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Energy Transition and Climate Policy Uncertainty in the US:

Green versus Polluting Firms

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Abstract

This paper applies a fractional integration framework to investigate the behaviour of the stock returns of two sets of representative US companies with different environmental profiles, namely green versus polluting firms, as well as of the widely used CPU (Climate Policy Uncertainty) index over the period from January 2017 to March 2025. This time span includes the first Trump administration and the following Biden one, with very different attitudes towards the environment. The analysis suggests that (i) the financial performance of stock returns of polluting companies was generally worse under the Biden administration, whilst there was no significant positive impact on green companies, as implied by the estimated time trend coefficients: (ii) the effects of shocks tend to fade away more quickly in both types of companies under the Biden administration, as implied by the estimates of the differencing parameter, though only in two cases they eventually vanish. Finally, CPU appears to have been decreasing under the Biden administration, whilst the effects of shocks seem to be transitory in both periods. On the whole, the Biden policies to combat climate changes appear to have reduced climate uncertainty and to have led to a better financial performance of environmentally friendly companies. Their reversal could have damaging effects on the environment.

JEL Classification: C22; K42; O51

Keywords: time series; trends; persistence; fractional integration; green and polluting firms; Climate Policy Uncertainty (CPU) index; Trump administration; Biden administration

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1. Introduction

In the presence of increasing disruptions to energy supply chains, higher energy prices, and worsening effects of climate change, renewable energy is increasingly emerging as a strategic and sustainable alternative. In this context, the Paris Agreement adopted in 2015 represents a critical international framework aimed at limiting global greenhouse gas emissions and lessening the effects of global warming (Dimitrov, 2016). Its successful implementation depends on the active participation of the governments of the signatory nations, especially those with significant influence (Parker and Karlsson, 2017). As one of the world's largest emitters of greenhouse gases (Ritchie et al., 2020), the US has a key role to play in terms of its climate policy choices. According to a report by the Energy Information Administration (EIA, 2023), renewable energy sources are becoming increasingly important in the US energy mix and being supported by policy measures such as the Inflation Reduction Act (IRA) introduced by the Biden administration in 2022. This landmark legislation allocated $370 billion to investments to accelerate green technologies, promote clean energy production, and create hundreds of thousands of green jobs. However, this momentum is vulnerable to political shifts. Under the current Trump administration, several measures have been taken to weaken environmental policies, including drastic budget cuts to environmental protection agencies, attempts to dismantle the IRA, and the gradual elimination of tax incentives for renewable energy, such as solar and wind tax credits. In a 2024 campaign speech, Donald Trump had already declared: "We're going to bring back coal, and we're going to bring it back strong," emphasiiesing his intention to revive the fossil fuel industry at the expense of sustainable alternatives. This policy stance has had a direct impact on the energy sector, affecting both fossil fuel and renewable energy companies (Nong and Siriwardana, 2018).

There is a clear ideological divergence between the left and the right in terms of environmental policies. Left-wing parties generally favour renewable energy development

(Carlitz and Povitkina, 2021 ; Neumayer, 2004). By contrast, President Trump, as a Republican on the right of the US political spectrum, has taken a stand against climate action, his first presidency (2017–2021) already being regarded as a setback for climate policies by most commentators (Mukanjari and Sterner, 2024). Several empirical studies have been conducted to understand the economic implications of such policy shifts. Barnett (2019) focused specifically on oil company stocks and observed positive abnormal returns following the 2016 US election, as well as negative abnormal returns in response to the Paris Agreement. Ramelli et al. (2021) analysed the behaviour of stock market returns in the US following the 2016 and 2020 presidential elections. Their findings indicate that carbon-intensive companies benefited from Trump's election, largely due to expectations of a relaxation in climate policies.

In another study, Antoniuk and Leirvik (2021) examined the impact on green bond yields and volatility of major political events such as the 2015 Paris Agreement and the 2017 US withdrawal from it, as well as the 2016 US presidential election. They found that the Paris Agreement had a positive effect on green bond indices, while the election of Donald Trump and the subsequent announcement of the US withdrawal had a negative impact, particularly on municipal green bonds. Similarly, Nerger et al. (2021) showed that the coal sector experienced favourable abnormal returns, while other sectors reacted negatively to Trump's unexpected victory on 8 November 2016. More recently, Pham et al. (2023) analysed the response of green stocks to climate-related events such as the Paris Agreement and US presidential elections. Their findings revealed abnormal returns, increased volatility, and fluctuations in trading volumes, which varied in intensity depending on the tightening or loosening of climate policies, as well as between different segments of green equities. Gong et al. (2024) confirmed that US climate policy decisions had a significant impact on the financial performance of energy companies, particularly in the context of the Paris Agreement.

In the light of the abovementioned growing global environmental concerns and threast of climate change, this study examines the impact of US politicies under the Trump and Biden administrations on the financial performance of companies with different environmental profiles. For this purpose, the analysis focuses on the behaviour of the monthly stock returns of two sets of representative US companies over the period from 1 January 2017 to 1 March 2025. These include major greenhouse gas emitters such as ExxonMobil, Chevron, Southern Company, and American Airlines, as well as key companies committed to the energy transition, such as NextEra Energy, First Solar, Tesla Energy, and Enphase Energy. In addition, the behaviour of the Climate Policy Uncertainty (CPU) index is also investigated.

Therefore, our study makes a threefold contribution to this area of the literature. First, whilst earlier papers such as Gong et al. (2024) and Pham et al. (2022) examine the impact of climate policies on companies from various countries, the current one provides more comprehensive evidence concerning US ones, which is of particular interest given their economic weight and global influence. Second, it applies a fractional integration framework which is more general and flexible than previously used ones based on the dichotomy between I(0) stationary and I(1) non-stationary series; in particular, by allowing the differencing parameter to take any real value, including fractional ones, this approach enables the researcher to shed light on the long memory and mean reversion properties of the variables of interest. Third, the analysis yields new valuable insights for policy makers responsible for taking appropriate action to transform the financial landscape of the energy sector and promote sustainable energy, and for investors to manage more effectively the risks arising from climate change.

The remainder of this paper is organised as follows. Section 2 provides a brief review of the relevant literature; Section 3 outlines the empirical framework: Section 4 describes the data and presents the empirical results; Section 5 offers some concluding remarks.

2. Literature Review

Climate policies and their effects on markets, especially on the renewable and fossil energy ones, have attracted increasing attention in academic research. The social responsibility of energy companies has risen significantly following the Paris Agreement (Xu and Wang, 2024), and global climate policy uncertainty has affected significantly financial markets (Ji et al., 2024).

In an international context, Pang et al. (2023) assessed the impact of the Paris Agreement on the total factor productivity (TFP) of enterprises in both the short and long term. Using an event study methodology and a sample of global publicly listed companies from 2013 to 2020, they found a negative short-term effect on TFP but a positive one in the long run. In addition, Ramiah et al. (2016) examined the abnormal returns of UK equities in response to environmental legislation, by carrying out a non-parametric event study over the period 2003–2012. Their results indicate that the chemical, oil, and gas sectors were affected negatively to environmental laws, while other polluting industries, such as construction and materials, exhibited a positive response. Further, Ramiah et al. (2015a) analysed the effects of environmental regulatory announcements on corporate performance in China and concluded that such regulations had a limited impact on the risk and return profiles in the Chinese stock market. Moreover, some of these regulations failed to achieve their intended objectives : unexpectedly, the coal sector benefited from these new measures, primarily due to the lack of effective enforcement of environmental regulations.

In the US context, Ramiah et al. (2015b) examined the interaction between environmental policies, financial markets, and the role of political leadership. Their study focused on the presidency of Barack Obama, known for his commitment to environmental regulation and green policies. They found that the largest polluters experienced negative abnormal returns, while more environmentally friendly companies were less affected. However, the observed reactions were generally not statistically significant, suggesting that these policies had a limited impact on financial markets. Wagner et al. (2018) analysed the effects of Donald Trump's election on expectations in financial markets and on corporate valuations. Their results indicated a shift in company expectations, particularly in response to anticipated changes in tax and trade policies. For example, lower corporate tax rates may have significantly influenced firm valuations. They also suggested the presence of a correlation between stock market reactions and the political affiliations of companies during the 2016 presidential election. Mukanjari and Sterner (2024) assessed the impact of major global climate decisions including the signing of the Paris Agreement and the US presidential election, on the market value of energy companies using event-based analysis methods. They found that both events had only moderate effects on equity markets, which suggests a limited response by investors to these significant climate-related announcements. Faccini et al. (2021) developed new indicators of both physical and transitional climate risks through a textual analysis of media coverage related to climate change over the period 2000–2018. Their analysis identified four key textual variables associated with US climate policy, international summits, natural disasters, and global warming. By examining the impact of these variables on the US stock market, they found that only the factor related to US climate policy was significantly priced by investors, particularly during the period from 2012 to 2018. Rainey et al. (2021) studied the oil and gas industry's response to stock market and option-implied volatility during four major political events related to the Paris Agreement and the election of Donald Trump. Their results show that Trump's election and the announcement of the US withdrawal from the Paris Agreement had a significant negative impact on the oil and gas sector, with exploration, production, and drilling segments being the most affected.

Hermwille and Sanderink (2019) empirically assessed the influence of the Paris Agreement as a normative signal to drive socio-technical systems toward decarbonisation.

Their study focused on the analysis of competing narratives in communications from leading associations and companies in the US fossil fuel industry, spanning from late 2014 until the announcement of the US withdrawal from the Paris Agreement in June 2017. Their evidence suggests that, despite the shift in political direction following the election of Donald Trump, the Paris Agreement contributed to institutionalising a resilient narrative paradigm. While the coal sector quickly adjusted its rhetoric in response to the new administration's direction, the oil and gas industries remained relatively silent, maintaining a narrative aligned with the objectives of the Accord.

3. Empirical Framework

This section outlines the fractional integration framework used for the empirical analysis. Fractional integration allows for the degree of differencing required to make a series stationary or I(0) to be a fractional value. More precisely, a time series is said to be integrated of order d or I(d) where d can be any real value, if it can be represented as:

$$(1 - B)^d \, x(t) = u\,(t), \quad t = 1, 2, \ldots, \tag{1}$$

Where B stands for the backshift-operator, i.e., $B^s x(t) = x(t-s)$, and u(t) is a short memory process, such as a white noise process with zero mean and constant variance, or one exhibiting weak autocorrelation.

Note that the fractional polynomial in (1) can be expanded as:

$$(1-B)^d = \sum_{j=0}^{\infty} \binom{d}{j} (-1)^j B^j = 1 - dB + \frac{d(d-1)}{2} B^2 - \cdots$$

and thus the equality appearing in Equation (1) can be expressed as :

$$x_t = d x_{t-1} - \frac{d(d-1)}{2} x_{t-2} + \ldots + u_t.$$

In this context, if d is a non-integer value, x_t will be a function of all its past history, and can be represented as an infinite autoregressive (AR) process. This type of processes was introduced in the early 1980s by Granger (1980), Granger and Joyeux (1980), Granger (1981) and Hosking (1981), and subsequently used for various empirical applcations. For instance, Gil-Alana and Robinson (1997) showed that the twelve US macroeconomic series examined in Nelson and Plosser (1982) were fractionally integrated, with an order of integration significantly below 1 and thus implying mean reversion, instead of exhibiting unit roots as previously concluded. Since then, such models have been estimated in many different fields, such as internet traffic and networking (Schennach, 2018), finance (Abbritti et al., 2016, 2023), tourism (Perez-Rodriguez et al., 2020; Gil-Alana and Payne, 2020), hydrology (Habib, 2020), climatology (Yuan et al., 2022), and environmental sciences (Gil-Alana et al., 2020a,b; Claudio-Quiroga and Gil-Alana, 2022, etc.).

For the empirical analysis carried out below, we assume that x_t in (1) are the errors in a regression model that includes a constant and a linear time trend, and we estimate and test the value of the differencing parameter by using the likelihood function in the frequency domain; for this purpose we follow a testing approach developed in Robinson (1994) that is based on the Lagrange Multiplier (LM) principle and that consists in testing the null hpothesis of $d = d_0$, where d_0 can be any real value, including those outside the stationary range. Since the limiting distribution is standard normal, confidence intervals can be constructed including the values of d_0 for which the null hypothesis cannot be rejected. This method is the most efficient one in the Pitman sense agaisnt local departures and under the null the differenced series are stationary. Using alternative parametric and semiparametric methods produced very similar results (not reported to save space).

4. Data and Empirical Results

Our purpose is to analyse the impact on the stock prices of US companies with different environmental profiles of climate policies during the first Trump administration and the following Biden one. Those introduced by the former included tax breaks for polluting industries and reduced support for clean energy investments. Specifically, the analysis focuses on the stock prices of two sets of companies : (i) high-emission ones such as ExxonMobil, Chevron, Southern Company, and American Airlines, all known for their significant greenhouse gas emissions; (ii) those committed to the energy transition, such as NextEra Energy, First Solar, Tesla Energy, and Enphase Energy - these stand out for their contributions to renewable energy and low carbon footprint, through solar and wind power production, as well as the development of innovative energy storage technologies. By contrast, as already mentioned, the Biden administration promoted the use of renewable energy through a range of policy measure contained in the 2022 Inflation Reduction Act (IRA). The analysis also includes the Climate Policy Uncertainty (CPU) index developed by Gavriilidis (2021) , which measures uncertainty related to US climate policy and has attracted growing interest in environmental and economic research. All series are monthly and cover the period from January 2017 to March 2025. Monthly data on US company stock prices were obtained from the website https://www.investing.com/, while the source for the data on the Climate Policy Uncertainty (CPU) index is the website https://www.policyuncertainty.com/.

For the estimation we use stock returns calculated as follows :

$$R^1{}_t = \text{Log}\left(\frac{P_t}{P_{t-1}}\right),$$

Where P_t stands for the stock price at time t.

Table 1 presents descriptive statistics on the stock returns of companies in the fossil fuel and renewable energy sectors, as well as for the Climate Policy Uncertainty (CPU) index. It can be see that renewable energy companies such as Enphase Energy and Tesla Energy, exhibit the highest average returns, being equal to 3.805% and 2.792% respectively, whilst the CPU index is the most volatile series as indicated by its standard deviation of 34.03. The Jarque-Bera test rejects the null of normality at the 1 % level only in the case of the Exxon Mobile and Chevron returns. The ADF test results imply that all series are stationary at the 1% significance level. Finally, the Q-test statistics based on a lag length or 20 indicate that all series, except the Exxon Mobile and Enphase Energy returns, exhibit autocorrelation.

Table 1 : Descriptive statistics for the stock returns

	Mean	Median	Std. Dev	JB	ADF	Q (20)	Q^2(20)
Exxon Mobile	0.3562	0.3523	8.369738	15.187 ***	-4.2899***	16.6	19.876 ***
Chevron	0.4154	0.7204	8.004038	11.393 ***	-4.5996***	17.771***	18.552***
Southern Company	0.6334	1.6320	5.478727	3.1715	-4.3524***	49.47***	25.218***
American Airlines	-1.4630	-0.3006	12.90518	6.7595	-5.3174***	17.608***	11.225***
Tesla Energy	2.792	1.645	18.00369	1.4976	-3.5125***	16.543***	28.564***
NextEra Energy	0.8463	1.1235	6.372576	7.1459	-3.7359***	22.176 ***	17.494***
First Solar	1.4282	0.3913	14.14777	1.4753	-3.4039***	17.695***	13.512***
Enphase Energy	3.805	2.946	22.22927	1.1586	-5.2781***	12.693	25.321***
CPU	0.78689	0.00365	34.02941	3.398	-6.4161***	29.336***	28.106***

Notes : The table reports descriptive statistics for the monthly returns of eight stock indices representing companies in the fossil fuel and renewable energy sectors, as well as for the Climate Policy Uncertainty (CPU) index, over the period from January 2017 to March 2025. The **Jarque-Bera** statistic tests the null hypothesis that a series is normally distributed by examining its first two moments; under the null, the statistic follows a chi-square distribution with two degrees of freedom. The **ADF** (Augmented Dickey-Fuller) is a unit root test. The **Q(20)** and **Q^2(20)** statistics are **Ljung-Box** tests used to examine the null hypothesis of no serial correlation up to the 20th lag, respectively for returns and squared returns. A 20-lag specification is chosen to capture serial dependence over a full six-month period.

*** indicate rejection of the null hypothesis at 1%

The estimated model is the following:

$$y(t) \;=\; \alpha + \beta t + x(t), \qquad (1 - L)^d x(t) \;=\; u(t), \qquad (1)$$

where y(t) stands for the time t observation of the series of interest; α and β are unknown parameters, specifically a constant and the coefficient on a linear time trend, and x(t) denotes the detrended series that is assumed to be integrated of order d, such that u(t) is a weakly autocorrelated process integrated of order 0 - for the latter, we use the exponential spectral model of Bloomfield (1973), which is a non-parametric approximation to AR structures.

Table 2 reports the full-sample estimates of d (and their corresponding 95% confidence bands) for three different specifications. In particular, column 4 displays those from the model with both an intercept and a time trend, column 3 those from the specification with a constant only, and column 2 those from the regressions without deterministic terms. The values in bold are those from the model selected on the basis of the statistical (in)significance of the regressors.

Table 2: Estimates of d using the full sample

Series	No terms	An intercept	An intercept and a linear time trend
Fossil Fuel Companies			
Exxon Mobile	0.91 (0.71, 1.23)	**1.01 (0.85, 1.23)**	1.01 (0.84, 1.24)
Chevron	0.90 (0.66, 1.22)	**0.91 (0.72, 1.19)**	0.91 (0.71, 1.19)
Southern Company	0.81 (0.53, 1.14)	0.61 (0.47, 0.81)	**0.44 (0.11, 0.78)**
American Airlines	0.94 (0.76, 1.18)	0.92 (0.71, 1.27)	**0.92 (0.71, 1.26)**
Renewable Energy Companies			
Series	No terms	An intercept	An intercept and a linear time trend
Tesla Energy	0.65 (0.49, 0.90)	0.68 (0.54, 0.92)	**0.61 (0.42, 0.91)**
NextEra Energy	0.78 (0.52, 1.07)	0.85 (0.67, 1.13)	**0.85 (0.67, 1.12)**
First Solar	0.85 (0.57, 1.40)	**1.03 (0.70, 1.52)**	1.03 (0.51, 1.53)
Enphase Energy	**0.80 (0.63, 1.03)**	0.81 (0.65, 1.03)	0.81 (0.63, 1.03)
Climate Policy Uncertainty			

Series	No terms	An intercept	An intercept and a linear time trend
CPU	0.77 (0.14, 1.23)	0.45 (0.14, 0.93)	**0.46 (-0.08, 0.94)**

This table reports the estimates of d along with their corresponding 95% confidence bands. In bold the coefficients
from the selected specification for each series.

It can be seen that the preferred model includes a time trend in a number of cases, namely for the stock returns of Southern Company and American Airlines among the fossil fuel companies, and also of Tesla Energy and Chevron Energy among the renewable energy ones, as well as for CPU. The estimates of d vary substantially across the series, ranging from 0.44 for the Southern Company to 1.01 for Exxon Mobile. In the former case, the series is found to be mean reverting, with shocks having only temporary effects, whilst for the returns of the other three fossil fuel companies the null hypothesis of a unit root (d = 1) cannot be rejected, which implies that shocks have permanent effects. As for the renewable energy companies, the results are fairly similar, with the returns of Tesla Energy exhibiting an estimate of d statistically smaller than one (d = 0.61) and evidence of unit roots (i.e., lack of mean reversion) for those of the other three. Finally, for CPU, the estimate of d is equal to 0.46 and the hypothesis of I(0) or short memory behaviour cannot be rejected. Table 3 reports the full set of the estimated coefficients from the selected models. It can be seen that there is evidence of a positive time trend in all cases except American Airlines for which the trend is negative.

Table 3: Estimated coefficients of the selected models in Table 2

Fossil Fuel Companies			
Series	d (95% conf. intv.)	Intercept (t-v)	Time trend (t-v)
Exxon Mobile	1.01 (0.85, 1.23)	83.915 (14.01)	---
Chevron	0.91 (0.72, 1.19)	111.440 (11.80)	---
Southern Company	0.44 (0.11, 0.78)^{MR}	45.321 (20.78)	0.387 (9.59)

American Airlines	0.92 (0.71, 1.26)	44.787 (15.63)	-0.348 (-1.68)
Renewable Energy Companies			
Series	d (95% conf. intv.)	Intercept (tv)	Time trend (t-v)
Tesla Energy	0.61 (0.42, 0.91)^{MR}	5.004 (2.18)	2.987 (4.36)
NextEra Energy	0.85 (0.67, 1.12)	30.948 (7.14)	0.425 (1.78)
First Solar	1.03 (0.70, 1.52)	30.988 (1.75)	---
Enphase Energy	0.80 (0.63, 1.03)	---	---
Climate Policy Uncertainty			
Series	d (95% conf. intv.)	Intercept (t-v)	Time tren (t-v)
CPU	0.46 (-0.08, 0.94)^{MR}	176.961 (4.13)	1.439 (1.77)

The values in column 2 are the estimates of d (with the 95% confidence bands in brackets), and those in columns 3 and 4 the estimates of the constant and of the coefficient on the linear time trend (with t-values in brackets). MR indicates Mean Reversion at the 95% level.. ---- indicates lack of statistical significance.

Next, we re-estimate the model over two subsamples corresponding to the first Trump administration (from January 2017 to December 2020) and the following Biden administration (from January 2021 to December 2024). The results are reported in Tables 4 and 5 for the former and in Tables 6 and 7 for the latter.

Table 4 shows that the estimates of d range between 0.77 (Chevron) and 1.33 (Southern Company) for the returns of the fossil fuel companies whilst the corresponding values are much smaller for those of the renewable energy companies, ranging from 0.52 (First Solar) to 0.89 (Enphase Energy), and there is statistical evidence of mean reversion in the case of Tesla. Finally, for CPU the estimate of d is -0.20 and the null of I(0) behaviour cannot be rejected. Table 5 displays the full set of estimated coefficients. It can be seen that returns of three of the fossil fuel companies (Exxon Mobile, Chevron, American Airlines) exhibit a positive trend, whilst the trend is negative for those of three of the renewable energy companies (Tesla Energy, Chevron Energy and Enphase Energy) and positive for only one of them (First Solar), as well as for CPU.

Table 4: Estimates of d using the sample for the TRUMP administration

Fossil Fuels			
Series	No terms	An intercept	An intercept and a linear time trend
Exxon Mobile	0.79 (0.05, 1.36)	0.68 (0.00, 1.31)	**0.78 (0.31, 1.30)**
Chevron	0.79 (0.48, 1.29)	0.83 (0.62, 1.18)	**0.77 (0.45, 1.22)**
Southern Company	1.25 (0.83, 1.71)	**1.33 (0.70, 1.83)**	1.33 (0.66, 1.82)
American Airlines	1.04 (0.19, 2.41)	0.99 (0.13, 2.41)	**1.05 (0.37, 2.42)**
Renewable Energy Companies			
Series	No terms	An intercept	An intercept and a linear time trend
Tesla Energy	0.85 (0.48, 1.35)	0.74 (0.55, 0.97)	**0.64 (0.38, 0.96)**
NextEra Energy	0.83 (0.44, 1.35)	0.72 (0.49, 1.01)	**0.66 (0.39, 1.01)**
First Solar	0.70 (0.11, 1.31)	0.62 (0.34, 1.08)	**0.52 (0.01, 1.11)**
Enphase Energy	0.95 (0.65, 1.37)	0.94 (0.71, 1.50)	**0.89 (0.23, 1.50)**
Climate Policy Uncertainty			
Series	No terms	An intercept	An intercept and a linear time trend
CPU	0.03 (-0.09, 0.52)	0.0 (-0.20, 0.46)	**-0.20 (-0.52, 0.34)**

This table reports the estimates of d (with their corresponding 95% confidence bands in brackets).
In bold the estimates from the selected specification in each case.

Table 5: Estimated coefficients of the selected models in Table 4

Fossil Fuels			
Series	d (95% conf. intv.)	Intercept (t-v)	Time trend (t-v)
Exxon Mobile	0.78 (0.31, 1.30)	0.303 (2.53)	3.686 (3.34)
Chevron	0.77 (0.45, 1.22)	29.790 (13.42)	0.935 (6.10)
Southern Company	1.33 (0.70, 1.83)	30.132 (4.68)	---
American Airlines	1.05 (0.37, 2.42)	-1.847 (-2.20)	3.875 (2.53)
Renewable Energies			

Series	d (95% conf. intv.)	Intercept (t-v)	Time trend (t-v)
Tesla Energy	0.64 (0.38, 0.96)[MR]	86.403 (20.19)	-0.942 (-4.41)
NextEra Energy	0.66 (0.39, 1.01)	113.906 (16.69)	-0.574 (-1.61)
First Solar	0.52 (0.01, 1.11)	47.911 (21.04)	0.233 (2.53)
Enphase Energy	0.89 (0.23, 1.50)	45.375 (12.69)	-0.654 (-1.83)
Climate Policy Uncertainty			
Series	d (95% conf. intv.)	Intercept (t-v)	Time trend (t-v)
CPU	-0.20 (-0.52, 0.34)	141.158 (17.68)	1.529 (5.01)

The values in column 2 are the estimates of d (with the 95% confidence bands in brackets), and those in columns 3 and 4 the estimates of the constant and of the coefficient on the linear time trend (with t-values in brackets). MR indicates Mean Reersion at the 95% level. ---- indicates lack of statistical significance.

Table 6: Estimates of d using the sample for the BIDEN administration

Series	No terms	An intercept	An intercept and a linear time trend
Exxon Mobile	0.37 (0.26, 1.14)	0.78 (0.52, 1.24)	**0.79 (0.46, 1.23)**
Chevron	0.89 (0.40, 1.38)	**0.86 (0.49, 1.28)**	0.88 (0.58, 1.25)
Southern Company	0.90 (0.57, 1.28)	0.21 (-0.35, 0.77)	**0.33 (-0.76, 0.78)**
American Airlines	0.96 (0.56, 1.56)	0.56 (0.27, 1.52)	**0.20 (-0.31, 1.52)**
Series	No terms	An intercept	An intercept and a linear time trend
Tesla Energy	0.99 (0.56, 1.53)	**0.23 (-0.16, 1.08)**	0.14 (-0.39, 1.08)
NextEra Energy	0.87 (0.56, 1.22)	**0.60 (0.27, 1.14)**	0.55 (-0.13, 1.14)
First Solar	0.48 (0.31, 1.07)	**0.86 (0.53, 1.69)**	0.78 (-0.32, 1.65)
Enphase Energy	0.61 (0.29, 0.96)	0.55 (0.27, 0.92)	**0.51 (0.15, 0.92)**
Climate Policy Uncertainty			
Series	No terms	An intercept	An intercept and a linear time trend
CPU	0.10 (-0.28, 0.44)	**-0.36 (-0.73, 0.74)**	-0.16 (-0.67, 0.81)

This table reports the estimates of d (with their corresponding 95% confidence bands in brackets).
In bold the estimates from the selected specification in each case.

Tables 6 and 7 report the results for the period of the Biden administration. It can be seen from Table 6 that the estimated values of d imply that mean reversion occurs only in the case of the returns of one of the fossil fuel companies, namely the Southern Company (d = 0.33), and one of the renewable energy ones, namely Enphase Energy (d = 0.51). For the returns of the other companies, such as American Airlines and Tesla Energy, the values of d are also low (0.20 and 0.23) but the confidence intervals are so wide that neither the I(0) nor the I(1) hypotheses can be rejected, while in the case of CPU the value of d is -0.36 and the I(0) hypothesis cannot be rejected. Table 7 shows that returns of three of the fossil fuel companies exhibit a significant time trend, this being positive in the case of Exxon Mobile and the Southern Company and negative in the case of American Airlines. As for the returns of the renewable energy companies, only those of Enphase Energy exhibit a significant, negative trend.

Table 7: Estimated coefficients of the selected models in Table 6

Series	d (95% conf. intv.)	Intercept (t-v)	Time trend (t-v)
Exxon Mobile	0.79 (0.46, 1.23)	45.722 (7.08)	1.431 (3.03)
Chevron	0.86 (0.49, 1.28)	88.543 (8.15)	----
Southern Company	0.33 (-0.76, 0.78)^{MR}	59.625 (26.67)	0.481 (6.26)
American Airlines	0.20 (-0.31, 1.52)	20.346 (23.23)	-0.177 (-5.93)
Series	d (95% conf. intv.)	Intercept (t-v)	Time trend (t-v)
Tesla Energy	0.23 (-0.16, 1.08)	248..899 (25.88)	---
NextEra Energy	0.60 (0.27, 1.14)	77.671 (18.87)	---
First Solar	0.86 (0.53, 1.69)	99.429 (2.24)	---
Enphase Energy	0.51 (0.15, 0.92)^{MR}	195.567 (8.34)	-2.014 (-2.15)
Climate Policy Uncertainty			
Series	d (95% conf. intv.)	Intercept (t-v)	Time trend (t-v)

CPU	-0.36 (-0.73, 0.74)^{MR}	222.655 (42.20)	---

The values in column 2 are the estimates of d (with the 95% confidence bands in brackets), and those in columns 3
and 4 the estimates of the constant and of the coefficient on the linear time trend (with t-values in brackets). MR indicates Mean Reversion at the 95% level. ---- indicates lack of statistical significance.

Tables 8 and 9 compare the results for the two administrations in terms of the time trend coefficients and of the estimates of d respectively. Specifically, Table 8 shows that in the case of the returns of the fossil fuel companies the time trend switches over the two periods from positive to negative for American Airlines, whilst the positive coefficient for Exxon Mobile becomes smaller, and for the Southern company moves from insignificant to positive. As for the returns of the renewable energy companies, the time trend is negative in the first period and insignificant in the second in the case of Tesla Energy and Chevron Energy, whilst for First Solar it moves from positive to insignificant, and for Enpahse Energy the negative coefficient increases in absolute value in the second period. Interestingly, the time trend is reversed in the case of CPU, switching from positive to negative.

Table 8: Comparison between the Trump and Biden administrations in terms of the time trend coefficients

	Series	**TRUMP Adm.**	**BIDEN Adm.**
Fossil Fuel Companies	Exxon Mobile	3.686 (3.34)	1.431 (3.03)
	Chevron	0.935 (6.10)	----
	Southern Company	---	0.481 (6.26)
	American Airlines	3.875 (2.53)	-0.177 (-5.93)
	Series	**TRUMP Adm.**	**BIDEN Adm.**
Renewable Energy Companies	Tesla Energy	-0.942 (-4.41)	---
	NextEra Energy	-0.574 (-1.61)	---
	First Solar	0.233 (2.53)	---
	Enphase Energy	-0.654 (-1.83)	-2.014 (-2.15)

	Series	TRUMP Adm.	BIDEN Adm.
	CPU	1.529 (5.01)	---

In brackets the t-values.

Table 9 reports the evidence on persistence in the series during the two administrations. It can be seen that, in the case of the returns of the fossil fuel companies, the estimate of d is almost identical in the two periods for Exxon Mobile (0.77 under Trump and 0.79 under Biden); there is a slight increase in the case of Chevron (0.77 under Trump and 0.86 under Biden), whilst there is a sizeable fall in the second period in the case of the Southern Company (from 1.33 to 0.33) and American Airlines (1.05 to 0.20). Note that mean reversion occurs only in the case of the returns of the Southern Company and American Airlines and only during the Biden administration. Regarding for results for the returns of the renewable energy companies, there is a reduction in the degree of persistence in three out of the four series, namely Tesla (d decreases from 0.64 under Trump to 0.23 under Biden), Chevron Energy (from 0.66 to 0.60), and Enphase Energy (from 0.89 to 0.51), whilst there is an increase in the case of First Solar (from 0.52 to 0.86). Finally, in the case of CPU, the estimates of d are negative and imply I(0) behaviour under both administrations.

Table 9: Comparison between the Trump and Biden administrations in terms of the differencing parameter

	Series	TRUMP Adm.	BIDEN Adm.
Fossil Fuel Companies	Exxon Mobile	0.78 (0.31, 1.30)	0.79 (0.46, 1.23)
	Chevron	0.77 (0.45, 1.22)	0.86 (0.49, 1.28)
	Southern Company	1.33 (0.70, 1.83)	0.33 (-0.76, 0.78)^{MR}
	American Airlines	1.05 (0.37, 2.42)	0.20 (-0.31, 1.52)
	Series	**TRUMP Adm.**	**BIDEN Adm.**
	Tesla Energy	0.64 (0.38, 0.96)^{MR}	0.23 (-0.16, 1.08)

Renewable Energy Companies	NextEra Energy	0.66 (0.39, 1.01)	0.60 (0.27, 1.14)
	First Solar	0.52 (0.01, 1.11)	0.86 (0.53, 1.69)
	Enphase Energy	0.89 (0.23, 1.50)	0.51 (0.15, 0.92)^{MR}
	Series	**TRUMP Adm.**	**BIDEN Adm.**
	CPU	-0.20 (-0.52, 0.34)	-0.36 (-0.73, 0.74)^{MR}

In brackets the confidence intervals. MR indicates the presence of mean reversion,

5. Conclusions

This paper applies a fractional integration framework to investigate the behaviour of the stock returns of two sets of representative US companies with different environmental profiles, namely green versus pollutimg firms, as well as of the widely used CPU (Climate Policy Uncertainty) index over the period from January 2017 to March 2025. This time span includes the first Trump administration and the following Biden one, with very different attitudes towards the environment. Therefore the analysis is conducted not only for the full sample, but also for the two sub-samples corresponding to those two administrations with the aim of establishing whether their respective climate policies had a significant impact on the related uncertainty and on the returns of companies adopting different environmental strategies. The chosen modelling approach is most suited to our purposes, since it sheds light on the long memory and mean reversion properties of the series, and thus on whether shocks have permanent or transitory effects. This information is crucial for both policy makers and market participants, since different policies and investment strategies respectively will be required depending on the degree of persistence of stock returns: more decisive policy actions and greater portfolio adjustments are clearly necessary when the effects of shocks are long-lived rather than quickly vanishing.

In brief, a comparison between the periods corresponding to the two administrations covered by the analysis suggests that (i) the financial performance of stock returns of polluting companies was generally worse under the Biden administration, whilst there was no significant positive impact on green companies, as implied by the estimate time trend coefficients : (ii) the effects of shocks tend to fade away more quickly in both types of companies under the Biden administration, as implied by the estimates of d, though only in two cases they eventually vanish. Finally, CPU appears to have been decreasing under the Biden administration, whilst the effects of shocks seem to be transitory in both periods. On the whole, policies to combat climate changes, such as those introduced by President Biden through the Inflation Reduction Act (IRA) of 2022, appear to have reduced climate uncertainty, and also to have led to a better financial performance of environmentally friendly companies, to which they provided various incentives. Therefore, a reversal of such policies under the current Trump administration can be expected to reward instead polluting firms with damaging effects on the environment.

Future work should test for the possible presence of structural breaks in the series as overlooking them could produce spurious evidence of fractional integration (Diebold and Inoue, 2001). In addition, the role of the fundamentals driving stock prices under different political administrations could be examined by using the fractional cointegration VAR (FCVAR) framework developed by Johansen and Nielsen (2010, 2012).

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