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Nonlinear Effects of Climate Policy Uncertainty on Carbon Allowance and ESG Prices: Evidence From the US

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We examine the nonlinear effects of climate policy uncertainty (CPU) on California carbon allowance prices (CCA) and S&P 500 ESG stock prices (SPESG). We used the nonlinear ARDL method on monthly data from December 2013 to August 2022. Using inflation uncertainty and *WTI* oil prices as control variables, we found that increases in *CPU* positively affect carbon allowance and ESG stock prices in the short and long term.

I. Introduction

Extreme climate events have become a global challenge. In order to respond to such an alarming issue, several stakeholders have prioritized transitioning to carbon-neutral practices and started implementing various policies on green development as it can reduce climate uncertainty. Climate uncertainty arises from many factors, such as policy changes, geopolitical aspects, energy security, increased carbon emissions, and frequent natural calamities. Climate policy uncertainty (*CPU*) refers to the unpredictability surrounding the design, scope, and stringency of climate regulations and the potential changes in government policies over time. Thus, climate policies accompany a certain degree of uncertainty, which can significantly influence market dynamics and investor behavior. This uncertainty surrounding climate policy implementation and future regulatory frameworks has significant implications for market participants, particularly in the carbon emission allowance ETF and environmental, social, and governance (ESG) investors. For example, changes in the *CPU* can lead to asymmetric reactions of carbon and *ESG* investors. Investors in carbon assets may perceive risks and opportunities, while *ESG* investors may become more cautious and inclined to invest in sustainable alternatives. The reactions of these investors are driven by their differing priorities, time horizons, and the impact of *CPU* on their investment strategies and objectives. A carbon emission allowance ETF is a fund that lets investors trade on the market for carbon credits, supporting environmentally responsible practices. Understanding how *CPU* influences carbon emission allowance prices and the *ESG* index can provide valuable information on the dynamics of these markets and the challenges investors and policymakers face in navigating the transition to a sustainable future. Therefore, this study investigates the nonlinear effects of *CPU* on carbon allowance prices and the *ESG* index prices.

By analyzing the relationship between *CPU*, carbon allowance prices, and *ESG* index prices, this study contributes to the existing literature on the intersection of climate change, financial markets, and sustainable investing. This study is the first to investigate the nonlinear effects of *CPU* on carbon allowance and *ESG* prices. Additionally, it examined how inflation uncertainty affects carbon allowance and *ESG* prices. The findings can inform investors, asset managers, and policymakers about the potential risks and opportunities associated with *CPU*, helping them make informed decisions and develop effective strategies to navigate this complex landscape.

We structure the paper as follows. Section II reviews the literature on the relationship between *CPU*, carbon emission allowance, and *ESG* index prices. Section III describes the nonlinear ARDL (NARDL) method, while Section IV describes the data. Section V discusses the results, and Section VI concludes.

II. Literature Review

Investor sentiment and behavior are crucial in shaping the relationship between climate policy uncertainty and market prices. The relationship between *CPU*, carbon allowance prices, and *ESG* stock prices can exhibit nonlinear characteristics. Initially, uncertainty can lead to erratic price movements and volatility. However, as market participants gain more information, experience, and understanding of policy developments, the relationship between uncertainty and market prices may become more stable and less nonlinear. Uncertainty about climate policies can influence market participants' expectations and decision-mak-

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ing processes, affecting carbon allowance and *ESG* stock prices.

The nonlinear relationship between *CPU* and market prices can also arise from interactions between multiple policies and regulations. Different policy measures implemented at various levels (local, national, or international) may have overlapping or conflicting impacts on carbon allowance and *ESG* prices. Ding et al. (2022) show that *CPU* significantly affects carbon-intensive assets, i.e., clean energy and *ESG* stock prices. However, the authors did not indicate whether changes in *CPU* cause asymmetric price changes. On the contrary, Akpa et al. (2023) find that *CPU* does not affect the persistence of sustainable green asset returns. Wang and Li (2023) find that Chinese climate uncertainty significantly affects CSI 300 *ESG* volatility. Similarly, US firms tend to disclose more *ESG* information during times of increased climate policy uncertainty (Hoang, 2023), which can affect *ESG* stock prices. However, previous studies have not examined whether positive and negative changes in climate policy uncertainty affect carbon allowance and *ESG* stock prices differently. Understanding the relationship between *CPU*, carbon allowance prices, and *ESG* performance can facilitate the transition to a low-carbon emission regime. Therefore, the present study examines nonlinear relationships between *CPU*, carbon allowance, and *ESG* stock prices.

III. Method

We employed the NARDL model as it can effectively capture an explanatory variable's short- and long-term asymmetric impact on the dependent variable (Tang et al., 2023). Unlike the ARDL, which cannot account for the positive and negative changes in *CPU*, NARDL captures the effects due to the positive and negative changes in the *CPU*. Given the nonstationary nature of most price series, the NARDL model is a suitable choice for examining and establishing the correlation between *CCA*, S&P 500 *ESG* index prices, and *WTI* oil futures prices, and inflation uncertainty (Chattopadhyay & Mitra, 2015). Additionally, this method can address multicollinearity by selecting the appropriate lag order for the included variables and avoid endogeneity problems by capturing the dynamic interactions between the variables (Shin et al., 2014). Besides, the nonlinear characteristics of the data, as shown in Table 2, support the NARDL application.

The baseline NARDL model can be written as in Equation (1):

$$y_t = \beta^+ x_t^+ + \beta^- x_t^- + u_t \tag{1}$$

where, u_t is an error term, $\beta^+$and β^- are the asymmetric long-run parameters, and x_t is a vector of independent variables decomposed as in Equation (2):

$$x_t = x_0 + x_t^+ + x_t^- \tag{2}$$

where, x_0 is an initial value, x_t^+ and x_t^- are partial sum processes corresponding to positive and negative changes in x_t, as shown for *CPU* in Equations (3) and (4).

$$CPU_t^+ = \sum_{j=1}^{t} \Delta CPU_j^+ = \sum_{j=1}^{t} \max\left(\Delta CPU_j, 0\right) \tag{3}$$

$$CPU_t^- = \sum_{j=1}^{t} \Delta CPU_j^- = \sum_{j=1}^{t} min(\Delta CPU_j, 0) \tag{4}$$

The NARDL error correction model can be defined as follows, from Equations (5) to (6):

$$\begin{aligned} lnCCA_t = \alpha_0 + \alpha_1 \ln CCA_{t-1} + \beta_1 lnCPU_{t-1}^+ \\ +\beta_2 \ln CPU_{t-1}^- + \beta_3 \ln WTI_{t-1} \\ +\beta_4 \ln VIX_{t-1} + \sum_{i=0}^{p} \phi_3 lnWTI_{t-i} \\ + \sum_{i=0}^{q} \phi_4 lnVIX_{t-i} + \sum_{i=0}^{r} \phi_j \Delta lnCCA_{t-i} \\ + \sum_{i=0}^{s} (\pi_t^+ \Delta lnCPU_{t-i}^+ + \pi_t^- \Delta lnCPU_{t-i}^-) + \varepsilon_t \end{aligned} \tag{5}$$

$$\begin{aligned} lnSPESG_t = \alpha_0 + \alpha_1 \ln SPESG_{t-1} + \beta_1 lnCPU_{t-1}^+ \\ +\beta_2 \ln CPU_{t-1}^- + \beta_3 \ln WTI_{t-1} \\ +\beta_4 \ln VIX_{t-1} + \sum_{i=0}^{p} \phi_3 lnWTI_{t-i} \\ + \sum_{i=0}^{q} \phi_4 lnVIX_{t-i} + \sum_{i=0}^{r} \phi_j \Delta lnSPESG_{t-i} \\ + \sum_{i=0}^{s} (\pi_t^+ \Delta lnCPU_{t-i}^+ + \pi_t^- \Delta lnCPU_{t-i}^-) + \varepsilon_t \end{aligned} \tag{6}$$

The asymmetric effect in the short run holds true if $\pi_i^+ \neq \pi_i^-$ for all $i = 0, \ldots, r$. Similarly, if $\beta_1 \neq \beta_2$, the long-run asymmetric effect holds true. For the NARDL framework, the BDM test statistic (t_{BDM}) (Banerjee et al., 1998) and the PSS F statistic (F_{PSS}) test (Pesaran & Yongcheol Shin, 2001) are used to check for cointegration. The null hypothesis (H_0) of F_{PSS} can be written as follows:

$$H_0 = \alpha_1 = \beta_1 = \beta_2 = \beta_3, \ldots, = \beta_n = 0$$

Cointegration exists if the test statistic exceeds the upper-bound values. In contrast, no cointegration exists if the test statistic falls between the upper and lower bounds or is less than the lower bound.

IV. Data

We used monthly data on California carbon allowance ETF prices (*CCA*), S&P 500 *ESG* index prices (*SPESG*), *CPU*, *WTI* oil futures (*WTI*), and inflation uncertainty index (*IU*) from December 2013 to August 2022. Data availability defines data duration. We extracted California carbon allowance prices, S&P 500 *ESG* index prices, and *WTI* oil futures from the Bloomberg database, while the inflation uncertainty index is extracted from https://sites.google.com/site/inflationuncertainty/home, and the climate policy uncertainty data developed by (Gavriilidis, 2021) from https://www.policyuncertainty.com.

We used the Brock, Dechert, and Scheinkman (BDS) test to examine the nonlinearity of the selected data.

V. Results and Discussion

Table 3 shows the nonlinear effects of *CPU* on California carbon allowance prices and SP 500 *ESG* index prices. The results indicate that increases in *CPU* positively affect carbon allowance and *ESG* index prices by 1.2% and 0.29%, respectively, in the short term. Carbon allowances represent the right to emit a certain amount of carbon dioxide or other greenhouse gases. If there is uncertainty surrounding

Table 1. Summary statistics

	CCA	*SPESG*	*CPU*	*WTI*	*IU*
Mean	4.7628	5.4577	4.9687	4.1301	3.3733
Maximum	5.3237	6.0272	6.0192	4.7355	4.0775
Minimum	4.5720	5.0610	3.8943	2.9359	2.9957
Std. Dev.	0.1929	0.2892	0.4753	0.3341	0.2391
Skewness	1.6013	0.4114	-0.1301	-0.3089	0.8386
Kurtosis	4.6889	1.9066	2.2490	3.1364	3.0760
JB	57.3582***	8.1933**	2.7631**	1.7521**	11.6299***
ADF I(0)	-0.2989	-0.8978	-4.1210***	-2.3309	-2.9292***
ADF I(1)	-8.3834***	-11.5949***	-14.2498***	-11.1756***	-11.3860***
KPSS I(0)	0.9011	1.082466	1.057567	0.4792*	0.7042*
KPSS I(1)	0.1223***	0.0801***	0.0726***	0.2293***	0.0824***

Notes: This table reports the summary statistics of monthly data. ***, **, and * denote the significance levels at 1%, 5%, and 10%, respectively.

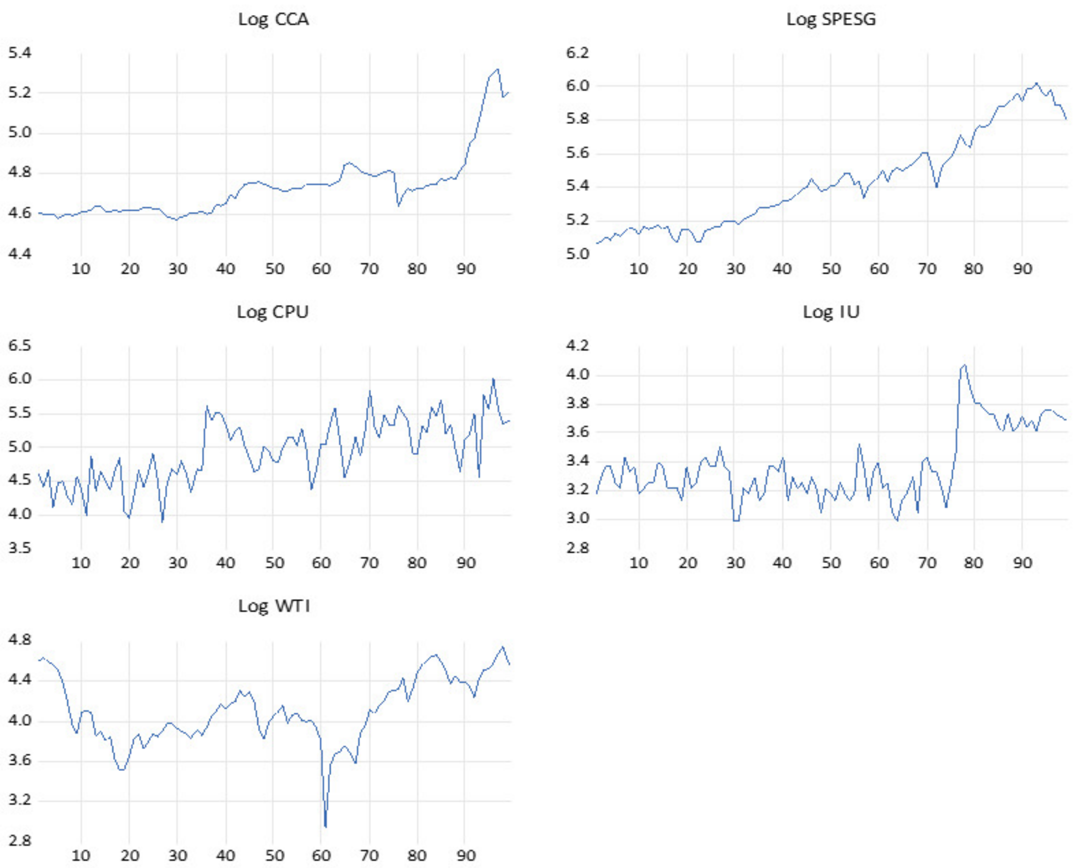

Figure 1. Plots of logarithmic changes in variables (12M2013—08M2022)

Notes. This figure shows California carbon allowance prices S&P 500 ESG, *CPU*, *WTI*, and inflation uncertainty index.

climate policies, companies may anticipate stricter regulations or a more limited supply of allowances in the future. This expectation can drive up demand for existing carbon allowances, leading to higher prices. Similarly, uncertainty in climate policies can increase investors' awareness and concern about climate change. They may prioritize investments in companies that demonstrate strong *ESG* practices, including efforts to reduce carbon emissions and mitigate environmental risks. As a result, the demand for their stocks and bonds could increase, pushing their prices. On the contrary, a unit decrease in *CPU* does not adversely affect carbon allowance prices. A unit reduction in *CPU* negatively affects *SPESG* by 0.11%. The volatility of *WTI* positively affects *CCA* prices, while inflation uncertainty negatively affects both *CCA* and *ESG* prices. The past prices of *CCA* and *ESG* positively influence their respective future values.

Table 2. BDS test for nonlinearity

Dimension	*CCA*	*ESG*	*CPU*	*WTI*	*IU*
2	0.1759***	0.1806***	0.0686***	0.1383***	0.1310***
3	0.2871***	0.3042***	0.1164***	0.2241***	0.2228***
4	0.3579***	0.3898***	0.1484***	0.2769***	0.2827***
5	0.4011***	0.4491***	0.1584***	0.3108***	0.3193***
6	0.4265***	0.4869***	0.1561***	0.3221***	0.3383***

Note: *** denotes the significance level at 1%.

In the long term, a unit of positive change in *CPU* increases the *CCA* and *SPESG* prices by 0.78% and 0.22%, while a unit decrease in *CPU* negatively affects the *CCA* and *SPESG* prices by 0.18% and 0.10%. An increase in climate policy uncertainty can positively affect carbon allowance and *ESG* prices in the long term. This can occur due to the anticipated scarcity of carbon allowances, the increased investor demand for *ESG*-focused investments, the proactive adoption of sustainable practices by companies, and the promotion of market confidence and stability. *WTI* prices have positive impacts, while inflation uncertainty negatively impacts *CCA* and *SPESG* prices. The inflation uncertainty index has a negative impact on carbon allowance prices and *ESG* prices. This occurs primarily due to increased risk aversion among investors, reduced investment demand, the opportunity cost of seeking safer options, potential effects on business operations and costs, and increased market volatility. However, the relationship between inflation uncertainty and these asset prices is influenced by various factors and may vary depending on the uncertainty's overall market conditions and duration.

The ECM term indicates a rapid adjustment of the deviation from the previous year in the current year, with 56% and 64% of errors from previous years being corrected in *CCA* and *SPESG*, respectively. The diagnostic statistics show that the residuals of the NARDL models have a normal distribution, equal variance, and are serially uncorrelated, and thus the models are well specified.

Figure 2(a) shows that a 1% shock to *CPU* lifts carbon allowance prices (*CCA*) by 0.04% within five months, with a significant short-term boost in the first two months. The magnitude of positive changes is more persistent than negative changes. Figure 2(b) shows that a 1% shock to *CPU* lifts the *CCA* of *ESG* prices by 0.03% within two months, with a significant short-term boost in the first month. This asymmetry is significant, as shown by the asymmetry curve and its 95% confidence interval.

VI. Conclusion

We examine the nonlinear effects of *CPU* on California carbon allowance (*CCA*) and *ESG* stock prices. The findings indicate that increases in *CPU* positively affect *CCA* and *ESG* stock prices, while decreases adversely influence *CCA* and *ESG* stock prices. The inflation uncertainty index negatively affects these prices, while the volatility of *WTI* crude oil positively affects them. Dynamic multiplier effects indicate that positive changes in the *CPU* increase the *CCA* and *ESG* stock prices. Under adverse changes, investors can hedge *CCA* and *ESG* assets with other green stocks. Furthermore, investors can use this information to construct green portfolios with carbon allowance and *ESG* stocks, while environmentalists and policymakers can exploit these findings in policymaking for carbon allowance and *ESG* markets.

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Table 3. Nonlinear effects of *CPU* on carbon emission allowance and ESG index prices

Variables	*CPU* effect on *CCA*		Variables	*CPU*'s effects on *SPESG*	
	Coefficients	**Std. Error**		**Coefficients**	**Std. Error**
Short-term estimates					
ΔCPU^{+}	1.2091***	0.0166	ΔCPU^{+}	0.2921***	0.1083
$\Delta CPU^{+}(-1)$	0.6823***	0.1142	ΔCPU^{-}	-0.1105***	0.0146
ΔCPU^{-}	0.1428***	0.0675	ΔWTI	0.1982**	0.0385
ΔWTI	0.3319***	0.1206	ΔIU	-0.2231**	0.0279
ΔIU	-0.2964**	0.0518	$\Delta IU(-1)$	-0.1291***	0.1420
$\Delta CCA(-1)$	0.1264***	0.0182	$\Delta SPESG(-1)$	0.0629**	0.0147
Long-term estimates					
CPU^{+}	0.7819***	0.0150	CPU^{+}	0.2205**	0.0500
CPU^{-}	-0.1898***	0.0536	CPU^{-}	-0.1031***	0.0129
WTI	0.2369**	0.1092	WTI	0.2672***	0.0385
IU	-0.1829***	0.0513	IU	-0.0944**	0.0341
Bounds tests					
F_{PSS}	6.9287***		6.3791***		
t_{BDM}	-4.5031***		-3.0144***		
Asymmetries					
W_{SR}	3.0399**		W_{SR}	5.4600***	
W_{LR}	5.0340***		W_{LR}	6.5431***	
Diagnostic tests					
ECT (-1)	-0.5609***		ECT (-1)	-0.6472***	
R^2	0.7635		R^2	0.8935	
χ^2_{HET}	1.8732**		χ^2_{HET}	1.9703**	
χ^2_{SC}	2.0561**		χ^2_{SC}	1.2738**	
χ^2_{NOR}	1.3920**		χ^2_{NOR}	0.9952**	
Cusum sq	Stable		Cusum sq	Stable	

Notes:***p<0.01, **p<0.05,*p<0.1. The superscripts "+" and "-" imply positive and negative cumulative sums. W_{SR} and W_{LR} are short- and long-run Wald-test results. $\chi2_{HETR}$, $\chi2_{SC}$, and χ^2_{NOR} represent heteroskedasticity, serial correlation, and normality tests.

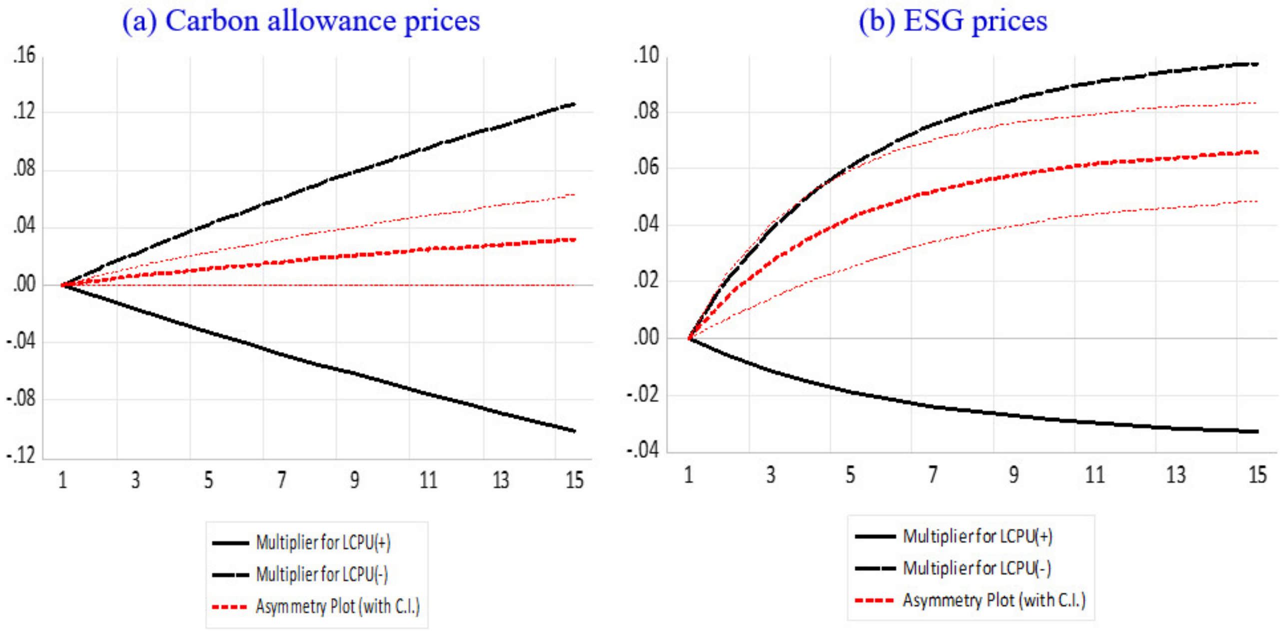

Figure 2. The effects of dynamic multipliers on carbon allowance and ESG prices

Notes. This figure shows the asymmetric changes in California carbon allowance prices and S&P 500 ESG prices due to the changes in CPU.

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