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Araştırma Makalesi

NAVIGATING US CLIMATE POLICY UNCERTAINTY: NOVEL EVIDENCE FROM CARBON MARKETS, CRYPTOCURRENCY (DeFi), AND RENEWABLE ENERGY INNOVATIONS

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Abstract[1]

The aim of this study is to reveal the dynamics between climate policy uncertainty (CPU) and S&P Global Carbon Credit Index (CARBON), S&P Cryptocurrency DeFi Index (DeFi), and WilderHill New Energy Global Innovation Index (NEX) using data from December 2017 to March 2024 in the US. Fourier Bootstrap ARDL, Fourier Bootstrap quantile causality, and KRLS methods are used in the study. The findings reveal that there is a negative relationship between the CARBON and the CPU index in the long term. Although the DeFi does not have a statistically significant effect in the long term, it reveals that it has a negative effect on the CPU index in the short term. In contrast, the NEX has a positive relationship with the CPU index in both the short and long term. Moreover, there is a U-shaped non-linear relationship between the NEX and the CPU index, which weakens in moderate climate uncertainties and strengthens again in high uncertainty. Considering the causality results, there exists a causality from CARBON to CPU in the 2nd, 3rd, and 4th quantiles, and from CPU to CARBON in the 2nd and 3rd quantiles. Additionally, there is a causality from DeFi to CPU in the 8th quantile and from CPU to DeFi in the 1st quantile. Finally, there is a causal relationship from NEX to CPU in the 2nd, 3rd, 4th, and 5th quantiles and from CPU to NEX in the 9th quantile.

Keywords: *Climate Policy Uncertainty, Decentralized Finance* **(***DeFi), Renewable Energy, Carbon Credit.*

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ABD İKLİM POLİTİKASI BELİRSİZLİĞİNİ ANLAMAK: KARBON PİYASALARI, MERKEZİYETSİZ FİNANS (DeFi) VE YENİLENEBİLİR ENERJİ İNOVASYONLARINDAN YENİLİKÇİ KANITLAR

Öz

Bu çalışmanın amacı, ABD'de Aralık 2017 ile Mart 2024 arasındaki verileri kullanarak iklim politikası belirsizliği (CPU) ile S&P Küresel Karbon Kredi Endeksi (CARBON), S&P Kripto Para DeFi Endeksi (DeFi) ve WilderHill Yeni Enerji Küresel İnovasyon Endeksi (NEX) arasındaki dinamikleri ortaya koymaktır. Çalışmada Fourier Bootstrap ARDL, Fourier Bootstrap kantil nedensellik ve KRLS yöntemleri kullanılmıştır. Bulgular, CARBON ile CPU endeksi arasında uzun vadede negatif bir ilişki olduğunu ortaya koymaktadır. DeFi'nin uzun vadede istatistiksel olarak anlamlı bir etkisi olmasa da, kısa vadede CPU endeksi üzerinde negatif bir etkisi olduğunu ortaya koymaktadır. Buna karşılık, NEX'in hem kısa hem de uzun vadede CPU endeksi ile pozitif bir ilişkisi vardır. Ayrıca, NEX ile CPU endeksi arasında ılımlı iklim belirsizliklerinde zayıflayan ve yüksek belirsizlikte tekrar güçlenen U şeklinde doğrusal olmayan bir ilişki vardır. Nedensellik sonuçlarını göz önünde bulundurarak, 2., 3. ve 4. kantillerde CARBON'dan CPU'ya ve 2. ve 3. kantillerde CPU'dan CARBON'a bir nedensellik vardır. Ek olarak, 8. kantilde DeFi'den CPU'ya ve 1. kantilde CPU'dan DeFi'ye bir nedensellik bulunmaktadır. Son olarak, 2., 3., 4. ve 5. kantillerde NEX'ten CPU'ya ve 9. kantilde CPU'dan NEX'e doğru bir nedensellik ilişkisi bulunmaktadır.

Anahtar Kelimeler: *İklim Politika Belirsizliği, Merkeziyetsiz Finans* **(***DeFi), Yenilenebilir Enerji, Karbon Kredileri.*

INTRODUCTION

Uncertainty in climate policy has been a characteristic that mainly caused an impact on a number of fields, ranging from financial markets to investment strategy (Tommaso et al., 2024, pp.1-2). Policy direction deviations, problems with regulation, and compliance costs-an incubator of market volatility-are the reasons for cautious investing behavior receiving a counterpart (Faccini et al., 2023, p.2; Hoque & Azlan Shah Zaidi, 2020, pp.53-54; Pástor et al., 2021, pp.1-3; Wu & Liu, 2023, pp.1-2). Regulatory uncertainty involves promoting carbon pricing and emission trading schemes, which substantially influences competition and tactical investments within the energy and renewable industries (Sautner et al., 2023, pp.1449-1452). With the outstanding performance of the green firms over the brown enterprises, this hopefully raises the investors' awareness of climate risks. In this regard, the effect of uncertainty in climate policy on the stock market performance prediction is very high (Ghani et al., 2024, pp.1-2; Pástor et al., 2021, pp.1-3). It is of greater importance in both developed and emerging markets because there is a search for a balance between energy dependence and environmental sustainability (Syed et al., 2024, p.1). However, the attainment of reduction targets of carbon emissions largely depends on renewable energy investments. How climate policy uncertainty shapes investment in these sectors therefore comes out as an important issue (Ghani et al., 2024, pp.1-2; Hoque & Azlan Shah Zaidi, 2020, pp.53-54; Wu & Liu, 2023, pp.1-2). Besides that, the potential effect of Climate policy uncertainty on cryptocurrency markets would also become worthy of research concerning the consequence it has on the market's volatility and investment decisions regarding the same. These rising global environmental hazards and climate transition risks bring up, besides mushrooming economic losses, the need to construct policies effectively towards a silent sustainable future. Thus, perception and management of Climate policy uncertainty become of prime need to achieve both financial as well as environmental stability (Ghani et al., 2024, pp.1-2; Su et al., 2024, pp.1-2). Against this backdrop, two of the most pertinent questions would relate to: How does one measure uncertainty in climate policy effectively? In what way do the financial markets of the United States, considering it has the largest economy in the world, influence climate policy uncertainty while trying to balance energy dependence with environmental sustainability?

To solve this problem, Gavriilidis (2021, pp.1-9) suggested a newly constructed index of Climate Policy Uncertainty (CPU). It is measured by statements released from the US presidency combined with climate-related uncertainty as reported in US media coverage. In recent years, a growing body of literature has focused on studies related to the CPU index. A comprehensive review of these studies reveals a focus on the relationships between Climate Policy Uncertainty (CPU) and financial markets (Ameen & Afşar, 2022, pp.1-20; Bouri et al., 2022, pp.1-5; Du & Guo, 2023, pp.1-11; Ghani et al., 2024, pp.1-7; Huang, 2023, pp.1-3; Li et al., 2024, pp.1-8; Liang et al., 2022, pp.1-13; Lv & Li, 2023, pp.1-13; Mao & Huang, 2022, pp.1-14; Ozkan et al., 2024, pp.1-15; Ren et al., 2022, pp.1-11; Su et al., 2024, pp.1-11; Tedeschi et al., 2024, pp.1-5; Tommaso et al., 2024, pp.1-10; Treepongkaruna et al., 2023, pp.1-8; Wu et al., 2022, pp.1-13; Xu et al., 2023, pp. 1-16; Zhang at al., 2023, pp.1-22; Zhao & Luo, 2024, pp.1-6), decentralized finance (Dong et al., 2024, pp.1-10; Gürsoy et al., 2024, 1-14), corporate finance (Amin et al., 2023, pp.1-20; Hoang, 2022, pp.1-14; Vo et al., 2024, pp.1-10), renewable energy, and CO_2 emissions (Amin et al., 2023, pp.1-20; Athari & Kirikkaleli, 2024, pp.1-19; Cavlak, 2022, pp.1-20; Guesmi et al., 2023, pp.1-20; Işık et al., 2024, pp.1-9; Sarker et al., 2023, pp.1-11; Syed et al., 2024, pp.1-6; Tian et al., 2024, pp.1-13; Xu et al., 2022, pp.1-8; Yousfi et al., 2023, pp.1-13; Zhou et al., 2023, pp.722-732). However, most of these studies considered the impact of changes in the Climate Policy Uncertainty index on financial markets, while very few pieces of research have been conducted in US financial markets. In particular, studies investigating the impact of carbon markets and crypto markets on climate uncertainty are relatively scarce.

In this study, we aim to contribute to the literature in threefold. First, in this paper, the effects of S&P Global Carbon Credit Index (CARBON), which characterizes the price movement in the carbon credit market and represents a kind of permit purchased by U.S. companies to reduce carbon emissions, will be considered regarding CPU. Furthermore, we analyze the influence of the S&P Cryptocurrency DeFi Index DeFi, which tracks the market performance of some digital assets making possible the provision of DeFi services/products on CPU. We also analyze the effect of WilderHill New Energy Global Innovation Index NEX, which gauges the activity of companies around the world involved in renewable energy and clean technology, on the CPU. This study aims to be the first to explore how firms focus on renewable energy and innovative technologies for carbon reduction, as well as those utilizing carbon credits, interact with climate policy uncertainty, alongside the still-ambiguous role of decentralized financial assets in this context. Accordingly, this paper utilizes the latest dataset and explores the short and long run relationships of the variables using the recently proposed Fourier Bootstrap ARDL cointegration test, which considers smooth transitions in structural breaks and further enhances the robustness of the estimated results. Therefore, the present study reinvestigates the low-medium-high quantile causal linkages of CARBON, DeFi, and NEX with CPU by applying the newly developed Fourier Bootstrap Quantile Causality test to give a current contribution to the literature.

Our findings show that, though the long run cointegration is negative between the firm performance in the CARBON market and CPU, it is positive between firm performance investing in renewable energy and innovative technology, NEX. We find no evidence to support or establish the cointegration relationship in the long run between DeFi and climate policy uncertainty, CPU. On the other hand, the results indicate that in the short run, both in the current period and in the two-lagged periods, decentralized finance (DeFi) negatively impacts climate policy uncertainty (CPU), while in the short run, climate policy uncertainty (CPU) positively influences the performance of firms investing in renewable energy and innovative technology (NEX). In the short term, the performance of firms in the carbon credits (CARBON) market has no effect on the uncertainty about climate policy. Causality results we find evidence of causality from the performance of firms in the carbon credits (CARBON) market to climate policy uncertainty from the 2nd, 3rd, and 4th quantiles, and from climate policy uncertainty to the performance of firms in the carbon credits market from the 2nd and 3rd quantiles. There is a causal relationship from decentralized finance (DeFi) to climate policy uncertainty (CPU) in the 8th quantile, while there is a causal relationship from climate policy uncertainty (CPU) to decentralized finance (DeFi) in the 1st quantile. We find evidence of causality from the performance of firms that invest in renewable energy and innovative technology, NEX, to the uncertainty of climate policy, CPU, in the 2nd, 3rd, 4th, and 5th quantiles and from CPU to NEX in the 9th quantile.

In the following sections of this study, the second section presents the literature review, the third section covers the dataset and methodology, the fourth section discusses the empirical findings, and the fifth section provides the conclusion and policy recommendations.

LITERATURE REVIEW

This study aims to analyze the effects and possible impacts that these following indices will produce on CPU: New Energy Global Innovations in the United States, the decentralized finance cryptocurrency system, and world carbon credits. Gavriilidis (2021, pp.1-9) has constructed a new Climate Policy Uncertainty-CPU index by using news reports about climate policy. This index indicates a robust negative relationship between climate policy uncertainty and carbon dioxide (CO_2) emissions through the analysis of news reports that incorporate uncertainties related to climate policy events. The CPU Index indicates that emissions may decrease during periods of considerable uncertainty owing to changes in corporate financial behaviors or the government's contradictory position. It is now an efficient proxy for the social and political turmoil about climate policy, indicating the role of the public conversation in policy output and environmental action. This indicator has gained momentum since events like the introduction of new emission standards to worldwide protests on climate change, and announcements by the U.S. This position highlights the substantial impact of political and social variables on the uncertainties surrounding climate policy. The literature has proposed the Climate Policy Uncertainty (CPU) index as a new tool for understanding uncertainties related to climate policy. Several studies have utilized the CPU index in recent years, garnering significant academic attention. The CPU index is influenced by pronouncements from the U.S. government and media reporting, raising the relevant research issue of whether these communications are affected by financial markets. This research comprehensively assesses the literature on the CPU index, classifying the associations between CPU and financial markets, decentralized finance, corporate finance, renewable energy, and CO_2 emissions into four thematic categories.

The first strand of the literature review, the works on the Climate Policy Uncertainty Index in the financial markets, can be considered along three subgroups: China, Europe, and the USA. Research on China has explored, quite comprehensively, the multifaceted effects of CPU on the country's financial markets. Indeed, Zhao and Luo (2024, pp.1-6) focused on the green indices of China, and their findings revealed that local CPU and general climate uncertainty (CU) have significant effects on China's green market movement, while the US's CPU has not had a very crucial impact. This finding underscores the central role of China-specific climate policies in shaping local market dynamics. Li et al. (2024, pp.1-8) investigated stock price synchrony (SYN) in Chinese firms. Researchers have demonstrated a significant decrease in SYN owing to

CPU, especially in high-pollution industries. The effect has intensified after the ratification of the Paris Agreement, signifying the increasing influence of climate policy on market dynamics. Xu et al. (2023, pp.1-16) assessed the nonlinear and lagged effects of CPU indices on stock market behaviors in China and the U.S., finding significant cross-country differences between the influence of CPU on returns and volatility. In fact, Lv and Li (2023, pp.1-16) researched the predictive power of CPU over sector-specific market volatility in China and found that this factor has a great influence on the utilities sector. How large the impact varies significantly between different levels of volatility and at different moments in time, reflecting the unique way in which CPU influences sector dynamics. Mao and Huang (2022, pp.1-14) investigated the influence of CPU on green innovation. The study suggests that CPU has impeded green innovation by intensifying funding limitations, whereas government subsidies somewhat alleviate these impacts. Ren et al. (2022, pp.1-11) investigated the impact of CPU on firm-level total factor productivity (TFP), determining that CPU adversely affects TFP, especially in non-state-owned and capital-intensive enterprises, by hindering R&D investments. Du and Guo (2023, pp.1-11) examined the role of green credit policy (GCP) in promoting green innovation and showed that while CPU supports GCP's effectiveness, high levels of uncertainty weaken this relationship, potentially undermining green financing efforts. Lastly, Zhang et al. (2023, pp.1-22) assessed the negative impact of CPU on corporate investment efficiency (CIE), particularly in non-state-owned and technology-intensive firms. They also noted that leadership quality plays a crucial role in mitigating CPU's adverse effects.

Empirical evidence conducted in Europe takes a broader perspective on the effects of CPU on financial markets. Tommaso et al. (2024, pp.1-10) developed an Italy-specific CPU index and demonstrated that rising uncertainty negatively impacts Italy's financial market performance, leading to reduced market stability and performance. Tedeschi et al. (2024, pp.1-5) examined the influence of CPU on European stock markets, revealing a positive effect on clean energy stock returns and a negative impact on crude oil stocks, particularly following the COVID-19 pandemic. Their findings indicate that CPU promotes investment in sustainable assets and highlights the significance of CPU in risk mitigation strategies during periods of uncertainty. Su et al. (2024, pp.1-11) investigated the influence of CPU on the European Union Emissions Trading System (EU ETS) and identified a positive correlation with carbon trading prices (CTP) in the medium to long term, although short term effects were mixed. The above points to the importance of CPU in determining carbon market stability and the roles of pricing strategies. Wu et al. (2022, pp.1-11) applied the EGARCH-MIDAS-CPU in predicting the volatility of EUAF and proved that CPU dampens volatility, hence stable policies can work in ensuring carbon market stability. This paper investigates the impact of CPU on European markets by means of a variety of financial instruments.

Moreover, the issue of CPU has been addressed in many studies conducted solely in the US context regarding green financial markets. Ghani et al. (2024, pp.1-7) conducted an analysis of the ESG and CPU indices to ascertain and analyze the influence both factors have on volatility within the United States stock market with regard to predictive performance outputs. It was from these analyses that the two indices were significant in predicting the financial market risk involved during situations of uncertainty and thus indicated the importance of CPU in financial risk management. Huang (2023, pp.1-3) examine the stifling effect of CPU on the green patenting activity of U.S. firms and showed how such uncertainty tends to crowd out investments in low-carbon innovations that are an essential ingredient of technological progress. Husain et al. (2022, pp.1-15) studied the sensitivity of the U.S. green markets towards CPU and noticed that the green equities were pretty responsive compared to green bonds, particularly so in bear market conditions, pointing toward possible portfolio diversification benefits. Ameen and Afşar (2022, pp.1-20) analyzed the impact of CPU on the US petroleum market. Their findings reveal that there is no causality between CPU and petroleum market indices, indicating a low level of interaction and slow market efficiency in response to climate-related risks. Ozkan et al. (2024, 1-15) reveal that the interconnectedness between clean energy, green, and sustainable markets and found that the CPU enhances interconnectedness between these markets. This finding then implies the spillover effects of the CPU factor across segments. In fact, using U.S. stocks, Treepongkaruna et al. (2023, pp.1-8) have documented that a CPU factor outperforms conventional size and value factors in terms of cross-sectional variation in U.S. stock returns. They emphasized the significance of CPU in asset pricing models, particularly in a world characterized by climate uncertainty. Liang et al. (2022, pp.1-13) discovered that CPU serves as a highly effective predictor of renewable energy market volatility, surpassing other uncertainty indices, and is thus a crucial factor in improving renewable energy market stability. Bouri et al. (2022, pp.1-5) present evidence illustrating the substantial impact of CPU on the performance of green and brown energy equities. They documented that investors regard green assets as safe haven asset in during crises, highlighting the significant influence of CPU on investor preferences and market strategies.

A second strand of the literature review shows the relationships between CPU and energy prices, carbon emissions, and Bitcoin dynamics. Gürsoy et al. (2024, pp.1-14) investigate interdependencies between CPU variables, clean energy prices, carbon allowance prices, and returns of the Bitcoin currency. Their findings indicate that there is a positive relationship between BTC with carbon emission prices and CPU, while it is negatively associated with clean energy prices. These results show that the higher carbon costs and regulatory uncertainties could affect Bitcoin returns, which thus appear somewhat sensitive to climate policy. Dong et al. (2024, pp.1-10) discuss the determinants of the Bitcoin carbon footprint, which tends to prove that the US dollar decreases the BCF more significantly in comparison with other assets, while fossil fuels increase BCF at low quantiles. Renewable energy, in turn, cut BCF consistently across all levels. On the other hand, the indices of economic policy uncertainty, CPU, and market volatility have been found to have a negative impact on BCF, especially in extreme quantiles; thus, such uncertainties indirectly restrain the environmental impact of mining Bitcoins. These studies, together, put the sources of energy and policy uncertainties at the heart of shaping Bitcoin's returns and carbon footprint, with multi-faceted impacts of the regulatory and market factors on crypto-currency-related environmental outcomes.

In the third strand of the literature review, a critical review is given with respect to how CPU influences CSR, tax avoidance, and R&D investments. Vo et al. (2024, pp.1-10), in studying the effects of CSR investments, indicate that CPU persuades companies to increase their CSR activities as a means of reduction of policy-related risks and reducing their debt. This is particularly true of those industries that are highly carbon intensive. Therefore, companies view CSR as a method of reducing uncertainties and possible regulatory limitations. Amin et al. (2023, pp.1-20) also find that firms adopt more aggressive corporate tax avoidance strategies due to higher levels of CPU. The cash savings due to reduced tax payments are utilized for dividends and not for investment-a prudent strategy, considering the uncertainty of the policy situation. On the other hand, Hoang (2022, pp.1-14) presents the fact that CPU exerts a negative impact on R&D investments by high emission US enterprises because the latter are induced to adopt a "wait-and-see" attitude, whereas general firms prefer to expand R&D under CPU. The impact of CPU on R&D investments is also contingent upon technological uncertainty, management sentiment, managerial ability, and firm maturation. This suggests that leadership qualities have a substantial impact on strategic responses to policy uncertainty. These studies demonstrate that CPU exerts a multifaceted influence on CSR, tax strategies, and R&D spending. They emphasize the necessity for robust climate regulations to mitigate the adverse effects of CPU on sustainable innovation, particularly in high-emission industries.

The fourth strand of the literature review: we explore the relationship between climate policy uncertainty and Renewable Energy (RE), and these press for direct effects and nuanced effects of CPU on energy policy. Tian et al. (2024, pp.1-13) examine the asymmetric effects of AI and CPU on the development of RE in China, showing that AI has a positive effect on RE, especially under an unfavorable economy, and reduced CPU significantly enhances the RE investment by enabling a favorable policy environment that can promote such investment. In this respect, Athari and Kirikkaleli (2024, pp.1-19) use the wavelet power spectrum and wavelet coherence methods in order to show the time-varying causality between CPU and the Renewable Energy and Clean Technology Index. They underline that RECT caused CPU until 2018, while thereafter CPU started to affect RECT, reflecting an increase in interdependence between policy and clean energy sectors. Zhou et al. (2023, pp.722-732) estimate a time-varying parameter model and find evidence that CPU generally increases the price of oil and renewable energy consumption, with heterogeneous effects across the different renewables. Sarker et al. (2023, pp.1-20) also show asymmetric impacts of CPU, geopolitical risk, and oil price on clean energy return and volatility; the increase in CPU thus indicates stronger positive short run impacts on clean energy returns, while its decline negatively shocks the prices of clean energy, thus showing the complicated nexus between uncertainty and energy market behavior. Along the same vein, Xu et al. (2022, pp.1-8) demonstrate that the CPU index is an effective predictor of global RE market returns and that its predictive power increased after the Paris Agreement, thus indicating the importance of CPU in asset allocation decisions for energy markets. Cavlak (2022, pp.1-20) also finds asymmetric impacts of increasing and decreasing renewable energy consumption and oil price on CPU, which shows that energy market dynamics significantly influence uncertainties related to climate policy. Finally, Syed et al. (2024, pp.1-6) find that CPU exerts a negative impact on renewable and non-renewable energy productions across various quantiles and time frequencies of the U.S., thus justifying the fact that high CPU diminishes investments and their productions in the energy sectors. Besides results of previous studies, these findings underline that clearly defined and stable climate policies are urgently required to avoid uncertainty deterring renewable energy development and point to complex interdependencies of policy uncertainty, the dynamics of energy markets, and renewable progress.

On the other hand, the literature comprehensively discusses not only how climate policy uncertainty influences CO_2 emissions but also under what conditions and to what extent. Işık et al. (2024, pp.1-9) suggest the ratio of domestic exports/re-exports as a new determinant of environmental pollution models and recognize that higher shares of re-exports reduce CO_2 emissions in the U.S., while CPU does not have an effective impact on the variation of CO_2 levels. That means an increase in CPU within the U.S. does not directly affect raising or lowering the levels of emissions. This simply shows that policy uncertainties have limited direct influences on pollution. Yousfi et al. (2023, pp.1-13) investigate the nexus of business conditions and changing climate policy with CO_2 emissions. They find that such a relationship is pre-set by economic conditions, and it becomes more complex, even bidirectional, when the economy goes through crisis modes such as the COVID-19 pandemic. They find that the changes in climate policy have higher impacts on CO_2 emissions across fluctuating business conditions; hence, policy stability is crucial in controlling the United States' emissions. Guesmi et al. (2023, pp.1-20) apply a Factor-Augmented Vector Autoregressive model in quantifying the impacts of climate risk and CPU on CO_2 emission within the U.S. and find out that political disagreements and natural disaster costs have major roles in determining reductions for emissions and renewable energy consumption. They have seen political conflicts increased, leading to an improvement in CO_2 emissions and hence explaining the variability in the use of renewable energy since partisan dynamics influence energy and emission performance. In addition, natural disasters heighten conflictive CPU and political consensus, an indication of the disrupting role of climate events in stability and consensus in policy making. All these studies together provide detailed evidence on how the CPU impacts CO_2 emissions and show just how different economic and political factors mold the relationship.

DATA AND METHODOLOGY

Data

In this study, we examine the effects of the S&P Global Carbon Credit Index, the S&P Cryptocurrency DeFi Index-USD, and the WilderHill New Energy Global Innovation Index on Climate Policy Uncertainty Index (CPU) using monthly time series data between December 2007 and March 2024. We use Climate Policy Uncertainty Index (CPU) as a dependent variable. Gavriilidis (2021, pp.1-9) calculated the Climate Policy Uncertainty (CPU) index as the ratio of the number of news articles containing specific climate – related terms and policy statements to the total number of news articles in eight major newspapers in the US since April 1987. The author created a monthly CPU index by normalizing these data obtained from newspapers over their standard deviation and mean values. The first independent variable of this study, the S&P Global Carbon Credit Index (CARBON), is an index that measures price movements in the carbon credit market. Carbon credits are permits purchased by companies to limit or reduce their carbon emissions (carbon footprint). This index tracks the cost of carbon credits and market trends for companies seeking to reduce their carbon emissions and combat climate change through carbon trading. The second independent variable, S&P Cryptocurrency DeFi Index-USD (DeFi), is an indicator of decentralized finance. This index tracks the performance of cryptocurrencies within the decentralized finance DeFi ecosystem. This index also reflects the price changes of cryptocurrencies (e.g., Ethereum, Chain-link, etc.) that are important in the DeFi space and show the performance of these assets for investors. DeFi is based on block chain technologies that enable the delivery of traditional financial services through decentralized platforms. The third independent variable, the WilderHill New Energy Global Innovation Index (NEX), measures the performance of companies operating globally in renewable energy and clean technology. This index includes companies operating in clean energy sectors such as solar, wind, and biofuels and tracks the overall trend of investments in these sectors. The Climate Policy Uncertainty Index (CPU), the S&P Global Carbon Credit Index

(CARBON), the S&P Cryptocurrency DeFi Index-USD (DeFi), and the WilderHill New Energy Global Innovation Index (NEX) are compiled from their official websites and they are shown in table 1.

Table 1: Variables and Databases

Proxy	Variables	Database
CPU	Climate Policy Uncertainty Index	https://www.policyuncertainty.com/climate_uncertainty.html, (accessed on 3 August 2024).
CARBON	S&P Global Carbon Credit Index	https://www.spglobal.com/spdji/en/indices/commodities/sp-global-carbon-credit-index/#overview, (accessed on 3 August 2024).
DeFi	S&P Cryptocurrency DeFi Index	https://www.spglobal.com/spdji/en/indices/digital-assets/sp-cryptocurrency-defi-index/#overview, (accessed on 3 August 2024).
NEX	WilderHill New Energy Global Innovation Index	https://cleanenergyindex.com/, (accessed on 3 August 2024).

The mean and median values of CPU and NEX have the highest value in the dataset. The lowest average and widest range occur for the DeFi index, so we can say that it is extremely volatile. This same fact is supported by the large standard deviation for DeFi. In doing so, there is more variation in CARBON and DeFi relative to other indices. Skewness and kurtosis reveal that DeFi follows a positively skewed and leptokurtic distribution; hence, there exist extreme values. Moreover, the Jarque – Bera test statistic has ensured that none of the indices are normally distributed ($p > 0.05$). From the analysis of correlation, it is observed that CPU depicts a positive and significant association, as evidenced by CARBON and NEX. In addition, CARBON shares the strongest positive correlation with NEX, and DeFi shows significant negative correlations with other indices, such as with CPU. From these results, we can indicate that there is no high correlation among the independent variables; thus, suitability for the regression analysis process is ensured.

Table 2: Descriptive Statistics and Correlation Matrix

	CPU	CARBON	DeFi	NEX
Mean	201.54	441.88	56.06	270.56
Median	203.61	365.38	32.96	246.15
Maximum	411.29	740.98	286.25	494.29
Minimum	79.47	122.86	15.07	148.54

Std. Dev.	61.68	209.07	54.49	95.21
Skewness	0.59	0.13	2.22	0.54
Kurtosis	3.91	1.35	8.36	2.07
Jarque-Bera	6.97**	8.87***	153.26***	6.50**
Probability	0.031	0.012	0.000	0.039
Sum	15317	33583	4261	20563
Sum Sq. Dev.	285293	3278177	222657	679940
Observations	76	76	76	76
CPU	1.000			
CARBON	0.381***	1.000		
DeFi	-0.237***	-0.218***	1.000	
NEX	0.366***	0.535***	0.210*	1.000

Note: "*", "**" and "***" indicates statistical significance at 10, 5 and 1% level, respectively. The Climate Policy Uncertainty Index, S&P Global Carbon Credit Index, S&P Cryptocurrency DeFi Index, and WilderHill New Energy Global Innovation Index represent CPU, CARBON, DeFi, and NEX, respectively.

Methodology

In econometric analyses, whether a series or multiple series fluctuates around some type of mean, in other words, whether they are stationary, is of paramount importance in properly choosing the appropriate tests and analyses. There have been tests carried out with several methods both without as well as with structural breaks. New approaches recently used include tests incorporating Fourier functions. One such test is the Fourier ADF unit root test devised by Enders and Lee (2012). The Fourier series defined as an expansion of a periodic function "y_t" into the sum of cosines and sines. The main strength of this test lies in its consideration of structural breaks with smooth transitions, by which one can observe and identify abrupt changes in the series, too. Christopoulos and León-Ledesma (2010) and Yilanci and Eris, (2013) further support these strengths of the Fourier ADF test; hence, this study has chosen to conduct the test with the following model specification:

$$y_t = \lambda_0 + \lambda_1 \sin\left(\frac{2\pi kt}{T}\right) + \lambda_2 \cos\left(\frac{2\pi kt}{T}\right) + v_t \tag{1}$$

Where, "T" represents the sample size, "λ1" and "λ2" are the Fourier coefficients, "π" is the constant 3.1416, and "k" is the frequency value used to find the optimal value that minimizes the sum of squared residuals.

The equation $\lambda_0 + \lambda_1 \sin\left(\frac{2\pi k t}{T}\right) + \lambda_2 \cos\left(\frac{2\pi k t}{T}\right)$ has been developed as a Fourier function form capable of capturing several smooth structural breaks in y_t unknown form. In Equation 1, "*k=1,2,3….*" represents the number of frequencies in the Fourier function, "*t",* denotes the trend term, "*T*", stands for the sample size, and π is the mathematical constant approximately equal to 3.1416. According to Equation 1, the null hypothesis assumes that v_t has a unit root, while the alternative hypothesis suggests that v_t exhibits linear or nonlinear stationarity (Zhou & Kutan, 2014).

In the time series analyses, there are two critical issues: stationarity tests or, in other words, whether the series has a unit root, and analysis of whether there is a cointegration relationship among the series when there exists a unit root. If the series are stationary at different levels, traditional time series analysis is not appropriate (Fendoğlu & Gökçe, 2021). To solve this problem, Pesaran et al. (2001) put forward the ARDL bounds testing approach. This test allows researchers to use a dependent variable in *I*(1) form and independent variables in *I*(1) and *I*(0) forms. The ARDL approach is essentially based on F and t statistics. It specifically considers the upper and lower critical bounds, defined as *I*(1) and *I*(0), respectively. Where the critical value of the upper bound is surpassed by the test statistic from the ARDL, the null hypothesis would be rejected. The null essentially postulates that no cointegration relationship exists. The following can be expressed using the ARDL model developed by Pesaran et al. (2001):

$$\Delta CPU_t = \beta_0 + \beta_1 CPU_{t-1} + \beta_2 CARBON_{t-1} + \beta_3 DeFi_{t-1} + \beta_4 NEX_{t-1} + \sum_{i=1}^{p-1} \varphi_i' \Delta CARBON_{t-i} + \sum_{i=1}^{p-1} \theta_i' \Delta DeFi_{t-i} + \sum_{i=1}^{p-1} \omega_i' \Delta NEX_{t-i} + e_t \quad (2)$$

Where, Δ represents the first-difference operator, and p denotes the lag length, while e_t represents the error term. The optimal lag length is determined based on the Akaike Information Criterion (AIC). According to Pesaran et al. (2001), to establish the existence of a cointegration relationship using the ARDL approach, the null hypotheses $H_{0A}: \beta_1 = \beta_2 = \beta_3 = 0$ and $H_{0B}: \beta_1 = 0$ must be rejected, taking into account the F and t test statistics (Fendoğlu & Gökçe, 2021).

In the ARDL process, test statistics obtained from both bounds upwards and downwards do not conclude with certainty whether there is cointegration between the series. Therefore, to overcome this limitation, Pesaran et al. (2001) extended the ARDL model by incorporating hypothesis $H_{0C}: \beta_2 = \beta_3 = 0$and computed F-statistic (F_b) through bootstrapping methods (McNown et al., 2018). Through this approach, one is required to reject all the three hypotheses in order to conclude the existence of the cointegration relationship between the series. This newly proposed method also underlines that ARDL approach does not impose any restriction on the different integration orders of the explanatory variables and provides more robust results as compared to traditional ARDL approaches (McNown et al., 2018).

Although the Fourier function incorporated into the ARDL method has strengthened the test, structural changes in the time series can negatively affect the strength of the relationship between the series. To address these adverse effects of structural breaks on the Fourier ARDL test, Yilanci et al. (2020) introduced several enhancements, thereby improving the robustness of the Fourier ARDL test. The Fourier function in sine and cosine formats, as proposed by Yilanci et al. (2020) for the ARDL model, is expressed as follows:

$$d(t) = \sum_{k=1}^{n} a_k \sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} b_k \cos\left(\frac{2\pi kt}{T}\right) \tag{3}$$

Here, "*k*" represents the selected specific frequency number, *"n"* denotes the frequency number, "$\pi = 3,1416$" is the mathematical constant, *"t"* indicates the trend term, and *"T"* represents the sample size. In the model, the single-frequency framework proposed by Becker et al. (2006) and Ludlow and Enders, (2000) is considered, as described below (Fendoğlu & Gökçe, 2021):

$$d(t) = \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) \tag{4}$$

Within the framework of the model established in this study, the Fourier ARDL model developed by Yilanci et al. (2020) is expressed as follows:

$$\Delta CPU_t = \beta_0 + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \beta_1 CPU_{t-1} + \beta_2 CARBON_{t-1} + \beta_3 DeFi_{t-1} + \beta_4 NEX_{t-1} + \sum_{i=1}^{p-1} \varphi_i' \Delta CARBON_{t-i} + \sum_{i=1}^{p-1} \theta_i' \Delta DeFi_{t-i} + \sum_{i=1}^{p-1} \omega_i' \Delta NEX_{t-i} + e_t \tag{5}$$

Since this study analyzes the stationarity and cointegration relationships of the series with Fourier functions, the causality relationships between the series are also investigated using the Fourier Quantile Causality test developed by Cheng et al. (2021) abbreviated as BFGC-Q. This test has been designed to specifically respond to the shortcomings of the Fourier Toda-Yamamoto causality test as set forth by Nazlioglu et al. (2016), which does not take into account nonlinear causalities and tail-causality relationships revealed by Akyol et al. (2023). This methodology is critically contributing to the literature with respect to a robust causality test to complement a number of tests stemming from the standard Granger causality framework that Fareed et al. (2021) have mentioned.

The null hypothesis of the Fourier Quantile Causality (BFGC-Q) test, stated as "does not cause" is tested using two procedures. In the first stage, to control smooth transitions in structural breaks, the deterministic term *d(t)*, which is part of the Fourier expansion function as shown in Equation (2), is incorporated into the Granger causality equation as follows:

$$Y_t = \gamma_0 + \gamma_1 \sin\left(\frac{2\pi kt}{T}\right) + \gamma_2 \cos\left(\frac{2\pi kt}{T}\right) + \sum_{i=1}^{p+h} \theta_i Y_{t-i} + \sum_{j=1}^{m} \sum_{i=1}^{p+h} \vartheta_{j,i} X_{j,t-i} + \varepsilon_t \quad (6)$$

Here, *Y* and *X* represent the dependent and independent variables, respectively, "p" denotes the lag length, "h" represents the maximum order of integration, and "m" refers to the number of covariates. To estimate Equation (2), the optimal value of "k" is identified as k^*; "s", and the appropriate lag length is denoted as p^*. After this process, for each "(i = 1,2,3,…,p)", the Akaike Information Criterion (AIC) is used to determine the appropriate lag length p^* and to select the $k = k^*$ value that minimizes the Sum of Squared Residuals SSR. In this stage, the null hypothesis $\gamma_1 = \gamma_2 = 0$ is tested using the standard restricted *F* test statistic. Once k^* and p^* are selected, Equation (2) is estimated not use the OLS estimator but instead with quantile regression, as expressed below:

$$\begin{aligned} Q_{Y_t}(\tau \mid \mathrm{Z}) = \gamma_0(\tau) + \gamma_1(\tau) \sin\left(\frac{2\pi k^* t}{T}\right) + \gamma_2(\tau) \cos\left(\frac{2\pi k^* t}{T}\right) \\ + \sum_{i=1}^{p^*+h} \theta_i(\tau) Y_{t-i} + \sum_{i=1}^{p^*+h} \vartheta_{j,i}(\tau) X_{j,t-i} + \varepsilon_t \end{aligned} \quad (7)$$

The *Z* value represents the entire covariance matrix of regression Equation (7). Using this approach, Equation (7) is estimated via the quantile regression method, allowing for testing at different quantiles, $\tau \in (0,1)$. The null hypothesis, "no causality (X↛⊖Y)" can then be tested as follows:

$$\mathrm{H}_0: \hat{\vartheta}_{j,1}(\tau) = \hat{\vartheta}_{j,2}(\tau) = \cdots = \hat{\vartheta}_{j,p^*}(\tau) = 0,\ \forall \tau \in (0,1) \quad (8)$$

The null hypothesis of "no causality" (X↛⊖Y) is tested under the constraint of Hypothesis (8) using the Wald test, which is calculated as follows:

$$\mathrm{Wald} = \left[\mathrm{T}\left(\left(\hat{\vartheta}_j(\tau)\right)' \left(\hat{\Omega}(\tau)\right)^{-1} \left(\hat{\vartheta}_j(\tau)\right)\right)\right] / \tau(1-\tau) \quad (9)$$

Here, "$\hat{\vartheta}_j(\tau)$") represents the estimated coefficient vector for the τ quantile, and $\hat{\Omega}(\tau)$ is the consistent estimator of the variance-covariance matrix for $\hat{\vartheta}_j(\tau)$. Cheng et al. (2021) emphasize that during the development of the Fourier Quantile Causality test, issues such as autoregressive conditional heteroscedasticity (ARCH) effects—commonly observed in data—could lead to deviations from asymptotic distributions of the Wald statistic, particularly when the data do not exhibit normal distribution (Hatemi-J & Uddin, 2012). To overcome this issue, the approach includes critical values at the 10%, 5%, and 1% significance levels obtained from empirical distributions underlying the their method. In addition, a simulation method using 10,000 iterations tests the null hypotheses of sine and cosine terms in Equation, which uses a restricted F statistic.

To give the robustness to the results, we also use KRLS (kernel-based regularized least squares) method developed by Hainmueller and Hazlett, (2014). The machine learning-based KRLS approach has gained much popularity in finance due to its several advantages. For instance, its applicability for nonlinear models, flexibility in accommodating classical regression assumptions, interpretation of complex relationships, the computing of marginal effects efficiently on its radial basis functional structure, optimization model performance based on the metric of leave-one-out loss, automatic selection of hyper parameters, such as kernel bandwidth and regularization parameter, applicability to small samples and high-dimensional datasets, and finally being able to allow for heterogeneity of effects of independent variables on the dependent variable make the KRLS approach robust method in quantitative research. The partial derivatives taking part in the KRLS approach can be represented in an elaborate, short mathematical form shown in equation 10:

$$\frac{\delta_{\hat{y}}}{\delta x_j^{(d)}} = \frac{-2}{\sigma^2} \sum_i c_i e^{\frac{-x_i - x_i^2}{\sigma^2}} \left(x_i^{(d)} - x_j^{(d)} \right) \tag{10}$$

Here, $\frac{\delta_y'}{\delta x_j^{(6)}}$ is the derivative of the Climate Policy Uncertainty (CPU), with respect to the S&P Global Carbon Credit Index (CARBON), S&P Cryptocurrency DeFi Index-USD (DeFi), WilderHill New Energy Global Innovation Index (NEX) have evaluated at a given point. c_i represents scaled and weighted predictors. Meanwhile, σ^2 is the kernel bandwidth; "i" is the total number of observations, while "j" is an individual observation. In order to analyze the marginal effects of the input variables in the KRLS method, one calculates the partial derivatives of the dependent variable individually for each independent variable. The estimation of KRLS is expressed in equation (11):

$$\mathrm{CPU}_{2_t} = \lambda\, CPU_{2_{t-1}} + \delta_1 \text{ CARBON }_{t-1} + \delta_2 \text{ DeFi }_{t-1} + \delta_3 \text{ NEX }_{t-1} + \upsilon_t \tag{11}$$

KRLS models provide a closed-form estimation of pointwise marginal derivatives and assess the marginal effects of covariates for each individual data point (Kartal et al., 2023). In equation (11), λ and δ_1 to δ_3 represent the mean marginal effects calculated through the KRLS method. υ_t, is the error term of the machine learning model estimation. Additionally, the KRLS approach enables the visualization of increasing or decreasing returns through graphical representations of average binary marginal effects. This method effectively captures and highlights the interactions between the pointwise marginal derivatives of a variable and other parameters (Choi & Lee, 2020).

EMPIRICAL RESULTS

In the first step of the analysis, we explored the stationarity level of the series. We conducted Fourier ADF unit root tests for stationarity and presented them in Table 3. Due to the findings, strongly non-stationary variables of CPU, DeFi, and NEX variables were in constant and constant & trend models. From the constant model, at 5% and 10%, respectively, we could observe that the CARBON variable is stationary. However, in a constant and trend model, it is not stationary at all levels. Thus, we realized that there is a high tendency of non-stationarity of the CARBON variable. Moreover, the analyzed results depict that all series are not stationary at the first deference from the constant and constant & trend model. We therefore concluded that all series are stationary at the *I*(1).

Table 3: Fourier ADF Unit Root Test Results

Variables	Test Stats.		Critical values			Test Stats.		Critical values		
	Constant	ψ	1%	5%	10%	Constant & Trend	ψ	1%	5%	10%
CPU	-2.66	3	−3.77	−3.07	−2.71	-2.27	3	−4.45	−3.78	−3.44
CARBON	-3.89**	1	−4.42	−3.81	−3.49	-3.25	1	−4.95	−4.35	−4.05
DeFi	-2.31	2	−3.97	−3.27	−2.91	-1.51	2	−4.69	−4.05	−3.71
NEX	-2.96	1	−4.42	−3.81	−3.49	-2.90	1	−4.95	−4.35	−4.05
ΔCPU	-13.29***	5	−3.58	−2.93	−2.60	-13.21***	5	−4.20	−3.56	−3.22
ΔCARBON	-9.07***	2	−3.97	−3.27	−2.91	-9.15***	1	−4.95	−4.35	−4.05
ΔDeFi	-3.69***	4	−3.64	−2.97	−2.64	-4.81**	1	−4.95	−4.35	−4.05
ΔNEX	-8.25***	1	−4.42	−3.81	−3.49	-8.21***	1	−4.95	−4.35	−4.05

Note: "*", "**" and "***" indicates statistical significance at 10, 5 and 1% level, respectively. "Ψ" represent Fourier number. The null of the Fourier ADF unit root test would be designed as "there exists a unit root=the series is not stationary." The test statistics computed hereby are then compared to the critical values provided by the study of Enders and Lee (2012) in order to analyze whether a unit root exists. If the absolute value of the Fourier ADF test statistics are less than the critical values, the null hypothesis of non-stationarity cannot be rejected. Otherwise, in the case where the test statistic in absolute value is greater than the critical values, the null hypothesis of non-stationarity is to be rejected against all the alternatives, indicating that the series is stationary.

Table 4: Fourier Bootstrap ARDL Test Results

FARDL Model a: (1,0,0,1)	
FARDL Model b: (1,0,0,1)	k=3.20
FARDL Model c: (1,0,0,1)	AIC: 0.224866

FARDL Model d: (1,2,1,1)				
		Bootstrap Critical Values		
	Test Statistics	10%	5%	1%
F_a	8.06	4.85	5.47	7.38
t	-5.54	-3.88	-4.25	-5.07
F_b	3.60	5.01	5.93	7.91

Note: "*", "**" and "***" indicates statistical significance at 10, 5 and 1% level, respectively. "k" represents the optimal number of frequencies; and "AIC" refers to the Akaike information criterion test statistic. The null hypothesis of the FARDL cointegration test, similar to the classical ARDL test, is formulated as "Ho: There is no cointegration relationship between the series." If the FARDL test statistic is greater in absolute terms than the bootstrap critical values, it can be concluded that there is a cointegration relationship between the series; otherwise, no cointegration relationship is present.

According to the Fourier ADF unit root test results, the fact that all series are stationary at the $I(1)$ level raises the question of whether there is a cointegration relationship among the series. In the second stage of the analysis, we examined the existence of a long term relationship between CPU and CARBON, DeFi, and NEX using the Fourier ARDL bootstrap cointegration test, and the results are presented in Table 4. The results show that there exists a cointegration relationship between the series, according to the "F_a" test statistic (8.06), which has surpassed the bootstrap critical values at 10%, 5%, and 1% levels of significance, which are represented by 4.85, 5.47, and 7.38, respectively. Also, the "t" test statistic (-5.54) has exceeded the bootstrap critical values at 10%, 5%, and 1% significance levels represented by -3.88, -4.25, and -5.07, respectively, thus inferring that there is a cointegration relationship among the series. However, because the 'F_b' test statistic (3.60) is below the bootstrap critical values at 10%, 5%, and 1% significance levels, which are 5.01, 5.93, and 7.91 correspondingly, one can claim no cointegration relationship between the series. In summary, according to the results of "F_a" and "t" tests, it can be said that there is a cointegration relationship between CPU and CARBON, DeFi, and NEX.

Table 5: Fourier ARDL Long and Short – term Coefficient Test Results

Variables	FARDL Long Term Cointegration Results			
	Coefficient	Standard Errors	T- Stat.	*p*- value
CARBON	-0.852**	0.391	-2.178	0.033
DeFi	0.080	0.112	0.713	0.478
NEX	0.369*	0.203	1.813	0.075

FARDL Short Term Cointegration and ECT Results				
Variables	Coefficient	Standard Errors	T- Stat.	*p*- value
Constant Term	6.159***	0.788	7.816	0.000
@TREND	0.020***	0.003	6.938	0.000
ΔDeFi	-0.237**	0.113	-2.098	0.040
ΔDeFi $_{t-1}$	-0.170	0.104	-1.636	0.107
ΔDeFi $_{t-2}$	-0.249**	0.106	-2.339	0.023
ΔNEX	1.098***	0.399	2.750	0.008
SİN	-0.039	0.047	-0.824	0.413
COS	-0.158***	0.051	-3.127	0.003
ECTt-1	-0.863***	0.109	-7.908	0.000
Model Specification Test Results				
Heteroscedasticity Test Stat	1.115 [0.347]	Jargue - Bera Test Stat.		3.357 [0.186]
Serial Correlation LM Test Stat.	0.469 [0.628]	Ramsey Reset Test		2.355 [0.081]

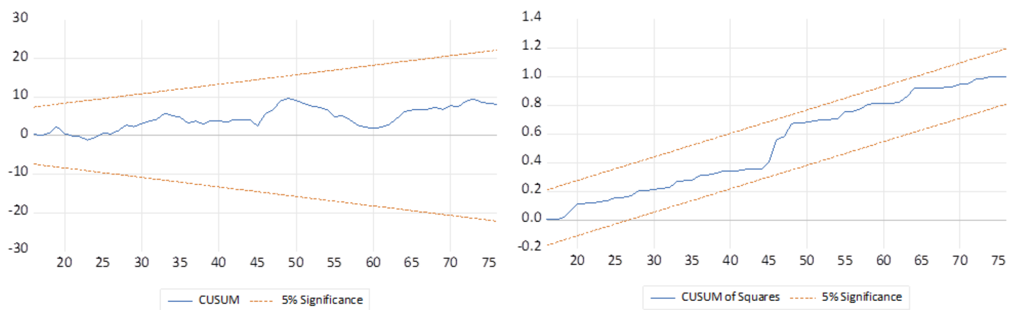
Note: "*", "**" and "***" indicates statistical significance at 10, 5 and 1% level, respectively. The estimation method have been constructed using Huber-White-Hinkley (HC_1) heteroscedasticity consistent standard errors and covariance.

In the third stage of the analysis process, we derive the long run and short run coefficient estimation results of the Fourier ARDL cointegration test and illustrate them in Table 5. Considering the FARDL long run coefficient estimates, there is a statistically significant long run cointegration relationship between CARBON and CPU index at the 5% significance level, and the coefficient estimate is estimated at -0.852. Hence, a 1% increase in the CARBON variable is associated with a 0.85% decrease in the CPU index in the long run. This indicates that increases in price movements in the carbon credit market serve a mitigating function in climate uncertainty in the long run. These findings of the study corroborate the study of Wu et al. (2022), which asserts that there is a negative relationship between European Union allowance futures and CPU. On the other hand, this study does not support the idea put forward by Su et al. (2024) that there is a positive relationship between the European Union Emissions Trading System and high quantiles of the CPU. This implies that the long run effects of changes in carbon markets on climate uncertainty in the EU countries are still ambiguous. However, based on the results of this study, the carbon market in the U.S. is increasingly comprehended by regulatory frameworks at the global level, and carbon trading is acknowledged as an investment instrument. This may signal that the carbon market in the U.S. has gained an institutionalized structure and may reduce climate uncertainty. When we look at the short run relationship, changes in carbon markets do not have any impact on the CPU. Therefore, policymakers need to implement the strategy of reducing climate policy uncertainty via adjustments in carbon markets in a long term rather than a short term framework. Drawing on these results, this study aims to be the first in investigating the short term effects of fluctuations in carbon market dynamics on climate policy uncertainty (CPU).

Moreover, we identify that the impact of DeFi on climate policy uncertainty (CPU) varies in the short and long run. In the long run, the coefficient of DeFi on CPU is positive yet statistically insignificant. This could suggest that the financial innovations and uncertainties created by the DeFi may not have a lasting impact on the long term objectives and strategic frameworks of climate policies. Moreover, the advancement of DeFi markets and the establishment of regulatory frameworks may have diminished the influence on climate policy uncertainty insignificantly. Considering the short term dynamics (the dataset is structured at a monthly frequency), the effect of the current period change in DeFi (ΔDeFi) on CPU is significant at the 5% level and its coefficient is -0.237. Notably, the current period change in DeFi corresponds to a 0.237% reduction in CPU. Moreover, the effect of the change in DeFi two months ago ($\Delta DeFi_{t-2}$) on CPU is statistically significant at the 5% level, and its coefficient is -0.249. This finding suggests that the change in the DeFi two months ago decreased the CPU by 0.249%. Although the one-month lagged change in ($\Delta DeFi_{t-1}$) is not statistically significant ($p>0.10$), it appears to exert a negative impact on CPU. This study corroborates the perspective that climate uncertainty negatively affects bitcoin carbon footprint as proposed by Dong et al. (2024), but does not corroborate the view that bitcoin returns increase climate uncertainty as proposed by Gürsoy et al. (2024).

Finally, we examine the long term and short term effects of NEX. NEX is statistically positive and significant at 10% for CPU in the long run, and its coefficient is 0.369. This finding suggests that the current period change in NEX results in a 0.369% rise in CPU. A similar result is observed within the short term framework. The monthly fluctuation in NEX (ΔNEX) is statistically significant at the 1% level for CPU, and its coefficient is 1.098. From this result, we can conclude that the monthly variation in the NEX variable induces a 1.098% increment on the CPU. These results suggest that investors increase demand for clean energy stocks during periods of heightened climate uncertainty. This approach supports studies claiming that climate uncertainty increases stock returns in Europe (Tedeschi et al., 2024); climate policy uncertainty is a strong indicator of renewable energy market volatility in the US (Liang et al., 2022); and green investments are perceived to be safer in uncertain environments (Bouri et al., 2022). Consequently, it is evident that we perceive that investors increase their investments in green energy, which are sustainable assets, with a “strategic market” approach during periods of increased climate policy uncertainty in the US.

Figure 1: CUSUM and CUSUM of Square Test Results



To ensure the consistency of the results, this study also evaluates the model specification tests using the FARDL test. The heteroscedasticity test (test stat. 1.115, p>0.05) demonstrates that the variance of the error terms is constant and there is no heteroscedasticity problem in the model. The Jarque-Bera test (test stat.: 3.357, p>0.05) confirms that the residuals satisfy the assumption of normal distribution. The LM test for serial correlation (test statistic: 0.469, p>0.05) reveals that there is no serial correlation between the residuals. Finally, the Ramsey RESET test (test statistic: 2.355, p>0.05) shows that there is no specification error in the model at 1% and 5% significance levels. All these results imply that the model satisfies the basic assumption and is methodologically robust for use. One of the key assumptions for the model validity is that the coefficient of the error correction term (ECT) must exhibit a negative sign and attain statistical significance. The ECT coefficient of the FARDL model derived in this analysis is -0.863 and p<0.01. This finding demonstrates that the discrepancies arising among the variables in the model in each period are adjusted by 86.3% in the next period and converge towards the long run equilibrium. This indicates that the discrepancies diminish over time and the model functions efficiently in resolving inconsistencies. Finally, Figure 1 shows the CUSUM and CUSUM of square test results. Both results validate the parameter stability and reliability of the model. These results suggest that the long run performance of the model is consistent and that there are no structural breaks.

ROBUSTNESS CHECK

To give robustness to the results of the study, we present the KRLS (kernel-based regularized least squares) non-linear machine learning test results in Table 7 and the marginal effects obtained with the derivative in Figures 2, 3, and 4, respectively. Moreover, this study investigates the causal relationship between CARBON, DeFi, NEX, and CPU with a novel Fourier bootstrap quantile causality test and shows it in Table 8.

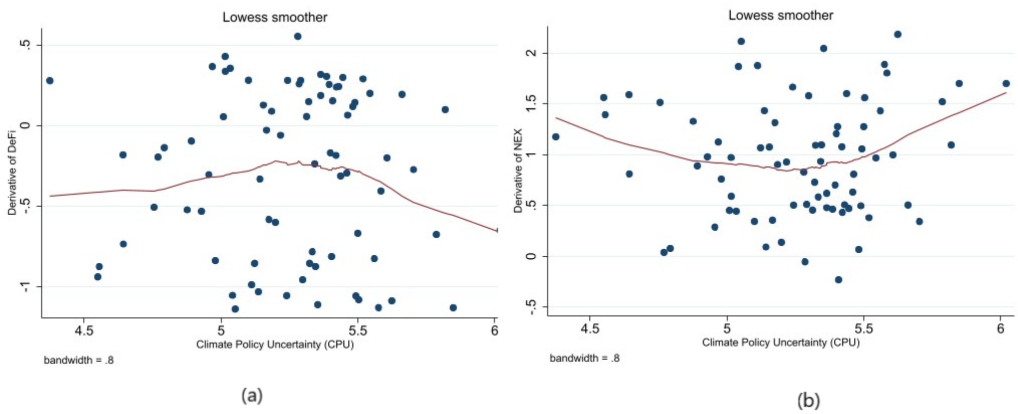
Table 7: KRLS Non – linear Machine Learning Test Results

Variables	Avg.	SE	*t*	P>t	P_{25}	P_{50}	P_{75}
Lltolerans: (.20)							
CARBON	0.057	0.129	0.441	0.660	-0.549	0.321	0.466
DeFi	-0.289***	0.062	-4.704	0.000	-0.796	-0.205	0.193
NEX	0.909***	0.167	5.443	0.000	0.481	0.900	1.310
Ltolerans: (.40)							
CARBON	0.057	0.129	0.441	0.660	-0.549	0.321	0.466
DeFi	-0.289***	0.062	-4.704	0.000	-0.796	-0.205	0.193
NEX	0.909***	0.167	5.443	0.000	0.481	0.900	1.310
Ltolerans: (.60)							
CARBON	0.045	0.120	0.378	0.706	-0.495	0.270	0.433
DeFi	-0.280***	0.060	-4.707	0.000	-0.767	-0.210	0.189
NEX	0.851***	0.159	5.340	0.000	0.477	0.841	1.223
Ltolerans: (.80)							
CARBON	0.033	0.109	0.297	0.767	-0.455	0.223	0.403
DeFi	-0.267***	0.057	-4.677	0.000	-0.727	-0.212	0.177
NEX	0.778***	0.150	5.183	0.000	0.452	0.750	1.068

Note: “*”, “**” and “***” indicates statistical significance at 10%, 5% and 1% level, respectively.

The results of the Table 7 nonlinear machine learning test show that there is no statistically significant relationship between carbon and CPU at all tolerance levels, which is consistent with the long term results of the FARDL. This suggests that the relationship between carbon credit and climate policy uncertainty has a short term effect. On the other hand, the relationship between DeFi and CPU is statistically significant at the 1% level. These results support the related results in FARDL short term. Hence, it reveals that DeFi has a short term rather than a long term relationship. Finally, the relationship between NEX and CPU is positively significant at the 1% level. This result corroborates both the long run and short run findings of FARDL. In addition to these results, the relationship between DeFi and CPU and between NEX and CPU is examined with “lowess smoother” plots, assessing the impacts of DeFi and NEX derivatives at low, medium, and high values of CPU (since CARBON is not statistically significant, the graph for this variable is ignored). Figure 2 shows the relationship between the marginal effects of DeFi and NEX (variations in their respective derivatives) and CPU.

Figure 2: DeFi and NEX Marginal Effect on CPU



Considering Figure 2(a), DeFi has a negative and statistically significant effect on CPU. However, the strength of this effect varies depending on the CPU level. At low CPU levels, the impact of DeFi is weaker, whereas the negative impact becomes stronger as uncertainty increases. During periods of low climate policy uncertainty in the US, the attractiveness of DeFi declines as investors turn to traditional markets. In contrast, during periods of high uncertainty, investors gravitate toward DeFi, which initially increases market volatility. However, as uncertainty deepens, DeFi markets act as a kind of “challenging market,” reacting to inadequate policy interventions and pricing mechanisms that reflect stronger signals. Figure 2(b) shows that there is a U-shaped relationship between NEX and CPU. As CPU increases, the positive effect of the relationship between NEX and CPU decreases. The relationship in question attains its minimum positive correlation at the intermediate CPU level. However, with further increases in CPU, the relationship between NEX and CPU reverts to a positive point as time progresses. These findings reinforce our idea that investors increase their investments in green energy as a sustainable asset with a “strategic market” approach during periods of increased uncertainty in climate policies in the US.

In this context, DeFi and NEX respond to climate policy uncertainty clearly demonstrate that investors diversify their portfolios between these two markets. DeFi may function as a “challenging market” against inadequate climate policy. In conditions of high uncertainty, NEX commence to play the role of a “strategic market”. However, strong uncertainty in climate policy leads to heightened volatility in the NEX markets, which may exacerbate climate uncertainty. For this reason, US policymakers need to develop more predictable and effective policies on climate issues; these would contribute to balancing the market's immediate reactions and investor behavior.

Table 8: Fourier Bootstrap Quantile Causality Test Results

CARBON → CPU					CPU → CARBON				
Optimum lags and frequency (1, 2.70)					Optimum lags and frequency (1,2)				
Quantiles	Walt Stats.	(%10)	BCV (%5)	(%1)	Quantiles	Walt Stats.	(%10)	BCV (%5)	(%1)
Q10	4.788	4.878	5.311	8.669	Q10	2.418	2.857	4.119	9.179
Q20	5.355*	5.179	7.562	12.18	Q20	3.714**	2.331	3.319	6.822
Q30	7.033**	4.037	6.260	10.98	Q30	1.583*	1.193	1.983	5.912
Q40	7.523**	4.461	5.814	9.203	Q40	0.524	1.143	1.832	2.734
Q50	3.200	4.009	4.736	8.447	Q50	0.557	1.341	1.954	2.833
Q60	1.357	3.873	5.712	7.852	Q60	0.779	1.387	2.082	3.720
Q70	1.274	4.007	5.215	9.671	Q70	1.464	1.829	2.041	3.263
Q80	0.398	4.820	7.196	10.84	Q80	1.878	1.977	2.874	5.763
Q90	4.248	5.658	7.724	14.89	Q90	0.004	2.815	4.962	8.039
DeFi → CPU					CPU → DeFi				
Optimum lags and frequency (1, 0.80)					Optimum lags and frequency (4, 1.80)				
Quantiles	Walt Stats.	(%10)	BCV (%5)	(%1)	Quantiles	Walt Stats.	(%10)	BCV (%5)	(%1)
Q10	0.413	3.721	4.376	13.465	Q10	13.59***	8.535	9.694	13.50
Q20	0.136	3.047	3.928	6.877	Q20	5.328	7.383	8.345	8.896
Q30	0.413	2.461	3.611	5.743	Q30	2.988	5.937	7.960	11.15
Q40	0.169	2.374	3.191	5.555	Q40	2.025	5.504	7.101	11.05
Q50	0.260	1.975	3.766	5.585	Q50	3.080	5.893	6.917	11.45
Q60	0.450	2.107	2.575	3.807	Q60	2.882	6.469	6.931	11.53
Q70	1.541	2.019	3.179	4.346	Q70	5.474	6.800	8.530	12.28
Q80	3.124**	2.195	3.114	5.445	Q80	2.964	8.933	10.458	12.96
Q90	0.106	3.777	4.174	7.746	Q90	0.573	11.93	15.902	21.41
NEX → CPU					CPU → NEX				
Optimum lags and frequency (1, 0.80)					Optimum lags and frequency (1, 0.70)				
Quantiles	Walt Stats.	(%10)	BCV (%5)	(%1)	Quantiles	Walt Stats.	(%10)	BCV (%5)	(%1)
Q10	1.323	4.087	6.821	13.44	Q10	0.892	3.245	4.357	7.682
Q20	6.410**	2.997	4.650	8.770	Q20	0.026	1.926	2.258	3.342
Q30	3.347*	2.951	3.890	5.048	Q30	0.167	1.645	2.342	4.749

Q40	3.266*	2.546	3.456	5.978	Q40	0.007	1.500	2.664	5.666
Q50	3.757**	2.241	3.347	4.947	Q50	0.110	1.590	2.923	5.109
Q60	0.287	3.023	4.809	6.727	Q60	0.001	1.774	2.904	5.542
Q70	0.717	3.998	6.038	8.668	Q70	0.008	2.607	3.593	6.722
Q80	1.698	3.531	6.851	9.341	Q80	0.295	3.165	3.897	7.676
Q90	0.046	4.166	6.550	10.02	Q90*	4.417	4.100	5.477	10.28

Note: "*," "**," and "***" indicate statistical significance at the 10%, 5%, and 1% levels, respectively. BCV, CPU, CARBON, DeFi, NEX represent Bootstrap Critical Value, Climate Policy Uncertainty, S&P Global Carbon Credit Index, S&P Cryptocurrency DeFi Index, and WilderHill New Energy Global Innovation Index, respectively.

Table 8 shows the Fourier bootstrap quantile causality test results. The initial finding is that there exists a causality from CARBON to CPU in the 2^{nd}, 3^{rd}, and 4^{th} quantiles, and from CPU to CARBON in the 2^{nd} and 3^{rd} quantiles. This indicates that in the long run, the development of carbon markets and the clarification of the rules and framework for climate policies may mitigate climate policy uncertainty. However, in the medium term, price volatility in carbon markets may amplify uncertainty, especially in the intermediate quantiles of the CPU. The causality from CPU to CARBON suggests that policy uncertainty leads to volatility and price volatility in carbon markets. Next, we identify that there is a causality from DeFi to CPU in the 8^{th} quantile and from CPU to DeFi in the 1st quantile. The causality from DeFi to CPU is clear in the upper quantiles. This finding suggests that increased market volatility in crypto markets may amplify uncertainty by exerting pressure on regulatory authorities. The causality from CPU to DeFi shows the negligible influence of policy uncertainty on DeFi markets at lower quantiles. Finally, there is a causal relationship from NEX to CPU in the 2^{nd}, 3^{rd}, 4^{th}, and 5^{th} quantiles and from CPU to NEX in the 9^{th} quantile. This shows that investors' risk perception is shaped during periods of moderate levels of climate uncertainty. From this point on, investors aim to invest in green energy technologies, which are sustainable assets in the long run. On the other hand, climate uncertainty can only affect these markets when they are at its highest levels.

CONCLUSION AND POLICY IMPLICATIONS

This study aims to investigate the effects of carbon credits (S&P Global Carbon Credit Index), decentralized finance (S&P Cryptocurrency DeFi Index), and the market dynamics of renewable energy-focused global companies (WilderHill New Energy Global Innovation Index) on climate policy uncertainty (CPU) in the US. Fourier ADF, Fourier Bootstrap ARDL, and Fourier Bootstrap Quantile causality analyses are conducted using monthly data for the period December 2017–March 2024. In addition, to enhance the robustness of the study, the results are analyzed in depth with KRSL tests developed based on machine learning, which reveal non-linear dynamics.

The results indicate a negative long run relationship between carbon credits (CARBON) and CPU. This would suggest that institutionalization of the carbon markets in the legislative framework creates an uncertainty-reducing effect. However, in the short run, no significant effect of changes in CARBON on CPU is detected. In addition, nonlinear machine learning techniques (KRLS) support these views. These findings are consistent with the results of Wu et al. (2022), but do not corroborate the results of Su et al. (2024). Moreover, the results indicate that the impact of DeFi on CPU is insignificant statistically and thereby implies that DeFi does not have a long run effect on climate policies. In the short run, the relationship is negative and statistically significant. These results are supported by Dong et al. (2024), who argue that market volatility has a negative impact on climate uncertainty during periods of high climate uncertainty. This study additionally finds that the impact of DeFi on CPU varies with different levels of climate uncertainty. For example, we find that the impact of DeFi on climate uncertainty weakens when climate uncertainty is low and the impact of DeFi strengthens when climate uncertainty increases. According to these results, during periods of high climate uncertainty, DeFi functions as a “challenging market” for investors as a substitute for traditional markets and responds more strongly to deepening uncertainties. Finally, NEX has a positive and significant impact on climate policy uncertainty (CPU) in both the short and long run. These findings are corroborated by existing literature (Bouri et al., 2022; Liang et al., 2022; Tedeschi et al., 2024). Specifically, however, this study finds that during periods of heightened climate policy uncertainty, investors tend to allocate more capital toward renewable energy stocks, which are sustainable assets. Moreover, the reactivity of renewable energy stocks with respect to climate uncertainty is moderated during medium climate uncertainty periods and rises when uncertainty is high. Here, DeFi is a “challenging market” vis-à-vis inadequate climate policies, while the volatility of renewable energy stocks becomes a sort of “strategic market” during periods of higher uncertainty.

Regarding policy recommendations, this study offers many recommendations for the carbon credits strategy, cryptocurrency DeFi markets and global new energy innovations for the US. First, given the uncertainty-reducing effect of carbon markets in the long run, these markets need to be more institutionalized and regulated. Carbon credits should be priced transparently, and market operations should be reinforced by domestic and transnational legislative frameworks. Institutionalization efforts and a review of pricing policy will enhance investor trust and ensure conformity with ecological objectives. Second, Volatility in the DeFi markets is demonstrated to exert a negative impact on the CPU in the short term. Therefore, it is imperative that DeFi markets are reorganized, legislative frameworks are prioritized within legislative discourse, and investors are informed with a transparent management approach. These regulations should foster investor confidence and protect their interests, while at the same time being flexible in a way that does not hinder innovation. Aligned with the US climate policy goals for 2026, the integration of WEFI into carbon markets and sustainable finance can also make a substantial impact on achieving these goals. Finally, at the global level, US-led countries, international cooperation, and long term strategic policies should be developed to manage the positive impact of NEX on the CPU and promote sustainable energy investments. In particular, the renewable energy sector and carbon markets should be integrated with international standards, as in DeFi. In addition, global funding mechanisms should be established to support clean technology innovations, and access to green financing instruments from international financial institutions should be facilitated. In this process, the US should legislate tax incentives and R&D investment incentives for innovation-based energy solutions. Finally, energy projects should be promoted to the public, and the participation of local communities in these projects should be increased.

There are two limitations to this study. First, the results of this study are assessed for a single national context because the climate uncertainty index was developed for the United States. Second, since the climate uncertainty index is a newly developed index, the time series comprises only 76 observations. In further studies, the factors affecting the climate uncertainty index can be examined for different country groups. In addition, the financial markets and indices affected by the index in question are limited due to the specifications of the newly developed Fourier function methodologies in our study. The findings and claims of our study can be revalidated with different methods.

Conflict of Interest: This study is single-authored, with a 100% contribution from the author, and there are no conflicts of interest.

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