTA (MIOTA), and XTZ (Tezos). However, unlike the traditional cryptocurrencies that have been extensively explored from several dimensions in previous empirical literature, the existing literature has investigated their interrelationships with traditional stock markets, oil prices, exchange rates, economic policy uncertainty, geopolitical disturbances, and more (Colon et al., 2021; Corelli, 2018; Maghyereh & Abdoh, 2021; Nguyen, 2022; Okorie & Lin, 2020; Yilmazkuday, 2024). The literature on green cryptocurrencies and their responses to various financial and macroeconomic dimensions is in its initial stage of development. Except for a few recent studies, such as Patel et al.'s (2024), which investigated the connections between green cryptocurrencies, energy cryptocurrencies, and the cryptocurrency environment's attention index, and Ali et al.'s (2024), which elucidated the interrelationships between green cryptocurrencies, equity markets, and non-green cryptocurrencies, the literature on green cryptocurrencies remains inadequate.

Against this backdrop and to contribute to the developing literature on green cryptocurrencies, this study aims to explore the asymmetric impact of climate policy uncertainty (CPU) and global economic policy uncertainty (GEPU) on the emerging green cryptocurrency market. The present study examines the impact of CPU on green cryptocurrencies, as it is evident that green cryptocurrencies are a by-product of rising climate initiatives. However, recent inconsistencies in climate policies have led to uncertainties in these initiatives. The prominent reasons for CPU stem from political shifts, changes in leadership and policy directions, inconsistent regulatory frameworks, and lobbying by fossil fuel industries, among others. Existing literature suggests that these interconnected factors contribute to unpredictable investment environments, which in turn indirectly influence green financing (Dong et al., 2024). Climate uncertainty can also adversely influence green cryptocurrencies by creating regulatory unpredictability that impedes investment and operational stability. For instance, the proposed climate tax on cryptocurrency mining, designed to generate up to $5.2 billion annually by charging $0.045 per kilowatt-hour used by miners, has direct financial implications for crypto operations.

Additionally, the literature indicates that CPU plays a crucial role in determining the performance of green energy assets, with higher uncertainty often leading to reduced investment in green technologies. This environment of uncertainty can obstruct investment in green cryptocurrencies, as investors may seek alternative stable opportunities in the face of fluctuating policies. Several studies have predicted an inverse relationship between CPU and green financial instruments, such as green bonds and green equity markets (Chen et al., 2025; Wang et al., 2023). Moreover, alongside the investigation into the implications of CPU for green cryptocurrencies, several authors have also examined the impact of CPU on traditional stock markets and cryptocurrencies and concluded similar outcomes (see Sarker et al., 2023). Nevertheless, there is no existing literature that has examined how green cryptocurrencies react to rising CPU. To answer this question, the present study attempts to explore the asymmetric impact of CPU on green cryptocurrencies.

In addition to exploring the asymmetric impact of CPU on green cryptocurrencies, the study also investigates the role of GEPU on green cryptocurrencies. The idea of including GEPU emerges from the fact that the world economy has recently experienced a series of significant disruptive events, including the COVID-19 pandemic and the Russia-Ukraine war. These events have created a complex economic environment. Several studies have explored the implications of GEPU for a range of financial instruments, including stock markets, cryptocurrencies, digital assets, and green bonds (Doğan et al., 2023; Gyamerah & Asare, 2024; Hoque & Zaidi, 2019). Several studies have concluded that some investment alternatives are immune to the effects of GEPU, while others are affected by the rising GEPU (Raza et al., 2023; Sun & Zhang, 2023). Therefore, in the present situation, it will be pertinent to explore how green cryptocurrencies respond to the rising GEPU. Investigating the above relationship will help provide an alternative investment option to investors amid the rise of GEPU.

The study makes a significant contribution to the existing literature in the following ways. First, to the best of the author's knowledge, this is one of the few recent studies that contribute to the development of a research strand on green cryptocurrencies. Green finance, or alternative forms of green assets, has been extensively explored in previous empirical literature. However, a notable gap remains in the literature regarding the exploration of green cryptocurrencies. Therefore, studying green cryptocurrencies will significantly contribute to the developing literature on alternative forms of green financing. Second, the present study examines the implications of CPU and GEPU for green cryptocurrencies, which have received little attention in prior empirical research concerning green cryptocurrencies. However, numerous studies have explored the implications of CPU and GEPU for various financial assets. Investigating the aforementioned relationship within the framework of green cryptocurrencies will provide new insights for investors. The outcome will help investors capitalise on the diversification benefits of green cryptocurrencies compared to conventional equity markets, traditional cryptocurrencies, and green finance products. Third, the empirical outcome will aid policymakers and environmentalists in understanding the relationship between climate uncertainties and their impact on green crypto mining, which will assist in defining concrete regulations for blockchain and cryptocurrency functioning. Finally, the study also contributes toward methodological innovation by incorporating a comprehensive set of different asset classes and employing advanced empirical models. In conclusion, the present study will contribute to understanding the resilience of green cryptocurrencies, specifically whether the selected green cryptocurrencies offer not only environmental benefits but also hedge and safe-haven benefits superior to those of their non-green counterparts.

The remaining part of the study is summarised as follows. The second section presents a comprehensive overview of existing literature on green cryptocurrencies. The third and fourth sections exhibit the data and methodology employed. The fifth section summarises the result analysis and discussion, and finally, the last section covers the concluding remarks.

LITERATURE REVIEW

Existing literature has extensively examined the implications of economic policy uncertainty for various dimensions of the economic system. However, studies investigating the impact of CPU and GEPU on the financial markets are still in a nascent stage. In this context, the subsequent section aims to provide a comprehensive overview of the existing literature examining the impact of CPU and GEPU on financial markets, with a specific focus on cryptocurrencies. To make the literature review more comprehensive, we have divided it into two parts. The first part reviews the existing literature on the interaction between CPU, GEPU, and cryptocurrencies. The second part focuses on the developing literature on green cryptocurrencies and their interaction with various economic complexities.

Literature on the Interplay between Global Economic Policy Uncertainty, Climate Policy Uncertainty, and Cryptocurrencies

In one of the earliest studies on the interaction between policy uncertainties and cryptocurrencies, Qian et al. (2020) examined the impact of GEPU on the cryptocurrency index and the global stock market portfolio using a dynamic conditional correlation model. The authors concluded that the impact of GEPU is much more severe on the stock markets, and the cryptocurrency index can be used as a hedging instrument against conventional stock markets. Yen and Cheng (2021) also supported the above outcome while exploring the safe-haven characteristics of non-green cryptocurrencies in response to economic policy uncertainties in China, the U.S., Japan, and Korea. Their analysis concluded that Bitcoin and Litecoin serve as effective hedging instruments against these economic uncertainties. Umar et al. (2023) contradicted the above findings when exploring the link between the returns of 100 cryptocurrencies and economic uncertainty using quantile regression. They concluded that during the post-COVID-19 period, cryptocurrencies act more like traditional financial assets, and their returns are negatively affected by rising GEPU in the higher quartiles. Based on the inconclusive outcomes between cryptocurrencies and economic policy uncertainty, He et al. (2024) re-examined the above relationship by investigating the link between Bitcoin, Ethereum, Tether and GEPU using a combination of methodologies, including quantile and asymmetric analysis. These authors suggested that Bitcoin and Ethereum can serve as hedging tools in the short term, whereas in the long run, these securities perform similarly to conventional assets; i.e., Bitcoin and Ethereum share a negative association with GEPU in the long run. Recently, Ali et al. (2025) investigated the consequences of policy uncertainty on the volatility of cryptocurrencies, specifically focusing on Bitcoin as a representative digital asset. The empirical estimate reveals that the volatility of Bitcoin increases with the increase in policy uncertainty, and the authors reiterated that cryptocurrencies behave as speculative rather than safe-haven assets during periods of policy instability. In addition to the aforementioned studies, several other authors also examined the implications of economic policy uncertainty and GEPU for the cryptocurrency markets (Colon et al., 2021; Nguyen, 2022; Qin et al., 2025).

Recently, due to the rising concern of climate change, in addition to exploring the effects of GEPU on cryptocurrencies, scholars have also investigated the implications of CPU for crypto markets. In this context, Sarker et al. (2023) examined the asymmetric impact of CPU on Bitcoin prices and concluded that Bitcoin prices are negatively affected by climate uncertainties, and investors need to consider the risk associated with CPU while investing in Bitcoin. Extending the line of research, Jin and Yu (2023) explored the volatilities of cryptocurrencies against CPU using mixed-frequency volatility models. The empirical estimate concluded that CPU exerts a positive impact on cryptocurrency price volatility. The authors also highlighted that different cryptocurrencies exhibit different reactions to CPU. The study conducted by Gursoy et al. (2024) contradicted the notion of a negative relationship between Bitcoin prices and CPU and concluded that CPU exerts a positive impact on the Bitcoin prices, citing that regulatory uncertainty increases the demand for decentralized, non-sovereign assets like Bitcoin as a hedge against regulatory and policy risks, thus, strengthening the safe-haven characteristics of Bitcoin against conventional financial instruments. Gaies et al. (2025) re-examined the relationship between Bitcoin mining and CPU, concluding that Bitcoin mining is negatively impacted by CPU during periods of increased environmental concern. Moreover, the energy-intensive nature of Bitcoin contributes to increasing CPU usage. In addition to the aforementioned studies, a few other scholars have also attempted to explore the consequences of CPU on the cryptocurrency market (Ben Yaala & Henchiri, 2025; Zribi et al., 2023).

The abovementioned literature review on the interaction of GEPU, CPU, and conventional cryptocurrencies reveals the following findings. First, the literature review indicates that scholars have extensively explored the impact of economic uncertainty on cryptocurrencies; nevertheless, the study investigating the effect of CPU on cryptocurrencies is still in the developing stage. Second, the existing literature review investigating the impact of GEPU on conventional cryptocurrencies indicates inconclusive findings. Numerous studies indicate that conventional cryptocurrencies are not immune to policy uncertainties. Nevertheless, a strand of literature suggests that, in the short term, Bitcoin can serve as a safe haven and hedge against conventional stock markets amid economic uncertainty. Third, the literature review on the interaction between CPUs and cryptocurrencies reveals that the field is still in its infancy, with most existing studies indicating that CPUs have a negative impact on traditional cryptocurrencies.

Literature on Green Cryptocurrencies and Their Interaction with Various Economic Complexities

The rise of cryptocurrencies has made them sought-after assets. However, the increasing carbon footprint of traditional cryptocurrencies and the ongoing debate about using more sustainable financial instruments have shifted investor attention toward environmentally sustainable cryptocurrencies, i.e., green cryptocurrencies. Since the introduction of green cryptocurrencies, several studies have been conducted to evaluate their significance in comparison to traditional cryptocurrencies and financial assets. In this context, Ren and Lucey (2022) conducted one of the pioneering studies by exploring the interconnectedness between clean energy indices, dirty cryptocurrencies, and clean cryptocurrencies during extreme economic environments. They concluded that clean cryptocurrencies cannot be considered a safe haven asset against clean energy indices during extreme bearish markets. Building on the study of Ren and Lucey (2022), Pham et al. (2022) explored the interconnection between green and non-green cryptocurrencies using the quantile connectedness framework. This study represents one of the initial instances in which the term “green cryptocurrencies” has been used to refer to clean cryptocurrencies. The empirical estimates indicate that green cryptocurrencies are weakly connected to Bitcoin and Ethereum, and their net connectedness is almost zero.

Therefore, green cryptocurrencies may serve as a viable hedge against the price volatility of Bitcoin and Ethereum. Husain et al. (2023) contradicted the above outcome while exploring the dynamic connectedness of green cryptocurrencies, green investment, conventional commodities, and equities using the wavelet coherence technique. The authors indicated that green cryptocurrencies do not exhibit hedge or safe-haven properties; instead, they behave no differently than risk diversifiers. Additionally, they highlighted similarities between green cryptocurrencies and their conventional counterparts. They argued that although green cryptocurrencies are linked with sustainability, they are highly speculative and sensitive to overall market movements. Their price often correlates with broader asset classes rather than moving inversely during downturns. Consequently, they act more as risk diversifiers than as safe-haven assets. Recently, Ali et al. (2024) investigated the diversification benefits of selected green cryptocurrencies compared to equity portfolios and non-green cryptocurrencies, employing a four-step selection procedure. The findings suggest that green cryptocurrencies offer diversification benefits that surpass those of conventional cryptocurrencies. Moreover, among the selected green cryptocurrencies, Cardano and Tezos provide the maximum diversification benefits.

In conclusion, the literature review indicates that, while the increasing concern regarding climate change has garnered interest from both investors and scholars in green cryptocurrencies, their full potential remains unexplored. The majority of the above studies on green cryptocurrencies have investigated the interconnectedness of green cryptocurrencies with non-green cryptocurrencies or conventional stock markets. As per the author's understanding, there is no existing study that has explored the impact of CPU and GEPU on the green cryptocurrency. Against this backdrop, and in light of the recently growing complexities in CPU and GEPU, the present study attempts to explore the implications of CPU and GEPU for green cryptocurrencies. Exploring the above relationship will contribute to the developing literature on green cryptocurrencies and help understand how these cryptocurrencies, which are the by-products of climate initiatives, respond to increasing climate and global economic policy uncertainties. Moreover, investigating the aforementioned relationship will also contribute to understanding the nature of green cryptocurrencies in comparison to alternative green financial instruments, such as green bonds.

Additionally, most existing literature exploring green cryptocurrencies and their connection with conventional financial instruments has employed wavelet coherence and quantile connectedness frameworks (Ali et al., 2024; Husain et al., 2023;

Pham et al., 2022). There are no existing studies that have measured the above relationship employing an asymmetric approach. Unlike the wavelet and quantile connectedness frameworks, non-linear autoregressive distributed lag (NARDL) captures non-linear relationships between variables, which is particularly relevant in financial markets where shocks can have asymmetric effects. Moreover, the NARDL model's ability to distinguish between short- and long-run dynamics, handle asymmetries, and be robust to structural changes makes it a powerful tool for analysing financial market connectivity, often outperforming the wavelet coherence approach in financial contexts. In light of the above literature gap and drawing inference from the theoretical framework established by modern portfolio theory and the insights on financial market integration put forth by Forbes and Rigobon (2002), which elucidate the integration of financial markets and the construction of optimal portfolios while accounting for risk and return profiles, we construct the following hypotheses:

H1: Green cryptocurrencies have a negative non-linear relationship with CPU.

H2: Green cryptocurrencies have a positive non-linear relationship with GEPU.

DATA DESCRIPTION

The study examines the asymmetric impact of CPU and GEPU on green cryptocurrencies. The main daunting task in this analysis was the selection of green cryptocurrencies due to the following reasons. First, the studies on green cryptocurrency are limited; second, there are more than 22,900 cryptocurrencies, including both green and non-green cryptocurrencies; and lastly, in the majority of the earlier studies on green cryptocurrencies, the clear rationale for including green cryptocurrencies was not mentioned (Haq et al., 2023; Husain et al., 2023; Pham et al., 2022; Ren & Lucey, 2022). Therefore, following the work of Ali et al. (2024), we have included the following five green cryptocurrencies: Cardano, EOSIS, MIOTA, Stellar, and Tezos. The inclusion of these green cryptocurrencies is based on the following rationale. On the one hand, these green cryptocurrencies are among the top 150 cryptocurrencies, which account for more than 98 per cent of market capitalisation. On the other hand, these cryptocurrencies are preferred due to their mining mechanism, energy-intensive hardware requirements, high media attention, trading mechanisms, and data availability. We have collected the monthly average data of all green cryptocurrencies, expressed in USD, from 1 January 2018 to 1 March 2025.

To measure CPU and GEPU, we have referred to the US climate policy uncertainty index and the global economic policy uncertainty proposed by Baker et al. (2025) and Gavriilidis (2021). Following prior work, we have also included certain other factors that may affect green cryptocurrencies as control variables, like Bitcoin prices, gold prices, interest rates, the U.S. dollar index, S&P green bonds, and the S&P 500 index. We have included the following control variables to further understand how green cryptocurrencies react to conventional stock markets, green assets, non-green cryptocurrencies, gold, which is considered a safe-haven asset, and other macroeconomic dimensions. We have collected the monthly data for all the independent and control variables from 1 January 2018 to 1 March 2025. This period was chosen based on data availability and because it includes the timeline of some of the major global events, such as the pandemic outbreak, trade war, and AI revolution. Moreover, all the variables were further converted into natural logarithmic form to maintain data consistency. Table 1 exhibits the detail of the variables included, their abbreviations, and sources.

Table 1.

Data Description and Sources

Variable	Symbol	Description	Source
Dependent variables:			
Green Cryptocurrencies			
Cardano	ADA	Developed by Charles Hoskinson, it can perform 1,000 transactions per second, compared to seven transactions performed by Bitcoin. It works on a POS mechanism.	Investing.com
EOSIS	EOS	It is a public blockchain that is cost-effective, highly scalable, and operates on a POS mechanism.	
MIOTA	IOTA	It works on a fast probabilistic consensus mechanism. Each transaction uses just 0.11-watt hours, which is lower than those of well-established financial networks such as VISA and Mastercard, and is therefore energy-efficient.	
Stellar	XLM	It operates on a unique consensus protocol (SCP), which is considered an energy-efficient alternative. This mechanism is much faster and keeps energy usage and cost to a minimum. This is also considered an alternative to PayPal.	
Tezos	XTZ	It operates on an on-chain governance mechanism that enables the network to improve continuously and automatically, making it an energy-efficient green cryptocurrency.	

Table 1 (continued)

Variable	Symbol	Description	Source
Independent variables:			
U.S. Climate Policy Uncertainty	CPU	Developed by Baker et al. (2025), this measure is based on news articles that include keywords related to economic policy uncertainty, such as "economic uncertainty," "tax policy," "government spending," and other relevant indicators. Higher scores indicate greater uncertainty, while lower scores suggest low economic uncertainty.	Policyuncertainty.com
Global Economic Policy Uncertainty	GEPU	It is a GDP-weighted average of national economic policy uncertainty indices for 20 countries.	https://fred.stlouisfed.org
Control variables:			
U.S Green Bond index	GB	It is a financial index that tracks the performance of green bonds issued by U.S. entities.	https://www.spglobal.com
U.S. S&P 500 index	SPE	It is a benchmark for the U.S. stock market and is used to measure the performance of the highly capitalised and traded companies in the United States.	
Interest Rate	INT	Short-term interest rates are proxied by one month's U.S. Treasury interest rate.	https://fred.stlouisfed.org
Bitcoin	BT	It is the first and most widely recognised cryptocurrency, which operates on a decentralised, peer-to-peer network without a central authority, such as a bank or government.	World Economic Indicators
U.S. Dollar Index	USD	It measures the exchange rate of the United States dollar compared to the nations with which it trades the most.	https://finance.yahoo.org
Gold Index	GI	It measures and tracks gold's price movements, volatility, and correlation with other assets.	https://www.gold.org

Source: Author`s elaboration.

METHODOLOGY

This study employs the NARDL model, using EViews, to investigate the asymmetric effects of CPU and GEPU on the aforementioned green cryptocurrencies. The NARDL model introduced by Shin et al. (2014) effectively encapsulates the advantages inherent in the traditional linear ARDL model established by Pesaran et al. (1999). The use of a single-equation NARDL model, combined with a partial sum decomposition approach, facilitates the identification of both long-run and short-run asymmetric relationships between the explanatory variables and the outcome variables. Furthermore, the NARDL model has been selected due to its resilience to convergence bias, which is a common issue in traditional vector error correction models. It effectively tackles the challenges of endogeneity and omitted lag bias, making it especially suitable for small samples (Syed et al., 2022). Given the benefits and the paucity of research on the non-linear effects of GEPU and CPU on green cryptocurrencies, we have adopted the following methodology:

The NARDL model is an extension of the linear ARDL model; therefore, for model estimation, we have referred to the baseline ARDL symmetric model in Equation 1:

$$\Delta R_{xt} = \emptyset_{CPU}CPU_{t-1} + \emptyset_{GEPU}GEPU_{t-1} + \emptyset_{SPE}SPE_{t-1} + \emptyset_{GB}GB_{t-1} + \emptyset_{INT}INT_{t-1} + \emptyset_{BT}BT_{t-1} + \emptyset_{USD}USD_{t-1} + \emptyset_{GI}GI_{t-1} + \sum_{j=1}^{q}\varphi_R \Delta R_{xt-j} + \sum_{j=1}^{r}\varphi_{CPU}\Delta CPU_{t-j} + \sum_{j=1}^{r}\varphi_{GEPU}\Delta GEPU_{t-j} + \sum_{j=1}^{r}\varphi_{SPE}\Delta SPE_{t-j} + \sum_{j=1}^{r}\varphi_{GB}\Delta GB_{t-j} + \sum_{j=1}^{r}\varphi_{INT}\Delta INT_{t-j} + \sum_{j=1}^{r}\varphi_{BT}\Delta BT_{t-j} + \sum_{j=1}^{r}\varphi_{USD}\Delta USD_{t-j} + \sum_{j=1}^{r}\varphi_{GI}\Delta GI_{t-j} + \mu_t \quad [1]$$

In the above equation, R_{xt} explains the return of the five green cryptocurrencies exhibited by *x*. CPU and GEPU are the independent variables, whereas SPE, GB, INT, BT, USD, and GI are the main control variables. μ_t is the error term, q and r denote lead and lag order based on the Schwarz criteria, and Δ is the first order difference. Following the work of Shin et al. (2014), we have rewritten Equation 1 as Equation 2:

$$\Delta Rxt = \phi_0 + \omega 1R_{xt-1} + \phi^+_2\, CPU^+_{t-1} + \phi^-_3\, CPU^-_{t-1} + \phi^+_4\, GEPU^+_{t-1} + \phi^-_5\, GEPU^-_{t-1} + \phi_6 SPE_{t-1} + \phi_7 GB_{t-1} + \phi_8 INT_{t-1} + \phi_9 BT_{t-1} + \phi_{10} USD_{t-1} + \phi_{11} GI_{t-1} + \sum_{j=1}^{q} q\varphi_{1j}\,\Delta Rx_{t-j} + \sum_{j=1}^{r}\varphi^+_{2j} + \Delta CPU^+_{t-j} + \sum_{j=0}^{r}\varphi^-_{3j}\,\Delta CPU^-_{t-j} + \sum_{j=0}^{r}\varphi^+_{4j}\,\Delta GEPU^+_{t-j} + \sum_{j=0}^{r}\varphi^-_{5j}\Delta GEPU^-_{t-j} + \sum_{j=0}^{r}\phi_6 SPE_{t-j} + \sum_{j=0}^{r}\phi_7 GB_{t-j} + \sum_{j=0}^{r}\phi_8 INT_{t-j} + \sum_{j=0}^{r}\phi_9 BT_{t-j} + \sum_{j=0}^{r}\phi_{10} USD_{t-j} + \sum_{j=0}^{r}\phi_{11} GI_{t-j} + \mu_t \quad [2]$$

In Equation 2, ϕ and φ indicate the short and long run coefficients, whereas, CPU^+_{t-j}, CPU^-_{t-1}, $GEPU^+_{t-1}$, $GEPU^-_{t-1}$, demonstrate the positive and negative shocks of climate policy uncertainty and global economic policy uncertainty. In Equation 2, short-run parameters explain the effect of independent variables on the dependent variables whereas the long run parameters estimate the speed of adjustments. The positive and negative variation of the independent variables can be further described as Equations 3 to 6:

$$CPU^+_t = \sum_j^t \Delta CPU^+_j = \sum_{j=1}^t max\,(CPU_{j,}0) \quad [3]$$

$$CPU^-_t = = \sum_{j=1}^t \Delta CPU^-_j = \sum_{j=1}^t \min\,(\Delta CPU_j, 0) \quad [4]$$

$$GEPU^+_t \sum_{j=1}^t \Delta GEPU^+_j = \sum_{j=1}^t \max\,(\Delta GEPU_j, 0) \quad [5]$$

$$GEPU^-_t = \sum_{j=1}^t \Delta GEPU^-_j = \sum_{j=1}^t \min\,(\Delta GEPU_j, 0) \quad [6]$$

In Equation 2 above, the long run positive and negative impact of CPU and GEPU on R_{xt} is computed as $\phi^+_{CPU} = \phi^+_2/\omega_1$ $\phi^-_{CPU} = \phi^-_3/\omega_1$ and $\phi^-_{GEPU} = \phi^+_4/\omega_1$, $\phi^-_{GEPU} = \phi^-_5/\omega_1$, whereas, the positive and negative shocks of CPU and GEPU on R_{xt} is computed as $\sum_{i=1}^{j}\varphi_{2j}^{+}$, $\sum_{i=1}^{j}\varphi_{3j}^{-}$, $\sum_{i=1}^{j}\varphi_{4j}^{+}$, $\sum_{i=1}^{j}\varphi_{5j}^{-}$. After confirming the long-run asymmetric effect the short run non-linear relationship is estimated employing the dynamic multiplier (Equations 7 and 8):

$$M_l^{+} = \sum_{j=0}^{k} \frac{nR_{xt+j}}{nCPU_j^{+}}$$

$$M_l^{+} = \sum_{j=0}^{k} \frac{nR_{xt+j}}{nCPU_j^{-}},\ 1 = 0, 1, 2 \qquad [7]$$

$$M_l^{+} = \sum_{j=0}^{k} \frac{nR_{xt+j}}{nGEPU_j^{+}}$$

$$M_l^{+} = \sum_{j=0}^{k} \frac{nR_{xt+j}}{nGEPU_j^{-}},\ 1 = 0, 1, 2 \qquad [8]$$

Note: As k $\rightarrow\infty, M_l^{+} \rightarrow \varphi_2^{+}$, $M_l^{-} \rightarrow \varphi_2^{-}$

In addition to exploring the asymmetric relationship between the explanatory and the outcome variables, we also conducted a series of post-tests. For instance, we confirmed the presence of a unit root by applying the Phillips-Perron (PP) and Augmented Dickey-Fuller (ADF) unit root tests. We also confirmed the presence of structural breaks (SBs) and non-linearity by referring to Zivot and Andrews's (2002) SB test and Broock et al.'s (1996) BDS test. Subsequently, after confirming the level of stationarity, structural breakage, and non-linearity, we also examined asymmetric cointegration by utilising Pesaran et al.'s (2001) bounds testing approach. Under bound testing, we examined the *F*-statistic value and assessed its lower and upper bound values to ascertain the presence of cointegration. We confirmed an asymmetric cointegration if the *F*-statistic exceeds the lower and upper bound values. Finally, we also conducted various diagnostic tests, including the Wald test, to confirm the model's validity.

DATA ANALYSIS AND DISCUSSION

In our empirical analysis, before proceeding with model estimation, we present the descriptive properties of the explanatory and outcome variables (see Table 2). The descriptive statistics indicate mixed skewness across variables; the kurtosis value suggests the absence of extreme outliers or heavy-tailed behaviour, whereas the probability value of the Jarque-Bera test indicates a non-normality issue. The outcomes of the descriptive statistics reinforce the application of the asymmetric model.

Table 2.

Descriptive Statistics

	Mean	Maximum	Minimum	Std. Dev	Skewness	Kurtosis	Jarque Bera	Prob.
ADA	0.26	32.34	-39.43	4.89	0.45	3.46	18.29	0.00
EOS	0.14	57.12	-39.21	5.38	0.39	9.23	14.52	0.00
IOTA	0.14	38.54	-42.44	5.63	0.39	4.67	12.40	0.00
XLM	0.13	63.25	-37.24	5.21	1.23	13.65	22.34	0.00
XTZ	0.19	30.56	-41.42	6.12	0.09	4.15	19.32	0.00
CPU	4.32	6.04	4.12	0.32	-0.44	6.24	12.94	0.00
GEPU	4.12	5.38	4.81	0.29	-0.45	8.34	16.31	0.00
GB	0.006	5.63	-2.65	0.32	-0.68	7.82	11.21	0.00
SPE	0.034	7.82	-10.04	1.11	-0.83	12.32	13.50	0.00
INT	0.02	0.03	0.00	0.008	0.12	1.24	11.17	0.00
BT	0.15	18.24	-35.42	4.12	0.42	7.35	14.28	0.00
USD	3.56	5.52	5.32	0.05	0.63	3.54	10.46	0.00
GI	6.24	6.74	6.12	0.14	-0.15	1.23	18.38	0.00

Source: Author`s elaboration.

Existing literature posits that the application of the NARDL model warrants confirming the presence of a unit root (Ullah et al., 2024). Therefore, to test the presence of unit roots, we employed the ADF and PP unit root tests at constant and trend specifications (see Table 3). The results of the unit root test indicate that some of the variables are not integrated at levels, i.e., I(0). Nonetheless, after applying first differencing, all variables exhibit integration at the 1 % level of significance. The result also indicates that none of the variables are integrated at the I(2) level. The mixed level of integration and the absence of integration at I(2) support the application of the NARDL model.

Table 3.

Unit Root Test

	ADF unit root test				PP unit root test			
	At 1(0)		At 1(1)		At I(0)		At I(1)	
	Constant	Constant and trend	Constant	Constant and trend	Constant	Constant and trend	Constant	Constant and trend
ADA	-1.294**	-2.495***	-2.394***	-4.693***	-3.334**	-4.583**	-3.583***	-4.693***
EOS	-2.853***	-4.830***	-7.593***	-8.194***	-2.495*	-4.294**	-5.194***	-7.402***
IOTA	-2.482***	-3.125***	-2.395***	-3.0694***	-3.501***	-5.501***	-4.952***	-6.318***
XLM	-2.593	-4.593	-4.492***	-5.195***	-3.582	-4.012**	-3.693***	-5.693***
XTZ	-3.082	-4.301	-5.093***	-6.953***	-4.113***	-5.594***	-5.053***	-7.582***
CPU	-4.391**	-6.246**	-4.582***	-6.294***	-4.952**	-7.412**	-7.291***	-11.482**
GEPU	-2.185**	-4.582**	-3.963***	-4.812***	-3.567	-5.298	-4.528***	-6.218***
GB	-3.589	-5.904	-6.291***	-7.112***	-4.094**	-6.318**	-6.204***	-8.413***
SPE	-4.121**	-6.230**	-4.912***	-5.954***	-6.295**	-8.921**	-7.381***	-9.462***
INT	-5.082**	-6.453**	-5.253***	-7.392***	-4.509	-6.352	-3.204***	-4.513***
BT	-4.212***	-5.291***	-8.332***	-11.492***	-2.496***	-4.194***	-3.512***	-5.381***
USD	-6.294	-8.382**	-6.693***	-9.385***	-1.395	-2.495**	-2.402***	-4.118***
GI	-2.482**	-3.583**	-3.582***	-4.592***	-2.185**	-4.582**	-4.510***	-6.382***

Note: *, **, and *** indicate significance level at 10, 5, and 1 per cent.

Source: Author`s elaboration.

The conventional unit root tests are not equipped to detect the presence of SBs, which may lead to spurious estimates. Therefore, following the work of Ullah et al. (2024), we have employed Zivot and Andrews's SB unit root test. This test not only estimates a single SB but also evaluates the level of integration. In our case, Zivot and Andrews's SB test reports the presence of an SB in all the series. In most of the series, the month of SB is reported to be around 2020–2021 (see Table 4), a period defined by the COVID-19 pandemic and the subsequent recovery period. The observed SBs can be attributed to a combination of factors, including the COVID-19 pandemic; global economic uncertainty stemming from an unpredictable business landscape caused by worldwide lockdowns; inflationary pressures; changes in investor behaviour and asset valuations; and transitioning from traditional to digital assets (Elsayed et al., 2022; Wang et al., 2024). In addition, Zivot and Andrews's test also validates that none of the variables is integrated at the second order.

Table 4.

Zivot and Andrews's Test

	At level		At first difference	
	At I(0)	**At 1(1)**	**At I(0)**	**At 1(1)**
	T-statistics	Break	*T*-statistics	Break
ADA	-2.294***	2021(M2)	-3.582***	2021(M2)
EOS	-2.452***	2021(M4)	-3.052***	2021(M4)
IOTA	-3.520***	2021(M4)	-4.683***	2021(M4)
XLM	-4.619***	2021(M11)	-5.911***	2021(M11)
XTZ	-3.102**	2021(M4)	-4.092**	2021(M1)
CPU	-2.592***	2021(M11)	-3.104***	2021(M9)
GEPU	-2.143**	2020(M3)	-3.491***	2020(M3)
GB	-3.522**	2020(M3)	-3.961***	2020(M3)
SPE	-4.255***	2020(M3)	-5.593***	2020(M3)
INT	-2.582**	2022(M3)	-3.692***	2022(M3)
BT	-3.119**	2020(M11)	-4.014**	2020(M12)
USD	-4.095**	2022(M4)	-4.228***	2022(M4)
GI	-2.104***	2020(M3)	-3.119***	2020(M3)

Note: *, **, and *** indicate significance level at 10, 5, and 1 per cent.

Source: Author`s elaboration.

Although Zivot and Andrews's test is capable of detecting SBs, one of its limitations is that it only considers the presence of a single SB. Therefore, to overcome the above limitation, we also employed the Clemente-Montanes-Reyes unit root test. This test is capable of detecting the presence of two SBs, even in the absence of prior information regarding break dates in the series. In the above test, the null hypothesis indicates the presence of an SB with a unit root, whereas the alternative hypothesis explains the presence of an SB without a unit root. In our case, we reject the null hypothesis, as the test statistic exceeds the critical value. Moreover, similar to Zivot and Andrews's test, the Clemente-Montanes-Reyes unit root test also indicates a common interval of SBs for most of the series, which are around 2020–2021 (see Table 5).

Table 5.

Clemente-Montanes-Reyes Unit Root Test Including Two SBs

	Innovative outliers				Additive outliers			
	T-stats	**SB1**	**SB2**	**Outcome**	**T-stats**	**SB1**	**SB2**	**Outcome**
ADA	-2.592***	2021(M2)	2022(M6)	First Diff	-2.193**	2021(M2)	2022(M6)	First Diff
EOS	-3.184**	2021(M4)	2022(M5)	First Diff	-3.504**	2021(M4)	2022(M5)	First Diff
IOTA	-3.403***	2020(M4)	2021(M4)	First Diff	-4.492***	2020(M4)	2021(M4)	First Diff
XLM	-4.094**	2020(M11)	2024(M11)	First Diff	-5.180**	2020(M11)	2024(M11)	First Diff
XTZ	-2.432**	2020(M1)	2021(M4)	First Diff	-3.274**	2020(M1)	2021(M4)	First Diff
CPU	-3.283***	2020(M3)	2021(M11)	First Diff	-3.295***	2020(M3)	2021(M11)	First Diff
GEPU	-3.391**	2020(M3)	2021(M11)	First Diff	-4.406**	2020(M3)	2021(M11)	First Diff
GB	-3.482***	2020(M3)	2021(M11)	First Diff	-3.101***	2020(M3)	2021(M11)	First Diff
SPE	-2.110***	2019(M1)	2020(M3)	First Diff	-4.294**	2019(M1)	2020(M3)	First Diff
INT	-3.122**	2020(M3)	2022(M3)	First Diff	-4.183**	2020(M3)	2022(M3)	First Diff
BT	-3.283**	2019(M1)	2021(M1)	First Diff	-3.304***	2019(M1)	2021(M1)	First Diff
USD	-4.194**	2022(M4)	2022(M8)	First Diff	-2.498**	2022(M4)	2022(M8)	First Diff
GI	-2.403**	2020(M3)	2020(M3)	First Diff	-3.204**	2020(M3)	2020(M3)	First Diff

Note: SB explain the dates of SBs; *, **, and *** explain the significance level at 10, 5, and 1 per cent.

Source: Author`s elaboration.

After confirming the presence of an SB, we tested for non-linearity in the series by employing the Brock, Dechert, and Scheinkman (BDS) non-linearity test. The BDS test is considered superior for detecting non-linearity because it spots model misspecifications, removes linear dependencies, and estimates residuals using the VAR model. In this test, the null hypothesis states that the series is identically distributed and linear, whereas the alternative hypothesis claims non-linearity. The BDS test statistics report a significant value at the 1 per cent level of significance and thus reject the claim of linearity and conclude the presence of non-linearity, which further validates the application of the NARDL model (see Table 6).

Table 6.

BDS Non-Linearity Test

BDS statistic	m = 2	m = 3	m = 4	m = 5	m = 6
ADA	0.013***	0.312***	0.384***	0.411***	0.579***
EOS	0.183***	0.234***	0.299***	0.356***	0.419***
IOTA	0.274***	0.292***	0.312***	0.431***	0.598***
XLM	0.283***	0.314***	0.383***	0.485***	0.512***
XTZ	0.215***	0.312***	0.467***	0.413***	0.576***
CPU	0.291***	0.298***	0.303***	0.387***	0.412***
GEPU	0.217***	0.312***	0.378***	0.418***	0.528***
GB	0.121***	0.177***	0.342***	0.389***	0.410***
SPE	0.318***	0.398***	0.417***	0.422***	0.517***
INT	0.198***	0.255***	0.305***	0.410***	0.544***
BT	0.241***	0.392***	0.417***	0.433***	0.449***
USD	0.276***	0.299***	0.306***	0.482***	0.518***
GI	0.119***	0.201***	0.373***	0.389***	0.501***

Note: *, **, and *** explain the significance level at 10, 5, and 1 per cent.

Source: Author`s elaboration.

Before proceeding with the model estimation and delineating the short-run and long-run asymmetric relationship between the explanatory and outcome variables, we also examined the long-run cointegration relationship. The selection of optimum lag is an essential prerequisite for cointegration analysis; for this reason, we referred to the Schwarz Bayesian Information Criterion (SIC), which suggests that the lag is appropriate. The *F*-statistic value and the T-BDM test statistics for all the green cryptocurrencies exceed the tabulated upper bound values (see Table 7), which suggests a long-run cointegration relationship exists between the green cryptocurrencies, CPU, GEPU, green bonds, the S&P 500 index, interest rate, Bitcoin, the dollar index, and the gold index.

Finally, after confirming the presence of long-run cointegration, we proceed with the short-run and long-run NARDL estimation. Before discussing the short-run and long-run results, we also determined the asymmetric association between green cryptocurrencies, CPU, and GEPU using the Wald test. The Wald test result indicates a short-run asymmetric effect of CPU on all the green cryptocurrencies with the exception of IOTA and XTZ. In the context of GEPU, the Wald test indicates a short-run asymmetric effect of GEPU on all the green cryptocurrencies (see Table 8). Next, we discuss the coefficient and the size of the effect of the independent variable on the dependent variable in the short run.

Table 7.

Bound Cointegration test

Estimated equation (selection model)	*R = f (CPU⁺, CPU⁻, GEPU⁺, GEPU⁻, GB, SPE, INT, BT, USD, GI)*		
	***F*-statistics**	**T-BDM**	**Cointegration**
ADA (4,6,6,5,4,6,6,6,4,4,5)	7.193	-5.291	Cointegration exists
EOS (6,6,6,5,5,5,4,4,5,4,6)	6.591	-7.940	Cointegration exists
IOTA (6,6,6,6,5,5,4,4,5,5,5)	11.395	-9.385	Cointegration exists
XLM (6,5,5,5,5,4,4,4,6,6,5)	8.129	-6.139	Cointegration exists
XTZ (5,6,6,6,5,5,5,6,6,6,6)	6.295	-8.482	Cointegration exists

*Note***.** *R* refers to the dependent variable green cryptocurrencies, i.e., ADA, EOS, IOTA, XLM, and XTZ. *F*-statistics refer to the Pesaran et al. (2001) bound test statistics. The upper bound critical values at 10 %, 5 % and 1 % significance levels are 3.08, 4.12, and 4.78 (Narayan, 2005). T-BDM refers to the test statistics given by Banerjee et al. (1998); here, the upper bound values at 10 %, 5 % and 1 % significance levels are -4.12, -4.54, and -4.82, respectively.

The short-run result, as shown in Table 8, indicates that the positive effect of CPU has a positive impact on ADA, EOS, and XLM, whereas it has a negative impact on IOTA and XTZ. A one per cent increase in CPU increases the return of ADA, EOS and XLM by 0.543, 0.484 and 0.099 per cent, whereas it decreases the return of IOTA and XTZ by -0.182 and -0.692 per cent, respectively. A one per cent decrease in CPU decreases ADA, EOS, IOTA, XLM, and XTZ by -0.108, -0.129, -0.026, -0.051, and -0.033, respectively. It implies that in the short run, during heightened climate uncertainty, investors can consider ADA, EOS and XLM as hedging instruments. In the short term, an increase in CPU can lead to higher returns for cryptocurrencies such as ADA, EOS, and XLM. The probable explanation for the above relationship is as follows: firstly, we can associate it with the flight-to-safety phenomenon. Existing literature suggests that, similar to non-green cryptocurrencies, investors prefer these assets as alternative investments, especially during periods of heightened policy uncertainty (Pham et al., 2022). Several studies have shown that during periods of increased climate uncertainty, investors often seek assets with lower correlations to traditional financial markets, such as cryptocurrencies, leading to increased demand and higher returns (Ben Yaala & Henchiri, 2025). Moreover, the decentralised nature of these currencies makes them a preferred choice during regulatory uncertainty because they are less vulnerable to direct government interventions.

This characteristic attracts investors to such cryptocurrencies as a hedge against the adverse consequences of climate policies on conventional financial instruments. Literature also suggests that the enhanced integration of blockchain technology across various sectors, including environmental management and energy, increases the likelihood of these cryptocurrencies during periods of heightened climate uncertainty, as they are considered integral to the evolving digital economy. However, when CPU eases, investors start reallocating capital to traditional assets, as they are perceived as less risky and stable. This reduces the demand for alternative green cryptocurrencies, and thus the negative shock of CPU exerts a negative push on the returns of the aforementioned green cryptocurrencies in the short run. Hence, we can conclude that during periods of heightened CPU, investors may consider investing in ADA, EOS, and XLM as alternative hedging instruments. These outcomes are also in line with the study by Mnif et al. (2025), which explains the potential of green cryptocurrencies in mitigating short-term uncertainties. Additionally, these short-run outcomes in the case of green cryptocurrencies, including ADA, EOS, and XLM, provide us with the rationale to reject H1, which asserts that green cryptocurrencies share a negative asymmetric relationship with CPU. However, in the case of IOTA and XTZ, we cannot reject the null H1, as these cryptocurrencies share a negative relationship with CPU.

Table 8.

Short-Run NARDL Results

Dependent variables	ADA	EOS	IOTA	XLM	XTZ
ΔCPU^{+}	0.543 (0.142)**	0.484 (0.132)**	-0.182 (0.016)**	0.099 (0.014)*	-0.692 (0.108)**
ΔCPU^{-}	-0.108 (0.091)**	-0.129 (0.103)**	-0.026 (0.028)*	-0.051 (0.013)**	-0.033 (0.013)*
$\Delta GEPU^{+}$	-0.721 (0.310)**	-0.592 (0.285)**	-0.475 (0.184)**	-0.384 (0.132)**	-0.728 (0.281)**
$\Delta GEPU^{-}$	0.408 (0.292)***	0.301 (0.115)**	0.318 (0.119)**	0.218 (0.063)**	0.490 (0.132)**
ΔGB	0.152 (0.060)**	-0.075 (0.017)	0.042 (0.016)**	0.183 (0.072)*	0.284 (0.047)*
ΔSPE	0.326 (0.143)	-0.118 (0.038)***	-0.154 (0.018)**	-0.098 (0.052)**	-0.141 (0.102)**
ΔINT	-0.013 (0.005)***	-0.019 (0.012)**	-0.010 (0.008)**	-0.032 (0.010)*	-0.127 (0.056)*
ΔBT	0.438 (0.261)**	-0.130 (0.023)**	-0.112 (0.092)**	0.318 (0.057)*	-0.183 (0.031)*
ΔUSD	0.112 (0.091)**	0.108 (0.043)**	0.072 (0.017)**	0.184 (0.101)**	0.284 (0.102)**
ΔGI	-0.016 (0.012)	-0.021 (0.005)**	-0.183 (0.102)**	-0.294 (0.092)**	-0.121 (0.058)**
Wald test					
CPU_{SR}	14.582***	11.309***	8.824	13.392***	5.385
$GEPU_{SR}$	8.382**	6.482**	11.482**	9.042**	3.948**

Note. *, **, and *** explain the significance level at 10, 5, and 1 per cent.

Source: Author`s elaboration.

In the context of GEPU, the short-term result highlights that the positive shocks of GEPU have a negative impact on all the selected green cryptocurrencies, and vice versa. A one per cent increase in GEPU decreases the return of ADA, EOS, IOTA, XLM, and XTZ by -0.721, -0.592, -0.475, -0.384, and -0.728, respectively, whereas a one per cent decrease in GEPU increases the return of ADA, EOS, IOTA, XLM, and XTZ by 0.408, 0.301, 0.318, 0.218, and 0.490, respectively. The coefficient value for the positive shocks is greater than that for the negative shocks, implying that increased GEPU has a greater impact on the selected green cryptocurrencies. Based on the above findings, we can conclude that the selected green cryptocurrencies cannot be considered as safe-haven assets against GEPU. Investors cannot perceive these assets as hedging instruments against GEPU. The likely explanation for the above outcome can be attributed to heightened investor risk aversion and a reduced appetite for speculation. Studies conducted by Bouri et al. (2022) and Kayani et al. (2024) highlight that periods of heightened economic uncertainty often result in capital outflow from unstable and less-regulated markets, such as cryptocurrencies, to traditional safe-haven instruments like gold, and vice versa. The selected green cryptocurrencies, although considered environmentally friendly, still exhibit high price volatility and speculative traits that make them susceptible to investor withdrawals amid fluctuating macroeconomic conditions. Existing literature suggests that global economic uncertainties lower investor confidence and hinder inflows into the crypto market, particularly among institutional investors who exhibit heightened sensitivity to policy-related risks (He et al., 2024). Therefore, we can say that the returns on these green cryptocurrencies, similar to those of conventional cryptocurrencies, tend to decline as demand subsides amid broader market caution and portfolio adjustments. These justifications can be corroborated with recent literature that aligns global economic uncertainty shocks with negative effects on digital asset performance (Chua et al., 2022). Conclusively, based on the NARDL short-run estimate, we can conclude that green cryptocurrencies, i.e., ADA, EOS, and XLM, can be considered a safe haven against CPUs. However, we cannot view these cryptocurrencies as a hedge against rising GEPU in the short run. These short-run results also reject the null H2, which asserts that green cryptocurrencies share a positive non-linear relationship with GEPU.

Moving to the other independent variables, the NARDL short-run results indicate that, except for EOS, all the other green cryptocurrencies share a positive association with green bonds. A one per cent increase in green bonds increases the return of ADA, IOTA, XLM and XTZ by 0.152, 0.042, 0.183 and 0.284, respectively. It implies that green cryptocurrencies perform similarly to green bonds, and therefore, these cryptocurrencies cannot be considered a hedge against green bonds. The probable explanation for a comparable relationship can be attributed to the fact that both the above-mentioned green cryptocurrencies and green bonds belong to the same category of assets, which are aligned with the broader environmental, social, and governance investment trend and attract investors who prioritise environmental considerations. These outcomes also align with the existing literature on the market linkage between green bonds and clean cryptocurrencies, which indicates a positive association between clean cryptocurrencies and green bonds (see Mnif et al., 2025).

In relation to the S&P 500, the results show that, except for ADA, all other green cryptocurrencies exhibit an inverse relationship with the index. A one per cent increase in SPE decreases the return of EOS, IOTA, XLM, and XTZ by -0.118, -0.154, -0.098, and -0.141, respectively. Existing literature suggests that green and non-green cryptocurrencies exhibit an inverse relationship with the traditional equity market, as investors shift funds from traditional assets to cryptocurrencies during market declines, perceiving them as viable alternative investments (Rashid et al., 2023). However, when the market stabilises, investors reallocate funds back towards traditional stocks, considering them safer and more stable, leading to a decline in cryptocurrency values. The short-run results further indicate that ADA and XLM exhibit a positive relationship with Bitcoin, whereas EOS, IOTA, and XTZ show an inverse relationship with Bitcoin. It implies that with an increase in Bitcoin, the returns of ADA and XLM increase, whereas those of EOS, IOTA, and XTZ decrease. The coefficient sizes of ADA and XLM are much higher compared to those of EOS, IOTA, and XTZ. The diverse responses of the above green cryptocurrencies can be linked to variations in market positioning, investor sentiment, and network fundamentals. ADA and XLM share a positive relationship with Bitcoin because they are considered more reliable and established assets within the cryptocurrency realm. This notion attracts investors seeking relatively stable alternatives to Bitcoin, resulting in higher demand and potential returns when Bitcoin's price rises. Existing literature indicates that EOS, IOTA, and XTZ encounter various obstacles, including governance challenges, scalability issues, and a lag in adoption rates. These factors may erode investor confidence, potentially leading to reduced returns in the context of Bitcoin's price fluctuations. Moreover, we can also link the above relationship with the rotation effect observed in the cryptocurrency market, which suggests that investors move funds from underperforming assets to those with better prospects, further adding to the divergent performance of the above cryptocurrencies against Bitcoin (Chowdhury et al., 2022).

Finally, in the context of interest rates, the dollar index and the gold index, the green cryptocurrencies share a similar relationship to traditional assets; i.e., with an increase in interest rates and the gold index, the returns of all the green cryptocurrencies decrease. Conversely, when the dollar index increases, the returns of all green cryptocurrencies also increase. The inverse relationship between interest rates, gold and green cryptocurrencies highlights the typical investor's sentiment amid stricter monetary policies. Higher rates increase the likelihood of fixed-income instruments, shifting capital away from riskier cryptocurrencies. Likewise, rising gold prices underscore risk aversion, compelling investors to buy gold over speculative assets. The positive relationship between green cryptocurrencies and the U.S. dollar index, although contradictory to the standard outcome, may suggest that a strong dollar increases investor confidence and risk appetite, benefiting green cryptocurrencies. This pattern aligns with the studies of Maghyereh and Abdoh (2021) and Qin et al. (2025), highlighting the evolving role of green cryptocurrencies in diversified portfolios, akin to macroeconomic signals.

In contrast to the short-run results, the long-run NARDL estimate presented in Table 9 indicates that, in the long run, positive CPU shocks have a negative impact on the returns of green cryptocurrencies, and vice versa. It implies that in the long run, heightened CPU decreases the performance of green cryptocurrencies. A one per cent increase in CPU decreases the return of ADA, EOS, IOTA, XLM, and XTZ by -0.238, -0.319, -0.198, -0.112, and -0.294, respectively. While a one per cent decrease in CPU increases the return of ADA, EOS, IOTA, XLM and XTZ by 0.212, 0.298, 0.145, 0.096 and 0.134 per cent, respectively, validating H1, which posits that green cryptocurrencies share a negative non-linear relationship with CPU. The observed relationship can be explained through the existing literature on financial ambiguity, environmental asset pricing and investor behaviour. Existing literature indicates that heightened climate uncertainty increases regulatory ambiguity regarding the long-term viability of green technologies and climate action, subsequently diminishing investor confidence in financial instruments associated with these technologies (Ren et al., 2023). CPU acts as a tax on investments, resulting in lower capital allocation, which extends to the aforementioned green cryptocurrencies due to their association with sustainable innovations. Bouri et al. (2022) and Pham et al. (2024) demonstrated that climate-induced uncertainty, particularly related to regulatory issues, leads to asset revaluation as market expectations evolve. When CPU increases, the demand for green digital financial assets lowers, which reduces their intrinsic value. Moreover, Ren et al. (2023) indicated that, while exploring the interaction between CPU and green assets, green assets are more susceptible to policy uncertainty, leading to underperformance over time. The long-term inverse relationship between CPUs and green cryptocurrencies can also be justified through the lens of behavioural finance, which explains the uncertainty aversion that leads investors to avoid speculative assets like green cryptocurrencies. These long-run findings explain that consistent and stable climate policies are crucial for maintaining investor interest and fostering the development of environmentally friendly financial innovations.

Table 9.

Long-Run NARDL Results

Dependent variables	**ADA**	**EOS**	**IOTA**	**XLM**	**XTZ**
ΔCPU^{+}	-0.238 (0.056)**	-0.319 (0.218)**	-0.198 (0.121)**	-0.112 (0.023)**	-0.294 (0.194)**
ΔCPU^{-}	0.212 (0.189)**	0.298 (0.112)**	0.145 (0.094)**	0.096 (0.127)**	0.134 (0.119)***
$\Delta GEPU^{+}$	-0.284 (0.112)**	-0.184 (0.037)***	-0.189 (0.013)*	-0.391 (0.098)**	-0.193 (0.043)**
$\Delta GEPU^{-}$	0.145 (0.109)**	0.104 (0.094)***	0.113 (0.048)**	0.294 (0.195)**	0.104 (0.090)**
ΔGB	0.184 (0.183)***	0.081 (0.073)**	0.078 (0.032)**	0.095 (0.123)**	0.139 (0.238)**
ΔSPE	0.183 (0.248)	-0.012 (0.183)**	-0.021 (0.128)	-0.294 (0.193)***	-0.245 (0.138)***
ΔINT	-0.007 (0.001)***	-0.005 (0.012)**	-0.014 (0.008)**	-0.018 (0.031)***	-0.018 (0.012)**
ΔBT	0.128 (0.172)**	0.078 (0.054)**	0.087 (0.013)**	0.114 (0.159)***	0.092 (0.105)**
ΔUSD	-0.049 (0.052)*	-0.042 (0.021)**	-0.024 (0.005)	-0.090 (0.053)	-0.018 (0.043)**
ΔGI	-0.012 (0.009)**	-0.011 (0.002)**	-0.021 (0.011)	-0.028 (0.010)	-0.016 (0.018)**
Wald test					
CPU_{LR}	12.274**	9.119**	15.153**	10.392**	8.492**
$GEPU_{LR}$	10.184**	6.184**	7.382***	9.417**	6.382**
Ramsey reset	1.183 (0.642)	1.748 (0.692)	1.583 (0.482)	1.105 (0.539)	1.395 (0.294)
LM test	1.297 (0.732)	1.385 (0.583)	1.164 (0.890)	1.193 (0.998)	1.693 (0.802)
Breusch Pegan	0.607 (0.213)	0.395 (0.294)	0.649 (0.395)	0.485 (0.563)	0.792 (0.592)
CUSUM					
ECM_{t-1}	-0.0719 (0.00**)	-0.0813 (0.00**)	-0.0763 (0.00**)	-0.0931 (0.00**)	-0.0595 (0.00**)
Adj. R^2	0.862	0.821	0.758	0.871	0.783

Note. *, **, and *** explain the significance level at 10, 5, and 1 per cent.

Source: Author`s elaboration.

Regarding GEPU, the long-run NARDL results align with the short-run estimates. It implies that the positive shocks of GEPU exert a negative impact on the aforementioned green cryptocurrencies, whereas negative shocks in GEPU assist in increasing the return of the selected green cryptocurrency. A one per cent increase in GEPU lowers the return of ADA, EOS, IOTA, XLM, and XTZ by -0.284, -0.184, -0.189, -0.391, and -0.193, respectively, thus rejecting H2, which claims a positive non-linear relationship between green cryptocurrencies and GEPU. In the long run, GEPU reduces the performance of the above green cryptocurrencies due to their inherently volatile and speculative nature. Existing literature also supports the above outcome, concluding that during periods of increased economic uncertainty, investors adopt a risk-averse approach, favouring stable assets such as government bonds and gold, while steering clear of speculative investments like cryptocurrencies (Colon et al., 2021). Therefore, it can be inferred that in the context of GEPU, green cryptocurrencies perform similarly to non-green cryptocurrencies, and thus, they cannot be regarded as a reliable safe haven in the face of increasing GEPU. The long-run Wald test, as presented in Table 9, validates the long-term asymmetric relationship between CPU, GEPU, and selected green cryptocurrencies. Furthermore, when considering the other independent variables, the long-run NARDL estimates reveal that green bonds, interest rates, and the gold index have a similar relationship with all selected green cryptocurrencies, which is consistent with the short-run estimates. In other words, a green bond exerts a positive impact, whereas interest rates and the gold index exert a negative impact on the selected green cryptocurrencies. On the contrary, in the long run, unlike the short-term estimates, Bitcoin, the US dollar index, and the SPE index share a distinct relationship with the aforementioned green cryptocurrencies. The long-run NARDL estimate indicates that Bitcoin exerts a positive impact on all the selected green cryptocurrencies, whereas the US dollar index and SPE demonstrate a negative effect on the selected cryptocurrencies. The NARDL long-run estimate indicates that, with the exception of ADA and IOTA, all other green cryptocurrencies exhibit a negative relationship with SPE. In contrast, regarding the US dollar index, all other green cryptocurrencies, except for IOTA and XLM, exhibit a negative relationship with the USD. From the investor's perspective, these long-run estimates suggest that green bonds and Bitcoin are not safe havens, but rather risk diversifiers. In contrast, the aforementioned green cryptocurrencies can be considered safe havens for the USD index, SPE index, gold, and interest rates. These outcomes corroborate the study by Hussain et al. (2023) and Pham et al.

(2022), which examined the safe-haven characteristics of green cryptocurrencies compared to non-green cryptocurrencies.

Finally, we also performed multiple diagnostic tests to estimate the robustness of our long-run estimate. We used the RESET test to assess functional accuracy, the LM test to check for serial correlation, the Breusch test to verify heteroskedasticity, and the CUSUM dynamic multiplier graph to confirm the consistency of our empirical estimates (see Table 9 for diagnostic tests and Figure 1 for the dynamic multiplier graph). The diagnostic test validates that the model is correctly specified and does not exhibit serial correlation and heteroskedasticity. Moreover, the negative and significant ECM indicates a robust and statistically relevant rationale for the observed adjustment.

Figure 1.

Dynamic Multiplier Graph

Multiplier Graph GEPU

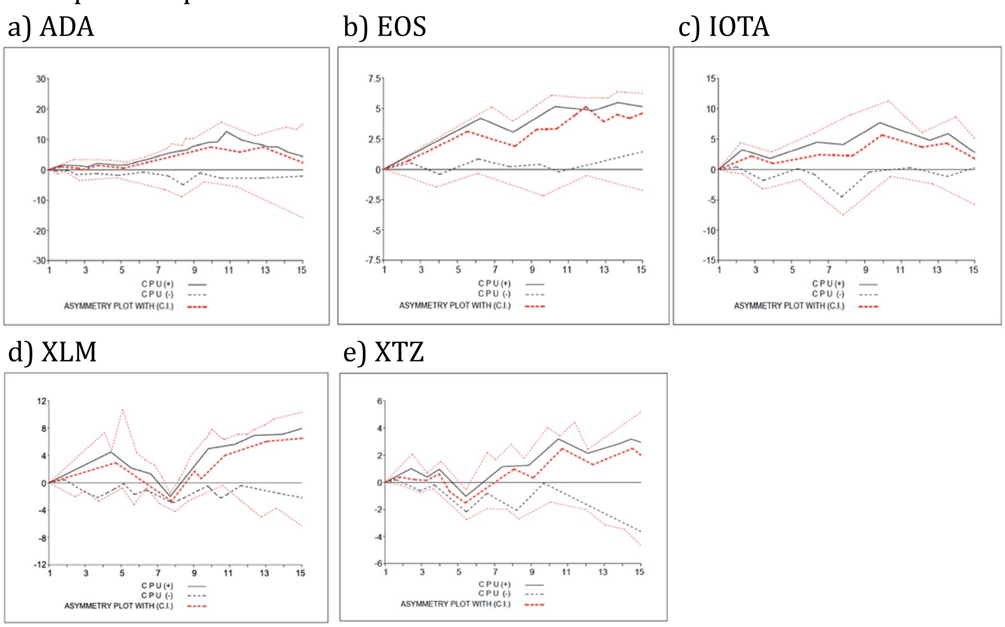
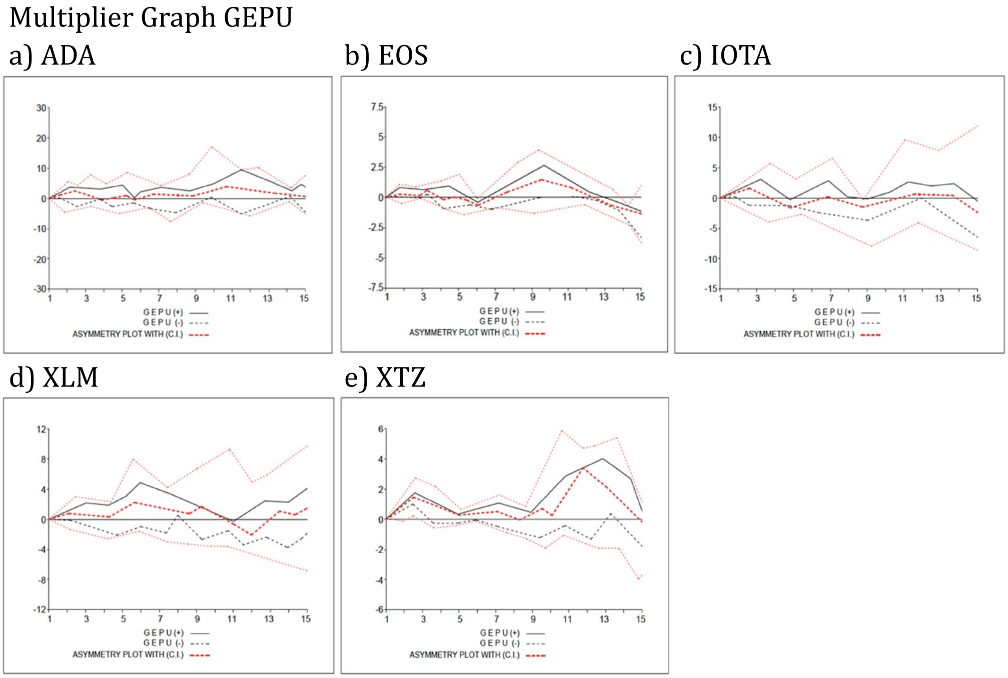


Figure 1 (continued)



Source: Author`s elaboration.

CONCLUSIONS

In light of the evolving innovations in blockchain technologies and the increasing environmental and global economic uncertainties, this study aims to investigate the safe haven and hedging potential of green cryptocurrencies by analysing the asymmetric impact of global economic uncertainty and CPU on these cryptocurrencies. In addition to the stated objective, the study further examined the short- and long-term effects of various alternative assets, including Bitcoin, green bonds, the S&P 500 index, the US dollar index, the gold index, and interest rates on the selected green cryptocurrencies. To achieve the stated objectives, the study utilised a variety of econometric tests, including standard unit root tests such as the ADF, Zivot and Andrews's, and PP tests; SB tests like BDS and Clemente-Montanes-Reyes; a bound test for long-run cointegration; and, finally, the NARDL model to determine both short- and long-run asymmetric relationships. The initial empirical findings indicate a mixed order of integration, the presence of SBs, and the existence of long-run cointegration between the selected green cryptocurrencies and the independent variables, i.e., GEPU, CPU, Bitcoin, green bonds, the S&P 500 index, the US dollar index, the gold index, and interest rates.

Finally, in the context of our main empirical estimate, the short-run and long-run NARDL models indicate the following findings. The short-run NARDL model reveals that ADA, EOS, and XLM exhibit an asymmetric relationship with CPU; with an increase in CPU, the returns of the following green cryptocurrencies increase, and vice versa. However, in the long run, all the green cryptocurrencies—i.e., ADA, EOS, IOTA, XLM, and XTZ—share an inverse asymmetric relationship. In the long term, an increase in CPU leads to a decrease in the return of the previously mentioned green cryptocurrencies, and vice versa. Moreover, in relation to GEPU, the short-run and long-run estimates indicate that all the selected green cryptocurrencies—i.e., ADA, EOS, IOTA, XLM, and XTZ—share an asymmetric relationship with GEPU. The NARDL model suggests that with an increase in GEPU, the return of all green cryptocurrencies decreases, and vice versa. From the investor's point of view, the asymmetric relationship between CPU, GEPU, and green cryptocurrencies indicates that, in the short run, investors can include ADA, EOS, and XLM in their portfolios as a risk-hedging instrument. Nevertheless, in the long run, similar to the conventional assets, an investor cannot rely on green cryptocurrencies as a safe haven or hedging financial instrument against CPU and GEPU. In the context of the other alternative assets, the short- and long-run NARDL models conclude that green bonds exert a positive impact on all the green cryptocurrencies, whereas interest rates, SPE, and gold indices exert a negative impact on all the green cryptocurrencies except for ADA in the case of SPE, which shares an insignificant relationship with SPE. It implies that within the framework of green bonds, green cryptocurrencies cannot be substituted as a safe haven; nonetheless, they can be considered as an instrument for risk diversification. Moreover, regarding interest rates, gold indices, and SPE, the selected green cryptocurrencies can be viewed as a hedge or safe-haven instrument. Finally, regarding Bitcoin and USD, the short-run and long-run NARDL estimates indicate contrary outcomes. In the short term, Bitcoin exhibits a negative correlation with EOS, IOTA, and XTZ, and a positive correlation with ADA and XLM. Whereas in the long run, Bitcoin shares a positive relationship with all the green cryptocurrencies. On the other hand, in the short run, USD shares a positive relationship, whereas in the long run, USD shares a negative relationship with all the green cryptocurrencies. From an investor's standpoint, in the short term, EOS, IOTA, and XTZ can be considered hedging instruments; however, in the long term, green cryptocurrencies cannot be viewed as a safe haven or hedging instruments for Bitcoin. However, to an extent, they can be viewed as risk-diversifying instruments. Additionally, in the context of the USD index, we can conclude that, in contrast to the short term, green cryptocurrencies can serve as hedging instruments in the long run.

The aforementioned conclusion offers important implications for investors, stakeholders, and portfolio managers. From an investor's standpoint, the asymmetric responses of green cryptocurrencies to CPU and GEPU indicate their potential as effective short-term hedging instruments. Specifically, ADA, EOS, and XLM demonstrate this capability against CPU, while all selected green cryptocurrencies, including ADA, EOS, IOTA, XLM, and XTZ, show effectiveness against GEPU. Nevertheless, their long-term inefficacy in serving as safe havens underscores their constraints in terms of long-term risk management. For policymakers, the sensitivity of green cryptocurrencies to CPU and GEPU suggests that transparent and stable economic and climate policies are required to maintain stability in the cryptocurrency market. For example, efforts must be made to maintain fiscal discipline, provide clear guidance on interest rates, and ensure macroeconomic transparency in economic policy, which could help enhance investor confidence. Likewise, policymakers must focus on prioritising the execution of robust climate policies, which may include clearly defined carbon pricing mechanisms, incentives for sustainable investments over time, and collaborative efforts on climate regulations at the international level. The implementation of these initiatives may play a significant role in mitigating the volatility associated with green cryptocurrencies. The positive relationship with green bonds explains a complementary role rather than a substitutive one, reinforcing policy initiatives aimed at fostering diversified green financial markets. From the perspective of portfolio construction, green cryptocurrencies offer diversification benefits, particularly when combined with green bonds and conventional assets, such as Bitcoin and the US dollar. The potential for risk hedging appears to fluctuate across different timeframes. Therefore, it is advisable to implement dynamic portfolio strategies that involve the selective use of green cryptocurrency assets, taking into account the current economic uncertainties and the specific investment timelines.

The current study offers valuable insights into the hedging and safe-haven potential of green cryptocurrencies in response to growing economic and climate uncertainties. Nonetheless, the study presents several limitations. Firstly, the study scope narrows down to a specific group of green cryptocurrencies and macroeconomic data, potentially ignoring a wider spectrum of market dynamics. Secondly, the application of historical data alongside the NARDL model, although robust, may not be efficient enough to capture the dynamics of evolving market structures or the rapid technological advancements within blockchain ecosystems. The analysis does not consider investor sentiment or regulatory changes, both of which could potentially impact market behaviour. Moreover, the analyses in the present study were conducted for the period 2018–2025, which encompasses the COVID-19 pandemic, so there are atypical data that may generate some distortions in the results obtained. Consequently, these limitations provide ample opportunities for future research direction. Subsequently, future studies can broaden their focus by incorporating a wider array of green digital assets, utilising high-frequency data, employing regime-switching models, and analysing the effects of emerging policy frameworks and environmental disclosures on green cryptocurrency markets.

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The authors are the sole contributors of this manuscript from idea generation to conceptualisation, data analysis and final drafting of the manuscript.

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DATA AVAILABILITY

The data are retrieved from an open repository and can be made available upon reasonable request.

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