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ORIGINAL PAPER

Identifying the influence of climate policy uncertainty and oil prices on modern renewable energies: novel evidence from the United States

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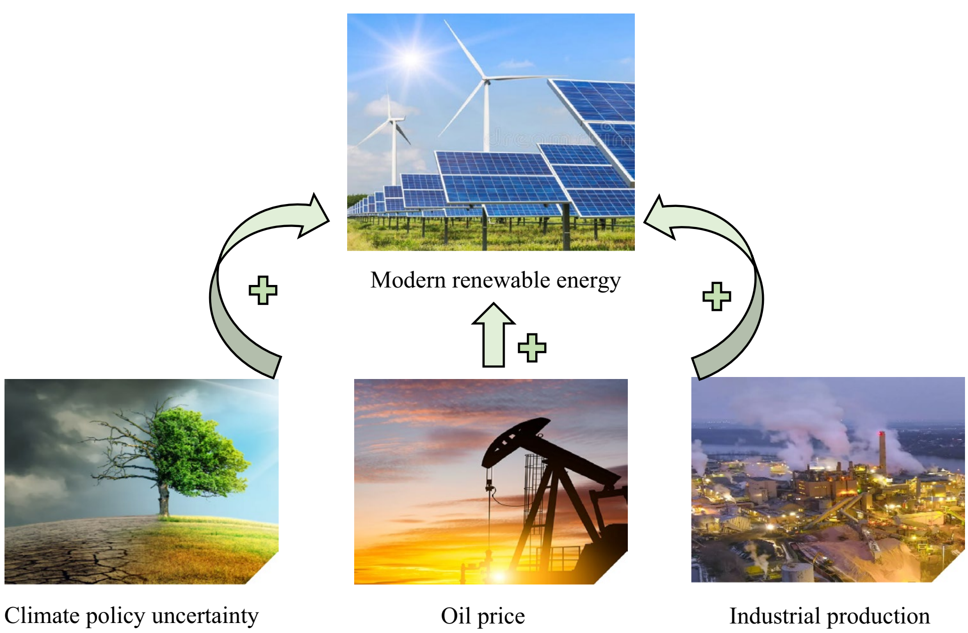
Abstract
The policy uncertainty surrounding climate change can intensify the urgency of implementing climate policies and influence investment decisions, thereby serving as a catalyst for policy transformation. In this context, given its withdrawal from and subsequent re-commitment to the Paris Agreement, the United States (US) may experience policy uncertainty over climate change. Given this backdrop, it is of paramount importance to explore how the uncertainties caused by shifts in climate policy affect clean energy. This study delves into the impact of climate policy uncertainty and oil prices on modern renewable energy sources, such as solar, wind, geothermal, and biofuels. The most recent monthly data from 1989 to 2023 are used by conducting the Residual Augmented Least Squares (RALS) methodology. The empirical findings show that the uncertainty surrounding climate policy is leading to a shift in the US energy composition, with a focus on solar energy, wind energy, and biofuels. Moreover, the fluctuation in oil prices has a significant effect on the deployment of wind and biofuels, but no discernible effect on solar power. These findings provide significant insights for aligning climate policy in the US with Sustainable Development Goal (SDG) 7, highlighting the crucial importance of encouraging investments in solar energy, wind energy, and biofuels.

Graphical abstract



Keywords Climate policy uncertainty · Renewable energy · Oil price · The United States · Energy transition

Extended author information available on the last page of the article

Introduction

The majority of environmental issues that contribute to global warming have their roots in human activities. Increasing reliance on fossil fuels leads to higher levels of greenhouse gases (GHG), which pose a serious threat to ecological sustainability and a quickening pace of global warming (Huo et al. 2023). In this context, following the 2015 Paris Agreement, countries have shifted their focus to adjusting climate policies in an effort to achieve a net-zero economy. In addition, in 2015, the United Nations (UN) implemented the Sustainable Development Goals (SDG), encompassing economic, social, and environmental aspects. SDG-7 and SDG-13 are specifically focused on promoting renewable energy and addressing the urgent issue of climate change. In 2023, the UN hosted the Climate Change Conference (COP28) with the same goal of finding solutions to the climate crisis and reaching zero emissions. Achieving a net-zero economy is a challenging process that requires significant policy adjustments (Gavriilidis 2021; Hoque et al., 2022; Tiwari et al. 2022). Herein, renewable energy (RE) plays a pivotal role as the driving force behind long-term economic progress, improved global energy infrastructure, safeguarded ecosystems, and lessening the consequences of climate risk (Gozgor et al. 2020).

Climate policy is designed to address climate-related issues and has been shown to introduce significant uncertainty and risk (Li et al. 2023). Confronting climate uncertainties and their associated challenges necessitates collective action from the global community, especially from advanced nations, in fulfilling their obligations to reduce emissions and invest in RE technologies. In this perspective, the increases in fossil fuel costs as part of climate change legislation may encourage the construction of renewable power plants and hasten the switch to RE as a result of the price effect (Li and Lee 2022). The utilization of RE sources for decarbonizing energy systems can potentially mitigate the susceptibility and fragility of societies toward climate risks and impacts, while concurrently augmenting their social and economic functionality (Sarma and Zabaniotou 2021; Kim and Park 2023).

The heart of climate policy uncertainty (CPU) lies at the intersection of RE and fossil fuel realms, representing the duality of climate concerns. Changes in climate change policies negatively impact fossil fuels, which are the main sources of CO_2 emissions. However, the uncertainty surrounding climate policy can provide incentives for renewable energy investment, which in turn accelerates the process of decarbonization (Gavriilidis 2021). The presence of the CPU gives rise to increasing apprehension regarding the intensifying climate crisis and its deleterious impacts on the environment. Therefore, investors may choose to

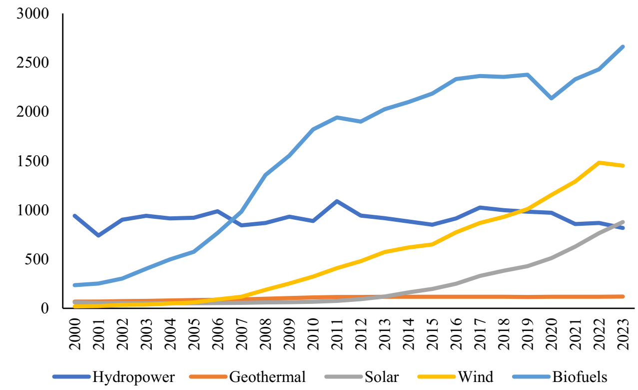


Fig. 1 The US renewable energy consumption by energy source. *Source*: U.S. Energy Information Administration (2024)

allocate funds toward eco-friendly technologies as a strategy to combat the negative environmental conditions caused by the climate crisis. Consequently, given that fossil fuels are the primary drivers of GHG, promoting RE utilization and enhancing energy-efficient technologies play a key part in mitigating climate-related risk.

On the other hand, the lack of clarity in climate policy has a direct impact on future energy decisions and leads to increased uncertainty, which in turn influences energy prices by impeding investment. The CPU levels are yet unclear because of the global energy crisis, which drives up the costs of energy-intensive industries. Furthermore, the coal and natural gas prices, along with the regular fluctuations in oil prices, add to climate uncertainty. Moreover, the escalation of oil, coal, and gas prices and heightened volatility, coupled with their detrimental impact on the environment, can gradually direct the replacement of these energy sources with alternatives (Cao et al. 2020). Hence, the volatility of non-RE prices, along with the presence of CPU, can direct investors to allocate their investments toward RE sources since they are more resilient to fluctuations in prices. Due to the substitution effect, a rise in the fossil fuel prices drives up production costs, which in turn encourages companies to generate more RE (Samour and Pata 2022).

In light of the aforementioned context, this paper focuses on the US, which is a key player in the renewable energy sector, owing to its status as a worldwide frontrunner in eco-friendly technologies and its dedication to diminishing GHG emissions. Figure 1 represents the shares of RE consumption by source in the US between 2000 and 2023. In 2000, hydropower was the most extensively utilized RE source, although it subsequently ranked fourth by 2023. Between 2000 and 2023, geothermal energy consumption has relatively flat trend. Additionally, biofuels, solar, and wind energy are the primary contributors of the rise in RE consumption from 2007 to 2023. As of 2023, the most consumed RE is biofuels, followed by wind, solar, hydro, and geothermal energy. According to the data presented in Fig. 1, biofuels are the most widely used form of RE in 2023, followed by wind, solar, hydro, and geothermal energy. This shows that the US has made great significant in modernizing its renewable energy sources, which aligns with SDG-7, which emphasizes the necessity of clean energy.

Particularly, modern renewables have experienced a swift expansion due to a combination of declining costs and supportive policies from governmental entities (IEA 2023). Their progress has the capacity to alleviate the degrading impacts of climate crisis within the US. However, its decision to withdraw from the Paris Agreement in 2017 and subsequently re-sign it in 2021 has raised concerns about the potential risks linked to climate policies. After that, in 2021, the US has reiterated its commitment to accomplishing climate change goals, primarily through the implementation of a forceful new nationally determined contribution (NDC) that pledges to diminish GHG emissions by 50–52% from 2005 levels by 2030. Additionally, the country has set a goal of achieving 100% clean energy by 2035 and a net-zero target by 2050 (EIA 2023). Nevertheless, even with these objectives, there may still be considerable ambiguity regarding the execution of these measures. Hence, it is of the utmost importance to determine the extent to which CPU impacts modern RE sources.

Given this background, this study analyzes the impact of climate policy uncertainty and non-RE energy prices on the deployment of modern RE. The first contribution of the paper lies in its specific emphasis on the US. The country is the foremost investor in clean energy globally, and it ranked the second country with the highest capacity of solar and wind power addition on global scale (REN21, 2023). Despite these advancements in clean technologies, the withdrawal and re-signing of the Paris Agreement can continue to raise concerns about climate policies and their implementation. This makes the US an important case study. Second, this study presents a unique approach compared to previous research on RE consumption and CPU. It focuses on specific types of modern renewables, such as solar, wind, biofuels, and geothermal, rather than considering total RE consumption. Given their carbon-neutral nature, modern renewables are the primary focus of this study as they help to move toward a more reliable and sustainable energy supply, which is a requirement of SDG-7. In addition, the impact of the CPU on various types of modern renewables can vary due to the distinct characteristics, production costs, and technological requirements associated with each form of renewable energy. Hence, it is crucial to ascertain the degree to which the CPU impacts various forms of modern renewable energy. Determining the type of modern renewables that is most influenced by CPU provides a conclusive decision regarding the specific type of modern renewables that the focal country should prioritize in its climate policies. Hence, the findings of the study can enable a more targeted approach to sustainable development. Third, despite the many studies that have investigated the linkage between oil prices and renewable energy (Guo et al. 2021; Sahu et al. 2022; Shang et al. 2022; Zhao et al. 2024), there are differing viewpoints on the mentioned linkage. Some studies observe a positive influence of oil prices on renewables, while others assert the opposite. These studies only considered the total renewable energy without analyzing each specific type of renewable energy. The question of whether or not oil prices can facilitate the expansion of modern renewables, such as solar power, wind power, biofuels, and geothermal energy, remains unanswered. Depending on the country's energy structure, the types of renewable energy used, and other factors, the effect of oil price fluctuations can vary. Therefore, this requires further investigation, and this study is the first to examine the influence of oil prices on each type of modern renewable energy. Fourth, this study analyzes the most recent intersectional data available from 1989 to 2023 for climate policy uncertainty, oil prices, and modern renewables. Overall, policymakers can get valuable insights from this study regarding the shortcomings identified, particularly in relation to climate policy development aligned with SDG-7.

The remainder of the paper is structured as follows: Section "Literature review" presents an overview of the earlier literature regarding the determinants of renewable energy. Section "Data and model" discusses the detailed data and methodology. Section "Empirical results" provides the empirical results and discussion, followed by Section "Conclusion and policy implications" which concludes the study and presents policy implications.

Literature review

Policy uncertainty and renewables

Various types of uncertainties arise as a consequence of frequent policy changes, leading to significant volatility in the field of RE and subsequently affecting its use. The economy, energy, and climate policies are the primary areas of uncertainty. The adoption of RE plays a crucial role in addressing climate risk. Therefore, in order to formulate the most effective policies in this domain, it is crucial to comprehend how these uncertainties impact RE.

According to Balcilar et al. (2019), economic policy uncertainty (EPU) is negatively related to macroeconomic conditions that impede investment and consequently affect the expansion of RE. They also emphasize the importance of mitigating energy market uncertainty as a critical factor for achieving a successful transition toward RE in Europe. Shafiullah et al. (2021) emphasize that EPU has the potential to disrupt the progress of RE and impede its development in the US. Khan and Su (2022) demonstrate that EPU leads to a decrease in RE usage in the US. Pata et al. (2023) observe that EPU poses a substantial barrier to investment in RE in the G7 economies. Yi et al. (2023) reveal that heightened EPU, specifically an unstable policy regime in the US, results in a decrease in the utilization of RE sources. Chishti and Dogan (2024) discover that macroeconomic policy uncertainty poses a significant risk to RE in 10 countries, including the US. Meo et al. (2024) find that uncertainty in energy policy discourages investment in solar and biomass energy in Germany.

In order to effectively address anomalous climate change, Drouet et al. (2015) state that it is crucial to quantify and incorporate uncertainty into policy frameworks. This motivated Gavriilidis (2021) to create a CPU indicator, a novel way to quantify the risk associated with climate policy. Afterward, climate policies became a prominent topic of discussion in the academic literature. For instance, Ren et al. (2022) show that CPU is associated with a decrease in investment expenditure among energy-related firms in China. Huo et al. (2023) highlight that CPU positively impacts solar and wind power, whereas it has no significant impact on hydropower and geothermal in China. Zhou et al. (2023) find that the impact of CPU rises short-term usage of hydropower and wind energy. In addition, they discover that CPU reduces the utilization of solar and geothermal energy.

In the case of the US, Shang et al. (2022) highlight that CPU has a beneficial impact on RE sources. In other words, uncertainty regarding climate policy leads to a significant rise in the utilization of RE. Li et al. (2023) observe a mixed pattern of negative and positive causality between RE and climate change policy uncertainty, which may be largely attributable to the stance taken by authorities in the US toward climate change. Sarker et al. (2023) show that the heightened level of CPU serves as a driving force for investors to allocate their resources toward environmentally friendly investments. Accordingly, increased investment in clean energy may result in higher demand. Syed et al. (2023) point out that CPU reduces the demand for renewables in the US. According to their results, people continue to rely on non-renewable resources and minimize their usage of renewable ones until a definitive climate strategy is put in place.

Energy prices and renewables

Due to the strategic role of crude oil in the global energy market, the current research mostly concentrates on analyzing the influence of oil price (OIL) fluctuations, which serve as a proxy for fossil fuel pricing, on RE sources. The conclusions, however, remain contradictory. A group of scholars emphasizes the favorable effect of changes in OIL on RE sources. Wang et al. (2020) show that OIL significantly increases RE usage in G20 countries. Li and Leung (2021) observe that as coal and natural gas prices rise, there is a greater inclination toward RE technology in EU countries. Li and Lee (2022) report that the rise in coal prices has a more significant beneficial impact on the RE capacity than natural gas in OECD countries. Atems et al. (2023) demonstrate that after a positive price shock in the non-RE sector, solar, biomass, and geothermal energy consumption increases.

Another group of scholars has emphasized the adverse impact of OIL on the use of RE resources. Cao et al. (2020) reveal that the variation in OIL has an adverse impact on investments in RE in China. They also state that the variability in OIL may also strengthen the association between risk and investment prospects. Mukhtarov et al. (2020) document that a rise in OIL has an adverse impact on the utilization of RE sources in Azerbaijan. Karacan et al. (2021) reveal that the increase in OIL impeded the progress of the shift from traditional energy sources to RE alternatives in Russia. Samour and Pata (2022) observe that OIL reduces RE usage in Turkey. In China, Yu et al. (2023) highlight the negative linkage between OIL imports and RE usage. In other words, the consumption of RE sources has a diminishing effect on crude oil imports. They noted that the actions taken to achieve carbon neutrality have raised a heightened focus on the utilization of RE sources while reducing reliance on non-RE alternatives. Deka et al. (2023) uncover that OIL has a decreasing impact on RE development in seven developing economies. Zhao et al. (2024) show that volatility in OIL dampens investment in RE in China.

In the case of the US, several studies have investigated the impact of OIL volatility on total RE consumption. For instance, Shah et al. (2018) discover that OIL is positively related to RE industry. They further reveal that OIL accounted for a significant portion, around 22%, of the variance in RE investment. Guo et al. (2021) indicate that rising OIL stimulates RE investment and the subsequent development of RE infrastructure, resulting in an increase in its overall consumption. Sahu et al. (2022) show that OIL is positively associated with a rise in the utilization of RE. Husain et al. (2024) document that a rise in OIL has a moderate impact on RE, primarily through the substitution effect. On the contrary, Shang et al. (2022) state that a rise in OIL leads to a decrease in demand for RE and a corresponding increase in reliance on oil.

Economic growth and renewable energy

Sadorsky (2009) shows that economic progress is the primary driver of RE utilization in G7 countries. Ohler and Fetters (2014) note the positive correlation between various forms of RE sources such as hydroelectricity, wind, biomass, and waste energy. Bamati and Raoofi (2020) highlight that increases in economic growth (EG) have a larger impact on RE growth in industrialized nations than in less developed ones. Tudor and Sova (2021) find a positive association between EG and RE use. Apergis and Danuleti (2014) show that RE investment is positively correlated with EG. Dogan et al. (2023) conclude that the utilization of RE is positively impacted by EG in 25 selected EU countries. Kilinc-Ata and Dolmatov (2023) observe that there is a positive linkage between EG and installed RE capacity. In other words, EG rises the capacity for RE in the BRICS and 34 OECD countries.

There have been few studies that have used industrial production (IP) as a measure of economic growth. Sari et al. (2008) demonstrate that IP is the primary driver of hydropower, waste, and wood energy consumption. In addition, they also state that the production of industrial goods results in a decrease in the demand for both natural gas and solar energy. Salim et al. (2014) discover a bidirectional causal connection between RE and IP in 29 OECD countries. Employing continuous wavelet transform analyses, Bilgili (2015) reports a positive correlation between RE and IP in the US. Marques et al. (2016) document that as industrial production expands, there is a corresponding rise in the utilization of non-RE sources in Greece. Hoang et al. (2020) find a positive linkage between IP and RE, with biomass energy derived from waste, biofuel, and wood exhibiting the strongest association in the US. Su et al. (2022) point out that industrialization level hinders the expansion of RE consumption due to alterations in the economic structure in 116 countries.

Data and model

This study delves into the influence of CPU, oil prices, and industrial production on modern renewables in the US economy. The monthly data are used from 1989M1 to 2023M12 for this purpose. First, the dependent variable is modern renewables, including solar, wind, biofuels, and geothermal. The reason for choosing them is based on their carbon-neutral characteristics and their significant role in achieving SDG-7. The US ranks first in biofuel production and second in solar and wind power installations worldwide. Because of their centrality to the country's energy strategy, these sources must be seriously considered. Second, the core explanatory variable is the CPU index, which was established by Gavriilidis (2021). In accordance with the approach utilized in the economic policy uncertainty index developed by Baker et al. (2016), this variable was constructed through the identification of specific terms in eight leading US newspapers. These terms include "climate risk," "global warming," "CO_2 emissions," "greenhouse gas emissions," "green energy," "climate change," "renewable energy," and "environmental," as well as their respective variants such as "regulatory," "uncertainties," and "policies." Integrating this index into analysis is important because the US may face prolonged uncertainty in climate policies due to its withdrawal from and then re-commitment to the Paris Agreement. Therefore, this could potentially pose challenges to the stability and coherence of the nation's climate policies. Third, industrial production (IP) as an economic progress is included to capture the income effect on energy demand. The rationale behind this selection is that the US industrial sector is the most energy-consuming sector, and the country ranks second in industrial production on a global scale. Fourth, oil prices are chosen as an indicator of non-RE energy prices due to the US ranking first among global oil producers. Additionally, rising oil prices may result in cost-effectiveness favoring investment in modern renewables, thereby incentivizing the country to increase production of such sources. Consequently, the empirical models can be expressed as follows:

$$lnSOLAR_t = \beta_1 + \beta_2 lnIP_t + \beta_3 lnCPU_t + \beta_4 lnOIL_t + \varepsilon_t \quad (1)$$

$$lnWIND_t = \beta_1 + \beta_2 lnIP_t + \beta_3 lnCPU_t + \beta_4 lnOIL_t + \varepsilon_t \quad (2)$$

$$lnBIO_t = \beta_1 + \beta_2 lnIP_t + \beta_3 lnCPU_t + \beta_4 lnOIL_t + \varepsilon_t \quad (3)$$

$$lnGEO_t = \beta_1 + \beta_2 lnIP_t + \beta_3 lnCPU_t + \beta_4 lnOIL_t + \varepsilon_t \quad (4)$$

where SOLAR, WIND, BIO, and GEO stand for solar energy, wind energy, biofuel energy, and geothermal energy. In Eq. 1 to Eq. 4, β_1 is the constant, $\beta_{2,3,4}$ are the long-run coefficients, ln is the logarithm form, and ε_t is the error

Table 1 Variable definitions

Symbol	Variable	Definition	Source
SOLAR	Solar energy consumption	Trillion btu	EIA (2024)
WIND	Wind energy consumption	Trillion btu	EIA (2024)
BIO	Biofuel consumption	Trillion btu	EIA (2024)
GEO	Geothermal energy consumption	Trillion btu	EIA (2024)
IP	Industrial production	Total index	FRED
CPU	Climate policy uncertainty	Index	Gavriilidis (2021)
OIL	Crude oil prices	$ per barrel	FRED

EIA: Energy Information Administration; FRED: Federal Reserve Economic Data

Table 2 Descriptive statistics

	LnSOLAR	LnWIND	LnBIO	LnGEO	LnIP	LnCPU	LnOIL
Mean	2.1505	1.9878	3.8433	1.9917	4.4747	4.5390	3.7101
Median	1.7708	2.0410	3.7406	1.9739	4.5320	4.5040	3.8075
Maximum	4.5818	5.0595	5.3660	2.3710	4.6455	6.0192	4.8969
Minimum	1.0086	− 6.9077	1.9821	1.2944	4.0994	3.3379	2.4292
Std. dev	0.9228	2.1184	1.1786	0.2719	0.1691	0.4874	0.6358
Skewness	1.0746	− 0.4256	0.0064	− 0.2454	− 1.0567	0.4695	− 0.0510
Kurtosis	2.8967	2.6878	1.3033	1.7522	2.6935	2.8855	1.6349

term. IP denotes industrial production, CPU stands for the climate policy uncertainty index, and OIL represents oil prices. To facilitate the computation of elasticities and prevent non-normality and heteroscedasticity, a logarithmic transformation is applied to all variables in the model. Table 1 illustrates the detailed definitions of the variables.

Table 2 represents descriptive statistics for all variables considered. On average, CPU exhibits the highest value, whereas WIND demonstrates the lowest value. The median value of IP is the highest, followed by CPU. The variables SOLAR, BIO, and CPU exhibit a right-skewed distribution, while WIND, GEO, and OIL demonstrate a left-skewed.

Econometric methodology

The present study examines the stability of the variables of concern by using the Augmented Dickey–Fuller (ADF) (Dickey and Fuller 1979) and the Residual Augmented Least Squares ADF (RALS-ADF) (Im et al., 2014) unit root examinations. Following the establishment of the stationary characteristics of the variables, the identification of long-term associations is conducted through the utilization of Engle and Granger (EG) (Engle and Granger 1987) and Residual Augmented Least Squares EG (RALS-EG) (Lee et al. 2015).

The EG test is conducted using a two-step cointegration approach, which was selected based on the residuals framework and standard t-statistics. After determining the stationarity level of integration in the first step of the test, the next step involves estimating the regression using the ordinary least squares (OLS) method.

$$y_t = \beta z_t + \varepsilon_t \tag{2}$$

Subsequently, the residuals, denoted as $(\hat{u}_t)$, are subjected to decomposition from the model, and an Augmented Dickey–Fuller (ADF) test is utilized to assess their degree of integration.

$$\Delta\hat{u}_t = \varphi_0 + \varphi_1\hat{u}_{t-1} + \sum_{i=1}^{p}\varphi_{i+1}\Delta\hat{u}_{t-1} + e_t \tag{3}$$

Moreover, the RALS method implemented by Lee et al. (2015) is used as an extension of the EG cointegration test. The RALS cointegration test offers several advantages. First, assuming the non-normal error terms adhere to a normal distribution is a typical mistake (Im and Schmidt 2008). If the errors do not exhibit a normal distribution, the higher moments of the error term provide insights into the characteristics of non-normal errors. The RALS method enables the utilization of supplementary high-order moment information that is inherent in non-normal errors in linear model structures. However, the conventional cointegration test disregards data that contain non-normal errors. This is because the limiting distribution of test statistics does not rely on the error distribution assumption. Hence, in contrast to other traditional cointegration methods, the RALS technique has the potential to yield more robust outcomes in cases where the error term conforms to a non-normal distribution (Lee et al. 2015). Second, compared to tests based on a linear framework, nonlinear cointegration tests are less powerful statistically when dealing with non-normal errors. To lessen power loss, RALS uses the standard least squares estimation approach for non-normal errors (Oh et al., 2020). The third advantage is that the RALS cointegration test is formulated by incorporating a novel term that is derived from the second and third moments of the residuals

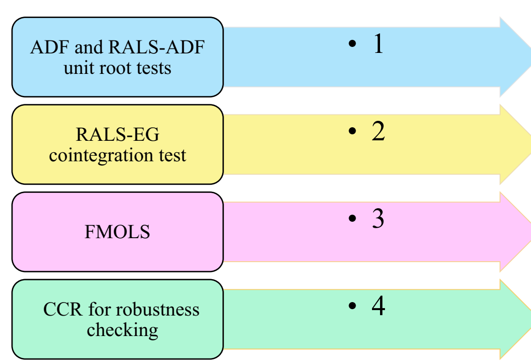


Fig. 2 Empirical flowchart of the study

obtained from conventional cointegration tests. In order to implement the RALS methodology, Eq. (3) is expanded by the inclusion of the subsequent term.

$$\hat{\omega}_t = p(\hat{e}_t) - \hat{K} - \hat{e}_t\hat{D}_t,\ t = 1,2,3,4,\ldots,T,$$

The residuals obtained from Eq. (3) are represented by $\hat{e}_t$ and $p(\hat{e}_t) = [\hat{e}_t^2 \hat{e}_t^3]$, $\hat{K} = \frac{1}{T}\sum_{i=1}^{T} p(\hat{e}_t)$, and $\hat{D}_t = \frac{1}{T}\sum_{i=1}^{T} p\prime(\hat{e}_t)$. Additionally, the subsequent equation denotes the RALS term formulated by Meng et al. (2017).

$$\hat{w}_t = [\hat{e}_t^2 - m_2, \hat{e}_t^3 - m_3 - 3m_2\hat{e}_t] \tag{4}$$

where $m_j = T^{-1}\sum_{i=1}^{T}\hat{e}_t^j$. The RALS cointegration regression model is derived by incorporating the variable $\hat{w}_t$ into Eq. (3).

$$\Delta\hat{u}_t = \varphi_1\hat{u}_{t-1} + \sum_{i=1}^{p}\varphi_{i+1}\Delta\hat{u}_{t-1} + \hat{w}_t\gamma + v_t \tag{5}$$

The standard t-statistics are utilized to test the null hypothesis (α1 = 0) in Eq. (5). The asymptotic distribution of the test statistic can be found by the following equation, which is based on the assumption that there is no cointegration:

$$t^* \rightarrow \rho.t + \sqrt{1-\rho^2}.Z \tag{6}$$

where t^* represents the RALS-EG test statistics, while t is used to denote the EG test statistics. The variable denoted as Z in the equation represents the standard normal random variable, whereas ρ signifies the long-term correlations of the residuals derived from Eq. (3) and Eq. (5).

Finally, long-run coefficients are obtained by the fully modified least squares (FMOLS) (Phillips and Hansen 1990) and canonical cointegrating regression (CCR) methods (Park 1992). Figure 2 illustrates the empirical flowchart of the study.

Table 3 Unit root test results

Variables	ADF	RALS-ADF	
	Test statistics	Test statistics	ρ^2
Level			
LnSOLAR	– 0.792 (15)	– 1.439 (15)	0.788
LnWIND	– 0.497 (11)	– 1.052 (11)	0.754
LnGEO	– 1.076 (15)	– 1.596 (15)	0.751
LnBIO	– 0.569 (12)	– 1.109 (12)	0.872
LnIP	– 1.958 (2)	– 2.119 (2)	0.729
LnCPU	– 2.234 (5)	– 2.404 (5)	0.981
LnOIL	– 2.195 (1)	– 1.714 (1)	0.871
First differences			
Δ LnSOLAR	– 15.847* (14)	– 15.968* (14)	0.985
Δ LnWIND	– 13.436* (10)	– 15.711* (10)	0.753
Δ LnGEO	– 6.650* (14)	– 6.724* (14)	0.753
Δ LnBIO	– 5.797* (11)	– 7.527* (11)	0.873
Δ LnIP	– 14.940* (1)	– 18.646* (1)	0.729
Δ LnCPU	– 13.484* (5)	– 13.269* (5)	0.985
Δ LnOIL	– 15.363* (0)	– 15.679* (0)	0.867

(1) The optimal lag length, ascertained through recursive t-statistics, is indicated by the numbers in parentheses. (2) 1%, 5%, and 10% critical values for ADF test are – 3.45, – 2.87, and – 2.57, respectively. (3) 1%, 5%, and 10% critical values for RALS-ADF test are – 3.88, – 3.33 and, – 3.05, respectively. (4) * represents the significance level at 1%

Table 4 Cointegration results

Method	k	Test stat	ρ^2
Model 1–SOLAR			
EG	14	– 3.802***	–
RALS-EG	14	– 7.389*	0.513
Model 2–WIND			
EG	0	– 9.698*	–
RALS-EG	0	– 8.290*	0.856
Model 3–BIO			
EG	1	– 4.415**	–
RALS-EG	1	– 11.935*	0.586
Model 4–GEO			
EG	12	– 2.958	–
RALS-EG	12	0.000	0.845

(1) *, **, and *** represent the significance level at 1%, 5%, and 10%. (2) 1%, 5%, and 10% significance level critical values for RALS-EG are – 4.71, – 4.09, and – 3.75

Empirical results

The initial stage of empirical analysis involves conducting a unit root test to determine the spuriousness of the dataset being used. In this regard, this study considers the ADF and RALS-ADF, to assess the stationary and non-stationary properties of the variables. Based on the findings of the ADF and RALS-ADF assessments outlined in Table 3, it can be inferred that SOLAR, WIND, GEO, BIO, IP, CPU, and OIL have demonstrated stationarity subsequent to the implementation of the first-order differences. These results allow for the investigation of the cointegration association among the variables.

Conducting a test for long-term association is a prerequisite for assessing the impact of IP, CPU, and OIL on modern renewables. Therefore, to ascertain the presence of the said linkage, the EG and RALS-EG cointegration tests are utilized prior to estimation. The outcomes of the cointegration tests are shown in Table 4. There is statistical

Table 5 Estimation results with FMOLS

Models	SOLAR		WIND		BIO	
Variables	Coefficients	*p* value	Coefficients	*p* value	Coefficients	*p* value
LnIP	2.217**	0.034	4.356*	0.000	2.424*	0.000
LnCPU	2.083*	0.000	1.808*	0.000	0.945*	0.000
LnOIL	− 0.441	0.1243	1.302*	0.000	0.811*	0.000
Constant	− 15.637*	0.001	− 30.532*	0.000	− 14.314*	0.000
R^2	0.766		0.783		0.818	

* and ** represent the significance level at 1% and 5%

Table 6 Estimation results with CCR

Models	SOLAR		WIND		BIO	
Variables	Coefficients	p value	Coefficients	p value	Coefficients	p value
LnIP	1.938*	0.004	4.356*	0.000	2.431*	0.000
LnCPU	1.621*	0.000	1.874*	0.000	0.981*	0.000
LnOIL	− 0.241	0.1046	1.280*	0.000	0.797*	0.000
Constant	− 13.002*	0.000	− 30.753*	0.000	− 14.454*	0.000
R^2	0.666		0.781		0.816	

* represents the significance level at 1%

significance observed in the estimated test statistics for EG and RALS-EG in Models 1 to 3. This signifies the rejection of the null hypothesis of no cointegration at a significance level of 1%. The results reveal the existence of a cointegration linkage among SOLAR, WIND, BIO, IP, CPU, and OIL. Nevertheless, the cointegration of GEO with IP, CPU, and OIL is absent. The FMOLS technique is utilized in the final stage to ascertain the long-term effects of the explanatory variables. Table 5 displays the estimated values for the long-term coefficients.

The findings from the FMOLS method show that IP has a favorable effect on modern renewable usage. Precisely, a 1% increase in industrial production increases solar, wind, and biofuel energy by 2.217%, 4.356%, and 2.424%, respectively. In other words, industrial production is the driving factor of modern renewable use. This finding suggests that as income levels rise, the US government provides greater incentives for the adoption of SOLAR, WIND, and BIO. This, in turn, contributes to the country's goal of achieving carbon neutrality. This outcome is consistent with Hoang et al. (2020), who reveal a strong linkage between IP and RE in the US economy.

Modern RE sources are favorably correlated with CPU, as predicted. CPU encourages the utilization of solar, wind, and biofuels. Specifically, a rise of 1% in the level of uncertainty pertaining to climate policy is related to a corresponding rise in SOLAR, WIND, and BIO by 2.083%, 1.808%, and 0.945%, respectively. The results show that the SOLAR, WIND, and BIO consumption increase as the degree of uncertainty over climate policy increases. This implies that climate-related concerns impact investor decision-making,

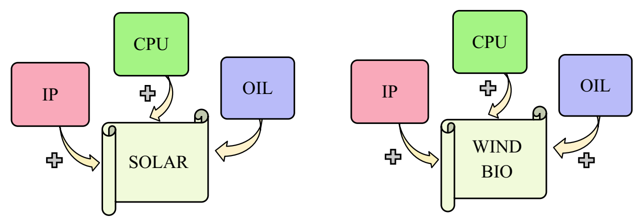


Fig. 3 Visual representation of the empirical results

potentially fostering investment in modern renewables, which are characterized by zero-carbon. In addition, the presence of CPU gives rise to market volatility, leading investors to actively pursue stability in zero-carbon energy sources. In other words, the results suggest that policymakers or investors respond to climate policy risk by directing their interest in and investment decisions for solar power, wind power, and biofuels. In a shifting energy landscape characterized by climate risk, this makes renewable energy investments more appealing. The result is consistent with the results obtained by Shang et al. (2022) and Sarker et al. (2023) for the US. Ding et al. (2024) also claim that climate risk has a substantial promotional impact on RE in the US. Furthermore, Van der Ploeg and Rezai (2020) point out that a potential decline in investments in the capital necessary for fossil fuel extraction results from uncertain situations in climate policy. However, it contradicts the findings of Li et al. (2023).

The impact of OIL on different forms of modern renewables varies. It has an increasing impact on wind energy and biofuels. Surprisingly, though, OIL has no discernible effect on solar power. Precisely, a 1% upsurge in oil prices leads to a corresponding 1.808% and 0.945% increase in wind energy and biofuels, respectively. This suggests that the escalation of oil prices has prompted the government to promote the increased utilization of WIND and BIO. Therefore, the consideration of oil prices is crucial when formulating renewable energy policies. It can be said that as the cost of oil increases, the feasibility of investing in and manufacturing wind energy and biofuels becomes more economically advantageous. The outcomes are in accordance with expectations, as the rise in OIL incentivizes the US to adopt more cost-effective energy substitutes. Karlilar Pata and Balcilar (2024) provide evidence that wind power partially replaces fossil fuels, whereas biomass power totally replaces them. Moreover, the findings contribute to the achievement of the goal of attaining cost-effective, modern, and sustainable energy, as envisioned in the SDG-7 outlined by the UN. This finding aligns with prior studies conducted by Guo et al. (2021) and Sahu et al. (2022), which reveal that oil prices are one of the key contributors of RE utilization. In addition, Magazzino et al. (2024) discover a bidirectional causal link between OIL and WIND and GEO in Italy.

To assess the reliability of the FMOLS estimation outcomes, the CCR method is also employed, and the findings are illustrated in Table 6. According to the CCR method regression results, industrial production, and climate policy uncertainty exhibit positive and significant effects on solar, wind, and biofuels energy consumption. In addition, oil price is positively associated with wind and biofuels energy, whereas it has no impact with solar energy. Consequently, it can be inferred that the findings of the robust check conducted in this research have yielded conclusions that are consistent and dependable with those of the FMOLS results. Figure 3 illustrates the visual representation of the estimation results.

Conclusion and policy implications

Climate change has been a concern for the international community, prompting nations to take action toward achieving a net-zero economy. This endeavor has led to numerous modifications and advancements in climate policy. In this regard, RE has been extensively documented as playing a crucial role in mitigating GHG and addressing the environmental crisis. Accordingly, the determinants that influence the utilization of RE sources have been an essential issue in the pursuit of sustainable ecological conditions, given the present circumstances of global warming, climate change, and energy security. Therefore, this paper investigates the determinants that contribute to the interest in modern RE sources in the US. To this end, monthly data on IP, CPU, OIL, SOLAR, WIND, GEO, and BIO from January 1989 to December 2023 were utilized. The EG and RALS-EG are applied for the purpose of assessing cointegration, while the FMOLS and CCR methods are conducted to estimate the long-term coefficients.

The study has the following outcomes. First, there is a positive linkage between IP and SOLAR, WIND, and BIO energy. The findings imply that the utilization of IP has a positive impact on the surge in demand for modern renewables in the US. This is in line with the outcome of Hoang et al. (2020). Second, higher costs for oil incentivize the utilization of modern energy alternatives. In other words, in response to escalating oil prices, the US augments its demand for wind and biofuel energy and reduces its reliance on fossil fuel-based sources. Hence, OIL is a significant driver of wind and biofuels utilization. However, it has no impact on solar energy. This outcome is consistent with the findings of Husain et al. (2024) and contradicts the conclusion of Shang et al. (2022). Third, CPU has a positive impact on the utilization of solar, wind, and biofuel energy. The positive influence of CPU is evident in its capacity to stimulate increased interest in clean energy, particularly solar, wind, and biofuel. This, in turn, leads to more investment in research and development (R&D) for these sources, resulting in a corresponding increase in modern renewables. This is in line with the conclusions of Shang et al. (2022) and Sarker et al. (2023) for the US, but they solely focus on total RE in their analysis. In addition, the imposition of pollution taxes by the US government on firms that contribute to environmental degradation may serve as a motivating factor for producers to decrease their reliance on fossil fuels.

The potential consequences of uncertainty in climate policy should be carefully considered by policymakers prior to making the investment decision. It is critical to build investments that are resilient to rising vulnerabilities while considering the intrinsic volatility and unpredictability of climate policy. Hence, given that CPU mostly stems from the divergent climate policies of state and federal governments, both types of governments should establish a unified climate policy. Moreover, promoting sustainable methods and practices should be a top priority for the US government since they can lead to a variety of investment opportunities. As a result, investors are better able to channel their funds into modern renewables, as this strategy reduces the perceived risks associated with climate legislation. Additionally, supporting global collaboration on climate action in the US can pave the way for technological transfer and concerted attempts to tackle climate-related uncertainties and challenges on a global scale. Furthermore, policymakers should develop strategies and guidelines that promote the utilization of clean energy to boost its effectiveness in addressing medium- and long-term challenges to climate policy. Herein, the US government should adjust its emission reduction policies and strategies in response to the observed correlation between CPU and modern RE sources. This adjustment can specifically target solar, wind, and biofuels, with the aim of attaining carbon neutrality and fostering a robust and sustainable energy sector within the energy market. In light of climatic uncertainties, modern renewables have enhanced prospects as safe havens when compared to fossil fuel energy. As a result, policymakers can promote a more stable climate policy for sustainable investments by implementing these guidelines. In the end, this can draw in a larger pool of investors to zero-carbon energy sources and strengthen eco-friendly activities.

This study has some limitations. First, future studies can analyze the asymmetric impact of CPU on various sources of RE. Second, further investigation can be conducted to analyze the impact of CPU on sector-specific fossil energy. Third, this study solely investigates the impact of uncertainty pertaining to climate policy, while disregarding the impact of other types of policy uncertainty, such as those related to energy markets and trade policies. Hence, future research can enhance the framework of the study by incorporating these variables. Fourth, future studies can use recent advanced methodologies like wavelet coherence, quantile and quantile methods.

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Declarations

Conflict of interest The authors declare that they have no competing interests.

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