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Carbon Futures and Clean Energy Stocks: Do They Hedge or Safe Haven against the Climate Policy Uncertainty?

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Abstract: Using the GARCH model and quantile regression with dummy variables, we investigate the hedging and safe haven properties of carbon futures and clean energy stocks against the U.S. climate policy uncertainty (*CPU*). We discover that carbon futures and clean energy stocks have a weak hedge and a semi-strong safe haven in different market conditions. Carbon futures exhibit a strong safe haven in both bull and bear markets, depending on the degree of uncertainty. Clean energy stocks, on the other hand, possess a weak hedge across market conditions and a strong safe haven in bull markets. Sub-sample analyses of prior- and post-Paris Agreement of 2016 also exhibit consistent results for safe haven properties of carbon futures and clean energy stocks.

Keywords: climate policy uncertainty; hedge; safe haven; carbon futures; clean energy stocks; GARCH model; quantile regression

JEL Classification: C58; D81; G11; G12; G13; G14

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1. Introduction

Empirical research has been contributing to the ongoing discussion about the hedge and safe haven features of financial asset classes in the event of any form of uncertainty.[1] There are different levels and sources of uncertainties, and climate policy uncertainty is one of them. Uncertainty resulting from climate-related events or uncertainty surrounding government policy measures for mitigating climate risk are both considered to be climate policy uncertainties. Hence, in an attempt to identify assets that can serve as a hedge and a safe haven against the U.S. climate policy uncertainty (*CPU*), the usage of a recently introduced U.S. *CPU* index developed by Gavriilidis (2021) would, therefore, be beneficial in providing new insights and understanding the effects of uncertainty in climate policy risk.

The asset pricing mechanism and fund flow into carbon futures and clean energy stocks are related to energy market development and climate policy. Uncertainty related to carbon-pricing policy has a negative influence on energy industry investment (Jotzo et al. 2012). In the energy industry, high-capital-cost projects are urged to be delayed until climate policy uncertainty is resolved, since it makes the cash flow of an investment project less predictable. Such actions will change how revenue is generated for energy companies, which could negatively impact the intrinsic value and share price (Schall 1972). Several studies have discussed that the Paris Agreement of 2016 has had adverse and long-term impacts on the U.S. oil and gas industry, suggesting that climate-related policies have considerable implications for dirty energy stocks[2] (Diaz-Rainey et al. 2021).[3] Following that, various studies have empirically addressed how the alternative or clean energy industry and stocks benefit from shocks in the dirty energy market.

Similarly, the carbon market reacts to overall energy market development (Khalfaoui et al. 2022; Tiwari et al. 2022). As a result, they could be acting as a hedge or a safe haven tool against the U.S. *CPU*. A weak (strong) hedge occurs when an asset is uncorrelated (positively correlated) with the U.S. *CPU*, and a weak (strong) safe haven arises when an asset is uncorrelated (positively correlated) with the U.S. *CPU* at times of market stress or turmoil. Additionally, Kuang (2021) indicates that clean energy stocks effectively mitigate the downside risks associated with dirty energy stocks. This risk mitigation capacity is continued during times of market stress. Therefore, the investors of the dirty energy sector could intend to have some hedge and safe haven assets against their *CPU* risk in dirty energy stocks.

The literature strand related to the impact of *CPU* on stock returns and performance is in its early stages. Hsu et al. (2022) discovered evidence of the substantial influence of uncertainty in environmental policies and regulations on the returns of a cross-section of emission portfolios. Fried et al. (2021) found that climate policy risk decreases carbon emissions by shrinking the capital stock and making it cleaner. In support, Pástor et al. (2021) highlighted that when investors' concerns about climate mount, they shift their investment from brown to green sectors, so green stocks significantly outperform brown stocks. Diaz-Rainey et al. (2021) revealed that the 2016 Paris Agreement has a negative impact on the U.S. oil and gas sector. Bouri et al. (2022) demonstrated that *CPU* is more of a key predictor of performance of green energy stocks than brown energy stocks and could impact the investors' choice of energy sector stocks. Saeed et al. (2020) showed evidence of the safe-haven property of green energy stocks against brown energy stocks. Liang et al. (2022) found that *CPU* has a significant negative impact on the long-term volatility of renewable energy, and it has an excellent out-of-sample prediction effect on renewable energy volatility.

Against this backdrop, the current study fills the gap in the existing literature by examining whether carbon futures and clean energy stocks are a hedge and a safe haven asset against the U.S. *CPU*. Since the 2016 Paris Agreement, corporations and global policymakers have turned their focus to climate policy (Diaz-Rainey et al. 2021; Pham et al. 2019). However, several interventions and changes may occur while implementing climate policy, making it less likely for an economy to achieve a greater steady state (Golub et al. 2020). Several studies have argued that financial markets have reacted to the events or policy changes related to climate risk (Antoniuk and Leirvik 2021; Diaz-Rainey et al. 2021; Monasterolo and De Angelis 2020; Pham et al. 2019; Qian et al. 2020). Therefore, in this study, we also compare the hedging and safe haven features of carbon futures and clean energy stocks prior to and after the Paris Agreement of 2016.

As a result, this research makes a few important contributions to the fields of climate finance theory and risk management. First of all, the current study is one of the first to seek safe haven assets against uncertainties of climate policy. In contrast to Bouri et al. (2022) and Liang et al. (2022), it has included the impact of *CPU* on carbon futures to investigate its usefulness as a safe haven against the U.S. *CPU*. Henceforth, this study offers fresh perspectives on how investors in brown energy stocks or high carbon-intensive firms can hedge and manage risk against climate uncertainty using carbon futures and clean energy stocks. Second, the present work adds to the body of research on textual-based uncertainty measures, including economic policy uncertainty and geopolitical risk, by demonstrating how textual-based climate uncertainty affects energy stock returns (Pham et al. 2019; Wang and Kong 2022; X. Zhao 2020; R. Zhao 2021). Furthermore, this study expands the existing literature on climate policy uncertainty, carbon futures, and clean energy by adding new evidence that carbon futures exhibit a strong safe haven property in both bull and bear markets, and clean energy stocks possess a weak hedge across market conditions and a strong safe haven in bull markets.

The remainder of the paper is structured as follows: Section 2 describes the proposed empirical model and methodology. Section 3 outlines the sources of the data. Section 4 presents the results and discussion. Finally, Section 5 provides the conclusion and policy implications.

2. Empirical Model and Methodology

Following Baur and Lucey (2010); Bouri et al. (2017); and Wu et al. (2019), we employ a GARCH model and a quantile regression model with dummy variables for examining the hedge and safe haven properties of carbon futures and clean energy stocks against the U.S. *CPU*. Baur and Lucey (2010) have assumed the various return conditions on average, however, in reality, returns perform differently in bullish and bearish market conditions (Mokni et al. 2021, 2022; Wu et al. 2019). Moreover, asset responses to uncertainties depend on market conditions. Hence, combining Baur and Lucey's (2010) method with a quantile regression may help to better capture the return conditions in which an asset may possess the safe haven property.

At first, we estimate the following GARCH model as in Equation (1) using the maximum likelihood method.

$$R_t = \alpha + \beta_0 R_{t-1} + \gamma_1\, CPU_t + \gamma_2\, D(CPU_{q90})CPU_t + \gamma_3\, D(CPU_{q95})CPU_t + \gamma_4\, D(CPU_{q99})CPU_t + \epsilon_t, \tag{1}$$

$$\sigma_t^2 = \delta_0 + \delta_1 \epsilon_t^2 + \delta_2 \sigma_{t-1}^2 \tag{2}$$

where R_t, denotes returns for carbon futures and clean energy stocks. CPU_t stands for changes in the CPU index. $D(CPU_{q90})$ is a dummy variable that takes a value of 1 if the change of CPU is higher than 90%, representing 90% quantile, and 0, otherwise. $D(CPU_{q95})$ and $D(CPU_{q99})$ stand for 95% quantile and 99% quantile, respectively. A similar process has been followed for constructing dummies for 95% and 99% quantile. Equation (2) shows that since past values of the σ_t^2 process are fed back into the present value, the conditional standard deviation can exhibit more persistent periods of high or low volatility.

In accordance with the research of Iqbal (2017) and Wu et al. (2019), we consider when the U.S. *CPU* increases the prices of carbon futures and clean energy stocks adjust in the same direction. In other words, the positive correlation of carbon futures and clean energy stocks with the U.S. *CPU* will represent the ability of an asset to act as a hedge and safe haven against uncertainty. More specifically, we define that if parameter $\gamma_1 > 0$, then carbon futures or clean energy stocks are a hedge against the U.S. *CPU*; if parameter $\gamma_2 > 0$, then carbon futures or clean energy stocks are a safe haven against the *CPU* at the 90% quantile; if parameter $\gamma_3 > 0$, then carbon futures or clean energy stocks are a safe haven at the 95% quantile of the *CPU*; and if $\gamma_4 > 0$, then carbon futures or clean energy stocks are a safe haven at the 99% quantile of the *CPU*.

In the quantile regression approach with dummy variables, R represents returns of clean energy stocks and carbon futures, while X denotes *CPU* changes. Henceforth, the R is a real-valued random variable with cumulative distribution function $F_R(r) = P(R \le r)$, the τth conditional quantile of R given $X = x$ is defined in Equation (3):

$$\mathrm{Q}_{R/x}(\tau) = \hat{\mathrm{F}}_{\mathrm{r}_i}^{-1}(\tau) = \inf\{\, r : \mathrm{F}_{r/x}(r) \ge \tau\}; \; 0 < \tau < 1, \tag{3}$$

where $\mathrm{Q}_{R/x}(\tau) = \acute{x}\gamma_{(\tau)}$, and $\gamma_{(\tau)}$ is coefficient of x at τ quantile, therefore, Equation (4) presents

$$\hat{\gamma}_{(\tau)} = \underset{\gamma}{\mathrm{arg}min} \sum \rho_\gamma(r_i - \acute{x}\gamma), \tag{4}$$

where, $\rho_\tau(r) = r(\tau - I(r < 0))$, $I(.)$ is an indication function. Therefore, we employ the following quantile model as shown in Equation (5) for examining the hedge and safe haven properties of carbon futures and clean energy stocks against the U.S. *CPU*.

$$\mathrm{Q}_{R/x}(\tau) = \alpha + \gamma_{1(\tau)}\, CPU_t + \gamma_{2(\tau)}\, D(CPU_{q90})CPU_t + \gamma_{3(\tau)}\, D(CPU_{q95})CPU_t + \gamma_{4(\tau)}\, D(CPU_{q99})CPU_t + \varepsilon_t, \tag{5}$$

where τ denotes conditional quantile, and other specifications are as previously shown.

3. Data

The study sample consists of carbon futures, clean energy stocks, and the U.S. *CPU* index. This study employs monthly time series data covering the period of August 2005 to March 2021. The S&P global clean energy (*CLE*) index is proxied for clean energy stocks and its index data is extracted from https://www.investing.com/ (accessed on 3 January 2022). The European Union Allowance (EUA) futures price is used as a proxy for carbon futures and obtained from DataStream International. It accounts for 90% of the global market for carbon credits in 2021 (Varsani and Gupta 2022), making it the most liquid and developed emissions-trading system in the world.

Following Baker et al. (2016), Gavriilidis (2021) construct the *CPU* index, which utilizes the number of news articles containing the terms {"uncertainty" or "uncertain"} and {"carbon dioxide" or "climate" or "climate risk" or "greenhouse gas emissions" or "greenhouse" or "CO_2" or "emissions" or "global warming" or "climate change" or "green energy" or "renewable energy" or "environmental"} and ("regulation" or "legislation" or "White House" or "Congress" or "EPA" or "law" or "policy"} (including variants such as "uncertainties", "regulatory", "policies", etc.). The series is based on eight leading U.S. newspapers: Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today, and the Wall Street Journal. Each paper-specific monthly series is standardized to have a unit standard deviation and then averaged across newspapers by month. Finally, the averaged series is normalized to have a mean value of 100.[4] The U.S. *CPU* index is gathered from http://www.policyuncertainty.com/ (accessed on 5 January 2022). In the constructing return data series, this study employs logarithmic returns of carbon futures and clean energy stocks. A similar process is followed for changes in the U.S. *CPU* index.

4. Results and Discussion

Table 1 presents the summary statistics for the variables included in the study. While clean energy stocks have the lowest mean returns and standard deviation, carbon futures have the highest mean returns as well as the highest standard deviation. This risk-return relationship is in line with the risk-return theory, which articulates that higher risk is associated with a greater probability of higher return, and vice versa. Furthermore, the skewness and kurtosis of variables are suggesting high-thin distribution. The Jarque–Bera test indicates non-normality of distribution, and the ADF unit root test suggests stationary series.

Focusing on Table 2, we find a weak hedge property of carbon futures and clean energy stocks, but they show a safe haven property during higher levels of *CPU*. The asymmetric correlation of *CPU* further motivates us to look at how carbon futures and clean energy stocks act under different conditions against *CPU*. Bouri et al. (2022) show that differing uncertainty levels affect the reallocation of assets. In Table 3 (which presents quantile estimation with dummies), Panel A, the results of carbon futures are demonstrated, and we find that the coefficients of *CPU* are negative across the quantile, suggesting that carbon futures do not hold hedge properties against the *CPU*. However, *CPU90* coefficients are positive across quantiles, implying that it shows a strong safe haven feature at the 90% quantile across different market conditions. The *CPU99* coefficients for carbon futures are positive across the quantiles, but significant at the bear condition, inferring that carbon futures show a weak safe haven feature at the 99% quantile across market conditions.

Furthermore, focusing on Panel B of Table 3, we note that *CPU* coefficients are positive but insignificant at the 20% quantile to 95% quantile, suggesting that clean energy stocks hold a weak hedge across quantiles. The coefficients of *CPU90* exhibit positive but insignificant at the 20% quantile to 90% quantile, which means clean energy stocks hold a weak safe haven feature at the 90% quantile across market conditions. The results also show that *CPU99* coefficients for clean energy stocks are positive, but they are significant in bear and bull market conditions. Hence, clean energy stocks have a strong safe haven feature at the 99% quantile of the U.S. *CPU*. Both carbon futures and clean energy stocks do not show safe haven features at the 95% quantiles of the U.S. *CPU*. Such findings reflect some inconsistency in exhibiting safe haven characteristics.[5] These findings are quite similar to those of Yousaf et al. (2022), who find that clean energy is a safe haven subject to market uncertainty levels.

Table 1. Descriptive statistics and unit root test.

	Mean	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	ADF	GLS-ADF
Panel A: Full Sample							
CPU	0.008	0.616	0.099	4.802	25.50 ***	−7.30 ***	−4.25 ***
EUA	0.229	1.079	7.692	66.873	33,452.50 ***	−4.93 ***	−4.86 ***
CLE	0.004	0.079	−0.840	5.526	71.32 ***	−11.27 ***	−3.01 ***
Panel B: Sub-sample 08:2005–12:2015							
CPU	0.012	0.666	0.131	4.664	14.42 ***	11.95 ***	2.01 ***
EUA	0.330	1.322	6.162	43.460	9093.40 ***	5.16 ***	5.09 ***
CLE	−0.002	0.083	−0.930	5.383	46.44 ***	8.10 ***	8.12 ***
Panel C: Sub-sample 01:2016–03:2021							
CPU	−0.001	0.514	−0.037	4.027	2.828 *	−3.13 ***	−1.94 **
EUA	0.036	0.018	0.968	3.719	11.369 ***	−4.12 ***	−7.42 ***
CLE	0.018	0.069	−0.341	4.842	10.287 ***	−6.95 ***	−3.14 ***

Note: *CPU*: Changes in climate policy uncertainty, *EUA*: Returns of carbon futures, *CLE*: Returns of clean energy stocks. ***, **, and * represent statistically significant at 1%, 5%, and 10%, respectively.

Table 2. GARCH (1,1) with dummy.

	Carbon Futures		Clean Energy Stocks	
Variable	**Coefficient**	**t-Statistic**	**Coefficient**	**t-Statistic**
Mean Equation				
C	0.006	(9.049)	0.004	(0.73)
Lag (−1)	1.418	(109.49) ***	0.087	(0.90)
CPU	0.002	(1.27)	0.003	(0.16)
CPU90	0.115	(3.190) ***	−0.011	(−0.50)
CPU95	−0.002	(−0.29)	−0.046	(−1.28)
CPU99	−0.092	(−20.12) ***	0.127	(1.98) **
Variance Equation				
Delta			0.001	(1.82)
beta	0.394	(35.77) ***	0.217	(2.47) **
Gamma	0.606	(55.10) ***	0.695	(6.17) ***

Note: IGARCH (1,1) and GARCH (1,1) are employed for carbon futures and clean energy stocks, respectively. The numbers in parentheses are t-statistics. *CPU*: Changes in climate policy uncertainty. *CPU90*, *CPU95*, and *CPU99* denote uncertainty at the 90%, 95%, and 99% quantile, respectively. ***, **, and * represent statistically significant at 1%, 5%, and 10%, respectively.

Table 3. Quantile regression with dummies.

Quantiles	0.1	0.2	0.3	0.5	0.7	0.8	0.9	0.95
				Panel A: Carbon futures				
C	0.015 (9.48) ***	0.020 (11.00) ***	0.024 (12.02) ***	0.034 (14.14) ***	0.049 (13.15) ***	0.066 (9.38) ***	0.145 (3.88) ***	0.499 (4.40) ***
CPU	−0.002 (−0.63)	−0.002 (−0.56)	−0.003 (−0.70)	−0.004 (−0.85)	−0.006 (−1.03)	−0.006 (−0.49)	−0.065 (−2.63) **	−0.453 (−2.19) **
CPU90	−0.001 (−0.04)	0.021 (0.67)	0.039 (2.89) ***	0.031 (1.98) **	0.115 (2.99) **	0.151 (4.48) ***	1.550 (27.38) ***	1.581 (5.98) ***
CPU95	0.002 (0.08)	−0.020 (−0.61)	−0.040 (−2.55) **	−0.025 (−1.43)	−0.120 (−3.05) **	−0.165 (−5.22) **	−1.522 (−35.11) ***	−1.183 (−3.78) ***
CPU99	0.024 (2.01) **	0.019 (1.30)	0.020 (1.16)	0.006 (0.31)	0.022 (1.32)	0.014 (0.82)	0.013 (0.471)	0.088 (0.547)
				Panel B: Clean energy stocks				
C	−0.087 (−4.70) ***	−0.043 (−5.09) ***	−0.022 (−3.03) ***	0.011 (1.73) *	0.046 (6.34) ***	0.060 (8.51) ***	0.097 (9.44) ***	0.115 (10.91) ***
CPU	−0.001 (−0.01)	0.003 (0.19)	0.009 (0.70)	0.013 (1.04)	0.007 (0.56)	0.010 (0.95)	0.017 (1.37)	0.026 (2.35) **
CPU90	−0.027 (−0.35)	0.010 (0.32)	0.004 (0.146)	0.007 (0.16)	0.012 (0.31)	0.010 (0.29)	0.006 (0.12)	−0.021 (−0.61)
CPU95	−0.131 (−1.09)	−0.033 (−0.58)	−0.019 (−0.56)	−0.042 (−0.99)	−0.059 (−1.49)	−0.068 (−1.92)	−0.097 (−2.19)	−0.098 (−3.25)
CPU99	0.273 (4.34) ***	0.086 (1.39)	0.043 (0.91)	0.023 (0.41)	0.098 (2.05) **	0.088 (2.31) **	0.069 (2.12) ***	0.059 (2.19) **

Note: The numbers in parentheses are t-statistics. *CPU*: Changes in climate policy uncertainty. *CPU90*, *CPU95*, and *CPU99* denote uncertainty at 90%, 95%, and 99% quantile, respectively. ***, **, and * represents statistically significant at 1%, 5%, and 10%, respectively.

4.1. Prior- and Post-Paris Agreement of 2016

We are motivated to look at different sub-samples because the climate policy transition occurred after the Paris Agreement of 2016, so we estimate the quantile regression with dummies for examining hedging and safe haven features of clean energy stocks and carbon futures against the U.S. *CPU* during the prior- and post-Paris Agreement of 2016. The estimated results for the sub-samples prior- and post-Paris Agreement of 2016 are presented in Tables 4 and 5, respectively.

Focusing on Panel A of Table 4, we find that *CPU* coefficients for carbon futures are negative and insignificant, thus they do not have hedging properties. The *CPU*95 coefficients for carbon futures are positive but significant, meaning that carbon futures have strong safe haven properties at the 95% quantile of the U.S. *CPU* in average and bull market conditions. Furthermore, when we focus on Panel B of Table 4, we find that *CPU* coefficients for clean energy stocks are negative and insignificant, hence clean energy stocks exhibit no hedging properties against the U.S. *CPU*. However, the *CPU*90 coefficients for clean energy stocks are positive across quantiles, suggesting a weak safe haven of clean energy stocks against the 90% quantile of the U.S. *CPU* across all market conditions. We also evidenced that *CPU*99 coefficients for clean energy stocks are positive across quantiles, but they are significant at extreme bull and bear market conditions; thus, it also shows a strong safe haven at the 99% quantile of the U.S. *CPU* in bearish and bullish conditions.

Table 4. Quantile regression with dummy for sub-sample: prior-Paris Agreement of 2016.

	Quantiles							
	0.1	**0.2**	**0.3**	**0.5**	**0.7**	**0.8**	**0.9**	**0.95**
	Panel A: Carbon futures							
C	0.016 (5.98) ***	0.020 (6.17) ***	0.025 (6.64) ***	0.036 (9.11)	0.062 (7.73) ***	0.108 (4.02) ***	0.297 (1.68) *	0.685 (1.50)
CPU	−0.004 (−0.72)	−0.003 (−0.40)	−0.007 (−0.92)	−0.008 (−1.12)	−0.001 (−0.02)	−0.050 (−1.12)	−0.296 (−0.79)	−0.271 (−0.41)
CPU90	0.053 (1.59)	0.048 (1.12)	0.086 (1.59)	0.129 (2.28) **	0.148 (3.05) **	0.152 (2.62) **	1.628 (6.56) ***	1.214 (1.10)
CPU95	−0.050 (−1.46)	−0.045 (−1.03)	−0.083 (−1.55)	−0.126 (−2.16) ***	−0.178 (−3.80) ***	−0.131 (−1.69) *	−1.327 (−3.21) ***	−1.35 (−2.22)
CPU99	0.026 (1.72)	0.019 (1.02)	0.022 (0.99)	0.014 (0.58)	0.021 (1.02)	0.027 (0.63)	0.059 (0.39)	0.054 (0.33)
	Panel B: Clean energy stocks							
C	−0.103 (−5.06) ***	−0.061 (−4.84)	−0.031 (−3.17) ***	−0.001 (−0.15)	0.036 (3.94) ***	0.062 (6.44) ***	0.092 (8.49) ***	0.098 (11.34) ***
CPU	−0.017 (−0.37)	−0.004 (−0.16)	0.001 (0.04)	−0.001 (−0.03)	−0.001 (−0.08)	−0.003 (−0.22)	0.006 (0.40)	−0.002 (−0.15)
CPU90	0.095 (1.53)	0.055 (1.23)	0.021 (0.49)	0.029 (0.63)	0.084 (1.91) *	0.060 (1.63)	0.046 (1.16)	0.047 (1.54)
CPU95	−0.205 (−2.24) ***	0.001 (0.04)	−0.001 (−0.03)	−0.036 (−0.68)	−0.105 (−2.23) **	−0.095 (−2.46) **	−0.121 (−3.16) **	−0.119 (−4.08) ***
CPU99	0.274 (3.86) ***	0.040 (0.69)	0.035 (0.54)	0.035 (0.46)	0.098 (1.49)	0.089 (1.74) *	0.079 (1.78) *	0.088 (2.20) ***

Note: The numbers in parentheses are t-statistics. *CPU*: Changes in climate policy uncertainty. *CPU90*, *CPU95*, and *CPU99* denote uncertainty at the 90%, 95%, and 99% quantile, respectively. ***, **, and * represent statistically significant at 1%, 5%, and 10%, respectively.

Table 5 demonstrates the hedging and safe haven features of carbon futures and clean energy stocks after the Paris Agreement of 2016. Focusing on Panel A, we find that *CPU* coefficients for carbon futures are negative for all quantiles, with the exception of those with return conditions of 20% and 30%. Hence, it infers carbon futures provide no hedge against the U.S. *CPU*. The *CPU95* coefficients for carbon futures are positive and significant at average return conditions, implying that it only has strong safe haven features at the 95% quantile of the U.S. *CPU* in average conditions.

On the other hand, focusing on Panel B, *CPU* coefficients for clean energy stocks are positive and insignificant across quantile excluding 10% quantile, implying that clean energy stocks exhibit weak hedge properties against the U.S. *CPU* across market conditions. The *CPU90* coefficients for clean energy stocks are positive across quantiles, but they are significant in bear and bull market conditions, suggesting that they exhibit a strong safe haven at the 90% quantile of US *CPU* in bear and bull market conditions. We also noted that the *CPU99* coefficients for clean energy stocks are mostly positive, but significant at the 10% quantile. These findings suggest that clean energy stocks show weak safe haven properties at the 99% quantile of the U.S. *CPU* on average in a bullish market, but at the same uncertainty, it shows strong safe haven properties in a bearish market.

Table 5. Quantile regression with dummy for sub-sample: post-Paris Agreement of 2016.

	0.1	**0.2**	**0.3**	**0.5**	**0.7**	**0.8**	**0.9**
			Panel A: Carbon futures				
C	0.016 (6.22)	0.021 (8.31) ***	0.026 (9.28) ***	0.032 (10.80) ***	0.038 (12.44) ***	0.047 (8.74) ***	0.059 (10.10) ***
CPU	−0.002 (−0.45)	0.001 (0.162)	0.004 (0.59)	−0.001 (−0.14)	−0.007 (−0.75)	−0.002 (−0.20)	0.009 (0.84)
CPU90	−0.001 (−0.02)	−0.007 (−0.39)	−0.013 (−0.58)	0.029 (2.19) **	0.028 (2.31) **	0.016 (1.16)	−0.002 (−0.20)
CPU95	0.026 (1.50)	0.024 (1.19)	0.023 (0.89)	−0.0169 (−1.05)	−0.001 (−0.02)	−0.001 (−0.04)	−0.001 (−0.12)
CPU99	−0.020 (−1.69)	−0.022 (−1.58)	−0.024 (−1.38)	−0.026 (−1.50)	−0.037 (−2.02) **	−0.041 (−2.00) **	−0.051 (−2.69) **
			Panel B: Clean energy stocks				
C	−0.057 (−3.05) **	−0.022 (−2.00) **	−0.008 (−0.82)	0.018 (1.81)	0.043 (3.83) ***	0.058 (5.10) ***	0.095 (5.09) ***
CPU	−0.012 (−0.62)	0.007 (0.41)	0.003 (0.14)	0.003 (0.11)	0.002 (0.047)	0.014 (0.42)	0.047 (1.32)
CPU90	0.119 (3.39) **	0.074 (2.46) **	0.062 (1.78) ***	0.041 (1.00)	0.096 (1.36)	0.074 (2.28) **	0.017 (0.33)
CPU95	−0.108 (−3.74) ***	−0.122 (−2.99)	−0.120 (−2.58) **	−0.093 (−2.03) **	−0.152 (−2.10) ***	−0.153 (−2.61) **	−0.156 (−3.35) ***
CPU99	0.074 (2.34) **	0.068 (1.63)	0.069 (1.44)	0.036 (0.70)	0.018 (0.33)	0.007 (0.16)	−0.019 (−0.44)

Note: The numbers in parentheses are t-statistics. *CPU*: Changes in climate policy uncertainty. *CPU90*, *CPU95*, and *CPU99* denote uncertainty at the 90%, 95%, and 99% quantile, respectively. ***, **, and * represent statistically significant at 1%, 5%, and 10%, respectively.

4.2. Robustness Testing

We also run a robustness check with another indicator, the U.S. environmental policy index (*ENP*) introduced by Noailly et al. (2021). Here, *ENP90*, *ENP95*, and *ENP99* quantile dummies have been created using a method similar to that used to create *CPU* quantile dummies. In this robustness testing, the main intention is to confirm the asymmetric and heterogeneity of the safe haven properties of clean energy stocks and carbon futures. The estimated results of the quantiles with dummies *ENP90*, *ENP95*, and *ENP99* are presented in Table 6. We observe that both carbon futures and clean energy stocks do not hold hedge properties. They do, however, exhibit strong safe haven characteristics depending on the level of uncertainty and market conditions, implying asymmetric and heterogeneous safe haven properties. Henceforth, the quantiles demonstrating safe haven characteristics of carbon futures and clean energy stocks confirm the robustness of the estimated results presented in Tables 3–5.

Table 6. Robustness checking with environmental policy uncertainty.

	0.1	**0.2**	**0.3**	**0.5**	**0.7**	**0.8**	**0.9**	**0.95**
				Panel A: Carbon futures				
C	0.017 (7.63) ***	0.023 (10.02) ***	0.028 (10.91) ***	0.041 (12.55)	0.06 (10.87)	0.092 (5.37)	0.213 (1.95)	0.725 (1.32)
ENP	0.002 (0.20)	0.011 (0.95)	0.015 (1.16)	0.016 (0.89)	0.044 (1.46)	0.132 (2.44) **	0.35 (1.51)	−0.736 (−0.35)
ENP90	−0.005 (−0.69)	−0.014 (−1.49)	−0.019 (−1.81) **	−0.028 (−2.25) **	−0.041 (−2.42) **	−0.086 (−2.27) **	−0.14 (−0.71)	−0.284 (−0.23)
ENP95	0.009 (0.99)	0.008 (0.72)	0.009 (0.66)	0.012 (0.826)	0.045 (2.59) **	0.082 (2.23) **	−0.08 (−0.94)	−0.011 (−0.06)
ENP99	−0.002 (−0.13)	−0.003 (−0.15)	−0.005 (−0.25)	0.01 (0.43)	−0.01 (−0.39)	−0.039 (−1.38)	−0.134 (−2.10) **	0.004 (0.02)
				Panel B: Clean energy stocks				
C	−0.084 (−7.28) ***	−0.047 (−5.68) ***	−0.026 (−3.85) ***	0.003 (0.42)	0.034 (4.56) ***	0.053 (6.56) ***	0.09 (8.36) ***	0.113 (8.99) ***
ENP	0.056 (1.33)	0.074 (1.71) *	0.006 (0.15)	0.033 (0.80)	0.06 (1.30)	0.044 (0.65)	0.015 (0.244)	0.044 (0.67)
ENP90	−0.05 (−0.83)	0.013 (0.42)	0.024 (0.92)	0.015 (0.60)	−0.019 (−0.76)	−0.025 (−0.85)	−0.028 (−0.931)	−0.06 (−1.98) **
ENP95	−0.136 (−1.74) *	−0.068 (−0.96)	−0.012 (−0.14)	0.03 (0.86)	0.024 (0.77)	0.068 (1.99) **	0.098 (2.05) **	0.025 (1.28)
ENP99	0.178 (2.94) **	0.001 (0.01)	−0.052 (−0.60)	−0.071 (−1.22)	−0.074 (−1.50)	−0.104 (−2.62) **	−0.105 (−3.30) ***	−0.107 (−3.87) ***

Note: The numbers in parentheses are t-statistics. *ENP*: Changes in environmental policy uncertainty. *ENP90*, *ENP95*, and *ENP99* denote environmental policy uncertainty at the 90%, 95%, and 99% quantile, respectively. ***, **, and * represent statistically significant at 1%, 5%, and 10%, respectively. The sample period covers months from August 2005 to March 2019.

5. Conclusions and Policy Implications

We study the hedging and safe haven properties of carbon futures and clean energy stocks against the U.S. *CPU* using the GARCH model and quantile regression with dummy variables. Carbon futures and clean energy stocks have a weak hedge and a semi-strong safe haven across market conditions. Carbon futures hold significant safe haven characteristics in both bullish and bearish markets, depending on the level of uncertainty. Clean energy stocks hold a weak hedge across the market condition and a strong safe haven in bull markets. Yousaf et al. (2022) also find that these clean energy investments have the potential to serve as a safe haven. Sub-sample analyses of prior- and post-Paris Agreement of 2016 also show consistent results that hedge and safe haven features of carbon futures and clean energy stocks are correlated with bull and bear market conditions.

Our findings also offer policy implications and future research directions. When forecasting and managing carbon futures and clean energy stocks, these findings suggest that investors should adjust their investment strategy in response to changes in climate uncertainty, considering hedge and safe haven properties as well as market conditions. This technique will assist investors in making more informed judgments when it comes to selecting the optimal portfolio, and maximizing the use of carbon futures and clean energy stocks to achieve superior portfolio returns (Ali et al. 2021). Moreover, the inclusion of clean energy stocks in the portfolio could generate higher returns (Yousaf et al. 2022). Additionally, green investment has been emerging as a necessity for improved financial stability and performance (Bouri et al. 2022; Liang et al. 2022; Pástor et al. 2021; Yousaf et al. 2022). The safe-haven feature of clean energy stocks against the *CPU* suggests that it could help investors to maintain stable portfolio returns even during some uncertain periods.

Moreover, the performance of clean energy stocks against climate uncertainty also suggests that sub-sector rotation could be employed depending on the level of uncertainties.

Furthermore, while carbon futures and clean energy stocks act as a hedge and a safe haven asset for *CPU*, future research may explore different portfolio strategies with asset combinations of dirty energy stocks, carbon futures, and clean energy stocks. For example, hedged, optimal, and undiversified portfolio strategies can be explored. Precious metals have demonstrated safe haven properties in the face of various types of policy uncertainties; therefore, it may be worthwhile to investigate whether gold and silver provide a safe haven in the face of climate policy uncertainties.

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Notes

[1] See Ghazali et al. (2020); Mokni et al. (2021); Wu et al. (2019) for a detailed literature review.

[2] Non-renewable, non-clean, or non-green energy stocks.

[3] The Paris Agreement is a legally binding international treaty on climate change. It was adopted by 196 parties at COP 21 in Paris on 12 December 2015 and entered into force on 4 November 2016.

[4] The series is normalized for the period of January 2000 to March 2021.

[5] An extended discussion of empirical results will be provided upon request.

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