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The impact of climate policy uncertainty on renewable and non-renewable energy demand in the United States

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A R T I C L E I N F O

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A B S T R A C T

This paper evaluates the impact of climate policy uncertainty on renewable and non-renewable energy consumption in the United States over the quarterly data from 2000Q1 to 2021Q3. Economic growth and crude oil prices are added to the energy consumption functions as control variables. The paper considers several approaches to model both renewable and non-renewable energy demand. It is found that crude oil prices promote non-renewable energy demand and climate policy uncertainty reduces it. Surprisingly, the impact of economic growth on non-renewable energy consumption is positive but insignificant. It is also observed that economic growth promotes renewable energy demand, and crude oil prices reduce it. Furthermore, climate policy uncertainty positively affects renewable energy demand in the long run. Some policy implications are provided for reducing non-renewable energy consumption and promoting renewable energy use in the United States through climate policy implementation.

1. Introduction

Climate change is one of the leading problems in the 21st century. Scholars have demonstrated that risks and uncertainties related to climate change can affect various dimensions of the global economic system [1,2]. Climate change is attributed to global warming, environmental pollution, and caused by greenhouse gas emissions. Also, CO_2 emissions are driven by fossil fuels and non-renewable energy sources [3,4]. Therefore, the transition from fossil fuels to green renewable energy is an important policy tool to transfer economies to the low carbon economy. It is suggested that higher renewable energy consumption can slow down the negative consequences of climate change on the economic system [5,6]. Similarly [7], argued that promoting renewable energy usage in consumption and production activities can also reduce the adverse impact of climate change and global warming on living human beings and natural habitats in the long run. Therefore, the determinants of the non-renewable and renewable energy demand are crucial for designing climate change policies in developing and developed economies.

Since the early 1990s, the transformation from non-renewable to renewable energy has increased in advanced countries and some developing economies. This transformation to renewable and other alternative energy sources has four aspects. The first reason is the progress in technology, and the costs of new investments in energy sources have been significantly reduced [8–10]. The second issue is governments' renewable energy supporting policies (e.g., defining portfolio standards, providing cheaper credits and tax benefits on renewable energy investments) [11–13]. The third aspect is the climate change crisis. Negative outcomes of climate change are related to greenhouse gas emissions. Fossil fuels (non-renewable energy sources) increase greenhouse gas emissions. In other words, renewable energy sources can decrease greenhouse gas emissions, favouring the slowdown of climate change [14–16]. Finally, the price volatility in crude oil due to the geopolitical risks and market uncertainty has increased the interest in alternative energy sources [17,18].

Given this backdrop, this paper analyses the determinants of the non-

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renewable and renewable energy demand. The paper focuses on the quarterly 21st century data of the largest CO_2 emitter economy in the World, i.e., the United States, from 2000Q1 to 2021Q3. Note that the United States is also the largest primary energy consumer in the World, with a share of 15.8% in 2020, and the share of CO_2 emission is 13.8% in 2020 [19]. The country's electricity generation from renewable energy is increasing yearly, and this transformation in the energy mix decreases carbon dioxide emissions [61]. Despite this effort, Fig. 1 shows that the carbon emissions are increasing in the United States compared to other emerging economies of the World from 2012 to 2018.

The United States economy is chosen for our analysis because it is one of the advanced economies where fossil fuel consumption per capita is 60,167 kWh in 2020, keeping the United States as the number one country, followed by China is 23,674 kWh (4th), and India is 5, 7888 kWh (9th).[1] It shows that the economy like the United States is lagging behind other growing countries in increasing renewable energy investment and reducing fossil fuel consumption and carbon emissions. Moreover, renewable energy investment as % of gross domestic product (GDP) in 2015 was 0.2% for the United States, which is much lower than other emerging countries, i.e. South Africa (1.4%), China (0.9%), India (0.5%), and Brazil (0.4%). Therefore, when the World is facing the threat of climate change and global warming, our study is timing one and motivates us to explore the determinants of non-renewable and renewable energy demand for the United States so that better climate change mitigating policy could be designed for sustainable environment in long-run.

This paper uses a new potential energy demand driver, i.e., the index of climate policy uncertainty introduced by Ref. [20]. The Climate Policy Uncertainty index is similar to the Economic Policy Uncertainty index. Precisely, it measures the changes in government policies on environmental issues (e.g., changes in subsidiaries and tax regulations). The policy changes can create uncertainties that can delay consumption and investment decisions by consumers and firms. For example, uncertainty about subsidiaries and tax regulations can create extra costs for the firms. Therefore, climate policy uncertainty can affect firms by delaying or postponing investments and reducing economic output. The possible changes in energy consumption and investments can also affect economic performance [21].

As we discuss in the next section, few papers in the empirical literature consider the determinants of renewable energy demand in the United States [22]; Schumacher and [23]; Yang, 2018) but ignores the role of Climate Policy Uncertainty index of [20] on non-renewable and renewable energy demand. However, to the best of our knowledge, there is no paper in the literature to consider the Climate Policy Uncertainty index of [20] in the renewable and non-renewable energy demand functions for the United States. This paper contributes to the empirical literature by using the climate policy uncertainty index as a new measure of environmental policy or regulation affecting non-renewable and renewable energy demand. Both economic growth and oil price are included in renewable and non-renewable energy demand functions as control variables, following the existing studies (Sadosrky et al., 2009a, 2009b; [7,24–26]. The paper uses various time-series techniques to focus on the case of the United States with the quarterly data from 2000Q1 to 2021Q3. The paper shows that climate policy uncertainty reduces non-renewable energy demand. Furthermore, climate policy uncertainty positively affects renewable energy demand in the long run. Therefore, climate policy uncertainty is crucial in changing the energy demand in the United States economy in the long run. This evidence is reflected in Fig. 2 & 3, where one can see the long-run relation between the climate policy uncertainty and the pattern of non-renewable and non-renewable energy demand in the United States. Interestingly, the relationship between climate policy uncertainty and renewable energy consumption appears close to that between non-renewable energy consumption and climate policy uncertainty in the United States. This issue is another motivation for us to understand whether climate policy uncertainty equally promotes the renewable and non-renewable energy demand in the United States.

The rest of the paper is organized as follows. Section 2 reviews the previous papers in the empirical literature for the determinants of energy demand and the impact of climate change uncertainty on energy variables. Section 3 explains the details of the data and the methodology. Section 4 discusses the empirical results and their implications. Section 5 highlights policy implications. Section 6 concludes with evaluates limitations and future research.

2. Literature review

2.1. Determinants of energy demand

There are various papers to analyse the determinants of energy demand. Among the earliest studies [17], examines the determinants of renewable energy in the G7 countries and finds that per capita income and CO2 emissions increase renewable energy, but oil price harms it. In a further study [18], illustrates that the per capita income positively relates to renewable energy in 18 emerging economies. However, [24]; using the panel technique for 24 European countries, found that income level and carbon dioxide emissions are the important drivers of renewable energy demand. Their findings indicate that European countries can reduce their dependence on fossil fuels (i.e. coal, oil, and natural gas) if they can invest more in renewable energy deployment with the increased income level support.

[25] observe the impacts of income, carbon dioxide emissions and crude oil price on renewable energy consumption in six major emerging economies (i.e. Brazil, China, India, Indonesia, Philippines, and Turkey). They indicate that the crude oil price is the main determinant of the renewable energy demand in China and Indonesia, where oil price reduces the adoption of clean energy. They also find the positive impact of per capita income on renewable energy demand in all six emerging economies, while pollutant emissions increase the renewable energy in Brazil, China, India, and Indonesia). Their findings provide valuable insights for emerging economies to reduce carbon intensity by improving the share of renewable energy in the primary energy mix [26]. investigate the drivers of renewable energy demand in 64 countries from 1990 to 2011. They find that income level and carbon emissions positively and significantly impact renewable energy demand, whereas oil prices harm it.

Similarly [27], study the determinants of renewable energy demand in 38 countries. Carbon emissions and income levels are significant drivers of renewable energy growth. [22]; using 1990–2008 state-level panel data for the United States' electricity market, studied the reasons for the development of renewable energy and found that promoting renewable energy projects as a potential job creator is one of the main drivers of renewable energy projects. Lin and Moubarak [60] show that economic output and financial development positively affect renewable electricity consumption, while trade openness, FDI inflows and traditional energy lobby activities reduce it in China.

Meanwhile [28], indicate that domestic and foreign capitals promote clean energy use in the EU, the G20, and the OECD countries from 1993 to 2012. [29]; using China's regional data, finds that economic development enhances renewable energy production [30]. shows that economic freedom positively affects renewable energy demand in 28 member states. Schumacher and Yang [31], using the state-level data in the United States, find that financial incentives and regulatory measures are weak indicators of wind energy growth [7]. indicate that economic globalization increases the renewable energy demand in the panel dataset of 30 OECD countries from 1970 to 2015. They further indicate the positive effects of per capita income, oil price and per capita carbon emissions on renewable energy for a sample of 30 OECD economies. Their findings provide insightful insights for advanced economies where

[1] https://ourworldindata.org/grapher/fossil-fuels-per-capita.

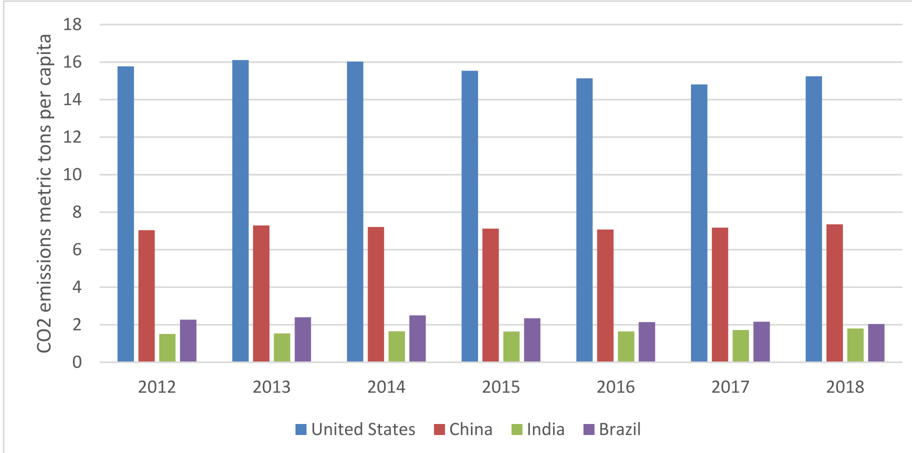

Fig. 1. The trend of CO_2 emissions per capita in the United States, India, China, and Brazil.

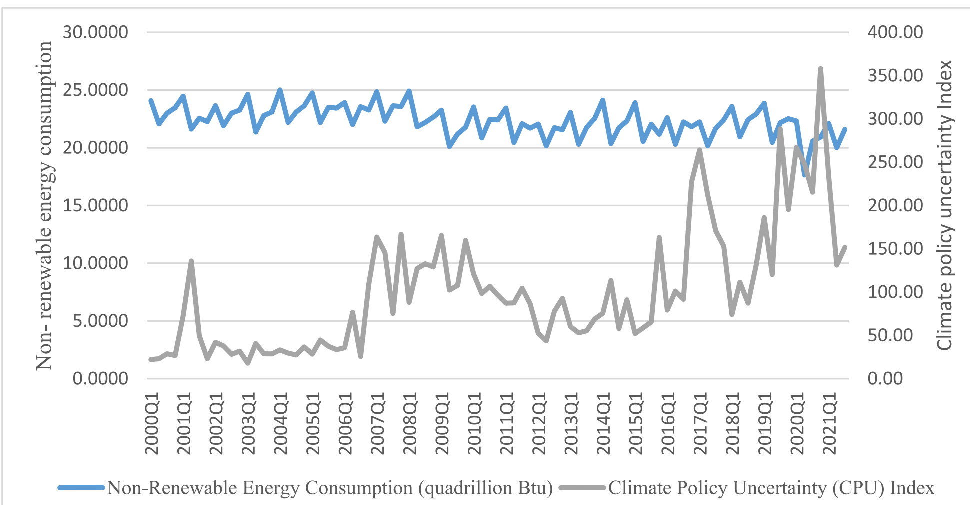

Fig. 2. The trend of non-renewable energy consumption and climate policy uncertainty in the United States.

they can improve the quality of the natural environment by increasing the share of renewable energy in the total primary energy mix with the help of income generation and increased oil price.

In addition [32], studied the determinants of renewable energy consumption using the panel data from 1995 to 2015 for a sample of 97 countries. They find that in countries where better democratic rights of the people are preserved, higher economic growth increases the use of renewable energy and vice-versa for less democratic countries. They also find that real oil prices induce renewable energy demand in less democratic countries and play no significant role in more democratic countries. Their findings show that democratic institutions are crucial in channelling economic growth to renewable energy [33]. examine the determinants of the energy demand in the panel dataset of 25 OECD economies from 1978 to 2016. The authors utilised various panel data estimation techniques and observed that real per capita income increases the energy demand. In addition, real energy prices and economic complexity decrease the energy demand. The authors conclude that technological progress measured by economic complexity decreases the necessity of energy consumption [34]. analyse the effects of age dependency and urbanisation on renewable and non-renewable energy consumption in Brazil, India, China, and South Africa from 1990 to 2019. The authors observe that age dependency ratios and urbanisation reduce the renewable and non-renewable energy demand. However, economic growth promotes renewable and non-renewable energy demand. It is also found that globalisation (measured by FDI) has a mixed impact on inflows on energy demand in the related economies.

[23]; using the annual data from 1990 to 2020 for the United States, study the drivers of energy efficiency. They find that investment in renewable energy sources benefits energy efficiency, while industrial production, trade openness and financial inclusion improve it. [35]; using the panel data from 1993 to 2018 for a sample of 20 OECD countries, examine the role of energy prices and economic growth in renewable energy capacity expansion. They indicate economic growth and coal oil prices drive renewable energy capacity development. They also find the positive impact of natural gas prices on renewable energy capacity. Also, they found a positive impact of coal oil price on renewable energy capacity development than the price of natural gas. Their findings suggest having a quick transition to renewable energy through price effect, which is key to sustainable development [36]. studied the impact of higher oil prices, carbon emissions, and income on renewable energy consumption in resource-rich countries like Iran from 1980 to 2019. They indicate that oil price and carbon emissions have significant and negative impacts on renewable energy consumption, while income does not significantly impact it.

Few papers have considered uncertainty measures as a possible driver of the energy demand [37–39]. For instance Ref. [37], examine

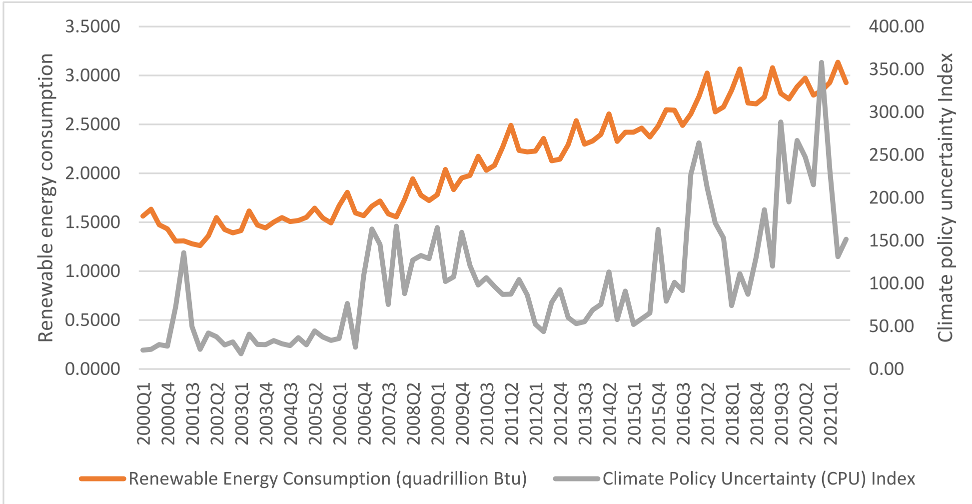

Fig. 3. The trend of renewable energy consumption and climate policy uncertainty in the United States.

the impact of economic policy uncertainty (EPU) on renewable energy consumption in the USA using the monthly data from 1986 to 2019. They find that higher economic policy uncertainty lowers renewable energy consumption and vice-versa [38]. studies the asymmetric impact of policy-induced uncertainty on renewable energy consumption in G7 countries from 1997 to 2019. As control variables, income, institutions, and innovation are included in renewable energy consumption. The non-linear autoregressive lag model results indicate that both a negative and a positive shock in lagged policy uncertainty reduce renewable energy consumption in the long run. It shows that policy uncertainty is also a significant driver of renewable energy demand but not asymmetric in the short run. It is further found that income and investment in research & development drive renewable energy consumption in the long run. Their findings suggested promoting renewable energy use by reducing policy uncertainty and improving technological advances from a policy perspective.

Similarly [39], investigate the impact of the EPU on the per capita energy consumption in a panel dataset of 72 developing and developed economies from 1960 to 2016. The novel finding of the paper is that the EPU spurs energy consumption. Several econometric methods show that per income increases energy demand, but energy prices reduce it. These findings are robust enough to utilize different econometric techniques and exclude various countries from the dataset.

2.2. *Effects of climate policy uncertainty measure on energy and environmental pollution indicators*

The index of Climate Policy Uncertainty is a new indicator to measure changes in environmental policies, particularly in the United States. It may also measure the level of technology uncertainty related to environmental pollution. There are a few papers in the empirical literature for using the Climate Policy Uncertainty index of [20] on energy and environmental pollution indicators. For instance Ref. [40], investigate the impact of climate policy uncertainty of [20] on the return performances of brown and green energy stocks. It is observed that the index of climate policy uncertainty increases the returns of green stocks compared to brown stocks, especially during crisis periods.

[41] show the significant effects of the indices of the Economic Policy Uncertainty in China and Climate Policy Uncertainty of [20] on the price volatility of the Wind Carbon-Neutral Concept (CNCI) index. The Climate Policy Uncertainty has a higher forecast ability for the CNCI values during volatile market times [42]. investigates the impact of the index of the Climate Policy Uncertainty on Research and Development (R&D) investments of various firms in the United States from 2000 to 2019. There is a significant positive impact of the Climate Policy Uncertainty on the R&D investments of firms in general. However, the Climate Policy Uncertainty harms the R&D investments of heavy-emitter firms in the United States. [43]; using the monthly data from January 1988 to August 2017, study the impact of global energy market uncertainty and economic policy uncertainty on oil prices. They find that oil price variation is primarily contributed by the energy market uncertainty shock than the economic policy uncertainty shock following 12 months. It clearly shows that since oil price changes respond more to the energy market uncertainty, consumers and producers need to consider the shock coming from the energy market uncertainty before buying the oil from the open market. Otherwise, non-renewable energy consumers and producers will pay more to mitigate their consumption and production activities while buying the oil needed. Their findings also provide valuable insights into the policymakers' need to consider different types of uncertainty in the energy demand framework.

Overall, reviewing the existing studies indicates that there are various papers on the determinants of energy demand (Sadosrky et al., 2009a, 2009b; [7,24–26,35–39], but there are a few papers [40–42] in the empirical literature to consider the role of Climate Policy Uncertainty index of [20] on green stocks and innovation. This paper contributes to the empirical literature by using this new measure as a potential determinant of the non-renewable and renewable energy demand in the United States, with the quarterly data spanning from 2000Q1 to 2021Q3. The climate policy uncertainty reduces non-renewable energy demand. Moreover, the climate policy uncertainty positively affects renewable energy demand in the long run.

3. Data and methodology

3.1. *Data*

The paper focuses on the United States economy over the quarterly data from 2000Q1 to 2021Q3. The quarterly data period from 2000Q1 to 2021Q3 was chosen. Note that climate policy uncertainty data are only available for the United States. The quarterly data with a higher frequency enables us to effectively understand the relationships between the variables. Moreover, quarterly information increases the sample size and captures the significant policy changes in domestic and globalized countries related to mitigating climate change and achieving energy conservation [44].

The dependent variable is the source's primary energy consumption (quadrillion Btu). We divide primary energy consumption into non-renewable energy (*Non-REC*) and renewable energy consumption

(*REC*). The related data are downloaded from the US Energy Information Administration [62].

We use two control variables. The first captures the income effect on the energy demand: gross domestic product (GDP) per capita in the USD with the seasonally-adjusted annual rate (*LNGDPC*). Secondly, we control the price effect, measured by crude oil prices, based on the West Texas Intermediate (*WTI*)-Cushing, Oklahoma, USD per barrel. These data are obtained from the St. Louis Fed [45].

The main variable of interest is the United States Climate Policy Uncertainty (CPU) index introduced by Ref. [20]. Following the methodology of the economic policy uncertainty (EPU) index of Baker et al. (2016) [20], constructs the CPU index by searching words in eight leading United States, such as "uncertainty", "carbon dioxide", "climate risk", "greenhouse gas emissions", "CO_2 emissions" "global warming", "climate change", "green energy", "renewable energy" or "environmental", including the variants such as "uncertainties", "regulatory", "policies". These eight series are standardised to have a unit standard deviation and then averaged across newspapers by the period. Finally, the averaged series are normalised to have a mean value of 100 for the corresponding period under concern [20]. scales the number of relevant articles per month with each newspaper's total number of articles. The CPU index data are downloaded from the website https://www.policyuncertainty.com/climate_uncertainty.html.

Since we use the quarterly data for the United States, it is important to check the seasonality of the variables. Except for real GDP per capita, all remaining variables (i.e. NON-REC, REC, WTI, and CPU) possess seasonality in the data series. The seasonality present in the data series is adjusted with the help of additive and multiplicative decompositions. The seasonality adjusted series are considered for our empirical modelling. However, the values of other variables are small, have minimal variation and are highly predictable, which is not the case for real GDP per capita. Therefore, we use the natural logarithm to real GDP per capita to reduce skewness and bring homogeneity in data series values [44].

3.2. Conceptual framework

Existing studies identify various determinants of energy demand (Sadosrky et al., 2009a, 2009b; [7,24–26,35–39]. The results are inconclusive due to the missing important factors in energy demand modelling. Therefore, the key purpose of this analysis is to investigate the effects of climate policy uncertainty on renewable and non-renewable energy in the United States by controlling the economic growth and crude oil prices. Adding economic growth and crude oil prices in modelling renewable and non-renewable energy consumption helps us avoid omitted variable bias. To do so, we have employed the following equations for the United States economy within time series estimations:

$$NON-REC_t = f(\mathrm{LNGDPC}_t,\ WTI_t,\ CPU_t) \tag{1}$$

$$REC_t = f(\mathrm{LNGDPC}_t,\ WTI_t,\ CPU_t) \tag{2}$$

where $NON-REC_t$ and REC_t stand for non-renewable energy consumption and renewable energy consumption at period t. LNGDPC_t measures real GDP per capita used as a proxy for income level. WTI_t refers to the West Texas Intermediate used as a proxy for crude oil prices. CPU_t stands for climate policy uncertainty index. It is also essential for someone to understand the effects of income, crude oil price, and climate policy uncertainty on non-renewable and renewable energy consumption. Income can drive the demand for non-renewable and renewable energy. One can argue that the rising income of the people can enable them to buy renewable and non-renewable energy from the open energy market because it is required to carry out their consumption and production activities. Thus, we hypothesize that the higher the income, the higher the renewable and non-renewable energy demand. Crude oil price is also another determinant of non-renewable and renewable energy demand. Crude oil prices can increase the demand for non-renewable energy if renewable energy price becomes expensive for the people in the open energy market. In addition, crude oil prices can reduce renewable energy consumption if the government provides oil subsidies to cover the cost of oil producers and consumers. Finally, climate policy uncertainty can reduce the demand for non-renewable energy. As we know, producers often want profit maximization at the cost of the natural environment. Such a situation calls for stringent environmental regulation imposed on the producers if they use dirty energy in their business, which generates pollution and threatens the balance of the eco-system. Therefore, a strict climate change mitigating policy can reduce the non-renewable energy demand. Also, stringent climate change policy can increase the demand for renewable energy. This issue is because people want to escape the pollution tax imposition under the climate policy regulation. One can conclude that climate policy uncertainty is the crucial determinant of non-renewable and renewable energy demand.

Since we aim to understand renewable and non-renewable energy consumption determinants, we have created separate energy consumption Models (Model1 & Model2) for our empirical setting. To be used for empirical estimation, Equations (1) and (2) are converted to econometric format in the form of intercept, the coefficients and error terms as specified in Eq. (3) and Eq. (4). Equations (3) and (4) indicate that variables are in a semi-logarithm form where the real GDP per capita is only converted into the logarithm. The data converted to their natural logarithm form reduces the skewed distribution of the variables and enables us to get the best estimates of the renewable and non-renewable energy consumption modelling.

$$Model\ 1:\ NON-REC_t = \alpha_1 + \alpha_2\mathrm{LNGDPC}_t + \alpha_3 WTI_t + \alpha_4 CPU_t + \varepsilon_{1t} \tag{3}$$

$$Model\ 2:\ REC_t = \alpha_1 + \alpha_2\mathrm{LNGDPC}_t + \alpha_3 WTI_t + \alpha_4 CPU_t + \varepsilon_{2t} \tag{4}$$

In Model1, ε_{1t} is the error term with the satisfying property of the normal distribution and $\alpha_1, \alpha_2, \alpha_3, \alpha_4$ are the intercept, coefficients of real economic growth, crude oil prices, and climate policy uncertainty. A similar interpretation also applies to Model2. However, *LN* is the natural log taken for real GDP per capita to reduce the skewness in data series values.

3.3. Econometric procedures

3.3.1. Unit root tests

In time series analysis, preventing the problem of spurious regression is essential [46]. Hence, the unit root was examined first with the help of Augmented Dickey and Fuller (ADF) [47] and the Phillips and Perron (PP) [48] tests. We account for the criticism levied at both tests regarding their size vulnerability, poor strength and incapacity to consider breaks in the series. The used variables have been further applied to a structural break test proposed by Ref. [49] to capture the structural changes arising in the data series. The linear Autoregressive Distributed Lag (ARDL) model accommodates a single structural break occurring in the data series. The method can also avoid the endogeneity arising from the link between independent variables and error terms while estimating the carbon dioxide emissions models.

3.3.2. ARDL model

This study uses the ARDL bound test [50,51] to investigate the presence of long-term cointegration among the variables. The significant benefits of the ARDL bound testing approach over other cointegration approaches, such as [52]; are that it does not really place any constraint on data of any type and also estimates the energy demand models in the presence of mixed order of integration, i.e. I (1) or I (0). The usage of this model can be handicapped if the series are found to be integrated at I(2). It is also an ideal model for small size samples and addresses the issue of endogeneity associated with the linkage between independent variables and the error term.

The ARDL bounds testing approach's unrestricted error correction models (UECM) for the first model shown in above Eq. (3) and Eq. (4) can also be defined in Eq. (5):

$$\Delta NON-REC_t = \theta_1 + \theta_2 \mathrm{LNGDPC}_{t-1} + \theta_3 WTI_{t-1} + \theta_4 CPU_{t-1} + \sum_{i=1}^{p} \alpha_{2i} \Delta NON-REC_{t-i} + \sum_{i=0}^{m} \alpha_{3i} \Delta \mathrm{LNGDPC}_{t-i} + \sum_{i=0}^{n} \alpha_{4i} \Delta WTI_{t-i} + \sum_{i=0}^{k} \alpha_{5i} \Delta CPU_{t-i} + \varepsilon_{1t} \quad (5)$$

where Δ represents lag operator; θ_1 is the constant; ε_{1t} symbolises the error term by satisfying the normal distribution's zero mean and constant variance. Moreover, the error term includes other non-renewable and renewable energy determinants assumed to be neutral. The first half of Eq. (5) deals with the long-run dynamics, whereas the second half with the summation sign also stands for the short-run dynamics between the variables. The ARDL bounds testing approach of the long-run cointegrating relationship is selected based on the F-test values based on the coefficient of the variables at their lagged levels. Hence, the null hypothesis of no cointegration relationship between the variables shown in Eq. (5) is estimated as $H_0: \theta_2 = \theta_3 = \theta_4$ against the alternative hypothesis of the long-run relationship as H_1: $\theta_2 \neq \theta_3 \neq \theta_4$.

Suppose measured F-statistics surpass upper critical thresholds, i.e., lower and upper bounds critical values. In that case, the null hypothesis of no cointegration can be rejected. Therefore, the long-run relationship between the variables exists. The null hypothesis cannot be opposed if the F-statistics calculated are lower than the lower bound critical limits, enabling us to conclude that there is no long-term relationship between the variables. Suppose the calculated value of F-statistics lies between the lower and upper limits of the critical values. In that case, there can be no decisive conclusion on cointegration between the variables. If a long-term relationship is formed in Eq. (5), then the long-run relationship and related short-run dynamic error correction models (ECM) can be obtained using Eq. (6).

$$\Delta NON-REC_t = \theta_1 + \sum_{i=1}^{p} \alpha_{2i} \Delta NON-REC_{t-i} + \sum_{i=0}^{m} \alpha_{3i} \Delta \mathrm{LNGDPC}_{t-i} + \sum_{i=0}^{n} \alpha_{4i} \Delta WTI_{t-i} + \sum_{i=0}^{k} \alpha_{5i} \Delta CPU_{t-i} + \gamma_1 ECM_t + \varepsilon_{1t} \quad (6)$$

where γ_1 is the coefficient of system adjustment speed to long-term equilibrium between the variables. Finally, we use the Akaike Information Criterion (AIC) to select lag order in the ARDL model. Similarly, the second model is shown in above Eq. (4) for estimating both the long run and short-run relationships between the variables is also specified in Eq. (7) and Eq (8). The estimation process of the ARDL model for the following Eq. (7) and Eq. (8) is the same as the above. The long-run form is specified in Eq. (7) as follows:

$$\Delta REC_t = \theta_1 + \theta_2 \mathrm{LNGDPC}_{t-1} + \theta_3 WTI_{t-1} + \theta_4 CPU_{t-1} + \sum_{i=1}^{p} \alpha_{2i} \Delta REC_{t-i} + \sum_{i=0}^{m} \alpha_{3i} \Delta \mathrm{LNGDPC}_{t-i} + \sum_{i=0}^{n} \alpha_{4i} \Delta WTI_{t-i} + \sum_{i=0}^{k} \alpha_{5i} \Delta CPU_{t-i} + \varepsilon_{2t} \quad (7)$$

The ECM is further shown in Eq. (8) as follows:

$$\Delta REC_t = \theta_1 + \sum_{i=1}^{p} \alpha_{2i} \Delta REC_{t-i} + \sum_{i=0}^{m} \alpha_{3i} \Delta \mathrm{LNGDPC}_{t-i} + \sum_{i=0}^{n} \alpha_{4i} \Delta WTI_{t-i} + \sum_{i=0}^{k} \alpha_{5i} \Delta CPU_{t-i} + \gamma_1 ECM_t + \varepsilon_{2t} \quad (8)$$

To evaluate the robustness of our estimated results, we have further employed the Fully-Modified Ordinary Least Squares (FMOLS) of [53] and the Dynamic Ordinary Least Squares (DOLS) of [54]. The estimated results are in line with the specified ARDL models.

4. Empirical results and discussion

4.1. Baseline analyses and discussion

Before proceeding to some unit root tests, it is essential to check the descriptive statistics and correlation of the series. Table 1 shows the presence of normality and minimal heterogeneity in the data series.

Table 2 also shows the correlation matrix and does not show any threat of multi-collinearity due to the low correlation present in the series. The low variance inflation factor also confirms this finding. Interestingly, a negative and significant correlation between climate policy uncertainty and non-renewable energy demand is found. In contrast, climate policy uncertainty and renewable energy demand have a positive and significant relationship. This issue allows us to use the linear technique for modelling the pattern of renewable energy and non-renewable energy demand functions for the United States economy. It further indicates the important role of climate policy uncertainty in the pattern of renewable and non-renewable energy demand.

This study also undertakes some unit root tests. We adopt two frequently used time series based unit root tests (the ADF, 1979 and the PP, 1988) to evaluate the stationary and non-stationary properties of the variables. Moreover, Zivot & Andrew's (2002) unit root test is applied to ensure the structural break of the examination. The unit root consequences are reported in Table 3.

Table 3 shows that the original series of each variable cannot deny the null hypothesis of the existence of a unit root across most of the variables (*REC*, *LNGDPC*, *WTI*), but their first order difference series deny the null hypothesis significantly at the 1% level. This evidence signifies that these are the first-order difference and can support cointegration examinations.

Table 4 shows the presence of the mixed-order of integration with structural breaks present in the data series. Moreover, other variables (*Non-REC*, *CPU*) are stationary at their levels. Finally, it shows that series signal the mixed order of integration, i.e. I(0) & I(1). These results justify an application of the ARDL bounds test to cointegration.

Table 5 shows the consequences of cointegration by applying Pesaran's cointegration approach. It is found that each test statistic significantly rejects the null hypothesis that no cointegration linkage

Table 1
Descriptive statistics.

	Non-REC	REC	LNGDPC	WTI	CPU
Mean	22.34	2.11	10.82	60.83	100.95
Median	22.31	2.15	10.81	58.08	87.25
Maximum	23.74	3.02	11.16	123.95	358.12
Minimum	19.04	1.23	10.48	20.40	17.84
Std. Dev.	0.90	0.54	0.18	25.38	70.94
Skewness	−0.57	0.12	−0.12	0.41	1.22
Kurtosis	3.63	1.57	2.04	2.26	4.33
Jarque-Bera (chi-square value)	6.21**	7.57**	3.54	4.40	27.91***
Observations	87				

Notes: LN is the natural log taken to enhance the smoothness of the data. *** and ** are 1% and 5% levels of significance. Non-REC, REC, GDP, WTI, and CPU are non-renewable energy consumption, renewable energy consumption, gross domestic product (economic growth), west texas intermediate (crude oil prices), and climate policy uncertainty. Except for real GDP per capita, all remaining variables possess seasonality in the data series. The seasonality present in the data series is adjusted with the help of additive and multiplicative decompositions. The seasonality adjusted series are considered.
Source: Authors' estimation.

Table 2
Pair-wise correlations and the VIF.

Variables	Non_REC	REC	LNGDPC	WTI	CPU
Non_REC	1.000				
REC	−0.548***	1.000			
LNGDPC	−0.414***	0.948***	1.000		
WTI	−0.126	0.267**	0.297**	1.000	
CPU	−0.353***	0.621***	0.674***	0.041	1.000
Average Variance Inflation Factor (VIF)	1.73				

Note: *** and ** represent 1% and 5% levels of significance.
Source: Authors' estimation.

exists among the variables. This evidence indicates that these variables own stable equilibrium in the long run, and estimation of these variables can be done.

Table 6 reports the long-run estimation results of the variables in models 1 & 2. As revealed in Model 1 of Table 6, the outcome indicates that the impact of economic growth on non-renewable energy consumption is ineffective as its coefficient remains insignificant in the long run. This result suggests that even if people in the United States have income, they do not spend money buying non-renewable energy from the open market. This evidence is because they think about environmental protection and spend money on alternative energy compatible with nature.

The influence of the United States crude oil prices on non-renewable energy consumption are positive and insignificant. This result indicates that even if crude oil prices rise, it does not effectively increase the non-renewable energy demand of the people in the United States. This evidence could be because the efficiency involved in non-renewable energy sources than renewable energy sources does not convince many people in the United States. For example, consumers are habituated to the usage of fossil fuels. They know how to use and do the work quickly, but this is not the case when they go for renewable energy sources. Therefore, this motivates fewer people in the United States to demand more fossil fuels when crude oil prices rise.

The climate policy uncertainty adversely influences non-renewable energy consumption in the United States. This outcome indicates that the higher the climate policy uncertainty, the lesser demand for fossil fuels will be. This issue could be one of the reasons for the producers to reduce their fossil fuel demand when the government in the United States imposes taxes on pollution creating firms. The pollution tax imposition can come when firms use dirty energy extensively.

The first quarter of 2008 structural break also significantly reduced the demand for non-renewable energy in the United States. This result indicates that 2008 was the sub-prime crisis that originated from the banking and real estate sectors of the United States [44,55] and affected fossil fuel demand. This evidence is related to the issue because people in the United States have their income loss due to rising unemployment in the construction and banking industries. This result denies people to consumption of more fossil fuels.

As revealed in Model 2 of Table 6, the outcome indicates that economic growth positively affects renewable energy demand in the United States. One explanation might be that rising economic growth in the

Table 3
ADF (1979) and PP (1988) unit root test results.

	Levels		Ist differences		Decision
	Intercept	Intercept & Trend	Intercept	Intercept & Trend	
ADF					
Non-REC	−8.087 (−3.530)	−10.156 (−4.071)	−17.212 (−3.531)	−17.112 (−4.073)	I(0)
REC	−1.026 (−3.530)	−6.319 (−4.071)	−11.471 (−3.531)	−11.438 (−4.073)	I(1)
LNGDPC	−0.375 (−3.530)	−2.688 (−4.071)	−10.467 (−3.531)	−10.403 (−4.073)	I(1)
WTI	−2.167 (−3.530)	−2.133 (−4.071)	−7.307 (−3.531)	−7.274 (−4.073)	I(1)
CPU	−3.607 (−3.530)	−5.026 (−4.071)	−13.534 (−3.531)	−13.456 (−4.073)	I(0)
PP					
Non-REC	−8.087 (−3.530)	−10.187 (−4.071)	−34.177 (−3.531)	−34.023 (−4.073)	I(0
REC	−1.026 (−3.530)	−6.078 (−4.071)	−16.234 (−3.531)	−16.414 (−4.073)	I(1)
LNGDPC	−0.374 (−3.530)	−2.734 (−4.071)	−10.565 (−3.531)	−10.402 (−4.073)	I(1)
WTI	−2.285 (−3.530)	−2.273 (−4.071)	−7.160 (−3.531)	−7.120 (−4.073)	I(1)
CPU	−3.396 (−3.530)	−5.067 (−4.071)	−14.351 (−3.531)	−14.252 (−4.073)	I(0)

Note: MacKinnon's approximate p-value is at a 1% significance level inside the parenthesis ().
Source: Authors' estimation.

Table 4
Zivot-Andrews (2002) unit root test results.

	Levels			1st difference		
	T statistics	Time break	Decision	T statistics	Time break	Decision
Non-REC	−11.4284***	2008Q1 No Break##	I(0)	−7.8292***	2008Q1	I(0)
REC	−7.6872***	2009Q1 2009Q1##	I(0)	−11.6718	2002Q1	I(0)
LNGDPC	−4.956*	2008Q3 2003Q3## 2008Q3##	I(1)	−12.673***	2019Q4	I(0)
WTI	−4.5495	2014Q3 2003Q4## 2008Q3## 2014Q3##	(1)	−7.729***	2008Q1	I(0)
CPU	−5.9773 ***	2019Q2 2006Q3## 2015Q3##	I(0)	−14.502***	2020Q4	I(0)

Notes: *** and * represent 1% and 5% significance levels. Critical values: 0.01 = −5.57, 0.05 = −5.08, 0.1 = −4.82.
Break points based on Bia-Perron Test.
Source: Authors' estimation

Table 5
ARDL bounds testing cointegration results.

Bound testing to cointegration				Diagnostic tests			
Estimated model	Lag length	Break year [dependent variable break year]	F-statistics	Jarque-Bera for Normality	Ramsey RESET Test	Heteroskedasticity Test: Breusch-Pagan-Godfrey	Breusch-Godfrey Serial Correlation LM Test:
Model-1 Non-REC = f (LNGDPC, WTI, CPU)	(1, 1, 1, 0, 1)	2008Q1	6.45***	2.82 (P-value: 0.2437)	F-statistic 2.62 (P-Value: 0.0106)	0.27 (P-value: 0.9744)	2.02E-05 (P-value: 0.9964)
Model-2 REC = f(LNGDPC, WTI, CPU)	(1, 0, 3, 0, 3)	2009Q1	5.90***	2.07 (P-value: 0.3550)	2.75 (P-value: 0.0493)	1.07 (P-value: 0.3929)	1.54 (P-value: 0.2119)
Significance Levels	Model-1 Critical values (n = 87, k = 4)			Model-2 Critical values (n = 87, k = 4)			
Narayan (2005) tabulated values	Lower bound	Upper bound			Lower bound	Upper bound	
10%	2.303	3.22			2.303	3.22	
5%	2.688	3.698			2.688	3.698	
1%	3.602	4.787			3.602	4.787	

Notes: ***, ** and * represent at 1%, 5%, and 10% levels of significance, respectively. The lag length is in parenthesis (), n is the actual sample size, and k is the number of explanatory variables, including the dummy accommodated for the single structural break.
Source: Authors' estimation.

United States implies households have higher income levels and continue to demand more renewable energy from the open market for environmental protection. Moreover, producers with larger income support (i.e. subsidy) from the government increase the number and scale of factories and use environmental-friendly technology to expand production, resulting in tremendous renewable energy consumption. This result suggests that increasing the United States' economic growth adds to renewable energy consumption. This empirical evidence is consistent with the findings of [17] for G7 countries [18], for 18 emerging market economies [24], for 24 European countries [25], for six emerging economies [27], for 38 countries [26], for 64 countries [22], for the United States, Lin and Moubarak [60] for the Chinese economy [7], for 30 OECD countries [34], for selected emerging economies, and [35] for 20 OECD countries where they observe the positive impact of economic growth on renewable energy demand.

The coefficient of crude oil prices on renewable energy consumption is negative and significant at the 1% level. This finding can be interpreted as the effect of crude oil price inflation on clean energy demand in the United States. This result shows that consumers usually adopt a lifestyle based on affordable crude oil prices. Consumers decrease renewable energy consumption when crude oil prices rise. This finding indicates the right choice of consumers in the United States, even if non-renewable energy is more expensive than renewable energy. This result is basically due to consumers' lifestyle choices in their day-to-day lives. Also, producers reduce their dependence on renewable energy when crude oil prices rise. This evidence is because they are already habituated to fossil fuel usage. This empirical evidence is consistent with the studies of [25] for China and Indonesia and [26] for 64 countries where they observe the adverse effect of oil prices on renewable energy demand. The empirical evidence from our analysis is also inconsistent with a few recent studies by Ref. [7] for 30 OECD economies and [35] for 20 OECD countries, where they find the promoting role of oil price on renewable energy demand. Our finding is inconsistent with a few studies [7,35] because their panel-based renewable energy demand modelling.

The impact of climate policy uncertainty on renewable energy consumption is positive and insignificant. This result indicates that the climate mitigating policy imposed by the United States policymakers does not become effective in increasing renewable energy consumption. This finding may be because accessing renewable energy is expensive for people. As long as producers are concerned, it can be a subsidy of the United States government that fails to incentivize producers to use renewable energy in production expansion.

Furthermore, the effect of structural break found in the initial quarter of 2009 on renewable energy consumption is positive and significant at a 1% level. This result indicates that this was the year of the sub-prime financial crisis in the banking sector. The consumers who have taken loans from the banks following the banking crisis prefer to spend more on renewable energy consumption. This is because consumers know that the banking crisis triggered by the real estate builders will sustain, and the possible loan wave could benefit consumers not to return money to the banks.

However, short-run results are different from long-run results, as reported in Table 6. For instance, economic growth has a positive and significant impact on non-renewable energy but is insignificant in the long run. This evidence may be true in the short-run because people in the United States spend money buying non-renewable energy from the open market with their increased income level. This evidence reveals that people lack environmental awareness in the short run. Similarly, crude oil prices negatively and significantly impact non-renewable energy in the short run. Though people in the United States habituated to crude oil usage, increasing crude oil prices discouraged people from consuming less non-renewable energy. This issue may be because rising crude oil prices are evidence of an inflationary situation that can hurt people's financial savings in the United States.

Finally, the impact of crude oil prices on renewable energy is positive and significant in the short run. It shows the crucial role of crude oil prices in adopting renewable energy in the short run. This evidence could be true because people in the United States know that consuming more non-renewable energy at rising crude oil prices reduces their financial saving capacity and impedes the environmental quality by discharging higher amounts of carbon into the atmosphere. Therefore, increasing crude oil prices encourage people in the United States to prefer energy transitioning of renewable energy demand over non-renewable energy.

The coefficients of all the error correction terms are negative and significant, supporting the validity of the error correction specification. More specifically, the negative and significant levels of the error correction model (i.e. convergence coefficient) are −0.377 for non-renewable energy use and −0.362 for renewable energy consumption. It justifies the presence of a long-run cointegrating relationship between the variables, and also, short-run disequilibrium for both Models 1 & 2 is corrected towards owning the long-run equilibrium. It further indicates that short-run disequilibrium correction is marginally higher (−0.377) for non-renewable energy consumption than the renewable energy demand, which is −0.362. It implies that the United States economy will take more than 268 (276) quarters to reach the long-run equilibrium of non-renewable energy demand (renewable energy consumption).

The R-squared values for Models 1 & 2 indicate that the factors included in the modelling energy demand equations explain more non-renewable energy use variation than renewable energy consumption.

Table 6
Estimated long-run and short-run coefficients based on the ARDL bounds tests.

Long-run analysis			
Model-1: Dependent variable (Non-REC)			
Independent variables	Coefficient	Std. Error	t-Statistics
LNGDPC	0.706	1.269	0.556
WTI	0.006	0.006	1.057
CPU	−0.004*	0.002	−1.679
DU_{2008Q1}	−1.492***	0.465	−3.208
C	15.281	13.412	1.139
Model-2: Dependent variable (REC)			
Independent variables			
LNGDPC	2.071***	0.206	10.054
WTI	−0.003***	0.0009	−3.662
CPU	0.0001	0.0003	0.299
DU_{2009Q1}	0.495***	0.067	7.369
C	−20.384***	2.176	−9.365
Short-run analysis			
Model-1: Dependent variable (Non-REC)			
Independent variables			
D(LNGDPC)	17.045***	2.598	6.558
D(WTI)	−0.009**	0.004	−2.284
D(DUMMY_BREAK_NON_REC)	0.435	0.389	1.116
ecm(-1)	−0.377***	0.058	−6.421
Short-run diagnostics			
R^2	0.500	R^2_a	0.482
SE of regression	0.387		
Std. Deviation of DV	0.539	Mean of DV	−0.013
D-W statistics	1.994		
Model-2: Dependent variable (REC)			
Independent variables			
D(WTI)	−0.0003	0.0006	−0.538
D(WTI(-1))	0.002***	0.0007	2.953
D(WTI(-2))	0.001**	0.0007	1.937
D(DUMMY_BREAK_REC)	0.167**	0.070	2.356
D(DUMMY_BREAK_REC(-1))	0.075	0.071	1.053
D(DUMMY_BREAK_REC(-2))	−0.148***	0.060	−2.470
ecm(-1)	−0.362***	0.058	−6.157
Short-run diagnostics			
R^2	0.361	R^2_a	0.311
SE of regression	0.055		
Std. Deviation of DV	0.066	Mean of DV	0.017
D-W statistics	1.919		

Notes: DV means the dependent variable. R^2_a indicates adjusted R^2. D-W statistics shows the Durbin–Watson statistic; it talks about the presence of autocorrelation. The value of the Durbin–Watson statistic lies between 0 and 4. If the value is 2, then there is no autocorrelation. If the value is between 0- and <2, there is a positive autocorrelation. If the value is between >2-and 4, there is a negative autocorrelation. ***, **, and * represent 1%, 5%, and 10% levels of significance.
Source: Authors' estimations.

The climate policy uncertainty could be the main reason for this difference. The threat of autocorrelation in Durbin-Watson (D-W) statistics is minimal across Models 1 & 2. We also use Cumulative Sum Square (CUSUM) and CUSUM of squares (CUSUMsq) of recursive residuals proposed by Ref. [56] to check the ARDL model stability. Figs. 4 and 5 indicate the model stability at a 5% significance level for the non-renewable and renewable energy consumption. This result enables us to confirm the findings of the ARDL models shown in Table 6.

Finally, the FMOLS and the DOLS methods also check the robustness of the results. The results in Table 7 indicate similar results as noticed in Table 6. This evidence suggests that these are efficient findings that can be used by policymakers and governments of the United States and other advanced economies while mitigating climate change and global warming.

4.2. Robustness checks

Robustness checks are implemented in this section by taking three steps. First, we examine whether baseline findings hold for alternative estimators, i.e. structural break unit root test and cointegration with regime shifts. Second, we test that the main results are robust to the ARDL model. We have added new structural breaks arising in the data series. Third, we also use both FMOLS and DOLS for estimation in the presence of new structural breaks.

Tables 8 and 9 present econometric methodological comparisons of structural break unit root and cointegration with regime changes. The results reported in Tables 8 and 9 confirm the robustness of our baseline estimation results. However, it is worth noting that using new structural breaks in the ARDL bounds test, short-run and long-run, as well as in FMOLS and DOLS models, does not materially alter the economic magnitude and statistical significance of coefficients on renewable energy and non-renewable energy consumption in the United States (see Tables A1, A2, and A3 of the Appendix). The evidence reported in Tables A2 and A3 confirms that climate policy uncertainty is essential to the USA economy's renewable and non-renewable energy demand.

5. Policy implications

The findings of this study bear important policy implications. The United States is one of the mature economies where economic growth is not the driving factor of non-renewable energy use. It shows that policymakers in the United States need to understand whether the energy impact of income level is shifting to renewable energy sources. If it happens to be true, it is a good sign for the natural environment in the United States. Crude oil prices also increase non-renewable energy demand in the long run. It shows that rising crude oil prices encourage people to use non-renewable energy. The positive impact of rising crude oil prices on non-renewable energy use is beneficial for the people in the United States because of oil efficiency and subsidy. For instance, people can buy oil because it is available in the open energy market whenever needed. Even if the oil price is much higher for the people, but still the demand for oil increases because they know that oil price could sometimes be reduced later because of the oil subsidy provided by the government to the oil producers to avoid the adverse effect on the economy [25]. Hence, these reasons motivate people to use more fuel in economic activities and limit its availability for future generations. It is also a matter of concern as excessive usage of fossil fuels can put the quality of

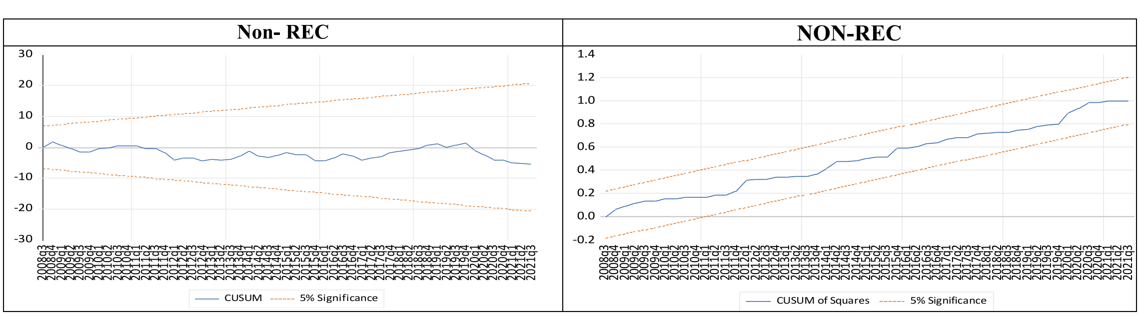

Fig. 4. Cumulative sum and cumulative sum of the squares at the 5% level of significance.

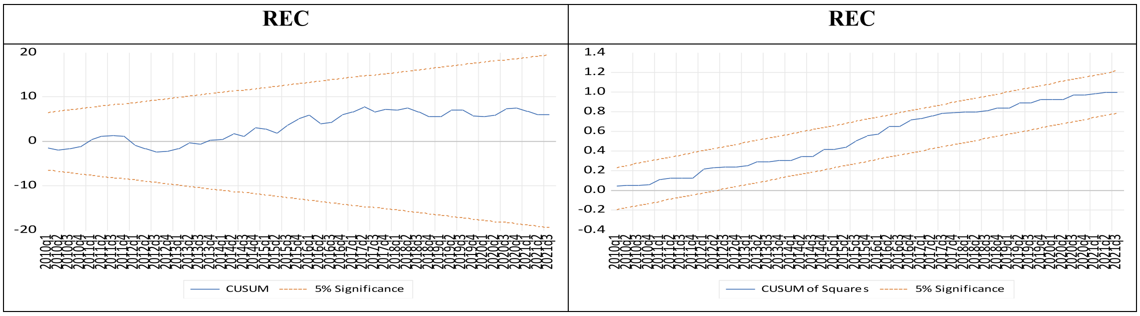

Fig. 5. Cumulative sum and cumulative sum of the squares at the 5% level of significance.

Table 7
DOLS and FMOLS robust checking results.

	NON-REC: Dependent Variable		REC: Dependent Variable	
Variable	DOLS	FMOLS	DOLS	FMOLS
LNGDPC	2.177*** [71.616]	2.178*** [94.793]	0.091*** [7.870]	0.130*** [12.594]
WTI	0.006 [1.313]	0.007** [2.004]	−0.001 [-0.984]	−0.0009 [-0.575]
CPU	−0.005*** [-2.981]	−0.004*** [-3.480]	0.004*** [6.915]	0.002*** [4.713]
DUMMY_BREAK	−1.756*** [-5.978]	−1.920*** [-8.316]	0.736*** [8.898]	0.770*** [8.466]
R^2	0.750	0.588	0.968	0.826
Adjusted R^2	0.695	0.573	0.948	0.819

Notes: *** and ** indicate 1% and 5% levels of significance. [] shows the t-statistics. 2008Q1 is a break year for NON_REC, and 2009Q1 is for REC. The dummy break is used for the structural break year. Lag 1 (3), decided by the Akaike Information criteria, is chosen for NON-REC (REC) variable. These lags apply only to the DOLS technique.
Source: Authors' estimations.

the natural environment at risk through increasing greenhouse gases in the atmosphere. Therefore, policymakers in the United States need to understand the role of crude oil prices in energy conservation building and mitigating climate strategies.

Interestingly, climate policy uncertainty significantly reduces non-renewable energy use in the long run. The government imposes a higher pollution tax on producers because they use dirty energy extensively in production activity. It further indicates that increasing the pollution tax reduces the usage of non-renewable energy in the United States, which is a good signal, keeping its beneficial environmental quality in mind. Hence, the policymakers should consider the role of climate policy uncertainty in energy conservation and climate change mitigating policies.

We also find economic growth's crucial positive and significant role on renewable energy demand in the United States. This finding confirms [22] study conducted for the United States. It indicates that economic growth has become remarkable for the people as it increases their income through employment generation. As a result, people with rising income levels buy renewable energy for consumption and production activities. Similarly, the fiscal government should invest more in renewable energy capacity generation that can be supplied to the open market on a bigger scale. Thus, increased renewable energy supply over demand can reduce the price in the open energy market. Reducing renewable energy prices can motivate people in the United States to

Table 8
[34] Structural break unit root test.

	Levels			1st difference		
	T-statistics	Time break	Decision	T-statistics	Time break	Decision
Non-REC	−5.75***	2008Q2	I(0)	−6.41	2017Q3	I(0)
REC	−3.59	2009Q4	I(1)	−8.21	2016Q4	I(0)
LNGDPC	−4.482**	2008Q2	I(1)	−12.67***	2019Q4	I(0)
WTI	−5.19***	2014Q2	(0)	−7.67***	2014Q1	I(0)
CPU	−4.33**	2016Q2	I(0)	−7.43***	2016Q2	I(0)

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

Table 9
Gregory and Hansen test [26] for cointegration with regime shifts.

Statistics	Variables	Test Statistic	Breakpoint	Critical Values			Cointegrated
				1%	5%	10%	
ADF	Non-REC	−6.07**	2008Q3	−6.51	−6.00	−5.75	Yes
	REC	−5.97*	2008Q4				Yes
Zt	Non-REC	−6.43**	2008Q3	−6.51	−6.00	−5.75	Yes
	REC	−6.00*	2008Q4				Yes

Note: ** and * represent significance at the 5% and 10% levels, respectively.

extensively use renewable energy in both consumption and production activities. Eventually, the massive usage of renewable energy also promotes the quality of the natural environment and habituates the future generation for its use. Thus, the policymakers need to consider the role of economic growth while designing clean energy building policy for sustainable development and the environment in the long run [7].

We further confirm crude oil prices' negative and significant impact on renewable energy. It indicates that higher crude oil prices reduce renewable energy use in the United States. Even if oil prices rise, people in the United States still reduce renewable energy demand and increase their dependence on oil. The possible reason might be that people are habituated to oil usage because of its higher efficiency than renewable energy. Another reason might be that renewable energy has a limited supply and is becoming expensive for people to afford. Furthermore, oil is imported by the United States to mitigate the domestic market requirements. Therefore, the rising oil price is also subsidized by the government of the United States to avoid its adverse impact on the economy [25]. These are why people in the United States reduce their demand for renewable energy and increase the demand for non-renewable energy, which is also evident in our analysis. Therefore, the policymakers should design a policy toward making renewable energy at an affordable rate. As a result, the adoption of renewable energy should be higher by the people in the United States for a sustainable environment.

Finally, the study confirms climate price uncertainty's negative and insignificant impact on renewable energy consumption. It shows that climate policy uncertainty is ineffective in increasing renewable energy in the United States. Thus, the policymakers should provide effective financial support to enlarge the extensive demand for renewable energy because of its expensive nature. Since renewable energy is costlier than fossil fuels and beneficial for the natural environment, imposing less pollution tax on green producers should be implemented. As a result, such producers would think of producing and supplying more renewable energy into the open market. In such a way, the scale of energy production would occur massively, benefiting the producers in maximizing their profit and reducing the clean energy market uncertainty. Reducing clean energy market uncertainty reduces clean energy insecurity and poverty and promotes the quality of the natural environment [43].

6. Conclusion

The determinants of energy consumption patterns have been an important issue in achieving sustainable environmental quality in the current context of energy depletion, climate change, and global warming. The following facts motivated us to explore the topic. The first fact is that the concept of "green recovery" or "green economic growth" in 2020 has reignited the debate among scholars about the influence of climate policy uncertainty, economic growth and crude oil prices on the pattern of energy consumption (non-renewable and renewable) pressure. The second fact is that the relevant empirical findings are inconclusive when they are based on the influences of economic growth and crude oil prices on the energy consumption pattern. This evidence suggests that we should use climate policy uncertainty as to the key factor in non-renewable and renewable energy consumption functions, which need to be further investigated empirically using the right methods. The third fact is that advanced economies like the United States are the leading energy consumers and second-best pollution creating countries globally; experiencing the factual findings can provide effective policy recommendations for their authorities and departments to adopt energy sustainability measures. This result can promote sustainable environmental quality for the United States and other growing economies in the long run.

In this connection, we argue that this is the first study that motivates us to examine the effects of climate policy uncertainty on renewable and non-renewable energy consumption in the United States over the quarterly data from 2000Q1 to 2021Q3. As control variables, economic growth and crude oil prices are added to non-renewable and renewable energy functions. This objective is modelled by applying the ARDL bounds test to cointegration. This model helps us to estimate the long-run and short-run results. Moreover, the DOLS and the FMOLS techniques are used as results of robust checking purposes.

The empirical results from the ARDL model display the positive and insignificant impact of economic growth on non-renewable energy consumption in the United States. This finding shows that economic growth is ineffective in stimulating non-renewable energy use. Non-renewable energy use is positively (negatively) related to crude oil prices (climate policy uncertainty). These results indicate that though rising crude oil prices enhance non-renewable energy demand but remain insignificant, the greater climate policy uncertainty reduces it. The results also show the positive and significant impact of economic growth on renewable energy use in the long run. However, rising crude oil prices reduce renewable energy. Surprisingly, climate policy uncertainty positively affects renewable energy use but is insignificant, indicating that any climate change mitigating policy does not encourage people to use clean energy in the United States.

Our study is not free from limitations. One limitation is that our theoretical framework on the impact of climate policy uncertainty on renewable and non-renewable energy consumption needs to be expanded further. Second, this study only considers the role of climate policy uncertainty on renewable and non-renewable energy consumption in the United States but neglects the effects of economic policy uncertainty and energy market uncertainty [37,43]. Interestingly, existing studies have shown that environmental regulation and technological innovation can influence the energy demand in developed and emerging economies [57–59]; Hao et al., 2018; Liu et al., 2018). Given this, future research can introduce these variables into the framework. Finally, the long-term nature of climate policy changes posed by the threat of climate change and global warming inevitably requires more research from advanced methodological viewpoints over an extended period. What is clear is that the issue of energy demand determinants that we address in this paper cannot be resolved based on aggregate empirical analysis alone [58]. Therefore, more research is needed on non-renewable and renewable energy consumption determinants in developed and emerging economies within a panel framework. As a result, the findings emerging from panel studies can have generalization possibility, which can help policymakers to design the right clean energy transition policy for mitigating climate change and global warming.

Authors' contributions

Yunfeng Shang: Writing – Original Draft; Conceptualisation, **Ding Han:** Writing – Original Draft; Final Input, **Giray Gozgor:** Writing – Original Draft; Supervision, **Mantu Kumar Mahalik:** Writing – Revised Draft; Supervision, **Bimal Kishore Sahoo:** Data Curation; Investigation; Writing – Formal Analysis, We all confirm no known conflicts of interest associated with this research, and there has been no significant financial support for this work that could have influenced its outcome.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table A1
ARDL Bounds Testing Cointegration Results

Bound testing to cointegration				Diagnostic tests			
Estimated models	Lag length	Break year [dependent variable break year]	F-statistics	Jarque-Bera for Normality	Ramsey RESET Test	Heteroskedasticity Test: Breusch-Pagan-Godfrey	Breusch-Godfrey Serial Correlation LM Test:
Model-1 Non-REC = f (LNGDP, WTI, CPU)	(1, 1, 1, 0, 0)	2008Q2	6.394***	3.205 (0.201)	F-statistics: 7.436 (P-value: 0.007)	F-statistics: 0.212 (P-value: 0.98)	F-statistics: 0.099 (P-Value: 0.75)
Model-2 Non-REC = f (LNGDP, WTI, CPU)	(1, 1, 1, 0, 0)	2008Q3	6.804***	2.727 (0.255)	F-statistics: 8.70 (P-value: 0.004)	F-statistics: 0.104 (P-value: 0.997)	F-statistics: 0.823 (P-value: 0.366)
Model-3 REC = f(LNGDP, WTI, CPU)	(1, 0, 1, 0, 0)	2009Q4	4.40**	8.82 (0.01)	0.42 (0.65)	0.80 (0.57)	1.179 (0.31)
Model-4 REC = f(LNGD, WTI, CPU)	(1, 0, 3, 0, 4)	2008Q4	6.11***	1.79 (0.40)	2.87 (0.02)	1.15 (0.33)	1.34 (0.26)
Significance levels	Model1: Critical values [n = 87, k = 4]		Model2: Critical values [n = 87, k = 4]		Model3(4): Critical values [n = 87, k = 4]		
Narayan (2005) tabulated values	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	
10%	2.303	3.22	2.303	3.22	2.303(2.303)	3.22(3.22)	
5%	2.688	3.698	2.688	3.698	2.688(2.688)	3.698(3.698)	
1%	3.602	4.787	3.602	4.787	3.602(3.602)	4.787(4.787)	

Notes: P-values are in parenthesis (). The lag length is selected based on the Akaike Information Criteria. ***, ** and * indicate 1%, 5%, and 10% levels, respectively. n is the actual sample size, and k is the number of explanatory variables.

Table A2
Estimated Long-run and Short-run Coefficients Using the ARDL Bounds Test Approach

Long-run analysis			
Model-1: Dependent variable (Non-REC)			
Independent variables	Coefficient	Std. Error	t-Statistics
LNGDPC	0.900	1.229	0.732
WTI	0.008	0.005	1.448
CPU	−0.003*	0.002	−1.665
DU_{2008Q2}	−1.639***	0.428	−3.821
C	13.195	12.982	1.016
Model-2: Dependent variable (Non-REC)			
Independent variables	Coefficient	Std. Error	t-Statistics
LNGDPC	1.133	1.149	0.986
WTI	0.006	0.004	1.279
CPU	−0.004**	0.002	−1.933
DU_{2008Q3}	−1.670***	0.382	−4.364
C	10.822	12.123	0.892
Model-3: Dependent variable (REC)			
Independent variables	Coefficient	Std. Error	t-Statistics
LNGDPC	2.011***	0.283	7.084
WTI	−0.001*	0.001	−1.733
CPU	0.0003	0.0004	0.812
DU_{2009Q4}	0.435***	0.085	5.078
C	−19.774***	2.995	−6.600
Model-4: Dependent variable (REC)			
Independent variables	Coefficient	Std. Error	t-Statistics
LNGDPC	2.099	0.195	10.743
WTI	−0.003	0.0008	−3.742
CPU	9.44E-05	0.0003	0.289
DU_{2008Q4}	0.489	0.065	7.457
C	−20.694	2.066	−10.014
Short-run analysis			
Model-1: Dependent variable (Non-REC)			
Independent variables	Coefficient	Std. Error	t-Statistics
D(LNGDPC)	16.552	2.595	6.377
D(DES_WTI)	−0.009	0.004	−2.115
ecm(-1)	−0.385	0.060	−6.389
Short-run diagnostics			
R-squared	0.494	Adjusted R^2	0.482
SE of regression	0.387		
Std. Deviation of DV	0.539	Mean of DV	−0.013
D-W statistics	1.944		

(*continued on next page*)

Table A2 (*continued*)

CUSUM at 5% level	Stable		
CUSUM sq at 5% level	Stable		
Model-2: Dependent variable (Non-REC)			
Independent variables	Coefficient	Std. Error	t-Statistics
D(LNGDPC)	16.717***	2.568	6.508
D(DES_WTI)	−0.011***	0.004	−2.677
ecm(-1)	−0.414***	0.062	−6.591
Short-run diagnostics			
R-squared	0.504	Adjusted R^2	0.492
SE of regression	0.383		
Std. Deviation of DV	0.539	Mean of DV	−0.013
D-W statistics	1.856		
CUSUM at 5% level	Stable		
CUSUM SQ at 5% level	Stable		
Model-3: Dependent variable (REC)			
Independent variables	Coefficient	Std. Error	t-Statistics
D(WTI)	0.0004	0.0006	0.809
ecm(-1)	−0.270***	0.051	−5.300
Short-run diagnostics			
R^2	0.22	Adjusted R^2	0.21
SE of regression	0.058		
Std. Deviation of DV	0.065	Mean of DV	0.017
D-W statistics	1.940		
CUSUM at 5% level	Stable		
CUSUM sq at 5% level	Stable		
Model-4: Dependent variable (REC)			
Independent variables	Coefficient	Std. Error	t-Statistics
D(WTI)	−0.0002	0.0007	−0.319
D(WTI(-1))	0.002	0.0007	2.953
D(WTI(-2))	0.001	0.0008	1.831
D(DUMMY_Q4_2008_REC)	0.023	0.075	0.314
D(DUMMY_Q4_2008_REC(-1))	−0.018	0.074	−0.246
D(DUMMY_Q4_2008_REC(-2))	0.066	0.075	0.880
D(DUMMY_Q4_2008_REC(-3))	−0.153	0.061	−2.517
ecm(-1)	−0.389	0.062	−6.268
Short-run diagnostics			
R^2	0.37	Adjusted R^2	0.31
SE of regression	0.055		
Std. Deviation of DV	0.066	Mean of DV	0.018143
D-W statistics	1.726		

Notes: DV means the dependent variable. R_a^2 indicates adjusted R^2. D-W statistics shows the Durbin–Watson statistic; it talks about the presence of autocorrelation. The value of the Durbin–Watson statistic lies between 0 and 4. If the value is 2, then there is no autocorrelation. There is a positive autocorrelation if the value is between 0 and 2. There is a negative autocorrelation if the value is between 2 and 4. ***, **, and * represent 1%, 5%, and 10% levels of significance.
Source: Authors' estimation.

Table A3
DOLS and FMOLS Results

Variable	Model1: NON-REC: Dependent Variable [2008Q2 as break year]		Model2:NON-REC: Dependent Variable [2008Q3 as break year]		Model3:REC: Dependent Variable [2009Q4 as break year]		Model4:REC: Dependent Variable [2008Q4 as break year]	
	DOLS	FMOLS	DOLS	FMOLS	DOLS	FMOLS	DOLS	FMOLS
LNGDPC	2.177*** [74.267]	2.179*** [98.121]	2.181*** [77.412]	2.185*** [101.837]	0.118*** [12.438]	0.133*** [15.223]	0.081*** [6.511]	0.130*** [11.723]
WTI	0.006 [1.353]	0.007** [1.992]	0.005 [1.183]	0.005* [1.684]	−0.0009 [-0.812]	−0.001 [-0.765]	−0.0002 [-0.1763]	−0.001 [-0.632]
CPU	−0.005*** [-3.188]	−0.004*** [-3.602]	−0.006*** [-3.503]	−0.005*** [-4.060]	0.003*** [6.872]	0.002*** [5.625]	0.005*** [6.505]	0.002*** [4.303]
DUMMY_BREAK	−1.749*** [-6.435]	−1.922*** [-8.896]	−1.685*** [-6.536]	−1.854*** [-9.322]	0.761*** [11.949]	0.805*** [10.799]	0.633*** [6.1703]	0.769*** [7.773]
R^2	0.76	0.63	0.77	0.65	0.96	0.87	0.98	0.80
Adjusted R^2	0.70	0.62	0.72	0.64	0.94	0.86	0.96	0.79

Notes: ***, ** and * indicate 1%, 5% and 10% levels of significance. [] shows the t-statistics. Lag 1 is for Models 1 & 2 and Lags 2 & 4 for Models 3 & 4, which the Akaike Information Criteria decide. These lags apply only to the DOLS technique.

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