Ankara Hacı Bayram Veli Üniversitesi
İktisadi ve İdari Bilimler Fakültesi Dergisi 24/2 (2022) 757-776
E-ISSN 2667-405X

A Nonlinear Autoregressive Distributed Lag (NARDL) Approach for U.S. Climate Policy Uncertainty Index, Renewable Energy Consumption, and Oil Prices

Özge DİNÇ CAVLAK*

Geliş Tarihi (Received): 09.01.2022– Kabul Tarihi (Accepted): 06.05.2022

Abstract

This study aims to reveal the asymmetric relationship among climate policy uncertainty, oil prices, and renewable energy consumption over the period of January 2000-March 2021 in the U.S. The long- and short-run dynamic impacts of oil prices and renewable energy consumption on climate policy uncertainty are mainly examined utilizing a nonlinear autoregressive distributed lag (NARDL) approach. The findings of the study depict that there exists an asymmetric cointegrating relationship among climate policy uncertainty, renewable energy consumption, and crude oil prices in the long run. Climate policy uncertainty is affected by both negative and positive variations in renewable energy consumption and oil prices in the long-run period. The NARDL estimation results reveal that an increment in renewable energy consumption causes an increase in climate policy uncertainty while a decrease in renewable energy consumption also causes an increase in climate policy uncertainty in the long-run period. Further, an increase in oil prices causes a rise in climate policy uncertainty while a reduction in oil prices results in a decrease in the climate policy uncertainty for a long-run period.

Keywords: NARDL, U.S. climate policy uncertainty, renewable energy consumption, oil prices

ABD İklim Politikası Belirsizliği Endeksi, Yenilenebilir Enerji Tüketimi ve Petrol Fiyatları için Doğrusal Olmayan Sınır Testi Yaklaşımı

Öz

Bu çalışma, Ocak 2000-Mart 2021 dönemini kapsayan periyotta ABD iklim politikası belirsizliği, yenilenebilir enerji tüketimi ve petrol fiyatları arasındaki asimetrik ilişkiyi ortaya koymayı amaçlamaktadır. Petrol fiyatlarının ve yenilenebilir enerji tüketiminin iklim politikası belirsizliği üzerindeki uzun vadeli ve kısa vadeli dinamik etkileri, Doğrusal Olmayan Sınır Testi (NARDL) yaklaşımı kullanılarak incelenmektedir. Bulgular, uzun vadede iklim politikası belirsizliği, yenilenebilir enerji tüketimi ve ham petrol fiyatları arasında bir asimetrik eşbütünleşme ilişkisi olduğunu göstermektedir. İklim politikası belirsizliği, uzun vadede yenilenebilir enerji tüketimi ve petrol fiyatlarındaki hem olumsuz hem de olumlu değişikliklerden etkilenmektedir. NARDL tahmin sonuçları, yenilenebilir enerji tüketimindeki bir artışın iklim politikası belirsizliğini artırırken, yenilenebilir enerji tüketimindeki bir düşüşün de iklim politikası belirsizliğinde uzun vadede bir artışa yol açtığını göstermektedir. Ayrıca, petrol fiyatlarındaki bir artış iklim politikası belirsizliğinde bir artışa yol açarken, petrol fiyatlarındaki düşüş iklim politikası belirsizliğinde uzun vadede bir azalmaya yol açmaktadır.

Anahtar Kelimeler: NARDL, ABD iklim politikası belirsizliği, yenilenebilir enerji tüketimi, petrol fiyatları

* Arş. Gör. Dr., Ankara Hacı Bayram Veli Üniversitesi, İktisadi ve İdari Bilimler Fakültesi, İşletme Bölümü, ozge.dinc@hbv.edu.tr, ORCID ID: 0000-0002-7728-983X

Introduction

Climate change, which has been a recent phenomenon all over the world, refers to long-term shifts in weather patterns and temperatures. Although the source of these changes may be attributable to some natural reasons such as changes in the solar cycle, the major driver of climate change has been considered to result from human activities mainly induced by burning fossil fuels, which leads to a rise in greenhouse gas emissions in the atmosphere (United Nations, 2021). An increase in greenhouse gas concentration means an increase in emission that causes to be retained more heat in the atmosphere. Thus, this increase in the greenhouse gas concentration induces a rise in the Earth's average temperature, affects the patterns and amounts of precipitation, decreases ice and snow cover, increases sea level, raises the acid amount of the oceans, and changes ecosystem characteristics (U.S. Environmental Protection Agency, 2017). These changes have catastrophic effects on people's food supply, water resources, infrastructure, and ecosystems. Besides these effects, climate change has also several impacts on human health to some extent. Since the average temperature increases, the number of hot days also increases, which causes heat-related deaths. Also, climate change affects weather quality unfavorably that can cause asthma attacks and cardiovascular health problems (Crimmins et. al., 2016). People can also be exposed to drinking contaminated water because climate change induces more heavy rains and storms, which increases the presence of waterborne diseases. Shifts in average temperature and air pollution derived from climate change may influence mortality and morbidity (Lou et al., 2019). It has also substantial effects on food and nutrition, which increases the risk of the inclusion of chemical contaminants. Finally, as well as physical diseases, a set of mental illnesses are observed (Crimmins et. al., 2016). Along with the physical and environmental damages of climate change, serious economic consequences are mainly observed for the cost of technology to reduce carbon dioxide emissions. Especially for developed countries, the energy demand steadily increases and correspondingly, the cost of investment for energy infrastructure also increases (Sadorsky, 2009). Therefore, mitigation of climate change has vital importance both for governments and companies since uncertainty in climate response to decrease gas emissions leads to uncertainty in economic impacts of climate change, which leads to uncertainty in climate policy for the long-run horizon (International Energy Agency, 2007). These serious consequences of climate change have attracted the attention of policymakers to take the necessary actions, and examining the uncertainty in climate policies of countries has become of vital importance. In this context, several countries have developed policies to mitigate the impact of climate change for a few decades by decreasing greenhouse gas emissions to reach a more sustainable future. however, there has been confronted considerable uncertainty by implementing these policies such as the withdrawal of the U.S. government from the Paris Accord in 2017 (Gavriilidis, 2021). In this direction, a new index, called climate policy uncertainty index (CPU), has been developed to measure climate policy uncertainty by using the frequency of articles in eight major newspapers on a scaled basis in the U.S. by Gavriilidis (2021). While the CPU index has been created, Gavriilidis (2021) has focused on the news about climate policy that may result in uncertainty. Thus, a new proxy has been developed to measure uncertainty in climate policy by using a textual analysis on newspapers as in previous studies (Baker et al., 2016; Caldara and Iacoviello, 2018). It is of great importance to detect the possible factors that may affect the CPU index in mitigating climate change. Since the main driver of global warming is cited as CO_2 emissions, there are serious attempts to decrease fossil fuel usage and increase renewable energy consumption in climate change mitigation (Sadorsky, 2009). Besides, the Paris Agreement (United Nations Framework Convention on Climate Change, 2015) and the Kyoto Protocol (United Nations, 1998) encourage countries to use renewable energy sources to manage climate change. Therefore, the sources of renewable energy are considered as one of the primary factors of climate change mitigation policies, and climate change policies may have substantial effects on the oil market (Dike, 2014). While examining the associations between climate change, CO_2 emissions, energy consumption, and oil prices, linear impacts are generally considered, and to the best knowledge of this researcher, just quite a few studies exist which examine asymmetric or nonlinear associations among these factors. For example, a nonlinear relationship was found between renewable energy and oil prices for four oil-importing countries (Murshed and Tanha, 2021). However, linear models may not detect the asymmetric impact of uncertainty (Liang et al., 2020) and they might be overly restrictive and unrealistic, which causes unbiased consequences (Katrakilidis and Trachanas, 2012). In this direction, the current study is an attempt to find the dynamic and asymmetric relationship among the climate policy uncertainty (CPU), renewable energy consumption (REC), and oil prices (OPs) both in the long- and short-run horizon enabling to detect both the short-run and long-run shocks to OPs and REC on CPU. In light of the extant literature, the asymmetric impacts of OPs and REC on the CPU index are explored in the present study by performing a nonlinear autoregressive distributed lag (NARDL) technique introduced by Shin et al. (2014) for the U.S. The main reason for using this methodology is that both the asymmetric impacts of negative and positive shocks can be observed in the long- and short-run periods. Besides, ARDL models assume the linear and symmetric relationship among variables which might result in an unrealistic assumption. Thus, NARDL methodology presents flexible, nonlinear, and capable of simultaneously and coherently modeling asymmetries in a dynamic framework (Shin et al., 2014).

This study contributes to the extant literature in several aspects. First of all, it examines the cointegrating relation among CPU index, OPs, and REC for the U.S., which has not been investigated previously. Second, a nonlinear and dynamic approach (NARDL) is employed in detecting the cointegrating relationship between those variables, and the presence of asymmetric impacts was mainly revealed in the long-run. Last, both short- and long-run shocks of OPs and REC on CPU are mainly depicted.

The rest of the study proceeds in the following order. In the second section, background information about the climate policy uncertainty index and a summary of the relevant literature is presented. The third section depicts the data and the methodology. Last, the findings of the empirical analysis, the conclusion, and the discussion are reported.

1. Background Information of the CPU Index and Summary of Literature

Uncertainty refers to any divergence from the full determinism (Walker et al., 2003), and uncertainty itself has occurred when policymakers implement policies (Kurov and Stan, 2018). Governmental policies and regulations, economic developments, energy markets, and technological advances become gradually unpredictable, which leads to uncertainty in climate policies. Climate policy uncertainties may have serious effects on some sectors such as investments in low-carbon technologies in the long-run period (International Energy Agency, 2007). It also leads to short-term consequences such as fluctuations in electricity prices and the process of creating investment cycles. When these serious consequences of climate policy uncertainties are considered, it is very important to reveal the sources of climate policy uncertainty. The uncertainties of climate change stem from concerns about the potential physical damages of increased greenhouse gas concentrations in the atmosphere, as well as concerns about the expense of reducing gas emissions to reduce this accumulation (International Energy Agency, 2007). The two main components of climate system uncertainty are considered as the rise in greenhouse gas concentrations and the rate of heat at which the deep ocean absorbs (Forest et al., 2002). In this direction, it is of great importance of investigating the factors that affect the amount of greenhouse gas concentrations and temperature which ultimately affect climate policy uncertainty. Survey data results from 250 European firms reveal a positive relationship between uncertainty caused by climate policy regulation and a firm's decision to invest in reducing their ecological footprint (Lopez et al., 2017). In addition to survey data, the investigation related to climate policy uncertainty is scarce in the relevant literature. While the climate change policies have been mitigated, greenhouse gas emissions are required to be reduced (Intergovernmental Panel on Climate Change, 2007). Besides, renewable energy sources (RESs) are considered major drivers of climate change mitigation policies (Dike, 2014), and renewable energy technologies are mainly utilized to adapt and mitigate climate change (Suman, 2021). Since the main driver of global warming is cited as CO_2 emissions, there are serious attempts to decrease fossil fuel usage and increase REC to moderate the adverse effect of climate change (Sadorsky, 2009). The Federation of American Scientists (2021) declared that shifting to the sources of renewable energy like biofuels, wind, and solar are crucial in countering climate change. The linkage between environmental degradation and renewable energy has been discussed in several studies. The usage of renewable energy decreases greenhouse gas emissions in the atmosphere and reduces air pollution, which contributes to the natural environment (Surendra et al., 2011). Also, the efficiency of renewable energy in decreasing carbon emissions was mainly confirmed by utilizing the FMOLS technique (Saidi and Omri, 2020). The environmental impacts of various RESs were presented by utilizing a network-based environmental impact assessment method (Sebestyén, 2021). By employing a panel data approach, Bilgili et al. (2016) also found that REC reduced carbon emissions. As well as carbon emissions, ecological footprints were also considered to explain environmental degradation (Ulucak and Bilgili, 2018), and further, renewable energy should be considered as a driver of ecological footprints, which may highly affect the environmental viability (Sharma et al., 2021). Accordingly, a study conducted for eight developing countries of Asia demonstrated that renewable energy utilization reduced ecological footprints enhancing environmental quality (Sharma et al., 2021). Along with the environmental benefits of renewable energy sources, they may have certain economic and social aspects concerning public accessibility, increased economic profitability, and improvement in the standard of living (Czekała et al., 2021). On the other hand, there has also been discussed certain adverse environmental impacts of renewable energy utilization to mitigate climate change. Based on a life-cycle assessment approach, the related literature has been reviewed for the Finland case, and the impacts of several RESs such as wind power, hydropower, solar power, forest residues, biogas have been discussed (Sokka, 2016). The results of the study revealed that forest residue harvesting may negatively affect biodiversity. Another drawback of the utilization of renewable energy sources is considered the high investment costs of non-conventional energy production (Marks-Bielska et al., 2020).

Furthermore, the relationship between the energy policy uncertainty index and renewable energy investments was investigated, and significant increases and decreases were observed in the energy policy uncertainty index resulting from the changes in energy and emissions reduction policies (Burns, 2019). The study's findings also pointed out that as the level of uncertainty in energy policy increased, the level of renewable energy investments decreased indicating an inverse relationship between the energy policy uncertainty index and renewable energy investments in the U.S. Besides, a lead relationship was observed between the years 2010 and 2012.

Climate policy is also affected by oil prices since any shift in the oil prices results in a change in demand for oil and its substitutes, which affects carbon dioxide emissions. Therefore, uncertainty in oil prices is effective in forming climate policies (Torvanger et al., 2012). Federal Climate Policies deploy some tools developed by the U.S. federal government in mitigating climate change by reducing greenhouse gas emissions. In this context, they execute carbon pricing policies, technology and innovation subsidies, and performance standards in three main categories. Further, they take into account the Paris Agreement which is a globally binding consensus in which the countries are responsible for making an effort in the reduction of global warming (Newell, 2021). Climate policies formed in line with these goals may be affected by various factors, especially by energy-related variables. Thus, possible reasons for uncertainties that occurred in climate policies should be deeply investigated, and therefore, the linkage among carbon emissions, oil prices, renewable energy consumption, and climate policy uncertainty calls for further investigation. Gavriilidis (2021) applied an empirical procedure examining the associations between climate policy uncertainty and carbon dioxide emissions by using vector autoregression models, and the findings revealed that climate policy uncertainty strongly and negatively affects carbon dioxide emissions. The relationship between carbon intensity, which is an indicator of climate change mitigation, and crude oil prices are also examined. Mitigation policies for climate change are found to have substantial effects on oil prices, and the results suggest that carbon intensity positively affects crude oil prices for both short- and long-run periods (Dike, 2014). Additionally, policies of climate and negotiations for developed countries supported by the Kyoto Protocol may reduce the crude oil products consumption, causing a reduction in oil demand globally (Barnett et al., 2004). High oil prices may also have an impact on agents' actions concerning energy consumption, and high oil prices cannot be considered a substitute for efficient climate policy by using a computable general equilibrium model (Vielle and Viguier, 2007).

In several studies, a two-sided relationship was reported between OPs and RCE. A panel cointegration analysis revealed an inverse association between OPs and per capita REC. The findings of the study also suggest that real GDP per capita and CO_2 per capita are considered as the primary factors affecting REC. These findings are supported by utilizing panel cointegration analyses (Sadorsky, 2009). A nonlinear relationship was also observed between OPs and REC for four oil-importing countries by using the panel DOLS and FMOLS approaches (Murshed and Tanha, 2021). Further, the effects of OPs and CO_2 emissions on REC were tested by employing the VECMs and the Canonical Cointegrating Regression technique (Karacan et al., 2021). Their findings pointed out the negative impacts of oil prices on REC for the Russia case. Omri and Nguyen (2014) also reported that oil prices negatively affect REC. Several studies also provided empirical evidence supporting the positive impact of oil prices on REC. For example, since sources of renewable energy were considered substitutes for fossil fuels, an increase in crude oil prices leads to an increase in the prices of renewable energy sources (Ferrer et al., 2018). Also, Apergis and Payne (2014a, 2014b) found long-run cointegrating relationships between per capita REC and OPs by employing the linear and nonlinear panel models (Apergis and Payne, 2014a, 2014b).

2. Data and Methodology

2.1.Data

The monthly data set covers the period from January 2000 to March 2021 for all sample series. The Climate Policy Uncertainty (CPU) Index was developed by Gavriilidis (2021) based on the eight major U.S. newspapers. He scaled the number of mainstream articles published each month to the overall number of articles published that month by considering the terms such as uncertainty, climate change, greenhouse gas emissions, and global warming in these newspapers. Then, these eight series were standardized and normalized for the whole period. Renewable energy consumption data was retrieved from the U.S. Energy Information Administration. The data for crude oil prices was retrieved from West Texas Intermediate, and the natural logarithm of the series was utilized to satisfy the normality assumption. The publicly available data are utilized in this study and the sources of data series are reported in the footnote[1]

[1] https://www.eia.gov/totalenergy/data/monthly/
https://fred.stlouisfed.org/series/MCOILWTICO
https://www.policyuncertainty.com/climate_uncertainty.html

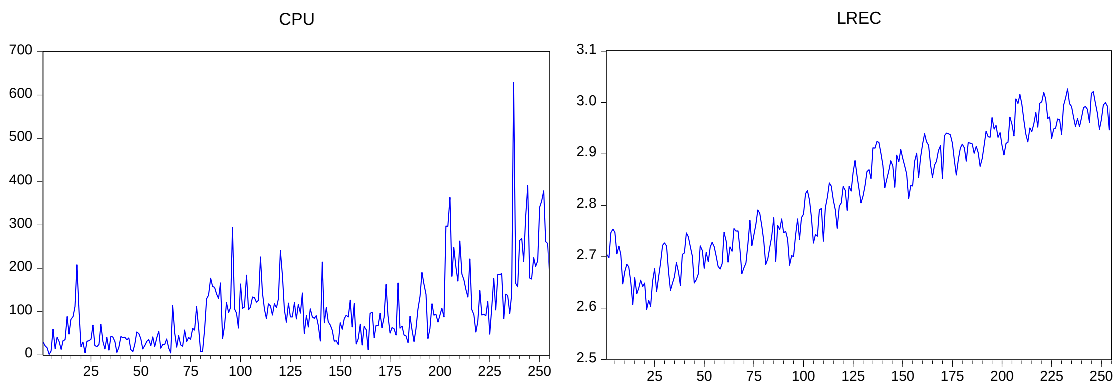
Table-1 reports the descriptive statistics for the corresponding variables in the data set. The data set consists of 255 observations. CPU refers to climate policy uncertainty index; LREC refers to the natural logarithm of renewable energy consumption; LOP refers to the natural logarithm of oil prices. Since CPU Index was previously normalized while it was developed, the natural logarithm of the series was not taken. The average value of the CPU index is approximately 100, while the mean of the LREC is 2.827, and LOP is 1.705.

Table-1. Descriptive Statistics

	CPU	LREC	LOP
Mean	100.001	2.827	1.705
Median	86.500	2.837	1.729
Maximum	629.020	3.037	2.107
Minimum	1.230	2.598	1.181
Std. Dev.	82.952	0.117	0.216
Skewness	2.028	-0.079	-0.305
Kurtosis	10.023	1.714	2.216
Jarque-Bera	698.801	17.826	10.481
Probability	0.000	0.000	0.005
Sum	25500.12	720.893	434.822
Sum Sq. Dev.	1747763	3.457	11.838

Note: The number of observations is 255. *CPU* denotes climate policy uncertainty index; *LREC* and *LOP* are the logarithmic forms of renewable energy consumption and oil prices, respectively.

Figure-1 depicts the historical values of the CPU index, LREC, and LOP. The figure reveals a trend in the data series, which will be analyzed in detail by using the unit root tests. While a steady increase can be observed in REC, the CPU index and OPs fluctuate.



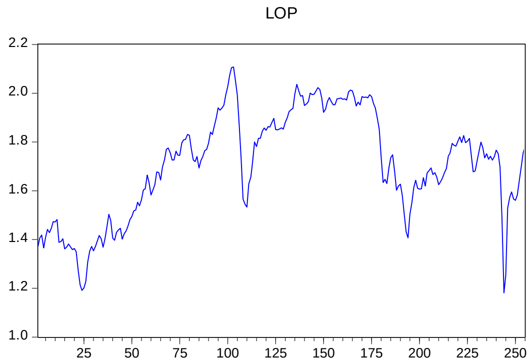


Figure-1. Historical CPU, LREC, and LOP

Linear and nonlinear ARDL models assume that the order of integration variables can be 0 or 1, but not integrated of order 2 suggested by Pesaran and Shin (1998) and Pesaran et al. (2001). In the linear and nonlinear ARDL methodology, the order of integration of series can be mixed, and the models work well even in small samples, which provides a distinct advantage (Ghatak and Siddiki, 2001). First, unit root tests are performed to explore the stationarity condition of the data series. Five-unit root tests are examined, which are Dickey and Fuller (1979) (ADF), Dickey and Fuller (1979) (DF-GLS), Phillips and Perron (1988) (PP), Kwiatkowski et al. (1992) (KPSS), and Ng and Perron's MZα (2001) (NPZa). The Akaike Information Criterion (AIC) was utilized to determine the optimal lag lengths. Table-2 and Table-3 indicate the unit root test results for levels and first differences with intercept and without intercept, respectively. The results suggest that all the data series are integrated of order 0 and 1, which are consistent with ARDL and NARDL models (Shin et al., 2014; Peseran and Shin, 1998).

Table-2. Unit Root Tests (Levels)

		ADF	DF_GLS	PP	KPSS	NPZa
		Stat.	Stat.	Stat.	Stat.	Stat.
CPU	Intercept	-1.288 (9)	-0.323 (9)	-7.877^{***}	1.242^{***}	-2.602
LREC		-0.654 (14)	0.999 (14)	-1.574	2.009^{***}	1.627
LOP		-2.383 (2)	-1.140 (2)	-2.308	0.704^{**}	-3.085
CPU	Intercept and Trend	-2.458 (9)	-2.492 (9)	-10.359^{***}	0.168^{**}	-43.818^{***}
LREC		-3.551^{**} (14)	-1.930 (14)	-7.084^{***}	0.168^{**}	-4.428
LOP		-2.411 (2)	-2.158 (2)	-2.302	0.404^{**}	-9.771

Lag lengths are determined by AIC. Superscripts ***, ** and * represent significance at 1%, 5%, and 10%, respectively.

Table-3. Unit Root Tests (First- Differences)

		ADF	DF_GLS	PP	KPSS	NPZa
		Stat.	Stat.	Stat.	Stat.	Stat.
CPU	Intercept	-7.840*** (8)	-2.354** (14)	-47.646***	0.037	-187.229***
LREC		-4.637*** (13)	-1.911* (14)	-40.302***	0.193	4.608***
LOP		-10.953*** (1)	-4.568*** (4)	-9.455***	0.081	-87.804***
CPU	Intercept and Trend	-7.851*** (8)	-2.198 (14)	-47.766***	0.037	-187.787***
LREC		-4.583*** (13)	0.262*** (14)	-41.883***	0.104	2.291***
LOP		-10.943*** (1)	-10.206*** (1)	-9.433***	0.040	-153.623***

Lag lengths are determined by AIC. Superscripts ***, ** and * represent significance at 1%, 5%, and 10%, respectively.

2.2.Methodology

ARDL models can detect the linear, and dynamic relationship among variables, which is a flexible approach enabling us to test if the variable is integrated of order 0 or 1. Further, the estimated coefficients are unbiased and efficient even for small sample sizes (Pesaran et.al., 2001; Pesaran and Shin, 2002). However, the linearity assumption of ARDL models can be unrealistic, and it cannot capture the asymmetric relationship between variables. The nonlinear autoregressive distributed lag (NARDL) approach is deployed to test the short-run and long-run asymmetric impacts and the cointegration relationships. The asymmetric relationship reveals whether negative or positive impacts of a variable differ in both the short- and long-run suggesting that the direction of asymmetry might shift between short and long-run periods. While a positive shock may have a higher impact in the short -run, a negative shock might have a higher impact in the long-run (Shin et al., 2014), which emphasizes the importance of a nonlinear approach. To account for this prospect, the current study employs the NARDL technique (Shin et al., 2014) to test the nonlinear and asymmetric associations among CPU, REC, and crude OPs, which relaxes the assumption of linearity assumed in ARDL models. Thus, negative and positive shocks can be detected both in the short-run and long-run. Also, the NARDL technique presents a dynamic framework that enables us to test simultaneously the asymmetric and nonlinear relationships between variables. In this direction, the long-run asymmetric relationship suggested by the NARDL model (Shin et al., 2014) is illustrated with the following equation;

$$Y_t = \beta^+ X_t^+ + \beta^- X_t^- + \varepsilon_t \tag{1}$$

where Y_t denotes the $k\ x\ 1$vector of CPU index at time t; β^+ and β^- denote the long-run asymmetric parameters; X_t indicates the $k\ x\ 1$ regressors' vector which can be expressed in the following equation;

$$X_{t=} X_0 + X_t^+ + X_t^- \qquad (2)$$

where X_0 refers to the initial value while X_t^+ and X_t^- denote the partial sum decompositions of positive and negative coefficients for the independent variables, respectively. X_t is defined by the following equations;

$$X_t^+ = \sum_{i=1}^{t} \Delta X_i^+ = \sum_{i=1}^{t} \max(\Delta X_i, 0) \qquad (3)$$

$$X_t^- = \sum_{i=1}^{t} \Delta X_i^- = \sum_{i=1}^{t} \min\,(\Delta X_i, 0) \qquad (4)$$

where ΔXi represents the changes in independent variables; the '+' and '−' signs denote the positive and negative shocks in the independent variables.

The short-run and long-run relationships between variables suggested by the NARDL model are demonstrated by the following equation, respectively;

$$\begin{aligned} \Delta CPU_t = \alpha + \omega CPU_{t-1} + \gamma_1^+ LREC_{t-1}^+ + \gamma_1^- LREC_{t-1}^- + \gamma_2^+ LOP_{t-1}^+ + \gamma_2^- LOP_{t-1}^- \\ + \sum_{i=1}^{p} \delta \Delta CPU_{t-i} + \sum_{i=1}^{q} \rho_1^+ \Delta LREC_{t-i}^+ + \sum_{i=1}^{q} \rho_1^- \Delta LREC_{t-i}^- + \sum_{i=1}^{q} \rho_2^+ \Delta LOP_{t-i}^+ \\ + \sum_{i=1}^{q} \rho_2^- \Delta LOP_{t-i}^- + \varepsilon_t \qquad (5) \end{aligned}$$

where p denotes the lag order for the dependent variable and q represents the lag order for explanatory variables. $LREC^+$, $LREC^-$, LOP^+, and LOP^- demonstrate the partial sum of positive and negative changes in renewable energy consumption and oil prices in the climate policy uncertainty index. The parameters of ω and γ_n indicate the long-run coefficients while the parameters of δ_n and ρ_n show the short-run coefficients.

The long-run ($\gamma^+ = \gamma^-$) and short-run ($\rho^+ = \rho^-$) asymmetries are tested by Wald Test (Shin et al., 2014) and the null hypotheses which assert that there is no asymmetric relationship between variables are tested for both short-run and long-run horizon.

3. Empirical Results

The Bound testing procedure is employed to test the asymmetric cointegration relationship between variables in the long-run period. The null hypothesis asserts that no asymmetric cointegrating relationship exists between corresponding variables. The rejection of the null leads to the conclusion that there are significant associations among variables. The Bounds test results indicate that there exists an asymmetric relationship among climate policy uncertainty, renewable energy consumption, and oil prices in the long-run when CPU is the dependent variable, which requires further exploration of the short-run and long-run associations among variables.

Table 4. Bounds Testing Procedure Results

Cointegration Hypotheses	F Statistics
F(CPU\LREC LOP)	**8.324*** **
F(LREC\CPU LOP)	**10.353*** **
F(LOP\LREC CPU)	**3.071**

Notes: Full sample. Lag length is 4, as suggested by the AIC. Superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Within the scope of the present study, the asymmetric impacts of REC and OPs on the climate policy uncertainty index are investigated, however, only the results of the estimated NARDL model when the dependent variable is the CPU index is reported. Table-5 illustrates the short-run and long-run parameters and their significance level. The results indicate that the CPU index is affected by both negative and positive changes in REC in the long run. Similarly, the CPU index is affected by both negative and positive changes in OPs in the long run. The presence of asymmetric relationships confirms the suitability of the data for the NARDL model. The NARDL estimation results indicate that a rise in REC increases climate policy uncertainty, while a reduction in REC also causes a rise in climate policy uncertainty for a long-run period. Accordingly, possible changes in REC may increase the uncertainty of climate change policies of the government. Positive shocks of REC triggers climate policy uncertainty. Similarly, negative shocks of REC also increase climate policy uncertainty. This result is partially supported by the study of Burns (2019) which has shown significant negative and lead relationships between energy policy uncertainty and renewable energy investment. Further, a rise in OPs causes an increase in climate policy uncertainty while a decrease in OPs leads to a reduction in the uncertainty in climate policy for the long-run period. Chen et al. (2019) support this result by asserting that there exists an asymmetry in oil price shocks by using a non-linear approach.

Table-5. Estimation Results of NARDL Model

Variable	Coefficient	Standard Error	t-statistics	Probability
Panel A: Asymmetric Parameters for Short-Run Coefficients				
C	-23.647	17.614	-1.343	0.181
CPU(-1)	-0.513	0.096	-5.312	0.000
DCPU(-1)	-0.180	0.069	-2.617	0.010
DCPU(-2)	-0.131	0.077	-1.694	0.092
DLREC_POS	-374.217	260.786	-1.435	0.153
DLREC_POS(-1)	465.407	228.716	2.035	0.043
DLREC_POS(-2)	-46.933	257.296	-0.182	0.855
DLREC_POS(-3)	729.621	198.852	3.669	0.000
DLREC_NEG	-256.612	257.965	-0.995	0.321
DLREC_NEG(-1)	286.707	265.393	1.080	0.281
DLREC_NEG(-2)	55.128	264.443	0.208	0.835
DLREC_NEG(-3)	-864.172	366.817	-2.356	0.019
DLOP_POS	-261.359	114.659	-2.279	0.024
DLOP_POS(-1)	-42.061	144.436	-0.291	0.771
DLOP_POS(-2)	-286.607	97.450	-2.941	0.004
Panel B: Asymmetric Parameters for Long-Run Coefficients				
LOP_NEG(-1)	-72.830^{***}	24.929	-2.921	***0.004***
LOP_POS(-1)	83.099^{**}	33.560	2.476	***0.014***
LREC_NEG(-1)	-341.813^{**}	163.723	-2.088	***0.038***
LREC_POS(-1)	-446.205^{***}	149.542	-2.984	***0.003***

Panel A represents the asymmetric parameters for the short-run coefficients. Panel B represents the asymmetric parameters for the long-run coefficients with positive and negative changes of the corresponding variables. Superscripts ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The adjusted R Square is 0.351.

Additionally, the Wald Test results confirm the short-run and the long-run asymmetric relationships among variables in Table-6. While the long-run asymmetrical relationship exists for REC and OPs on the CPU index; no significant asymmetrical relationship exists between variables in the short-run, which is an expected outcome in line with the findings in the previous literature. Moreover, since climate change is a long-term phenomenon, any impact on climate policy uncertainty is expected to occur in the long term.

Table-6. The Wald Test Results

Panel A: Short Run Asymmetry		
Dependent Variable	WSR(LREC)	WSR(LOP)
CPU	2.599	-
Panel B: Long Run Asymmetry		
Dependent Variable	WLR(LREC)	WLR(LOP)
CPU	5.111**	14.691***

WSR(LREC) and WSR(LOP) refer to the Wald test for the null of short-run symmetry for explanatory variables, respectively. WLR(LREC), and WLR(LOP) refer to the Wald test for the null of the additive long-run symmetry condition for explanatory variables, respectively. Superscripts ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Figure-2 demonstrates the impacts of positive and negative shocks in REC on climate policy uncertainty. The black lines show the cumulative adjustment pattern of REC. The asymmetry curve refers to (the dark red dotted line) the difference between the positive and negative shock of a dynamic multiplier of each independent variable. As indicated in the figure, the asymmetry curve is between upper and lower dotted red lines implying a long-run asymmetry at the 95 % significance level. Figure-3 demonstrates the impacts of positive and negative shocks in OPs on CPU. The black lines show the cumulative adjustment pattern of oil prices. The asymmetry curve refers to (the dark red dotted line) the difference between the positive and negative shock of a dynamic multiplier of each independent variable. As Figure-3 illustrates, the asymmetry curve is between upper and lower dotted red lines suggesting a long-run asymmetry at the 95 % significance level.

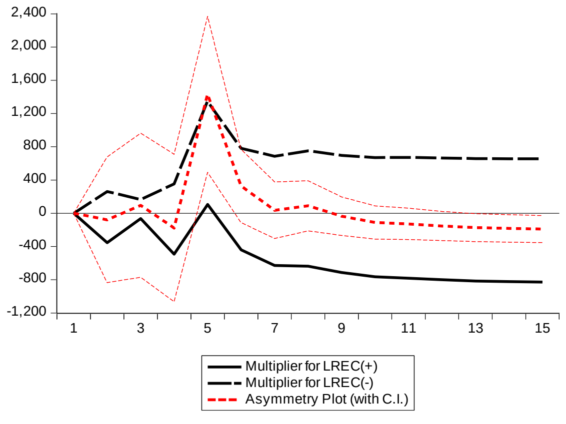


Figure-2. Dynamic Multiplier Graph for LREC

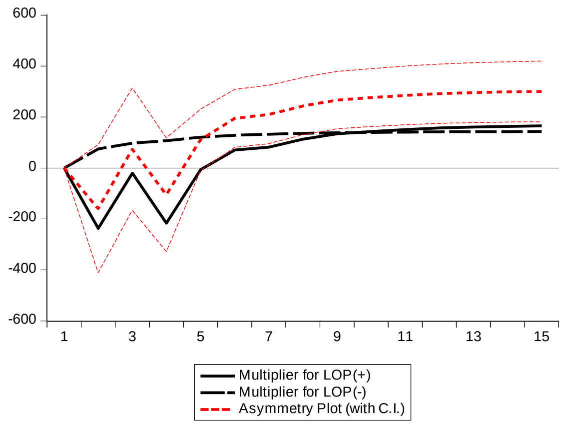


Figure-3. Dynamic Multiplier Graph for LOP

Diagnostic Test Results

Diagnostic tests are performed to check the robustness of the estimated model. Breusch-Godfrey Serial Correlation LM Test result (p >.05) asserts that there is no serial correlation, Breusch-Pagan-Godfrey Heteroscedasticity Test result (p > .05) indicates that there is no heteroscedasticity and Ramsey Reset Stability Test result (p > .05) suggests that the model is well specified.

Table-7. Residual Diagnostic Tests

Test	*F Statistics*	*p-value*
Breusch-Godfrey Serial Correlation LM Test	.628	.535
Breusch-Pagan-Godfrey Heteroscedasticity Test	.679	.831
Ramsey Reset Stability Test	.442	.507

4. Conclusion

This study explores the dynamic asymmetrical relationship between the climate policy uncertainty (CPU) index, renewable energy consumption (REC), and crude oil prices (OPs) for January 2000-March 2021 in the U.S. by using the NARDL cointegration methodology developed by Shin et al. (2014). As an advanced technique, the NARDL approach can capture the asymmetrical dynamic associations between variables, and it is an effective approach in transferring the positive and negative shocks in each explanatory variable to the dependent variable. The findings confirm that there exists an asymmetric relationship among CPU, REC, and OPs in the long run. CPU is affected by both negative and positive changes in REC and OPs in the long term. The NARDL estimation results imply that an increase in REC increases CPU, while a decrease in REC also causes a rise in CPU in the long term. Further, an increment in oil prices causes a rise in CPU while a reduction in OPs causes a decrease in the CPU in the long-run horizon. Although a long-run asymmetrical relationship is found among variables, no short-run asymmetric impacts could be confirmed. This finding may be attributable to the changes in climate policies that have occurred in the long-run period. The specific findings of the study offer useful insights to governmental bodies and policymakers in formulating appropriate strategies by taking the necessary climate change mitigation activities. This study also emphasizes the energy-related factors creating considerable changes in climate policy uncertainty, which investors in the energy sector should be seriously considered.

5. Discussion

Climate change has been considered a serious threat that should be globally mitigated. Mitigation of climate change has attracted the attention of policymakers and governments to take the necessary actions and examining the uncertainty in climate policies of countries has become of vital importance. Several countries have developed policies to mitigate the impact of climate change for a few decades by decreasing greenhouse gas emissions to reach a more sustainable future. Several European countries set achievable goals to decrease the effects of climate policy uncertainties by promoting the utilization of renewable energy, reduction of carbon emissions, and enhancing an energy efficiency approach in the investments. They also employ adaptation strategies on both the local and international basis, which comprises several areas such as agriculture, disaster risk reduction, ecosystems, and water management (European Environmental Agency, 2020). However, uncertainties exist by implementing these policies such as the withdrawal of the U.S. government from the Paris Accord in 2017 (Gavriilidis, 2021). No matter how governments try to mitigate the climate policy uncertainties, policy credibility which refers to that the policies are not altered during the period is urgently needed. Furthermore, national emission targets should be set for each sector such as transportation, agriculture, housing, and national targets for renewable energy utilization are also required. A legal framework should be promoted concerning safe carbon usage (European Environmental Agency, 2020). However, individual national governments do not have full control over policy credibility and it depends on the international actions of other governments and companies. Besides, a trade-off exists between flexibility and certainty of climate policies. While a flexible policy may capture the information concerning the developments in climate change, an uncertain policy poses a risk regarding the total costs of companies (International Energy Agency, 2007). Therefore, to mitigate climate policy uncertainty, worldwide action should be taken in which companies and governments are part of it.

References

Apergis, N., & Payne, J. E. (2014a). The causal dynamics between renewable energy, real GDP, emissions and oil prices: evidence from OECD countries. *Applied Economics*, 46(36), 4519-4525.

Apergis, N., & Payne, J. E. (2014b). Renewable energy, output, CO2 emissions, and fossil fuel prices in Central America: Evidence from a nonlinear panel smooth transition vector error correction model. *Energy Economics*, 42, 226-232.

Baker, S.R., Bloom, N. & Davis, S.J. (2016). Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, 131(4),1593-1636.

Barnett, J., Dessai, S., & Webber, M. (2004). Will OPEC lose from the Kyoto Protocol?. *Energy Policy*, 32(18), 2077-2088.

Bilgili, F., Koçak, E., & Bulut, Ü. (2016). The dynamic impact of renewable energy consumption on CO2 emissions: a revisited Environmental Kuznets Curve approach. *Renewable and Sustainable Energy Reviews*, 54, 838-845.

Burns, K. (2019). On the Relationship between Policy Uncertainty and Investment in Renewable Energy. In *IAEE Energy Forum Montr. Spec* (No. 2017, pp. 33-35).

Caldara, D. & Iacoviello, M. (2018). Measuring Geopolitical Risk. *International Finance Discussion Papers*, (1222).

Chen, J., Jin, F., Ouyang, G., Ouyang, J., & Wen, F. (2019). Oil price shocks, economic policy uncertainty and industrial economic growth in China. *PloS one*, *14*(5), e0215397.

Crimmins, A., J. Balbus, J.L. Gamble, C.B. Beard, J.E. Bell, D. Dodgen, R.J. Eisen, N. Fann, M.D. Hawkins, S.C. Herring, L. Jantarasami, D.M. Mills, S. Saha, M.C. Sarofim, J. Trtanj, and L. Ziska, 2016: Executive Summary. *The Impacts of Climate Change on Human Health in the United States: A Scientific Assessment.* U.S. Global Change Research Program, Washington, DC, page 1-24. http://dx.doi.org/10.7930/J00P0WXS.

Czekała, W., Tarkowski, F., & Pochwatka, P. (2021). Social aspects of energy production from renewable sources. *Problemy Ekorozwoju*, 16(1).

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427-431.

Dike, J. C. (2014). Does climate change mitigation activity affect crude oil prices? Evidence from dynamic panel model. *Journal of Energy*, 2014.

European Environmental Agency (2020). *Climate Change Policies.* https://www.eea.europa.eu/themes/climate/policy-context

Federation of American Scientists (2021). Countering Climate Change With Renewable Energy Technologies, By Lindsay Milliken, Tricia White and Michael A. Fisher, Science Policy, https://fas.org/blogs/sciencepolicy/countering-climate-change-with-renewable-energy-technologies/.

Ferrer, R., Shahzad, S. J. H., López, R., & Jareño, F. (2018). Time and frequency dynamics of connectedness between renewable energy stocks and crude oil prices. *Energy Economics*, 76, 1-20.

Forest, C. E., Stone, P. H., Sokolov, A. P., Allen, M. R., & Webster, M. D. (2002). Quantifying uncertainties in climate system properties with the use of recent climate observations. *Science*, *295*(5552), 113-117.

Gavriilidis, K. (2021). Measuring Climate Policy Uncertainty. Available at SSRN: https://ssrn.com/abstract=3847388.

Ghatak, S., & Siddiki, J. U. (2001). The use of the ARDL approach in estimating virtual exchange rates in India. *Journal of Applied Statistics*, 28(5), 573-583.

International Energy Agency (2007). *Climate Policy Uncertainty and Investment Risk.* IEA/OECD: Paris.

Intergovernmental Panel on Climate Change (2007). *Contribution of Working Group III to the Fourth Assessment Report,* Cambridge University Press, Cambridge, UK.

Karacan, R., Mukhtarov, S., Barış, İ., İşleyen, A., & Yardımcı, M. E. (2021). The Impact of Oil Price on Transition toward Renewable Energy Consumption? Evidence from Russia. *Energies,* 14(10), 2947.

Katrakilidis, C. & E. Trachanas (2012). What Drives Housing Price Dynamics in Greece: New Evidence from Asymmetric ARDL Cointegration, *Economic Modelling*, 29, 1064-1069.

Kurov, A., & Stan, R. (2018). Monetary policy uncertainty and the market reaction to macroeconomic news. *Journal of Banking & Finance*, 86, 127-142.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., & Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?. *Journal of Econometrics*, *54*(1-3), 159-178.

Liang, C.C. & C. Troy & E. Rouyer (2020). U.S. Uncertainty and Asian Stock Prices: Evidence from the Asymmetric NARDL Model. *The North American Journal of Economics and Finance,* 51, 101046.

Lopez, J. M. R., Sakhel, A., & Busch, T. (2017). Corporate investments and environmental regulation: The role of regulatory uncertainty, regulation-induced uncertainty, and investment history. *European Management Journal,* 35(1), 91-101.

Lou, J., Wu, Y., Liu, P., Kota, S. H., & Huang, L. (2019). Health effects of climate change through temperature and air pollution. *Current Pollution Reports*, *5*(3), 144-158.

Marks-Bielska, R., Bielski, S., Pik, K., & Kurowska, K. (2020). The importance of renewable energy sources in Poland's energy mix. *Energies*, 13(18), 4624.

Murshed, M., & Tanha, M. M. (2021). Oil price shocks and renewable energy transition: Empirical evidence from net oil-importing South Asian economies. *Energy, Ecology and Environment*, 6, 183-203.

Newell, R. G. (2021). Federal Climate Policy 101: Reducing Emissions. 207th issue of Resources magazine.

Ng, S., & Perron, P. (2001). Lag length selection and the construction of unit root tests with good size and power. *Econometrica*, *69*(6), 1519-1554.

Omri, A., & Nguyen, D. K. (2014). On the determinants of renewable energy consumption: International evidence. *Energy,* 72, 554-560.

Pesaran, M. H., & Shin, Y. (1998). An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis. *Econometric Society Monographs*, 31, 371-413.

Pesaran, M. H., & Shin, Y. (2002). Long-run structural modelling. *Econometric Reviews,* 21(1), 49-87.

Pesaran, M. H., Shin, Y., & Smith, R. J. (2001). Bounds testing approaches to the analysis of level relationships. *Journal of Applied Econometrics*, 16(3), 289-326.

Phillips, P. C., & Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2), 335-346.

Sadorsky, P. (2009). Renewable energy consumption, CO2 emissions and oil prices in the G7 countries. *Energy Economics,* 31(3), 456-462.

Saidi, K., & Omri, A. (2020). The impact of renewable energy on carbon emissions and economic growth in 15 major renewable energy-consuming countries. *Environmental Research*, 186, 109567.

Sebestyén, V. (2021). Renewable and Sustainable Energy Reviews: Environmental impact networks of renewable energy power plants. *Renewable and Sustainable Energy Reviews*, *151*, 111626.

Sharma, R., Sinha, A., & Kautish, P. (2021). Does renewable energy consumption reduce ecological footprint? Evidence from eight developing countries of Asia. *Journal of Cleaner Production*, *285*, 124867.

Shin, Y. & B. Yu & M. Greenwood-Nimmo (2014), "Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ARDL framework", in: *Festschrift in Honor of Peter Schmidt,* Springer, New York, NY, 281-314.

Sokka, L., Sinkko, T., Holma, A., Manninen, K., Pasanen, K., Rantala, M., & Leskinen, P. (2016). Environmental impacts of the national renewable energy targets–A case study from Finland. *Renewable and Sustainable Energy Reviews*, 59, 1599-1610.

Suman, A. (2021). Role of renewable energy technologies in climate change adaptation and mitigation: A brief review from Nepal. *Renewable and Sustainable Energy Reviews*, 151, 111524.

Surendra, K. C., Khanal, S. K., Shrestha, P., & Lamsal, B. (2011). Current status of renewable energy in Nepal: Opportunities and challenges. *Renewable and Sustainable Energy Reviews*, *15*(8), 4107-4117.

Torvanger, A., Kallbekken, S., & Tollefsen, P. (2012). Oil price scenarios and climate policy: welfare effects of including transportation in the E.U. emissions trading system. *Mitigation and Adaptation Strategies for Global Change*, 17(7), 753-768.

U.S. Environmental Protection Agency (2017). Future of Climate Change. https://19january2017snapshot.epa.gov/climate-change-science/future-climate-change_.html

Ulucak, R., & Bilgili, F. (2018). A reinvestigation of EKC model by ecological footprint measurement for high, middle and low income countries. *Journal of Cleaner Production*, 188, 144-157.

United Nations (1998). Kyoto protocol to the united nations framework convention on climate change. https://unfccc.int/resource/docs/convkp/kpeng.pdf.

United Nations (2021). What is Climate Change? https://www.un.org/en/climatechange/what-is-climate-change

United Nations Framework Convention on Climate Change, V. (2015). Adoption of the Paris agreement. Proposal by the President. https://unfccc.int/sites/default/files/english_paris_agreement.pdf.

Vielle, M., & Viguier, L. (2007). On the climate change effects of high oil prices. *Energy Policy*, 35(2), 844-849.

Walker, W. E., Harremoës, P., Rotmans, J., Van Der Sluijs, J. P., Van Asselt, M. B., Janssen, P., & Krayer von Krauss, M. P. (2003). Defining uncertainty: a conceptual basis for uncertainty management in model-based decision support. *Integrated Assessment*, 4(1), 5-17.