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Does climate policy uncertainty affect carbon emissions in China? A novel dynamic ARDL simulation perspective

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This study provides new insights into the impact of climate policy uncertainty, energy consumption, and economic development on China's carbon emissions. In doing so, we develop a novel index of China's climate policy uncertainty (CCPU). We then use the newly constructed dynamic autoregressive distributed lag (ARDL) simulation model, the frequency-domain causality (FDC) test, and the fully modified OLS (FMOLS) estimation to investigate these potential relationships from 2005 to 2021. The empirical results suggest that increasing CCPU reduces carbon emissions in most parts of China, which improves environmental degradation. Furthermore, the effects of energy consumption and economic growth on carbon emissions are confirmed to be positive in each location. Finally, the results of the FDC and FMOLS confirm the robustness of the model. Our findings suggest that information from the CCPU can be used to forecast CO_2 emissions in China. Furthermore, the government should strike a balance between economic growth and environmental regulation and promote the use of renewable energy to reduce carbon emissions. Proactively developing climate policy is important to achieve the goal of carbon neutrality.

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Introduction

Climate risk has created an unparalleled obstacle to long-term economic growth in a large number of countries (Diffenbaugh and Burke, 2019; Pástor et al., 2021). The Paris Agreement, which went into force in November 2016, is a significant milestone that has strengthened the global response to climate change and provided a new framework for climate policy. Consequently, policies aimed at addressing climate change have been of high priority to governments for decades and all are working to reduce greenhouse gas (GHG) emissions (Lee and Chen, 2020; Sun et al., 2021). Nevertheless, there still exist significant uncertainties in the course of such climate policy implementation. The most recent example is the US withdrawal from the Paris Agreement in 2017, which has created significant uncertainty regarding the execution of climate policies.

Climate policy uncertainty refers to the degree of ambiguity and unpredictability surrounding government policies and regulations related to climate change mitigation and adaptation. It arises from potential changes in policy or regulation, such as the implementation or elimination of carbon taxes, subsidies for renewable energy, or the adoption of new emissions targets. These uncertainties might have far-reaching consequences for the macroeconomy and the carbon neutrality target (Lee et al., 2021; Su et al., 2021; Wang et al., 2019; Wen et al., 2022).

Over the past two decades, China has experienced the highest rate of economic expansion and energy consumption among emerging economies (Khan et al., 2022). The past economic development model has led to a multiplication of greenhouse gas (GHG) emissions such as CO_2, accounting for 27% of the total global GHG emissions in 2019. However, the Paris Agreement aims to cut CO_2 emissions and mitigate climate deterioration, with the objective of keeping the global temperature rise under 2°C within this century. As the largest carbon emitter, China needs to take action. Indeed, the Chinese government has already committed to peaking its CO_2 emissions by 2030 and achieving the carbon neutrality target by 2060 (Wang et al., 2019). To this end, it is of great policy importance to measure how China's climate policy has changed and whether the policy changes have an impact on carbon emissions. Understanding the influence of climate policy uncertainty on carbon emissions and investigating the underlying mechanism is vital for authorities and policy-makers to achieve these goals in China.

Among existing studies, several potential channels could explain the theoretical link between policy uncertainty and CO_2 emission (Jiang et al., 2019; Ullah et al., 2021; Yu et al., 2021; Wan et al., 2022; Wen et al., 2022). These include the direct policy adjustment channel (Jiang et al., 2019), the energy intensity effect (Yu et al., 2021), and the innovation investment channel (Wan et al., 2022; Wen et al., 2022). For example, high levels of uncertainty about climate risk or climate policy could hinder energy consumption and nonessential transportation for individuals and firms. At the same time, the increase in CPU might encourage renewable energy consumption and increase research and development (R&D) innovation on climate-friendly innovation, thus leading to lower CO_2 emissions (Gavriilidis, 2021).

Considering the abovementioned reality, the current study aims to analyze the influence of CPU on carbon emissions in China. The following are the main contributions of the current paper to the literature. First, we made a novel China's climate policy uncertainty index. We take newspaper content from nine major Chinese newspapers and then search for relevant keywords to construct the index. Our novel index is in line with key domestic climate policy changes. The index construction provides a new perspective for quantifying climate policy change. Second, although some studies have examined the impact of basic determinants on CO_2 emissions such as economic growth and energy consumption, they have not elaborated on the impacts of climate policy uncertainty on CO_2 emissions. In view of this, this study considers the important role of climate policy uncertainty and analyzes whether and how uncertainty regarding climate policy affects CO_2 emissions, enriching the study of the macro effects of climate policy. Moreover, to uncover the heterogeneity of the influence of climate policy uncertainty on carbon emissions, this paper explores this relationship from a regional perspective. Finally, we employ the dynamic autoregressive distributed lag (DARDL) framework to reveal the long- and short-run effects of the concerned variables on carbon emissions and the frequency-domain causality (FDC) test for the robustness check. By doing so, our papers contribute to a better understanding of how climate policy uncertainty affects carbon emissions, which helps to achieve the goal of carbon neutrality.

Literature review

The impact of policy uncertainty, energy consumption, and economic growth on carbon emissions has been the subject of extensive research in recent years, particularly in the context of the energy transition and low-carbon development initiatives. Understanding the relationship between these factors is crucial for effective policy-making and sustainable development.

Several studies have examined the influence of energy consumption on carbon emissions. For example, Adedoyin and Zakari (2020) conducted a study on the UK and found that energy use has a significant and beneficial effect on carbon emissions in the long term. Adams et al. (2020) investigated 10 resource-rich economies and identified a significant relationship between energy use and carbon emissions. Similarly, Abbasi and Adedoyin (2021) focused on China and found that energy consumption has a substantial positive impact on carbon emissions in both the short and long term.

Moreover, for the sake of sustainable development, scholars have studied the relationship between renewable energy consumption and carbon emissions. Khan et al. (2022) examined four East Asian economies and found that renewable energy consumption mitigates CO_2 emissions. Atsu and Adams (2021) analyzed BRICS countries and found a significantly negative impact of renewable energy use on carbon emissions. However, Xue et al. (2022) found no significant long-term effect of clean energy usage on carbon emissions in France.

Besides that, the existing research has also extensively explored the relationship between economic growth and carbon emissions, often using the environmental Kuznets curve (EKC) hypothesis. Adedoyin and Zakari (2020) found a significant positive effect of economic growth on carbon emissions in the UK. Shahbaz et al. (2020) supported the EKC hypothesis by finding an inverted U-shaped relationship between carbon emissions and economic development in the UK. Adams et al. (2020) identified a positive relationship between economic growth and carbon emissions in 10 resource-rich countries. Abbasi and Adedoyin (2021) found significant positive effects of economic growth on China's carbon emissions. Syed et al. (2022) documented that economic development increases carbon emissions across different quantiles in BRICS economies.

In addition, the impact of policy uncertainty on carbon emissions has gained attention in recent years, but the findings in the literature are inconsistent. Some studies have found positive relationships, indicating that increasing policy uncertainty can lead to environmental aggravation. Jiang et al. (2019), Adams et al. (2020), and Pirgaip and Dinçergök (2020) found positive correlations between policy uncertainty and carbon emissions. Atsu and Adams (2021) also found a significant positive impact of policy uncertainty on carbon emissions in BRICS economies. Anser et al. (2021) and Yu et al. (2021) provided further evidence of the positive effects of policy uncertainty on carbon emissions.

Contrary to these findings, some studies have shown that increased policy uncertainty could slow carbon emissions. Adedoyin and Zakari (2020), Ahmed et al. (2021), and Syed et al. (2022) found evidence of the negative impact of policy uncertainty on carbon emissions. Gavriilidis (2021) and Liu and Zhang (2022) documented the negative influences of policy uncertainty on carbon emissions in their respective studies. However, contradictory findings have also been reported, with Abbasi and Adedoyin (2021) and Nakhli et al. (2022) finding no significant influence of policy uncertainty on carbon emissions in specific contexts. The disparities in findings may be attributed to variations in sampling periods and methodological frameworks employed in these studies.

Several shortcomings and weaknesses should be addressed and improved upon based on the preceding literature research. First, although several studies in the literature have focused on the factors driving China's carbon emissions and considered the role of energy use and economic development, the majority of them have primarily used national carbon emissions and do not consider the impact of policy uncertainty. Besides that, several types of research have uncovered that carbon emissions are influenced by policy uncertainty. However, few studies detect the effect of climate policy uncertainty on CO_2 emissions. Climate challenges have been increasingly prominent in recent years, as have the corresponding climate governance policy uncertainties. Therefore, exploring the impact of climate policy uncertainty on carbon emissions has policy implications. Based on the above discussion, the current paper aims to add to the body of evidence that climate policy uncertainty can be used to explain changes in China's CO_2 emissions.

Theoretical model, methodology, and data

Theoretical model. In this section, we adopt the approach of Fried et al. (2021) and employ a general dynamic environment Cobb-Douglas model. This model is a well-established and widely used theoretical approach for analyzing the relationships between environmental issues and underlying determinants. Our goal is to uncover the influence of CCPU on carbon emissions. We assume that the economy comprises entrepreneurs and workers with infinite lives, which has two sectors: the "fossil" sector that emits carbon and the "clean" sector that does not. y is the final good in the economy, which is produced from labor input l, a clean intermediate input x^c, and a carbon-intensive fossil intermediate input x^f. Moreover, we assume that interest rates and labor supply are exogenous variables. Therefore, the aggregate output y can be written as:

$$y = (x^c)^{\gamma}(x^c)^{\theta} l^{1-\gamma-\theta} \tag{1}$$

where γ and θ indicate the factor shares of the clean and fossil inputs, x^c is clean capital (k^c), and x^f is fossil intermediate that satisfies the minimum between fossil fuel and fossil capital ($\min[k^f, f]$). Both production functions have constant returns to scale.

Taking prices as given, the representative firms choose the optimal share of fossil and clean inputs and labor to maximize profits. If the government implements a specific climate policy, all choices are made at the start of the term. The first-order conditions (F.O.C.) suggest the following expressions for the prices of the fossil and clean inputs, p^f and p^c:

$$p^f = \theta(x^c)^{\gamma}(x^f)^{\theta-1} \text{ and } p^c = \gamma(x^c)^{\gamma-1}(x^f)^{\theta} \tag{2}$$

Let $V^c(k^c)$ represent the clean firm's value function in the steady-state before the policy change, and $T^c(k^c)$ imply the value function in period t of the transition after the government implements the new climate policy. Therefore, the clean firm's value function in the steady state before the policy change equals:

$$V^c(k^c) = \max_{k^{c'}}\left\{p^c k^c - i^c + \left(\tfrac{1}{1+r}\right)[\rho T_1^c(k^{c'}) + (1-\rho)V^c(k^{c'})]\right\}$$
$$s.t.\ k^{c'} = (1-\delta)k^c + i^c \tag{3}$$

where $p^c k^c$ denotes the total revenue from production, i^c represents the investment ρ is the probability of uncertainty due to the government introduction of climate policy, r indicates the exogenous interest rate, and δ denotes the depreciation rate.

Moreover, the clean firm's value function in period t of the transition equals:

$$T_t^c(k^c) = \max_{k^{c'}}\left\{p^c k^c - i^c + \left(\tfrac{1}{1+r}\right) T_{t+1}^c(k^{c'})\right\}$$
$$s.t.\ k^{c'} = (1-\delta)k^c + i^c \tag{4}$$

Since all uncertainty is eliminated after the implementation of the established climate policy by the government, the firm's value in the period t of the transition equals the value function in the period $t+1$ of the transition.

In a similar vein, the fossil firm's value function in the pre-policy steady-state equals:

$$V^f(k^f) = \max_{k^{f'},f}\left\{p^f k^f - \xi f - i^f + \left(\tfrac{1}{1+r}\right)[\rho T_1^f(k^{f'}) + (1-\rho)V^f(k^{f'})]\right\}$$
$$s.t.\ k^{f'} = (1-\delta)k^f + i^f \tag{5}$$

where $p^f k^f$ denotes the total revenue from production, ξf implies the expenses on fossil fuel, i^f represents the investment ρ is the probability of uncertainty due to government introduction of climate policy, r indicates the exogenous interest rate, and δ denotes the depreciation rate.

Likewise, the fossil firm's value function in period t of the transition equals:

$$T_t^{f(k^f)} = \max_{k^{f'},f}\left\{p^f k^f - \xi f - i^f + \left(\tfrac{1}{1+r}\right) T_{t+1}^f(k^{f'})\right\}$$
$$s.t.\ k^{f'} = (1-\delta)k^f + i^f \tag{6}$$

Therefore, by constructing the Lagrange equation, we solve that:

$$K^c = \left(\frac{r}{r+\delta}\right)^{\frac{1}{1-\gamma-\theta}}\left(\frac{r+\delta}{r+\delta+\xi+\rho}\right)^{\frac{\theta}{1-\gamma-\theta}}\left(\frac{\theta}{r}\right)^{\frac{\theta}{1-\gamma-\theta}} \tag{7}$$

$$K^f = \left(\frac{r}{r+\delta}\right)^{\frac{1}{1-\gamma-\theta}}\left(\frac{r+\delta}{r+\delta+\xi+\rho}\right)^{\frac{1-r}{1-\gamma-\theta}}\left(\frac{\theta}{r}\right)^{\frac{1-r}{1-\gamma-\theta}} \tag{8}$$

Dividing Eq. (7) by Eq. (8), we finally obtain the following relationship between ρ and the ratio of fossil capital to clean capital:

$$\frac{K^f}{K^c} = \left(\frac{r+\delta}{r+\delta+\xi+\rho}\right)\left(\frac{\theta}{r}\right) \tag{9}$$

Specifically, the ratio of fossil capital to clean capital decreases when climate policy uncertainty increases (ρ increase). Moreover, since the equilibrium use of fossil fuels is equal to the level of fossil capital, a lower ratio of fossil to clean capital further reduces carbon emissions from firm production.

Methodology. To investigate the influence of CCPU on carbon emissions, we employ the novel DARDL simulation method to uncover this effect. Unlike the conventional ARDL model, the novel DARDL approach proposed by Jordan and Philips (2019)

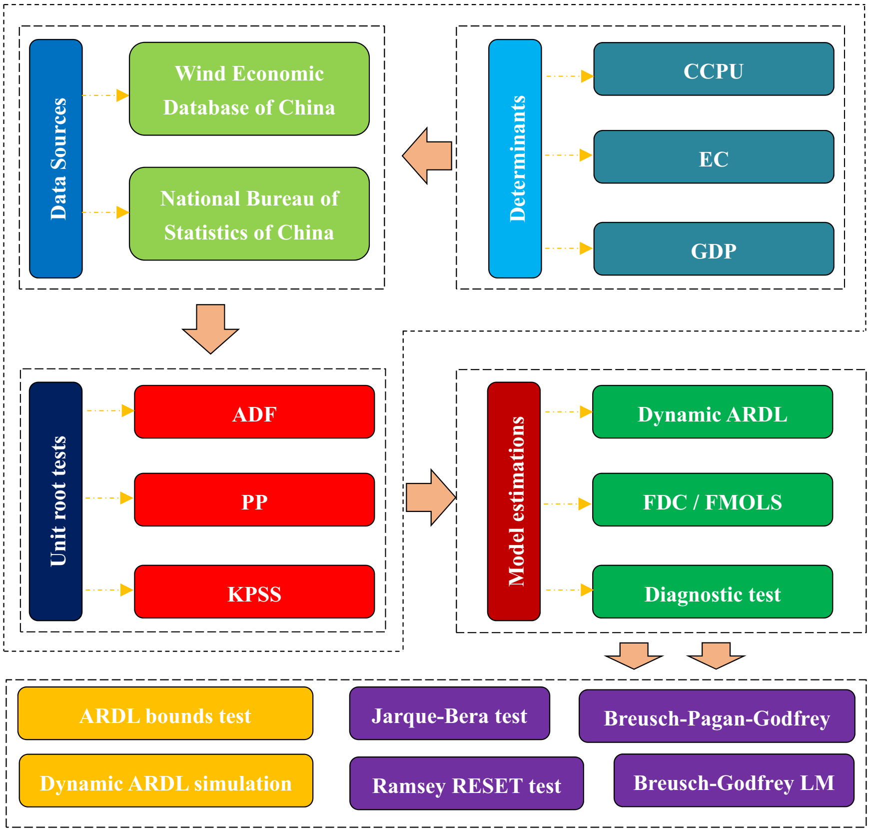


Fig. 1 Methodological framework in the current study.

can forecast and automatically plot one predictive shift on the dependent variable. Moreover, the DARDL model maintains the stability of the other independent variables when analyzing the effects of short- and long-term estimations. Besides that, the DARDL approach also has higher robustness in small sample cases, which is in line with the current dataset. Another advantage of DARDL estimation is that the co-integration test can be performed as long as they are not *I* (2), which is much different from the traditional method.

Jordan and Philips (2019) state that the DARDL error correction form in the current study is as follows:

$$\Delta(lnCO_2)_t = \alpha_0 + \theta_0(lnCO_2)_{t-1} + \beta_1\Delta lnCCPU_t + \theta_1 lnCCPU_{t-1} + \beta_2\Delta lnEC_t + \theta_2 lnEC_{t-1} + \beta_3\Delta lnGDP_t + \theta_3 lnGDP_{t-1} + \varepsilon_t \quad (10)$$

where CO_2 denotes the carbon dioxide emission, the explained variable in the current study. *CCPU* is the climate policy uncertainty in China, the main explanatory variable. *EC* implies energy consumption and *GDP* shows the gross domestic product, which are the control variables in this paper. ε_t is the error term.

Furthermore, the FDC introduced by Breitung and Candelon (2006) is used in this article to support the robustness of the DARDL model. Compared with the traditional Granger causality test, the FDC analysis method used in this study helps to predict the response between variables within a specific time frequency. The FDC equation is expressed as follows:

$$x_t = \alpha_1 x_{t-1} + \alpha_2 x_{t-2} + \cdots + \alpha_p x_{t-p} + \beta_1 y_{t-1} + \beta_2 y_{t-2} + \cdots + \beta_p y_{t-p} + \varepsilon_t \quad (11)$$

where ε_t is the error term and α and β are the estimated parameters in time (t), and lag (p), respectively. Figure 1 reveals the framework of the methodology in the study.

Table 1 Regional divisions.

Region	Provinces
North China	Beijing, Tianjin, Hebei, Shanxi
Northeast China	Liaoning, Jilin, Heilongjiang, Inner Mongolia
Eastern China	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong
Southcentral China	Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan
Southwest China	Sichuan, Guizhou, Yunnan, Chongqing
Northwest China	Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

Data collection. The primary goal of this article is to investigate the impact of CCPU on carbon emissions in six distinct areas of China. To this end, we have followed the methods of Baker et al. (2016) and Huang and Luk (2020) to construct a novel CCPU index[1]. The datasets of CO_2 emissions in the current paper have been collected from the China Energy Statistics Yearbook (Table 1).

In addition, to rule out the influence of other underlying factors on CO_2 emissions, we used the principles given by Shahbaz et al. (2018), Adams et al. (2020), Adedoyin and Zakari (2020), Shahbaz et al. (2020), Abbasi et al. (2021), and Syed et al. (2022), controlling the effect of economic growth and energy use on carbon emissions. Specifically, we have selected the total energy consumption (EC) and the gross domestic product (GDP) of each region as proxy variables. The corresponding data were collected from the Wind Economic Database and the National Bureau of Statistics of China. Considering the availability of the data, the datasets in the current study span from 2005 to 2021. In addition, we use a logarithmic form for each data point. Table 2 reports the

Table 2 Descriptive statistics.

Variable	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Probability
North China									
CO_2	14.420	14.513	14.740	13.973	0.223	−0.600	2.392	1.131	0.568
CCPU	7.035	7.042	7.562	6.282	0.373	−0.742	3.101	1.383	0.501
EC	11.233	11.311	11.455	10.856	0.174	−0.832	2.610	1.826	0.401
GDP	11.178	11.354	11.685	10.276	0.465	−0.688	2.116	1.670	0.434
Northeast China									
CO_2	13.660	13.750	13.831	13.273	0.168	−1.083	2.939	2.933	0.231
CCPU	7.035	7.042	7.562	6.282	0.373	−0.742	3.101	1.383	0.501
EC	10.560	10.629	10.730	10.203	0.155	−1.174	3.170	3.463	0.177
GDP	10.573	10.771	10.965	9.752	0.410	−0.839	2.269	2.095	0.351
Eastern China									
CO_2	14.759	14.840	14.992	14.372	0.184	−0.766	2.491	1.628	0.443
CCPU	7.035	7.042	7.562	6.282	0.373	−0.742	3.101	1.383	0.501
EC	11.665	11.736	11.886	11.271	0.189	−0.778	2.423	1.723	0.423
GDP	12.151	12.249	12.836	11.233	0.509	−0.384	1.945	1.065	0.587
Southcentral China									
CO_2	14.352	14.436	14.509	13.965	0.166	−1.098	3.013	3.013	0.222
CCPU	7.035	7.042	7.562	6.282	0.373	−0.742	3.101	1.383	0.501
EC	11.368	11.456	11.545	10.969	0.182	−0.996	2.703	2.536	0.281
GDP	11.797	11.898	12.521	10.844	0.528	−0.375	1.957	1.030	0.597
Southwest China									
CO_2	13.599	13.701	13.751	13.181	0.186	−1.100	2.788	3.054	0.217
CCPU	7.035	7.042	7.562	6.282	0.373	−0.742	3.101	1.383	0.501
EC	10.671	10.760	10.864	10.255	0.201	−0.875	2.366	2.165	0.339
GDP	10.749	10.868	11.610	9.700	0.611	−0.288	1.855	1.026	0.599
Northwest China									
CO_2	13.507	13.648	13.981	12.846	0.379	−0.465	1.768	1.491	0.475
CCPU	7.035	7.042	7.562	6.282	0.373	−0.742	3.101	1.383	0.501
EC	10.444	10.533	10.853	9.886	0.326	−0.337	1.684	1.366	0.505
GDP	10.200	10.369	10.912	9.172	0.563	−0.487	1.923	1.318	0.517

statistical characteristics of the CO_2 emissions, CCPU, EC, and GDP in different regions of China.

The descriptive statistics show that these series are clearly heterogeneous. To begin with, there are significant differences in the logarithmic pattern of the CO_2 emission series for each region. Second, we have also noticed that the averages of CO_2 emissions are much larger than those of the other variables for each region. Third, the standard deviation indicates that the GDP value is the largest, followed by the CCPU, suggesting that there have been more changes in climate policies during the sample period, and each region also witnessed a great fluctuation in economic growth. In addition, the normal distribution trend of each series has been statistically verified by the Jarque-Bera test, as each series cannot reject the null hypothesis.

Empirical result

Unit root test. Table 3 shows the unit root test results for each concerned variable. The Augmented-Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test are jointly utilized to examine the stationarity of these series. Based on the outcomes of the ADF test, PP test, and KPSS test, we find that CCPU and CO_2 emissions for North China and Northwest China series are $I(1)$ processes, whereas the remaining variables are $I(0)$ processes. Overall, the evidence of the unit root test reveals that none of the series is stationary at $I(2)$, which meets the requirements of the dynamic ARDL model simulation.

ARDL bounds test analysis. Since not all series are $I(1)$ processes, it becomes critical to test the validity of the co-integration relationship. This paper uses the ARDL bound technique to detect whether there is a long-term link between the variables. Table 4 displays the outcomes of the ARDL bound test for different regions in China. The t-statistic value is discovered to be larger than the upper limit value at the 10% level of significance, except for Northeast China. Moreover, the F-statistic is also utilized for the evaluation of co-integration and we note that the F-statistic value is higher than the upper bound value at the 1% level of significance for each region. Combining the above two statistical results, we conclude that there is co-integration between the series.

Dynamic ARDL estimation results. The outcomes of the dynamic ARDL estimation for six regions of China are shown in Table 5. First, the adjustment speed from short-term disequilibrium to a new long-term equilibrium is assessed by the error correction term (ECT). We notice that the coefficient of ECT for each scenario is significantly negative, which suggests that 35.8% to 88.8% of the disequilibrium is corrected in the long term. The results are consistent with Abbasi and Adedoyin (2021) and Abbasi et al. (2022), who report that the value of ECT is negative indicating that the adjustment speed is significant.

Specifically, from the short-term perspective, the coefficient of CCPU is negative and significant in Eastern (−0.020) and Southcentral China (−0.051). These outcomes show that a 1% increase in CCPU would decrease carbon emissions by 0.020% and 0.051% in both regions (Liu and Zhang, 2022). In other words, the CCPU has a beneficial effect on environmental improvement. These results are supported by Pirgaip and Dinçergök (2020), Gavriilidis (2021), and Liu and Zhang (2022). However, the coefficient of CCPU is significantly positive in North China (0.093), suggesting that the positive shock of CCPU has a positive influence on environmental deterioration. North China is rich in coal resources, and the coal resources in

Table 3 Unit root examinations.

	ADF (level)	ADF (first difference)	PP (level)	PP (first difference)	KPSS (level)	KPSS (first difference)	Remark
North China							
CO_2	-1.883	-2.342	-1.883	-2.342	0.574**	0.223	I (1)
CCPU	-2.338	-2.791*	-2.350	-2.791*	0.165	0.314	I (1)
EC	-3.306**	-2.237	-2.969*	-2.216	0.571**	0.376*	I (0)
GDP	-4.941***	-0.976	-6.719***	-1.447	0.579**	0.503**	I (0)
Northeast China							
CO_2	-1.503	-2.234	-4.696***	-2.234	0.529**	0.405*	I (0)
CCPU	-2.338	-2.791*	-2.350	-2.791*	0.165	0.314	I (1)
EC	-3.899**	-2.061	-3.690**	-1.998	0.442*	0.409*	I (0)
GDP	-3.523**	-0.481	-3.052*	-1.781	0.508**	0.464**	I (0)
Eastern China							
CO_2	-2.142	-2.139	-3.899**	-2.158	0.585**	0.395*	I (0)
CCPU	-2.338	-2.791*	-2.350	-2.791*	0.165	0.314	I (1)
EC	-5.410***	-2.054	-9.605***	-2.051	0.583**	0.469**	I (0)
GDP	-4.735***	-1.771	-13.893***	-1.469	0.603**	0.504**	I (0)
Southcentral China							
CO_2	-2.363	-2.487	-7.835***	-2.542	0.528**	0.409*	I (0)
CCPU	-2.338	-2.791*	-2.350	-2.791*	0.165	0.314	I (1)
EC	-4.188***	-2.297	-6.731	-2.246	0.550**	0.440*	I (0)
GDP	-4.094***	-1.976	-11.536***	-1.826	0.605**	0.479**	I (0)
Southwest China							
CO_2	-5.037***	-1.926	-4.445***	-1.925	0.503**	0.484**	I (0)
CCPU	-2.338	-2.791*	-2.350	-2.791*	0.165	0.314	I (1)
EC	-3.212**	-2.656	-4.982***	-2.656	0.549**	0.479**	I (0)
GDP	-2.716*	-1.986	-3.453**	-1.895	0.605**	0.435*	I (0)
Northwest China							
CO_2	-1.571	-2.195	-2.153	-1.529	0.588**	0.311	I (1)
CCPU	-2.338	-2.791*	-2.350	-2.791*	0.165	0.314	I (1)
EC	-1.440	-1.484	-2.992*	-1.528	0.597**	0.363	I (0)
GDP	-3.519**	-1.978	-3.642**	-1.904	0.595**	0.435*	I (0)

Note: (***, **, *) denotes 1%, 5%, and 10% significance levels, respectively.

Table 4 Bounds test results.

	North China	Northeast China	Eastern China	Southcentral China	Southwest China	Northwest China
$CO_2 = f$ (CCPU, EC, GDP)						
F-statistics	9.612***	10.668***	10.274***	15.868***	12.396***	8.342***
t-statistics	−4.246***	−1.487	−4.125**	−7.389***	−6.406***	−2.728*
Critical values (CV)	*F*-statistics CV ($k = 3$)			*t*-statistics CV ($k = 3$)		
H_0: no co-integration	10%	5%	1%	10%	5%	1%
H_0: no co-integration	3.550	4.653	7.888	−2.636	−3.098	−4.156

Note: (***, **, *) denote 1%, 5%, and 10% significance levels, respectively.

this region are most concentrated in Shanxi Province. Therefore, industries in this region rely heavily on carbon-intensive production methods. These industries might increase production ahead of future climate policy implementation, leading to increased carbon emissions. This finding backs with previous research (Adams et al., 2020; Anser et al., 2021).

In the long-term perspective, we observe a significant and negative coefficient of CCPU for most regions, indicating that higher levels of policy uncertainty have a dampening effect on CO_2 emissions. This finding suggests that when faced with uncertain climate policies, economic agents tend to err on the side of caution and adopt measures that lead to a reduction in energy consumption and thus lower carbon emissions (Gavriilidis, 2021). This economic behavior can be attributed to the risk-averse nature of firms and individuals, who are uncertain about the future regulatory environment and therefore choose more conservative energy use strategies to make long-term investment decisions aimed at reducing their carbon footprint.

However, the estimated result for Southwest China presents a contrasting picture. We find that a 1% positive shock in CCPU leads to an increase in CO_2 emissions by 0.121%. This implies that in Southwest China, higher levels of policy uncertainty can have a stimulating effect on carbon emissions. The outcomes are in line with Atsu and Adams (2021) and Xue et al. (2022). One economic explanation for this phenomenon is that the region is characterized by industries that heavily rely on carbon-intensive production methods. In the face of uncertain climate policies, these industries may perceive a temporary window of opportunity to increase production before potential future policies are implemented, which increases emissions.

In addition, the estimated short-term and long-term coefficients of EC are significant and show positive signs in each scenario, indicating that EC has a positive influence on CO_2 emissions. This outcome is similar to Lin and Xu (2020) and Abbasi and Adedoyin (2021). This finding can be attributed to the fundamental relationship between energy consumption and

Table 5 Dynamic ARDL simulation results.

Determinants	North China	Northeast China	Eastern China	Southcentral China	Southwest China	Northwest China
Constant	2.907*** (0.436)	0.076*** (0.024)	3.374*** (0.475)	2.860*** (0.215)	4.203*** (0.486)	5.844*** (0.812)
ECT_{t-1}	−0.859*** (0.203)	−0.358** (0.141)	−0.811*** (0.197)	−0.888*** (0.130)	−0.550*** (0.086)	−0.459*** (0.096)
$\Delta lnCCPU_t$	0.093*** (0.035)	−0.049 (0.027)	−0.020* (0.011)	−0.051** (0.016)	−0.028 (0.018)	−0.013 (0.011)
$\Delta lnEC_t$	2.544*** (0.443)	0.615*** (0.181)	0.728** (0.349)	1.280*** (0.182)	0.267** (0.132)	0.395** (0.161)
$\Delta lnGDP_t$	0.935*** (0.276)	0.116*** (0.029)	0.011 (0.102)	0.370** (0.185)	0.001 (0.030)	0.460*** (0.075)
$lnCCPU_{t-1}$	−0.039** (0.018)	−0.138** (0.057)	−0.002 (0.029)	−0.057*** (0.019)	0.121*** (0.036)	−0.078** (0.036)
$lnEC_{t-1}$	2.862*** (0.342)	1.719*** (0.195)	0.897** (0.365)	1.441*** (0.030)	0.486** (0.210)	1.282** (0.592)
$lnGDP_{t-1}$	0.564*** (0.124)	0.325* (0.184)	0.103* (0.062)	0.143*** (0.024)	0.002 (0.054)	1.441*** (0.350)
Statistics and diagnostics						
Adj.R^2	0.726	0.823	0.741	0.820	0.647	0.781
Serial Correlation LM test	[0.307]	[0.772]	[0.291]	[0.139]	[0.386]	[0.182]
Heteroscedasticity test	[0.253]	[0.373]	[0.434]	[0.592]	[0.417]	[0.273]
Ramsey RESET test	[0.787]	[0.458]	[0.436]	[0.206]	[0.255]	[0.883]
Normally test	[0.899]	[0.816]	[0.634]	[0.607]	[0.568]	[0.219]
CUSUM	Stable	Stable	Stable	Stable	Stable	Stable

Note: Standard errors are in parentheses. *P*-values in brackets. (***, **, *) denote 1%, 5%, and 10% significance levels, respectively. *ECT* refers to the error correction term.

economic activity. As economic growth and industrial production increase, the energy demand also increases, leading to higher levels of energy consumption and subsequent carbon emissions. Our findings suggest that the growing energy consumption without a proper replenishment mechanism will further accelerate environmental degradation and hinder its achievement of carbon neutrality goals.

In addition, the empirical outcomes show that 1% GDP growth will lead to a short-term increase in CO_2 emissions ranging from 0.116% to 0.935%, and a long-term increase ranging from 0.103% to 0.564%, respectively. The significant and positive coefficients of GDP in the short- and long-term analyses indicate a positive relationship between GDP and CO_2 emissions. This finding is related to the fact that economic growth drives an increase in consumer demand and the expansion of businesses, which leads to a large amount of energy use and a subsequent increase in carbon emissions. These results are supported by Chen et al. (2019), Wang et al. (2019), Adams et al. (2020), Abbasi and Adedoyin (2021), and Syed et al. (2022).

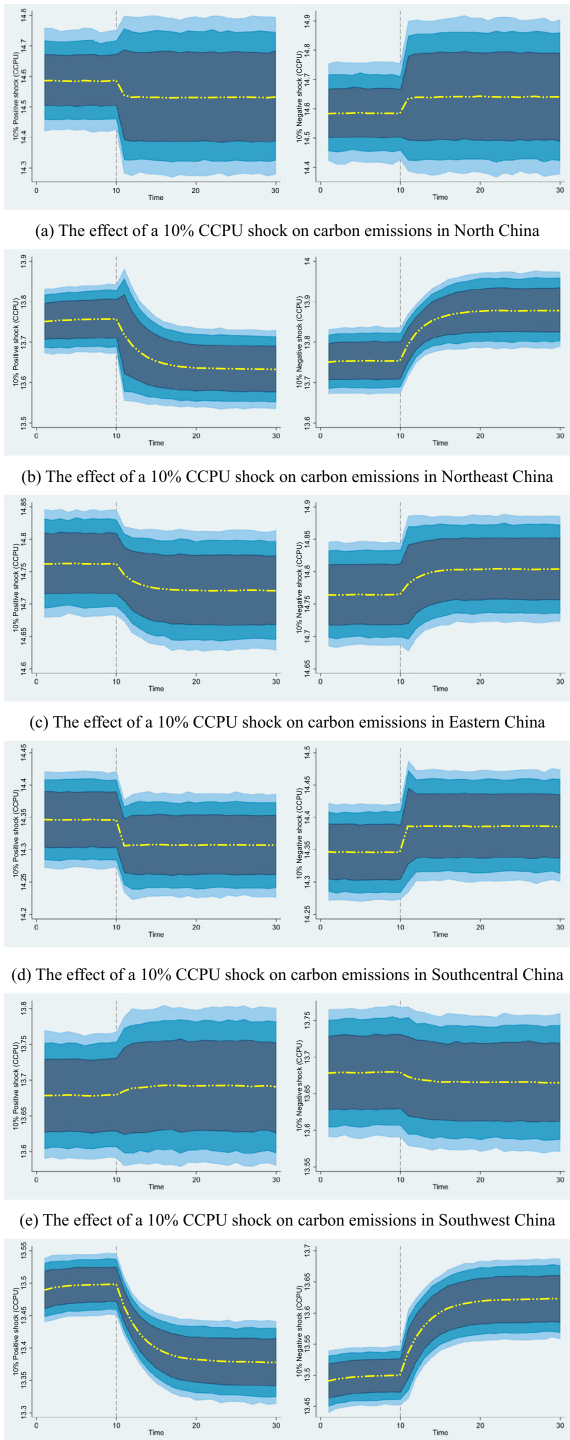
In order to validate the appropriate model, several statistics and diagnostics are utilized at the bottom of Table 5. The outcomes reveal that the null hypothesis of serial correlation LM tests and heteroscedasticity tests are not refuted in each scenario. Therefore, serial correlation and heteroskedasticity do not exist in the estimation model. Moreover, the null hypothesis is also not rejected by the Ramsey RESET tests and normal tests, implying that the model is correctly measured and the residuals are normally distributed. In addition, this study also uses the CUSUM to measure the stability of the coefficients in both the long- and short-term specifications, and the results indicate that the short- and long-term parameters are stable.

Dynamic ARDL simulation forecasts. While keeping the values of other variables constant, the dynamic ARDL simulation forecasts illustrate predictions of the actual regressor shift and its effect on the explained variable. In particular, a 10% positive or negative shock in the main explanatory variable (CCPU) is predicted in the current study, which could be used to measure its impact on CO_2 emissions in different areas of China. Specifically, the impulse response results are shown in Fig. 2a–f. The yellow broken line indicates predicted mean values, and the light blue area to dark blue area denotes 70%, 90%, and 95% confidence intervals.

Figure 2a represents the influence of a 10% positive and negative shock in the CCPU on CO_2 emissions in North China. The impulse response graph reveals that a 10% increase in CCPU reduces carbon emissions, which improves environmental deterioration. In comparison, a 10% decline in CCPU increases CO_2 emissions; that is, it has a positive effect on environmental deterioration. Figure 2b shows the impulse response of the influence of CCPU on carbon emissions in Northeast China. The graph reveals that a 10% increase in CCPU has a significantly negative impact on environmental degradation. However, a 10% reduction in CCPU has a beneficial effect on environmental degradation. As discussed above, CCPU plays a key role in whether there is a detrimental or favorable impact on carbon emissions.

In the same vein, Fig. 2c shows the impulse response graph in Eastern China, which indicates the impact of CCPU on carbon emissions. A 10% positive change in CCPU hurts CO_2 emissions, which improves environmental deterioration. In contrast, a 10% negative change in CCPU has a positive influence on environmental aggravation. In addition, Fig. 2d depicts the forecast for examining the influence of CCPU on CO_2 emissions in Southcentral China. A 10% increase in CCPU has a beneficial effect on environmental improvement. However, a 10% negative change in CCPU has a positive influence on CO_2 emissions, suggesting that CCPU could play a key role in the environmental deterioration in Southcentral China.

Different from the above findings, the impulse response plot in Fig. 2e illustrates that a 10% positive change in CCPU positively affects carbon emissions in Southwest China. In comparison, a 10% negative change in CCPU harms CO_2 emissions. This outcome is consistent with the dynamic ARDL estimation result.



(a) The effect of a 10% CCPU shock on carbon emissions in North China

(b) The effect of a 10% CCPU shock on carbon emissions in Northeast China

(c) The effect of a 10% CCPU shock on carbon emissions in Eastern China

(d) The effect of a 10% CCPU shock on carbon emissions in Southcentral China

(e) The effect of a 10% CCPU shock on carbon emissions in Southwest China

(f) The effect of a 10% CCPU shock on carbon emissions in Northwest China

Fig. 2 The impulse response for a 10% positive or negative shock in the CCPU and its effect on carbon emissions in six regions of China. a The effect of a 10% CCPU shock on carbon emissions in North China. **b** The effect of a 10% CCPU shock on carbon emissions in Northeast China. **c** The effect of a 10% CCPU shock on carbon emissions in Eastern China. **d** The effect of a 10% CCPU shock on carbon emissions in Southcentral China. **e** The effect of a 10% CCPU shock on carbon emissions in Southwest China. **f** The effect of a 10% CCPU shock on carbon emissions in Northwest China. The yellow broken line indicates predicted mean values and the light blue area to dark blue area denotes 70%, 90%, and 95% confidence intervals.

Besides that, Fig. 2f shows the connection between CCPU and carbon emissions in Northwest China. The impulse response reflects that a 10% positive change in CCPU has a beneficial influence on environmental improvement, while a 10% decline in CCPU suggests that it has a positive influence on environmental deterioration.

Sensitivity analysis results. To further validate the robustness of the DARDL estimation results, the FDC model and the fully modified least squares (FMOLS) are employed as a sensitivity check. The corresponding outcomes are shown in Tables 6 and 7, which suggest that CCPU has the expected influence on CO_2 emissions in different areas of China. Therefore, the robustness test indicates that the empirical outcomes of the current study are valid and dependable. Our outcomes are supported by Gavriilidis (2021), suggesting that high levels of uncertainty about climate policy could hinder energy consumption and, thus lead to lower CO_2 emissions.

Moreover, the statistical shreds of evidence of EC show that EC is the key determinant of carbon emissions in China. The outcomes are similar to those (Hussain et al., 2020; Kwakwa et al., 2020; Abbasi et al., 2021). Besides that, with the exception of Southwest China, GDP has the same influence on CO_2 emissions in the long- and short-term. This outcome is reinforced by Sunday et al. (2017) and Adedoyin and Zakari (2020), indicating that economic expansion has a major influence on CO_2 emissions and the environment.

Conclusion and policy implications

The purpose of the paper is to detect whether CCPU affects the achievement of the carbon neutrality target of China and to investigate the influence of CCPU on CO_2 emissions. To this end, we constructed a novel CCPU index that is based on the methods of Baker et al. (2016). Then, we applied the newly developed DARDL model to detect the potential relationships with Chinese data from 2005 to 2021. Considering the heterogeneity of China's CO_2 emissions across regions, this study investigates the influence of CCPU on carbon emissions from a regional perspective.

After controlling for the effect of economic growth and energy use on carbon emissions, our outcomes suggest that a rise in CCPU reduces carbon emissions in North, Northeast, Southcentral, and Northwest China, which improves environmental deterioration. In comparison, the positive change in CCPU increases CO_2 emissions in Southwest China; that is, it has a positive effect on environmental aggravation. This finding implies that the information originating from the CCPU can provide useful information to predict CO_2 emissions in China. In addition, the impact of energy consumption on carbon emissions is also affirmed to be positive in each scenario. In this case, authorities should consider other alternative renewable energy uses to deal with the negative impact of these emissions. Moreover, economic development has shown a significant positive influence on carbon emissions. Therefore, while promoting economic growth, the negative impact on the environment cannot be ignored.

These results provide the following important policy recommendations. First, the CCPU effectively affects the movement of carbon emissions in different regions of China. As a result, taking this into consideration, policymakers should pay close attention to the changes experienced in climate policies, to avoid excessive CO_2 emissions. Moreover, since regional carbon emissions show heterogeneous reactions to the CCPU, local governments should note the characteristics of the CCPU and treat the impact of the CCPU differently to control regional carbon emissions more effectively. Second, since non-renewable energy use increases CO_2

Table 6 Frequency-domain causality test results.

Direction of causality	North China	Northeast China	Eastern China	Southcentral China	Southwest China	Northwest China
Short-run						
$CCPU => CO_2$	5.734*	4.354	5.091*	4.526*	6.231**	9.302***
$EC => CO_2$	11.236***	23.452***	6.034**	7.506**	5.352*	8.439**
$GDP => CO_2$	6.712**	9.537***	6.321**	5.712*	2.073	5.367*
Long-run						
$CCPU => CO_2$	4.883*	5.305**	6.583**	5.715*	6.045**	9.351***
$EC => CO_2$	7.231**	10.235***	4.512*	9.232***	8.420**	13.215***
$GDP => CO_2$	6.233**	8.965**	6.361**	5.423*	7.139**	6.089**

Note: (***, **, *) denote 1%, 5%, and 10% significance levels, respectively.

Table 7 Fully modified OLS simulation results.

Determinants	North China	Northeast China	Eastern China	Southcentral China	Southwest China	Northwest China
Constant	5.821***	3.242***	4.829***	3.845***	5.532***	3.196***
	(0.023)	(0.170)	(0.117)	(0.115)	(0.501)	(0.085)
$lnCCPU_{t-1}$	−0.046***	−0.112***	−0.023	−0.014***	−0.164**	−0.039***
	(0.010)	(0.024)	(0.074)	(0.001)	(0.034)	(0.011)
$lnEC_{t-1}$	0.232***	0.210***	0.255***	0.144***	0.487***	0.392***
	(0.006)	(0.004)	(0.056)	(0.026)	(0.031)	(0.059)
$lnGDP_{t-1}$	0.312***	0.217**	0.471***	0.278***	0.308***	0.218***
	(0.020)	(0.110)	(0.031)	(0.102)	(0.037)	(0.011)
Adj.R^2	0.814	0.732	0.882	0.783	0.785	0.801

Note: Standard errors are in parentheses. (***, **) denote 1% and 5% significance levels.

emissions, the government should spend more on renewable energy projects and encourage innovation in environmentally friendly energy use to increase green energy production. In addition, the government should support the development of renewable energy technologies and provide appropriate subsidy policies, which will aid in the reduction of carbon emissions. Third, the outcomes of this study show that economic expansion has a positive influence on carbon emissions. Therefore, the government should balance economic development with environmental governance. Economic development should not come at the expense of the environment. In addition, further improving the quality of economic development is critical to achieving carbon neutrality.

Although we have explored the impact of climate policy uncertainty on CO_2 emissions from a dynamic perspective, there are still some limitations. Firstly, although we have constructed a novel CCPU index in the current study, it is not a large enough sample size. Therefore, additional research should be conducted with richer data that can predict the influences of CCPU more accurately. Secondly, future research should explore the potential relationships between CCPU and CO_2 emissions across countries, which could shed light on the impact of CCPU on CO_2 from a worldwide perspective.

Data availability

We collected the data from the China Energy Statistics Yearbook, the National Bureau of Statistics of China, and the Wind Economic Database. The datasets analyzed during the current study are available from the corresponding author upon reasonable request.

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Note

1 See Supplementary Appendix 1 for the index construction process.

References

Abbasi KR, Adedoyin FF (2021) Do energy use and economic policy uncertainty affect CO_2 emissions in China? Empirical evidence from the dynamic ARDL simulation approach. Environ Sci Pollut Res 28:23323–23335

Abbasi KR, Adedoyin FF, Abbas J, Hussain K (2021) The impact of energy depletion and renewable energy on CO_2 emissions in Thailand: fresh evidence from the novel dynamic ARDL simulation. Renew Energy 180:1–12

Abbasi KR, Hussain K, Haddad AM, Salman A, Ozturk I (2022) The role of financial development and technological innovation towards sustainable development in Pakistan: fresh insights from consumption and territory-based emissions. Technol Forecast Soc Chang 176:121444

Adams S, Adedoyin F, Olaniran E, Bekun FV (2020) Energy consumption, economic policy u ncertainty and carbon emissions; causality evidence from resource rich economies. Econ Anal Policy 68:179–190

Adedoyin FF, Zakari A (2020) Energy consumption, economic expansion, and CO_2 emission in the UK: The role of economic policy uncertainty. Sci Total Environ 738:140014

Ahmed Z, Cary M, Shahbaz M, Vo XV (2021) Asymmetric nexus between economic policy uncertainty, renewable energy technology budgets, and environmental sustainability: evidence from the United States. J Clean Prod 313:127723

Anser MK, Apergis N, Syed QR (2021) Impact of economic policy uncertainty on CO_2 emissions: evidence from top ten carbon emitter countries. Environ Sci Pollut Res 28:29369–29378

Atsu F, Adams S (2021) Energy consumption, finance, and climate change: does policy uncertainty matter?. Econ Anal Policy 70:490–501

Baker SR, Bloom NA, Davis SJ (2016) Measuring economic policy Uncertainty. Q J Econ 131:1593–1636

Breitung J, Candelon B (2006) Testing for short- and long-run causality: a frequency domain approach. J Econom 132:363–378

Chen Y, Wang Z, Zhong Z (2019) CO_2 emissions, economic growth, renewable and non-renewable energy production and foreign trade in China. Renew Energy 131:208–216

Diffenbaugh N, Burke M (2019) Global warming has increased global economic inequality. Proc Natl Acad Sci USA 116:9808–9813

Fried S, Novan K, Peterman W (2021) The Macro Effects of Climate Policy Uncertainty. Federal Reserve Bank of San Francisco Working Paper 2021–06. Available at https://doi.org/10.24148/wp2021-06

Gavriilidis K (2021) Measuring climate policy uncertainty. Available at SSRN: https://ssrn.com/abstract=3847388

Huang Y, Luk P (2020) Measuring economic policy uncertainty in China. China Econ Rev 59:101367

Hussain J, Khan A, Zhou K (2020) The impact of natural resource depletion on energy use and CO_2 emission in Belt & Road Initiative countries: a cross-country analysis. Energy 199:117409

Jiang Y, Zhou Z, Liu C (2019) Does economic policy uncertainty matter for carbon emission? Evidence from US sector level data. Environ Sci Pollut Res 26:24380–24394

Jordan S, Philips AQ (2019) Dynamic simulation and testing for single-equation cointegrating and stationary autoregressive distributed lag models. R J 10:469–488

Khan Y, Hassan T, Kirikkaleli D, Zhang X, Cai S (2022) The impact of economic policy uncertainty on carbon emissions: evaluating the role of foreign capital investment and renewable energy in East Asian economies. Environ Sci Pollut Res 29:18527–18545

Kwakwa PA, Alhassan H, Adu G (2020) Effect of natural resources extraction on energy consumption and carbon dioxide emission in Ghana. Int J Energy Sect Manag 14:20–39

Lee CC, Chen MP (2020) Do natural disasters and geopolitical risks matter for cross-border country exchange-traded fund returns?. North Am J Econ Financ 51:101054

Lee CC, Wang CW, Ho SJ, Wu TP (2021) The impact of natural disaster on energy consumption: international evidence. Energy Econ 97:105021

Lin B, Xu B (2020) How does fossil energy abundance affect China's economic growth and CO_2 emissions? Sci Total Environ 719:137503

Liu Y, Zhang Z (2022) How does economic policy uncertainty affect CO_2 emissions? A regional analysis in China. Environ Sci Pollut Res 29:4276–4290

Nakhli MS, Shahbaz M, Ben Jebli M, Wang S (2022) Nexus between economic policy uncertainty, renewable & non-renewable energy and carbon emissions: contextual evidence in carbon neutrality dream of USA. Renew Energy. 185:75–85

Pástor L, Stambaugh RF, Taylor LA (2021) Sustainable investing in equilibrium. J Financ Econ 142:550–571

Pirgaip B, Dinçergök B (2020) Economic policy uncertainty, energy consumption and carbon emissions in G7 countries: evidence from a panel Granger causality analysis. Environ Sci Pollut Res 27:30050–30066

Shahbaz M, Nasir MA, Roubaud D (2018) Environmental degradation in France: The effects of FDI, financial development, and energy innovations. Energy Econ 74:843–857

Shahbaz M, Nasir MA, Hille E, Mahalik MK (2020) UK's net-zero carbon emissions target: investigating the potential role of economic growth, financial development, and R&D expenditures based on historical data (1870–2017). Technol Forecast Soc Change 161:120255

Su CW, Yuan X, Tao R, Umar M (2021) Can new energy vehicles help to achieve carbon neutrality targets? J Environ Manag 297:113348

Sun T, Su CW, Mirza N, Umar M (2021) How does trade policy uncertainty affect agricultural commodity prices? Pac Basin Financ J 66:101514

Sunday J, Song D, Shu Y, Kamah M (2017) Decoupling CO_2 emission and economic growth in China: is there consistency in estimation results in analyzing environmental Kuznets curve? J Clean Prod 166:1448–1461

Syed QR, Bhowmik R, Adedoyin FF, Alola AA, Khalid N (2022) Do economic policy uncertainty and geopolitical risk surge CO_2 emissions? New insights from panel quantile regression approach. Environ Sci Pollut Res. https://doi.org/10.1007/s11356-021-17707-9

Ullah S, Ozturk I, Sohail S (2021) The asymmetric effects of fiscal and monetary policy instruments on Pakistan's environmental pollution. Environ Sci Pollut Res 28:7450–7461

Wan Q, Chen J, Yao Z, Yuan L (2022) Preferential tax policy and R&D personnel flow for technological innovation efficiency of China's high-tech industry in an emerging economy. Technol Forecast Soc Chang 174:121228

Wang Z, Huang W, Chen Z (2019) The peak of CO_2 emissions in China: a new approach using survival models. Energy Econ 81:1099–1108

Wen H, Lee C, Zhou F (2022) How does fiscal policy uncertainty affect corporate innovation investment? Evidence from China's new energy industry. Energy Econ 105:105767

Xue C, Shahbaz M, Ahmed Z, Ahmad M, Sinha A (2022) Clean energy consumption, economic growth, and environmental sustainability: what is the role of economic policy uncertainty? Renew Energy 184:899–907

Yu J, Shi XP, Guo DM, Yang LJ (2021) Economic policy uncertainty (EPU) and firm carbon emissions: evidence using a China provincial EPU index. Energy Econ 94:105071

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