# Climate Policy Uncertainty and the Demand for Renewable Energy in the United States of America: Evidence from a Non-Linear Threshold Autoregressive Model

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## Abstract

This study examines the relationship between climate policy uncertainty and the demand for renewable energy in the United States. The primary findings suggest that there is a nonlinear threshold effect resulting from climate policy uncertainty, as measured by the Climate Policy Uncertainty Index (CPU) and the Environmental Policy Uncertainty Index (ENVPU), on renewable energy demand (REC). The findings indicate a negative relationship between the CPU and the REC when the CPU is beyond a specific threshold. This suggests that economic agents adopt a cautious approach, sometimes referred to as the "wait and see" policy, in their renewable energy allocation. In essence, customers may opt to reduce their utilization of renewable energy in favor of alternate sources as a means to circumvent the investment risks associated with renewable alternatives.

JEL codes: C24, Q28, Q43.
Keywords: Climate policy uncertainty, Renewable energy demand, Crude oil price.

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## I. Introduction

The severe risks and uncertainties associated with climate change have the potential to adversely impact both the environment and the global economic system. As such, climate change has gained prominence and come to the forefront of global policy discussions (Sadorsky, 2008; Chen et al., 2021; Shang et al., 2022). In response to this collective issue, world governments have, through international negotiations, agreed upon and adopted policy measures to mitigate the effects of climate change. For instance, the 1997 Kyoto Protocol established binding emissions reduction targets for specific nations and pledged state parties to reduce greenhouse gas (GHG) emissions to an average of 5.2% below 1990 levels for the period of 2008 to 2012 (UNFCCC, 1997; Miyamoto & Takeuchi, 2019; Najarzadeh et al., 2021). The Paris Agreement of 2015 is another example, in which signatory states committed to pursue the efforts to limit temperature increase to 1.5°C above pre-industrial levels and hold the increase in global average temperature below 2°C (UNFCCC, 2015; Bauer & Menrad, 2019). The recent COP26 in Glasgow marked a significant milestone, as 153 countries pledged to achieve net zero emissions by 2050 (UNFCCC, 2022; Ma et al., 2023; Cao et al., 2023).

Despite the global commitment to address the issues pertaining to and mitigate climate change, significant uncertainties persist in the implementation of climate policy. For instance, Noailly et al. (2022) highlighted that, during the Trump Administration, a numerous amount of climate policies from previous administrations, most notably those of the Obama Administration, were rolled back. Several examples include the decision to withdraw from the Paris Agreement and the revocation of the Clean Power Plan, which were politically-motivated decisions that heightened the uncertainty for economic actors (Li et al., 2022). This reversal of policies had contradicted the previous administrations' efforts to transition from non-renewable to renewable energy consumption in order to move towards carbon neutrality. Consequently, this abrupt policy change caused a substantial shock to climate policy uncertainty (CPU), as depicted in Figure 1 and Figure 2.

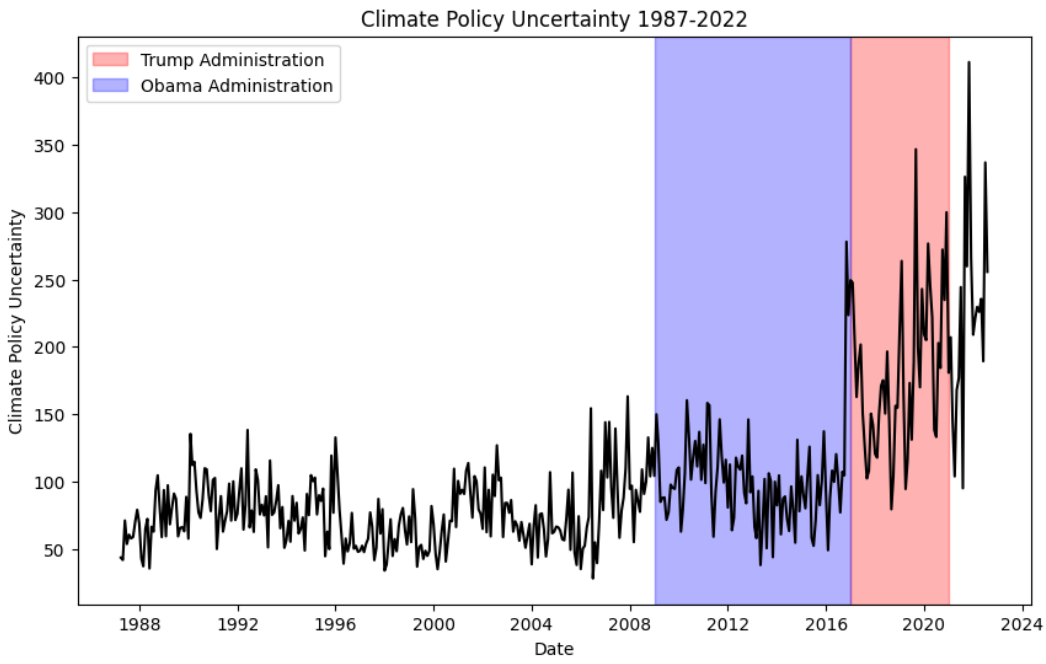


**Figure 1.** Climate Policy Uncertainty in the US

**Source:** Gavriilidis, 2021

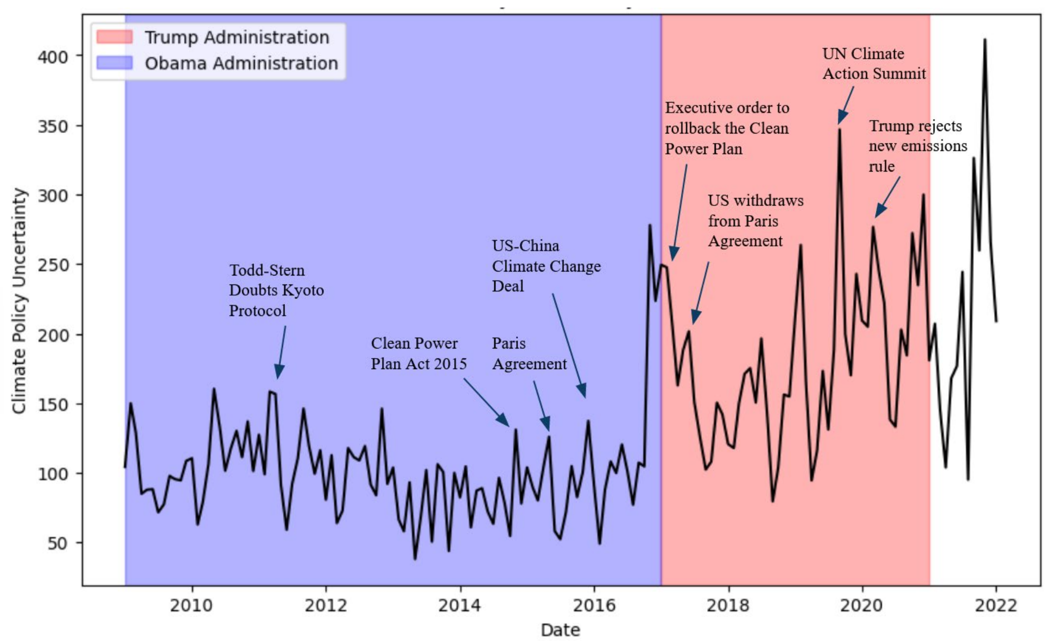


**Figure 2.** Climate Policy Uncertainty in the US between 2009-2022

**Source:** Gavriilidis, 2022

With that in mind, the current literature have discussed the potential of REC as a method to mitigate climate change (Anwar et al., 2021; Gozgor et al., 2020), as well as the factors that affect the consumption of renewable energy, including economic growth (Ocal & Aslan, 2013, Apergis & Danuletiu, 2014; Sari et al., 2008), oil prices (Brini et al., 2017; Sahu et al., 2022; Murshed & Tanha, 2021), and carbon dioxide emissions (Sadorsky, 2009; Olanrewaju et al., 2019; Karaaslan & Camkaya, 2022; Menyah & Wolde-Rufael, 2010). Despite this, the discourse has yet to establish the connection between CPU and REC. As CPU is a relatively novel metric, we have only found four papers examining this relationship directly. Shang et al. (2022), using an ARDL model, found that CPU has no effects on REC. To account for structural breaks in the series, Syed et al. (2023) utilized a Fourier-Augmented ARDL model, in which they found that CPU negatively affects REC. Zhou et al. (2023) found that CPU positively affects REC in most time periods. Meanwhile, Li et al. (2023) utilized a VAR model with a time-varying rolling-window bootstrap causality test and found that the effect of CPU on REC differs by time, mainly due to the government's attitude driving the CPU shocks.

That said, this paper analyzes the nonlinear threshold effects of CPU on REC. This paper focuses on the monthly data from the United States, starting from 1987M04 – 2022M08. The motivation behind selecting the US for this analysis is that it is an advanced economy ranked first in terms of the amount of fossil fuel consumption per capita in 2022, at around 63,836 kWh (OurWorldinData, 2022). It is also lagging behind many other countries in terms of renewable energy investment as a percentage of GDP, as the US had only invested 0.2% in the year 2015, while others had invested more, such as South Africa (1.4%), China (0.9%), and India (0.5%), among others. However, the findings of this paper should be relevant for other developing countries aiming to implement policies incentivizing renewable energy consumption. Using the novel climate policy uncertainty index developed by Gavriilidis (2021), which follows the methods of Baker, Bloom, and Davis (2016), inference could be made regarding the existence and magnitude of the effect of CPU on REC.

The contributions of this paper are as follows. The first is in consideration with the current literature on CPU-REC, as the findings of one paper may contradict the findings of other paper. Second, past researches have only looked into the CPU-REC nexus using linear models, which assume that the behavior of economic actors do not change with different levels of uncertainty. These examples are shown in the prior discussion. The last contribution is towards policymakers, as this study provides insights into how the economy reacts to CPU with respect to their consumption of renewable energy based on different regimes of uncertainty. Due to these insights, policymakers should be able to infer the best method of enacting new climate policies to ensure that the uncertainty does not pose adverse effects on the consumption of renewable energy.

The rest of the paper is organized into five more sections. Section 2 reviews the literature on the CPU-REC nexus and the factors that influence REC. Section 3 discusses the methodology used to observe the nonlinear threshold effects, including the pretests, the main model, and its assumptions. Section 4 presents the main results and robustness checks. Section 5 discusses the results. Section 6 concludes the paper by summarizing the findings and providing implications.

## II. Motivation and Literature Review

The bulk of research on renewable energy consumption have been centered around the Environmental Kuznets Curve (EKC), including Sari et al. (2008), Ocal & Aslan (2013), Apergis & Danuletiu (2014), Bimanatya & Widodo (2018), Alam et al. (2022), among others. This is not surprising, as studying the effect of climate policy uncertainty have been tedious prior to the development of the CPU index by Gavriilidis (2021). With the presence of the new metric, several studies began the examination on the effect of CPU on REC. One such study was Shang et al. (2021), who adopted the ARDL approach to find the short and long-run impacts of climate policy uncertainty on non-renewable and renewable energy consumption. Their findings indicated that CPU does not significantly affect REC in both the short or long term, although there does seem to be a negative effect of CPU on fossil fuels.

Meanwhile, Zhou et al. (2023) followed a different approach, as they explored the time-varying relationship between CPU, oil prices, and REC. Using a time-varying parameter vector autoregressive (TSP-SV-VAR) model, they found that CPU positively affects oil prices and REC in most time periods. They explained the validity of their results as being due to the aim of climate policy, which tends to be reducing carbon emissions, thus incentivizing the consumption of renewable energy. This is unlike the effect of economic policy uncertainty on REC, which, according to Shafiullah et al. (2021), tends to be negative.

Similarly, Li et al. (2023) had also delved into the CPU-REC relationship while also considering time-varying effects. In doing so, 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 the procurement time-varying causality in various subsamples. They discovered that the causality between CPU and REC varies depending on the attitude of the authorities towards the mitigation of climate change. This implies that regimes that are generally supportive of mitigating climate change will see a positive CPU-REC nexus, and vice versa.

In an attempt to find the impacts of uncertainty on the five types of renewable energy consumption, Xi et al. (2023) employed a vector autoregressive (VAR) model with Granger causality tests. They found that, in average, CPU affects REC, and solar as well as wind energy, but not geothermal nor hydroelectric energy. After applying time-varying tests, while no impacts were found on geothermal energy consumption, there were impacts on the other types, although discontinuously. Thus, Xi et al. (2023) concluded that the influence of CPU on REC varies with time.

Syed et al. (2023), in an attempt to also consider structural breaks in modelling the CPU-REC nexus, utilized a Fourier Augmented ARDL (FA-ARDL) model. They found that CPU decreases REC in both the short and long-run, and could be attributed to the lack of clarity in relation to long-term planning and the investment to consume renewable energy, as well as individuals taking 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 had looked into the effect of the economic policy uncertainty (EPU) on REC, such as Shafiullah et al. (2021), who discovered through a nonlinear model and Granger causality analysis that there does exist a nonlinear causal effect of EPU on REC, which is negative in the long-run. Yi et al. (2023) utilized a CS-ARDL model on a panel of top renewable energy consuming countries and found that EPU negatively affects REC in both the short and long-run. Ivanovski & Marinucci (2021), using numerous parametric models, found that EPU is negatively associated with REC. Feng & Zheng (2022) used panel fixed effects on 22 countries to find that EPU has a positive effect on renewable energy innovation. Additionally, further subsample analysis helped them in confirming that OECD members and right-wing countries tend to have higher growth in renewable energy.

As for the factors that may have an effect on REC, previous literature suggest three factors that may be of interest. The first factor is economic growth, commonly proxied by GDP growth or industrial productivity. Previous researches posit that higher growth may lead to increases in income, thus increasing the accessibility of renewable energy to consumers. Several studies have found this to be the case, such as Ocal & Aslan (2013), who found that there exists a unidirectional causality between economic growth and REC in Turkey using the ARDL and Toda-Yamamoto Causality tests. Apergis & Danuletiu (2014) provided evidences for long-run positive bidirectional causality between GDP and REC using the Canning-Pedroni Dynamic Error Correction Model (ECM) from 80 countries.

The second factor commonly discussed in modelling REC is carbon dioxide emissions (CO2), which, according to Bhattacharyya (2012) and Goldemberg (2004), is the primary catalyst of REC. Considering that the modern world has become heavily reliant on fossil fuels and non-renewable energy sources, there has been a drastic increase in the concentration of greenhouse gases (GHG), which also include CO2. This, in turn, leads to the abnormal changes in the earth's climate. Thus, $CO_2$ emissions serve as a warning to the global economy, incentivizing consumers to shift to renewable sources of energy for their daily consumption of energy to mitigate climate change. This has been shown to be the case by Sadorsky (2009), for instance, who found that per capita income and $CO_2$ emissions increase REC in G7 countries. Olanrewaju et al. (2019), within the context of the African states, found that $CO_2$ emissions are negatively associated with REC. Meanwhile, other studies found that REC impacts $CO_2$ emissions. Karaaslan & Camkaya (2022), within the context of the use of ARDL and Toda-Yamamoto Causality test by Turkey, found a unidirectional causal effect between REC and $CO_2$ emissions in the long-run. In contrast to both these strands of research, Menyah & Wolde-Rufael (2010), using a modified Granger Causality test, found no causal relationship between REC and $CO_2$ emissions.

Another factor that may be considered is the price of oil, typically proxied by the West Texas Intermediate (WTI) crude oil prices, given that REC acts as a substitute for non-renewable sources of energy, which could be affected by the changes in oil price. For example, Brini et al. (2017) utilized the data from Tunisia covering the period of 1980 to 2011 using the ARDL model, and found that oil prices are positively associated with REC. In the United States, Sahu et al. (2022) used the Nonlinear Autoregressive Distributed Lag (NARDL) model and found that both an increase in GDP and oil prices increase REC in both the short and long-run.

## III. Methodology

### 3.1 Data

For the purpose of this study, the paper focuses on the United States economy with the monthly data from 1987M04 to 2022M08. The dependent variable is the aggregate of renewable energy consumption (REC) from several sectors of the United States production side, of which the data are collected from the Energy Information Administration (EIA). The sources of energy recorded by the EIA include biomass, hydropower, geothermal, wind, and solar power.

Meanwhile, the independent variable of interest, namely the CPU, is collected from the online repository for policy uncertainty, with data from Gavriilidis (2021). Note that the data for the CPU is only available for the US. While other indicators for CPU exist, the only one made publicly available is the one by Gavriilidis (2021). The covariates we include, following the factors that affect REC discussed previously, are the $CO_2$ emissions ($CO_2$), the Index of Industrial Productivity (IIP), and the West Texas Intermediate Oil Prices (WTI). The $CO_2$ data are also sourced from the EIA, while the IIP and WTI are sourced from the Federal Reserve Economic Data (FRED).

We also source other data for the purpose of checking the robustness of our estimations. To ensure the robustness of the model with regard to the main variable of interest, we substitute the CPU for the Environmental Policy Uncertainty (ENVPU) index in one of our iterations. While it is essentially the same as the CPU, the ENVPU, developed by Noailly et al. (2022), uses a similar word search strategy strengthened with a Support Vector Machine (SVM) algorithm to classify whether an article constitutes uncertainty. They had argued that their method produces better predictions of uncertainty within the corpus of articles compared to the algorithm used by Gavriilidis (2021), which is based on the search strategy by Baker, Bloom, & Davis (2016). Noailly et al. (2022) found that their algorithm has a larger recall rate than the algorithm by Baker, Bloom, & Davis (2016), with the ENVPU having 70% recall rate while the other having only 8%. This means that, with regard to the true positives being correctly classified as uncertainty, the SVM algorithm performs substantially better, and the ENVPU is thereby a better metric. This data is sourced from the author's repository, but has lower observations, as the data spans only from 1990M01 to 2019M03.

Moreover, we also use the data on the household renewable energy consumption (RECHH) to find whether the same effect the CPU has on REC also holds in the household context. This data is sourced from the CEIC, with the monthly periodicity that is the same with the number of periods for the complete dataset.

### 3.2 Conceptual Framework

Considering the existing studies that have discussed the determinants of renewable energy demand, we employed the Threshold Autoregressive (TAR) model to estimate the nonlinear threshold effects of the CPU on REC. Borrowing the method of Bunzel and Enders (2010), the TAR model in this case can be specified as:

$$\Delta LREC_t = \begin{cases} \phi_{0,1} + \phi_{1,1}\Delta LCPU_t + \phi_{2,1}\Delta LREC_{t-n} + \phi_{3,1}\Delta LCO2_t + \phi_{4,1}\Delta LWTI_t + \phi_{5,1}\Delta LIIP_t + \varepsilon_t \ if\ \Delta LCPU_{t-d} < c \\ \phi_{0,2} + \phi_{1,2}\Delta LCPU_t + \phi_{2,2}\Delta LREC_{t-n} + \phi_{3,2}\Delta LCO2_t + \phi_{4,2}\Delta LWTI_t + \phi_{5,2}\Delta LIIP_t + \varepsilon_t \ if\ \Delta LCPU_{t-d} \geq c \end{cases}$$

In this model, $REC_t$ is the renewable energy consumption at time *t*, which in this case would be in monthly intervals. Meanwhile, $CPU_t$ is the climate policy uncertainty index, $REC_{t-n}$ are the lagged covariates of REC at time *t-n,* $CO2_t$ is the CO2 emissions, $WTI_t$ is the West Texas

Intermediate Crude Oil Price, and $IIP_t$ is the Industrial Production Index at month $t$. The $\Delta$ symbol denotes the variable which will be differentiated, and $L$ denotes the natural logarithmic transformation that will be applied to the set of variables. Meanwhile, $\phi_{v,r}$ denotes the coefficient values for variable $v$ in regime $r$. $\Delta LCPU_{t-d} < c$ and $\Delta LCPU_{t-d} \geq c$ are the thresholds, with $\Delta LCPU_{t-d}$, or the log-differenced climate policy uncertainty variable at month $t$, delayed by $d$ months, as the threshold variable and $c$ as the threshold value.

### 3.3 Econometric Procedures

To avoid the problem of spurious regression, the importance of which was noted by Newbold and Granger (1974), employing unit root tests to find the order of integration of each series is crucial before employing further regression analyses. By doing so, we would be able to maintain the stationarity of the data. To find the level of integration, we employed three standard unit root tests, which are the Augmented Dickey-Fuller (ADF) test (1979), Philips-Perron (PP) test (1988), and the Kwiatkowski-Philips-Schmidt-Shin (KPSS) test (1992).

However, it is also possible that structural breaks occur within the data points, and this might lead to the questionable validity of the prior tests. To ensure that the series are truly integrated at the level predicted from the prior tests, we employed the Zivot-Andrews (2002) breakpoint unit root tests. Despite seasonal unit roots being a possible issue, we had already dealt with this possibility using the STL decomposition for the first-differenced series, while the seasonally-differenced series had already dealt with the issue entirely.

To validate the use of the TAR model, which is a nonlinear model, we first tested whether nonlinearities exist in the data series. To do so, we employed the Brock-Dechert-Scheinkman-LeBaron (BDS) independence test (1996), which is a portmanteau test for time-based dependence in a series, without a specific alternative hypothesis (Enders, 2014). Thus, if the null hypothesis of linear dependence is rejected, there exists nonlinearities within the data. To further validate the results of the BDS test, we also applied the McLeod-Li test (1983), which is the exact Lagrange Multiplier (LM) test for ARCH errors, as it has great power to find numerous forms of nonlinearities (Enders, 2014).

After testing for the level of integration as well as for the presence of nonlinearities within the data, we then estimated the TAR model as specified before. To evaluate the model, we must ensure that the TAR model is stable and robust to the lag of the threshold. With regard to the stability of the model, recall from the original paper regarding the TAR model by Tong and Lim (1980) that the base assumption of the TAR model is the existence of a stable limit cycle. As such, the model itself is defined as the stabilizer of a nonlinear function to ensure the convergence of the recursion. Thus, the convergence of the TAR model itself is a testament to the stability of the model. Meanwhile, to test the robustness to the lag of the threshold, if we suppose that we procure a model with a threshold lag of *t-d*, then we can reiterate the model with a maximum lag of *t-d-n*, where *n* adds to the maximum lag. If the selected lag for the threshold persists, then the model is robust to the lag of the threshold.

## IV. Main Results and Discussion

### 4.1 Unit Root and Linearity Tests

Before proceeding to the unit root and linearity tests, it is important to check the descriptive statistics of all of the series used in this analysis, which are compiled in Table 1 and illustrated in Figure 3. The total sample in the dataset are 425 observations, with the exception of the ENVPU, which only has 351 observations. From the summary in Table 1, while the other variables tend to be normal, the CPU seems to be rather skewed and may have heavier tails than the normal distribution. Thus, we applied log-transformed variables to normalize the data points.

| | CPU | REC | CO2 | 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 |
| Std. Deviation | 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 1.** Descriptive Statistics

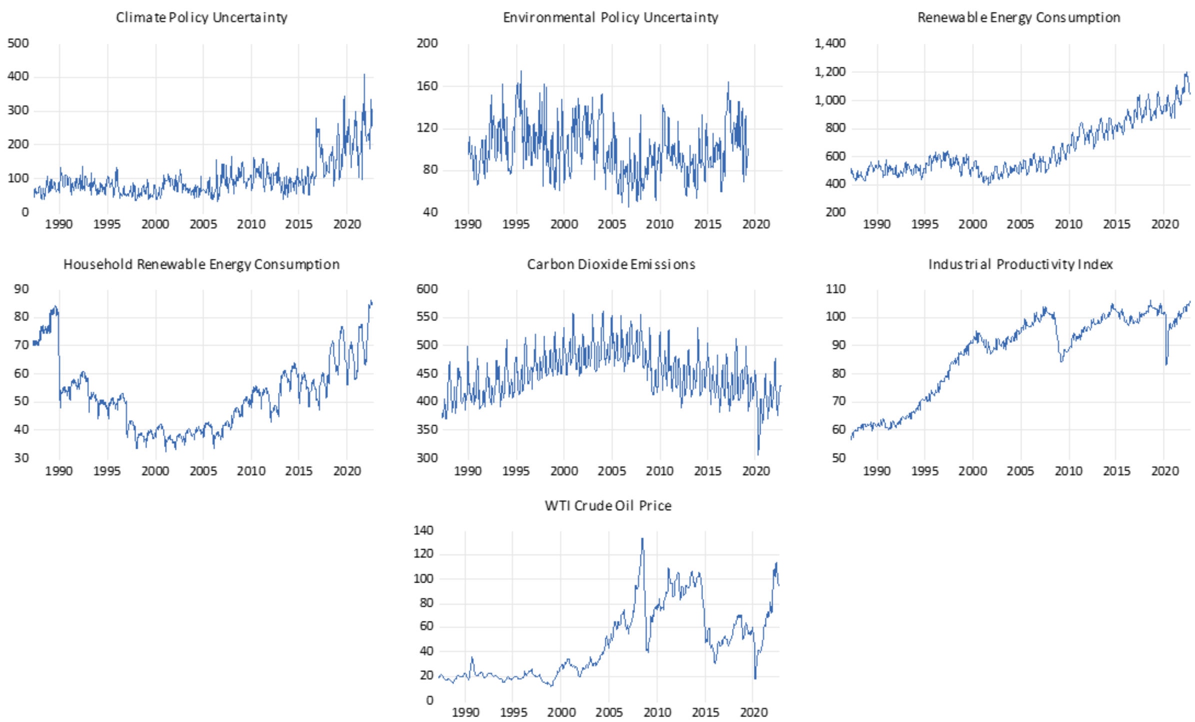


**Figure 3.** Dataset Series 1987-2022

Moving on to the unit root tests, we applied the standard unit root tests, which include the Augmented Dickey-Fuller tests, Phillips-Perron tests, and the KPSS tests in Table 2, and the Zivot-Andrews unit root tests in Table 3, to account for structural breaks that may occur within the series. From Table 2, we can infer that all of the data series are integrated at I(1). We also reached this conclusion from the Zivot-Andrews test in Table 3.

To support the use of a nonlinear threshold model, we applied the BDS Test for linearity and the McLeod-Li test, which are reported in Table 4 and Appendix 1, respectively. The results in Table 4 suggest that the null hypothesis that the series are linearly dependent is rejected. The findings in Appendix 1 add to the robustness of the previous findings, as the null hypothesis that the series are linear is rejected. However, do note that these findings do not suggest the shape of the nonlinearity, although we can reasonably conclude that nonlinearities exist in the data. Thereby, we can estimate a TAR model.

| | **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*** |

| | | | | | | |
|---|---|---|---|---|---|---|
| **CO2 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 2.** Standard Unit Root Tests on Dataset

| Series | | Constant | | Trend | | Constant & 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 |
| LCO2 | 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 3.** Zivot-Andrews Structural Unit Root Test Results

| | BDS Stat. | Std. Error | 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 | | | | | 0.677829 | 127315.0 | 4100437 |
| | 0.162895 | 0.007 | 23.730 | 0.0000 | | | 3 |
| 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 |
| **CO2 Emission** | | | | | | | |
| 2 | 0.073523 | 0.003 | 26.114 | 0.0000 | | | |
| 3 | 0.107972 | 0.004 | 24.184 | 0.0000 | | | |
| 4 | | | | | 0.140891 | 127203.0 | 4029717 |
| | 0.119859 | 0.005 | 22.604 | 0.0000 | | | 3 |
| 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 | | | | | 0.444801 | 127449.0 | 4028060 |
| | 0.369377 | 0.005 | 74.982 | 0.0000 | | | 3 |
| 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 | | | | | 1.067691 | 127463.0 | 3980071 |
| | 0.393758 | 0.004 | 105.01 | 0.0000 | | | 1 |
| 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 | | | | | 0.390901 | 86943.00 | 2276786 |
| | 0.058610 | 0.006 | 10.172 | 0.0000 | | | 5 |
| 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 | | | | | 0.313233 | 126429.0 | 4044703 |
| | 0.440002 | 0.007 | 65.645 | 0.0000 | | | 3 |
| 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 4.** Brock-Dechert-Scheinkman-LeBaron (BDS) Test Results

## 4.2 Main Results

The main results of the TAR model are reported in Table 5. As shown in Table 5, from the Bai-Perron Sequential L+1 Threshold vs L threshold selection, we acquire a threshold of 0.347 at lag 15, or a threshold set one year and three months prior to the current time *t*. This threshold selection is found to be robust to the lag of the threshold, as larger maximum lag selections do not change the threshold value selection and threshold lag. That said, the results in Table 5 suggest a negative nonlinear effect of CPU on REC, as the effects below and above the threshold are different. At the regime below the threshold, the effect of CPU on REC is not statistically significant, while only the covariates for REC at lag 1, lag 3, along with the index of industrial productivity are statistically significant and positive.

| Below Threshold (ΔLCPU(-15) < 0.3469225) – 295 Observations | | | | |
|---|---|---|---|---|
| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
| C | 0.000865 | 0.003042 | 0.284284 | 0.7763 |
| Seas ΔLCPU | 0.004166 | 0.006158 | 0.676496 | 0.4991 |
| Seas ΔLREC(-1) | 0.727514*** | 0.058747 | 12.38375 | 0.0000 |
| Seas ΔLREC(-2) | -0.104108 | 0.071017 | -1.465961 | 0.1435 |
| Seas ΔLREC(-3) | 0.238521*** | 0.058478 | 4.078843 | 0.0001 |
| First ΔLIIP | 0.638408** | 0.298019 | 2.142171 | 0.0328 |
| Seas ΔLCO2 | 0.020369 | 0.063281 | 0.321886 | 0.7477 |
| First ΔLWTI | 0.024522 | 0.033460 | 0.732883 | 0.4641 |
| Above Threshold (ΔLCPU(-15) >= 0.3469225) – 103 Observations | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
| C | 0.014263*** | 0.005369 | 2.656476 | 0.0082 |
| Seas ΔLCPU | -0.042094*** | 0.011864 | -3.547980 | 0.0004 |
| Seas ΔLREC(-1) | 0.614676*** | 0.085307 | 7.205422 | 0.0000 |
| Seas ΔLREC(-2) | -0.055285 | 0.111792 | -0.494531 | 0.6212 |
| Seas ΔLREC(-3) | 0.131103 | 0.086688 | 1.512349 | 0.1313 |
| First ΔLIIP | 0.805443** | 0.398331 | 2.022046 | 0.0439 |
| Seas ΔLCO2 | -0.256124** | 0.102485 | -2.499142 | 0.0129 |
| First ΔLWTI | -0.029500 | 0.048146 | -0.612734 | 0.5404 |

| | | | |
|---|---|---|---|
| R-Squared | 0.621082 | Log-Likelihood | 646.6672 |
| Adjusted R-Squared | 0.606203 | Akaike Info Criterion | -3.169182 |
| F-Statistic | 41.74228 | Schwarz Criterion | -3.008923 |
| Prob(F-Statistic) | 0.000000 | Hannan-Quinn Criterion | -3.105705 |

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

**Table 5.** Main Results using Threshold Autoregression (TAR) Estimation

Meanwhile, the relationship between CPU and REC at the regime above the threshold level is found to be statistically significant and negative. This suggests that, when uncertainty grows at a level above the threshold 15 months prior, the CPU affects REC negatively. These findings are in accordance with the findings of Syed et al. (2023), Zhou et al. (2023), and Li et al. (2023). However, these findings are unlike the findings of Shang et al. (2022), as they found that the effect of CPU on REC is not statistically significant. While their findings are similar to the results below the threshold, Shang et al. (2022) were not able to capture the nonlinear effect of CPU on REC above the threshold.

Regarding the threshold lag, it is reasonable to attribute this distant time to the time it takes to make a decision to consume renewable energy and making the necessary investments when it comes to companies generating their own source of renewable energy. Note that the data collected from the EIA are the sectoral data of the production side. Bhattacharyya (2012) discussed how energy projects tend to be more capital intensive, has a high degree of asset specificity, and has a generally longer life of assets and gestation periods. Thus, uncertainty could affect a company's decision to implement these projects for the sake of REC. Syed et al. (2023) noted a similar issue surrounding the uncertainty of the Production Tax Credit (PTC) for renewable energy consumption, which leads to difficulties in long-term planning and investment. As such, in accordance with Syed et al. (2023), the distance between current consumption and the threshold lag is rather reasonable.

Regarding the other variables, the first lag of the REC is significant and positive in both regimes but is slightly less positive above the threshold. Meanwhile, the quarterly lag of the REC is only significant under the threshold, suggesting that the consumers are less sensitive to older periods when uncertainty is high. The effect of the IIP is significant in both regimes, and becomes more positive above the threshold, which is similar to the findings of Shang et al. (2022), who had also found a significant positive effect of economic growth on REC. While the WTI does not seem to affect REC, CO2 emissions are associated with the decreases in REC above the threshold. Although quite surprising, this finding is in line with the finding of Syed et al. (2023), who found that the effect of CO2 on REC is negative in both the short and long-run. This could be due to the CO2 emissions capturing the effects of an increase in non-renewable energy consumption that is not captured by other variables.

## 4.3 Robustness Checks

To verify the robustness of the main results, Table 6 reports the results of the TAR estimation using the household renewable energy consumption (RECHH) as the dependent variable. Note that we instead use the first-differenced log-transformed version of the CO2 emissions variable, as using the seasonally-differenced variables lead to non-robust models due to the lag of the threshold. That said, the results in Table 6 suggest that there does exist a nonlinear threshold effect of the CPU on REC, but the direction is different in comparison to Table 5. While no significant effect of CPU on REC occurs below the threshold, the effect above the threshold is positive and statistically significant at 1%, and could be interpreted as a 1% increase in CPU, which is associated with a 0.046% increase in RECHH. Although this differs from the findings in the previous model, the shocks captured in the CPU by Gavriilidis (2021), in the context of household consumers, mostly pertain to policies aimed at reducing the CO2 emissions from non-renewable energy consumption. This could thus be interpreted as the adoption of a "just-in-case" policy.

In addition, the lags of the RECHH for all months above the threshold are statistically significant, unlike those below it, in which only the first lag is positively associated with the current RECHH. This may imply that, beyond a certain level of uncertainty, household consumers are more cautious and responsive to past consumption of renewable energy. In line with Bhattacharyya (2012), CO2 emissions also positively affects RECHH just as it does the REC, though its effects are intensified by 1.976 percentage points. The implication is that household consumers are more sensitive to changes in CO2 emissions as compared to producers above a certain threshold.

Following the "just-in-case" policy derived from the previous discussion, which shows the divergence in the behavior of companies and household consumers, it may be the case that the context behind the policy uncertainty affects the reaction of economic actors. Recall Li et al. (2022), who found that the effect of CPU on REC is dependent on the regime by which the uncertainty is founded. Hence, depending on the contextual attitude of the authorities, the relationship between CPU and REC may differ. We explore this possibility by removing the observations of the Trump Administration in the following results reported in Table 7 and Table 8.

| Below Threshold (ΔLCPU(-7) < 0.5134778) – 346 Observations | | | | |
|---|---|---|---|---|
| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
| C | -0.001307 | 0.002510 | -0.520572 | 0.6030 |
| Seas ΔLCPU | 0.007920 | 0.005582 | 1.418947 | 0.1567 |
| Seas ΔLRECHH(-1) | 0.938716*** | 0.046169 | 20.33214 | 0.0000 |
| Seas ΔLRECHH(-2) | 0.011640 | 0.062140 | 0.187322 | 0.8515 |
| Seas ΔLRECHH(-3) | -0.041244 | 0.045725 | -0.901992 | 0.3676 |
| First ΔLIIP | 0.348027 | 0.264887 | 1.313866 | 0.1897 |
| First ΔLCO2 | 0.148300* | 0.088317 | 1.679174 | 0.0939 |

| | | | | |
|---|---|---|---|---|
| First ΔLWTI | -0.011353 | 0.028495 | -0.398425 | 0.6905 |
| Above Threshold (ΔLCPU(-7) >= 0.5134778) – 60 Observations | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
| C | 0.009389 | 0.006360 | 1.476224 | 0.1407 |
| Seas ΔLCPU | 0.046226*** | 0.013834 | 3.341413 | 0.0009 |
| Seas ΔLRECHH(-1) | 0.947769*** | 0.284631 | 3.329812 | 0.0010 |
| Seas ΔLRECHH(-2) | -0.759567* | 0.410522 | -1.850248 | 0.0650 |
| Seas ΔLRECHH(-3) | 0.654903** | 0.316697 | 2.067917 | 0.0393 |
| First ΔLIIP | -1.041602** | 0.437778 | -2.379291 | 0.0178 |
| First ΔLCO2 | 2.123972*** | 0.221181 | 9.602863 | 0.0000 |
| First ΔLWTI | -0.072532 | 0.060618 | -1.196527 | 0.2322 |
| R-Squared | 0.851241 | Log-Likelihood | 682.5328 | |
| Adjusted R-Squared | 0.845520 | Akaike Info Criterion | -3.283413 | |
| F-Statistic | 148.7796 | Schwarz Criterion | -3.125527 | |
| Prob(F-Statistic) | 0.000000 | Hannan-Quinn Criterion | -3.220925 | |

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

**Table 6.** TAR Estimation Results using Household Renewable Energy Consumption (RECHH)

Prior to discussing the results, do acknowledge that the decision to exclude those observations are in accordance with Li et al. (2022), who found a negative effect of CPU on REC during the Trump Administration subsample, as well as Noailly et al. (2022), who, in the creation of their policy uncertainty metric, found that much of the policy shocks during the Trump Administration were due to the revocation of the policies of Obama's Administration that were aimed at reducing carbon emissions. These policies include the Clean Power Plan, the US-China deal on climate change, the Paris Accord, and the Keystone XL pipeline project. Do note that this is not a partisan stance, but rather an opportunity to explore the possibility of contextual dynamics in CPU, assumed from prior US government documents and academic literature that support the idea that the previous administrations within the dataset pursued policies supporting climate mitigation, regardless of whether they succeeded (Wampler, 2015; Royden, 2002; Blanchard, 2003). Thus, we hypothesize from previous researches that this exclusion would result in a generally positive climate policy uncertainty shocks.

| Below Threshold (ΔLCPU(-15) < 0.4434905) – 281 Observations | | | | |
|---|---|---|---|---|
| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
| C | -0.000575 | 0.003029 | -0.189678 | 0.8497 |
| Seas ΔLCPU | 0.002539 | 0.006470 | 0.392461 | 0.6950 |
| Seas ΔLREC(-1) | 0.682733*** | 0.057378 | 11.89894 | 0.0000 |
| Seas ΔLREC(-2) | -0.070243 | 0.071355 | -0.984418 | 0.3257 |
| Seas ΔLREC(-3) | 0.257744*** | 0.060449 | 4.263811 | 0.0000 |

| | | | | |
|---|---|---|---|---|
| First ΔLIIP | 0.467030 | 0.355702 | 1.312979 | 0.1901 |
| Seas ΔLCO2 | -0.053130 | 0.074100 | -0.716996 | 0.4739 |
| First ΔLWTI | 0.005102 | 0.036639 | 0.139238 | 0.8894 |
| Above Threshold (ΔLCPU(-15) >= 0.4434905) – 50 Observations | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
| C | 0.021686*** | 0.008093 | 2.679538 | 0.0078 |
| Seas ΔLCPU | -0.037364** | 0.018458 | -2.024326 | 0.0438 |
| Seas ΔLREC(-1) | 0.883040*** | 0.134146 | 6.582695 | 0.0000 |
| Seas ΔLREC(-2) | -0.197998 | 0.164322 | -1.204942 | 0.2291 |
| Seas ΔLREC(-3) | -0.055362 | 0.115333 | -0.480016 | 0.6315 |
| First ΔLIIP | -2.518850** | 1.026253 | -2.454416 | 0.0147 |
| Seas ΔLCO2 | -0.230994 | 0.201753 | -1.144935 | 0.2531 |
| First ΔLWTI | 0.092219 | 0.066359 | 1.389714 | 0.1656 |

| | | | |
|---|---|---|---|
| R-Squared | 0.660796 | Log-Likelihood | 543.7721 |
| Adjusted R-Squared | 0.644643 | Akaike Info Criterion | -3.188956 |
| F-Statistic | 40.90958 | Schwarz Criterion | -3.005167 |
| Prob(F-Statistic) | 0.000000 | Hannan-Quinn Criterion | -3.115653 |

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

**Table 7.** TAR Estimation Results using Sectoral Renewable Energy Consumption (REC) without Trump Administration

The results in Table 7 show that the threshold lag is the same as in Table 5, but with a value of 0.443. The notable discovery from this exploration is that, above the threshold, while the directionality of the CPU coefficient is similar to the results in Table 5, it has become less negative, seeing a 0.005 percentage point increase in comparison to the prior calculation. Meanwhile, the lagged REC for the prior month is positive and statistically significant in both threshold regimes, while the quarterly lagged REC is only significant below the threshold, suggesting that the consumers are more sensitive to more recent consumption decisions. The effect of the IIP on REC is quite unexpected, as it is negative above the threshold. While this finding differs from Shang et al. (2022), who found that economic growth is positively associated with REC, and Syed et al. (2023), who found no significant effect of IIP on REC, our findings are observed above a certain threshold, in which companies could become more sensitive to uncertainty and prefer to reduce their REC when uncertainty persists, despite the better economic condition.

As for the results on RECHH, as provided in Table 8, the selected threshold lag is similar to that in Table 6, though the threshold value is now 0.453. In comparison to the previous results in Table 6, the coefficient of the CPU above the threshold is also statistically significant and has increased by 0.046 percentage points. Similar to the previous estimation, the first lag of the RECHH is positive and statistically significant in both threshold regimes, while the second and third lags are significant only above the threshold, suggesting that household consumers are much more sensitive to decisions made during prior periods when uncertainty persists. Moreover, the CO2 emissions are positive and statistically significant in both regimes, but the effect becomes more pronounced above the threshold. In summary, akin to Li et al. (2022), we find suggestive evidences that the context of the CPU shocks may yield differing effects on REC.

To further complement the prior results, a similar TAR estimation was done using the ENVPU index by Noailly et al. (2022) as a substitute for the CPU index. Do recall that these indices are conceptually similar and meant to capture similar shocks, although their formation are different. The results of this estimation are summarized in Table 9.

A similar conclusion is found regarding the nonlinear effect, in which the estimations converge at lag 20. We find that, with regard to the other variables, it would seem that they behave similarly to prior estimations. However, instead of becoming more sensitive to the REC two and three months prior, as well as to CO2 emissions when uncertainty goes beyond a certain threshold, the consumers are now more reactive to the uncertainty in the current period and the previous period's REC, as they are the only statistically significant variables above the threshold.

| Below Threshold (ΔLCPU(-7) < 0.4530624) – 289 Observations | | | | |
|---|---|---|---|---|
| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
| C | -0.001919 | 0.002777 | -0.691023 | 0.4900 |
| Seas ΔLCPU | 0.009948 | 0.006155 | 1.616102 | 0.1070 |
| Seas ΔLRECHH(-1) | 0.952834*** | 0.049381 | 19.29542 | 0.0000 |
| Seas ΔLRECHH(-2) | -0.012063 | 0.067164 | -0.179606 | 0.8576 |
| Seas ΔLRECHH(-3) | -0.032370 | 0.049359 | -0.655820 | 0.5124 |
| First ΔLIIP | 0.229617 | 0.334864 | 0.685701 | 0.4934 |
| First ΔLCO2 | 0.204942* | 0.106924 | 1.916717 | 0.0562 |
| First ΔLWTI | -0.009926 | 0.032961 | -0.301135 | 0.7635 |
| Above Threshold (ΔLCPU(-7) >= 0.4530624) – 50 Observations | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
| C | 0.007518 | 0.007151 | 1.051301 | 0.2939 |
| Seas ΔLCPU | 0.092449*** | 0.018352 | 5.037420 | 0.0000 |
| Seas ΔLRECHH(-1) | 0.969519*** | 0.326962 | 2.965235 | 0.0032 |
| Seas ΔLRECHH(-2) | -0.848064** | 0.387465 | -2.188749 | 0.0293 |
| Seas ΔLRECHH(-3) | 0.785132*** | 0.259761 | 3.022515 | 0.0027 |
| First ΔLIIP | -0.843560 | 0.849202 | -0.993356 | 0.3213 |
| First ΔLCO2 | 2.070301*** | 0.230714 | 8.973448 | 0.0000 |
| First ΔLWTI | -0.081012 | 0.085420 | -0.948400 | 0.3436 |

| | | | |
|---|---|---|---|
| R-Squared | 0.856151 | Log-Likelihood | 568.1768 |
| Adjusted R-Squared | 0.849470 | Akaike Info Criterion | -3.257680 |
| F-Statistic | 128.1604 | Schwarz Criterion | -3.077102 |
| Prob(F-Statistic) | 0.000000 | Hannan-Quinn Criterion | -3.185720 |

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

**Table 8.** TAR Estimation Results using Household Renewable Energy Consumption (RECHH) without Trump Administration

Although the effect of the first period lag REC is expectedly positive, the effect of the ENVPU above the threshold is rather unexpected, since the coefficient is positive. These results imply that should the ENVPU 20 months prior surpass the threshold value, then a 1% increase in ENVPU is expected to increase REC by 0.024%. In light of these results along with the previous estimations, it can be inferred that a nonlinear threshold effect does exist from climate policy uncertainty to renewable energy consumption. As the effects of the uncertainty manifest above a certain threshold, this would suggest that when uncertainty is relatively low, other factors would better account for the variations in REC.

Despite the clear inference for the first hypothesis, an intriguing divergence emerges when discussing the effects of climate policy uncertainty above a certain threshold, as using the CPU and ENVPU leads to different implications. This new set of results suggest that greater policy uncertainty is associated with the increases in REC. Note that these differences may be a result of the differences in the development of the CPU by Gavriilidis (2021) and the ENVPU by

| Below Threshold (ΔLENVPU(-20) < -0.1081249) – 119 Observations | | | | |
|---|---|---|---|---|
| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
| C | 0.013342*** | 0.004558 | 2.927187 | 0.0037 |
| Seas ΔLENVPU | -0.016505 | 0.013078 | -1.262023 | 0.2079 |
| Seas ΔLREC(-1) | 0.728470*** | 0.078675 | 9.259196 | 0.0000 |
| Seas ΔLREC(-2) | -0.288773*** | 0.099667 | -2.897370 | 0.0040 |
| Seas ΔLREC(-3) | 0.332661*** | 0.086550 | 3.843563 | 0.0001 |
| First ΔLIIP | 0.913965 | 0.574713 | 1.590299 | 0.1128 |
| Seas ΔLCO2 | -0.293249** | 0.114575 | -2.559443 | 0.0110 |
| First ΔLWTI | -0.047832 | 0.052312 | -0.914361 | 0.3613 |
| Above Threshold (ΔLENVPU(-20) >= -0.1081249) – 200 Observations | | | | |
| Variable | Coefficient | Std. Error | t-Statistic | Prob.* |
| C | -0.002304 | 0.003508 | -0.656561 | 0.5120 |
| Seas ΔLENVPU | 0.024283** | 0.010107 | 2.402502 | 0.0169 |
| Seas ΔLREC(-1) | 0.692033*** | 0.072217 | 9.582752 | 0.0000 |
| Seas ΔLREC(-2) | 0.114622 | 0.089257 | 1.284179 | 0.2001 |
| Seas ΔLREC(-3) | 0.090973 | 0.067792 | 1.341953 | 0.1806 |
| First ΔLIIP | -0.180619 | 0.404969 | -0.446006 | 0.6559 |
| Seas ΔLCO2 | 0.059636 | 0.080749 | 0.738530 | 0.4608 |
| First ΔLWTI | 0.047535 | 0.040185 | 1.182902 | 0.2378 |

| | | | |
|---|---|---|---|
| R-Squared | 0.663763 | Log-Likelihood | 540.2831 |
| Adjusted R-Squared | 0.647118 | Akaike Info Criterion | -3.287041 |
| F-Statistic | 39.87672 | Schwarz Criterion | -3.098191 |
| Prob(F-Statistic) | 0.000000 | Hannan-Quinn Criterion | -3.211622 |

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

**Table 9.** TAR Estimation Results using Environmental Policy Uncertainty (ENVPU)

Noailly et al. (2022). Recall that, instead of using the naïve method of classification used by Gavriilidis (2021) following Baker et al. (2016), Noailly et al. (2022) uses an SVM algorithm to classify which article indicates uncertainty to develop their index.

According to Noailly et al. (2022), by testing their own algorithm against the algorithm used by Baker et al. (2016), they found out that the SVM algorithm has a larger recall rate, thus capable of capturing more true positives as compared to the naïve method used in the CPU. It can be said that the ENVPU is thus richer in information as compared to the CPU, which, according to Noailly et al. (2022), could lead to differences in the volatility of the index. From our calculations of the correlations and volatility of the indices in Table 10 as well as the visual form in Figure 4, we find that the CPU is considerably more volatile in comparison to the ENVPU, which is true for both at level and at first-differences.

| Correlation | CPU | ENVPU | Std. Dev | Volatility |
|---|---|---|---|---|
| CPU | 1.000000 | | 55.65215 | 1147.298 |
| ENVPU | 0.189888 | 1.000000 | 25.51904 | 478.0983 |
| Correlation | ΔCPU | ΔENVPU | Std. Dev | Volatility |
| ΔCPU | 1.000000 | | 0.458980 | 9.327576 |
| ΔENVPU | 0.215021 | 1.00000 | 0.321928 | 5.927323 |

**Table 10.** Correlation Matrix and Volatility of CPU and ENVPU

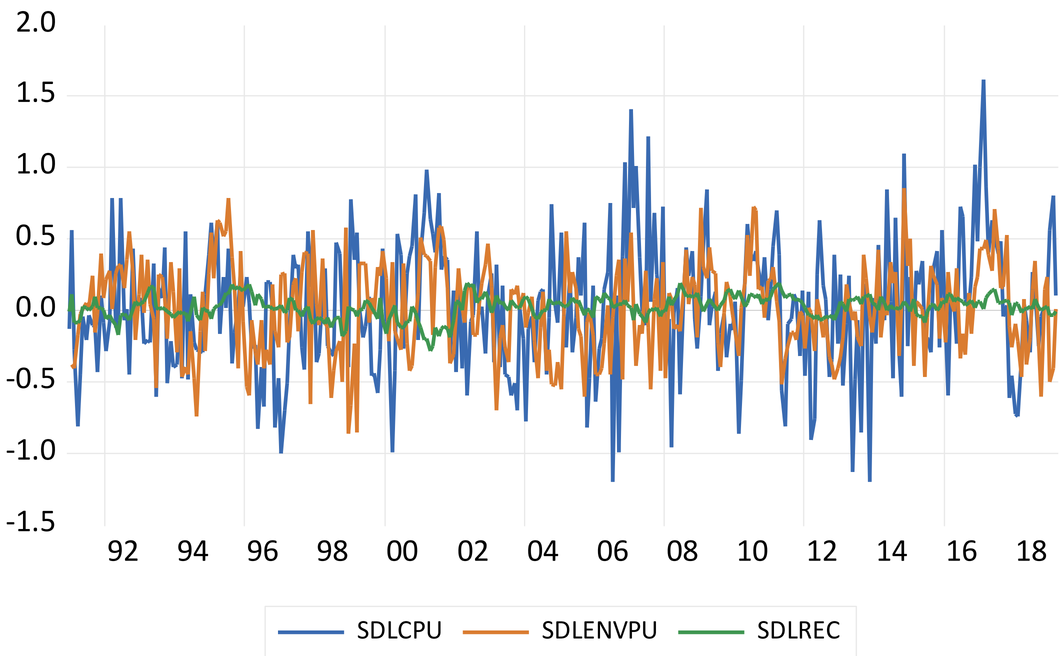


**Figure 4.** Seasonally Differenced Log-Transformed Version of Selected Variables

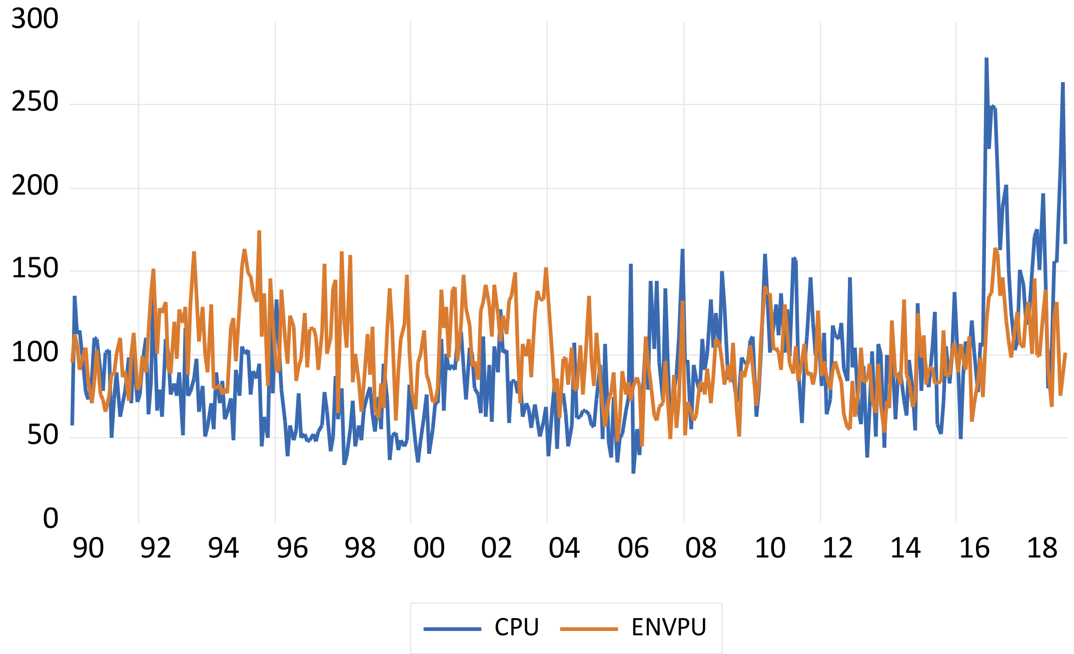


**Figure 5.** Raw CPU (Gavriilidis, 2021) and ENVPU (Noailly et al., 2022) Comparison

Moreover, it is also possible that there are significant differences in the intensities of the uncertainty that has been captured. From Figure 5, it can be seen that the CPU had risen drastically around 2017, while the ENVPU did not increase to such a similar extent. Furthermore, prior to the turn of the millennia, the ENVPU seems to be relatively higher compared to the CPU. Thus, it would seem that the CPU captures much greater uncertainty around the turn of the millennia and during the period coinciding with the Trump Administration. Recalling Li et al. (2022) and Noailly et al. (2022), since the uncertainty during the Trump Administration is possibly linked to policies that are not in favor of mitigating climate change and promoting non-renewable energy consumption, the magnitude of the shock to the CPU during that era may have amplified the negative association between the CPU and REC above the threshold. This is not necessarily the case with the ENVPU, considering that it is less volatile.

Hence, the results of the TAR model employing the ENVPU as the main variable of interest have led to a rather significant discovery, both in the endeavor to understand the climate policy and REC nexus, as well as the construction of an index with the purpose of capturing said uncertainty. With these set of results, we can reasonably conclude that there does exist a nonlinear threshold effect between the CPU and REC. However, due to the different directionality of said effects above the threshold, the best course of action would be to review the formulation of the policy uncertainty index that serves to measure climate policy uncertainty.

Despite this, considering the lack of volatility in the ENVPU index as well as the set of results from Table 6 and Table 8, it can be inferred that economic actors take a “just-in-case” policy approach when uncertainty moves beyond a certain threshold. Considering the prior discussions on the supportive political stances of all of the administrations prior to the Trump Administration, it can be understood that a “just-in-case” policy approach is done in anticipation of supportive policies that support the mitigation of climate change.

## V. Conclusion

Climate change is a crucial concern for the future of the planet, which has its influence on the global economy as well as the environment. With various international agreements and national efforts to achieve carbon neutrality, it is important to understand not just what policies need to be implemented, but how they should be delivered. Due to this immense global target, as the goal of the recent COP26 is to attain net zero emissions, understanding how policies are implemented and how uncertainty affects the behavior of economic actors towards renewable energy consumption are important.

The main results indicate that there exists a nonlinear threshold effect of climate policy uncertainty, both as proxied by the CPU and ENVPU, on REC. In the first set of results, the effect of the CPU on the REC above a certain threshold is negative, implying that companies follow a “wait and see” policy, in accordance with Syed et al. (2023). Essentially, consumers would reduce their renewable energy consumption for other sources to sidestep the investment risks linked with renewable alternatives.

To test the robustness of this model, we included further analysis using the RECHH, in which we discovered a different effect. Though the threshold effect still holds, the directionality becomes positive, implying a “just-in-case” policy approach, in which consumers will increase REC if uncertainty persists, expecting more supportive policies in the future. This is in accordance with Zhou et al. (2023), who had also observed a positive association between CPU and REC in most time periods.

To explore the possibility of different effects of CPU on REC based on the context of the shocks to the CPU, we follow the findings of Li et al. (2022) and Noailly et al. (2022) by excluding the Trump Administration observations to proxy for a positive CPU. Although we notice that this is a challenging assumption, following the policy reviews of several past papers

(Wampler, 2015; Royden, 2002; Blanchard, 2003) and the findings of Li et al. (2022), we believe that this is a reasonable assumption for exploring this possible dynamic. Our findings suggest that, without the Trump Administration observations, the results of the effect of CPU on REC and RECHH become more positive, increasing by 0.005 and 0.046 percentage points, respectively, despite the result of the effect of CPU on REC still being negative above the threshold.

An additional robustness check was added using the ENVPU by Noailly et al. (2022) to see whether the formation of the climate policy uncertainty index had any effect on the results. While the results of this new estimation diverge from the main findings, since the threshold effect of the ENVPU on REC is positive, we find a crucial insight. Since the ENVPU has a superior recall rate compared to the CPU, it has lower volatility and captures more true positives, which may affect the results of the model. Moreover, unlike the CPU, the ENVPU does not exacerbate the shock during the Trump Administration.

Though the results differ, we can still reasonably conclude that there does exist a nonlinear threshold effect of the climate policy uncertainty on REC, regardless of which index is utilized in the estimation. Despite the ambiguity in the results, considering the previous discussions on the robustness checks, we can conclude that there seems to be a positive effect of climate policy uncertainty on renewable energy consumption above the threshold. As such, in accordance with Zhou et al. (2023) and Li et al. (2022), it would seem that economic actors adopt a "just-in-case" policy approach towards REC when CPU surpasses a certain threshold.

There are several limitations to consider in this study, namely the inability to account for the contextual dynamics underlying the CPU index. Unlike economic policy uncertainty, in which the positivity or negativity of a given policy requires subjective judgements regarding different trade-offs, climate policy can be objectively discerned based on its stance on mitigating climate change and on supporting the environment (Basaglia et al., 2022). Although imperfect, this paper tries to account for this with the estimation without the Trump Administration, by assuming that we would have a generally positive CPU index. The unavailability of raw data further limits this study, as we are not able to infer on the Optimistic-CPU and Pessimistic-CPU indices such as the ones developed by Berestycki et al. (2022) and Basaglia et al. (2022). Thus, a recommendation for future academic research on climate policy uncertainty would be to incorporate the dynamic nature of this uncertainty. It would also be better to follow the approach of Noailly et al. (2022) to ensure better predictions in the development of the index, while also following Berestycki et al. (2022) and Basaglia et al. (2022) to capture the positive and negative dynamics.

As for policymakers, a key insight from these results is to ensure that uncertainty is beyond a certain threshold, or to deliver policies effectively to such a case that consumers would behave as if they are under the threshold. Enhancing clarity and certainty for consumers could be a better solution, as this would let other factors determine the REC, and policymakers can thus focus on creating policies that affect such factors to drive an increase in the REC. As for developing countries, this study has two implications. The first is in accordance with the general recommendation of ensuring that uncertainty is low. The second is to recognize that, should uncertainty grow beyond a certain threshold, the context of the policy itself, be it for or against carbon neutrality, for instance, could change how the uncertainty affects REC. The "just-in-case" policy by consumers might not be as generally applied in developing countries, as we derive our results from a developed country with a history of policies supporting carbon neutrality. Due to that, if the policymakers in developing countries deem this effort for carbon neutrality to be important, then they should implement policies that do not hinder this initiative, as even if uncertainty goes beyond a certain level, the behavior of consumers might still be in favor of consuming more renewable energy.

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## 4.5 Appendix

Appendix: McLeod-Li Test for Linearity on Each Series

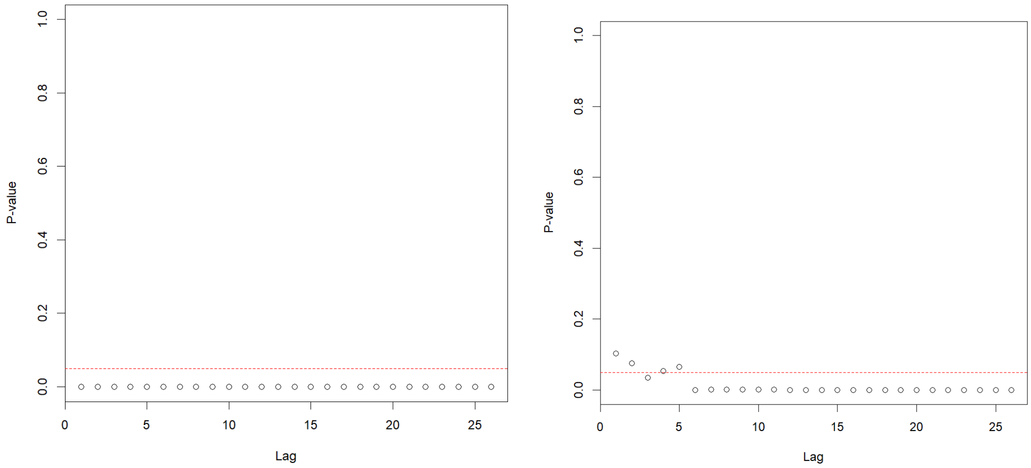


Figure A.1.1. McLeod-Li Test (Log-Transformed and Seasonally Differenced CPU)

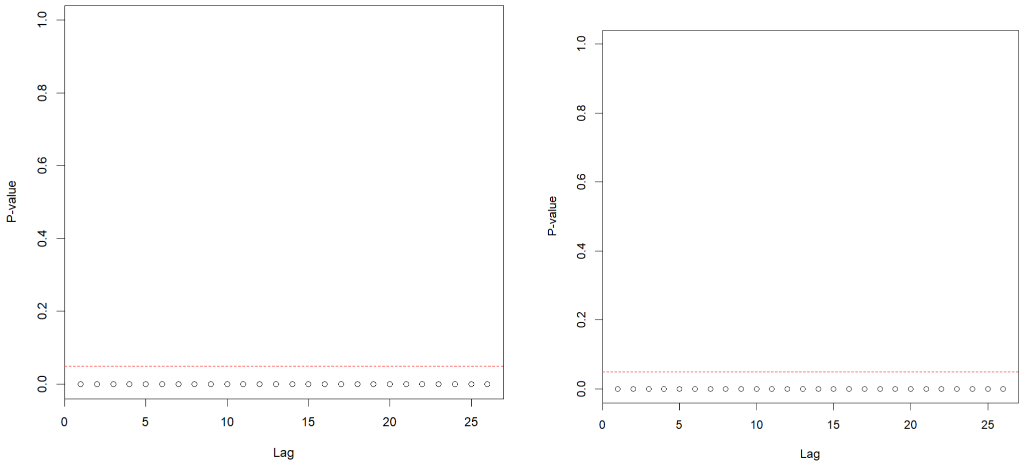


Figure A.1.2. McLeod-Li Test (Log-Transformed and Seasonally Differenced REC)

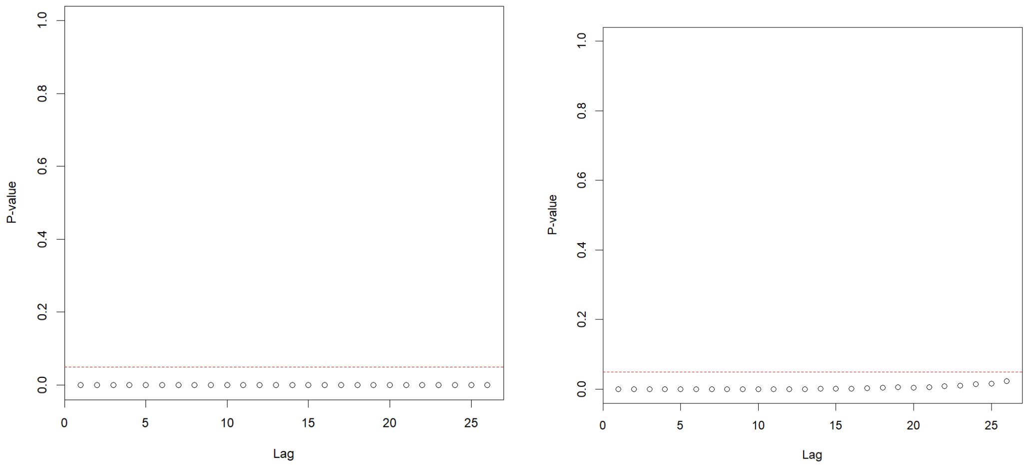


Figure A.1.3. McLeod-Li Test (Log-Transformed and Seasonally Differenced ENVPU)

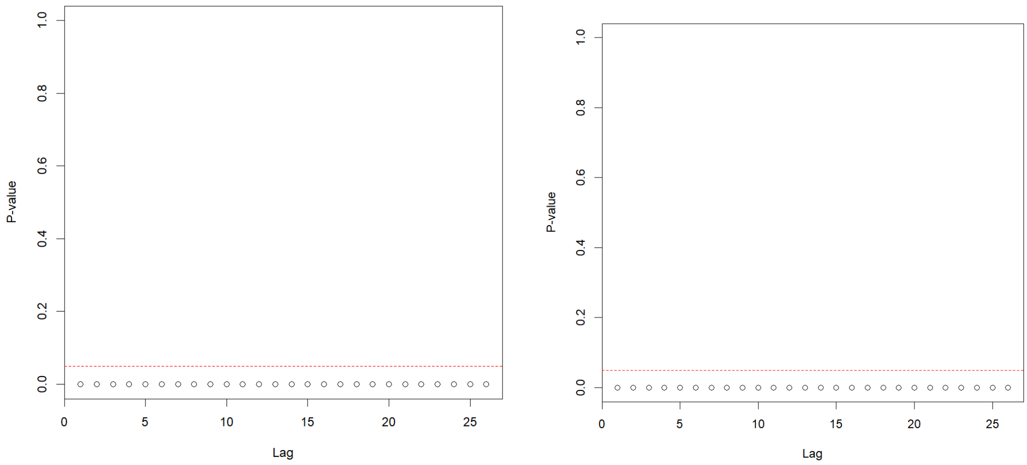


Figure A.1.4. McLeod-Li Test (Log-Transformed and Seasonally Differenced CO2)

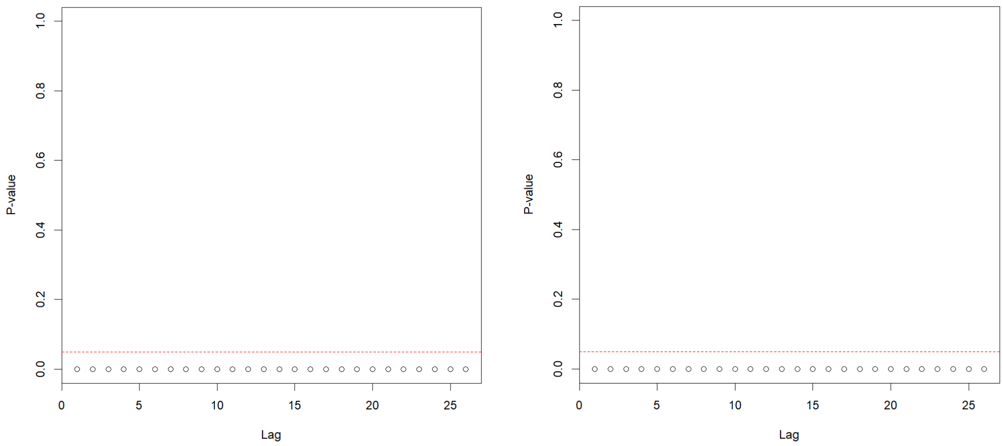


Figure A.1.5. McLeod-Li Test (Log-Transformed and Seasonally Differenced IIP)

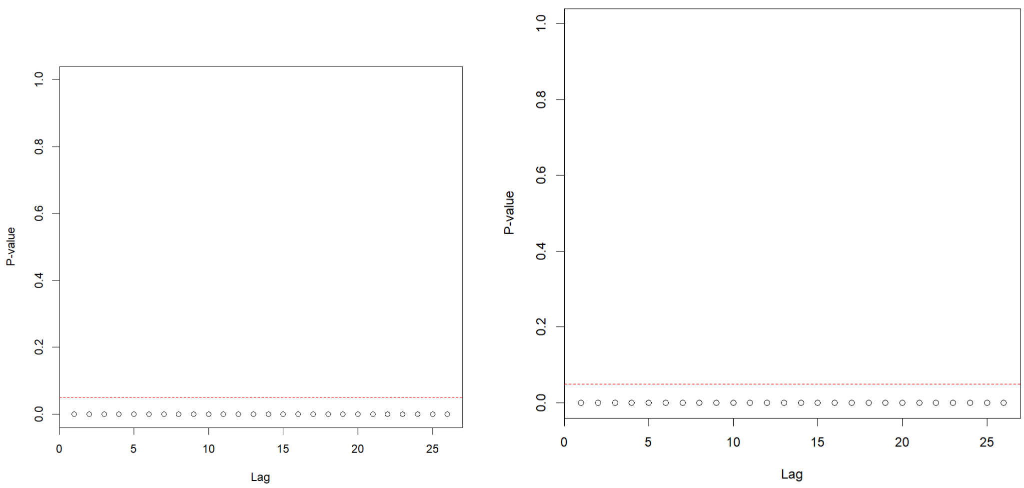


Figure A.1.6. McLeod-Li Test (Log-Transformed and Seasonally Differenced WTI)

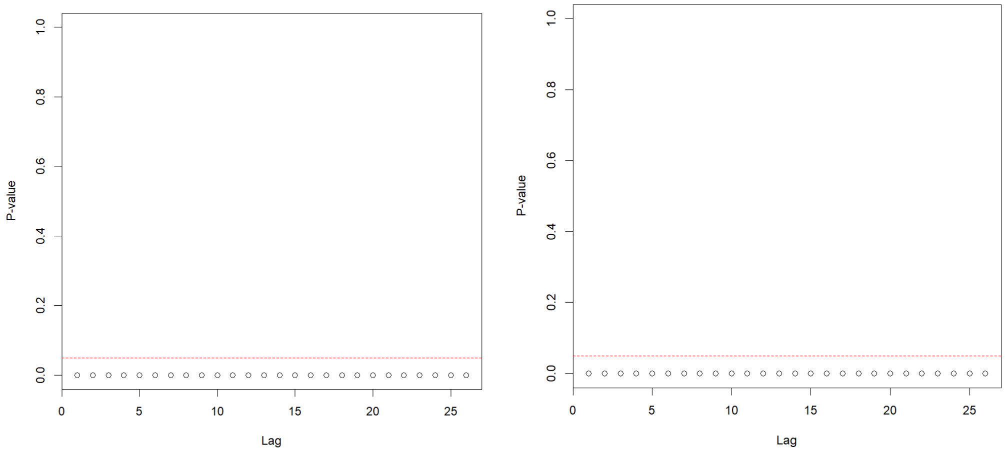


Figure A.1.7. McLeod-Li Test (Log-Transformed and Seasonally Differenced RECHH)