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Article

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The Nonlinear Nexus of Climate Policy Uncertainty and Renewable Energy Consumption in the United States of America: A Markov-Switching Approach

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ABSTRACT

We employ a Markov-Switching regression model using monthly US data from April 1987 to August 2022 to investigate the effect of climate policy uncertainty (CPU) on renewable energy consumption (REC). The main findings suggest the presence of a nonlinear relationship between CPU and REC. The baseline analysis using the CPU index reveals an adverse effect in regimes characterized by high levels of uncertainty. However, the effect is not statistically significant in a low uncertainty regime. To account for potential variations in the results, we perform a robustness analysis that considers the effect of CPU on REC, which may fluctuate based on the authorities' contextual perspectives (i.e., being in favor or against climate policy) and also the effect of CPU on REC by household. In addition, we incorporate a robustness check by utilizing the environmental policy uncertainty index developed by Noailly et al. (2022). The robustness test results confirm the results obtained from the baseline estimation.

Keywords: Climate Policy Uncertainty, Environmental Policy Uncertainty, Renewable Energy Demand, Markov-switching Regression
JEL Classifications: E61, E65, Q21, Q28, Q58

1. INTRODUCTION

In the past two decades, there has been a vast transformation from non-renewable to renewable energy in developed and many developing countries. Shang et al. (2022) mention that four key aspects push the transformation are: (1) technological progress that reduced the costs of new investments in energy sources, (2) the climate change crisis, (3) volatility of crude oil price, and (4) policies by the governments which support renewable energy through credit provisions and tax benefits on renewable energy investments.

But despite worldwide governments' commitment to tackle the issue and alleviate climate change, substantial uncertainty remains in executing the policies. For example, Noailly et al. (2022) observed that under the Trump Administration, a significant number of climate initiatives implemented by prior administrations, particularly those of the Obama Administration, were reversed. With this in mind, we aim to investigate the effects of climate policy uncertainty (CPU) on renewable energy consumption (REC) using monthly data from the United States from 1987M04 to 2022M08. Using Gavriilidis's (2021) novel climate policy uncertainty index, which followed the methods of Baker et al. (2016), we can examine the existence and magnitude of the effect from CPU to REC.

We choose the United States for this analysis because it is an advanced economy with the highest fossil fuel consumption per capita in 2022, at around 63,836 kWh (OurWorldinData, 2022). It also lags behind many other countries in terms of renewable energy investment as a percentage of GDP, with the US investing only 0.2% in 2015, while others, such as South Africa (1.4%), China (0.9%), India (0.5%), and others, invested more. However, the findings of this paper should also be relevant for other developing countries looking to implement climate policies that encourage the use of renewable energy.

Several studies have been conducted for the US economy exploring the effect of climate policy uncertainty (CPU) on renewable energy consumption (REC), but there is little consensus on the results. For example, Shang et al. (2022) use an augmented autoregressive distributed lags (ARDL) approach with quarterly US data from 2000Q1 to 2021Q3 and find that CPU reduces non-REC, and it positively affects REC in the long run. Meanwhile, using a novel Fourier augmented autoregressive distributed lags (FA-ARDL) approach, Syed et al. (2023) suggest that CPU reduces REC. In another study, Zhou et al. (2023) examine the short- to long-run relationships between CPU and REC and find that CPU positively affects REC in the short- and long-run, while a negative relationship exists between them in the medium-run.

Although studies investigating the CPU-REC nexus have been conducted, those studies have some limitations. First, Shang et al. (2022) use dummy variables to capture structural breaks. Syed et al. (2023) claim that the Fourier transformation they utilize outperforms the dummies approach because Shang et al. (2022) do not develop their analysis based on economic theory. The Fourier approximation Syed et al. (2023) developed does not require any prior information about the nature, frequency, and date/time of structural breaks. However, their model is limited to the neoclassical demand function assumption. Furthermore, these studies do not consider that the relationship between CPU-REC might evolve/change over time.

Li et al. (2023) employ a VAR model with a time-varying rolling-window causality test and discover that the causality between CPU-REC is both negative and positive-depending on the authorities' attitudes towards climate change. However, the robustness of this study is limited to the choice of a rolling window to generate the time-varying effect. In another study, Zhou et al. (2023) use the time-varying parameter vector autoregressive model with stochastic volatility (TVP-SV-VAR) model and find that the relationship between CPU-REC is time-varying and that the effects of CPU lead to higher oil prices in the short and medium-term and higher REC in the short and long term most of the time. Despite the interesting findings, they are inconsistent with the fact that CPU might have different effects depending on the source/nature of the change.

For example, Noailly et al. (2022) note that during the Trump Administration, several previous administrations' climate policies, most notably those of the Obama Administration, were reversed. Several examples include the withdrawal from the Paris Agreement and the repeal of the Clean Power Plan, both of which were politically motivated decisions that increased economic uncertainty (Li et al., 2023). This policy shift contradicted previous administrations' efforts to shift from non-renewable to renewable energy consumption to achieve carbon neutrality. As shown in Figure 1, this abrupt and massive policy change caused a substantial shock to climate policy uncertainty (CPU) and might have a different effect than when the change is small.

Our study makes the following contributions. First, previous research has mostly examined the CPU-REC nexus using linear models, which assume that economic actors' behavior does not change with different levels of uncertainty. While the time-varying model developed by Li et al. (2023) and Zhou et al. (2023) fail to identify a negative effect of CPU on REC in extreme periods such as the withdrawal from the Paris Agreement and the repeal of the Clean Power Plan during Trump's administration in the US. Second, all estimation was mainly carried out using one type of index-reducing the robustness of the results. Our study also estimates the CPU-REC relationship using the environmental policy uncertainty (ENVPU) index developed by Noailly et al. (2022). They use a word search strategy similar to Gavriilidis (2021) but strengthened with a Support Vector Machine (SVM) algorithm to classify whether an article constitutes uncertainty. Lastly, we also include data on household renewable energy consumption (RECHH) to find whether the same effect of CPU-REC also holds in the household context.

The remainder of the paper is divided into five sections. Section 2 examines the literature on the CPU-REC relationship and the factors that influence REC. Section 3 delves into the methodology. Section 4 summarizes the main findings and robustness tests. Section 5 discusses the findings. Section 6 wraps up the paper by summarizing the findings and discussing the implications.

2. LITERATURE REVIEW

The bulk of research on renewable energy consumption has centered around the Environmental Kuznets Curve (EKC), including Sari et al. (2008), Ocal and Aslan (2013), Apergis and Danuletiu (2014) and among others. This is not surprising, given that studying the effect of climate policy uncertainty was tedious before Gavriilidis developed the CPU index in 2021.

With the introduction of the new measure, several studies have begun to investigate the CPU-REC nexus. Shang et al. (2022) use the ARDL approach to determine the short and long-run effects of climate policy uncertainty on non-renewable and renewable energy consumption. Their findings indicated that CPU has no significant effect on REC in the short or long term, but it affects fossil fuels negatively. Meanwhile Zhou et al. (2023), taking a different approach, investigating the time-varying relationship between CPU, oil prices, and REC and find that CPU positively affects oil prices and REC in most periods using a time-varying parameter vector autoregressive model (TVP-SV-VAR). They explain the validity of their findings as being due to the goal of climate policy, which is to reduce carbon emissions and thus incentivize the use of renewable energy, which contrasts with the effect of economic policy uncertainty on REC, which, according to Shafiullah et al. (2021), is generally negative.

Similarly, Li et al. (2023) investigate the CPU-REC relationship while considering time-varying effects. They estimated a VAR model with an additional time-varying rolling-window bootstrap causality test to account for structural changes and parameter instability, which resulted in time-varying causality in various subsamples. They suggest that the causality between CPU and REC varies according to the authorities' attitudes toward climate change mitigation. This implies that regimes generally supportive of climate change mitigation will benefit from a positive CPU-REC nexus and vice versa.

Xi et al. (2023) use a vector autoregressive (VAR) model with Granger causality tests to investigate the effects of uncertainty on five types of REC. They discover that CPU affects REC on average, as well as solar and wind energy, but not geothermal or hydroelectric. While no effects are found on geothermal energy consumption after applying time-varying tests, there are effects on the other types, albeit discontinuously, leading the authors to conclude that the influence of CPU on REC varies with time.

Syed et al. (2023) employ a Fourier Augmented ARDL (FA-ARDL) model to account for structural breaks in modeling the CPU-REC nexus. They discover that CPU reduces REC in both the short and long run, which could be attributed to a lack of clarity for long-term planning and investment in renewable energy consumption, as well as individuals adopting a "wait and see" policy by purchasing non-renewable energy until the policy landscape becomes more certain.

Aside from the CPU-REC nexus, other studies have investigated the effect of economic policy uncertainty (EPU) on REC, such as Shafiullah et al. (2021), who use a nonlinear model and Granger causality analysis to find that there is a nonlinear causal effect from EPU to REC, which is harmful in the long run. Yi et al. (2023) utilize a CS-ARDL model on a panel of top renewable energy consumers and discovered that EPU negatively affects REC in both the short-and long-run. Using various parametric models, Ivanovski and Marinucci (2021) find that EPU is negatively associated with REC. While Feng and Zheng (2022) employ panel fixed effects on 22 countries to suggest that EPU positively affects renewable energy innovation. Further subsample analysis helped them confirm that OECD members and right-ring countries tend to have higher growth in renewable energy.

Regarding factors that influence REC, previous research has identified three that may be interesting. The first factor is economic growth, commonly proxied by GDP growth or industrial productivity, because previous research suggests that higher growth may lead to increases in income, increasing consumer access to renewable energy. Several studies have found this proper, including Ocal and Aslan (2013), who utilize the ARDL and Toda-Yamamoto Causality tests to discover unidirectional causality from economic growth to REC in Turkey. Using the Canning-Pedroni Dynamic Error Correction Model (ECM) and data from 80 countries, Apergis and Danuletiu (2014) demonstrate long-run positive bidirectional causality from GDP to REC.

The second factor commonly discussed in REC modeling is carbon dioxide emissions (CO_2), which is the primary catalyst of REC, according to Bhattacharyya (2012) and Goldemberg (2004). Given that the modern world is heavily reliant on fossil fuels and non-renewable energy sources, there has been a dramatic increase in the concentration of greenhouse gases (GHG), which includes CO2, resulting in abnormal changes in the earth's climate. As a result, CO_2 emissions serve as a warning to the global economy, incentivizing consumers to switch to renewable energy sources for their daily energy consumption to mitigate climate change, as demonstrated by Sadorsky (2009), who discover that per capita income and CO_2 emissions increase REC in the G7 countries.

Within the context of African countries, Olanrewaju et al. (2019) find that CO_2 emissions are negatively associated with REC. Meanwhile, other studies have discovered that REC affects CO_2 emissions. Karaaslan and Camkaya (2022) suggest a unidirectional causal effect from REC to CO_2 emissions in the long run, using the ARDL and Toda-Yamamoto Causality test in the context of Turkey. In contrast to both of these lines of research, Menyah and Wolde-Rufael (2010) find no causal relationship between REC and CO_2 emissions using a modified Granger Causality test.

Another factor to consider is the price of oil, typically proxied by West Texas Intermediate (WTI) crude oil prices, given that REC serves as a substitute for non-renewable energy sources and may be affected by changes in oil prices. For example, Brini et al. (2017) employ the ARDL model to analyze data from Tunisia from 1980 to 2011 and discover that oil prices are positively related to REC. Meanwhile, Sahu et al. (2022) use the Nonlinear Autoregressive Distributed Lag (NARDL) model in the United States and find that GDP and oil prices increase both REC in the short- and long-run.

3. METHODOLOGY

3.1. Data

This paper focuses on the US economy, using monthly data from 1987M04 to 2022M08. The dependent variable is the aggregate of REC from various sectors of the US production side, based on data from the Energy Information Administration (EIA) which includes different energy sources such as biomass, hydropower, geothermal, wind, and solar power. The independent variable of interest, CPU, is obtained from the online repository for policy uncertainty, along with data from Gavriilidis (2021). It should be noted that the CPU data is only available for the United States. While there are other CPU indicators, Gavriilidis's (2021) is the one that made publicly available. Following the previously discussed factors that influence REC, we include CO_2 emissions (CO_2), the Index of Industrial Productivity (IIP), and West Texas Intermediate Oil Prices as covariates (WTI). The EIA also provides CO_2 data, while the Federal Reserve Bank of St. Louis Economic Data (FRED) provides IIP and WTI (FRED, 2022; FRED, 2024).

We also collect additional data to test the robustness of our estimates. In one of our iterations, we substitute the CPU for the Environmental Policy Uncertainty (ENVPU) index to ensure the model's robustness concerning the main variable of interest. The ENVPU developed by Noailly et al. (2022) uses a similar word search strategy enhanced with a Support Vector Machine (SVM) algorithm to determine whether an article is uncertain. They contend that their method produces better predictions of uncertainty within the corpus of articles than the Gavriilidis (2021) algorithm, based on Baker et al. (2016). Noailly et al. (2022) discover that their algorithm has a higher recall rate than Baker et al.'s (2016) algorithm, with the ENVPU having 70%. The other has 8%, meaning that the SVM algorithm performs significantly better regarding true positives being correctly classified as uncertain. The ENVPU is, thus, a better metric. This data is sourced from the author's repository, but there are fewer observations because the data spans only from 1990M01 to 2019M03.

Finally, we also use data on household renewable energy consumption (RECHH) to see if the same effect of CPU on REC holds in the household context. This data is collected from the CEIC, with monthly periodicity spanning the entire dataset's number of periods (CEIC, 2018).

3.2. Conceptual Framework

Considering the existing studies that have discussed the determinants of renewable energy demand, we employ the Markov-Switching Autoregressive (MSAR) model to estimate the different regimes, thus specifying a first-order Markov process for the regime probabilities. This means that the probability of being in a regime depends on the previous state, which could be described as:

$$P\left(s_t = j | s_{t-1} = i\right) = p_{ij}\left(t\right) \tag{1}$$

where s_t=1 or 2 is an unobserved state variable, i is the regime in period t-1, j is the regime in period t. In a transition matrix, this could be represented as:

$$p\left(t\right) = \begin{bmatrix} P\left(s_t = 1 | s_{t-1} = 1\right) & P\left(s_t = 2 | s_{t-1} = 1\right) \\ P\left(s_t = 1 | s_{t-1} = 2\right) & P\left(s_t = 2 | s_{t-1} = 2\right) \end{bmatrix}$$
$$= \begin{bmatrix} p_{11}(t) & p_{12}(t) \\ p_{21}(t) & p_{22}(t) \end{bmatrix} \tag{2}$$

Following Goldfeld and Quandt (1973), Hamilton (1989), and Liu et al. (2022), we apply the Markov-Switching model to examine the effect of CPU on REC, which is specified below:

$$\Delta LREC_t = \phi_{0,s_t} + \phi_{1,s_t}\Delta LCPU_t + \phi_{2,s_t}\Delta LREC_{t-1} + \phi_{3,s_t}\Delta LCO2_t$$
$$+\phi_{4,s_t}\Delta LWTI_t + \phi_{5,s_t}\Delta LIIP_t + \varepsilon_t,\ \varepsilon_t \sim i.i.d.N\left(0,\ \sigma_{s_t}\right) \tag{3}$$

where REC_t is the renewable energy consumption at time , which in this case would be in monthly intervals, $s_t \in \{1,2\}$ is an irreducible and ergodic Markov regime-switching process, in which the first state (s_t=1) denotes the low uncertainty regime, while the second state (s_t=2) denotes the high uncertainty regime. CPU_t is the climate policy uncertainty index, $REC_{(t-n)}$ are the lagged covariates of REC at time *t-n,* $CO_2\,t$ is the CO_2 emissions, WTI_t is the West Texas Intermediate Crude Oil Price, and IIP_t is the Industrial Production Index at month t. The Δ symbol denotes the differentiated variable, and L denotes the natural logarithmic transformation applied to the variable. Finally, $\phi_{(v,s\_t)}$ denotes the coefficient values for coefficient c in state s_t, while ε_t is the random disturbance term under the regime-switching state based on the uncertainty.

3.3. Econometric Procedures

To avoid the spurious regression problem, which Granger and Newbold (1974) highlighted, it is critical to use unit root tests to determine the order of integration of each series before proceeding with further regression analyses. We use three standard unit root tests to determine the level of integration: the Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979), the Philips-Perron (PP) test (Phillips and Perron, 1988), and the Kwiatkowski-Philips-Schmidt-Shin (KPSS) test (Kwiatkowski et al., 1992).

However, structural breaks within the data points are possible, which could question the validity of the previous tests. We use the Zivot and Andrews (2002) breakpoint unit root tests to ensure that the series is truly integrated at the level predicted by the prior tests. Despite the possibility of seasonal unit roots, we will have dealt with this possibility using the STL decomposition for the first-differenced series. In contrast, the seasonally-differenced series will have dealt with it entirely.

To validate the use of the MS model, which is a nonlinear model, we must first test the data series for nonlinearities. To do so, we use the Brock-Dechert-Scheinkman-LeBaron (BDS) independence test (Brock et al., 1996), a portmanteau test for time-based dependence in a series that does not require a specific alternative hypothesis (Enders, 1994). If the null hypothesis of linear dependence is rejected, then the data contains nonlinearities. To validate the BDS test results, we also use the McLeod and Li (1983) test, which is the exact Lagrange Multiplier (LM) test for ARCH errors and has a high power to detect a variety of nonlinearities (Enders, 1994). After testing for the integration level and nonlinearities within the data, we can estimate the MS model as specified before.

4. MAIN RESULTS AND DISCUSSION

4.1. Unit Root and Linearity Tests

Before moving on to the unit root and linearity tests, it is necessary to review the descriptive statistics for all of the series used in this analysis, which are listed in Table 1. The dataset contains 425 observations-except the ENVPU, which has only 351 observations. While the other variables appear normal in the summary in Table 1, the CPU appears skewed and may have heavier tails than the normal distribution. As a result, log-transformed variables are used to normalize the data points.

Moving on to the unit root tests, we apply the standard unit root tests, which include the Augmented Dickey-Fuller tests, Phillips-Perron tests, and the KPSS tests in Table 2. From the table, we can infer that all of the data series are integrated at I(1). The Zivot-Andrews test with stuctural breaks in Table 3 also leads us to this conclusion.

We use the BDS Test for linearity and the McLeod-Li test to support using a nonlinear model, as shown in Table 4. According to the results in Table 4, the null hypothesis that the series are linearly dependent is rejected. However, keep in mind that these results do not indicate the shape of the nonlinearity, although we can reasonably conclude that nonlinearities exist in the data. As a result, we can estimate the MS model.

4.2. Main Results

The main findings of the MS model are documented in Table 5. Table 5 displays two results obtained for low and high uncertainty regimes. The data indicates a negative nonlinear relationship between CPU and REC, with differing effects observed between

Table 1: Descriptive statistics

	CPU	REC	CO_2	IIP	WTI	ENVPU	RECHH
Mean	100.0000	647.0932	450.2453	87.13729	46.77831	100.0000	52.60569
Median	86.59016	563.8750	450.6330	92.16290	38.03000	96.053	51.28300
Maximum	411.2888	1200.249	560.7700	106.1340	133.8800	174.641	85.90400
Minimum	28.16193	395.8400	305.2040	56.72620	11.35000	44.914	32.33000
SD	55.65215	189.0841	42.77749	14.75428	29.38094	25.519	12.55499
Skewness	2.019945	0.881984	0.143427	-0.72566	0.741345	0.407	0.649977
Kurtosis	8.075493	2.627666	2.896946	2.043739	2.411435	2.589	2.699449
Jarque-Bera	745.1903	57.55585	1.645202	53.49270	45.06379	12.160	31.52460
Observations	425	425	425	425	425	351	425

Table 2: Standard unit root tests on dataset

	Augmented dickey-fuller test		Phillips-perron test		Kwiatkowski-phillips-schmidt-shin test	
	Level	1st Diff	Level	1st Diff	Level	1st Diff
Climate policy uncertainty						
None	0.479	−13.26***	0.251	−85.26***		
Intercept	−2.326	−13.27***	−10.36***	−119.9***	1.646***	0.246
Trend and Intercept	−5.903***	−13.27***	−14.04***	−137.2***	0.364***	0.245***
CO_2 emission						
None	−0.044	−5.496***	0.392	−59.58***		
Intercept	−1.810	−5.489***	−7.844***	−59.48***	0.673**	0.246
Trend and Intercept	−1.922	−5.649***	−7.843***	−59.16***	0.665***	0.127*
Renewable energy consumption						
None	1.882	−4.841***	0.859	−36.16***		
Intercept	0.075	−5.399***	−1.626	−37.26***	2.161***	0.048
Trend and Intercept	−1.527	−5.494***	−4.778***	−38.90***	0.511***	0.017
WTI crude oil price						
None	0.231	−15.41***	0.559	−14.78***		
Intercept	−1.962	−15.40***	−1.479	−14.79***	1.973***	0.043
Trend and Intercept	−3.410*	−15.39***	−2.718	−14.76***	0.274***	0.043
Environmental policy uncertainty						
None	−0.200	−13.13***	−0.152	−148.9***		
Intercept	−6.084***	−13.11***	−12.64***	−151.7***	0.389*	0.155
Trend and Intercept	−6.193***	−13.09***	−12.76***	−156.7***	0.163**	0.154**
Industrial productivity						
None	1.650	−4.087***	2.105	−30.07***		
Intercept	−1.649	−5.010***	−1.987	−31.43***	2.159***	0.225
Trend and Intercept	−1.690	−5.097***	−2.118	−31.19***	0.529***	0.048

*, **, and ***indicate significance level at 10%, 5%, and 1%

Table 3: Zivot-andrews structural unit root test results

Series	Constant		Trend		Constant and trend	
	Min t-stat	Break	Min t-stat	Break	Min t-stat	Break
LCPU						
Level	−4.134	2016M09	−3.844	2014M04	−4.075	2016M09
Seas. Diff	−7.538***	2016M03	-	-	−7.612***	2016M03
LCO_2						
Level	−3.081	1995M07	−4.231*	2004M01	−4.281	2008M02
Seas. Diff	−6.707***	2008M02	−6.482***	1995M09	−6.794***	2008M02
LREC						
Level	−3.589	1997M11	−3.402	2001M10	−4.854*	2000M05
Seas. Diff	−5.466***	2001M12	−4.869***	1998M11	−6.004***	2001M12
LWTI						
Level	−4.573	2014M08	−3.694	2010M11	−4.570	2003M10
Seas. Diff	−4.377	2008M07	−3.996	2016M08	−4.686	2014M07
LENVPU						
Level	−4.416	2004M02	−3.716	2008M02	−4.552	2004M02
Seas. Diff	−5.666***	2008M06	−5.554***	1994M05	−5.653***	2007M09
LIIP						
Level	−4.344	1996M02	−5.036***	2000M07	−5.137**	1997M08
Seas. Diff	−4.206	2000M07	−4.061	1994M02	−4.515	2000M07

*, **, and*** indicate significance level at 10%, 5%, and 1%

Table 4: Brock-Dechert-Scheinkman-LeBaron (BDS) test results

	BDS Stat.	SE	z-Stat.	Prob.	Raw Epsilon	Pairs with Epsilon	Triples with Eps.
Climate policy uncertainty							
2	0.077451	0.004	21.364	0.0000			
3	0.129837	0.006	22.527	0.0000			
4	0.162895	0.007	23.730	0.0000	0.677829	127315.0	41004373
5	0.178910	0.007	25.003	0.0000		V-Stat:	V-Stat:
6	0.184340	0.007	26.712	0.0000		0.704858	0.534150
CO_2 emission							
2	0.073523	0.003	26.114	0.0000			
3	0.107972	0.004	24.184	0.0000			
4	0.119859	0.005	22.604	0.0000	0.140891	127203.0	40297173
5	0.123901	0.006	22.480	0.0000		V-Stat:	V-Stat:
6	0.127872	0.005	24.128	0.0000		0.704238	0.524938
Renewable energy consumption							
2	0.166916	0.003	64.002	0.0000			
3	0.286496	0.004	69.172	0.0000			
4	0.369377	0.005	74.982	0.0000	0.444801	127449.0	40280603
5	0.426271	0.005	83.137	0.0000		V-Stat:	V-Stat:
6	0.466022	0.005	94.393	0.0000		0.705600	0.524722
WTI crude oil price							
2	0.183153	0.002	92.030	0.0000			
3	0.308828	0.003	97.825	0.0000			
4	0.393758	0.004	105.01	0.0000	1.067691	127463.0	39800711
5	0.450577	0.004	115.61	0.0000		V-Stat:	V-Stat:
6	0.487993	0.004	130.23	0.0000		0.705678	0.518470
Environmental policy uncertainty							
2	0.031129	0.003	10.221	0.0000			
3	0.050972	0.005	10.530	0.0000			
4	0.058610	0.006	10.172	0.0000	0.390901	86943.00	22767865
5	0.061004	0.006	10.165	0.0000		V-Stat:	V-Stat:
6	0.059673	0.006	10.318	0.0000		0.705700	0.526503
Industrial productivity							
2	0.198684	0.004	55.352	0.0000			
3	0.340272	0.006	60.045	0.0000			
4	0.440002	0.007	65.645	0.0000	0.313233	126429.0	40447033
5	0.509573	0.007	73.441	0.0000		V-Stat:	V-Stat:
6	0.558012	0.007	83.969	0.0000		0.699953	0.526890

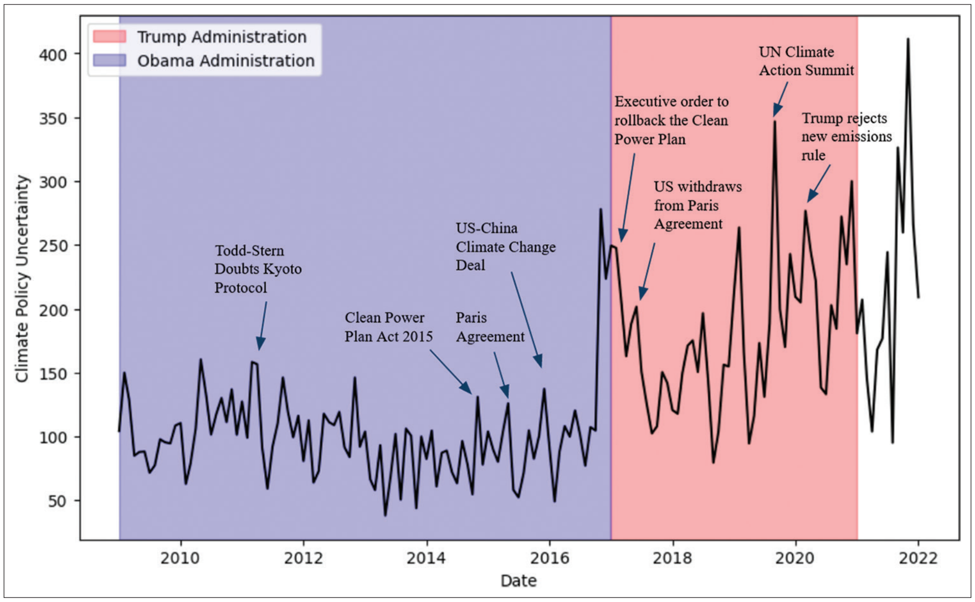
*, **, and ***indicate significance level at 10%, 5%, and 1%

Table 5: Main Results using Markov-Switching (MS) Model Estimation

Regime 1				
Variable	**Coefficient**	**SE**	**t-Statistic**	**Prob.***
C	0.075283***	0.005112	14.72598	0.0000
Seas ΔLCPU	−0.005453	0.008200	−0.664966	0.5061
First ΔLIIP	0.133791	0.310108	0.431432	0.6662
Seas ΔLCO2	0.323166***	0.094164	3.431937	0.0006
First ΔLWTI	0.020247	0.038291	0.528749	0.5970
Log (Sigma)	−2.996951***	0.055043	−54.44730	0.0000
Regime 2				
Variable	**Coefficient**	**SE**	**t-Statistic**	**Prob.***
C	−0.032645***	0.006346	−5.144081	0.0000
Seas ΔLCPU	−0.038527***	0.011588	−3.324593	0.0009
First ΔLIIP	1.229990**	0.522885	2.352312	0.0187
Seas ΔLCO2	0.167869	0.139708	1.201565	0.2295
First ΔLWTI	0.081298	0.060716	1.338985	0.1806
Log (Sigma)	−2.806659***	0.055124	−50.91531	0.0000
Transition Matrix Parameters				
P11-SDCPU	0.596931***	0.073658	8.104068	0.0000
P21-SDCPU	−0.587852***	0.078218	−7.515562	0.0000
Mean dependent var	0.024837	Log-Likelihood	559.9388	
S.D. dependent var	0.077647	Akaike Info Criterion	−2.643771	
Durbin-Watson stat	1.094442	Schwarz Criterion	−2.507383	
S.E. of regression	0.061702	Hannan-Quinn Criterion	−2.589828	

*, **, and ***indicate significance level at 10%, 5%, and 1%

Figure 1: Climate Policy Uncertainty in the US between 2009 and 2022



(Source: Gavriilidis, 2021)

the two regimes. In a regime characterized by low uncertainty, the effect of CPU on REC is not statistically significant. However, the CO_2 covariate is both statistically significant and positively correlated. A statistically significant and negative relationship between CPU and REC has been observed at the high uncertainty regime, which implies that when the level of uncertainty reaches a threshold that alters its state, the CPU has a detrimental effect on REC.

These findings align with the research conducted by Syed et al. (2023), Zhou et al. (2023), and Li et al. (2023). However, the results of Shang et al. (2022) differ from these findings since they conclude that the effect of CPU on REC is not statistically significant. Although Shang et al. (2022) observe comparable findings to those in the low uncertainty domain, they cannot accurately represent the negative nonlinear effect of CPU on REC in the high uncertainty regime.

The negative effect makes sense, as REC could require significant capital investments for companies to generate their own renewable energy source. Note that the data collected from the EIA are the sectoral data of the production side. Bhattacharyya (2019) discusses how energy projects tend to be more capital intensive, have a high degree of asset specificity, and have a generally longer life of assets and gestation periods. Thus, uncertainty can affect a company's decision to undergo these projects for the sake of REC. Syed et al. (2023) note a similar issue surrounding the uncertainty of the Production Tax Credit (PTC) on renewable energy consumption, which led to difficulties in long-term planning and investment. According to Syed et al. (2023), the adverse notions toward REC during a time of high uncertainty are reasonable.

Table 6 presents a matrix displaying the probabilities associated with being in the low or high uncertainty regimes. Additionally, Figure 2 illustrates the visual representation of the smoothed regime probabilities. Table 6 illustrates that the transition

Table 6: Transition probabilities for main estimation

Time-varying transition probabilities		
P (i, k) = P (s (t) = k|s (t-1) = i)		
(row=i/column=k)		
Mean	**1**	**2**
1	0.934271	0.065729
2	0.068212	0.931788
SD	**1**	**2**
1	0.016178	0.016178
2	0.016501	0.016501
Time-varying expected durations		
	1	**2**
Mean	16.28461	15.65433
SD	4.656862	4.389690

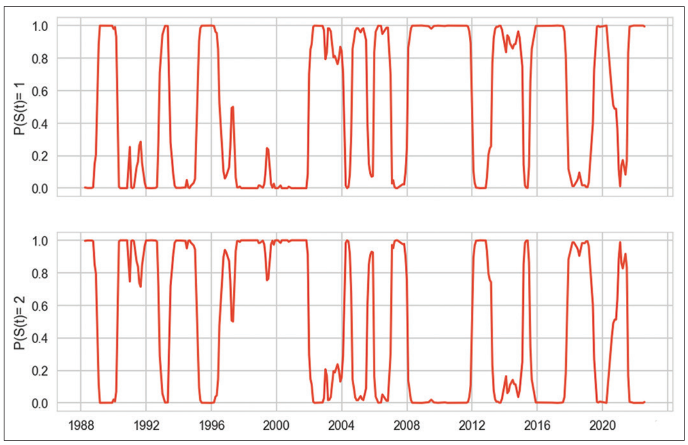
probability between different regimes is relatively low, whereas the probability of staying within a particular regime appears higher. The probability of transitioning between the low and high uncertainty regimes is approximately equal. Figure 2 displays the corresponding regimes for each period in the observation. During election periods, there is a greater level of uncertainty, whereas an unusual persistence is shown in the first years of the Bush Administration from 2001 to 2009. The initial state of increased uncertainty can be attributed to the uncertainties surrounding climate science, the deceleration of the US economy, and concerns about energy security. These factors prompted the Bush Administration to reject the Kyoto Protocol in 2001 and subsequently develop its own policies to address climate change issues (Blanchard, 2003).

4.3. Robustness Checks

In order to assess the robustness of the main findings, we re-estimate the model with the household renewable energy consumption (RECHH) serving as the dependent variable. The results in Table 7 indicate the presence of a significant nonlinear relationship between the CPU and RECHH. Specifically, in the low uncertainty regime, the coefficient for the log-differenced CPU has a positive effect on RECHH, whereas in the high-uncertainty regime, the effect is negative.

It is important to observe that the coefficient representing the effect of CPU on RECHH is greater in the high uncertainty regime compared to the low uncertainty domain. This indicates that the influence of the CPU is significantly bigger during periods of high uncertainty. Furthermore, the effect of the CPU in the low uncertainty regime differs from both the prior findings and those of Syed et al. (2023). It is important to acknowledge that the shocks observed in the CPU by Gavriilidis (2021), explicitly concerning household consumers, primarily focused on policies aimed at decreasing CO2 emissions from non-renewable energy sources.

Figure 2: Smoothed regime probabilities between 1987 and 2022 for main model. This figure shows the smoothed probabilities of state 1 and state 2 in the sample period. State 1 is the low uncertainty state and state 2 is the high uncertainty state



This can be interpreted as the implementation of a "just-in-case" strategy during periods of lower uncertainty. If the persistence continues, households will adopt the behavior of producers and adopt a "wait and see" approach, leading to a decrease in their usage of renewable energy until climate regulations become more definite.

According to Bhattacharyya (2012), CO_2 emissions positively affect RECHH, similar to their effect on REC. However, the effect of CO_2 emissions on RECHH becomes more significant during periods of increased uncertainty. Household consumers exhibit more sensitivity to fluctuations in CO_2 emissions than producers in the presence of increased uncertainty. Therefore, when the climate deteriorates, as indicated by the increase in CO_2 emissions, households tend to consume more renewable energy to counteract these adverse developments.

Table 8 presents the transition probabilities linked to the low and high uncertainty regimes for this estimation and the smoothed probabilities is shown in Figure 3.

As observed in Table 6, the likelihood of remaining in the same regime, based on the preceding regime, is significantly high. This is evident from the values of p_{11} and p_{22}, which are 0.959 and 0.942, respectively. Meanwhile, the values of p_{21} and p_{12} are 0.058 and 0.041, respectively. The data depicted in Figure 3 exhibit a distinct pattern compared to Figure 2, although many commonalities persist. For example, although the Bush Administration's refusal to accept the Kyoto Protocol may have contributed to greater uncertainty, the transition to a low-uncertainty regime happened quickly and was less enduring than the previous estimation.

Table 7: MS Estimation Results using Household Renewable Energy Consumption (RECHH)

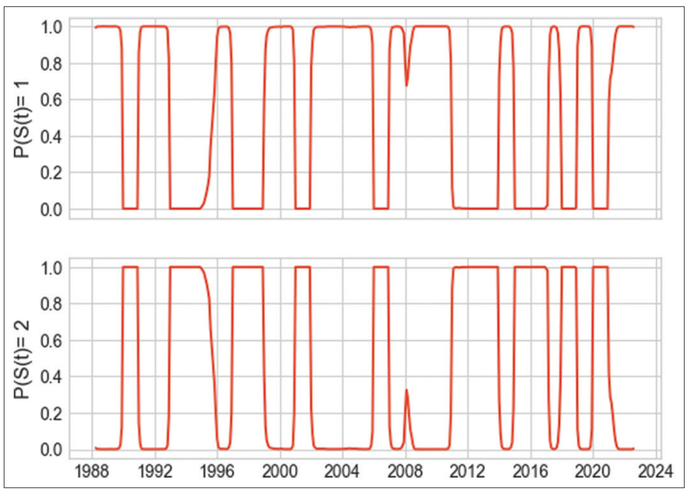
		Regime 1		
Variable	**Coefficient**	**SE**	**t-Statistic**	**Prob.***
C	0.055883***	0.002237	24.97753	0.0000
Seas ΔLCPU	0.010306**	0.004711	2.187765	0.0287
First ΔLIIP	−0.303737	0.207854	−1.461301	0.1439
Seas ΔLCO2	−0.013048	0.051440	−0.253654	0.7998
First ΔLWTI	−0.031235	0.023753	−1.315002	0.1885
Log (Sigma)	−3.629465***	0.067222	−53.99235	0.0000
		Regime 2		
Variable	**Coefficient**	**Std. Error**	**t−Statistic**	**Prob.***
C	−0.058916***	0.011729	−5.023265	0.0000
Seas ΔLCPU	−0.049700**	0.023647	−2.101688	0.0356
First ΔLIIP	−0.625660	0.861627	−0.726138	0.4678
Seas ΔLCO2	0.481012**	0.213415	2.253881	0.0242
First ΔLWTI	0.054305	0.110865	0.489831	0.6243
Log (Sigma)	−1.963364***	0.053721	−36.54767	0.0000
Transition Matrix Parameters				
P11-SDCPU	0.709087***	0.081568	8.693173	0.0000
P21-SDCPU	−0.627621***	0.074028	−8.478158	0.0000
Mean dependent var	0.000600	Log-Likelihood	541.5911	
S.D. dependent var	0.116254	Akaike Info Criterion	−2.554921	
Durbin-Watson stat	0.330833	Schwarz Criterion	−2.418533	
S.E. of regression	0.102462	Hannan-Quinn Criterion	−2.500978	

*, **, and ***indicate significance level at 10%, 5%, and 1%

Table 8: Transition probabilities for RECHH estimation

Time-varying transition probabilities		
P (i, k)=P (s (t)=k|s (t-1)=i)		
(row=i/column=k)		
Mean	**1**	**2**
1	0.958662	0.041338
2	0.057952	0.942048
SD	**1**	**2**
1	0.012311	0.012311
2	0.015088	0.015088
Time-varying expected durations		
	1	**2**
Mean	26.75776	18.62534
SD	9.518898	5.677899

Figure 3: Smoothed regime probabilities between 1987 and 2022 for RECHH model. This figure shows the smoothed probabilities of state 1 and state 2 in the sample period. State 1 is the low uncertainty state and state 2 is the high uncertainty state



We also observe that the high uncertainty regime's persistence has occurred in both the Obama and Trump Administrations. Although these factors were also included in the previous estimates, they were not as persistent. The significant level of uncertainty between these two administrations can be attributed to the findings of Noailly et al. (2022). They discover that a substantial portion of the policy shocks experienced during the Obama Administration resulted from implementing new policies to address climate change. Conversely, the shocks observed during the Trump Administration were primarily caused by the reversal of previous policies enacted by the Obama Administration, which aimed to reduce carbon emissions. The measures included the Clean Power Plan, the US-China agreement on climate change, the Paris Accord, and the disapproval of the Keystone XL pipeline project.

The result gives rise to an intriguing conundrum. Although the Obama and Trump Administrations had opposing views towards their programs, the underlying background behind these policies is only sometimes distinct, resulting in both periods experiencing increased uncertainty. Recall that Li et al. (2023) find that the effect from CPU to REC depends on the regime by which the uncertainty originated. Therefore, the relationship between CPU and REC may vary based on the contextual views of the authorities. We can investigate this potential by eliminating the observations made by the Trump Administration. Please note that this is not a biased position but rather an opportunity to examine the potential contextual factors in the CPU. This is based on previous US government documents and academic literature suggesting previous administrations in the dataset pursued policies to address climate change, regardless of their success (Wampler, 2015; Royden, 2002; Blanchard, 2003). Therefore, based on past research, this exclusion would lead to overall positive shocks in CPU. The estimation outcome of the MS model of the CPU on REC is presented in Table 9.

The findings in Table 9 indicate a high degree of similarity to those in Table 5, as the variables that exhibit statistical significance remain consistent. However, it is important to observe that the effect of CPU on REC in the high uncertainty regime has diminished. Initially, it was −0.039, but it has now fallen to −0.028, resulting in a 0.01% point rise. Nevertheless, the coefficient of IIP saw a fall from 1.229 to 1.15, indicating a reduction of 0.08% points. Similar to the findings of Li et al. (2022), we have discovered compelling evidence that the specific circumstances surrounding CPU shocks can have different effects on REC.

Table 10 presents the transition probabilities derived from the estimation in Table 9, whereas Figure 4 displays the smoothed regime probabilities. The likelihood of staying within the same regime, as observed in the Trump administration, remains quite high, with p_{11} and p_{22} are 0.943 and 0.931, respectively. Meanwhile, the values of p_{21} and p_{12} are 0.069 and 0.057, respectively. The results depicted in Figure 4 are mainly similar to those in Figure 2, with the notable distinction being the exclusion of data following the conclusion of the Obama Administration.

In order to further check the robustness of the previous findings, a comparable estimation using the ENVPU index developed by Noailly et al. (2022) is conducted as an alternative to the CPU index. It is important to remember that these indices are conceptually comparable and intended to capture similar shocks despite their distinct origin. The findings of this estimation are presented in Table 11.

While the main estimation and the estimation findings in Table 11 come to a similar conclusion, there has been a slight difference in the regime results. Specifically, the high uncertainty regime is now represented by s_t=1, while the low uncertainty regime is represented by s_t=2. The variables that are statistically significant remain unchanged, with CPU and IIP having a large effect on REC during the period of high uncertainty. The primary distinction between the two outcomes is that both coefficients have exhibited a more pronounced positive trend. Specifically, the CPU has risen by 0.004% points, while the IIP has experienced a substantial increase of 0.362% points.

Table 12 indicates that the transition probabilities are comparable, since they remain above 0.90 when moving between regimes based on the previous regime. Nevertheless, the likelihood of staying in the low uncertainty regime p_{22} is significantly higher than the likelihood of staying in the high uncertainty regime p_{11}.

Table 9: MS estimation results on REC prior to the trump administration

		Regime 1		
Variable	**Coefficient**	**SE**	**t-statistic**	**Prob.***
C	0.072703***	0.005277	13.77709	0.0000
Seas ΔLCPU	0.000113	0.009379	0.012092	0.9904
First ΔLIIP	−0.539482	0.468860	−1.150627	0.2499
Seas ΔLCO2	0.163297	0.101651	1.606444	0.1082
First ΔLWTI	0.018192	0.047054	0.386630	0.6990
Log (Sigma)	−2.975074***	0.057192	−52.01882	0.0000
		Regime 2		
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.***
C	−0.043088***	0.007571	−5.690843	0.0000
Seas ΔLCPU	−0.028021**	0.013739	−2.039538	0.0414
First ΔLIIP	1.150276*	0.662209	1.737027	0.0824
Seas ΔLCO2	0.025466	0.163966	0.155315	0.8766
First ΔLWTI	0.088745	0.071150	1.247301	0.2123
Log (Sigma)	−2.795352***	0.063807	−43.80943	0.0000
Transition Matrix Parameters				
P11-SDLCPU	0.647640***	0.084036	7.706704	0.0000
P21-SDLCPU	−0.600531***	0.089617	−6.701101	0.0000
Mean dependent var	0.021915	Log-Likelihood	465.8470	
S.D. dependent var	0.080520	Akaike Info Criterion	−2.611832	
Durbin-Watson stat	1.020107	Schwarz Criterion	−2.456196	
S.E. of regression	0.061818	Hannan-Quinn Criterion	−2.549858	

*, **, and ***indicate significance level at 10%, 5%, and 1%

Table 10: Transition Probabilities for MS Estimation without Trump Administration

	Time-varying transition probabilities	
	P (i, k)=P (s (t)=k|s (t-1)=i)	
	(row=i/column=k)	
Mean	**1**	**2**
1	0.942889	0.057111
2	0.069009	0.930991
SD	**1**	**2**
1	0.012221	0.012221
2	0.013494	0.013494
	Time-varying expected durations	
	1	**2**
Mean	18.31767	15.04926
SD	3.995922	2.996189

Figure 4: Smoothed Regime Probabilities between 1987-2017 for MS Model without trump administration. This figure shows the smoothed probabilities of state 1 and state 2 in the sample period. State 1 is the low uncertainty state and state 2 is the high uncertainty state

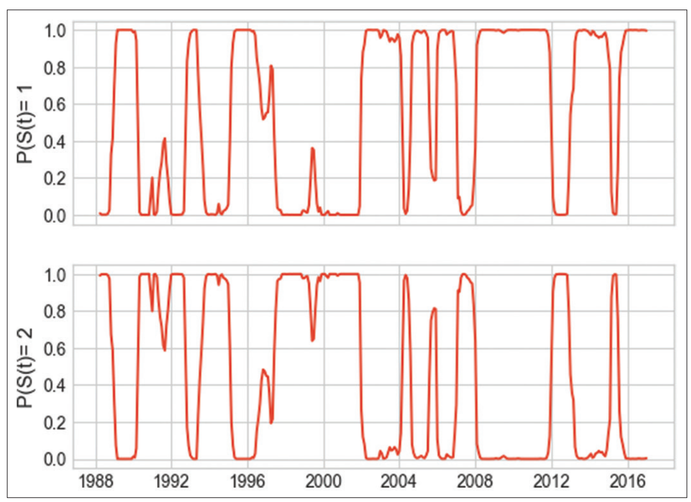


Figure 5 displays the smoothed probability of the low and high-uncertainty domains. Although the patterns exhibit similarities, the differences between the regimes are less prone to sudden and extreme fluctuations as compared to the original model utilizing the CPU.

The variations in the outcomes' magnitude can be attributed to the dissimilarities in the CPU's measure by Gavriilidis (2021) and the ENVPU by Noailly et al. (2022). It is worth noting that while Gavriilidis (2021) employ a simplistic classification approach based on Baker et al. (2016), Noailly et al. (2022) utilize an SVM algorithm to classify articles that indicate uncertainty in order to construct their index.

Noailly et al. (2022) find that while comparing their approach to the one used by Baker et al. (2016), the SVM algorithm had a higher recall rate. This means that the SVM algorithm was able to identify more true positives compared to the naïve method employed in the CPU. The ENVPU contains more information than the CPU, potentially resulting in variations in the index's volatility, as suggested by Noailly et al. (2022). Based on our analysis of the correlations and volatility of the indices shown in Table 13 and Figure 6, we have determined that the CPU exhibits significantly higher volatility than the ENVPU. This holds true for both in the level and first-differences.

Furthermore, it is plausible that there exist substantial variations in the magnitudes of the uncertainty that has been documented. Figure 7 illustrates a significant surge in CPU about 2017, although the ENVPU did not experience a comparable level of increase. Moreover, until the year 2000, the ENVPU appears to

Table 11: MS estimation results on REC using the ENVPU

	Regime 1			
Variable	**Coefficient**	**SE**	**t-statistic**	**Prob.***
C	−0.056072***	0.009567	−5.860909	0.0000
Seas ΔLENVPU	−0.034661*	0.019417	−1.785104	0.0742
First ΔLIIP	1.591850**	0.795867	2.000145	0.0455
Seas ΔLCO2	−0.058172	0.181567	−0.320389	0.7487
First ΔLWTI	0.075318	0.095221	0.790974	0.4290
Log (Sigma)	−2.790310***	0.075207	−37.10187	0.0000
	Regime 2			
Variable	**Coefficient**	**Std. Error**	**t-Statistic**	**Prob.***
C	0.060259***	0.005143	11.71564	0.0000
Seas ΔLENVPU	0.010047	0.013162	0.763386	0.4452
First ΔLIIP	−0.288903	0.465634	−0.620452	0.5350
Seas ΔLCO2	0.060800	0.093637	0.649314	0.5161
First ΔLWTI	0.004209	0.044267	0.095089	0.9242
Log (Sigma)	−2.983415***	0.055818	−53.44922	0.0000
Transition Matrix Parameters				
P11-SDLENVPU	0.517586***	0.087826	5.893328	0.0000
P21-SDLENVPU	−0.668264***	0.083318	−8.020686	0.0000
Mean dependent var	0.022189	Log-Likelihood	466.2835	
S.D. dependent var	0.077093	Akaike Info Criterion	−2.668339	
Durbin−Watson stat	1.024387	Schwarz Criterion	−2.510333	
S.E. of regression	0.060105	Hannan−Quinn Criterion	−2.605374	

*, **, and ***indicate significance level at 10%, 5%, and 1%

Table 12: Transition Probabilities for MS Estimation using the ENVPU

Time-varying transition probabilities		
P (i, k)=P (s (t) = k|s (t-1)=i)		
(row=i/column=k)		
Mean	**1**	**2**
1	0.913744	0.086256
2	0.045512	0.954488
SD	**1**	**2**
1	0.010786	0.010786
2	0.007724	0.007724
Time-varying expected durations		
	1	**2**
Mean	11.77114	22.58885
SD	1.442670	3.724887

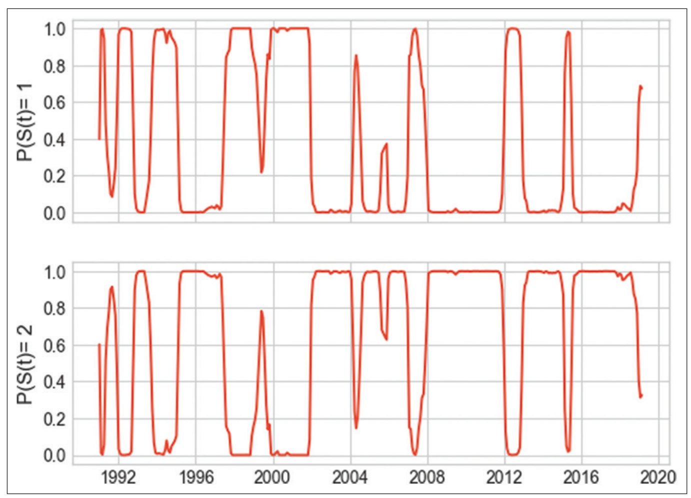
Table 13: Correlation matrix and volatility of CPU and ENVPU

Correlation	CPU	ENVPU	SD	Volatility
CPU	1.000000		55.65215	1147.298
ENVPU	0.189888	1.000000	25.51904	478.0983
Correlation	**ΔCPU**	**ΔENVPU**	**SD**	**Volatility**
ΔCPU	1.000000		0.458980	9.327576
ΔENVPU	0.215021	1.00000	0.321928	5.927323

be comparatively higher in comparison to the CPU. Therefore, it appears that the CPU experiences significantly higher levels of uncertainty around the turn of the millennia and during the period that aligns with the Trump Administration.

Referring to the studies conducted by Li et al. (2022) and Noailly et al. (2022), it is suggested that the uncertainty observed during the Trump Administration may be connected to policies that do not support efforts to address climate change and encourage the use of non-renewable energy sources. This uncertainty likely intensified the negative relationship between the central processing unit (CPU) and renewable energy consumption (REC) in a period of high uncertainty. The ENVPU is quite stable and not prone to volatility.

Figure 5: Smoothed Regime Probabilities between 1991 and 2019 using the ENVPU. This figure shows the smoothed probabilities of state 1 and state 2 in the sample period. State 1 is the high uncertainty state and state 2 is the low uncertainty state



Therefore, the utilization of the MS model with the ENVPU as the main variable of focus has resulted in a noteworthy finding. This finding contributes to our knowledge of the relationship between CPU and REC, as well as the development of an index to measure and represent this uncertainty. Based on these data, we can confidently infer the presence of a nonlinear relationship

Figure 6: Seasonally differenced log-transformed version of selected variables

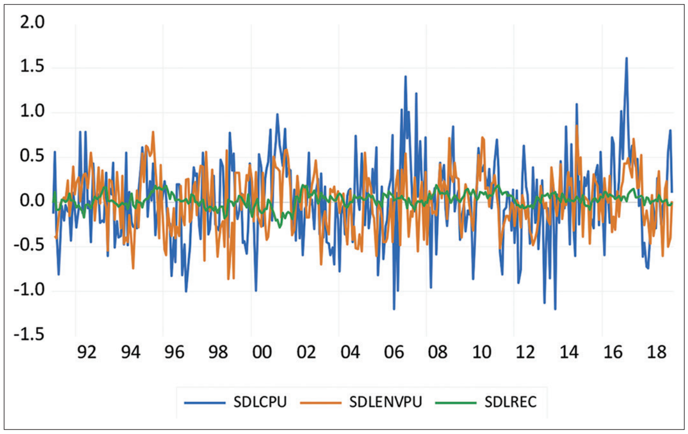
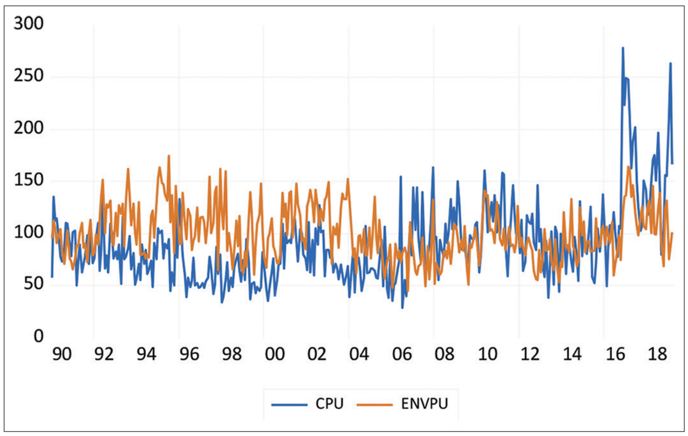


Figure 7: Raw CPU (Gavriilidis, 2021) and ENVPU (Noailly et al., 2022) comparison



between the CPU and REC. Therefore, it is important to thoroughly examine the construction of the climate policy uncertainty index, which is designed to quantify the level of uncertainty around climate policies.

5. CONCLUSION

Climate change is a crucial concern for the future of the planet, which influences the global economy and the environment. With various international agreements and national efforts to achieve carbon neutrality, it is vital to understand what policies must be implemented and how they should be delivered. Due to this immense global target, the goal of the recent COP26 was to attain net zero emissions, understand how policies are implemented, and how uncertainty affects economic actors' behavior towards renewable energy consumption.

The main findings of our study suggest that climate policy uncertainty, as measured by the CPU and ENVPU, has a nonlinear effect on REC. The baseline findings indicate that the CPU negatively affects the REC in the high uncertainty regime. This suggests that businesses adopt a cautious approach, commonly referred to as a "wait and see" policy, which aligns with the findings of Syed et al. (2023). Consumers would reduce their renewable energy consumption in favor of other sources to avoid the financial risks associated with renewable alternatives.

To assess the robustness of this model, we conduct an additional study utilizing the RECHH, through which we identified a comparable result. While the effect in the high-uncertainty range is also negative, there is a significant positive effect of CPU on REC in the low uncertainty regime, which suggests a "just-in-case" policy approach, where consumers will increase REC if uncertainty increases but remains within the low uncertainty regime, anticipating more favorable policies in the future. These findings align with the research conducted by Zhou et al. (2023), which likewise identified a positive relationship between CPU and REC over various time intervals.

To investigate the potential variations in the effect of CPU on REC, depending on the specific circumstances surrounding the CPU shocks, we use the approach of Li et al. (2022) and Noailly et al. (2022) by eliminating the observations related to the Trump Administration as a substitute for a positive CPU. Despite acknowledging the difficulty of this assumption, we find support for it from examining policy reviews in previous studies (Wampler, 2015; Royden, 2002; Blanchard, 2003) and the research conducted by Li et al. (2022). Consequently, this assumption is justifiable for investigating the potential dynamics involved. Our findings indicate that without the Trump Administration's observations, the effect from CPU to REC has become more positive, despite the result of the CPU to REC still being negative in the high uncertainty regime.

We perform an additional robustness check by using the Environmental Policy Uncertainty (ENVPU) index developed by Noailly et al. (2022). The robustness estimation demonstrate comparable effects to the baseline estimates, albeit with coefficients of greater positivity. Due to its higher recall rate than the CPU, the ENVPU exhibits less volatility and achieves a greater number of true positives, potentially impacting the model's outcomes. Therefore, unlike the CPU, the ENVPU does not intensify the shock experienced under the Trump Administration.

With several robustness tests we perform, thus, we can conclude that CPU has a detrimental nonlinear effect on REC, regardless of the specific index used, type of REC, and the contextual views of the policies (i.e., in favour vs. against climate change). According to Syed et al. (2023), economic agents tend to adopt a cautious approach called a "wait and see" policy when there is significant uncertainty in climate policy. This means they delay making decisions on REC until the uncertainty falls.

There are some caveats to consider in this study, for example the inability to precisely factor in the contextual dynamics that underlie the CPU index. Contrary to economic policy uncertainty, which involves subjective assessments of a policy's positive or negative impact and the trade-offs involved, climate policy can be objectively determined by evaluating its position on reducing climate change and promoting environmental protection (Basaglia et al., 2022). Despite its weakness, our research attempt to address this issue by making an estimation that does not consider the influence of the Trump Administration, thus assuming that the CPU index would have been predominantly positive. The absence of raw data imposes further constraints on this investigation, preventing us from making inferences about the Optimistic-CPU and Pessimistic-CPU indices, as formulated by Berestycki et al. (2022) and Basaglia et al. (2022). Hence, a suggestion for the subsequent scholarly investigation on CPU would be to integrate the evolving characteristic of this uncertainty. To enhance the accuracy of the index's development, it is advisable to adopt the methodology proposed by Noailly et al. (2022). Additionally, incorporating the findings of Berestycki et al. (2022) and Basaglia et al. (2022) will enable the inclusion of both positive and negative dynamics nature of the climate policies.

For policymakers, an important observation from these findings is the need to ensure that climate policies are implemented and communicated efficiently to minimize the negative consequences of uncertainties. Improving consumer transparency and confidence may be a more practical approach since this would allow other variables to determine the REC-thus, enabling policymakers to formulate policies that influence these variables to stimulate REC growth. With respect to developing countries, this study has two consequences. The first is in line with the overall suggestion of minimizing uncertainty. The second point is to acknowledge that if uncertainty increases and continues at a high level, the specific policy framework, such as whether it supports or opposes carbon neutrality, can mitigate the effect of CPU on REC. If policymakers in developing countries consider carbon neutrality necessary, they should implement policies that do not impede this initiative. Even if uncertainty exceeds a certain threshold, consumer behavior may still support increased renewable energy consumption.

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