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# Asymmetric quantile dependence between cryptocurrencies and climate policy uncertainty: evidence from cross-quantilogram

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## Abstract

**Purpose** – This study aims to explore the asymmetric effects of cryptocurrencies returns on climate policy uncertainty (CPU). We also wanted to explore cryptocurrencies' safe-haven and hedging properties to mitigate the climate risk during the financial turmoil period.

**Design/methodology/approach** – The study uses the monthly time series data of the CPU index and five major cryptocurrencies' data from July 2015 to September 2023. The study applied cross-quantilogram (CQ) to assess the asymmetric quantile based dependence between the CPU index and cryptocurrencies. The CQ results confirm the non-linear quantile based dependence between cryptocurrencies and the CPU index.

**Findings** – The finding of the heatmap reveals that Bitcoin and Tether are strong safe havens, while Ripple served as a weak safe haven for the CPU index during the bearish quantile (0.05). Dogecoin and Ethereum have a strong dependence with the CPU during the different quantiles. Lastly, the non-linear Granger confirms the asymmetric role of cryptocurrencies in causing CPU.

**Practical implications** – Our study findings provide useful insights for market investors and policymakers. Policymakers can focus on developing a policy to limit $CO_2$ emissions during cryptocurrencies mining because, during the high CPU period, investors can save their investments by investing in cryptocurrencies.

**Originality/value** – The present paper has a number of unique contributions in the literature. Firstly, our study is the first to investigate the asymmetric quantile dependence between cryptocurrencies and CPU during the bullish bearish and normal period. The study also investigated the hedging and safe-haven properties of cryptocurrencies to manage climate risk.

**Keywords** Climate policy uncertainty (CPU), Cross-quantilogram, Cryptocurrencies, Financial turmoil period

**Paper type** Research paper

## 1. Introduction

Climate change has been recognized as a critical and severe issue faced by human beings on our planet (He, Qin, Liu, & Wu, 2022). About 85% of the entire world's population is hurting due to climate change. Global climate change is occurring due to a series of activities including soaring urbanization, enhanced industrial activities and increased carbon emissions due to fast fashion, tourism, travel and other activities. The world's surface temperature from January to July was the third hottest in the 174-year history at 1.03°C (1.85°F) above the mean of 13.8°C (56.9°F) between 1901 and 2000 (NOAA, 2023). The global ocean surface temperature between January and July was the second warmest on record. Therefore, climate change is a threat not only to human beings and natural capital causing extreme events like floods,

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heatwaves, cyclones, droughts, etc. but also brings negative trends in the economy of the world. Different regions/countries focus on developing climate change policies to mitigate climate-related issues. The aim of these policies is to minimize abatement costs and explore innovative technologies for the reduction of greenhouse emissions in a number of sectors including transport, urban communities, energy and different industries, etc. Uncertainty would be associated with the climate change policy in terms of action plan implementation on time, misinformation, investment magnitude, stakeholder attitude and other anticipated reasons. Climate policy uncertainty (CPU) soars whenever a significant change has been observed in climate policy-related events, such as new emissions laws, worldwide climate change protests and presidential pronouncements (Ren, Zhang, Yan, & Gozgor, 2022).

Climate change policy uncertainty is directly linked with cryptocurrencies in two ways. Firstly, cryptocurrencies are considered power-hungry because the mining process involves powerful computers to solve complex mathematical puzzles. The whole process is energy intensive which eventually leads to carbon emissions. According to Zhang, Chen, Lau, and Xu (2023), each cryptocurrency requires an equal amount of power as a medium-sized country used. For example, Ethereum and Bitcoin basically operate on the mechanism of proof of work (PoW), this system is computationally intensive as more entities seek to validate transactions for coin rewards. Ethereum is projected to use 20 to 39% of the total worldwide electricity used by crypto assets by August 2022, while Bitcoin is expected to use 60 to 77% (Sapra, Shaikh, Roubaud, Asadi, & Grebinevych, 2024). High energy consumption in cryptocurrency operations raises serious threats to the climate. In the long run, the trading volume of Bitcoin has a higher impact on energy than on returns. Treepongkaruna, Chan, and Malik (2023) find that the cryptocurrency trade is positively correlated with the consumption of energy and the carbon footprint eventually adversely affects the climate. Therefore, due to the growing use of energy in cryptocurrencies, mining may be negatively affected after the global CPU. On the other hand, high climate risk adversely affects the equity markets, financial assets and the whole economy in both developed and developing countries. According to Guo, Long, and Luo (2022) the financial markets have already accounted for the long-term climate risks that are reflected in temperatures. Real options theory states that uncertainty may force businesses to postpone or reduce investment (Chi, Li, Trigeorgis, & Tsekrekos, 2019). Under these scenarios, policymakers are incredibly concerned and aggressively seeking out secure investments. Different studies (Bouri, Jalkh, Molnár, & Roubaud, 2017a; Bouri, Molnár, Azzi, Roubaud, & Hagfors, 2017b; Almeida & Gonçalves, 2022) prove cryptocurrencies can be used as a safe haven and hedging during turmoil periods.

The article offers numerous interesting contributions to the relevant literature. Firstly, this paper may be the first to examine the benefits of cryptocurrencies as a safe haven and a hedge against Climate change policy. Second, the present study has decided to test the safe-haven potential of the top five cryptocurrencies against CPU. We also wanted to verify whether CPU can be hedged by cryptocurrencies or not. We decided to identify the safe-haven and diversification abilities of cryptocurrencies to mitigate climate risk. The present study decided to apply the cross-quantilogram (CQ) technique suggested by Han, Linton, Oka, and Whang (2016) to achieve these research goals. The CQ approach provides useful intuitions for practical problems, such as asymmetric directional predictability and range of lag orders over quantiles. As a result, this offers a more thorough examination of the connection or dependence between cryptocurrency's return and CPU. The additional benefits of this method include its ability to handle heavily tailed financial data series and the fact that moment conditions and variance ratio statistics do not need to be computed using traditional correlograms and nonlinear estimators (Han *et al.*, 2016). After that, we decided to apply non-linear Granger causality in order to verify the results. To the best of the authors' knowledge, previous studies have not explored the quantile-dependence between CPU and cryptocurrencies, particularly when employing the relatively new and suitable CQ estimator.

The remaining portions of this study are organized as follows: literature reviews are explained in Section 2, Data and methods are shown in Section 3 and empirical findings and some useful policy implications are presented in Section 4 to wrap up the study.

## 2. Literature review

Cryptocurrency mining does not require discovering anything out of soil unless you consider the fossil fuel that is frequently used to power it. Heavy-duty computers are employed to run billions of calculations, finding solutions to generate virtual currency. This is known as "proof of work" (Bouri *et al.*, 2017a, b; Teufel, Sentic, & Barmet, 2019). The POW is energy intensive process since new blocks are created and added to the blockchain through a competitive, consensus-driven verification process that is carried out by alone or a consortium of "miners". Miners authenticate digital currency transactions whereas dealing to correctly deliver a unique transaction identifier or "hash," for a block. Miners who authenticate a specified number of transactions and submit the right hash identifier are rewarded with additional unity of cryptocurrency and a new block is added to the chain. Different studies (Bouri, Iqbal, & Klein, 2022; Townsend, 2016) pointed out that the extensive use of power in cryptocurrency mining is an enormous risk to the environment because a substantial percentage of the energy is derived from fossil fuels (natural gas and coal), contributing to greenhouse gas emissions. Large-scale mining operations of cryptocurrencies frequently look for the most inexpensive forms of electricity, which can cause environmental pollution and accelerate climate change. In the Asia Pacific region, coal prices and Bitcoin prices are positively correlated, according to Erdogan, Ahmed, and Sarkodie (2022), who simultaneously highlight that 65% of the energy utilized by cryptocurrency miners worldwide comes from coal. Clark, Lahiani, and Mefteh-Wali (2023) identify that Ethereum and Bitcoin are asymmetrically connected with fossil fuel markets. Non-linear connectedness between cryptocurrencies and fossil fuel markets is enhanced during the turmoil period.

Gavriilidis (2021) proposes a new metric known as the CPU index, which is based on data from extensive US newspapers, demonstrating uncertainty around adopting legislation to address climate change. He also pointed out that there is a direct relationship between $CO_2$ emissions and CPU. Another study (Atsu & Adams, 2021) conducted on BRICS economies reveals that fossil fuel consumption and policy uncertainty are contributing causes to $CO_2$ emissions, but bureaucracy's quality, financial development (FD) and renewable energy tend to curb emissions. Su, Wei, Wang, and Tao (2024) used wavelet based quantile approach to examine the effect of CPU on the trading price of carbon. The study shockingly identified that carbon trading prices are directly affected by the changing CPU. Bitcoin mining might emit up to 36.95 megatons of $CO_2$ each year, which is identical to or significantly higher than New Zealand's carbon footprint per capita (Almeida & Gonçalves, 2022). The crucial role of CPU in cryptocurrency pricing cannot be overstated. As a result of increasing anxiety about the ecological effects of present global climate change, more scrutiny should be devoted to the uncertainties that arise from climate-related policy changes. Side by side climate policy affected different markets (Dai & Zhang, 2023; Tedeschi, Foglia, Bouri, & Dai, 2024). Liang, Goodell, and Li (2024) study examine the CPU and carbon market asymmetrically effect the economic growth and financial market. Tedeschi *et al.* (2024) investigate the nature of relationship between European equity market, clean energy stock and CPU by employing time-varying parameter VAR model. The study results show that investment in clean energy stocks suddenly increased due to rising climate risks. It is highly recommended to limit the climate risk by implementing appropriate climate policy in order to bring stability in the financial markets.

On the other hand, cryptocurrencies can be used as safe-haven assets due to low or zero correlation during the turmoil period. Different studies (Feng, Wang, & Zhang, 2018; Mariana, Ekaputra, & Husodo, 2021) reveal that cryptocurrencies can be used as hedging and safe-haven assets for equity markets and sectoral indices. Few other studies (Colon, Kim, Kim, & Kim, 2021; Ilhan, Krueger, Sautner, & Starks, 2023) reveal that different risks including economic policy uncertainty and geopolitical uncertainty, can be hedged if cryptocurrencies are added to the portfolio. CPU is a comparatively new concept and few studies investigated green bonds and energy commodities as a safe-haven or hedging assets for climate risk/CPU. Previous literature studies lack of evidence on the asymmetric relationship between cryptocurrencies and CPU with peculiar safe-haven and hedging abilities. The present study addresses this literature gap and tries to identify the nature of the relationship between cryptocurrencies and CPU. Moreover, the study also investigates whether CPU can be hedged by adding cryptocurrencies to the portfolio. The literature review Table 1 given below:

## 3. Data and methodology

The present study is the non-linear relationship between the CPU index and cryptocurrencies. The study also verifies the five cryptocurrencies safe havens and diversification role for CPU during the bullish, normal and bearish time periods. The current study determined to use Gavriilidis's (2021) CPU, which comprises a number of terms like greenhouse, uncertainty, climate, regulation, carbon dioxide and legislation. The top five cryptocurrencies including Bitcoin, Ripple, Dogecoin, Tether and Ethereum are used in this paper. The monthly data on cryptocurrencies prices and CPU have been obtained from coinmaket.com and policyuncertainty.com. The sample spans from May 2013 to August 2023. The present paper employs a series of methodologies. Firstly, the study employ descriptive statistics and a time series graph to analyze the broad picture of the data. Then study applied three different unit root tests to examine the stationary of the data. Secondly, most of the time series are non-linear proven in the literature. Therefore the study has decided to use the CQ in order to analyze the quantile-based non-linear relationship between the variables. Hedging, diversification and safe-haven properties of individual cryptocurrencies against CPU are also tested by employing a CQ. Then non-linear Granger causality is applied for robustness check.

### *3.1 Cross-quantilogram*

Linton and Whang's (2007) quantilogram evaluates the predictability of different components of the statistical distribution in a stationary time series. In different phrases, the quantilogram is the correlogram of quantile hits (Han *et al.*, 2016) that tests the null hypothesis that each time series absences directional predictability (Linton & Whang, 2007). The predictability test is performed by comparing quantilograms to a point-specific and confidence interval. Han *et al.* (2016) adapted the univariate quantilogram framework to a multivariate setting in order to assess the dependence of quantiles on two stationary time series. The CQ approach utilizes conditional quantiles for quantifying the directional dependence among time frames after controlling for the information at the prediction in a conservative manner. More importantly, the applied distribution is asymptotically valid across a variety of quantiles. Han *et al.* (2016) emphasizes multiple perks for directional predictability for quantilogram over other tests, consisting of the idea that it is based on the quantile hits and needs no moment conditions, similar to classic correlogram avenues and that it is applicable for series that have large tails.

Let's reflect the monthly returns as $(x_{i,t})$ where i = 1, 2, 3 and t = 1, 2,3,. . ., T, where Index i specifies either the cryptocurrencies price's returns or the matching CPU index. $fi(\cdot)$ and $Fi(\cdot)$ are the particulars of the density and distribution functions for the series xi,t. The quantile of xi,t is referred to by a mathematical equation: $f_1(q_i) = \inf\{m : F_i(m) \geq q_i\}$

for $q_i$ (0, 1) and the computation of a 2-dimensional series of quantiles is symbolized by $(f_1(q_1) f_2(q_2))\tau$, for $q \equiv ((q_1, q_2)\tau)$. For the $q$-quantile with $l$ lags, the CQ approach (population) is denoted by.

$$\rho_q(l) = \frac{E\varphi_{q1}(x_{1t} - f_1(q_1))\varphi_{q2}(x_{2t-l} - f_2(q_2))}{\sqrt{E\varphi^2_{q1}(x_{1t} - f_1(q_1))}\sqrt{E\varphi^2_{q2}(x_{2t-l} - f_2(q_2))}} \quad (1)$$

The CQ estimates serial dependency between the both time series variables at different quantile magnitudes in Equation (1). The coefficients of cross-correlation between cryptocurrencies returns by $q$(k) being above or below certain quantile fret (qret) at the time (t) and CPU index return being above or below a specific quantile q cryptocurrencies ($q$ individual cryptocurrency) at the time (t−1). Consequently, $\rho_q(l) = 0$ exhibits that there is

**Table 1.** Literature review table

| Authors | Study period | Frequency of data | Journal | Econometric methods | Variables | Main findings |
|---|---|---|---|---|---|---|
| Zhang *et al.* (2023) | Jan 2019 – June 2021 | Daily | Technological Forecasting and Social Change | Diebold spill over | $CO_2$, Bitcoin returns and volatility, network difficulty change | The results reveal that directional predictability is present from electricity usage in the process of Bitcoin mining and $CO_2$ emission |
| Treepongkaruna *et al.* (2023) | Jan 2000 – Dec 2021 | Monthly | Finance Research Letters | Rolling regression | CPU, stock returns | CPU is directly linked with stock returns. Risk-averse investors are ready to pay more for low CPU stocks |
| Wang, Kan, Qiu, and Xu (2023) | Jan 2000 – August 2022 | Monthly | Economic Analysis and Policy | Quantile connectedness + quantile VAR | CPU, Agricultural and oil returns | Oil and agricultural products are strongly important for CPU formulation |
| Bouri *et al.* (2022) | July 2008 – March 2021 | Daily + Monthly | Finance Research Letters | Baur and Dermot regression | CPU, brown and green energy stocks | A significant relationship is present between the CPU and both independent variables of the study |
| Guo *et al.* (2022) | Jan 2000 – March 2021 | Monthly | International Review of Financial Analysis | TVP-VAR-SV model | CPU, financial speculation related to gas and oil | Asymmetric relationship present between CPU and energy commodities |
| Teufel *et al.* (2019) | 2014 – 2018 | Daily | Journal of Electronic Science and Technology | Non-linear ARDL | Energy, Monero and carbon emission | A significant amount of $CO_2$ emission is due to the massive usage of electricity in Monero mining |
| Krause and Tolaymat (2018) | January 2016 – June 2018 | Monthly | Nature sustainability | Safe haven regression + smooth transition | Energy, precious metals Monero, Ethereum, Litecoin and Bitcoin | As compared to precious metals, Cryptocurrencies mining consumes more energy |
| Bouri *et al.* (2017a, b) | July 2010 – Dec 2015 | Daily | Applied Economics | ADCC | Energy commodities, Bitcoin | Bitcoin can be used as a safe-haven asset for energy commodities |
| Townsend (2016) | January 2010 – July 2014 | Daily | HeinOnline | Regression | Blockchain, energy | Blockchain technology is asymmetrically associated with energy consumption |

**Source(s):** Authors' own work

no probability or time-lag influence to project between the CPU index and cryptocurrencies return at the time t, fails to give useful insight to figure out whether the returns on safe-haven assets will be below or above the quantile *fSHA*(*qSHA*) on the subsequent trading month. In contrast, $\rho_q(l) \neq 0$ expresses a one-day predictability in the direction of CPU index returns relevant to safe-haven asset (cryptocurrencies) returns at $q = qret(qSHA)$. The sample CQ equation is given below:

$$\widehat{\rho}_q(l) = \frac{\sum_{t=l+1}^{T} \varphi_{q1}\left(x_{1t} - \widehat{f}_1(q_1)\right)\varphi_{q2}\left(x_{2t-l} - \widehat{f}_2(q_2)\right)}{\sqrt{\sum_{t=l+1}^{T} \varphi_{q1}^2\left(x_{1t} - \widehat{f}_1(q_1)\right)}\sqrt{\sum_{t=l+1}^{T} \varphi_{q2}^2\left(x_{2t-l} - \widehat{f}_2(q_2)\right)}} \tag{2}$$

Where $\widehat{\rho}_q(l)$ Symbolizes the Han *et al.* (2016) specified unconditional sample quantile of $x_{i,t}$. A quantile version of the LjungBox-Pierce statistic can be described in this manner:

$$\widehat{F}_q^j = T(T+2)\sum_{J=1}^{\rho} \widehat{\rho}^2(j) \Big/ (T-J)$$

In conformity with Han *et al.* (2016), we utilize the stationary bootstrap of Politis and Romano (1994) for approximating the distribution of the testing statistic under the null hypothesis that may be utilized for the statistical inference considering the asymptotic distribution of CQ contains noise under the null hypothesis of no/zero directional predictability. In real terms, this is a portmanteau test $\widehat{F}_q^j$ for directional prediction/correlation from one time series to the other for up to p lags for different pairs of quantiles q = (q1,q2).

## 4. Results and finding

### *4.1 Descriptive statistics*

Table 2 demonstrates the descriptive statistics of five cryptocurrencies and the CPU index. Ethereum has the highest monthly average returns, while Tether provides the lowest monthly average returns. All variables are positively skewed and leptokurtic except Tether and CPU index, both of these variables have negative tails. XRP, Dogecoin and Tether have higher peak due to higher coefficient of kurtosis between to 8 to 9. While other variables have comparatively flat due to around zero coefficients of kurtosis. The P values of the JB statistics are below 0.05 (except CPU) which means that the null hypothesis failed to accept. The return series of all five cryptocurrencies is not normally distributed. Figure 1 demonstrate the time of variables during the normal, bearish and bullish period.

**Table 2.** Descriptive statistics

| | Mean | Min | Max | SD | Skewness | Kurtosis | JB | Probability |
|---|---|---|---|---|---|---|---|---|
| Bit | 0.011 | −0.944 | 1.233 | 0.349 | 0.268 | 1.220 | 7.326 | 0.026 |
| ETH | 0.072 | −0.769 | 1.094 | 0.348 | 0.670 | 0.949 | 11.112 | 0.004 |
| XRP | 0.042 | −1.106 | 2.320 | 0.454 | 2.305 | 9.030 | 424.007 | 0.000 |
| Dogecoin | 0.062 | −0.758 | 2.072 | 0.439 | 2.485 | 8.560 | 404.163 | 0.000 |
| Tether | 0.000 | −0.025 | 0.025 | 0.006 | −0.004 | 9.027 | 336.102 | 0.000 |
| CPU | 0.049 | −0.467 | 0.533 | 0.209 | −0.061 | −0.030 | 0.064 | 0.968 |

**Note(s):** CPU = Climate policy uncertainty Index, Bit = Bitcoin, ETH = Ethereum, XRP = Ripple, SD = Standard deviation, JB = Jarque Bera
**Source(s):** Authors' own work

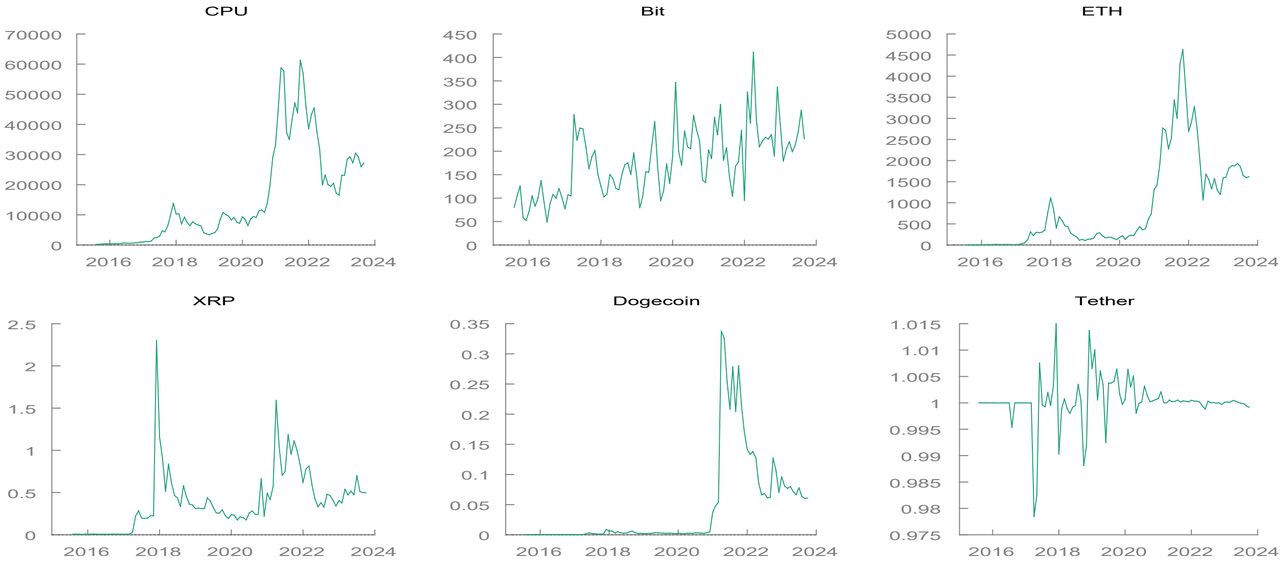


**Figure 1.** Time series plots of all variables. **Source(s):** Authors' own work

*4.2 The unit root test*

The present study has decided to apply three different unit roots test in order to identify the stationary of the variable. The results of the three unit root tests are presented in Table 3. The null hypothesis of the unit root states that the variables are non-stationary. The *P*-values of all three unit root tests are calculated at level and intercept. The *P*-value of all variables is insignificant which means that we failed to reject the null hypothesis of the unit root. In other words, CPU index, Bitcoin, Ethereum, XRP and Dogecoin are not stationary at the level. While Tether are stationary while performing only ADF test, but DF and ADF test shows non-stationary. Due to the majority of non-stationary variables, we have decided to apply CQ.

*4.3 Cross-quantilogram results*

The pair of cross-correlation heat maps between five cryptocurrencies and CPU are shown in Figure 2. Where predictability and asymmetries are evaluated. CPU index returns are represented on the *x*-axis and the cryptocurrencies returns are plotted on the *y*-axis. The degree of correlation (negative/positive directional and quantile causality spillovers) is shown by a color scale that varies from blue (very negative) to white (zero correlation/uncorrelated) to red (perfectly positive/co-movement). For the CPU index, each cryptocurrency is a weak safe

**Table 3.** Different unit root tests

| Variables | ADF (*P*-value) | DF (*P*-value) | PP (*P*-value) |
|---|---|---|---|
| CPU | 0.105 | 0.138 | 0.262 |
| Bit | 0.251 | 0.350 | 0.201 |
| ETH | 0.627 | 0.708 | 0.669 |
| XRP | 0.559 | 0.424 | 0.398 |
| Dogecoin | 0.692 | 0.425 | 0.482 |
| Tether | 0.031 | 0.12 | 0.160 |

**Note(s):** ADF = The Augmented Dickey–Fuller test, DF = Dickey–Fuller test and PP = Phillips–Perron
**Source(s):** Authors' own work

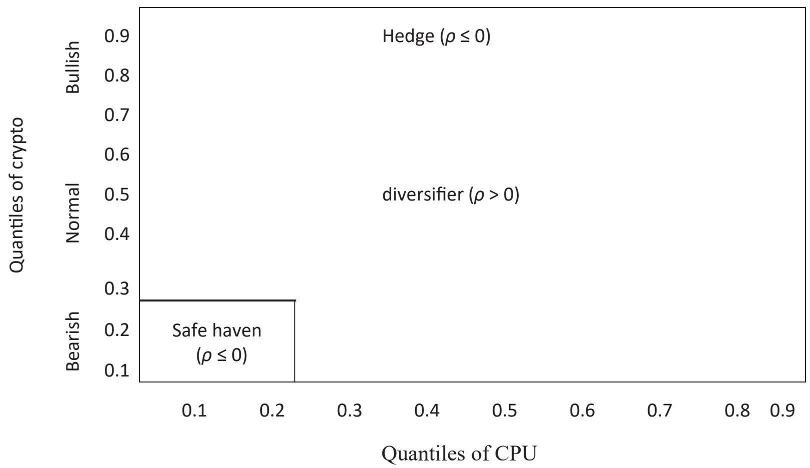


**Figure 2.** Pictorial representation of cross-qauntilogram based co-movement/safe haven testing procedure.
**Source(s):** Authors' own work

haven if the bottom-left region of the heatmap is white, implying that there is zero/no dependence among the lower quantiles (at the 0.05 quantile); alternatively, each cryptocurrency is a strong safe haven if the bottom-left region of the heatmap is blue (or light blue), i.e. the coefficients are negative, demonstrating that extremely negative CPU index returns are accompanied by future positive cryptocurrencies returns.

Figure 3 exhibits the negative predictability when both the CPU index and Bitcoin are in the lower quantiles, revealing Bitcoin's safe-haven attributes for restraining the CPU index. Further, there is a zero correlation found at the 90th and 9th quantiles, implying Bitcoin's diversification benefits against the CPU index. During the normal period, asymmetric

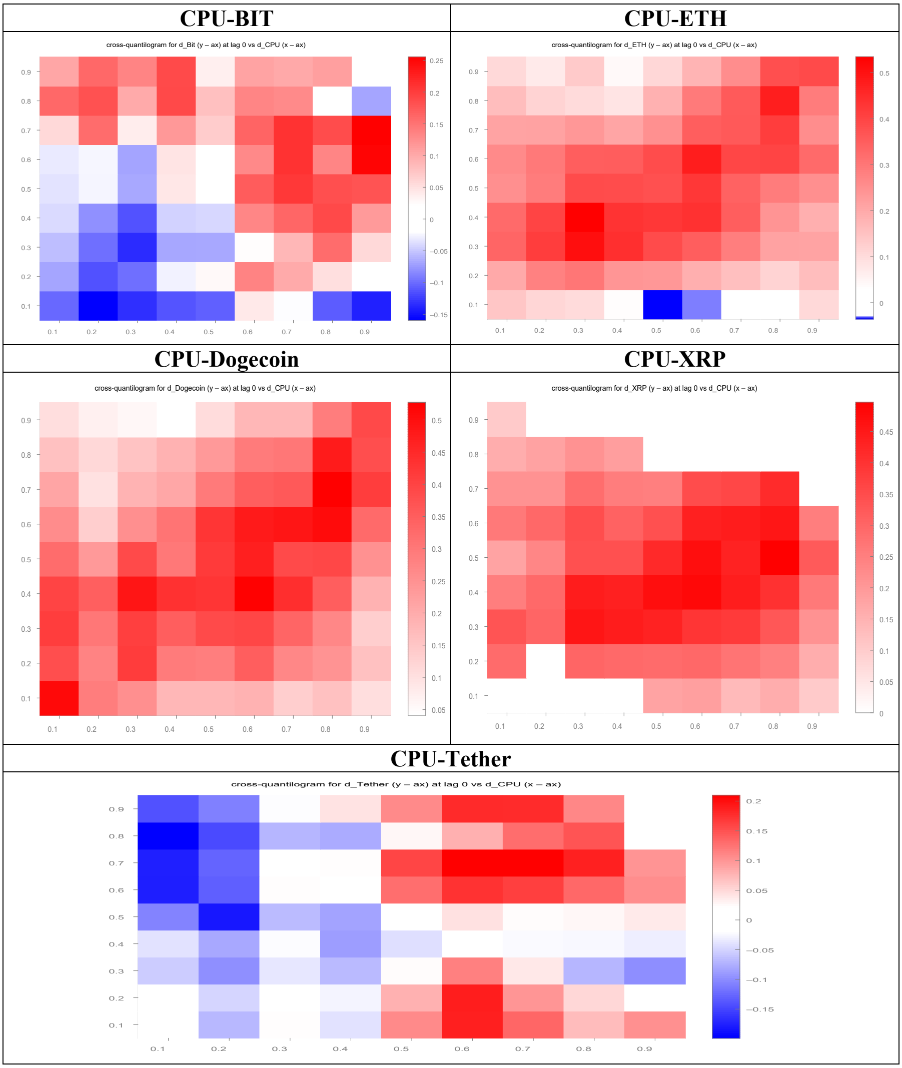


**Figure 3.** CQ based heatmap between climate policy uncertainty and cryptocurrencies. **Note:** The CQ based heatmap is depicted in the above graphics. When there is no significant directional predictability, the quantile levels are set to zero. The colorful rectangles represent predictably relevant Ljung-Box test locations. The horizontal axis in each heatmap reflects quantiles of climate policy uncertainty, while the vertical axis represents quantiles of cryptocurrencies return. **Source(s):** Authors' own work

dependence has been found between Bitcoin and CPU due to the presence of blue, red and white color. Our results are consistent with previous findings (Wendl, Doan, & Sassen, 2023) who conclude that cryptocurrencies are best refuges due to stable prices even during the financial turmoil period. Unlike the domains of red color in the ETH- CPU index heatmap at lower, middle and upper quantiles. The finding implies that Ethereum has a strong positive dependence with the CPU index. Ethereum cannot be used to mitigate the CPU risk during the turmoil period. Similarly, Dogecoin is positively correlated with CPU during different quantiles. On average and during normal periods, Ripple has a strong positive dependence with the CPU index. The findings support the argument of Zhang *et al.* (2023) who pointed out that soaring energy consumption has been fueled by the computationally complicated consensus strategy utilized by the cryptocurrency ecosystem to authenticate transaction legitimacy and assure network security. The explosive growth of blockchain technology and the cryptocurrency industry could threaten global efforts to alleviate climate change. But Ripple has insignificant dependence with the CPU index at bearish quantile (0.1) due to the presence of white color. It means that Ripple is a weak safe haven to mitigate the CPU (risk). Insignificant white portion has also been observed at the upper (90th) quantile, revealing the diversification attribute of Ripple to mitigate CPU (risk). Furthermore, Tether reveals a non-linear dependence with CPU due to the presence of blue, white and red colors through different quantile in the heatmap. Tether shows negative cross-correlations at the extreme bottom quantiles (0.1), signifying that Tether can help to over the CPU (risk) during the turmoil period due to the strong safe-haven ability of Tether for CPU. While the 90th quantile zero cross-correlations are observed hinting diversification benefits of Tether to overcome CPU during the normal period. Our heatmap results are in line with previous studies that claim that crptocurrencies are the best safe-haven assets during the bearish quantiles. Similarly, Sapra and Shaikh (2023) claim that investors may choose to transfer their money to the comparatively safer BTC market when the CPU changes quickly. When climate uncertainty soars, Investors may choose to park their money to the comparatively safer market named as cryptocurrency market when CPU changes quickly.

## 5. Robustness test, non-linear Granger causality

The present study applies the asymmetric Granger causality tests as robustness to verify the nature of the relationship between the CPU index and cryptocurrencies. Non-linear Granger causality helps to discover the causal linkages between challenging systems that display non-linear (asymmetric) behavior in different areas, including economics and finance. It is a valuable technique for uncovering hidden causal links that may be neglected by linear analysis. The p-value of asymmetric Granger causality (F-statistics) is presented in Table 4. The null hypothesis of non-linear Granger causality states that variable X does not Granger-cause Y. The p-values result indicates that Ripple, Tether and Dogecoin are statistically significant at 5%, while bitcoin is significant at 10%. It means that all five cryptocurrencies returns cause

**Table 4.** Non-linear Granger causality

| Variables | CPU | Bit | ETH | XRP | Dogecoin | Tether |
|---|---|---|---|---|---|---|
| CPU | | 0.659 | 0.204 | 0.476 | 0.09 | 0.086 |
| Bit | 0.068 | | 0.249 | 0.726 | 0.664 | 0.246 |
| ETH | 0.012 | 0.708 | | 0.2208 | 0.545 | 0.423 |
| XRP | 0.015 | 0.424 | 0.398 | | 0.638 | 0.199 |
| Dogecoin | 0.019 | 0.425 | 0.482 | 0.299 | | 0.17 |
| Tether | 0.293 | 0.92 | 0.086 | 0.45 | 0.502 | |

**Note(s):** CPU = Climate policy uncertainty Index, Bit = Bitcoin, ETH = Ethereum, XRP = Ripple
**Source(s):** Authors' own work

volatility in the CPU index returns during the entire sample period. The non-linear Granger-cause results are consistent with the notion that the CPU is extremely sensitive and positive and negative bring shocks in bitcoin returns (Wang *et al.*, 2023). The insignificant p values of all individual cryptocurrency is with different pairs of cryptocrrencies which means that cryptocurrencies does not Granger-cause each other. Similarly, CPU index does not cause cryptocurrencies except Tether.

## 6. Conclusion

Dealing with climate change has become an important issue for human survival and development. Climate risks may have a substantial and inevitable influence on the economic sectors, financial markets and households. In the face of escalating climate hazards, the government has been tasked with establishing CPU policies. Heavy amounts of electricity is consumed during the mining process of cryptocurrencies, which might result in greenhouse gas emissions. Due to the importance cryptocurrencies in emission of $CO_2$ and greenhouse gases, it is quite important to understand the nature of relationship between cryptocurrencies and the CPU index. We use time series of CPU index developed by Gavriilidis (2021) and five cryptocurrencies (Bitcoin, Ripple, Dogecoin, Tether, Ethereum). The frequency of the data is monthly data from the July 2015 to September 2023. CQ methodology has been applied to understand the asymmetric and quantile-based relationship between CPU index and cryptocurrencies. And asymmetric Granger causality has been applied for robustness check.

The descriptive statistics results indicate that variables are positively skewed and leptokurtic behavior. The time series graphs also indicate that the returns of the CPU index and five cryptocurrencies are non-linear trends and time varying behavior. Then, we applied the augmented Dickey–Fuller (ADF), (Dickey–Fuller) DF and Phillips–Perron (PP) tests to confirm the stationary of the variables. The results of all three unit root tests clearly show that all cryptocurrencies are non-stationary at level. This provides information about the non-stationarity and non-linearity nature of the data. The study has applied the non-linear quantilogram to understand the asymmetric quantile dependence between the Cryptocurrencies and CPU index. Bitcoin and Tether shows negative cross-correlations, while Ripple has insignificant dependence with the CPU index at a bearish quantile (0.1). The results confirm that Bitcoin and Tether are strong safe havens, while Ripple (XRP) served as weak safe haven for CPU index. These results align with previous studies (Zhang *et al.*, 2023; Feng *et al.*, 2018) that proved that cryptocurrencies are safe haven due to providing stable returns during bearish period. Doegcoin and Ethereum have strong dependence with CPU during the different quantiles. The results support the study Dai and Zhang (2023) who found that CPU positively co-move with financial and energy markets. Finally, the study applied the non-linear Granger causality for robustness check. The non-linear Granger causality reflects all cryptocurrencies brings shocks in the CPU index returns during entire sample period. The conclusions of the current paper have significance for policymakers and portfolio investors. Cryptocurrencies proved two edged sword for the CPU index. On the one side, cryptocurrencies brings volatility in climate change due to emission of $CO_2$, but on the other hand, cryptocurrencies can be used as hedge or safe haven during the CPU risk. Policymakers can focus to develop the policy to limit the $CO_2$ emissions during cryptocurrencies mining because during the high CPU period, investors can safeguard their investments by investing in cryptocurrencies. It is also highly important to implement the carbon taxing policy to reduce carbon emission and fossil fuels in the mining of cryptocurrencies. More importantly, educational campaigns are needed for different stakeholders, like those at industrial, individual and investor levels. The future studies can be extended on different dimensions by enhancing the number of cryptocurrencies. Secondly researchers can use any other index of climate risk to enhance understanding. We have incorporated more indexes like commodities clean energy stocks and checked their safe haven properties against CPU.

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