International Journal of Finance & Economics

WILEY

RESEARCH ARTICLE OPEN ACCESS

The Relationship Among Climate Policy Uncertainty and Energy Markets: Fossil Versus Renewable and Low-Carbon Assets

Dimitrios Asteriou[1] | Anastasia Dimiski[2]

[1]Oxford Brookes University, Oxford, UK | [2]London School of Economics, Hellenic Observatory, London, UK

Correspondence: Dimitrios Asteriou (dasteriou@brookes.ac.uk)

Received: 30 January 2025 | **Revised:** 13 January 2026 | **Accepted:** 11 February 2026

Keywords: climate policy uncertainty | energy markets | fossil-based energy assets | low-carbon energy | policy frameworks | renewable energy | robustness analysis | sustainability

ABSTRACT

This paper investigates the intricate relationship between climate policy uncertainty (CPU) and energy market dynamics, focusing on fossil-based and renewable/low-carbon energy assets. Utilising a comprehensive dataset spanning from April 1987 to December 2023, comprising monthly observations of CPU, stock market returns, spot oil prices and various energy commodity futures, we employ time series regressions to analyse the effects of CPU on market returns. Our findings reveal that fossil-based energy assets are significantly and negatively impacted by changes in CPU, while renewable and low-carbon energy assets exhibit minimal or negligible effects. Moreover, we identify a heightened negative impact of CPU during periods of increased uncertainty, underscoring investor sensitivity to abrupt spikes in climate policy uncertainty, particularly in fossil-based energy sectors. Robustness analysis confirms the efficacy of the CPU index as a reliable indicator, emphasising the importance of using comprehensive metrics to assess the influence of climate policy uncertainty on financial markets. Our study underscores the necessity for policymakers and industry stakeholders to recognise the implications of climate policy uncertainty on energy markets and prioritise efforts to establish clear and consistent policy frameworks to facilitate the transition to a more sustainable energy landscape.

JEL Classification: G11, G12, Q48, Q54

1 | Introduction

Addressing global warming has prompted urgent revisions to climate strategies in pursuit of a net-zero economy (Hoque et al. 2023). The Paris Agreement, established in 2015, committed 174 nations to reducing emissions, yet the path to a net-zero future remains uncertain due to unpredictable climate patterns, shifting public concerns and evolving technological and economic factors (Pham et al. 2019). This uncertainty, driven by political changes, international agreements and climate science complexities, complicates the design and implementation of effective climate policies. As climate change poses substantial risks to economies and markets, the ambiguity surrounding climate policies—especially their timing and impact—adds further challenges to the transition to a sustainable economy (Gavriilidis 2021).

Building on the uncertainty surrounding climate policies, the energy sector—particularly, the fossil fuel and renewable energy markets—is significantly shaped by the evolving political environment and the complexities of climate science. As discussed, the path to a net-zero future remains unclear due to fluctuating international agreements and shifting political landscapes, which create ambiguity about future policy directions (Blyth et al. 2007). This uncertainty is further compounded by the ongoing challenges in addressing climate change, where policies designed to mitigate extreme weather events remain under development and subject to considerable unpredictability. Investors, caught between carbon-intensive and low-carbon assets, are increasingly faced with difficult decisions on whether to delay investments or pivot towards sectors less impacted by policy shifts (Pástor et al. 2021). While some firms are adapting their strategies to hedge against climate risks, quantifying these impacts remains a challenge (Fried et al. 2021). As the call for a transition from fossil fuels to renewable alternatives grows (Brown 2016; Hosseini 2022), understanding how these policy shifts influence energy markets and investment patterns becomes crucial for guiding stakeholders through this uncertain transformation (Golub et al. 2020).

The key research question this study addresses is: how does climate policy uncertainty (CPU) shape the pricing of fossil-based versus renewable and low-carbon energy assets? To answer this, we employ the CPU index developed by Gavriilidis (2021), which captures uncertainty surrounding climate-related political and regulatory actions based on leading US newspapers.

Since the introduction of the CPU index, a growing literature has examined its effects on energy markets. Existing studies have documented important links between CPU and oil prices, green and brown energy stocks, volatility transmission and hedging or safe-haven properties of clean energy and carbon-related assets. For example, Bouri et al. (2022), Ding, Ji, et al. (2022), Ding, Liu, et al. (2022) and Hoque et al. (2023) analyse how CPU affects co-movements, volatility spillovers or risk transmission across traditional and green energy markets.

However, this literature has focused primarily on volatility, correlations and connectedness rather than on whether CPU is priced through predictable movements in future energy asset returns and whether such pricing differs systematically between fossil-based and renewable assets. In particular, little is known about whether CPU shocks generate persistent return effects, whether these effects are state-dependent and whether they are economically meaningful for investors.

This paper addresses these gaps. We examine whether shocks to CPU predict future returns in fossil-based and renewable/low-carbon energy assets and whether this predictability depends on market conditions. Our contribution is threefold. First, we show that increases in CPU predict persistent negative future returns for fossil-based energy assets, while renewable and low-carbon assets display negligible short-run pricing responses. Second, we demonstrate that these effects are state-dependent: they become substantially stronger during periods when CPU is salient and when overall market fear (measured by the VIX) is elevated, revealing an attention-based amplification channel that has not been explored in the existing literature. Third, we quantify the economic magnitude of these effects, showing that CPU shocks generate cumulative losses in fossil-based energy markets that are comparable to or larger than, typical multi-month returns.

To implement this analysis, we use monthly data on major fossil energy futures (WTI, Brent, heating oil and natural gas), spot oil prices, broad equity returns and a set of renewable and low-carbon energy indices from 1987 to 2023. This allows us to provide a comprehensive comparison of how CPU transmits across traditional and clean energy markets.

The remainder of this paper is structured as follows. Section 2 reviews related literature, Section 3 describes data and methodology, Section 4 presents and discusses findings and Section 5 concludes the study.

2 | Literature Review

The challenge of addressing global warming has prompted policymakers to urgently revise their climate strategies in pursuit of a net-zero economy (Hoque et al. 2023). As climate change increasingly impacts the stability of energy systems, its consequences have become a crucial factor in shaping energy security. The Paris Agreement, convened in late 2015, underscored the global commitment to reducing emissions and transitioning to sustainable, low-carbon energy sources (Pham et al. 2019). However, despite the commitment of 174 nations to these ambitious climate goals, the path towards a net-zero future remains fraught with significant uncertainties. These challenges arise from unpredictable climate patterns, shifting public concerns and evolving technological and economic conditions. The growing frequency of extreme weather events—such as rising temperatures, sea level rise, cyclones and wildfires—further exacerbates the situation, heightening risks to both energy infrastructure and societal stability (Ren et al. 2022). In this complex environment, the successful implementation of climate policies remains uncertain, as multiple factors shape the course of the transition to a low-carbon, sustainable economy (Gavriilidis 2021).

The uncertainty surrounding climate policy plays a pivotal role in shaping the energy landscape, especially at the intersection of fossil fuel and renewable energy sectors. This uncertainty arises from the shifting political environment, fluctuating international agreements and the complexities of climate science, creating a landscape where future policy directions remain unclear (Blyth et al. 2007). Fossil fuels, as the primary contributors to carbon emissions, face heightened risks from evolving climate regulations, which may disrupt their market position. Conversely, this very uncertainty could also fuel investments in renewable and low-carbon energy alternatives, which stand to benefit from policy-driven incentives aimed at decarbonisation (Gavriilidis 2021; Ding, Ji, et al. 2022). As countries refine their climate frameworks, the implications for both fossil and renewable energy assets are profound. A clearer understanding of how energy markets react to these unpredictable shifts in policy is essential for guiding investors through this transformative transition (Golub et al. 2020). The development of indicators such as the CPU metric, introduced by Gavriilidis 2021, highlights the degree of ambiguity surrounding climate policies, offering insights into how these uncertainties may impact energy consumption and emissions trajectories. Such measures provide critical evidence for navigating the complex terrain of energy transition and investment in the context of policy volatility.

Building on this uncertainty, the complexities of climate policy have a particularly pronounced effect on the crude oil market, where shifts in both supply and demand dynamics are directly influenced by the evolving regulatory landscape. As governments and institutions struggle to define clear and consistent climate strategies, the resulting ambiguity significantly impacts crude oil prices, with potential disruptions on both the supply and demand sides. This volatility is evident in studies by Ding, Liu et al. (2022) and Salisu et al. (2023), which explore the varying effects of CPU on oil prices across different time frames. Moreover, Guo et al. (2022) reveal a nonlinear relationship between CPU and energy prices, highlighting how this uncertainty increases market risks and price instability, particularly for fossil fuels. Consequently, such unpredictability complicates investment decisions in fossil fuel markets, further exacerbating the volatility in global crude oil prices.

Recent research has highlighted the interaction between CPU and both traditional fossil energy and sustainable green markets. Bouri et al. (2022) found that CPU positively impacts both green and brown energy stocks, with a stronger effect on green stocks. Ding, Ji, et al. (2022) explored CPU's influence on the correlation between carbon-intensive and low-carbon assets. Hoque and Batabyal (2022) used the GARCH model to assess the hedging and safe heaven properties of carbon futures and clean energy stocks, finding carbon futures as a strong safe haven across market conditions, while clean energy stocks offered limited hedging. Hoque et al. (2023) show that CPU, energy stocks and carbon emissions futures act as volatility spillover transmitters, while alternative energy stocks serve as receivers. Li et al. (2023) examine the bi-directional causality between renewable (REC) and non-renewable energy consumption (NEC) and policy uncertainty, finding a positive or negative relationship between REC and CPU depending on government attitudes towards climate change, while the link between NEC and CPU is generally positive, except during global financial crises. Ren et al. (2023) explore the dynamic causal relationship between CPU and both renewable and conventional energy assets, noting that this connection strengthens during periods of extreme climate policy fluctuations. They find that CPU acts more as a receiver of market volatility than a transmitter, with bidirectional causality observed between CPU and both traditional energy (oil, coal, natural gas) and green markets (clean energy, green bonds, carbon trading). Finally, the work of Tedeschi et al. (2024) underscores the time-varying impact of CPU on stock market returns, with increased climate risk leading to rising clean energy stock returns and a decrease in fossil fuel stocks, particularly, in Europe.

Building on the complexities of climate policy and its effects on energy markets, CPU plays a pivotal role in influencing both market prices and broader economic conditions. As mentioned earlier, shifts in the regulatory landscape and political decisions significantly impact the supply and demand dynamics in energy markets, including crude oil. This results in a bi-directional relationship between policy uncertainty and oil prices, where fluctuations in oil prices can increase economic uncertainty, prompting governments to introduce policies to mitigate the situation. At the same time, the uncertainty surrounding such policies can influence market sentiment, leading to further price volatility (Antonakakis et al. 2014; Dash and Maitra 2021; Su et al. 2021). Studies have shown that rising oil prices can negatively affect business productivity and investor confidence, which in turn reduces demand for oil (Rahman and Serletis 2011; Filis and Chatziantoniou 2014; Montoro 2012). Conversely, economic policy uncertainty often dampens investment and production, placing downward pressure on oil prices (Antonakakis et al. 2014; Pástor and Veronesi 2013). This ongoing cycle of price fluctuations and policy uncertainty is particularly evident in the context of climate change, where political actions—such as the US withdrawal from the Paris Agreement and inconsistent climate strategies from other nations—create further ambiguity in the energy landscape (Diaz-Rainey et al. 2021; Lin and Bega 2021).

3 | Data and Methodology

3.1 | The Data Set

This study incorporates a selection of four widely recognised fossil-based energy commodity futures (for fossil based traditional energy assets), including Brent Crude oil and WTI, which are historically significant in the global energy mix (Hanif et al. 2019; Mensah et al. 2019; Hasan and Hossain 2022) and highly relevant to climate policy discussions. In addition, we include five renewable and low-carbon energy assets (as the renewable source assets), chosen for their role in providing valuable insights into the energy transition as well as capturing investor sentiment and market trends. The study also leverages data from the S&P500 index and the spot prices of crude oil and petroleum products to serve as proxies for stock market performance. Central to our analysis is the CPU index, which we use as the primary independent variable to assess its impact on these energy assets, alongside other uncertainty indices to ensure robustness and offer a comparative perspective. All the variables and their respective sources are given in Table 1. The data set covers 441 monthly observations for the CPU index, for the stock market returns and for the fossil-based energy commodities from April 1987 to December 2023; and nearly 200 monthly observations for the renewable and low-carbon energy assets from December 2008 to December 2023 (for details with regards to small variations in dates among those indices check Table 1, data span information).

All data are in a monthly frequency, consistent with the CPU index availability. Additionally, logarithmic monthly returns are calculated for all assets to maintain consistency and ensure stationarity of the variables. All asset price series (equity, fossil energy futures, spot oil and renewable/low-carbon indices) are therefore expressed in logarithmic monthly returns. The CPU index is expressed in logarithmic monthly changes, consistent with the relevant literature. Because renewable and low-carbon indices become available later than fossil-based assets, the estimation sample differs across asset groups, as detailed in Table 1.

Additionally, all financial series are denominated in US dollars or are USD-based indices provided by the data vendors. The CPU index is constructed from US newspapers and is therefore also inherently US-dollar-based in its information content. No explicit seasonal adjustment is applied, as all variables are expressed in monthly logarithmic returns (or monthly log changes for CPU), which removes deterministic seasonal patterns in levels and is standard practice in the energy and financial economics literature.

TABLE 1 | Definition of variables.

Dimension	Variable	Abbreviation	Source	Data span
Risk related to climate policy uncertainty	Climate Policy Uncertainty Index	CPU	www.policyuncertainty.com	Apr 1987–Dec 2023 (441 Obs)
Risk related to stock market uncertainty	US Equity Market Volatility Index	EMV	www.policyuncertainty.com	Apr 1987–Dec 2023 (441 Obs)
	CBOE Volatility (VIX) index	VIX	www.investing.com	Feb 1990–Dec 2023 (407 Obs)
	Equity Market Volatility Tracker: Energy and Environmental Regulation	EEREMV	fred.stlouisfed.org	Apr 1987–Dec 2023 (441 Obs)
Stock market returns	Standard & Poor's 500 Index	S&P500	www.investing.com	Apr 1987–Dec 2023 (441 Obs)
	Spot Price for Crude Oil and Petroleum Products	OILP	www.eia.gov	Apr 1987–Dec 2023 (441 Obs)
Measures of fossil-based energy assets	Crude Oil WTI Futures Index	WTI	www.investing.com	Apr 1987–Dec 2023 (441 Obs)
	Brent Oil Futures Index	BRENT	www.investing.com	July 1988–Dec 2023 (426 Obs)
	Heating Oil Futures Index	HEAT	www.investing.com	Apr 1987–Dec 2023 (441 Obs)
	Natural Gas Futures Index	NAT_GAS	www.investing.com	May 1990–Dec 2023 (404 Obs)
Measures of renewable and low-carbon based energy assets	FTSE Environmental Opportunities Renewable and Alternative Energy	FTEORE	www.investing.com	Dec 2008–Dec 2023 (181 Obs)
	FTSE Environmental Opportunities Waste and Pollution Control Technology	FTEOWP	www.investing.com	Dec 2008–Dec 2023 (181 Obs)
	VanEck Low Carbon Energy ETF	SMOG	www.investing.com	July 2007–Dec 2023 (199 Obs)
	Ardour Solar Energy Historical	SOEN	www.investing.com	July 2006–Dec 2011 (199 Obs)
	S&P Global Clean Energy EURO TR	SPGE	www.investing.com	Jan 2005–Dec 2011 (228 Obs)

Note: All financial variables are converted to monthly logarithmic returns computed as $R_t = \ln(P_t) - \ln(P_{t-1})$. The Climate Policy Uncertainty (CPU) index is used in logarithmic first differences (ΔCPU), and an alternative specification considers only positive CPU changes (INC_CPU), as defined in Section 3.2. The fossil-based energy assets and CPU index are available from April 1987 to December 2023, whereas renewable and low-carbon indices begin later, mostly from 2005 onwards. Consequently, regressions including renewable/low-carbon indices are estimated over their available sample windows only, while fossil-based asset regressions use the full 1987–2023 period.

The return dynamics of all examined assets are volatile and time-varying, with CPU fluctuations particularly erratic. Despite sustained high volatility, the CPU shows less volatility during crises, such as the 2008 Global Financial Crisis and COVID-19. Heating oil and natural gas, among fossil energy futures, exhibit higher volatility clustering. Among renewable and low-carbon-based energy assets, all show similar return patterns with the highest volatility during COVID-19.

TABLE 2 | Descriptive statistics.

Variable	Obs	Mean	SD	Min	Max	Skewness	Kurtosis	DF tests
ΔCPU	440	0.0038	0.3618	−1.7013	1.2326	−0.176	3.802	−34.021
Stock market indices								
S&P500	442	0.0073	0.0438	−0.2176	0.1268	−0.756	5.052	−20.610
Fossil-based energy assets								
OILP	440	0.0030	0.0952	−0.5681	0.5456	−0.623	10.85	−15.733
WTI	442	0.0084	0.1046	−0.5424	0.8838	1.167	15.76	−18.259
BRENT	427	0.0088	0.0979	−0.5499	0.4617	0.016	7.368	−10.124
HEAT	442	0.0082	0.0932	−0.3221	0.3835	0.220	4.495	−17.083
NAT_GAS	405	0.0128	0.1574	−0.4162	0.6261	0.472	4.120	−18.547
Renewable and low-carbon based energy assets								
FTEORE	182	0.0035	0.0576	−0.1849	0.1706	−0.209	3.129	−19.940
FTEOWP	182	0.0074	0.0441	−0.1424	0.1269	−0.322	3.455	−13.174
SMOG	200	0.0025	0.0860	−0.3949	0.2714	−0.600	5.389	−13.981
SOEN	229	0.0042	0.0786	−0.3347	0.2054	−0.595	5.008	−12.622
SPGE	212	0.0039	0.0406	−0.0123	0.1873	−0.161	13.245	−12.803

Note: Descriptive statistics for monthly logarithmic returns of all financial and energy market variables and monthly logarithmic changes in the Climate Policy Uncertainty (CPU) index. The sample spans April 1987 to December 2023 for fossil-based assets and equity markets, while renewable and low-carbon assets have shorter available histories as indicated in Table 1. Data are collected from PolicyUncertainty.com, the US Energy Information Administration, FRED, and Investing.com.

Descriptive statistics are presented in Table 2 and reveal that CPU changes have the highest volatility of all the series. From the fossil-based assets, natural gas has the mean return and the highest volatility. Renewable and low-carbon assets generally have lower volatility than fossil energy assets. All renewable return series are negatively skewed, while fossil-based returns depict positive skewness, indicating asymmetric distributions in both cases. The kurtosis values are high suggesting leptokurtic distributions and heavy tails. Unit root tests confirm the absence of stationarity issues in return series and CPU changes. Pearson's correlations reported in Table 3 show generally very low correlations between CPU and fossil-based energy assets, as well as with renewable and low carbon-based assets.

3.2 | Methodology

To examine the impact of CPU on market returns, we perform the following time series regressions:

$$R_t = \beta_1 L5(\Delta CPU_t) + \beta_2 L5(R_t) + \beta_3 L5(R_t^2) + \beta_4 X_t + \varepsilon_t \tag{1}$$

where R_t denotes monthly logarithmic returns on the S&P500 index (*S&P500*), the spot oil price index (*OILP*), the crude oil WTI futures index (*WTI*), the Brent futures index (*BRENT*), the heating oil futures index (*HEAT*), the natural gas futures index (*NAT_GAS*), the FTSE environmental opportunities renewable energy index (*FTEORE*), the FTSE environmental opportunities waste and pollution control technology index (*FTEOWP*) the VanEck low carbon energy index (*SMOG*), the Ardour solar energy index (SOEN) and the S&P global clean energy index (*SPGE*). *ΔCPU* stands for the logarithmic change in the CPU index provided by Gavriilidis (2021). *L5* transforms a variable into a row vector consisting of five lags of that variable and X_t is a set of exogenous variables that includes an intercept and day-of-the-week indicators (except for Monday to avoid the dummy variable trap). Thus, in order to ensure that we capture fully the effect of CPU, we include in our regression models lagged terms of own returns as well as squared lagged returns.

Additionally, because people's attention might be limited, they are likely to focus on attention-grabbing changes in CPU or rather increases in CPU. This asymmetric effect with regards to limited attention span has been previously studied by Da et al. (2015), Wang et al. (2023) and Choi et al. (2020). Thus, in a similar fashion, we use an alternative CPU indicator which is the increase in CPU (*INC_CPU*). In particular, we define *INC_CPU* as follows:

$$INC_{CPU} = \left\{ \begin{array}{lll} \Delta CPU_t, & \text{if} & \Delta CPU_t > 0 \\ 0 \quad , & & \text{Otherwise} \end{array} \right\}$$

By doing this, the regression model in Equation (1) is now different and given by:

$$R_t = \beta_1 L5(INC\_CPU_t) + \beta_2 L5(R_t) + \beta_3 L5(R_t^2) + \beta_4 X_t + e_t \tag{2}$$

where *INC_CPU* is used instead of the change in CPU and all other variables are defined as before.

TABLE 3 | Correlation matrix.

	ΔCPU	S&P500	OILP	WTI	BRENT	HEAT	NAT_GAS	FTEORE	FTEOWP	SMOG	SOEN	SPGE
ΔCPU	1.000											
S&P500	0.019	1.000										
OILP	−0.035	0.213	1.000									
WTI	0.022	0.383	0.728	1.000								
BRENT	−0.003	0.429	0.665	0.908	1.000							
HEAT	−0.001	0.341	0.640	0.820	0.880	1.000						
NAT_GAS	0.087	0.107	0.020	0.074	0.081	0.123	1.000					
FTEORE	0.081	0.723	0.219	0.337	0.358	0.279	0.060	1.000				
FTEOWP	−0.015	0.908	0.204	0.375	0.413	0.314	0.083	0.797	1.000			
SMOG	0.086	0.769	0.174	0.320	0.352	0.262	0.071	0.843	0.793	1.000		
SOEN	0.095	0.584	0.171	0.231	0.256	0.170	0.102	0.780	0.632	0.854	1.000	
SPGE	−0.006	−0.014	−0.046	−0.074	−0.064	−0.058	0.127	−0.011	0.031	0.008	0.039	1.000

Note: Pearson's correlation coefficients based on monthly logarithmic returns of financial and energy assets and monthly logarithmic changes in the CPU index. Sample periods for each asset correspond to those reported in Table 1.
Source: PolicyUncertainty.com, FRED, EIA and Investing.com.

Furthermore, to examine deeper the attention-grabbing roe of CPU related changes, we re-estimate the basic model given in Equation (1) this time focusing on salient times, through the following model:

$$R_t = (E_t)\left[\beta_1 L5(\Delta CPU_t) + \beta_2 L5(R_t) + \beta_3 L5(R_t^2)\right] + \beta_4 X_t + u_t \tag{3}$$

where E_t is an indicator variable that takes the value of one if month t is at the top decile of ΔCPU_t. We postulate that for the months when the change in CPU is overwhelmingly positive (i.e., very high or in the top 10%), investors will find the consistent message to be salient and be more deterred than regular, compared to days with negative or neutral CPU levels.

Finally, we repeat the previous exercise for periods of elevated stock market fear using the VIX index. The regression model in this case is modified as follows:

$$R_t = (F_t)\left[\beta_1 L5(\Delta CPU_t) + \beta_2 L5(R_t) + \beta_3 L5(R_t^2)\right] + \beta_4 X_t + v_t \tag{4}$$

where this time F_t is an indicator variable that takes the value of one for the months that the VIX index is at the top decile and zero otherwise. In this model we combine extreme uncertainty in the stock market with uncertainty emanating from climate policy changes to check their possible combined effects in stock markets. All regression models are estimated with the Newey and West (1987) method to correct for heteroskedasticity. Table 4 summarises the four empirical specifications, the key regressors and the corresponding economic hypotheses tested. This clarifies how each model contributes to the overall identification strategy. The next section presents and discusses empirical results of those regression models.

4 | Empirical Results

In this section we discuss our main results. First, we show that the change in CPU predicts market return reversals, mostly for the fossil-based energy assets rather than the renewable and low carbon-based ones and the generic market returns captured by the S&P index. More specifically, Table 5 presents results from equation model (1) and we see that there are negative significant ΔCPU_{t-1} terms for *BRENT* and *HEAT* and ΔCPU_{t-2} terms for *OILP*, *WTI*, *BRENT* and *HEAT*, while *HEAT* is negatively affected by the fourth lag of *ΔCPU* as well. Conversely, the significant lagged *ΔCPU* terms for *S&P500*, *FTEORE* and *FTEOWP* are positive, while there are no significant lagged terms for *SMOG*, *SOEN* and *SPGE*. The magnitude of the effect is economically meaningful: the average impact of a one standard deviation shift in *ΔCPU* on the next month's *BRENT* and *HEAT* are 2.63 and 3.08 bps, respectively, which is nearly three and four times the size of their unconditional average monthly returns respectively (see Table 2 for descriptive statistics). We examine the lags of *ΔCPU* to determine the overall 5 months effect by calculating the sum of the lagged *ΔCPU* coefficients from $t-2$ to $t-5$. We observe that for one (*HEAT*) out of the five fossil-based assets the effect is negative and statistically significant for the 10%. Additionally, we test

TABLE 4 | Empirical model structure and tested hypotheses.

Model	Specification	Key regressor	Conditioning variable	Economic interpretation	Hypothesis tested
(1)	Baseline predictive regression	ΔCPU	None	Tests whether changes in climate policy uncertainty predict future energy and equity returns	H1: Climate policy uncertainty predicts returns, with asymmetric effects across fossil and renewable assets
(2)	Positive-shock regression	INC_CPU	None	Tests whether increases in CPU have stronger effects than neutral or negative changes (attention channel)	H2: Positive CPU shocks have larger pricing effects than average CPU changes
(3)	Salience model	ΔCPU × Top-decile (ΔCPU)	CPU salience	Tests whether extreme increases in CPU generate amplified return responses	H3: Salient CPU shocks trigger stronger investor reactions, especially in fossil assets
(4)	Joint-uncertainty model	ΔCPU × Top-decile (VIX)	Financial market fear	Tests whether CPU shocks are more powerful when general market uncertainty is high	H4: Climate policy uncertainty has stronger pricing effects during periods of elevated market stress

whether a reversal of the initial decline occurs in the following trading months by calculating the sum of the lagged *ΔCPU* coefficients from $t-2$ to $t-5$. In this case, the results are more striking since we observe that for four (*OILP*, *WTI*, *BRENT* and *HEAT*) out of the five fossil-based assets the effect is negative and statistically significant for the 10%. The results of the summed lagged terms for all other assets are either positive or very small negative but never statistically different from zero. Thus, we see clearly that the change in CPU has detrimental effects on the monthly stock returns of the fossil-based assets and no effects on the rest of the assets. Renewable energy assets are not negatively impacted by changes in CPU.

To gauge the economic magnitude of these effects, we scale the coefficients by the standard deviation of ΔCPU (0.3618; see Table 2). A one-standard-deviation increase in CPU lowers next-month BRENT and HEAT returns by about 0.95 and 1.11 percentage points, respectively, based on the ΔCPU ($t-1$) coefficients of −0.0263 and −0.0308. These effects are slightly larger than the corresponding unconditional average monthly returns of 0.88% for BRENT and 0.82% for HEAT (see Table 2). When we also consider the second lag of ΔCPU, the implied cumulative impact over the next 2 months amounts to roughly 2.0–2.4 percentage points for these two fossil-based assets, confirming that the predictive effect of CPU shocks is economically meaningful as well as statistically significant.

Table 6 presents results of equation model (2) where instead of *ΔCPU* we re-estimate the time series models for the cases where the change is CPU is positive. This way, we examine whether the impact of sudden increases in the uncertainty with regards to climate policy is more important in determining monthly stock returns. The results of this specification verify the analysis undertaken before. Namely, we observe again strong negative effects on the monthly returns of the fossil-based energy assets and weak positive effects for the rest of the stock market returns. This time the results are more robust than before since we have strong and statistically significant negative effects for *OILP*, *WTI* and *BRENT* (for 10% significance level) as well as for *HEAT* (for 5% significance level) for the sum of the first five lagged terms and for all four assets when it comes to the sum of the four lagged terms ($t-2$ to $t-5$) all significant for the 5% level. Thus, when the change is CPU is positive investors react negatively in terms of fossil-based assets, while there is no evidence of significant reaction for the renewable energy and low carbon-based one.

The cumulative effects of positive CPU shocks are also sizeable. Using the sums of the INC_CPU coefficients from $t-1$ to $t-5$ and the standard deviation of ΔCPU (0.3618), a one-standard-deviation increase in CPU implies a cumulative decline of about 1.05 percentage points for BRENT and 1.77 percentage points for HEAT over the subsequent 5 months. These losses correspond to roughly 1–2 months of typical returns for these assets, indicating that sharp increases in climate-policy uncertainty generate persistent and non-negligible adverse effects on fossil-based energy markets, whereas the corresponding cumulative effects for renewable and low-carbon assets remain close to zero.

Furthermore, Table 7 presents results for equation model (3) that examines the relationship among change in CPU and

TABLE 5 | The effect of climate policy uncertainty change on stock market assets.

		Fossil-based energy assets					Renewable and low carbon-based energy assets				
Variables	**S&P500**	**OILP**	**WTI**	**BRENT**	**HEAT**	**NAT_GAS**	**FTEORE**	**FTEOWP**	**SMOG**	**SOEN**	**SPGE**
ΔCPU $(t-1)$	−0.00109	−0.0175	−0.0238	−0.0263*	−0.0308**	−0.00932	0.0187	0.00936	0.00824	−0.00680	−0.0435
	(0.00627)	(0.0130)	(0.0151)	(0.0145)	(0.0137)	(0.0288)	(0.0140)	(0.0103)	(0.0218)	(0.0163)	(0.0830)
ΔCPU $(t-2)$	0.00461	−0.0285*	−0.0242*	−0.0302*	−0.0365**	−0.0391	0.00408	0.00899	−0.0252	−0.0215	−0.0738
	(0.00699)	(0.0170)	(0.0108)	(0.0173)	(0.0166)	(0.0315)	(0.0163)	(0.0116)	(0.0245)	(0.0189)	(0.112)
ΔCPU $(t-3)$	0.0144*	−0.0120	−0.0182	−0.0216	−0.0198	−0.0473	0.0350**	0.0225*	0.0132	0.00111	0.0418
	(0.00788)	(0.0161)	(0.0177)	(0.0174)	(0.0162)	(0.0351)	(0.0155)	(0.0114)	(0.0232)	(0.0187)	(0.0951)
ΔCPU $(t-4)$	0.00103	−0.0189	−0.0261	−0.0191	−0.0295*	−0.0140	0.0134	0.00240	0.00458	0.00792	−0.0688
	(0.00829)	(0.0158)	(0.0174)	(0.0174)	(0.0170)	(0.0330)	(0.0154)	(0.0127)	(0.0210)	(0.0183)	(0.109)
ΔCPU $(t-5)$	−0.00209	0.0131	0.0143	0.0180	0.00334	−0.0386	0.0132	0.00348	−1.49e−05	0.00321	0.0194
	(0.00630)	(0.0142)	(0.0168)	(0.0156)	(0.0140)	(0.0272)	(0.0124)	(0.00998)	(0.0182)	(0.0151)	(0.0857)
$R\ (t-1)$	0.00554	0.297***	0.171***	0.189***	0.134**	0.00470	0.0122	−0.0774	0.106	0.157*	−0.0281
	(0.0584)	(0.0691)	(0.0574)	(0.0654)	(0.0528)	(0.0646)	(0.0754)	(0.0917)	(0.0955)	(0.0842)	(0.0998)
$R\ (t-2)$	−0.0700	−0.0593	−0.178	−0.0757	−0.0185	−0.122**	−0.0590	−0.0340	−0.0361	0.0258	−0.0684
	(0.0557)	(0.0641)	(0.141)	(0.0675)	(0.0629)	(0.0553)	(0.0841)	(0.0867)	(0.0728)	(0.0786)	(0.0883)
$R\ (t-3)$	0.0602	0.00510	0.0266	−0.0143	−0.0105	−0.0189	0.0123	0.102	0.0259	−0.0121	0.0881
	(0.0648)	(0.0645)	(0.0535)	(0.0501)	(0.0484)	(0.0528)	(0.0716)	(0.0858)	(0.0869)	(0.0766)	(0.0933)
$R\ (t-4)$	0.0299	−0.0964**	−0.115*	−0.0982*	−0.0734	−0.0231	0.0642	0.0236	0.142	0.110	−0.0971
	(0.0599)	(0.0469)	(0.0588)	(0.0546)	(0.0542)	(0.0540)	(0.0775)	(0.0812)	(0.0904)	(0.0809)	(0.118)
$R\ (t-5)$	0.0625	−0.0434	−0.0459	−0.0402	−0.0636	0.00170	0.0903	0.0172	0.0566	−0.0126	0.122
	(0.0550)	(0.0465)	(0.0564)	(0.0477)	(0.0497)	(0.0579)	(0.0755)	(0.0838)	(0.0778)	(0.0804)	(0.127)
$R^2\ (t-1)$	−0.804	−0.378	−0.0729	0.204	−0.322	−0.132	1.082	1.314	−0.556	−0.150	−0.0141
	(0.815)	(0.532)	(0.112)	(0.347)	(0.373)	(0.239)	(0.742)	(1.394)	(0.677)	(0.602)	(0.0386)
$R^2\ (t-2)$	1.340**	1.316*	0.331	0.214	0.0129	−0.163	−0.228	1.447	1.053***	0.0347	0.0754
	(0.534)	(0.696)	(0.413)	(0.381)	(0.396)	(0.206)	(0.928)	(0.979)	(0.391)	(0.435)	(0.0463)

(Continues)

TABLE 5 | (Continued)

Variables	S&P500	OILP	WTI	BRENT	HEAT	NAT_GAS	FTEORE	FTEOWP	SMOG	SOEN	SPGE
		Fossil-based energy assets					Renewable and low carbon-based energy assets				
R^2 $(t-3)$	−0.0789	−0.515	0.00131	0.115	0.211	−0.0383	−0.304	−0.207	−0.372	0.0759	−0.0288
	(0.739)	(0.483)	(0.108)	(0.177)	(0.311)	(0.167)	(0.880)	(1.294)	(0.439)	(0.440)	(0.0411)
R^2 $(t-4)$	0.819	−0.626***	−0.0374	−0.257	−0.301	0.0109	2.627**	2.141*	0.00550	−0.116	0.0391
	(0.694)	(0.233)	(0.129)	(0.243)	(0.320)	(0.161)	(1.058)	(1.085)	(0.579)	(0.661)	(0.0803)
R^2 $(t-5)$	0.0561	0.568***	−0.0311	0.00941	−0.0241	−0.422**	1.179	0.973	0.251	0.110	−0.0249
	(0.694)	(0.179)	(0.0802)	(0.149)	(0.283)	(0.207)	(0.783)	(1.028)	(0.490)	(0.590)	(0.0693)
TUE	0.0108	0.0107	0.00840	0.000642	0.0169	0.0314	−0.00205	0.00364	−0.00823	0.0112	−0.0286
	(0.00679)	(0.0126)	(0.0154)	(0.0146)	(0.0147)	(0.0260)	(0.0156)	(0.0120)	(0.0210)	(0.0186)	(0.0775)
WED	0.00606	−0.00973	−0.00168	0.00993	0.00607	−0.00371	0.00595	0.00369	0.000388	−4.46e−05	−0.0557
	(0.00792)	(0.0146)	(0.0167)	(0.0163)	(0.0155)	(0.0261)	(0.0137)	(0.0117)	(0.0251)	(0.0186)	(0.0738)
THU	−0.00514	−0.00121	0.00566	0.00856	0.0150	0.00354	−0.0121	0.000313	−0.0207	−0.00659	0.0655
	(0.00747)	(0.0124)	(0.0146)	(0.0144)	(0.0136)	(0.0248)	(0.0150)	(0.0118)	(0.0189)	(0.0173)	(0.114)
FRI	0.00841	0.00750	0.0221	0.0107	0.0124	0.0475*	0.00580	0.00959	0.00167	0.00359	0.126
	(0.00631)	(0.0138)	(0.0172)	(0.0147)	(0.0150)	(0.0260)	(0.0139)	(0.0106)	(0.0182)	(0.0175)	(0.134)
Constant	0.00146	5.69e−05	0.00477	0.00460	0.00579	0.0204	−0.00871	−0.00561	0.00608	0.00533	0.00308
	(0.00515)	(0.00886)	(0.0101)	(0.0101)	(0.00944)	(0.0165)	(0.0101)	(0.00776)	(0.0123)	(0.0105)	(0.0552)
Sum $t-1$ to $t-5$	0.01686	−0.0638	−0.078	−0.0792	−0.11326	−0.14832	0.08438	0.04673	0.0008051	−0.01606	−0.1249
χ^2 (sum = 0)	1.14	1.69	1.77	1.76	2.04*	0.84	1.70	1.17	0.83	0.46	0.50
p	0.3396	0.1355	0.1186	0.1201	0.0726	0.5194	0.1368	0.3289	0.5306	0.8027	0.7746
Sum $t-2$ to $t-5$	0.01795	−0.0463	−0.0542	−0.0529	−0.08246	−0.139	0.06568	0.03737	−0.0074349	−0.00926	−0.0814
χ^2 (sum = 0)	1.26	2.04*	1.96*	1.95*	2.05*	1.00	1.81	1.40	0.81	0.57	0.55
p	0.2885	0.0886	0.0902	0.0915	0.0864	0.4056	0.1288	0.2358	0.5228	0.6811	0.6986
Observations	436	435	436	422	436	400	177	177	195	224	207

Note: Newey–West HAC robust estimates of Equation (1). The dependent variable is monthly logarithmic asset returns, while the key explanatory variable is the monthly logarithmic change in CPU. All variables are described in Table 1. Monthly data are used and sample lengths differ according to data availability. Standard errors are reported in parentheses.

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

Source: PolicyUncertainty.com, FRED, EIA and Investing.com.

TABLE 6 | The effect of increased climate policy uncertainty on stock market assets.

		Fossil-based energy assets					Renewable and low carbon-based energy assets				
Variables	**S&P500**	**OILP**	**WTI**	**BRENT**	**HEAT**	**NAT_GAS**	**FTEORE**	**FTEOWP**	**SMOG**	**SOEN**	**SPGE**
INC_CPU ($t-1$)	−0.00206	−0.0128	−0.0191	−0.0246	−0.0315	0.00801	0.0294	0.00494	0.0323	0.0156	−0.150
	(0.0101)	(0.0222)	(0.0216)	(0.0218)	(0.0205)	(0.0437)	(0.0216)	(0.0144)	(0.0320)	(0.0277)	(0.133)
INC_CPU ($t-2$)	0.00419	−0.0314*	−0.0307	−0.0382*	−0.0470**	−0.0494	−0.00213	0.00592	−0.0282	−0.0148	−0.235
	(0.00947)	(0.0189)	(0.0242)	(0.0218)	(0.0212)	(0.0412)	(0.0200)	(0.0156)	(0.0282)	(0.0236)	(0.168)
INC_CPU ($t-3$)	0.0244***	−0.00205	−0.00407	−0.0110	0.00925	−0.0552	0.0461**	0.0290**	0.0186	0.0213	0.0141
	(0.00935)	(0.0207)	(0.0246)	(0.0235)	(0.0230)	(0.0411)	(0.0216)	(0.0141)	(0.0315)	(0.0247)	(0.186)
INC_CPU ($t-4$)	−0.00406	−0.00843	−0.0205	−0.00679	−0.0115	0.0291	0.00616	−0.00684	−0.00269	0.0256	−0.100
	(0.0116)	(0.0251)	(0.0268)	(0.0257)	(0.0255)	(0.0441)	(0.0221)	(0.0192)	(0.0284)	(0.0270)	(0.156)
INC_CPU ($t-5$)	−0.00808	0.0396*	0.0496**	0.0516**	0.0319	−0.0281	0.0183	−0.00326	0.0120	0.0203	−0.0623
	(0.00965)	(0.0204)	(0.0242)	(0.0234)	(0.0221)	(0.0374)	(0.0181)	(0.0155)	(0.0255)	(0.0233)	(0.134)
R ($t-1$)	0.00797	0.297***	0.174***	0.191***	0.139***	0.00208	0.0193	−0.0749	0.103	0.147*	−0.0392
	(0.0590)	(0.0694)	(0.0571)	(0.0653)	(0.0532)	(0.0645)	(0.0786)	(0.0932)	(0.0954)	(0.0835)	(0.0978)
R ($t-2$)	−0.0709	−0.0579	−0.182	−0.0781	−0.0209	−0.117*	−0.0688	−0.0363	−0.0418	0.0187	−0.0794
	(0.0560)	(0.0650)	(0.142)	(0.0676)	(0.0638)	(0.0562)	(0.0838)	(0.0846)	(0.0726)	(0.0776)	(0.0911)
R ($t-3$)	0.0606	0.0116	0.0371	−0.00643	−0.000314	−0.0124	0.0154	0.0954	0.0307	−0.0153	0.0771
	(0.0642)	(0.0648)	(0.0540)	(0.0507)	(0.0488)	(0.0534)	(0.0732)	(0.0841)	(0.0875)	(0.0806)	(0.0935)
R ($t-4$)	0.0312	−0.0958**	−0.118**	−0.100*	−0.0759	−0.0245	0.0622	0.0157	0.142	0.107	−0.101
	(0.0601)	(0.0472)	(0.0598)	(0.0555)	(0.0556)	(0.0557)	(0.0777)	(0.0816)	(0.0895)	(0.0801)	(0.119)
R ($t-5$)	0.0604	−0.0399	−0.0389	−0.0353	−0.0568	0.00956	0.0779	0.00286	0.0546	−0.00631	0.123
	(0.0552)	(0.0468)	(0.0554)	(0.0470)	(0.0492)	(0.0584)	(0.0766)	(0.0839)	(0.0761)	(0.0817)	(0.126)
R^2 ($t-1$)	−0.749	−0.394	−0.0771	0.185	−0.354	−0.127	0.998	1.267	−0.598	−0.234	−0.0142
	(0.803)	(0.538)	(0.110)	(0.346)	(0.375)	(0.240)	(0.782)	(1.402)	(0.676)	(0.597)	(0.0384)
R^2 ($t-2$)	1.381**	1.343*	0.336	0.206	−0.0216	−0.171	−0.190	1.544	1.075***	0.0429	0.0807
	(0.543)	(0.695)	(0.409)	(0.379)	(0.393)	(0.202)	(0.944)	(0.988)	(0.384)	(0.430)	(0.0490)

(Continues)

TABLE 6 | (Continued)

		Fossil-based energy assets					Renewable and low carbon-based energy assets				
Variables	**S&P500**	**OILP**	**WTI**	**BRENT**	**HEAT**	**NAT_GAS**	**FTEORE**	**FTEOWP**	**SMOG**	**SOEN**	**SPGE**
$R^2\ (t-3)$	−0.0241	−0.520	−0.00401	0.114	0.199	−0.0626	−0.224	−0.257	−0.365	0.0809	−0.0280
	(0.745)	(0.479)	(0.106)	(0.185)	(0.318)	(0.166)	(0.903)	(1.285)	(0.435)	(0.464)	(0.0407)
$R^2\ (t-4)$	0.858	−0.632***	−0.0316	−0.259	−0.318	−0.0175	2.808***	2.240**	0.0690	−0.0875	0.0442
	(0.695)	(0.234)	(0.131)	(0.246)	(0.329)	(0.160)	(1.041)	(1.132)	(0.586)	(0.677)	(0.0780)
$R^2\ (t-5)$	0.0707	0.581***	−0.0273	0.0128	−0.0276	−0.440**	1.168	0.950	0.209	0.195	−0.0207
	(0.707)	(0.177)	(0.0779)	(0.148)	(0.282)	(0.206)	(0.840)	(0.997)	(0.493)	(0.569)	(0.0674)
TUE	0.0124*	0.00930	0.00751	−0.000964	0.0158	0.0280	−0.000293	0.00484	−0.00706	0.0125	−0.0346
	(0.00682)	(0.0125)	(0.0153)	(0.0143)	(0.0145)	(0.0265)	(0.0152)	(0.0118)	(0.0209)	(0.0184)	(0.0792)
WED	0.00659	−0.00924	−0.00109	0.00996	0.00639	−0.00666	0.00692	0.00455	0.000868	0.000461	−0.0576
	(0.00794)	(0.0147)	(0.0165)	(0.0162)	(0.0154)	(0.0262)	(0.0136)	(0.0118)	(0.0250)	(0.0187)	(0.0737)
THU	−0.00480	−0.00170	0.00479	0.00828	0.0154	0.00447	−0.0100	0.00118	−0.0208	−0.00529	0.0764
	(0.00765)	(0.0121)	(0.0142)	(0.0139)	(0.0133)	(0.0249)	(0.0150)	(0.0117)	(0.0192)	(0.0169)	(0.113)
FRI	0.0103	0.00458	0.0180	0.00585	0.00912	0.0427*	0.00830	0.0116	0.00184	0.00428	0.130
	(0.00626)	(0.0136)	(0.0173)	(0.0150)	(0.0150)	(0.0259)	(0.0134)	(0.0104)	(0.0176)	(0.0171)	(0.143)
Constant	−0.00182	0.00255	0.00880	0.00975	0.0136	0.0375	−0.0244*	−0.0105	0.00121	−0.00626	0.0781
	(0.00659)	(0.0127)	(0.0146)	(0.0144)	(0.0135)	(0.0240)	(0.0133)	(0.00997)	(0.0164)	(0.0149)	(0.0780)
Sum $t-1$ to $t-5$	0.01439	−0.01508	−0.02477	−0.02899	−0.04885	−0.09559	0.09783	0.02976	0.03201	0.068	−0.5332
χ^2 (sum = 0)	1.55	2.03*	1.97*	2.07*	2.26**	1.01	1.77	1.17	0.75	0.61	0.82
p	0.1735	0.0729	0.0813	0.0688	0.0481	0.04099	0.1212	0.3257	0.5865	0.6959	0.5331
Sum $t-1$ to $t-4$	0.01645	−0.00228	−0.00567	−0.00439	−0.01735	−0.1036	0.06843	0.02482	−0.00029	0.0524	−0.3832
χ^2 (sum = 0)	1.93	2.54**	2.43**	2.47**	2.62**	1.23	1.66	1.38	0.53	0.56	0.86
p	0.1042	0.0393	0.0472	0.0439	0.0344	0.2986	0.1617	0.2423	0.7117	0.6913	0.4921
Observations	436	435	436	422	436	400	177	177	195	224	207

Note: Standard errors in parentheses. Estimates of Equation (2), where INC_CPU denotes positive monthly changes in CPU, while zero otherwise. The dependent variable is monthly logarithmic asset returns. Monthly data are used; sample coverage varies across series as reported in Table 1. Standard errors are Newey–West corrected.

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

Source: PolicyUncertainty.com, FRED, EIA and Investing.com.

TABLE 7 | The effect of climate policy uncertainty change on stock market assets during salient times.

Variables	S&P500	Fossil-based energy assets					Renewable and low carbon-based energy assets				
		OILP	WTI	BRENT	HEAT	NAT_GAS	FTEORE	FTEOWP	SMOG	SOEN	SPGE
$E\times\Delta$CPU $(t-1)$	−0.00705	−0.0578***	−0.0493**	−0.0347	−0.0410**	0.0398	−0.0143	−4.84e−05	−0.0504	−0.0482**	0.231*
	(0.00864)	(0.0211)	(0.0223)	(0.0220)	(0.0192)	(0.0607)	(0.0245)	(0.0195)	(0.0326)	(0.0239)	(0.131)
$E\times\Delta$CPU $(t-2)$	−0.00308	−0.0881***	−0.0420	−0.0327	−0.0320	0.0820	0.00479	0.00874	−0.0728	−0.0414	0.0721
	(0.0120)	(0.0257)	(0.0319)	(0.0302)	(0.0286)	(0.0628)	(0.0436)	(0.0266)	(0.0535)	(0.0431)	(0.216)
$E\times\Delta$CPU $(t-3)$	−0.0141	−0.0584**	−0.0666*	−0.0757**	−0.0373	0.0434	0.0395	0.00671	−0.0767	−0.0407	0.205
	(0.0115)	(0.0290)	(0.0344)	(0.0366)	(0.0268)	(0.0819)	(0.0366)	(0.0225)	(0.0624)	(0.0411)	(0.227)
$E\times\Delta$CPU $(t-4)$	−0.0108	−0.0324	−0.0484	−0.0633*	−0.0309	0.0495	0.0135	−0.00940	−0.0457	−0.0156	−0.263
	(0.0141)	(0.0290)	(0.0331)	(0.0369)	(0.0328)	(0.0701)	(0.0418)	(0.0290)	(0.0505)	(0.0414)	(0.224)
$R\ (t-1)$	0.00213	0.300***	0.167***	0.188***	0.134**	−0.0269	0.0207	−0.0805	0.0947	0.161*	−0.0321
	(0.0580)	(0.0700)	(0.0576)	(0.0668)	(0.0552)	(0.0229)	(0.0770)	(0.0917)	(0.0944)	(0.0828)	(0.0995)
$R\ (t-2)$	−0.0820	−0.0475	−0.166	−0.0669	−0.00832	0.00532	−0.0588	−0.0432	−0.0281	0.0190	−0.0532
	(0.0556)	(0.0649)	(0.143)	(0.0692)	(0.0632)	(0.0641)	(0.0833)	(0.0851)	(0.0745)	(0.0791)	(0.0894)
$R\ (t-3)$	0.0460	0.00223	0.0201	−0.0192	−0.00651	−0.131**	−0.00198	0.0820	0.0547	0.00598	0.0653
	(0.0650)	(0.0652)	(0.0549)	(0.0516)	(0.0494)	(0.0560)	(0.0733)	(0.0831)	(0.0853)	(0.0725)	(0.0927)
$R\ (t-4)$	0.0185	−0.103**	−0.120**	−0.105*	−0.0811	−0.0162	0.0821	0.00523	0.137	0.115	−0.0805
	(0.0596)	(0.0478)	(0.0590)	(0.0552)	(0.0549)	(0.0525)	(0.0794)	(0.0803)	(0.0909)	(0.0806)	(0.115)
$R\ (t-5)$	0.0686	−0.0385	−0.0397	−0.0333	−0.0639	−0.0205	0.0442	0.0172	0.0451	0.00138	0.107
	(0.0541)	(0.0471)	(0.0569)	(0.0476)	(0.0495)	(0.0542)	(0.0787)	(0.0816)	(0.0826)	(0.0844)	(0.129)
$R^2\ (t-1)$	−0.853	−0.381	−0.0879	0.163	−0.382	0.000967	1.319*	1.283	−0.634	−0.184	−0.0147
	(0.805)	(0.542)	(0.115)	(0.353)	(0.384)	(0.0557)	(0.758)	(1.357)	(0.659)	(0.582)	(0.0372)
$R^2\ (t-2)$	1.310**	1.336*	0.327	0.221	−0.00712	−0.148	−0.337	1.420	1.155***	0.0411	0.0694
	(0.543)	(0.705)	(0.418)	(0.393)	(0.403)	(0.233)	(0.927)	(0.971)	(0.383)	(0.438)	(0.0503)
$R^2\ (t-3)$	−0.0807	−0.556	0.0368	0.139	0.241	−0.173	−0.257	−0.151	−0.390	0.0370	−0.0269
	(0.737)	(0.491)	(0.108)	(0.188)	(0.336)	(0.206)	(0.849)	(1.262)	(0.440)	(0.418)	(0.0422)

(Continues)

TABLE 7 | (Continued)

Variables	S&P500	Fossil-based energy assets					Renewable and low carbon-based energy assets				
		OILP	WTI	BRENT	HEAT	NAT_GAS	FTEORE	FTEOWP	SMOG	SOEN	SPGE
R^2 $(t-4)$	0.905	−0.580**	−0.0234	−0.236	−0.257	−0.0935	2.845***	2.168*	0.111	0.0449	0.0404
	(0.724)	(0.243)	(0.129)	(0.241)	(0.320)	(0.170)	(0.976)	(1.105)	(0.630)	(0.680)	(0.0801)
R^2 $(t-5)$	0.0722	0.571***	−0.0212	0.0736	0.00611	0.00223	0.654	0.708	0.167	0.110	−0.00999
	(0.683)	(0.184)	(0.0836)	(0.150)	(0.280)	(0.156)	(0.782)	(0.990)	(0.540)	(0.607)	(0.0670)
TUE	0.0107	0.00691	0.00372	−0.00312	0.0135	0.0316	0.000899	0.00478	−0.00436	0.00931	−0.00969
	(0.00671)	(0.0123)	(0.0149)	(0.0143)	(0.0144)	(0.0261)	(0.0153)	(0.0117)	(0.0206)	(0.0181)	(0.0820)
WED	0.00569	−0.0105	−0.00418	0.00752	0.00517	−0.00394	0.00950	0.00572	0.00273	0.000288	−0.0186
	(0.00795)	(0.0149)	(0.0169)	(0.0165)	(0.0159)	(0.0265)	(0.0141)	(0.0118)	(0.0247)	(0.0186)	(0.0719)
THU	−0.00576	−0.00258	0.00343	0.00611	0.0126	0.00401	−0.00892	0.000592	−0.0193	−0.00735	0.0797
	(0.00754)	(0.0124)	(0.0146)	(0.0144)	(0.0136)	(0.0247)	(0.0159)	(0.0124)	(0.0202)	(0.0175)	(0.112)
FRI	0.00911	0.00700	0.0204	0.00850	0.0105	0.0440*	0.0109	0.0110	0.00992	0.00736	0.137
	(0.00624)	(0.0137)	(0.0172)	(0.0149)	(0.0150)	(0.0259)	(0.0146)	(0.0110)	(0.0189)	(0.0172)	(0.133)
Constant	0.00157	0.000513	0.00506	0.00463	0.00607	0.0228	−0.0105	−0.00557	0.00366	0.00387	−0.0124
	(0.00521)	(0.00886)	(0.0101)	(0.0102)	(0.00952)	(0.0167)	(0.0108)	(0.00828)	(0.0129)	(0.0107)	(0.0548)
Sum $t-1$ to $t-4$	−0.03503	−0.2367	−0.2063	−0.2064	−0.1412	0.2147	0.04349	0.0060016	−0.2456	−0.1459	0.2451
χ^2 (sum = 0)	0.66	3.52***	2.82**	1.34	2.16*	0.77	0.62	0.15	0.81	1.03	1.87
p	0.6212	0.0077	0.0431	0.2536	0.0845	0.5459	0.6524	0.9645	0.519	0.3907	0.1179
Sum $t-2$ to $t-4$	−0.02798	−0.1789	−0.157	−0.1717	−0.1002	0.1749	0.05779	0.00605	−0.1952	−0.0977	0.0141
χ^2 (sum = 0)	0.58	4.02***	2.16*	2.48*	0.77	0.86	0.57	0.13	0.65	0.36	1.94
p	0.6284	0.0078	0.0956	0.0652	0.513	0.4615	0.6345	0.9406	0.5814	0.779	0.1244
Observations	437	435	437	422	437	400	177	177	195	224	207

Note: Estimates of Equation (3) during months when CPU changes fall within the top decile (salient CPU periods). The dependent variable is monthly logarithmic returns. Monthly data are used; sample spans follow Table 1 availability. Standard errors are Newey–West corrected.

*$p < 0.1$.

**$p < 0.05$.

***$p < 0.01$.

Source: PolicyUncertainty.com, FRED, EIA and Investing.com.

energy-based stock market during salient times. This is done by focusing our results on periods of overwhelmingly positive CPU by taking the observations that belong on the top 10% of the distribution of the variable. The results provide support in favour of the attention-grabbing role of changes in CPU with regard to the fossil-based assets. Specifically, we find that ΔCPU_{t-1} is negatively related with *OILP*, *WTI* and *HEAT*; ΔCPU_{t-2} is negatively related with *OILP*; ΔCPU_{t-3} is negatively related with *OILP*, *WTI* and *BRENT* and ΔCPU_{t-4} is negatively related with *BRENT*. The summed effects either for the first 5 months or for the 4 months after the initial monthly effect are again negative and statistically significant for most of the assets (the only exception is *NAT_GAS*, which seems to be unaffected). Regarding the renewable and low-carbon-based assets, we observe a negative first lag effect for *SOEN* and a positive first lag effect for *SPGE*. However, for both those two assets, as well as all other renewable energy assets, the overall (summed up) effects are statistically equal to zero.

During salient CPU episodes (months in the top decile of the ΔCPU distribution), the economic impact becomes very large. For instance, the sum of the $E \cdot \Delta CPU$ coefficients from $t-1$ to $t-4$ for HEAT equals −0.1412, which, when scaled by the standard deviation of ΔCPU (0.3618), corresponds to a cumulative decline of about 5.1 percentage points in HEAT returns over the 4 months following a salient CPU shock. This loss exceeds the asset's typical cumulative 4-month return, indicating that large CPU spikes attract strong investor attention and generate economically substantial declines in fossil-based energy markets, whereas the corresponding effects for renewable and low-carbon indices remain statistically and economically weak.

Additionally, the strong negative effect of the attention-grabbing hypothesis is further verified by the results presented in Table 8, that report findings of equation model (4). Here the change in CPU is interacted with the top 10% values of stock market uncertainty captured by the VIX index. From the obtained results we can clearly see that when the stock market uncertainty is happening in conjunction with high CPU then the negative effect on fossil-based assets is even larger. The resulting summed effects for 5 and 4 lagged months, respectively, are highly negative and statistically significant for the 1% level for all fossil-based assets bar *NAT_GAS*.

The interaction of CPU with periods of high stock market fear yields, particularly, large economic effects. Scaling the sums of the $F \cdot \Delta CPU$ coefficients from $t-1$ to $t-4$ by the standard deviation of ΔCPU (0.3618) shows that a one-standard-deviation CPU shock when the VIX is in its top decile reduces cumulative returns by about 13.1 percentage points for OILP, 8.5 percentage points for WTI, 6.3 percentage points for BRENT and 4.9 percentage points for HEAT over the following 4months. These losses are several times larger than the corresponding unconditional average monthly returns, highlighting that climate-policy uncertainty becomes an especially powerful downside risk factor for fossil-based energy assets in already stressed market conditions, while the corresponding effects for renewable and low-carbon indices remain small and statistically insignificant.

Thus, concluding, all our specifications show clearly that changes in CPU are negatively impacting fossil-based asset returns while they have either a small positive or negligible (near-zero) impact on the renewable energy sector assets. This aligns with previous studies by Liu et al. (2022), Guo et al. (2022), Ding, Liu, et al. (2022), Shang et al. (2022) and Salisu et al. (2023). Several factors contribute to this negative association, including stringent environmental regulations and potential carbon taxes, climate-related risks affecting investor sentiment, shifting public opinion towards cleaner energy sources, the global trend towards decarbonisation and CPU. These factors collectively reduce the attractiveness of fossil fuel investments in an evolving energy landscape. Conversely, the positive impact on renewable energy assets may stem from growing public enthusiasm for climate change mitigation, governments, which have been increasingly inclined to support renewable energy investments through measures such as subsidies, tax incentives and other forms of assistance and the hedging benefits of clean energy stocks (Olhoff and Christensen 2018; Mensah et al. 2019; Sarker et al. 2023; Ding, Ji, et al. 2022; Hoque and Batabyal 2022). Further, the near-zero impact on renewable energy assets may suggest that short-term uncertainties in climate policy do not immediately affect the financial system and the implementation of climate policy is complex and influenced by various factors, including substitution costs, geographic and political considerations (Kaiser and Welters 2019; Lobato et al. 2021; Umar et al. 2021).

Finally, further to the analysis presented for reasons of robustness we re-estimated all regression models substituting instead of *ΔCPU*, once using the VIX series as proxies of general stock market uncertainty and once using the Energy and Environmental Regulation Equity Market Volatility (EEREMV) as an alternative proxy the CPU index provided by Gavriilidis (2021).[1] The obtained results from those alternative uncertainty proxies reported again some negative correlations with the fossil-based assets and no effects with all other assets. However, those negative effects were more pronounced and statistically more significant when the change in the CPU index was used. This verifies that the CPU index is a good indicator, something that is verified by many other studies (Salisu et al. 2023; Liang et al. 2022; Ma et al. 2019; Wang et al. 2022).

An important question arising from the results is why renewable and low-carbon energy assets appear largely unaffected by CPU shocks, in contrast to fossil-based assets. One plausible explanation relates to the nature of transition-risk exposure across the two sectors. CPU is more directly linked to downside risk for carbon-intensive industries through the prospect of tighter regulation and stranded-asset concerns and the finance literature shows that markets price such stranded-asset and transition-risk channels in fossil-related valuations (Sen and von Schickfus 2020; von Dulong et al. 2023). By contrast, renewable and low-carbon technologies are generally aligned with the long-run direction of decarbonisation and are often supported by institutional frameworks that can reduce short-run revenue risk, including support schemes and stable remuneration structures (Barradale 2010; Alcorta et al. 2024). In addition, renewables frequently rely on long-term contracting arrangements such as power purchase agreements (PPAs), which can reduce exposure to short-run price volatility and provide more predictable cash flows, potentially dampening immediate transmission

TABLE 8 | The effect of climate policy uncertainty change on stock market assets during times of high fear.

Variables	S&P500	OILP	WTI	BRENT	HEAT	NAT_GAS	FTEORE	FTEOWP	SMOG	SOEN	SPGE
		Fossil-based energy assets					Renewable and low carbon-based energy assets				
$F\times\Delta$CPU $(t-1)$	0.0159	−0.0637**	−0.00542	−0.00184	−0.0110	0.0143	0.0311	0.0238	0.0142	0.00197	0.0147
	(0.0137)	(0.0314)	(0.0349)	(0.0328)	(0.0299)	(0.0606)	(0.0295)	(0.0179)	(0.0454)	(0.0314)	(0.141)
$F\times\Delta$CPU $(t-2)$	0.0243	−0.134***	−0.0731*	−0.0517	−0.0607	0.0672	0.0423	0.0441**	−0.00713	−0.0567	0.0556
	(0.0206)	(0.0368)	(0.0434)	(0.0426)	(0.0384)	(0.0694)	(0.0382)	(0.0211)	(0.0632)	(0.0510)	(0.206)
$F\times\Delta$CPU $(t-3)$	0.0216	−0.0853**	−0.0450	−0.0250	−6.03e−05	0.0859	0.0520	0.0428*	0.0153	−0.0505	0.169
	(0.0201)	(0.0381)	(0.0459)	(0.0448)	(0.0392)	(0.0721)	(0.0371)	(0.0227)	(0.0679)	(0.0531)	(0.200)
$F\times\Delta$CPU $(t-4)$	0.00113	−0.0794**	−0.110***	−0.0952**	−0.0637*	0.113*	0.00991	0.00605	−0.0167	−0.0397	−0.0428
	(0.0199)	(0.0325)	(0.0353)	(0.0373)	(0.0329)	(0.0596)	(0.0375)	(0.0249)	(0.0593)	(0.0526)	(0.229)
$R\ (t-1)$	0.00828	0.297***	0.166***	0.187***	0.131**	−0.0253	0.0171	−0.0687	0.0911	0.143*	−0.0158
	(0.0576)	(0.0688)	(0.0570)	(0.0678)	(0.0540)	(0.0231)	(0.0772)	(0.0900)	(0.0939)	(0.0849)	(0.102)
$R\ (t-2)$	−0.0774	−0.0538	−0.169	−0.0700	−0.00907	0.000576	−0.0785	−0.0462	−0.0563	0.0217	−0.0537
	(0.0553)	(0.0635)	(0.140)	(0.0676)	(0.0624)	(0.0642)	(0.0817)	(0.0858)	(0.0740)	(0.0788)	(0.0901)
$R\ (t-3)$	0.0532	0.0197	0.0343	−0.00769	−0.000398	−0.131**	0.0122	0.0950	0.0429	−0.00195	0.0800
	(0.0641)	(0.0654)	(0.0550)	(0.0514)	(0.0493)	(0.0570)	(0.0742)	(0.0805)	(0.0868)	(0.0750)	(0.0932)
$R\ (t-4)$	0.00868	−0.0982**	−0.110*	−0.0976*	−0.0750	−0.0195	0.0420	−0.0155	0.136	0.118	−0.101
	(0.0597)	(0.0471)	(0.0604)	(0.0557)	(0.0559)	(0.0528)	(0.0725)	(0.0804)	(0.0869)	(0.0804)	(0.120)
$R\ (t-5)$	0.0716	−0.0400	−0.0307	−0.0262	−0.0535	−0.0225	0.0906	0.0346	0.0677	−0.00562	0.113
	(0.0542)	(0.0478)	(0.0570)	(0.0483)	(0.0499)	(0.0551)	(0.0763)	(0.0793)	(0.0800)	(0.0812)	(0.127)
$R^2\ (t-1)$	−0.813	−0.358	−0.0728	0.183	−0.366	0.00408	1.049	1.207	−0.627	−0.255	−0.0242
	(0.802)	(0.508)	(0.116)	(0.372)	(0.377)	(0.0558)	(0.748)	(1.358)	(0.652)	(0.599)	(0.0412)
$R^2\ (t-2)$	1.256**	1.321*	0.348	0.240	0.00695	−0.153	−0.620	1.230	0.992**	0.0716	0.0760
	(0.530)	(0.688)	(0.416)	(0.387)	(0.394)	(0.232)	(0.943)	(0.977)	(0.391)	(0.447)	(0.0497)
$R^2\ (t-3)$	−0.0945	−0.529	0.0308	0.122	0.244	−0.171	0.0789	−0.293	−0.330	0.173	−0.0238
	(0.736)	(0.475)	(0.106)	(0.185)	(0.329)	(0.205)	(0.836)	(1.236)	(0.441)	(0.428)	(0.0428)

(Continues)

TABLE 8 | (Continued)

		Fossil-based energy assets					Renewable and low carbon-based energy assets				
Variables	**S&P500**	**OILP**	**WTI**	**BRENT**	**HEAT**	**NAT_GAS**	**FTEORE**	**FTEOWP**	**SMOG**	**SOEN**	**SPGE**
$R^2\ (t-4)$	0.756	−0.557**	−0.0421	−0.242	−0.284	−0.0862	2.762***	2.314**	0.0842	−0.0442	0.0426
	(0.716)	(0.235)	(0.130)	(0.238)	(0.322)	(0.172)	(0.894)	(1.135)	(0.612)	(0.662)	(0.0818)
$R^2\ (t-5)$	0.152	0.509***	−0.0355	0.0641	−0.0125	−0.0196	0.995	0.796	0.235	0.0899	−0.0126
	(0.697)	(0.181)	(0.0824)	(0.149)	(0.279)	(0.155)	(0.805)	(1.000)	(0.534)	(0.603)	(0.0674)
TUE	0.0114*	0.00872	0.00860	0.00129	0.0174	0.0295	0.00273	0.00642	−0.00307	0.0139	−0.0317
	(0.00669)	(0.0122)	(0.0147)	(0.0141)	(0.0143)	(0.0264)	(0.0150)	(0.0111)	(0.0202)	(0.0183)	(0.0778)
WED	0.00657	−0.0113	−0.00330	0.00946	0.00601	−0.00247	0.0107	0.00660	0.00555	0.00231	−0.0476
	(0.00792)	(0.0148)	(0.0166)	(0.0163)	(0.0155)	(0.0260)	(0.0136)	(0.0114)	(0.0248)	(0.0185)	(0.0730)
THU	−0.00594	−0.00119	0.00420	0.00706	0.0137	0.00446	−0.0116	0.000625	−0.0193	−0.00754	0.0680
	(0.00742)	(0.0123)	(0.0145)	(0.0143)	(0.0136)	(0.0244)	(0.0152)	(0.0115)	(0.0193)	(0.0177)	(0.112)
FRI	0.00873	0.00830	0.0215	0.00944	0.0111	0.0435*	0.0123	0.0120	0.00884	0.00808	0.126
	(0.00628)	(0.0137)	(0.0171)	(0.0148)	(0.0150)	(0.0257)	(0.0148)	(0.0110)	(0.0182)	(0.0175)	(0.136)
Constant	0.000879	0.00328	0.00522	0.00423	0.00638	0.0223	−0.0126	−0.00745	0.00270	0.00444	−0.00420
	(0.00521)	(0.00888)	(0.01000)	(0.0101)	(0.00938)	(0.0165)	(0.0105)	(0.00804)	(0.0122)	(0.0107)	(0.0560)
Sum $t-1$ to $t-4$	0.06293	−0.3624	−0.23352	−0.17374	−0.1354	0.2804	0.13531	0.11675	0.00567	−0.14493	0.1965
$\chi^2(\text{sum}=0)$	0.66	4.08***	3.88***	2.98**	3.19**	0.93	0.9	1.73	0.19	0.43	0.50
p	0.6213	0.003	0.0042	0.0191	0.0133	0.445	0.468	0.1465	0.9415	0.7904	0.7392
Sum $t-2$ to $t-4$	0.04703	−0.2987	−0.2281	−0.1719	−0.1244	0.2661	0.10421	0.09295	−0.00853	−0.1469	0.1818
$\chi^2(\text{sum}=0)$	0.8	5.35***	4.71***	3.45**	4.23***	1.21	1.11	2.26*	0.24	0.43	0.66
p	0.4926	0.0013	0.003	0.0166	0.0058	0.3061	0.3468	0.0835	0.8698	0.7351	0.578
Observations	437	435	437	422	437	400	177	177	195	224	207

Note: Estimates of Equation (4) for months in which the VIX index lies in its top decile, interacting high stock market fear with CPU changes. The dependent variable is monthly logarithmic returns. Monthly data are used with sample spans dependent on index availability. Standard errors are Newey–West corrected.
*$p < 0.1$.
**$p < 0.05$.
***$p < 0.01$.
Source: PolicyUncertainty.com, FRED, EIA and Investing.com.

from monthly policy-uncertainty shocks to asset returns (Gohdes et al. 2023). Consistent with a delayed-transmission interpretation, the clean-energy finance literature also finds that uncertainty effects can be more pronounced at lower frequencies (i.e., longer horizons) than at high-frequency monthly horizons (Seetharam and Nyakurukwa 2025). Taken together, these mechanisms provide an economic rationale for why renewable and low-carbon assets may display statistically weak and economically limited short-run responses to CPU, even though policy uncertainty remains relevant for longer-term renewable investment decisions.

5 | Conclusions

Concluding, fossil-based energy assets experience significant and adverse impacts from shifts in CPU, contrasting with the minimal effects observed on renewable and low-carbon energy assets. This discrepancy suggests a marked sensitivity among investors to heightened uncertainty surrounding climate policies, particularly concerning traditional fossil-based energy sources. Moreover, the exacerbating role of CPU during periods of increased uncertainty underscores the heightened negative influence on returns of fossil-based energy assets. This implies that investors exhibit heightened sensitivity to abrupt spikes in CPU, amplifying adverse outcomes for investments in fossil-based energy sectors. These findings underscore the critical importance of incorporating CPU into investment strategies, particularly within energy markets. Investors must recognise the divergent impacts of CPU on fossil-based versus renewable and low-carbon energy assets to make well-informed decisions aligned with long-term sustainability objectives.

Furthermore, the robustness analysis confirms the efficacy of the CPU index as a reliable indicator of CPU, as its significant effects on fossil-based asset returns persist even when alternative uncertainty proxies are considered. This highlights the necessity of employing comprehensive and dependable metrics to gauge the influence of CPU on financial markets accurately. Policymakers and industry stakeholders should acknowledge the ramifications of CPU on energy markets and prioritise efforts to establish clear and consistent policy frameworks. By providing stability and clarity in policy regulations, policymakers can alleviate investor apprehensions and stimulate investment in renewable and low-carbon energy sources, thereby facilitating the transition to a more sustainable energy landscape.

Our findings carry several implications for climate and financial policymakers. First, the strong and state-dependent negative pricing of CPU in fossil-based energy markets indicates that unclear or volatile climate policy frameworks impose real financing costs on carbon-intensive sectors. This suggests that regulatory ambiguity itself can accelerate capital reallocation away from fossil fuels by raising risk premia and increasing the cost of capital for carbon-intensive activities.

Second, the fact that renewable and low-carbon assets exhibit weak short-run sensitivity to CPU implies that existing support mechanisms, contracting structures and long-term policy commitments can insulate clean energy investments from short-term political fluctuations. This highlights the importance of stable and credible policy instruments—such as long-term subsidies, feed-in tariffs, contracts-for-difference and power purchase agreements—in supporting the energy transition.

Third, our evidence that CPU becomes particularly damaging during periods of high financial market stress underscores the value of policy credibility and communication in turbulent times. During macroeconomic or financial crises, abrupt or ambiguous climate-policy signals can amplify market instability in energy markets, suggesting that coordination between climate authorities and financial regulators is especially important in such periods.

While our analysis provides robust evidence that CPU is priced asymmetrically across fossil-based and renewable energy markets, it is subject to several limitations. First, we rely on aggregate energy and equity indices, which mask potentially important cross-firm heterogeneity in exposure to climate policy risk. Individual firms differ in technology, geographic footprint, regulatory exposure and transition readiness and these differences may lead to heterogeneous responses that cannot be observed at the index level. Second, our use of monthly data, dictated by the availability of the CPU index, may understate high-frequency adjustment dynamics within each month. Investor reactions to climate-policy news may occur rapidly around policy announcements or political events and such intra-month responses are averaged out in monthly returns. As a result, our estimates should be interpreted as capturing the medium-term pricing of CPU rather than short-run trading responses. Moving forward, future research endeavours should delve deeper into additional factors shaping the relationship between CPU and energy market dynamics, such as technological advancements, regulatory changes and international agreements, to provide further insights for academia and industry stakeholders alike.

Data Availability Statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Endnotes

[1] These results are not reported here for economy of space but are available from authors upon reasonable request.

References

Alcorta, P., M. P. Espinosa, and C. Pizarro-Irizar. 2024. "Right and Duty: Investment Risk Under Different Renewable Energy Support Policies." *Environmental and Resource Economics* 87: 3163–3204. https://doi.org/10.1007/s10640-024-00909-3.

Antonakakis, N., I. Chatziantoniou, and G. Filis. 2014. "Dynamic Spillovers of Oil Price Shocks and Economic Policy Uncertainty." *Energy Economics* 44: 433–447.

Barradale, M. J. 2010. "Impact of Public Policy Uncertainty on Renewable Energy Investment." *Energy Policy* 38, no. 12: 7698–7709.

Blyth, W., R. Bradley, D. Bunn, C. Clarke, T. Wilson, and M. Yang. 2007. "Investment Risks Under Uncertain Climate Change Policy." *Energy Policy* 35, no. 11: 5766–5773.

Bouri, E., N. Iqbal, and T. Klein. 2022. "Climate Policy Uncertainty and the Price Dynamics of Green and Brown Energy Stocks." *Finance Research Letters* 47: 102740.

Brown, L. R. 2016. "The Great Transition: Shifting From Fossil Fuels to Solar and Wind Energy." *Humanist* 76, no. 1: 27.

Choi, D., Z. Gao, and W. Jiang. 2020. "Attention to Global Warming." *Review of Financial Studies* 33, no. 3: 1112–1145.

Da, Z., J. Engelberg, and P. Gao. 2015. "The Sum of All Fears Investor Sentiment and Asset Prices." *Review of Financial Studies* 28, no. 1: 1–32.

Dash, S. R., and D. Maitra. 2021. "Do Oil and Gas Prices Influence Economic Policy Uncertainty Differently: Multi-Country Evidence Using Time-Frequency Approach." *Quarterly Review of Economics and Finance* 81: 397–420.

Diaz-Rainey, I., S. A. Gehricke, H. Roberts, and R. Zhang. 2021. "Trump vs. Paris: The Impact of Climate Policy on Us Listed Oil and Gas Firm Returns and Volatility." *International Review of Financial Analysis* 76: 101746.

Ding, H., Q. Ji, R. Ma, and P. Zhai. 2022. "High-Carbon Screening Out: A dcc-Midas-Climate Policy Risk Method." *Finance Research Letters* 47: 102818.

Ding, Y., Y. Liu, and P. Failler. 2022. "The Impact of Uncertainties on Crude Oil Prices: Based on a Quantile-On-Quantile Method." *Energies* 15, no. 10: 3510.

Filis, G., and I. Chatziantoniou. 2014. "Financial and Monetary Policy Responses to Oil Price Shocks: Evidence From Oil-Importing and Oil-Exporting Countries." *Review of Quantitative Finance and Accounting* 42: 709–729.

Fried, S., K. M. Novan, and W. Peterman. 2021. *The Macro Effects of Climate Policy Uncertainty. Finance and Economics Discussion Series 2021-018*. Board of Governors of the Federal Reserve System. https://doi.org/10.17016/FEDS.2021.018.

Gavriilidis, K. 2021. "Measuring Climate Policy Uncertainty." https://doi.org/10.2139/SSRN.3847388.

Gohdes, N., P. Simshauser, and C. Wilson. 2023. "Renewable Investments in Hybridised Energy Markets: Optimising the CfD-Merchant Revenue Mix." *Energy Economics* 125: 106824.

Golub, A. A., R. N. Lubowski, and P. Piris-Cabezas. 2020. "Business Responses to Climate Policy Uncertainty: Theoretical Analysis of a Twin Deferral Strategy and the Risk-Adjusted Price of Carbon." *Energy* 205: 117996.

Guo, J., S. Long, and W. Luo. 2022. "Nonlinear Effects of Climate Policy Uncertainty and Financial Speculation on the Global Prices of Oil and Gas." *International Review of Financial Analysis* 83: 102286.

Hanif, I., S. M. Faraz Raza, P. G. de Santos, and Q. Abbas. 2019. "Fossil Fuels, Foreign Direct Investment, and Economic Growth Have Triggered CO2 Emissions in Emerging Asian Economies: Some Empirical Evidence." *Energy* 171: 493–501.

Hasan, M. B., and M. N. Hossain. 2022. "Green Finance and Sustainable Development: A Case of the Bangladesh Economy." In *Handbook of Research on Big Data, Green Growth, and Technology Disruption in Asian Companies and Societies*, edited by P., Ordóñez de Pablos, X. Zhang, M. N. Almunawar, and J. E. L. Gayo, 58–81. IGI Global.

Hoque, M. E., and S. Batabyal. 2022. "Carbon Futures and Clean Energy Stocks: Do They Hedge or Safe Haven Against the Climate Policy Uncertainty?" *Journal of Risk and Financial Management* 15, no. 9: 397.

Hoque, M. E., L. Soo-Wah, F. Bilgili, and M. H. Ali. 2023. "Connectedness and Spillover Effects of Us Climate Policy Uncertainty on Energy Stock, Alternative Energy Stock, and Carbon Future." *Environmental Science and Pollution Research* 30, no. 7: 18956–18972.

Hosseini, S. E. 2022. "Transition Away From Fossil Fuels Toward Renewables: Lessons From Russia Ukraine Crisis." *Future Energy* 1, no. 1: 2–5.

Kaiser, L., and J. Welters. 2019. "Risk-Mitigating Effect of ESG on Momentum Portfolios." *Journal of Risk Finance* 20, no. 5: 542–555.

Li, Z. Z., C.-W. Su, N.-C. Moldovan, and M. Umar. 2023. "Energy Consumption Within Policy Uncertainty: Considering the Climate and Economic Factors." *Renewable Energy* 208: 567–576.

Liang, C., M. Umar, F. Ma, and T. L. Huynh. 2022. "Climate Policy Uncertainty and World Renewable Energy Index Volatility Forecasting." *Technological Forecasting and Social Change* 182: 121810.

Lin, B., and F. Bega. 2021. "China's Belt & Road Initiative Coal Power Cooperation: Transitioning Toward Low-Carbon Development." *Energy Policy* 156: 112438.

Liu, G., Q. Zeng, and J. Lei. 2022. "Dynamic Risks From Climate Policy Uncertainty: A Case Study for the Natural Gas Market." *Resources Policy* 79: 103014.

Lobato, M., J. Rodríguez, and H. Romero. 2021. "A Volatility-Match Approach to Measure Performance: The Case of Socially Responsible Exchange Traded Funds (ETFs)." *Journal of Risk Finance* 22, no. 1: 34–43.

Ma, F., Y. Liao, Y. Zhang, and Y. Cao. 2019. "Harnessing Jump Component for Crude Oil Volatility Forecasting in the Presence of Extreme Shocks." *Journal of Empirical Finance* 52: 40–55.

Mensah, I. A., M. Sun, C. Gao, et al. 2019. "Analysis on the Nexus of Economic Growth, Fossil Fuel Energy Consumption, co2 Emissions and Oil Price in Africa Based on a Pmg Panel Ardl Approach." *Journal of Cleaner Production* 228: 161–174.

Montoro, C. 2012. "Oil Shocks and Optimal Monetary Policy." *Macroeconomic Dynamics* 16, no. 2: 240–277.

Newey, W. K., and K. D. West. 1987. "A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix." *Econometrica* 55, no. 3: 703–708.

Olhoff, A., and J. M. Christensen. 2018. *Emissions Gap Report 2018*. United Nations Environment Programme.

Pástor, L., R. F. Stambaugh, and L. A. Taylor. 2021. "Sustainable Investing in Equilibrium." *Journal of Financial Economics* 142, no. 2: 550–571.

Pástor, L., and P. Veronesi. 2013. "Political Uncertainty and Risk Premia." *Journal of Financial Economics* 110, no. 3: 520–545.

Pham, H., V. Nguyen, V. Ramiah, K. Saleem, and N. Moosa. 2019. "The Effects of the Paris Climate Agreement on Stock Markets: Evidence From the German Stock Market." *Applied Economics* 51, no. 57: 6068–6075.

Rahman, S., and A. Serletis. 2011. "The Asymmetric Effects of Oil Price Shocks." *Macroeconomic Dynamics* 15, no. S3: 437–471.

Ren, X., J. Li, F. He, and B. Lucey. 2023. "Impact of Climate Policy Uncertainty on Traditional Energy and Green Markets: Evidence From Time-Varying Granger Tests." *Renewable and Sustainable Energy Reviews* 173: 113058.

Ren, X., Y. Shi, and C. Jin. 2022. "Climate Policy Uncertainty and Corporate Investment: Evidence From the Chinese Energy Industry." *Carbon Neutrality* 1, no. 1: 14.

Salisu, A., P. Omoke, and O. Fadiya. 2023. "Climate Policy Uncertainty and Crude Oil Market Volatility." *Energy Research Letters* 4, no. 1. https://doi.org/10.46557/001c.38781.

Sarker, P. K., E. Bouri, and C. K. L. Marco. 2023. "Asymmetric Effects of Climate Policy Uncertainty, Geopolitical Risk, and Crude Oil Prices on Clean Energy Prices." *Environmental Science and Pollution Research* 30, no. 6: 15797–15807.

Seetharam, Y., and K. Nyakurukwa. 2025. "The Impact of Twitter Economic Policy Uncertainty on Clean Energy Stocks." *Computational Economics*. https://doi.org/10.1007/s10614-025-10990-5.

Sen, S., and M. T. von Schickfus. 2020. "Climate Policy, Stranded Assets, and Investors' Expectations." *Journal of Environmental Economics and Management* 100: 102277. https://doi.org/10.1016/j.jeem.2019.102277.

Shang, Y., D. Han, G. Gozgor, M. K. Mahalik, and B. K. Sahoo. 2022. "The Impact of Climate Policy Uncertainty on Renewable and Non-Renewable Energy Demand in the United States." *Renewable Energy* 197: 654–667.

Su, C.-W., S.-W. Huang, M. Qin, and M. Umar. 2021. "Does Crude Oil Price Stimulate Economic Policy Uncertainty in BRICS?" *Pacific-Basin Finance Journal* 66: 101519.

Tedeschi, M., M. Foglia, E. Bouri, and P.-F. Dai. 2024. "How Does Climate Policy Uncertainty Affect Financial Markets? Evidence From Europe." *Economics Letters* 234: 111443.

Umar, M., C.-W. Su, S. K. A. Rizvi, and O.-R. Lobonţ. 2021. "Driven by Fundamentals or Exploded by Emotions: Detecting Bubbles in Oil Prices." *Energy* 231: 120873.

von Dulong, A., A. Gard-Murray, A. Hagen, N. Jaakkola, and S. Sen. 2023. "Stranded Assets: Research Gaps and Implications for Climate Policy." *Review of Environmental Economics and Policy* 17, no. 1: 161–169. https://doi.org/10.1086/723768.

Wang, J., F. Ma, E. Bouri, and J. Zhong. 2022. "Volatility of Clean Energy and Natural Gas, Uncertainty Indices, and Global Economic Conditions." *Energy Economics* 108: 105904.

Wang, K.-H., Z.-S. Wang, M. Yunis, and B. Kchouri. 2023. "Spillovers and Connectedness Among Climate Policy Uncertainty, Energy, Green Bond and Carbon Markets: A Global Perspective." *Energy Economics* 128: 107170.