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A Study on the Causal Effects and Mechanisms of Climate Policy Uncertainty on Urban Air Quality in China

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Abstract: The superposition of industrialization and urbanization has increased the pressure on China's carbon emissions and air pollution control. Policy implementation is full of uncertainty due to multiple disturbances. Clarifying how climate policy uncertainty dynamically affects urban air quality is a key gap in assessing the effectiveness of "dual control". Based on the daily air quality index (AQI) and China Climate Policy Uncertainty Index (CCPU) of 30 key cities from 2013 to 2023, this paper uses a Granger causality test and wavelet coherence analysis to study the dynamic correlation evolution process between CCPU and urban AQI. The results show that: (1) There is a two-way Granger causality between CCPU and AQI in the nonlinear framework, but CCPU has a significant guiding effect on AQI, while AQI has a relatively limited feedback effect on CCPU. (2) The coherence between CCPU and AQI has periodic heterogeneity at different time scales: in the short-period time scale (0-12 months), the coherence between CCPU and AQI is significant and positively correlated; in the medium-period time scale (12-36 months), the coherence of CCPU and AQI is weakened but still positively correlated; in the long-term time scale (36-60 months), CCPU and AQI coherence increased again and turned to be negatively correlated. (3) CCPU always leads or synchronizes with AQI throughout the cycle time scale, indicating that climate policy uncertainty is a forward-looking variable that drives urban air quality changes. This complex time-varying feature and its transmission mechanism can provide a scientific basis for the formulation of differentiated atmospheric governance and climate policies in the cycle.

Keywords: Climate policy uncertainty; Air quality index; Wavelet coherence analysis; Time-frequency characteristics

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1. Introduction

As the pace of industrialization and urbanization continues to accelerate, vast quantities of pollutants are being released into the atmosphere, leading to increasingly severe air pollution issues [1], thereby seriously affecting human health and environmental quality [2]. According to the latest assessment by the World Health Organization, about 4.2 million people worldwide die each year from air pollution-related diseases [3], posing a greater mortality burden than most infectious diseases. For countries in the process of rapid urbanization, air pollution has seriously hindered the sustainable development of cities. As the world's second largest economy and the largest developing country, China plays the dual role of "key contributor" and "key solution" to global carbon emissions. From the *Paris Agreement* to the *14th Five-Year Plan*, China has established the world's most systematic climate policy matrix, aiming to achieve a balance between economic growth and greenhouse gas emission reduction, while improving environmental quality. However, due to multiple factors in policy implementation, the effect of climate policy is highly uncertain [4–6], which has an important impact on the improvement of urban air quality. Therefore, taking climate policy uncertainty as the core explanatory variable and systematically evaluating its dynamic impact on urban air quality in China can help better understand the complex relationship between climate policy and air quality, and provide a scientific basis for environmental policymaking, thereby promoting sustainable development.

In order to quantify the risk of climate policy uncertainty, Gavriilidis (2021) used text mining methods to construct the US climate policy uncertainty index (CPU) for the first time [7]. Ma et al. (2024) further proposed the China Climate Policy Uncertainty Index (CCPU) [8]. These indices provide quantitative tools for climate policy risk research and promote related research in this field. With the aggravation of air pollution, research on air quality has expanded significantly, focusing primarily on its sources, driving factors, policy effects, and mitigation strategies. Early studies have found that industrial emissions, construction dust, coal combustion emissions, motor vehicle exhaust, and waste incineration are the main sources of air pollution [9]. Meanwhile, fossil energy, which involves substantial energy consumption during extraction and utilization processes, is also regarded as an important contributor to regional air pollution [10]. On this basis, scholars turn their perspective to the socio-economic dimension. At the macro level, air pollution is regarded as the by-product of rapid industrialization and urbanization. Empirical evidence suggests that industrialization and urbanization [11], transportation infrastructure expansion [12], and industrial structure evolution [13] are the key drivers of air pollution. In particular, in China, rapid urbanization has significantly intensified the concentration of major pollutants such as PM2.5 and Nox [14]. However, industrial structure upgrading has been shown to offset these negative effects partially. With the growing share of the service and high-tech sectors, air pollutant emissions, particularly haze pollution, have decreased significantly [15]. In recent years, the rise of green finance and the digital economy has provided new impetus for pollution control. On the one hand, the development of green finance has fostered green technological innovation, thereby indirectly improving ambient air quality [16]; on the other hand, the digital economy enhances technical efficiency, optimizes resource allocation, and facilitates industrial structure upgrading, thereby significantly reducing urban pollutant emissions and improving urban air quality [17]. Finally, at the policy level, a large number of studies have focused on causal identification and efficiency evaluation of policy interventions. Using quantitative methods, the effects of clean heating policy [18], pollutant discharge permit system [19], environmental protection tax [20], and air pollution prevention and control action plan on air quality were systematically evaluated. These findings suggest that a joint prevention and control mechanism can enhance policy effectiveness through regional coordination [21]. The existing literature has constructed a relatively complete air pollution research framework from the four dimensions of "source-cause-policy-effect". However, the literature still lacks a systematic investigation of the synergistic effects and long-run dynamic impacts under multiple concurrent policy interventions, highlighting an important research gap [22].

In summary, most existing studies focus on the relationship between climate policy uncertainty and the economy, or are limited to evaluating the policy effects of single climate policy events on air quality improvement [23]. However, they fail to capture the dynamic cumulative effects of policy uncertainty on air quality arising from long-term adjustments and overlapping impacts. In fact, the change of urban air quality in China is not the result of a single policy, but a comprehensive result of the long-term revision, superposition and uncertainty interaction of multiple climate policies. However, the transmission mechanism between climate policy uncertainty and the air quality index has not been systematically identified and quantified. Therefore, this paper aims to construct the influence path of climate policy uncertainty on air quality and quantify the macro-control effect of climate policy. This study introduces the wavelet coherence analysis method proposed by Torrence and Compo (1998) [24]. As an advanced time-frequency analysis tool, it can effectively capture the time-varying correlation between nonlinear and non-stationary time series [25,26], and fully reveal the time-varying characteristics and transmission mechanism of the impact of climate policy change uncertainty on urban air quality in China.

The main contributions of this paper are threefold. First, unlike previous studies that focus on the effects of single climate policy events on air pollution or the relationship between climate policy uncertainty and the economy, this paper examines the long-run dynamics, interactions, and uncertainty of multiple overlapping climate policies. It provides a useful complement to the existing literature by focusing on the dynamic cumulative effects of climate policy uncertainty on urban air quality in China. Second, this paper employs the Granger causality test and wavelet coherence analysis to systematically investigate the time-varying characteristics and transmission mechanisms of the impact of climate policy uncertainty on urban air quality in China, providing new empirical evidence for identifying and quantifying the underlying mechanisms in this field. Third, by revealing the short-, medium-, and long-run effects of climate policy uncertainty on air quality, this study offers empirical evidence for policy design under overlapping policy scenarios and provides a scientific basis for the formulation and implementation of climate policies.

2. Methodology

First, the Johansen cointegration test is employed to examine the cointegration relationship between climate policy uncertainty and the urban air quality index. Based on this, linear and nonlinear Granger causality tests are used to investigate the causal relationship between the two variables [27]. Finally, wavelet coherence analysis is applied to explore the evolution of the dynamic correlation between the two in the time domain and frequency domain of the quantized sequence. This approach provides a comprehensive and in-depth examination of the impact mechanism between climate policy uncertainty and urban air quality.

2.1. Data processing

Due to seasonal fluctuations, the Air Quality Index (AQI) is higher in spring and winter and lower in summer and autumn [28]. In order to eliminate seasonal interference, the data used are processed by the difference method.

$$\nabla_d X_t = X_t - X_{t-d} \tag{1}$$

Where X_t represents AQI value at time t, $t=1,\ldots,T$ $(T = 108)$, and d denotes the lag order, $d=12$.

2.2. Johansen cointegration test

In order to study the long-term equilibrium relationship between climate policy uncertainty and urban AQI, we use Johansen cointegration test to determine whether there is a cointegration relationship between their long-term trends. This method attempts to confirm that although there may be short-term deviations, over time, both variables move consistently around a specific equilibrium trajectory.

Let $Z_t=[Y_t,X_t]'$, a p-th order vector error correction model VECM is specified to capture both the short-run dynamics and the long-run equilibrium relationships among the variables.

$$\Delta Z_t = \Pi Z_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Z_{t-i} + \varepsilon_t \tag{2}$$

Here, ΔZ_t denotes the first-difference of Z_t; ΔZ_{t-i} represents the i-th order lagged difference term, where i indicates the lag order; Γ_i denotes the coefficient matrix associated with the i-th order lagged difference; Π represents the coefficient matrix of the p-th order lagged term; and ε_t denotes the error term.

(1) Trace test

$$H_0(r):\text{rank}(\Pi) \le r \text{ vs } H_1(r):\text{rank}(\Pi)>r$$

$$LR_{trace}(r) = -T\sum_{i=r+1}^{2}\ln\left(1-\hat{\lambda}_i\right) \tag{3}$$

Specifically, $\hat{\lambda}_i$ denotes the i-th largest eigenvalue, while T represents the sample size. λ-max test

$$H_0(r): rank(\Pi) = r vs H_1(r+1): rank(\Pi) = r+1 \tag{4}$$

$$LR_{max}(r) = -T\ln\left(1-\hat{\lambda}_{i+1}\right) \tag{5}$$

(2) Cointegration equation

If the test results indicate that r = 1, the normalized long-run cointegrating relationship can be expressed as:

$$y_t = \beta_0 + \beta_1 x_t + u_t \tag{6}$$

Where u_t denotes the stationary error correction term, and β_1 represents the estimated long-run elasticity.

2.3. Granger Causality Test

First, this study applies the Granger causality test to examine whether there is predictive causality between climate policy uncertainty and the urban AQI. Accordingly, we specify the following bivariate vector autoregressive model:

Equation for x:

$$x_t = \alpha_1 + \sum_{i=1}^{p}\phi_i x_{t-i} + \sum_{j=1}^{q}\theta_{12j} y_{t-j} + \varepsilon_{1t} \tag{7}$$

Equation for y:

$$y_t = \alpha_2 + \sum_{i=1}^{p} \gamma_i y_{t-i} + \sum_{j=1}^{q} \theta_{22j} x_{t-j} + \varepsilon_{2t} \tag{8}$$

Where α_1 and α_2 are constants; p and q denote the lag orders; ϕ_i and γ_i are the coefficients on the own-lag terms; and ε_{1t} and ε_{2t} are the error terms. The null hypothesis that Y does not Granger-cause X is $_{12j}=0 (j=1,2,...q)$; analogously, the null that X does not Granger-cause Y is $\theta_{22j}=0$ $(j=1,2,...q)$.

Since traditional Granger causality tests primarily examine linear causal relationships between climate policy uncertainty and urban air quality indices, they cannot reveal potential nonlinear causal mechanisms between variables. To obtain a more comprehensive assessment of causal relationships, this study further introduces nonlinear Granger causality tests (the Diks–Panchenko nonparametric method).

Define the lag vector:

$$W_t^L = \left(y_{t-L}, \ldots, y_{t-1}, x_{t-L}, \ldots, x_{t-1}\right)'', L = p = q \tag{9}$$

Test nonlinear causality of Y on X and establish a system of equations.

$$F_{x_t|W_t^L} = F_{x_t|W_{x,t}^L} \, vs. F_{x_t|W_t^L} \neq F_{x_t|W_{x,t}^L} \tag{10}$$

Where $W_{x,t}^L$ contains only the lagged values of X. Equality implies that Y does not nonlinearly Granger-cause X; inequality indicates the presence of nonlinear causality.

Dp test statistic T_n:

$$T_n = \sqrt{n}\,\frac{\hat{q}}{\hat{\sigma}_q}; \quad q = \frac{1}{n(n-1)} \sum_{i \neq j} K_{ij} \tag{11}$$

Where K_{ij} denotes Gaussian kernel weights, with bandwidth $h=1.5\hat{\sigma}n^{-1/(4+2L)}$.

By interchanging the roles of Y and X, one can test for nonlinear causality in the reverse direction.

2.4. Wavelet Coherence analysis

By applying wavelet coherence analysis to transform time series into the time-frequency domain, this study examines the temporal dynamics between climate policy uncertainty and urban air quality indices within a time-frequency quantified sequence. The methodology involves the following specific steps:

Define the time series $X(t) \in \{Y(t), X(t)\}$. Its Morlet wavelet transform is:

$$W_X(a,\tau) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} X(t)\,\psi^*\left(\frac{t-\tau}{a}\right) dt \tag{12}$$

Where $a > 0$ is the scale parameter, τ is the time shift, and $\psi^*(\cdot)$ denotes the complex conjugate of the Morlet mother wavelet.

Define the cross-wavelet power spectrum and wavelet coherence as:

$$W_{y,x}(a,\tau) = W_y(a,\tau)\,W_x^*(a,\tau) \tag{13}$$

Following Torrence and Compo (1998), the wavelet coherence is given by:

$$R^2(a,\tau) = \frac{\left|S\left\{W_{y,x}(a,\tau)\right\}\right|^2}{S\left\{\left|W_y(a,\tau)\right|^2\right\} S\left\{\left|W_x(a,\tau)\right|^2\right\}}, 0 \leq R^2(a,\tau) \leq 1 \tag{14}$$

Where S denotes a smoothing operator. Values of $0 \leq R^2(a,\tau) \leq 1$ closer to 1 indicate stronger local correlation between the two series.

The phase difference in the wavelet domain is:

$$\Phi_{y,x}(a,\tau) = arctan\left(\frac{\mathrm{Im}\left\{S\left[\tau^{-1}W_{y,x}(a,\tau)\right]\right\}}{\mathrm{Re}\left\{S\left[\tau^{-1}W_{y,x}(a,\tau)\right]\right\}}\right), \quad \Phi_{y,x}(a,\tau) \in [-\pi, \pi] \tag{15}$$

Where Im and Re denote the imaginary and real parts, respectively, of the smoothed cross-spectrum. The phase $\Phi \in [-\pi, \pi]$ characterizes the association between the series and reveals potential lead–lag (causal) relationships.

3. Sample selection and data sources

The original AQI data used in this study are derived from the "China Air Quality Online Monitoring Platform". The AQI is a dimensionless comprehensive index, which reflects the quantitative level of air pollution. The higher the AQI value, the more serious the air pollution and the higher the health risk. Since the data can be traced back to December 2013, this study takes 2013 as the starting point. This study extracted the daily AQI data of 30 key cities from 2013 to 2023 as samples, and calculated the monthly average air quality accordingly. In order to ensure the reliability and stability of the measurement results, Beijing, Shanghai, Guangzhou, Chengdu and Wuhan were further selected as control samples. Subsequently, a panel data set was constructed for empirical analysis.

The CCPU data used in this study are derived from the China Climate Policy Uncertainty Index developed by Ma et al. (2024) [8]. The index uses text mining technology based on deep learning and data from six major national news media to establish a national measurement index of China's climate policy uncertainty. The index can not only effectively capture the major international climate policy events affecting China, but also highlight the unique characteristics of the evolution and development of China's climate policy. Therefore, it accurately reflects the temporal variability and structural changes of China's climate policy uncertainty. **Figure 1** intuitively shows the temporal trend of China's urban AQI and its climate policy uncertainty.

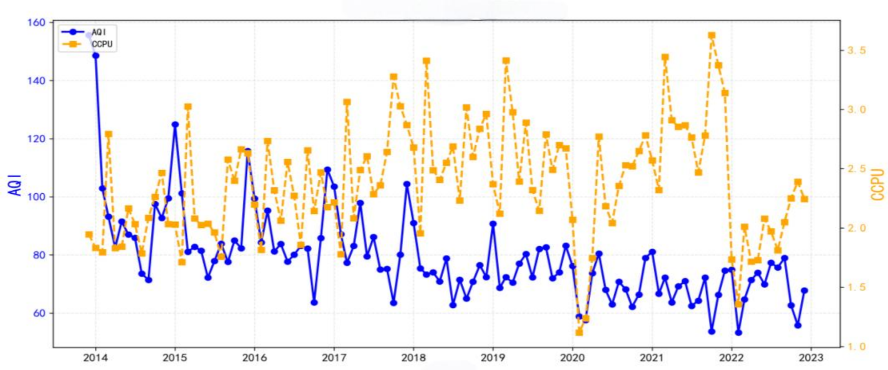

Figure 1. Time series of CCPU and AQI.

Table 1 summarizes the descriptive statistics of CCPU and AQI. The data show that the mean value of CCPU is 2.379, the variance is 0.234, the skewness is only 0.148, and the kurtosis is 2.937, indicating that its distribution pattern is close to the normal distribution. On the other hand, the mean value of AQI is 79.484, the variance is 260.60, the skewness is 1.988, and the kurtosis is as high as 9.326. This shows a significant right deviation and a "heavy-tailed peak distribution", indicating that the frequency of extremely high AQI values during the sample period exceeded normal expectations and there was significant temporal heterogeneity. This is related to the seasonal fluctuation of AQI, which usually has higher readings in spring and winter and lower readings in summer and autumn, resulting in extremely high values. The Jarque-Bera test results of AQI (JB value: 253.521) reject the normal distribution hypothesis at the 1% significance level, further confirming the non-normality of AQI. In addition, the ADF test results (-2.938 and-1.602, respectively) show that CCPU rejects the unit root hypothesis at the 1% significance level, which proves that the data are stable. In contrast, AQI failed to pass the critical value of 10%, showing non-stationary characteristics. Since both fail to meet the assumption of the same order unit root, it is necessary to re-evaluate the cointegration specification.

Table 1. Descriptive statistical results

Parameter	Mean	Variance	Maximum	Minimum	Skewness	Kernel	J-BTest	ADF Test
CCPU	2.379	0.234	3.627	1.117	0.148	2.937	0.416	-2.938**
AQI	79.484	260.600	155.600	53.300	1.988	9.326	253.521***	-1.602

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

4. Empirical analysis

4.1. Johansen cointegration test analysis

To eliminate seasonal interference, we first seasonally differ AQI with a lag of 12 orders, then perform the ADF stationarity test on the resulting series together with CCPU. **Table 2** shows that both variables are stationary after first-difference transformation, satisfying the I(1) sequence requirement and thus eligible for cointegration testing.

Table 2. ADF unit root test results

Variable	Test Target	Test Format	*p*-value	Conclusion
CCPU	LEVEL	(c, 0, 1)	0.0376**	Stationary I(0)
DCCPU	DIFF1	(c, 0, 1)	0.0036***	Stationary I(1)
AQI	LEVEL	(c, 0, 1)	0.1260	Non-stationary
DAQI	DIFF1	(c, 0, 1)	0.0000***	Stationary I(1)

Table 3 shows that for the relationship between CCPU and AQI, both the trace test and the maximum eigenvalue test rejected the null hypothesis of "$r = 0$" at the 5% significance level, but failed to reject "$r \leq 1$". This shows that there is at most one cointegrating vector, which is consistent with the theoretical expectation.

Table 3. Johansen cointegration test outcomes

Test Type	Null Hypothesis (H_0)	Eigenvalue	Test Statistic	5% Critical Value
Trace Test	$r = 0$	0.367	63.620	15.495
Trace Test	$r \leq 1$	0.191	20.161	3.842
Maximum Eigenvalue	$r = 0$	0.367	43.459	14.265
Maximum Eigenvalue	$r \leq 1$	0.191	20.161	3.842

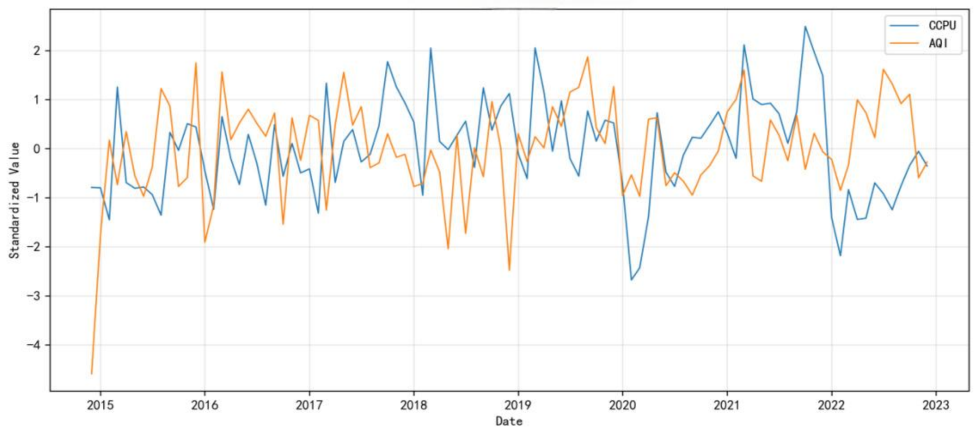

Figure 2. Standardized CCPU and AQI series.

Figure 2 shows the standardized CCPU and AQI time series. Although there are significant short-term fluctuations in these two curves, the overall trend shows a certain degree of synchronization, which intuitively supports the existence of cointegration.

Figure 3 shows the equilibrium residuals generated by the first cointegrating vector. These residuals fluctuate around zero and there is no systematic deviation. Significant deviations usually return to the equilibrium path in the subsequent period, further confirming the stability of the long-term equilibrium relationship.

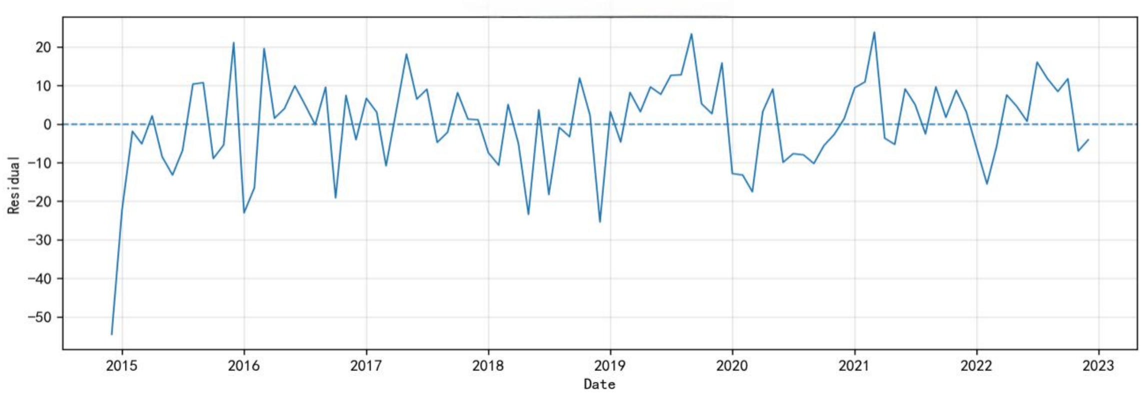

Figure 3. Cointegration residual plot.

4.2. Granger causality analysis

4.2.1. Linear Granger causality

According to the results of **Table 4**, the p-values of all lag orders in the Granal causality test are greater than 0.1. This shows that under the linear framework, no matter which direction (CCPU → AQI or AQI → CCPU), the null hypothesis cannot be rejected. Therefore, there is no statistically significant linear Granger causality between climate policy uncertainty and urban AQI. In view of the nonlinear characteristics of climate policy itself, this paper further uses a nonlinear Granger causality test to examine the potential nonlinear transmission mechanism between the two.

Table 4. Linear Granger causality results

Lags	1	2	3	4	5	6	7	8
CCPU→AQI(p-value)	0.3079	0.2577	0.3235	0.4640	0.3387	0.3376	0.2784	0.3183
AQI→CCPU(p-value)	0.2033	0.2835	0.2788	0.4608	0.7212	0.8707	0.7213	0.4651

4.2.2. Nonlinear Granger causality

Table 5 shows the nonlinear Granger causality between CCPU and AQI. The results show that CCPU significantly affects AQI at the 1% significance level during the lag period of 1-4, which indicates that it has obvious short-term effects. When the lag order is extended to the 5th-6th order, the nonlinear Granger causality is no longer significant, indicating that the influence of CCPU on AQI gradually decreases with the increase of lag time. However, within a longer lag period of 7-8 orders, the nonlinear Granger causality of CCPU to AQI becomes significant again at the 5% significance level, showing new predictive ability.

Table 5. Nonlinear Granger causality test results

Lags	1	2	3	4	5	6	7	8
CCPU→AQI(p-value)	0.0000***	0.0000***	5.052e-09***	0.0005***	0.513	0.267	0.016**	0.048**
AQI→CCPU(p-value)	0.0000***	2.22e-16***	0.0008***	0.225	0.893	0.734	0.049**	0.101

From the perspective of reverse causality, AQI shows a significant nonlinear Granger causality effect when the lag periods are 1–3 and 7, which can cause changes in CCPU. However, this effect disappears when the lag periods are 4- 6 and 8. This shows that the feedback effect of air quality on climate policy uncertainty is limited to short-term and specific medium- and long-term lag periods, and its significance is weaker than the CCPU → AQI causal chain. In general, CCPU and AQI show two-way Granger causality in a non-linear framework. However, since government-led climate policy adjustments often precede the response of market and environmental variables — and may be driven by exogenous institutional factors such as government policies and international agreements — CCPU has a significant nonlinear Granger causality effect on AQI. In contrast, the feedback effect of air quality changes on climate policy is still relatively limited.

4.3. Wavelet coherence analysis

Figure 4 shows the wavelet coherence time-frequency relationship between China's climate policy uncertainty index (CCPU) and China's urban AQI. Using the Morey wavelet basis, the red noise background is generated by Monte Carlo simulation, and only the area with significance higher than the 95% confidence level is retained (located in the thick black line). The horizontal axis represents the time axis, and the vertical axis represents the duration of the fluctuation cycle (in months). In this study, the time scale of the time-frequency period is divided into three different intervals: the short-term period is 0 to 12 months, the medium-term period is 12 to 36 months, and the long-term period is 36 to 60 months. The color scale indicates the intensity of coherence; the red region (0.64–1.0) indicates strong coherence, and the blue region (0.0–0.16) indicates extremely weak coherence. The arrow indicates the phase relationship: the horizontal right arrow indicates the positive synchronization correlation, and the horizontal left arrow indicates the negative synchronization correlation. The downward arrow indicates the leading relationship, and the upward arrow indicates the lagging relationship. The diagonal arrow combines phase information to convey both correlation and lead/lag dynamics.

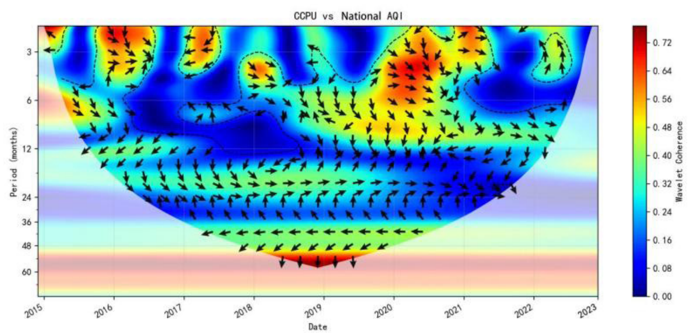

Figure 4. Wavelet coherence graph of CCPU for national AQI.

The figure reveals several key features: on the short-term time scale (0-12 months), multiple deep red high correlation regions appeared from 2015 to 2023, indicating that climate policy uncertainty has a significant short-term impact on urban AQI. The arrows in this area mainly point to the lower and right sides, indicating that there is a positive correlation between the two variables, in which CCPU is ahead of AQI. On the medium-term time scale (12–36 months), the overall correlation weakens, and only a banded area of moderate brightness is formed between 2017 and 2019. The arrows in the region mainly point to the right or lower right, indicating that the climate policy uncertainty is still positively correlated with the urban AQI, and the change of CCPU is synchronized with the fluctuation of AQI or slightly ahead. On the long-term time scale (36–60 months), a region with significant intensity correlation appeared from 2017 to 2020, and its peak appeared from the beginning of 2018 to the middle of 2019. This shows that during this period, climate policy uncertainty has the most significant long-term impact on urban air quality. In this region, the arrows mainly point to the left horizontal or lower left, indicating that there is a negative correlation; that is, in the long-term trend, climate policy uncertainty (CCPU) leads AQI.

In order to enhance the robustness of the research results, we selected five representative cities, Beijing, Shanghai, Chengdu, Wuhan and Guangzhou, and compared their wavelet coherence with their respective national monthly average sequences. The results are highly consistent with the national research results (**Figures 5–9**). The main features are as follows: On the short-term time scale, except for Shanghai, the other four cities show significant high coherence areas. Among them, climate policy uncertainty is positively correlated with urban AQI, and CCPU is ahead of AQI. Shanghai does not show significant correlation in this frequency band, which may be due to its advanced end processing and early warning system significantly reducing the policy impact. On the medium-term time scale, except for Wuhan, the overall correlation intensity of the four cities has weakened, and only a banded area of moderate intensity appears in the local period. The direction arrow maintains a downward rightward trajectory, which highlights the positive correlation between climate policy uncertainty and urban AQI. The AQI value of CCPU is the highest. However, Wuhan showed a high-intensity correlation area between the beginning of 2016 and the end of 2019, indicating that climate policy uncertainty had a significant impact on Wuhan's AQI during this period. This may be related to the high sensitivity of the city's heavy chemical industry structure to climate policy fluctuations. On the long-term time scale, the five cities all show deep red high correlation areas, indicating that climate policy uncertainty has the strongest long-term impact on urban AQI. The arrows mainly point to the bottom and left, revealing that there is a significant negative correlation between CCPU and AQI, and CCPU is ahead of AQI in the long-term trend. In general, the heterogeneity of inter-city correlation is mainly due to regional differences in industrial structure, energy endowment and policy implementation capacity.

The results show that the uncertainty of climate policy significantly affects the correlation of urban AQI on the short-term and long-term time scales, and the correlation is significantly weakened on the medium-term time scale. The transmission path is always manifested as a synchronous or leading relationship between the climate change policy indicator (CCPU) and AQI. In terms of correlation, CCPU was positively correlated with AQI at the short-term and medium-term scales, while it turned into a significant negative correlation at the long-term scale. This suggests that climate policy may exacerbate air quality fluctuations in the short term, but it is expected to promote continuous improvement of air quality in the longer term.

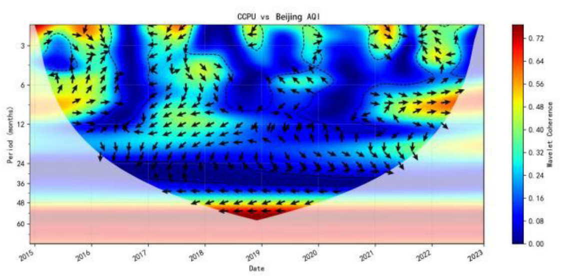

Figure 5. Wavelet coherence graph of CCPU for Beijing AQI.

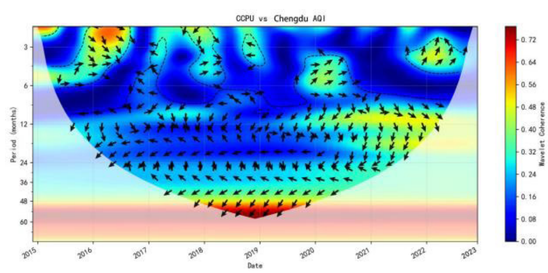

Figure 6. Wavelet coherence graph of CCPU for Chengdu AQI.

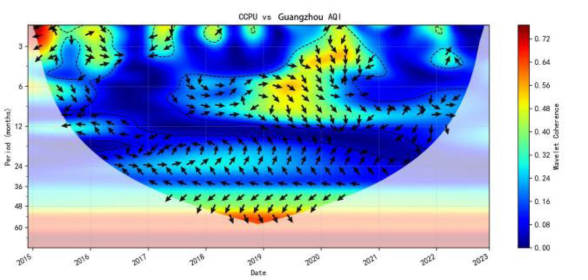

Figure 7. Wavelet coherence graph of CCPU for Guangzhou AQI.

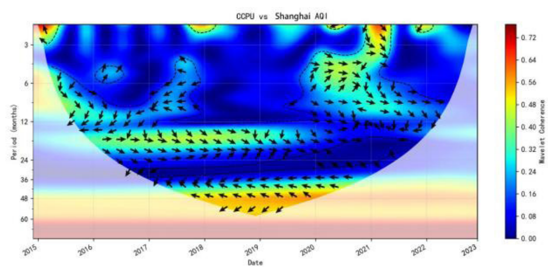

Figure 8. Wavelet coherence graph of CCPU for Shanghai AQI.

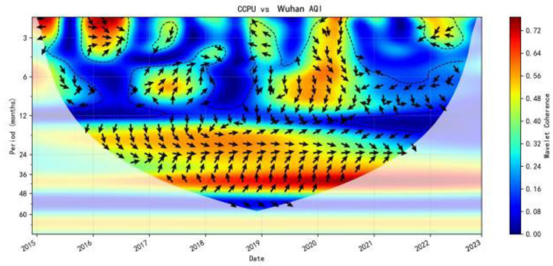

Figure 9. Wavelet coherence graph of CCPU for Wuhan AQI.

5. Findings and policy implications

5.1. Research findings

This study first uses the Johansen cointegration test to establish a long-term equilibrium relationship between climate policy uncertainty and urban AQI. Then, through the Granger causality test, the causal relationship between these two variables and their dynamic interaction are discussed. Finally, the wavelet coherence analysis is used to quantify the time-frequency evolution of the dynamic correlation between the CCPU index and AQI. Based on this comprehensive research method, the following conclusions are drawn.

(1) Through the application of nonlinear Granger causality analysis, it is found that there is a two-way nonlinear Granger causality between climate policy uncertainty and AQI. Because government-led climate policy adjustments often precede the response of environmental variables and may be driven by exogenous institutional factors such as government policies and international agreements, CCPU has a significant nonlinear Granger causality effect on AQI. In contrast, the feedback effect of air quality changes on climate policy is relatively limited.

(2) Through the wavelet coherence analysis of the dynamic correlation evolution of CCPU and AQI in the time domain and frequency domain, some obvious rules are found: CCPU and AQI show significant positive coherence on the short-term time scale (0–12 months). On the medium-term time scale (12–36 months), the overall coherence is weakened, but it still maintains a positive correlation. On the long-term time scale (36–60 months), the correlation between CCPU and AQI increased again and turned to a negative correlation. This suggests that climate policies may exacerbate air quality fluctuations in the short term, but have sustained regulatory potential to improve air quality in the long term. Throughout the cycle, CCPU has consistently outperformed or synchronized with AQI, confirming that climate policy uncertainty is the leading variable driving changes in urban air quality.

5.2. Implications of the study

Based on the above research results, some key policy implications are proposed.

Firstly, a dynamic adjustment mechanism is established. The results show that there is a significant causal relationship between urban pollution control policy and AQI, which links urban pollution control policy with air quality dynamics. These results indicate that urban pollution control policies may affect air quality in a variety of ways. Therefore, a real-time monitoring and evaluation system should be established to track the specific impact of policy adjustments on urban air pollution dynamics, and the policy effectiveness evaluation report should be updated regularly. At the same time, a resilient climate policy framework should be built by introducing climate policy scenario analysis tools. These tools can simulate air quality trends under different climate policy changes, so as to formulate coping strategies in advance. This will ensure that policies can quickly adapt to new environmental changes and effectively respond to future uncertainties.

Secondly, short-term pollution control measures should be optimized. The results show that there is a significant positive correlation between CCPU and AQI on a short-term time scale, which indicates that short-term fluctuations in climate policy will directly push up AQI and aggravate pollution. Once the uncertainty of climate policy is eliminated, it will immediately amplify pollution fluctuations in the short-term cycle. This highlights that “instant tools” such as emergency production limits and temporary emission caps remain the primary means of urban air quality management.

Therefore, the emergency response mechanism should be strengthened and more detailed pollution control measures should be developed. At the same time, pollutant emission standards should be dynamically adjusted according to climate policy changes and air quality monitoring data to ensure that air quality is effectively improved in the short term.

Third, promote technological innovation and green energy transformation. Studies have shown that the feedback effect of AQI on per capita carbon emissions is relatively limited, which indicates that relying solely on end-of-pipe treatment is not enough to cope with the long-term uncertainty caused by climate change. Therefore, it is very important to promote source emission reduction and green technology development. We should increase investment in research and development of green energy technologies such as solar energy and wind energy to reduce dependence on fossil fuels and fundamentally reduce pollutant emissions. At the same time, enterprises should be encouraged to adopt low- or zero-emission cleaner production technologies to minimize the impact on air quality from the source.

Fourth, improve the policy coordination mechanism to cope with cyclical fluctuations. The results show that the correlation between climate policy intensity and AQI is particularly significant in the short- and long-term cycles, while it is significantly weakened in the medium-term cycle. This shows that the coordination of policy shocks is poor, and market supervision and technical adjustment lag, resulting in a significant decline in the intensity of correlation. In addition, the positive correlation observed in the short-term and medium-term cycles will turn into a negative correlation in the long run, indicating that there is a “critical cumulative threshold” for climate policy. When the policy intensity and duration exceed this threshold, market expectations will shift from “wait-and-see / delay” to “investment/transformation”, thus driving air quality into a track of continuous improvement. Therefore, the government should strengthen structural policies (energy substitution, capacity renewal) to ensure the realization of the improvement dividend. Finally, we should strengthen the forward-looking research and strategic planning of climate policies, establish and improve the policy evaluation and adjustment mechanism, combine the short-term impact with the long-term development trend in the design of climate measures, and adjust the intensity and rhythm of these policies according to the changes in the domestic and global economic situation.

Disclosure statement

The authors declare no conflict of interest.

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