International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(1), 532-540.

China's Sustainable Development under Climate, Energy and Policy Uncertainty: A Focus on SDG 7 and SDG 13

Ozge Demirkale[1]*, Naime Irem Duran[2]

[1]Department of Business Administration, Faculty of Economics and Administrative Sciences, Istanbul Aydin University, Istanbul, Turkey, [2]Department of Capital Markets, Faculty of Economics and Administrative Sciences, Beykent University, Istanbul, Turkey. *Email: ozgedemirkale@aydin.edu.tr

Received: 09 September 2024 **Accepted:** 05 December 2024 **DOI:** https://doi.org/10.32479/ijeep.17653

ABSTRACT

This paper contributes to the literature through a focus on the case of China and an investigation into the effects that CPU, EPU, and EUI variables have upon SDG 13 and SDG 7 through using ARDL and NARDL models along with the Dynamic Multipliers Effect Test. The analysis period includes annual data from 2003 to 2022. In the case of this study, from the literature review, some readily available studies measured the impact of China's CPU, EPU, and EUI on the SDGs. It has also been observed that the degree of investigation on the effects of CPU on SDG 13 and SDG 7 has been shallow. Based on the results, the constructed SDG 7 and SDG 13 ARDL and NARDL models strongly validate the cointegration relationships among the taken variables. The test of symmetric effects on CPU in SDG13 from the results of the NARDL shows that the coefficients for $LCPU^{poz}$ and$LCPU^{neg}$ are positive, which means the effects of positive shocks are more dominant. Additionally, to ensure model robustness, three parametric methods—Fully Modified Ordinary Least Squares (FMOLS), Dynamic Ordinary Least Squares (DOLS), and Canonical Cointegration Regression (CCR) are utilized. According to results, CPU, EPU and EUI have a substantial impact on the SDG7 and SDG13 indices.

Keywords: Sustainable Development Goals, Climate Uncertainty, Policy Uncertainty, Energy Uncertainty
JEL Classifications: C58, G20, O44, Q50

1. INTRODUCTION

China's rapid urbanization and industrialization in recent decades have generally supported economic and social growth but have also placed significant pressure on the environment. As a key driver of economic growth in the Asia-Pacific region, China experienced its highest levels of environmental pollution and carbon dioxide emissions following a period of rapid economic expansion and reindustrialization in the first decade of the 21st century. In 2007, this increase led China to surpass the United States, becoming the world's largest emitter of carbon dioxide (Huo, 2023; Li and Liu, 2021). This environmental issue may be linked to the unsustainable use of fossil fuel-based energy sources. The combustion of fossil fuels results in air pollution (Tumala Mohammed et al., 2023; Liu et al., 2023a; Liu et al., 2023b). This situation has led to issues related to resources and energy, ecology and the environment, carbon emissions, and climate change emerging as critical barriers and constraints to economic and social progress. The Chinese government was thus committed to the global community that it would cut down carbon emissions to a "carbon neutral China" by 2060 and achieve the SDG, specifically 7 and 8 (Climate Ambition Summit, 2020).

The introduction of the Sustainable Development Goals (SDGs) by the United Nations in 2015 has heightened international awareness of sustainability concepts. Achieving these goals and enhancing the efficiency and sustainability of limited resources necessitates not only the actions of government authorities but also the private sector and society to operate with the same level of awareness. Government authorities should develop environmental policies to mitigate the effects of climate change and ensure their macro-level applicability worldwide while managing their countries at the micro level. The private sector should implement and advance these policies, and at the societal level, consumers should engage in consumption and investment activities that align with this awareness. Today, institutions such as central banks, commercial banks, and International Financial Institutions (IFIs) play an active role in international initiatives that emphasize the shared responsibilities of various stakeholders in society, such as the Sustainable Development Goals (SDGs) and the Paris Agreement (United Nations, 2015). Sustainable Development Goals (SDGs) encompass various dimensions. This study focuses on China's Sustainable Development Goals, specifically SDG 7 (Affordable and Clean Energy) and SDG 13 (Climate Action). Under SDG 7 (Affordable and Clean Energy), the focus is on electricity access, renewable energy, and international energy cooperation. Globally, increases in electrification in urban areas are monitored, while in China, significant growth in renewable energy capacity has been noted, with capacity increasing 2.12 times in 2021 compared to 2015. In developing countries, China achieved SDG 7 by raising per capita electricity consumption in 80 countries and supporting solar energy training programs for 133 countries. In the context of SDG 13, the emphases of the report are focused on four major themes: Disaster monitoring and mitigation actions, early warnings over the long term for climate change, the estimation of global terrestrial and oceanic carbon sinks, and education about climate change. A series of policies and measures in the Chinese government and other provincial governments have developed highly advanced disaster-reduction systems. China is relatively well-developed about education on climate change, but developing curriculum design and practical activities within the education process remains urgent. With the rise in global land temperatures, there has also been an increase in the frequency and intensity of heat waves, as well as in ocean heat content, salinity differences, and vertical stratification (Big Earth Data in Support of the Sustainable Development Goals 2022).

This study aims to contribute to the literature by examining the effects of CPU, EPU and EUI on SDG 13 and SDG 7, with a focus on China, using ARDL and NARDL models, as well as the Dynamic Multipliers Effect Test. The literature review reveals a limited number of studies measuring the impact of Climate Policy Uncertainty, Policy Uncertainty, and Energy-Related Uncertainty on Sustainable Development Goals in China. Additionally, it has been observed that there is insufficient analysis of the relationship between CPU and SDG 13 and SDG 7. In this context, the study aims to address a significant gap in the literature.

This article is organized as follows: Section 2 presents a review of the relevant literature, while Section 3 introduces the methods and dataset used. Section 4 presents the empirical results. Finally, Section 5 summarizes the findings, outlines policy implications, and discusses the limitations of the study, providing insights for future research.

2. LITERATURE REVIEW

2.1. Uncertainties and Sustainable Development Goals

In the literature, especially in recent years with the prominence of Sustainable Development Goals (SDGs), there are studies examining the relationship between uncertainty factors such as economic, political, and geopolitical risks and development goals. However, a review of the existing literature indicates that the relationship between CPU, EPU, EUI, and SDGs has been studied only to a limited extent. A review of studies considering uncertainty reveals that there are a limited number of works examining the relationship between geopolitical risk and SDGs. For example, Ahmad et al. (2024) affirm that financial development and eco-innovation policies are the predictors of Sustainable Development Goals in OECD nations. It also concluded that managing geopolitical risks is important in attaining these SDG goals. Bakhsh et al. (2024), in their work titled green finance, geopolitical risk, and sustainable development goals–a VAR assessment for OECD countries, analyse the green finance, geopolitics, and SDGs for members of OECD from the year 2000 to 2020. Based on the results analysis in this paper, green finance is a positive factor that can contribute to the enhancement of the SDGs, while high geopolitical risk can be a negative factor that influences the green finance activities. In the Nguyen et al. (2023) paper based on 41 countries it was identified that geopolitical risks may be detrimental to SDGs. The researchers concluded that the strains or competitiveness within the geopolitical structure have a more significant impact on sub-indices of the Consultative process of the Sustainable Development Goals: Issues based on SDGs are SDG8 and SDG13. Chu et al. (2023) noted that while discussing financing and identifying the necessity for the evaluation of the political risks of an alteration in order to transition to a sustainable environment, the panel studied 40 developed and developing nations over the period 2000-2018. When affected by geopolitical risk, both groups of countries experience a reduction in environmental degradation as inferred from the research.

2.2. Climate Policy Uncertainty

There are a great number of studies in the literature that analyze the relationship between CPU and financial assets, macroeconomic indicators, and energy markets. In this regard, research that explores the relationship between CPU and financial assets suggests that CPU may affect volatility and performance in stock markets (Hdom and Fuinhas, 2020; Bouri et al. 2022; Chen et al. 2023; Khalfaoui et al. 2022; Liang et al. 2022; Lv and Li, 2023; Pham et al., 2023; Raza et al. 2024; Tedeschi et al. 2023).

Along this vein, the research findings into the relationship between CPU with renewable energy, carbon emission, and other macroeconomic variables turn out to be inconclusive (Pattak et al., 2023; Yang et al., 2024; Işık et al., 2023; Huang, 2023; Guesmi et al., 2023; Omer & Capaldo, 2023). Yang et al. (2024) have further in this regard that the CPU shocks could have considerable influences on the United States economic cycle, while according to Işık et al. (2023), a surge of U.S. climate policy uncertainty is a little connected with CO_2 emissions. Omer and Capaldo (2023) reiterate that reduction of emissions would not be able to solve this, and thus expansive macroeconomic policy will be required to achieve sustainable and equitable growth in South Africa.

In the review of studies on China's climate policy conducted by the United States CPU, Ren et al. (2022a) present the way CPU in China leads to adverse decisions by mining companies on investments. Dai and Zhang (2023) establish how CPU can alter the risk-taking behavior of Chinese banks. On the other side, Ren et al. (2022b) document that CPU reduces excessive corporate debt and financing constraints of high technology and high-emission companies

Research Question: Can China's Climate Policy Uncertainty Index, Policy Uncertainty Indices, and Energy-Related Uncertainty Indexes support environmental sustainability by providing a long-term relationship with SDG 7 and SDG 13 targets?

In summary, the literature review has revealed a limited number of studies measuring the impact of China's CPU, EPU, and EUI on Sustainable Development Goals. Additionally, it has been observed that there is insufficient examination of the relationship between CPU and SDG 13 and SDG 7. This study aims to contribute to the literature by examining the effects of CPU, EPU, and EUI on SDG 13 and SDG 7, with a focus on China, using ARDL and NARDL models, as well as the Dynamic Multipliers Effect Test.

3. MODEL SPECIFICATIONS AND DATA

The ARDL model developed by Pesaran et al. (1996), Pesaran and Shin (1999), and Pesaran et al. (2001) can also be used for small samples. This test allows for the use of variables at different levels of integration, unlike the cointegration tests developed by Engle and Granger (1987) and Johansen (1988), which require variables to be stationary at the same level. Therefore, in the ARDL bounds testing approach, it is not necessary to determine the degrees of stationarity of the variables as a prerequisite (Narayan and Smyth, 2005:103). However, the ARDL model does not apply to those variables that are stationary at the second difference. This calls for a unit root test in order to ensure that the variables considered in the analysis are not stationary at the second difference. In this framework, the Augmented Dickey- Fuller and Phillips-Perron unit root tests were used in investigating the stationarity of variables.

In fact, taking into account the cointegration relationship among the variables, Pesaran et al. (2001) suggested using a bounds-testing approach. When the F-statistic values obtained from applying the Wald test to the levels of the variables fall below the critical values from the table, the null hypothesis would be inconclusive, and hence it would be concluded that there is no cointegration among the series (Narayan and Smyth, 2005:103).

Pesaran et al., (2001), general equation for the unrestricted error correction model the adapted forms of the models used in the study according to ARDL are shown as Equal 1 and Equal 2.

$$LSDG7_t = \alpha_0+\beta_1 LCPU_1+\beta_2 LCEPU_2+\beta_3 LEUI_3+\varepsilon_t \quad (1)$$

$$LSDG13_t = \alpha_0+\beta_1 LCPU_1+\beta_2 LCEPU_2+\beta_3 LEUI_3+\varepsilon_t \quad (2)$$

The hypotheses for the bounds test should be formulated as follows: (Pesaran et al. 2001: 296):

H_0: $\pi_{yy} = 0$, $\pi_{yx.x} = 0$ (There is no cointegration)
H_1: $\pi_{yy} \neq 0$, $\pi_{yx.x} \neq 0$ (There is cointegration)

The ARDL model assumes that only linear or symmetric relationships exist among the variables when evaluating cointegration relationships. The NARDL (Non-Linear Autoregressive Distributed Lag) model, developed by Shin et al. (2014), is an asymmetric extension of the standard ARDL approach designed to identify non-linear relationships and both short-term and long-term asymmetries in the series (Shahzad et al., 2017: 215). The NARDL approach identifies the effects of changes in the independent variable on the dependent variable by differentiating between the negative and positive partial sums of the independent variable.

The asymmetric cointegration model underlying the NARDL cointegration method can be expressed as follows (Shin et al., 2014:8):

$$y_t = \beta^+ X_t^+ + \beta^- X_t^- + u_t \quad (3)$$

The study also applies the dynamic multipliers effect test to understand the symmetric effects of the CPU on SDG 7 and SDG 13. In the Dynamic Multipliers Effect Test, the multiplier effect graphs trace the dynamic response of the dependent variable following the shocks of positive and negative independent variables.

In place of traditional cointegration tests, FMOLS, DOLS, and CCR methods are increasingly being used to determine long-term relationships between variables. Similar to the ARDL method, the FMOLS, DOLS, and CCR methods have demonstrated the ability to produce reliable results in small sample sizes (Erdoğan et al., 2018:47). FMOLS, proposed by Phillips and Hansen (1990), DOLS, developed by Stock and Watson (1993), and CCR, introduced by Park (1992), are preferred due to their ability to address the endogeneity problem in the estimation phase and the difficulty in interpreting long-term coefficients.

The FMOLS estimation results will be found using Equation (4) and Equation (5):

$$LFTXIN410_t = \alpha_0+\beta_1 LCPU_1+\beta_2 LCU_2+\beta_3 LCUM_3+\beta_4 LUCT_4+\varepsilon_t \quad (4)$$

$$LLSZEPI_t = \alpha_0+\beta_1 LCPU_1+\beta_2 LCU_2+\beta_3 LCUM_3+\beta_4 LUCT_4+\varepsilon_t \quad (5)$$

In the FMOLS method, by modifying the error terms to reduce the effects of autocorrelation and endogeneity, more accurate coefficient estimates are provided.

The DOLS estimation results will be found using Equation (6) and Equation (7):

$$LFTXIN410_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 \sum_{J=-p}^{p} \gamma_{1j} \Delta LCPU_{t-j} \sum_{J=-p}^{p} \gamma_{2j} \Delta LCU_{t-j} + \sum_{J=-p}^{p} \gamma_{3j} \Delta LCUM_{t-j} + \sum_{J=-p}^{p} \gamma_{4j} \Delta LUCT_{t-j} + \varepsilon_t \quad (6)$$

$$LLSZEPI_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 + \sum_{J=-p}^{p} \gamma_{1j} \Delta LCPU_{t-j} + \sum_{J=-p}^{p} \gamma_{2j} \Delta LCU_{t-j} + \sum_{J=-p}^{p} \gamma_{3j} \Delta LCUM_{t-j} + \sum_{J=-p}^{p} \gamma_{3j} \Delta LUCT_{t-j} + \varepsilon_t \quad (7)$$

In the DOLS model, estimates are made using the lagged and lead differences of the independent variables. The aim of this model is to provide more reliable estimates by controlling for endogeneity and autocorrelation.

The CCR estimation results will be found using Equation (8) and Equation (9):

$$LFTXIN410_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 + \varepsilon_t \quad (8)$$

$$LLSZEPI_t = \alpha_0 + \beta_1 LCPU_1 + \beta_2 LCU_2 + \beta_3 LCUM_3 + \beta_4 LUCT_4 + \varepsilon_t \quad (9)$$

The CCR method transforms the data in cointegration analyses by using only the stationary components and separates the error terms from the explanatory variables, providing more efficient and reliable estimates. Additionally, the CCR method allows for the asymptotic implementation of the Chi-square test.

Accordingly, this study will contribute to the literature by focusing on the case of China, analyzing the impacts of CPU, EPU, and EUI variables on SDG 13 and SDG 7 by using both ARDL and NARDL models, as well as the Dynamic Multipliers Effect Test. The period of analysis covers annual data ranging from 2003 to 2022. Descriptive information on the variables used in the analysis is depicted in Table 1.

4. ECONOMETRIC FINDINGS

In this context, stationarity levels of the variables were investigated by using ADF and PP unit root tests. According to the results of ADF and PP unit root tests, the series SDG13, CPU, EPU, and EUI obtained at I(0) stationarity level, while the variable of SDG7 was obtained at I(1) stationarity level. It was, in this regard, established that under I(2), none of the variables that were incorporated into the analysis was stationary Table 2.

4.1. Findings for SDG 7

The fact can be inferred from Table 3 that the ARDL and NARDL test results establish the presence of a long-run relationship among the variables. The F-statistic result in the table is significant at both 5% and 10% levels. Thus, the alternative hypothesis H_1, stating that there is cointegration between the variables, has been accepted.

Because cointegration among the series in question was identified, it became appropriate to estimate the long-term parameters reflecting the relationships from the ARDL (1, 0, 0, 2) model based on the AIC information criterion. Based on the diagnostic test of this model, no problem of autocorrelation or heteroskedasticity was exhibited. The obtained long-run coefficient from the ARDL is dynamically stable. Error correction term coefficient lies within the accepted range that is (−1<ECT<0), as shown in Table 4 and statistically significant also. The result of ARDL model shows that the long-term forecast of variables LCEPU and LEUI are statistically significant. A positive long term relationship observed between LSDG7 and the variable LEPU, LCPU LEUI are observed as shown by Table 4.

To test the symmetric effects of the LCPU variable on SDG7, the NARDL test was applied. The results of the NARDL model are summarized in Table 5. According to Table 5, the error correction term coefficient falls within the accepted range (−1<ECT<0) and is statistically significant, similar to the ARDL model. According to the diagnostic test results of the model, no issues of autocorrelation or heteroscedasticity have been observed. The long-term coefficients obtained from the NARDL model are dynamically stable. According to the long-term NARDL results, the coefficients for $LCPU^{poz}$ and $LCPU^{neg}$ are negative, indicating

Table 1: Definitions, Codes, and Sources of Variables

Variable	Symbol	Source
China sustainable development goals 13: Climate action	SDG13	Sachs et al., (2024).
China sustainable development goals 7: Affordable & clean energy	SDG7	Sachs et al., (2024).
China climate policy uncertainty	CPU	Gavriilidis (2021)
China policy uncertainty ındices	EPU	Davis et al., (2019)
Energy-related uncertainty	EUI	Dang et al., (2023)

Table 2: Unit root test[1]

	I(0)		I(1)	
ADF[2]	Intercept	Intercept and trend	Intercept	Intercept and trend
Variables	Prob.	Prob.	Prob.	Prob.
LSDG7	0.02	0.98	0.00	0.00
LSDG13	0.02	0.044	0.00	0.00
LCPU	0.00	0.009	0.00	0.01
LEPU	0.00	0.008	0.00	0.00
LEUI	0.00	0.001	0.00	0.00
	I(0)		I(1)	
PP[3]	Intercept	Intercept and trend	Intercept	Intercept and trend
Variables	Prob.	Prob.	Prob.	Prob.
LSDG7	0.020	0.079	0.00	0.00
LSDG13	0.025	0.045	0.00	0.00
LCPU	0.00	0.00	0.00	0.00
LEPU	0.00	0.00	0.00	0.00
LEUI	0.00	0.00	0.00	0.00

[1]The natural logarithms of all series have been taken
[2]Based on Schwartz ınfo criterion
[3]Based on Bartlett Kernel

Table 3: Bounds test for linear and nonlinear ARDL models for SDG7

Dependent variable: LSDG7	F-statistic	Significance level 10% I(0)	10% I(1)	5% I(0)	5% I(1)	Conclusion
ARDL model	5.15	2.37	3.2	2.79	3.67	Long-term relationship exists
NARDL model	9.81	2.2	3.09	2.56	3.49	Long-term relationship exists

Table 4: ARDL long-term test results for SD7

Variable	Coefficient	t-statistic	Prob.
Dependent variable: LSDG7			
LCPU	0.000	0.100	0.92
LEPU	0.011	2.369	0.03
LEUI	0.006	3.496	0.00
C	0.994	1.482	0.00
ECT_{t-1}[1]	−1.161	−5.803	0.00
Diagnostic Test Statistics			
R^2			0.66
Adjusted-R^2			0.62
Breusch-Godfrey LM Test (B-G LM) Prob.			0.67
Heteroskedasticity Test: B-P-G LM Prob.			0.79
Ramsey Reset (RR) Test			0.46
Jarque-Bera Normallik Test			0.80
CUSUM Test			Stationary
CUSUM-SQ Test			Stationary

1. $ECT_{t-1} = LSDG7 - (0{,}000LCPU + 0.011LCEPU + 0{,}006LEUI + 0{,}994)$

Table 5: NARDL long-term test results for SDG7

Variable	Coefficient	t-statistic	Prob.
Dependent variable: LSDG7			
$LCPU^{poz}$	−0.005	−2.64	0.033
$LCPU^{neg}$	−0.001	−1.13	0.29
LEPU	0.009	2.11	0.072
LEUI	0.002	1.79	0.11
C	1.004	1.59	0.00
ECT_{t-1}[2]	−1.567	−1.004	0.00
Diagnostic test statistics			
R^2			0.81
Adjusted-R^2			0.53
Breusch-Godfrey LM Test (B-G LM) Prob.			0.56
Heteroskedasticity test: B-P-G LM Prob.			0.087
Ramsey reset (RR) test			0.97
Jarque-Bera normalitytest			0.036
CUSUM test			Stationary
CUSUM-SQ test			Stationary

2. $ECT_{t-1} = LSDG7 - (-0{,}005LCPU^{poz} - 0{,}001LCPU^{neg} + 0{,}009LEPU + 0{,}002LEUI + 1.004)$

that the effects of negative shocks are more dominant. While the results show that $LCPU^{poz}$ is statistically significant, its impact on SDG 7 appears to be weak (Table 5).

Figure 1 shows the results of the dynamic multiplier effect test for examining the symmetric impact of LSDG7 on LCPU. According to the results, after the 5th period, positive and negative shocks have transitioned to symmetry, with the effects of negative shocks remaining limited and converging towards zero. The results obtained from the Dynamic Multiplier Effect test align with the NARDL results. The results indicate that while the variables $LCPU^{poz}$ ve $LCPU^{neg}$are statistically significant, their impact on SDG 7 is weak.

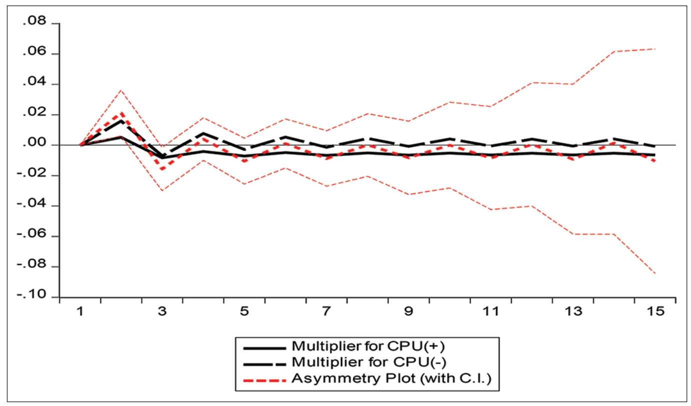
4.2. Findings for SDG 13

Table 6 presents the results of the cointegration test for linear and nonlinear ARDL models as specified in Equation 3. To investigate the presence of a cointegration relationship in ARDL models. It was found that the F-statistic values exceed both the lower and upper bound values in the ARDL and NARDL models. Consequently the alternative hypothesis (H_1) was supported indicating that a long-term relationship exists.

Table 6: Bounds test for linear and nonlinear ARDL models for SDG13

Dependent Variable: LSDG13	F-statistic	Significance level 10% I(0)	10% I(1)	5% I(0)	5% I(1)	Conclusion
ARDL Model	7.08	2.37	3.2	2.79	3.67	Long-term relationship exists
NARDL Model	4.14	2.2	3.09	2.56	3.49	Long-term relationship exists

Figure 1: Dynamic multiplier effect test results for SDG 7



Since cointegration was identified, the estimation procedure regarding the long-term parameters reflecting the relationship for the ARDL (7, 0, 1, 1) model was pursued with regard to the information criterion AIC. No autocorrelation or changing variance problems is contained as implied by the diagnostic test results. The estimated long-run coefficients from the ARDL model are dynamically stable. The estimation results of the ARDL model show that the variables LCPU and LEPU are significant statistically in the light of the long-term forecast. A positive long-run association between the SDG13 and the LCPU and negative long-run association with the variable LEPU was observed (Table 7).

To test the symmetric effects of the CPU on SDG13, the NARDL test was applied. The results of the NARDL model are summarized in Table 8. According to Table 8, the error correction term coefficient falls within the accepted range ($-1<ECT<0$) and is statistically significant, similar to the ARDL model. The diagnostic test results of the model indicate that it does not suffer from autocorrelation or changing variance issues. The long-term coefficients obtained from the NARDL models are dynamically stable, and no structural breaks are observed. The results obtained from the NARDL model show similarities to those of the ARDL model. Specifically, one could notice that the signs of coefficients for $LCPU^{poz}$ and $LCPU^{neg}$ are positive, evidencing the dominance of the effects of the positive shocks (Table 8).

Figure 2 shows the results of the dynamic multiplier effect test for examining the symmetric impact of LSDG13 on LCPU. According to the results, after the 4th period, positive and negative shocks have transitioned to symmetry, with the effects of negative shocks remaining limited and converging towards zero. The results

Table 7: ARDL long-term test results for SDG13

Variable	Coefficient	t-statistic	Prob.
Dependent variable: LSDG13			
LCPU	0.037	8.465	0.013
LEPU	−0.025	−6.350	0.023
LEUİ	−0.000	−0.576	0.622
C	0.979	1.482	0.00
ECT_{t-1} [3]	−3.714	−1.031	0.009
Diagnostic test statistics			
R^2			0.95
Adjusted-R^2			0.66
Breusch-Godfrey LM test (B-G LM) Prob.			0.60
Heteroskedasticity test: B-P-G LM Prob.			0.66
Ramsey reset (RR) test			0.70
Jarque-Bera normallik test			0.69
CUSUM test			Stationary
CUSUM-SQ test			Stationary

3. $ECT_{t-1} = LSDG13$ - (0,037$LCPU$ - 0.025$LEPU$ - 0,000$LEUI$ + 0,979)

Table 8: NARDL long-term test results for SDG13

Dependent variable: LSDG13			
Variable	Coefficient	t-Statistic	Prob.
$LCPU^{poz}$	0.043	2.385	0.048
$LCPU^{neg}$	0.040	2.250	0.059
LEPU	−0.015	−0.929	0.383
LEUİ	0.008	1.838	0.10
C	0.992	4.855	0.00
ECT_{t-1} [4]	−0.783	−6.531	0.00
Diagnostic test statistics			
R^2			0.73
Adjusted-R^2			0.329
Breusch-Godfrey LM Test (B-G LM) Prob.			0.25
Heteroskedasticity test: B-P-G LM Prob.			0.36
Ramsey reset (RR) test			0.33
Jarque-Bera normality test			0.81
CUSUM Test			Stationary
CUSUM-SQ Test			Stationary

4. $ECT_{t-1} = LSDG13$ - (0,043$LCPU^{poz}$ + 0,040$LCPU^{neg}$-0,015$LEPU$ + 0,008$LEUI$ + 0,992)

obtained from the dynamic multiplier effect test align with the NARDL results.

The results obtained from the ARDL technique in Table 9 and 10 were analyzed using the FMOLS, DOLS, and CCR techniques. These methods, which are increasingly preferred overtraditional cointegration tests, can be applied to both stationary and non-stationary series.

In the FMOLS model, a 1% increase in LCPU results in a 0.005% rise in the average LSDG7 and, a 1% increase in LEPU results in a 0.003% rise in the average LSDG7. On the contrary, a 1% increment of LEUI on average, 0.001% decline in LSDG7. According to the model all variables were found to be statistically significant. This result underscores their pivotal role in influencing sustainable energy access, highlighting the critical interdependencies between policy frameworks and energy dynamics.

In the DOLS model, the variable LEUI was determined to be statistically significant. A 1% increment in LEUI uplift an average of 0.024% in LSDG7. The variables LEPU and LCPU were

Table 9: FMOLS, DOLS, CCR results for SDG 7

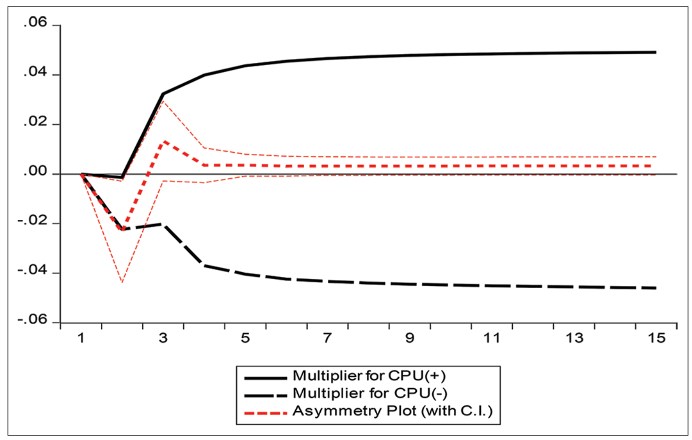
Dependent variable: LSDG7	FMOLS	DOLS	CCR
LCPU	0.005**	−0.010	0.023**
LEPU	0.003**	0.008	−0.016*
LEUI	−0.001*	0.024***	−0.004
C	1.00***	0.977***	0.017***

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

Table 10: FMOLS, DOLS, CCR results for SDG 13

Dependent variable: LSDG13	FMOLS	DOLS	CCR
LCPU	0.011**	0.017*	0.026***
LEPU	−0.009*	−0.012*	−0.026***
LEUI	0.003*	0.005	0.014***
C	0.980***	0.975***	0.971***

Figure 2: Dynamic multiplier effect test for SDG13



determined to be statistically insignificant. The significance of the Energy-Related Uncertainty variable in the DOLS model indicates that uncertainties in the energy sector have a substantial impact on SDG 7 (Affordable and Clean Energy). This finding suggests that addressing energy-related uncertainties is critical for enhancing access to clean energy and achieving sustainable energy policies.

In the CCR model, a 1% increment in LCPU uplift an average 0.023% of the LSDG7 average. On the contrary, a 1% increment of LEPU on average, 0.016% decline in LSDG7. The variable LEUI was determined to be statistically insignificant. According to the model results, the significance of the LEPU and LCPU Indices variables indicates that this method accurately identifies long-term cointegration relationships. This suggests that these variables have a long-term relationship with SDG7 and highlights the significant impact of policy uncertainties on climate and energy policies.

In the FMOLS model, a 1% increase in LCPU results in a 0.011% rise in the average LSDG13. On the contrary, a 1% increment in LEPU %0.009 decline of the LSDG13 average. A 1% incerase in LEUI results in a 0.003 % rise in the average LSDG13. When comparing the ARDL model and the FMOLS model, it is evident that both LCPU and LEPU variables exhibit comparable effects on the SDG 13 variable in each respective model. Moreover, the statistical significance of all variables in the FMOLS model, with SDG 13 (Climate Action) as the dependent variable, indicates that climate-related uncertainties, including China Climate Policy Uncertainty, China Policy Uncertainty Indices, and Energy-Related Uncertainty, collectively exert a meaningful influence on climate action and highlight the interconnectedness of these factors in addressing sustainability challenges.

In the DOLS model, a 1% increment in LCPU uplift an average of 0.017% in LSDG13. On the contrary, a 1% increment in LEPU %0.012 decline of the LSDG13.The variable LEUI was found to be statistically insignificant in the DOLS model. According to these results, the model suggests that while energy-related uncertainties may not have a direct or pronounced impact on the dependent variable, the uncertainties associated with climate and policy frameworks play a more critical role in influencing outcomes. This discrepancy may indicate that the effects of energy-related uncertainties are more nuanced or indirect, necessitating further investigation into their dynamics and interactions within the broader context of climate action.

In the CCR model, a 1% increment in, LCPU uplift an average 0.026% of the LSDG13 and a 1% increment in LEUI uplift 0.014% of the LSDG13. On the contrary, a 1% increment of LEPU on average, 0.026% decline in LSDG13. According to CCR model, all variables were determined to be statistically significant.

5. CONCLUSION AND POLICY RECOMMENDATIONS

This study aims to contribute to the literature by examining the effects of Climate Policy Uncertainty, Policy Uncertainty, and Energy-Related Uncertainty on SDG 13 and SDG 7, with a focus on China, using ARDL and NARDL models. The study also applies the Dynamic Multipliers Effect Test to better understand the symmetric effects of the CPU on SDG 7 and SDG 13. The literature review reveals a limited number of studies measuring the impact of CPU, EPU, and EUI on Sustainable Development Goals in China.

Firstly, The ARDL and NARDL models established for SDG 7 and SDG 13 clearly confirm the existence of cointegration relationships among the variables included in the analysis. According to the ARDL model established for SDG 7, a positive long-term relationship has been identified between SDG 7 and the CPU, EPU, and EUI variables. To test the symmetric effects of the LCPU variable on SDG7, the NARDL test was applied. According to the long-term NARDL results, the coefficients for $LCPU^{poz}$and $LCPU^{poz}$are negative, indicating that the effects of negative shocks are more dominant. While the results show that $LCPU^{poz}$ is statistically significant, its impact on SDG 7 appears to be weak. The robustness of the models was further ensured by applying FMOLS, DOLS, and CCR methods. When comparing the FMOLS, DOLS, and CCR estimates with the ARDL estimates, it is observed that the LEPU and LCPU variables have an long term effect in both the ARDL and FMOLS and CCR models, while the LEUI variable is found to be statistically significant in both the ARDL and DOLS models. Accordingly, the statistical significance of the LEPU variable in both the ARDL and FMOLS/CCR models indicates a strong influence of this variable on sustainable energy policies, while the significance of the LEUI variable in the ARDL and DOLS models suggests that the effects of climate policy uncertainty emerge differently under varying model specification.

The relation was long-term positive with SDG 13 and LCPU while that of the negative one was with the long-term relationship of the variable LEPU. For the coefficients of the NARDL model result, as shown, both $LCPU^{poz}$ and $LCPU^{neg}$depicted positive signs reflecting the dominancy of the positive shocks. The relationship between SDG 13 and the independent variables was examined using the FMOLS, DOLS, and CCR methodologies, it is found that all variables are statistically significant in both the FMOLS and CCR models, while the LEUI variable is identified as insignificant in the DOLS model. This finding, along with the signs of the coefficients, aligns with the results obtained from the ARDL estimation, indicating a coherent relationship across the methodologies.

These will, therefore, be highly significant results as far as deriving the implications of policy recommendations is concerned. The findings validate the time-varying relationship between positive and negative shocks in climate policy uncertainty and SDG 7, particularly SDG 13, and their impact on sustainable development goals. These results really pinpoint the dynamic interaction to be considered while formulating effective policies.

The study has found long-run positive relations of CPU with SDG 7 and SDG 13. Policymakers have to focus on the strengthening and stabilization of climate-related policies to reduce uncertainty and promote clean energy and climate action. The results from the NARDL test were symmetric effects of CPU to SDG 13. They showed that policies need to be designed in such a way as to dampen negative and positive fluctuations in climate policy. In this regard, the following measures can be designed:

- Both positive and negative shocks are important to CPU for SDG 13; policymakers should pay far greater priority to stabilization of the climate policy framework.
- Stakeholder involvement from the private sector, civil society, and academia contributes to a balanced and stable climate policy.
- Climate policy has to be designed in a way that allows flexibility and adaptation to positive and negative policy shocks.

REFERENCES

Ahmad, M., Ahmed, Z., Alvarado, R., Hussain, N., Khan, S.A. (2024), Financial development, resource richness, eco-innovation, and sustainable development: Does geopolitical risk matter? Journal of Environmental Management, 351, 119824.

Bakhsh, S., Alam, M.S.A., Zhang, W. (2024), Green finance and sustainable development goals: Is there a role for geopolitical uncertainty. Economic Change and Restructuring, 57, 137.

Big Earth Data in Support of the Sustainable Development Goals.

(2022). Available from: https://sdgs.un.org/sites/default/files/202306/China%20Big%20Data%20for%20SDGs%20report%202022.pdf

Bouri, E., Najaf, I., Tony, K. (2022), Climate policy uncertainty and the price dynamics of green and brown energy stocks. Finance Research Letters, 47, 102740.

Chen, Z., Li, Z., Chen, W. (2023), Does climate policy uncertainty affect Chinese stock market volatility? International Review of Economics and Finance, 84, 369-381.

Chu, L.K., Truong, H.H.D., Hoang, D.P. (2023), The varying ımpact of financial development on the environmental footprint due to geopolitical risk: The difference between high- and middle-income countries. Borsa Istanbul Review, 23, 1333-1355.

Climate Ambition Summit. (2020). Available from: https://www.climateambitionsummit2020.org/index.php#cop26

Dai, Z., Zhang, X. (2023), Climate policy uncertainty and risks taken by the bank: Evidence from China. International Review of Financial Analysis, 87, 102579.

Dang, T.H.N., Nguyen, C.P., Lee, G.S., Nguyen, B.Q., Le, T.T. (2023), Measuring the energy-related uncertainty index. Energy Economics, 124, 106817.

Engle, R.F., Granger C.W.J. (1987), Co-integration and error correction: Representation, estimation, and testing. Econometrica, 55(2), 251-276.

Erdoğan, L., Ceylan, R., Tiryaki, A. (2018), Türkiyede uzun dönem ekonomik belirleyicilerinin ARDL, FMOLS, DOLS ve CCR Yöntemleri ile Tahmini. Hacettepe Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 364, 39-58.

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

Guesmi, K., Makrychoriti, P., Spyrou, S. (2023), The relationship between climate risk, climate policy uncertainty, and CO_2 emissions: Empirical evidence from the US. Journal of Economic Behavior and Organization, 212, 610-628.

Huang, W. (2023), Climate policy uncertainty and green innovation. Economics Letters, 233, 111423.

Huo, W., Uz Zaman, B., Zulfiqar, M., Kocak, E., Shehzad, K. (2023), How do environmental technologies affect environmental degradation? Analyzing the direct and indirect impact of financial innovations and economic globalization. Environmental Technology and Innovation, 29, 102973.

Işık, C., Ongan, S., Ozdemir, D., Jabeen, G., Sharif, A., Alvarado, R., Amin, A., Rehman, A. (2023), Renewable energy, climate policy uncertainty, industrial production, domestic exports/re-exports, and CO_2 emissions in the USA: A SVAR approach. Gondwana Research, 127, 156-164.

Johansen, S. (1988), Statistical analysis of cointegration vectors. Journal of Economic Dynamics and Control, 12(2-3), 231-254.

Khalfaoui, R., Mefteh-Wali, S., Viviani, J.L., Jabeur, S.B., Abedin, M.Z., Lucey, B.M. (2022), How do climate risk and clean energy spillovers, and uncertainty affect U.S. stock markets? Technological Forecasting and Social Change, 185, 122083.

Li, Z., Lıu, Y. (2021), Research on the spatial distribution pattern and influencing factors of digital economy development in China. IEEE Access, 9, 63094-63106.

Liang, C., Umar, M., Ma, F., Huynh, T.L.D. (2022), Climate policy uncertainty and world renewable energy index volatility forecasting. Technological Forecasting and Social Change, 182, 121810.

Liu, H., Wong, W.K., Cong, P.T., Nassani, A.A., Haffar, M., Abu-Rumman, A. (2023b), Linkage among urbanization, energy consumption, economic growth and carbon emissions. Panel data analysis for China using ARDL model. Fuel, 332, 126122.

Liu, Y., Blankenburg, M., Wang, M. (2023a), Earnings expectations of grey and green energy firms: Analysis against the background of global climate change mitigation. Energy Economics, 121, 106692.

Lv, W., Li, B. (2023), Climate policy uncertainty and stock market volatility: Evidence from different sectors. Finance Research Letters, 51, 103506.

Narayan, P.K., Smyth, R. (2005), Trade liberalization and economic growth in Fiji. An empirical assessment using the ardl approach. Journal of The Asia Pacific Economy, 10(1), 96-115.

Nguyen, D.T., Le, T.H., Do, D.D., Nguyen, H.N. (2023), Does geopolitical risk hinder sustainable development goals? Evidence from a panel analysis. Journal of Environmental Management, 347, 119204.

Omer, O., Capaldo, J. (2023), The risks of the wrong climate policy for developing countries: Scenarios for South Africa. Ecological Economics, 211, 107874.

Park, J. (1992), Canonical cointegrating regressions. Econometrica, 60, 119-143.

Pattak, D.C., Tahrim, F., Salehi, M., Voumik, L.C., Akter, S., Ridwan, M., Sadowska, B., Zimon, G. (2023), The driving factors of Italy's CO_2 emissions based on the STIRPAT model: ARDL, FMOLS, DOLS, and CCR approaches. Energies, 16, 5845.

Pesaran, M.H., Shin, Y. (1999), An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis. Econometrics and Economic Theory in the 20th century: The Ragnar Frish Centennial Symposium. Ed./Steinar Strom. Cambridge: Cambridge University Press. p371-413.

Pesaran, M.H., Shin, Y., Smith, R.J. (1996), Testing for the "Existence of a Long-run Relationship". Cambridge Working Papers in Economics 9622, Faculty of Economics, University of Cambridge.

Pesaran, M.H., Yongcheol, S., Smith, R.J. (2001), Bounds testing approaches to the analysis of level relationships. Journal of Applied Econometrics, 16(3), S289-S326.

Pham, L., Hao, W., Truong, H., Trinh, H.H. (2023), The impact of climate policy on U.S. environmentally friendly firms: A firm-level examination of stock return, volatility, volume, and connectedness. Energy Economics, 119, 106564.

Phillips, P., Hansen, B. (1990), Statistical ınference in ınstrumental variables regression with I(1) processes. Review of Economic Studies, 57, 99-125.

Raza, S.A., Khan, K.A., Benkraiem, R., Guesmi, K. (2024), The importance of climate policy uncertainty in forecasting the green, clean and sustainable financial markets volatility. International Review of Financial Analysis, 91, 102984.

Ren, X., Li, Y., Qi, Y., Duan, K. (2022b), Asymmetric effects of decomposed oil-price shocks on the EU carbon market Dynamics. Energy, 254, 124172.

Ren, X., Zhang, X., Yan, C., Gozgor, G. (2022a), Climate policy uncertainty and firm-level total factor productivity: Evidence from China. Energy Economics, 113, 106209.

Sachs, J.D., Lafortune, G., Fuller, G. (2024), The SDGs and the UN summit of the future. Sustainable Development Report 2024. Paris: SDSN, Dublin: Dublin University Press.

Shahzad, S.J.H., Nor, M.S., Ferrer, R., Hammoudeh, S. (2017), Asymmetric determinants of cds spreads: U.S. industry-level evidence through nardl approach. Economic Modelling, 60, 211-230.

Shin, Y., Yu, B., Greenwood-Nimmo, M. (2014), Modelling asymmetric cointegration and dynamic multipliers in a nonlinear ardl framework. In: Horrace, W.C., Sickles, R.C., editors. Festschrift in Honor of Peter Schmidt: Econometric Methods and Applications İçinde (s. 281–314). New York: Springer.

Stock, J.H., Watson, M.W. (1993), A simple estimator of cointegrating vectors in higher order integrated system. Economometrica, 61, 783-820.

Tedeschi, M., Foglia, M., Bouri, E., Dai, P.F. (2023), How does climate policy uncertainty affect financial markets? Evidence from Europe. Economics Letters, 234, 111443.

Tumala Mohammed, M., Salisu, A., Nmadu, Y.B. (2023), Climate change and fossil fuel prices: A GARCH-MIDAS analysis. Energy Economics, 124, 106792.

United Nations. (2015), Sustainable Development Goals. United nations Department of Economic and Social Affairs, New York, United States. Available from: https://sdgs.un.org

Yang, J., Dong, D., Liang, C. (2024), Climate policy uncertainty and the U.S. economic cycle. Technological Forecasting and Social Change, 202, 123344.