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Research article

The adverse impact of climate policy uncertainty on air quality in China

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ABSTRACT

Climate policy uncertainty refers to the ambiguity, unpredictability, and lack of transparency in government policies, measures, regulations, and actions aimed at addressing climate issues. Previous studies have found that climate policy uncertainty affects carbon emissions. However, other environmental impacts of climate policy uncertainty have not been sufficiently analyzed in the literature. This study demonstrates that climate policy uncertainty has a negative impact on air quality in China. Based on data from 288 Chinese cities between 2001 and 2021, we find that climate policy uncertainty increases the concentrations of carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), fine particulate matter ($PM_{2.5}$), particulate matter with a diameter of 10 μm or less (PM_{10}), and sulfur dioxide (SO_2). Further analysis reveals that the impact of climate policy uncertainty exhibits regional heterogeneity. The effect is stronger in regions that rely more on fossil energy and have higher air pollution levels, but weaker in areas with greater clean energy adoption and lower pollution.

1. Introduction

1.1. Research background

Climate change and air pollution are two of the most pressing environmental challenges facing the world today. As the world's largest carbon emitter and one of the countries most severely affected by air pollution, China plays a pivotal role in addressing these issues. In recent years, the Chinese government has implemented a series of key climate and environmental policies, such as the carbon emissions trading system and green finance policy, aimed at reducing greenhouse gas emissions and improving air quality (Almond and Zhang, 2021; Li et al., 2024; Liu et al., 2021). Climate policies and air pollution control policies exhibit significant overlap, as fossil fuel combustion and industrial processes are major shared sources of both greenhouse gas and air pollutant emissions. Climate and air pollution control policies both emphasize measures such as energy structure transition, industrial emission reductions, and transportation electrification. Effective climate policies typically yield air quality co-benefits (Karlsson et al., 2020; Vandyck et al., 2020), while reliable air pollution control measures often contribute to carbon emission reductions (Gu et al., 2018; Qian et al., 2021). In China, the synergistic approach—"co-governance of air pollution reduction and carbon mitigation"—has become the government's core strategy for addressing climate and air pollution challenges (Yi et al., 2023).

It is notable that the effectiveness of climate and air quality policies is often constrained by uncertainties in their design, implementation, and enforcement (Gavriilidis, 2021). The uncertainties arise from multiple sources, including not only the inherent complexity of policy formulation and execution processes, but also external influences such as geopolitical and economic disruptions, technological advancements, and evolving public sentiment. The uncertainties surrounding climate policies have attracted attention from researchers (Athari and Kirikkaleli, 2025; Tedeschi et al., 2024). Such climate policy uncertainty (CPU) may lead to unintended environmental consequences, particularly in terms of its impact on emissions and pollution levels.

The influence of climate policy uncertainty on air pollution is ambiguous theoretically. On the one hand, CPU may cause increased pollution. Uncertainty in climate policies possibly leads to delayed investments in clean technologies and renewable energy, as firms facing an unclear outlook may adopt a wait-and-see approach (Attílio, 2025; Farooq et al., 2024). The ambiguity of policy could also lead to lax environmental enforcement, causing corporations and individuals to neglect long-term environmental sustainability and potentially exacerbating air pollution. On the other hand, CPU may generate a negative effect on pollution. Climate policy uncertainty probably heightens public concern about climate issues (Hania et al., 2025; Persakis et al.,

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2024), prompting greater emphasis on environmental issues and motivating stronger actions to protect air quality.

Although the literature on climate policy uncertainty has grown recently, few studies have empirically examined its impact on air pollution—particularly in the context of developing countries like China. China's unique institutional and economic characteristics—such as its complex policy system and reliance on fossil fuels—offer a distinctive lens through which to analyze the nexus between climate policy uncertainty and air pollution. Lessons from China's experience could provide valuable insights for other countries facing similar challenges. Moreover, understanding how climate policy uncertainty affects air pollution in China is critical for designing more effective environmental policies. It is hoped that well-designed emission reduction policies can simultaneously address both climate change and air pollution, thereby protecting the environment and public health in an efficient way (Pathak et al., 2023).

Some previous studies have examined the impact of climate policy uncertainty on carbon dioxide (CO_2) emissions, but their findings are inconsistent. For example, Li et al. (2025) and Pata (2024) reported that CPU increases carbon emissions in China and the US, whereas Borozan and Pirgaip (2024), Kisswani et al. (2025), and Tian and Li (2023) analyzed data from different regions, including China, the US, and Southeast Asia, and reported that CPU reduces carbon emissions.

There is relatively little research on the impact of CPU on pollutant emissions, and we have found two studies on this topic. One study is Wang et al. (2024), which examined the effect of CPU on pollution emissions from 1211 listed companies in China. In their study, pollution emissions are measured using pollutant discharge fees—charges imposed on companies for emitting four types of pollutants: industrial wastewater, sulfur dioxide, nitrogen oxides, and chemical oxygen demand. They reported that CPU increases the pollutant discharge fees levied on firms, implying higher pollution emissions. Another relevant study is Wang (2022), which analyzed data from 731 US firms and reported that CPU reduces toxic chemical emissions from American companies. However, since these studies only examined data from a limited sample of firms, we still do not know how CPU affects air pollution at the macro level. This issue requires further research.

To preliminarily assess the relationship between climate policy uncertainty and air pollution in China, we present Fig. 1. The graph consists of six subfigures, each of which is a binned scatter plot based on data from 288 Chinese cities between 2001 and 2021, controlling for region- and time-fixed effects. The horizontal axis of each subplot represents the degree of climate policy uncertainty, measured by the city-level CPU index provided by Ma et al. (2023). During the past decades, China has implemented various climate policies, such as the carbon emissions trading system, the clean energy demonstration provinces project, the comprehensive demonstration cities project for energy saving and emission reduction fiscal policies, the energy-use rights trading system, the new energy demonstration cities project, and the low-carbon city pilot project. Due to incomplete information transparency and the unpredictability of future developments, the public perceived a series of uncertainties at different stages of these climate policies, including their design, announcement, and implementation. For instance, the public might be unclear about the following: who is formulating the policies; when the policies will take effect; which regions are covered; which industries are affected; how long the policies will last; and what the exact details of the policies are. A higher CPU index indicates greater climate policy uncertainty. In the

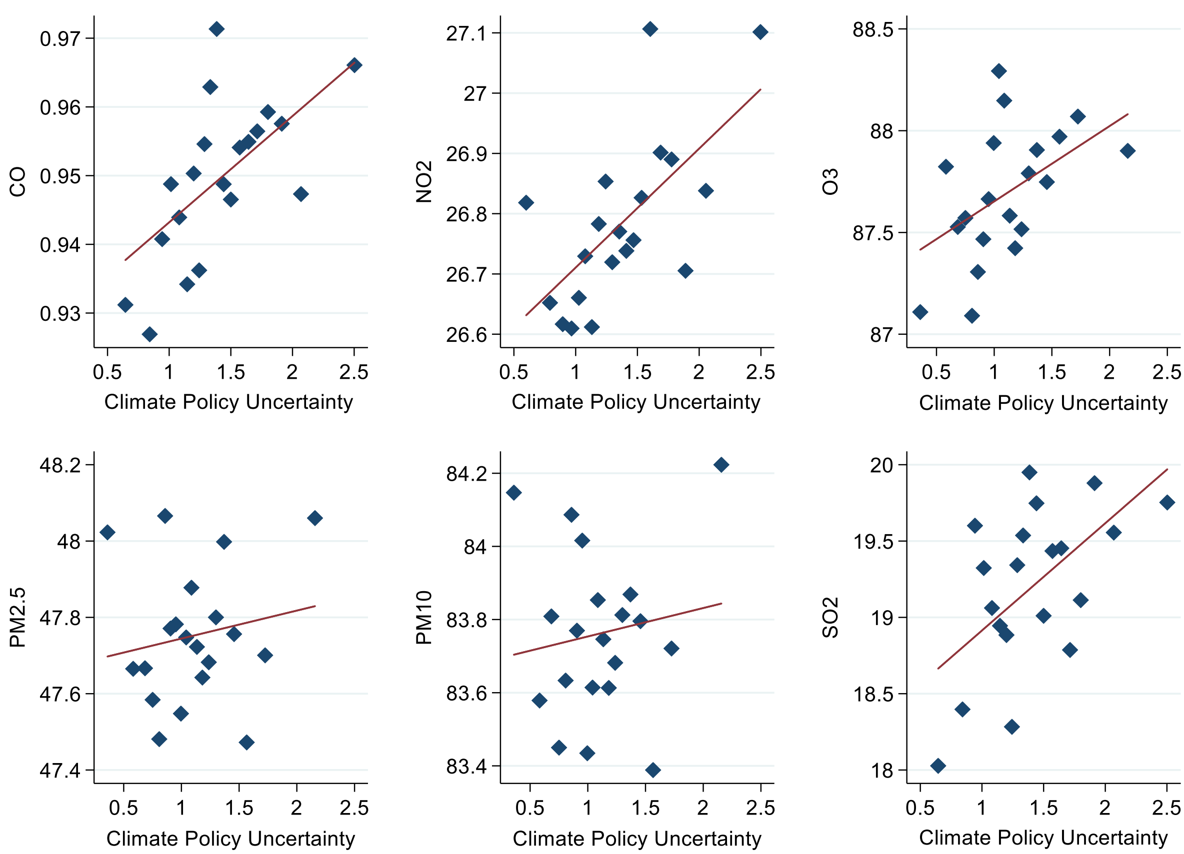

Fig. 1. The positive correlation between climate policy uncertainty and air pollution.
Note: (1) Air pollution is measured by the annual average concentration of several pollutants: carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), fine particulate matter ($PM_{2.5}$), particulate matter less than 10 μm in size (PM_{10}), and sulfur dioxide (SO_2). The measurement unit for CO is mg/m^3, while the unit for other pollutants is μg/m^3. Climate policy uncertainty is measured by the city-level CPU index provided by Ma et al. (2023). (2) The binned scatter plot is obtained by using 20 bins. The graph would be similar if other numbers of bins are used. (3) The detailed data sources are explained in Section 2.3.

graph, the vertical axis of each subplot shows the annual average concentrations of various ambient air pollutants, including carbon monoxide (CO), nitrogen dioxide (NO_2), ozone (O_3), fine particulate matter ($PM_{2.5}$), particulate matter less than 10 μm in size (PM_{10}), and sulfur dioxide (SO_2). As can be seen from Fig. 1, there is a positive correlation between climate policy uncertainty and air pollution concentrations. Based on this observation, we conjecture that climate policy uncertainty has a positive effect on air pollution—that is, climate policy uncertainty worsens air quality in China. To verify this conjecture, we need to utilize rigorous statistical methods for quantitative analysis.

1.2. Research purpose and contributions

This research aims to empirically quantify the impact of climate policy uncertainty on air pollution in China. Using a comprehensive dataset covering city-level air quality indicators and climate policy uncertainty index, we employ econometric methods to assess the extent to which climate policy uncertainty influences air pollution. Our study reveals that climate policy uncertainty significantly worsens air pollution, particularly in regions with higher dependence on fossil fuels. These findings highlight the importance of reducing policy uncertainty and accelerating the transition toward clean energy to achieve China's dual objectives of carbon neutrality and air quality improvement.

The contributions of this study are twofold. First, it provides novel empirical evidence on the environmental consequences of climate policy uncertainty. While prior literature has largely overlooked whether climate policy uncertainty affects air pollution, this study fills this research gap. Second, unlike some previous empirical studies on air pollution in China that typically focused on limited pollution indicators, our analysis examines multiple types of air pollutants, offering a more comprehensive perspective to understand China's air pollution problem.

2. Methods and materials

2.1. Regression model

We employ a multiple linear regression approach to quantify the impact of climate policy uncertainty on air pollution. The following two-way fixed-effects regression model is established:

$$AirPollution_{it} = \alpha CPU_{it} + \beta ControlVariables_{it} + \gamma OtherPolicies_{it} + u_i + v_t + \varepsilon_{it} \quad (1)$$

In Equation (1), the dependent variable $AirPollution_{it}$ denotes the level of air pollution in region i in year t. The core explanatory variable, CPU_{it}, captures the degree of climate policy uncertainty. The vector $ControlVariables_{it}$ includes a set of meteorological and socioeconomic covariates that may influence air pollution. Moreover, China has implemented numerous environmental and regional development policies, which could also affect local air quality. To account for these potential confounding effects, we include the vector $OtherPolicies_{it}$ in the model, which controls for some relevant policies. u_i represents time-invariant region-fixed effects for region i, v_t denotes nationwide time-fixed effects for period t, and ε_{it} is the residual term. The coefficients α, β, and γ measure the effects of respective independent variables on air pollution.

Our primary focus is the coefficient α for CPU. A statistically significant positive value of α would indicate that climate policy uncertainty exacerbates air pollution.

2.2. Variables

2.2.1. Dependent variables

The dependent variable $AirPollution_{it}$ represents air pollution levels. In this study, we examine the concentrations of six kinds of ambient air pollutants (CO, NO_2, O_3, $PM_{2.5}$, PM_{10}, SO_2), respectively. Higher pollutant concentrations indicate poorer air quality. The measurement unit for CO is mg/m^3, while the unit for other pollutants is $\mu g/m^3$.

2.2.2. Core explanatory variable of interest

The core explanatory variable is CPU_{it}, which captures the extent of climate policy uncertainty in region i during year t. Climate policy uncertainty refers to the ambiguity, unpredictability, and lack of transparency in government policies, measures, regulations, and actions aimed at addressing climate issues. Previous literature has employed two main approaches to measure CPU. The first approach uses specific climate policy or political events (e.g., the US withdrawal from the Paris Agreement, the introduction of crucial climate legislation, or US presidential transitions) to represent climate policy shocks and the resulting increase in uncertainty. The second approach constructs a climate policy uncertainty index based on textual analysis of media content (e.g., social media discourse or news reports). The underlying rationale is that although the level of uncertainty itself is not directly observable, public perceptions of climate policy uncertainty can be reflected in the information disseminated through the media. The shortcomings of the first approach are evident, as it can only capture the impact of a single policy and often conflates the intended measurement of CPU with the effects of the policy itself or non-climate-related policy uncertainty. In contrast, constructing a CPU index based on media information has a distinct advantage: the timeliness and diverse sources of media enable researchers to promptly capture variations in CPU across regions and over time. In particular, news reports from professional and authoritative newspapers provide a reliable source of information for building a CPU index.[1]

Ma et al. (2023) developed a climate policy uncertainty index for China by analyzing news reports from six major Chinese newspapers using deep learning algorithms and text mining techniques. The level of climate policy uncertainty is indicated by the share of news reports covering climate policy uncertainty topics among all news articles. In this research, we utilize their city-level index as the explanatory variable CPU_{it}. A larger value of CPU_{it} indicates a higher degree of climate policy uncertainty.

2.2.3. Covariates

Covariates are included in two vectors: $ControlVariables_{it}$ and $OtherPolicies_{it}$. $ControlVariables_{it}$ comprises 10 meteorological and socioeconomic variables: (1) $Precipitation_{it}$, annual precipitation level (dm); (2) $WindSpeed_{it}$, annual average wind speed (m/s); (3) $Temperature_{it}$, annual average temperature (°C); (4) $GDPPerCapita_{it}$, logarithm of per capita GDP (CNY, measured at the constant price level in 2000); (5) $PopulationDensity_{it}$, logarithm of population density per unit of land (person/km^2); (6) $ShareofAgriculture_{it}$, agricultural value added as a share of GDP; (7) $FinancialDevelopment_{it}$, financial development level, measured as the ratio of bank credits to GDP; (8) $TradeOpenness_{it}$, trade openness, measured as the ratio of international trade volume to GDP; (9) $HighSpeedRail_{it}$, binary dummy variable for high-speed rail access, which equals 1 if the city has at least one high-speed rail station, and equals 0 otherwise; (10) $RoadDensity_{it}$, logarithm of road density,

[1] Certainly, the news-based CPU index also has potential limitations. (1) News reports may contain subjective or one-sided perspectives. Some articles might rely on incomplete information or be influenced by specific interest groups, thus failing to accurately reflect objective facts. This could introduce bias in measuring policy uncertainty. To mitigate this issue, researchers can incorporate multiple news sources rather than relying on a single media outlet. (2) Given the vast number of news articles covering diverse policies, it is difficult to use current text-mining techniques to precisely identify the specific policy sources of uncertainty. If researchers aim to examine uncertainty stemming from a particular policy, they should supplement news data with additional data sources—such as in-depth policy document analysis or expert surveys—rather than relying solely on media reports.

calculated as total road length (km) divided by land area (km^2); (11) *TechnologicalProgress*, technological progress, proxied by the logarithm of the number of invention patent applications.

$OtherPolicies_{it}$ contains 31 variables controlling for 31 policies that may affect air pollution. These policies include: (1) action plan for air pollution prevention and control, (2) Broadband China pilot project, (3) carbon emissions trading system pilot zones, (4) circular-economy city pilot project, (5) clean energy demonstration provinces, (6) clean winter-heating plan in Northern China, (7) comprehensive demonstration cities for energy saving and emission reduction fiscal policies, (8) cross-border e-commerce comprehensive pilot zones, (9) demonstration zones for industrial transformation and upgrading in old industrial cities and resource-based cities, (10) ecological environment monitoring pilot zones, (11) e-commerce demonstration city project, (12) energy-use rights trading system pilot zones, (13) household registration system reform, (14) information benefiting-the-people pilot cities, (15) internet demonstration cities, (16) low-carbon city pilot project, (17) national big data comprehensive pilot zones, (18) national ecological conservation pilot zones, (19) national independent innovation demonstration zones, (20) national new-type urbanization comprehensive pilot zones, (21) national sustainable development plan for resource-based cities, (22) new energy demonstration cities, (23) pilot project to promote the integration of technology and finance, (24) plan on the rise of Central China, (25) pollution emissions trading system pilot zones, (26) resource-exhausted city support policy, (27) smart-city pilot project, (28) smart-tourism city pilot project, (29) south-to-north water diversion project, (30) three-year action plan to fight air pollution, and (31) environmental regulation. The first 30 policies are measured by binary dummy variables, which equal 1 if the corresponding policies are implemented, and equal 0 otherwise. The degree of environmental regulation is quantified by the proportion of environmental protection-related words in annual local government work reports. Fig. S1 in the Supplementary Material shows the policy timeline.

2.3. Data sources

2.3.1. Data sources of air pollution

The data were collected from several sources. The data source of CO, NO_2, O_3, $PM_{2.5}$, PM_{10}, and SO_2 was the GlobalHighAirPollutants (GHAP) dataset (Wei et al., 2021a, 2021b, 2022, 2023), in which the remote sensing and artificial intelligence techniques were utilized to generate grid data of ambient pollutants for China. Then, the grid data were processed to calculate the annual average values of pollution concentrations in each Chinese city. To reduce the uncertainties and possible errors in the estimation of air pollution levels, the researchers utilized artificial intelligence to address the spatiotemporal heterogeneity of pollution, based on multiple data sources such as atmospheric reanalysis, ground-based measurements, model simulations, and satellite remote sensing products. The compiled dataset exhibits high quality and accuracy. By comparing with the ground-based pollution measurements from monitoring stations, the pollution estimates from the dataset have high cross-validation coefficients of determination (CV-R^2) and low values of root-mean-square error (RMSE) and mean absolute error (MAE). Further technical details can be found in the corresponding literature.

2.3.2. Data source of CPU index

The data of CPU index were provided by Ma et al. (2023). CPU encompasses various uncertainties related to different aspects of climate policies, including the entities responsible for policymaking, policy timelines, policy content, and potential consequences of policies. Researchers determine whether a news report discusses CPU by analyzing the content of the report. For example, if a news article reports on a carbon tax policy in a region and expresses concerns about its uncertain prospects, it is classified as a CPU-related report for that region.

The research team first constructed a training dataset of approximately 30,000 news reports using manual auditing. This dataset was used to train a MacBERT deep learning model. MacBERT is a medium-sized, BERT (Bidirectional Encoder Representations from Transformers)-based pre-trained model specifically optimized for Chinese natural language processing tasks. The researchers did not train the base-level model from scratch. Instead, they adopted the initial parameters of the official MacBERT-Base-Chinese model. The model evaluated news articles through text mining of a very large number of keywords. A comprehensive listing of those keywords is impractical here. Typically, keywords such as "uncertain," "unknown," "greenhouse gases," "carbon emissions," "law," and "regulation" would be considered as highly relevant to CPU. The MacBERT model was then deployed to analyze over 1.75 million news items from six major newspapers, classifying each item as CPU-related or not. The CPU index is measured by the proportion of CPU-related news items across all reports.

Admittedly, news reporting inherently contains subjectivity and may not always accurately reflect objective facts. To mitigate potential biases arising from uncertainties in news reporting, researchers utilized six major newspapers as information sources rather than relying on a single newspaper. Furthermore, during the technical validation phase, four additional newspapers were incorporated to reconstruct the CPU index for comparative analysis, confirming the robustness of the index to variations in news source selection.

2.3.3. Data sources of covariates

Meteorological data were derived from the ERA5-Land dataset of the European Union's Copernicus Climate Change Service. The data of high-speed railway stations and patents were sourced from the Chinese Research Data Services Platform (CNRDS). The data about public policy implementations and local governments' annual work reports were compiled from government announcements, official reports, and verified news sources. The other socioeconomic variables such as GDP and population were from the EPS China Data.

2.4. Research sample

The sample selection was determined by data availability across key variables. In the spatial dimension, the research sample encompasses 288 Chinese cities, covering most areas of mainland China. In the time dimension, the sample spans 9 years (2013–2021) when analyzing CO and SO_2, 21 years (2001–2021) when analyzing O_3, $PM_{2.5}$, and PM_{10}, and 14 years (2008–2021) when analyzing NO_2. The number of observations ranges from 2567 to 6,019, depending on the type of pollutant analyzed. Table 1 reports the descriptive statistics of variables.

In our study, there are six dependent variables (i.e., six different air pollutants: CO, NO_2, O_3, $PM_{2.5}$, PM_{10}, and SO_2), each with varying numbers of observations. We construct six separate regression models for the six dependent variables. While all models use the same regression equation, i.e., Equation (1), each employs a specific air pollutant as its dependent variable. Each regression model is estimated separately using all available observations for the corresponding dependent variable. If, for a given region and year, independent variables have observations but the dependent variable under analysis lacks data, we exclude that sample point from the regression sample. Since the six regression models are independent of each other, differences in sample sizes across air pollutant indicators do not affect their respective regression estimates. Specifically, when analyzing the impact of CPU on CO and SO_2, we use 2567 observations; for NO_2, we use 4007 observations; for O_3, $PM_{2.5}$, and PM_{10}, we use 6019 observations.

3. Results

3.1. Main results

Table 2 reports the coefficient estimates of Equation (1). The CPU exhibits statistically significant positive correlations with all six

Table 1
Descriptive statistics of variables.

Variable	Number of observations	Mean	Standard Deviation	Minimum	Maximum
CO	2567	0.950	0.286	0.425	2.225
NO2	4007	26.784	9.063	9.125	54.265
O3	6019	87.692	10.018	57.195	122.407
PM2.5	6019	47.752	16.450	13.765	112.078
PM10	6019	83.762	29.622	24.522	195.416
SO2	2567	19.205	12.500	4.952	102.562
CPU	6019	1.108	0.655	0.000	4.057
Precipitation	6019	9.778	4.902	0.423	25.421
WindSpeed	6019	4.703	1.090	1.852	9.958
Temperature	6019	13.777	5.560	−3.876	25.726
GDPPerCapita	6019	9.760	0.763	7.216	11.723
PopulationDensity	6019	5.647	1.085	0.274	8.275
ShareofAgriculture	6019	0.144	0.093	0.000	0.572
FinancialDevelopment	6019	0.909	0.551	0.015	5.748
TradeOpenness	6019	0.232	0.632	0.000	17.176
HighSpeedRail	6019	0.303	0.460	0.000	1.000
RoadDensity	6019	−0.368	0.797	−5.578	1.650
TechnologicalProgress	6019	5.277	2.156	0.000	12.063

Note: To save space, the descriptive statistics of variables in *OtherPolicies* are not reported.

Table 2
Estimated impact of climate policy uncertainty on air pollution.

Variables	CO	NO_2	O_3	$PM_{2.5}$	PM_{10}	SO_2
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
CPU	0.00937**	0.297***	0.278*	0.372**	0.445*	0.574***
	[0.004]	*[0.075]*	*[0.155]*	*[0.162]*	*[0.250]*	*[0.214]*
Precipitation	0.00375**	−0.129***	−0.767***	−0.387***	−0.563***	−0.262***
	[0.002]	*[0.021]*	*[0.034]*	*[0.027]*	*[0.040]*	*[0.082]*
WindSpeed	−0.0141	−0.790***	−0.400	−1.415***	−1.548***	−0.0254
	[0.011]	*[0.143]*	*[0.253]*	*[0.248]*	*[0.379]*	*[0.549]*
Temperature	0.0364***	0.172**	1.188***	0.712***	2.981***	0.920***
	[0.006]	*[0.075]*	*[0.185]*	*[0.141]*	*[0.235]*	*[0.283]*
GDPPerCapita	−0.0194	1.120**	1.876***	−0.970*	−1.857**	4.159***
	[0.031]	*[0.444]*	*[0.653]*	*[0.548]*	*[0.831]*	*[1.542]*
PopulationDensity	−0.0614	−0.360	0.783	−0.289	−0.332	−1.907
	[0.061]	*[0.297]*	*[0.529]*	*[0.387]*	*[0.705]*	*[3.638]*
ShareofAgriculture	0.303*	3.423	−8.737**	10.05***	10.14**	32.24***
	[0.176]	*[2.549]*	*[3.501]*	*[2.888]*	*[4.186]*	*[8.522]*
FinancialDevelopment	−0.0102	−0.463**	0.353	−0.077	0.140	1.161
	[0.017]	*[0.208]*	*[0.664]*	*[0.351]*	*[0.597]*	*[0.928]*
TradeOpenness	0.0143***	0.169*	−1.104***	0.381**	0.827***	0.684***
	[0.005]	*[0.094]*	*[0.235]*	*[0.155]*	*[0.279]*	*[0.219]*
HighSpeedRail	0.00303	−0.104	−0.719**	−0.0832	0.0843	0.389
	[0.011]	*[0.146]*	*[0.360]*	*[0.284]*	*[0.420]*	*[0.493]*
RoadDensity	0.113***	0.601*	−0.374	1.076***	1.338***	3.151
	[0.036]	*[0.319]*	*[0.310]*	*[0.269]*	*[0.431]*	*[2.332]*
TechnologicalProgress	−0.0102	−0.0485	−0.144	−0.213*	−0.0434	−0.685**
	[0.008]	*[0.091]*	*[0.143]*	*[0.115]*	*[0.164]*	*[0.309]*
OtherPolicies	Yes	Yes	Yes	Yes	Yes	Yes
City-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of cities	288	288	288	288	288	288
Number of observations	2567	4007	6019	6019	6019	2567
Within R^2	0.821	0.771	0.754	0.880	0.877	0.839
Adjusted R^2	0.900	0.964	0.866	0.962	0.970	0.888

Note: *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively. Robust standard errors clustered at the city level are reported in brackets under the coefficient estimates. To save space, the coefficients of variables included in *OtherPolicies* are not reported in the table.

categories of air pollutants analyzed. If the estimated coefficients can reflect causal relationships, these results indicate that climate policy uncertainty deteriorates air quality and exacerbates air pollution levels in China. Based on the coefficient estimates, on average, a one-unit increase in the CPU index leads to nationwide concentration increases of 0.00937 mg/m^3, 0.297 $\mu g/m^3$, 0.278 $\mu g/m^3$, 0.372 $\mu g/m^3$, 0.445 $\mu g/m^3$, and 0.574 $\mu g/m^3$ for CO, NO_2, O_3, $PM_{2.5}$, PM_{10}, and SO_2, respectively.

Several covariates included in Equation (1) are also correlated with air pollution. For instance, precipitation, wind speed, temperature, GDP per capita, share of agriculture, financial development, trade openness, and road density have significant correlations with certain air pollutants. As these covariates are not the focus of this study, we refrain from detailed discussion of their coefficient values.

3.2. Addressing endogeneity concerns

In Section 3.1, we have reported the coefficient estimates of Equation (1). The results indicate a positive correlation between CPU and air pollution. However, caution is required when interpreting this correlation as a causal relationship. In our study, we are particularly concerned about two potential sources of bias. (1) First, "omitted variable bias" may exist. Although in the previous empirical analysis, we have controlled for a range of meteorological, socioeconomic, and policy covariates, there could still be unobserved confounding factors that simultaneously influence both CPU and air pollution, leading to a spurious correlation between them. For example, local governments' special policy preferences or region-specific economic or environmental characteristics might serve as omitted variables. (2) Second, "reverse causality" may be an issue. The level of local air pollution possibly influences the government's climate policy decision-making, which in turn affects CPU.

Both omitted variable bias and reverse causality lead to "endogeneity" of the explanatory variable in econometric regression analysis. Endogeneity prevents the regression coefficient from accurately reflecting the causal effect of the explanatory variable. To address endogeneity concerns, we employ the following four approaches.

3.2.1. Control for additional fixed effects

China's wide territory exhibits significant regional disparities. For instance, the country can be divided into three large regions: eastern, central, and western. Compared to the western region, the eastern and central regions have higher levels of economic development and industrialization, with a denser concentration of pollution-emitting industries. To highlight the priorities in air quality policies, the Chinese central government has designated 82 "key cities for air pollution prevention and control". Relative to other cities, these key cities face more severe air pollution, higher population density, and are the focal areas of the Chinese government's efforts to address air pollution. Additionally, energy structures vary across Chinese cities. Some cities have adopted higher levels of clean energy, while others remain heavily reliant on fossil fuels. Based on local characteristics, these different regions may have implemented differentiated policies or adopted distinct development pathways, which could influence CPU and air pollution. The covariates previously included in Equation (1) may not fully account for these factors.

To mitigate potential omitted variable bias, we augment Equation (1) by further controlling for (eastern, central, western) region-time, (air pollution prevention and control) key city-time, and (high or low) clean energy adoption level-time fixed effects. By incorporating these additional fixed effects, we can further eliminate some unobserved confounding factors related to regional characteristics. The regression results are presented in Row (a) of Table 3. For all six air pollutants, the coefficients of CPU remain significantly positive.

3.2.2. Use provincial-level CPU index

There may be reverse causality between city-level CPU and air pollution, as the two could influence each other. To mitigate this concern, we use the provincial-level CPU of the province where the city is located instead of the city-level CPU in Equation (1) as the explanatory variable. The rationale is that since a province covers a much larger geographical area than a city and provincial governments hold higher administrative authority than city-level governments, a province's CPU may affect air pollution in its cities, but a single city's air pollution is unlikely to cause substantial changes in the province's overall CPU. The regression results are reported in Row (b) of Table 3. When the dependent variables are NO_2, O_3, $PM_{2.5}$, and PM_{10}, the coefficients of CPU are all significantly positive. When the dependent variables are CO and SO_2, the coefficients of provincial-level CPU are statistically nonsignificant.

3.2.3. Use IV-2SLS estimation

A widely used approach to address endogeneity is instrumental variable (IV) regression. A valid IV must satisfy two conditions: relevance, i.e., the IV significantly affects the endogenous explanatory variable, and exogeneity, i.e., the IV does not directly affect the dependent variable except through the channel of the endogenous explanatory variable. We consider that the average CPU level of neighboring cities serves as a plausible IV for the following reasons. (1) Relevance: Neighboring cities' CPU can influence local residents' perceptions of climate policy uncertainty through information diffusion via public media and social networks, thereby affecting the local CPU level. For instance, if residents in neighboring cities perceive heightened CPU, such concerns and nervous emotions may spread to the local area, increasing local CPU. Thus, the relevance condition is satisfied. (2) Exogeneity: Neighboring cities' CPU reflects the perceptions of residents in those areas. Since these individuals do not live or engage in economic activities locally, they do not directly alter local production or daily life and thus do not directly affect local air pollution. Thus, the exogeneity condition is satisfied.

We define "neighboring cities" as follows. For a city i, city j is considered a neighbor if the straight-line distance between their urban centers is less than 600 km. We choose this threshold of 600 km because some Chinese cities are geographically vast, with the nearest adjacent cities nearly 600 km apart. A smaller threshold would leave some cities without neighbors, generating missing observations. (It is worth mentioning that we have tried alternative thresholds, such as 500 km, 800 km, and 1000 km, and found our results to be robust to these variations.) We compute the average CPU index of each city's neighboring cities and use this as the IV. Then, employing the classical IV-2SLS (instrumental variable two-stage least squares) regression method, we estimate CPU's effect on air pollution. The results are reported in Row (c) of Table 3. Although we find no statistically significant effect of CPU on SO_2, the estimated coefficients of CPU are positive and statistically significant for the other five air pollutants under study.

3.2.4. Use System GMM estimation

The System GMM (generalized method of moments) provides an alternative approach to mitigate endogeneity concerns. This method employs internally generated instruments, using lagged levels of the endogenous variable as instruments for first-differenced equations, and lagged first-differences as instruments for level equations (Roodman, 2009). By leveraging the model's inherent structure to generate internal instruments, System GMM reduces reliance on subjectively selected

Table 3
Regression results by using several approaches to address endogeneity concerns.

Variables	CO	NO_2	O_3	$PM_{2.5}$	PM_{10}	SO_2
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
(a) *CPU* (control for additional fixed effects)	0.00990**	0.264***	0.249*	0.339**	0.440**	0.545***
	[0.004]	*[0.069]*	*[0.130]*	*[0.131]*	*[0.217]*	*[0.201]*
(b) *CPU* (use provincial-level CPU index)	−0.00625	0.291**	1.651***	0.699***	0.700**	0.288
	[0.008]	*[0.131]*	*[0.208]*	*[0.248]*	*[0.354]*	*[0.360]*
(c) *CPU* (use IV-2SLS estimation)	0.0806***	2.357***	6.017***	2.330**	3.905**	0.448
	[0.028]	*[0.500]*	*[1.238]*	*[1.179]*	*[1.746]*	*[1.120]*
(d) *CPU* (use System GMM estimation)	0.0163*	0.428**	0.456***	0.695**	1.489***	1.042**
	[0.009]	*[0.181]*	*[0.176]*	*[0.272]*	*[0.491]*	*[0.432]*

Note: *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively. Robust standard errors clustered at the city level are reported in brackets under the coefficient estimates. To save space, the coefficients of covariates are not reported in the table.

external instrumental variables. We estimate CPU's impact using the System GMM regression and report the results in Row (d) of Table 3. The coefficients of CPU are consistently positive and statistically significant across all six air pollutants analyzed.

In short, after addressing endogeneity concerns through multiple empirical approaches, we generally find that the coefficients of CPU remain significantly positive. This is particularly evident for the four pollutants—NO_2, O_3, $PM_{2.5}$, and PM_{10}—where CPU exhibits statistically significant positive coefficients across all model specifications. These robust results strengthen our confidence in interpreting the positive coefficient of CPU in Equation (1) as evidence of its harmful effect on air quality.

3.3. Heterogeneity analysis

Our previous analysis has demonstrated that, on average, climate policy uncertainty significantly increases air pollution concentrations in China. However, does this effect exhibit consistent patterns across different regions? To investigate this question, we now proceed to conduct heterogeneity tests to examine whether the impact of climate policy uncertainty on air pollution varies across regions. Heterogeneity analysis can provide policymakers with more nuanced insights to facilitate the formulation of differentiated emission reduction strategies. We focus on differences in clean energy adoption levels and air pollution levels.

3.3.1. Differences in clean energy adoption levels

The impact of climate policy uncertainty on air pollution may be contingent on a region's level of clean energy adoption. The effect of CPU on air pollution is possibly stronger in regions with a lower share of clean energy in their energy consumption. This can be attributed to three main reasons. (1) First, regions with lower clean energy adoption tend to exhibit path dependence on traditional fossil fuels, and fluctuations in climate policy may delay corporate investments in green and low-carbon transition. (2) Second, local governments in regions lagging in clean energy development may have weaker environmental governance capacity and looser regulations, making them more likely to relax environmental regulation when faced with policy uncertainty. (3) Third, regions with lower clean energy adoption often lack sufficient low-carbon technology reserves and green innovation capabilities, limiting their ability to adapt to climate policy changes. In contrast, regions with a higher proportion of clean energy consumption benefit from a more diversified energy structure, a more robust environmental governance system, and greater green innovation potential, enabling them to better mitigate the adverse effects of climate policy uncertainty.

Based on whether their average shares of clean energy in total energy consumption during the study period were below the sample median, we categorized the sample cities into two groups: a low-share group and a high-share group. The clean energy share data were sourced from Yang et al. (2024). We set two binary dummy variables, $D_i^{LowCleanEnergyShare}$ and $D_i^{HighCleanEnergyShare}$, to indicate whether a city belongs to the low or high clean energy share group. These two dummy variables are defined as follows: if city i is in the low-share group, $D_i^{LowCleanEnergyShare} = 1$ and $D_i^{HighCleanEnergyShare} = 0$; conversely, if city i is in the high-share group, $D_i^{LowCleanEnergyShare} = 0$ and $D_i^{HighCleanEnergyShare} = 1$. We then multiply these dummy variables with the CPU index and generate two interaction terms: $CPU_{it} \times D_i^{LowCleanEnergyShare}$ and $CPU_{it} \times D_i^{HighCleanEnergyShare}$. These interaction terms are used to replace CPU_{it} in Equation (1), yielding Equation (2). The coefficients α_1 and α_2 in Equation (2) capture the heterogeneous effects of CPU on air pollution in cities with low versus high clean energy shares, respectively. The regression results are reported in Table 4.

$$AirPollution_{it} = \alpha_1 CPU_{it} \times D_i^{LowCleanEnergyShare} + \alpha_2 CPU_{it} \times D_i^{HighCleanEnergyShare} + \beta ControlVariables_{it} + \gamma OtherPolicies_{it} + u_i + v_t + \varepsilon_{it} \quad (2)$$

In regions with relatively low clean energy shares in total energy consumption, CPU shows statistically significant positive effects on all six types of air pollutant concentrations. However, in regions with relatively high clean energy shares, CPU exhibits no statistically significant impact on air pollution. This finding suggests that regions lagging in clean energy transition need more stable policy expectations and enhanced green technology support.

3.3.2. Differences in air pollution levels

The impact of climate policy uncertainty on air pollution may differ across regions with different air pollution levels. The influence of CPU may be more pronounced in regions with severe air pollution due to the following three reasons. (1) First, industrial lock-in effects in highly polluted cities hinder regional green transition. High-pollution cities typically rely on industrial and energy-intensive sectors, where transitioning is costly due to sunk costs and institutional constraints. Moreover, these industries face higher marginal abatement costs, making them more sensitive to climate policy shocks. When climate policy uncertainty rises, firms in these sectors are more likely to cut pollution control investments or delay technological upgrades, thereby exacerbating emissions. (2) Second, highly polluted cities often face more complex governance dilemmas. Many high-pollution cities in China serve as regional economic growth engines, placing local governments under significant pressure to prioritize economic expansion over environmental protection. When climate policy uncertainty increases, local authorities may favor economic growth by slashing environmental budgets and relaxing regulations. Persistent pollution also reflects weaker environmental governance capacity and higher public tolerance for pollution. These regional characteristics incentivize local

Table 4
Heterogeneity analysis on the differences in clean energy adoption levels.

Variables	CO	NO_2	O_3	$PM_{2.5}$	PM_{10}	SO_2
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$CPU \times D^{LowCleanEnergyShare}$	0.0149**	0.547***	0.832***	0.917***	1.295***	0.964**
	[0.006]	*[0.100]*	*[0.189]*	*[0.187]*	*[0.302]*	*[0.389]*
$CPU \times D^{HighCleanEnergyShare}$	0.00462	0.0611	−0.267	−0.164	−0.392	0.242
	[0.006]	*[0.093]*	*[0.188]*	*[0.194]*	*[0.288]*	*[0.219]*
ControlVariables	Yes	Yes	Yes	Yes	Yes	Yes
OtherPolicies	Yes	Yes	Yes	Yes	Yes	Yes
City-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of cities	288	288	288	288	288	288
Number of observations	2567	4007	6019	6019	6019	2567
Within R^2	0.821	0.772	0.755	0.881	0.878	0.840
Adjusted R^2	0.900	0.965	0.867	0.962	0.971	0.888

Note: *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively. Robust standard errors clustered at the city level are reported in brackets under the coefficient estimates. To save space, the coefficients of covariates are not reported in the table.

governments to opt for short-term economic gains when facing economic-environmental trade-offs. (3) Third, fossil fuel dependence is typically higher in highly polluted cities. The severity of air pollution in Chinese cities is strongly correlated with reliance on fossil fuels. As previously discussed in heterogeneity analysis based on clean energy adoption levels, cities heavily dependent on fossil fuels exhibit path dependence on traditional energy structures, fragile environmental governance systems, and poorer green innovation capacity. Consequently, they are less resilient to the adverse effects of climate policy uncertainty. In contrast, compared to high-pollution cities, low-pollution regions have lower industrialization levels, are less burdened by economic-environmental dilemmas, and possess more diversified energy sources. As a result, low-pollution regions probably experience less pronounced influences from climate policy uncertainty.

Based on whether their average air pollution levels during the study period were below the sample median, we classified the sample cities into two groups: a high-pollution group and a low-pollution group. (Considering the differences among various types of air pollutants, when analyzing each air pollutant, we classify the cities based on their concentrations of that specific air pollutant. For example, when analyzing $PM_{2.5}$, cities are classified based on their $PM_{2.5}$ concentrations; when analyzing SO_2, they are classified based on SO_2 concentrations.) We set two binary dummy variables, $D_i^{HighAirPollution}$ and $D_i^{LowAirPollution}$, to indicate whether a city belongs to the high- or low-pollution group. These two dummy variables are defined as follows: if city i is in the high-pollution group, $D_i^{HighAirPollution} = 1$ and $D_i^{LowAirPollution} = 0$; conversely, if city i belongs to the low-pollution group, $D_i^{HighAirPollution} = 0$ and $D_i^{LowAirPollution} = 1$. Then, these dummy variables are multiplied with the CPU index to generate two interaction terms: $CPU_{it} \times D_i^{HighAirPollution}$ and $CPU_{it} \times D_i^{LowAirPollution}$. These interaction terms are used to replace CPU_{it} in Equation (1), yielding Equation (3). The coefficients α_1 and α_2 in Equation (3) capture the heterogeneous effects of CPU on air pollution in cities with high versus low pollution levels, respectively. The regression results are reported in Table 5.

$$AirPollution_{it} = \alpha_1 CPU_{it} \times D_i^{HighAirPollution} + \alpha_2 CPU_{it} \times D_i^{LowAirPollution} + \beta ControlVariables_{it} + \gamma OtherPolicies_{it} + u_i + v_t + \varepsilon_{it} \quad (3)$$

The regression results show that the coefficients of $CPU_{it} \times D_i^{HighAirPolltion}$ are significantly positive for all six air pollutants analyzed, indicating that CPU significantly exacerbates various types of air pollution in highly polluted cities. In comparison, while the coefficients of $CPU_{it} \times D_i^{LowAirPolltion}$ are also positive, they are consistently smaller than those of $CPU_{it} \times D_i^{HighAirPolltion}$. Furthermore, the coefficients of $CPU_{it} \times D_i^{LowAirPolltion}$ are statistically significant only for NO_2 and SO_2, but not for the other four pollutants. These results imply that the adverse impact of CPU on air quality is relatively weaker in cities with less severe air pollution. The effects of CPU exhibit regional heterogeneity depending on air pollution levels, with more heavily polluted cities experiencing disproportionately larger impacts. These findings suggest that policy attention should particularly focus on the pollution effects of CPU in high-pollution regions.

4. Conclusions and discussion

4.1. Conclusions

While existing literature has analyzed the impact of climate policy uncertainty on carbon emissions, its broader environmental consequences remain underexplored. This study provides fresh evidence that climate policy uncertainty significantly deteriorates air quality in China. Utilizing a comprehensive dataset covering 288 Chinese cities from 2001 to 2021, we demonstrate that heightened policy uncertainty leads to increased atmospheric concentrations of CO, NO_2, O_3, $PM_{2.5}$, PM_{10}, and SO_2. Our analysis further reveals regional disparities in these effects. The adverse impacts are particularly pronounced in regions that rely more on fossil fuel-based energy systems and suffer from higher air pollution. Conversely, the effects are relatively weaker in areas characterized by higher clean energy adoption rates and lower pollution levels.

4.2. Discussion

Based on our research findings, we propose the following policy recommendations.

(1) Given that climate policy uncertainty significantly exacerbates air pollution, it is necessary to enhance the continuity and stability of climate policies and reduce their uncertainty. A long-term policy framework should be established, with legislative measures clarifying medium- and long-term climate policy objectives. This could minimize disruptions to market expectations caused by frequent policy adjustments. Additionally, transparency and predictability in the policy making process must be improved. This requires actively soliciting feedback from the public and enterprises before finalizing climate policies, and regularly publishing policy implementation assessment reports after their enactment to reinforce public confidence in policy effectiveness. Before introducing major climate and environmental policies, a reasonable transition period should be established to allow enterprises to gradually adapt.

(2) Since regions with high fossil energy dependence are more significantly affected by climate policy uncertainty, it is imperative to accelerate the clean energy transition in such areas. For instance, in fossil energy-intensive and heavy industry-

Table 5
Heterogeneity analysis on the differences in air pollution levels.

Variables	CO	NO_2	O_3	$PM_{2.5}$	PM_{10}	SO_2
	(i)	(ii)	(iii)	(iv)	(v)	(vi)
$CPU \times D^{HighAirPollution}$	0.0123**	0.448***	0.417**	0.612***	0.743**	0.679*
	[0.006]	[0.109]	[0.194]	[0.219]	[0.353]	[0.369]
$CPU \times D^{LowAirPollution}$	0.00646	0.144*	0.126	0.146	0.163	0.473**
	[0.006]	[0.086]	[0.189]	[0.167]	[0.244]	[0.235]
ControlVariables	Yes	Yes	Yes	Yes	Yes	Yes
OtherPolicies	Yes	Yes	Yes	Yes	Yes	Yes
City-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of cities	288	288	288	288	288	288
Number of observations	2567	4007	6019	6019	6019	2567
Within R^2	0.821	0.771	0.754	0.880	0.877	0.839
Adjusted R^2	0.900	0.965	0.866	0.962	0.970	0.888

Note: *, **, and *** represent significance levels of 10 %, 5 %, and 1 %, respectively. Robust standard errors clustered at the city level are reported in brackets under the coefficient estimates. To save space, the coefficients of covariates are not reported in the table.

concentrated regions (e.g., the East China area and some central provinces in China), fiscal subsidies and tax incentives should be provided to support enterprises in phasing out outdated production capacities and upgrading to cleaner technologies. In areas with suitable natural conditions, the development of clean energy projects—such as photovoltaic and offshore wind power—should be encouraged to reduce reliance on fossil fuels.

(3) Our analysis shows that, compared to the low-pollution areas, the impact of climate policy uncertainty on air pollution is more pronounced in high-pollution cities. This suggests the need for regionally differentiated environmental governance strategies. China's air pollution problem largely stems from anthropogenic emissions. High-pollution regions typically have larger economic scales, denser industrial clusters, and higher population densities, where anthropogenic emissions far exceed those in low-pollution areas. In regions with severe air pollution, it is crucial to strengthen pollution control, promote industrial upgrading, and accelerate the transition to clean energy—particularly through dynamic regulation of core cities and high-emission enterprises. Simultaneously, stable and sustained policy support should be enhanced to improve public expectations and confidence in climate policies, thereby reducing policy uncertainty in these areas. In contrast, low-pollution regions have relatively lower anthropogenic emissions, with pollution being more influenced by natural factors. For these areas, the focus should be on preserving existing environmental quality, consolidating current advantages, and enhancing resilience against potential policy fluctuations and uncertainties.

(4) The uncertainty associated with different policies may have dissimilar effects on air pollution. The impact of uncertainty from certain policies may be more critical. By identifying the specific policy sources of uncertainty to pinpoint a few key policies, governments can better focus on areas requiring policy adjustments. Governments can establish a policy classification and evaluation mechanism, conducting detailed assessments of uncertainty sources through methods such as social surveys or third-party evaluations. Through categorized impact assessments of various climate policies (such as carbon pricing, renewable energy subsidies, industrial emission standards, etc.), governments can identify which policies' uncertainties exert the most detrimental effects on air pollution. This enables more efficient allocation of limited fiscal resources and administrative capacity.

CRediT authorship contribution statement

Daxin Dong: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Diwei Zheng:** Writing – review & editing, Writing – original draft, Formal analysis, Data curation.

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Data availability

Data will be made available on request.

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