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The impact of climate policy uncertainty on urban climate risk: Evidence from 274 cities in China

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A R T I C L E I N F O

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Household deposit balance
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A B S T R A C T

Climate change mitigation policies must be developed to reduce the adverse effects of escalating climate risks. However, climate policies are fraught with uncertainty, which leads to unavoidable negative consequences. It is crucial to understand the impact of climate policy uncertainty on urban climate risk. This study uses the entropy weighting method to measure the urban climate risk of 274 prefectural-level cities in China from 2011 to 2021 based on the Hazard-Exposure-Vulnerability (H-E-V) adaptation decision-making framework, and employs the two-way fixed effects model to investigate the impact of climate policy uncertainty on urban climate risk through multidimensional empirical tests. The results indicate that: (1) Climate policy uncertainty significantly increases the level of urban climate risk. (2) Climate policy uncertainty affects the level of urban climate risk through the industrial structure of the production sector. (3) Deposit balances and insurance cost of the household sector exacerbate the positive relationship between climate policy uncertainty and urban climate risk. (4) Climate policy uncertainty has a greater impact on climate risk in capital cities than in non-capital cities and it has the most significant impact in cities with medium level of climate risk. The findings offer new perspectives on reducing urban climate change risk and achieving sustainable development.

List of acronyms

Acronym	Definition
CPU	Climate Policy Uncertainty
UCR	Urban Climate Risk
IPCC	Intergovernmental Panel on Climate Change
H-E-V	Hazard-Exposure-Vulnerability
ER	Environmental Regulation
IS	Industrial Structure
HDB	Household Deposit Balance
IC	Insurance Cost

1. Introduction

Extreme weather events, like heatwaves (Bi et al., 2023), floods (Hirabayashi et al., 2013; Liu et al., 2022), and droughts (Wang et al., 2020), are becoming more frequent. Climate change-related risks are increasing and have far-reaching consequences for social development (Estoque et al., 2020), agricultural systems (Su et al., 2021), energy security (Iyke, 2024), life and health (Carlson et al., 2022; Li et al., 2023a; Twining et al., 2022), and the financial and economic sectors (Sautner et al., 2023; Strauss et al., 2021). Rapid industrialization and urbanization have caused various ecological and environmental issues, raising the risk of climate change in urban areas (Wang et al., 2021). Simultaneously, cities in developing countries are facing enormous

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challenges in dealing with urgent climate change and have become the primary victims due to inadequate institutional, economic, and technological capacity (Karim et al., 2015; Wu et al., 2018).

According to *Cities on the Route to 2030: Building a zero emissions, resilient planet for all*, 93 % of cities are facing significant climate risks. Urban climate change and related risks have emerged as a primary concern, drawing the attention of academics, researchers, and policymakers (Broto & Bulkeley, 2013; Manoli et al., 2019; McCarthy et al., 2010). To effectively respond to climate change and achieve global sustainable development goals, policymakers have implemented several strategies to mitigate the effects of environmental degradation and global warming (Commane & Schiferl, 2022; Hanna et al., 2021; Hölscher et la., 2019; Liu & Feng, 2023; Ren et al., 2022a). From the United Nations Framework Convention on Climate Change to the Kyoto Protocol and the Paris Agreement, the fight against climate change has progressed from scientific understanding to political consensus, resulting in a global framework for climate governance. The 28th Conference of the Parties (COP28) to the United Nations Framework Convention on Climate Change (UNFCCC) adopted a framework of global adaptation goals, a work program on just transition pathways, and other vital decisions affecting developing countries, demonstrating the current collaborative efforts of the international community to respond climate change.

China, the largest developing country and emitter of greenhouse gases, plays a critical role in the global response to climate change and accepts international responsibility for climate governance (Hao et al., 2021; Nuvvula et al., 2022). On the one hand, China has experienced rapid urbanization, with many cities facing complex environmental challenges and climate risks as they expand (Sun et al., 2016). On the other hand, the Chinese government has recently gradually increased its emphasis on climate governance, launching several city-level policies to combat climate change, such as the *Action Program for Urban Adaptation to Climate Change* and the *Pilot Program for Climate Adaptive City Construction*. Clearly, climate change mitigation policies seek to reduce future adverse effects of climate change by implementing effective political and governance measures (Arnll et al., 2013; Harvey, 2007; Khalid & Okitasari, 2023; Victor, 2015). However, the time, scope, and conditions for designing and implementing climate policies are subject to a significant degree of uncertainty, resulting in unavoidable negative consequences (Gavriilidis, 2021; Li et al., 2023b).

In recent years, countries have recognized climate policy uncertainty (CPU) as a critical factor influencing their ability to meet climate targets. Ambiguous climate policies will prevent countries from achieving their goals while jeopardizing their ability to mitigate and respond to climate change (Li et al., 2023b; Qin et al., 2023), potentially exacerbating climate risks. Consequently, CPU, a critical issue that has yet to receive adequate discussion, may be closely related to climate risk.

Throughout the global response to climate change, academics and policymakers have paid close attention to the potential impact of CPU on urban climate risk (UCR). Regarding CPU measurement, current research primarily relies on big data text mining from newspapers, incorporating two types of word frequency analysis (Gavriilidis, 2021; Ma et al., 2023) and machine learning algorithm (Noailly et al., 2022). Regarding the impact of CPU, studies have primarily focused on the energy sector, exploring how CPU affects energy consumption (Huo yet al., 2023; Li et al., 2023b), energy transition (Lin & Cheung, 2024; Yang et al., 2024), energy demand (Tu et al., 2024), and energy prices (Fu et al., 2024), revealing the negative effects of CPU on the energy market (Siddique et al., 2023). Studies have also investigated the effects of CPU on innovation (Sun et al., 2024), the economy (Fried et al., 2021; Iqbal et al., 2024), finance (Fuss et al., 2008), and productivity (Ren et al., 2022b) at various levels, including national (Chen et al., 2023), city (Dai & Zhu, 2024), and firm levels (Ren et al., 2022b) and others. Studies have shown that CPU frequently leads actors to take a wait-and-see approach in decision-making, which inhibits long-term investment (Pham et al., 2024) and green technology innovation (Niu et al., 2023), resulting in unavoidable negative consequences.

At the same time, some studies have investigated the impact of CPU on environmental governance, with a particular emphasis on pollution emissions (Tian & Li, 2023) and climate risk (Sun et al., 2023). There also have been studies on systematic and standardized approaches to assessing and predicting climate change risks based on indicators (Gandini et al., 2021; Han et al., 2024; Laino et al., 2024; Liu et al., 2022; Simpson et al., 2021). However, while existing research has revealed the complex effects of CPU on economic development and climate governance at various levels, a lack of research on the logical relationship between climate policy uncertainty and the risk at city level to provide theoretical support and empirical evidence for governments and policymakers offers a broad perspective for further exploration in this field.

This study aims to fill this research gap by investigating the impact of CPU on UCR and the underlying mechanisms. Based on this, this study introduces the Hazard-Exposure-Vulnerability (H-E-V) adaptation decision-making framework proposed by the IPCC (2012, 2014) to assess urban climate risk in 274 Chinese cities between 2011 and 2021. It also investigates the impact of CPU on UCR, the mechanism role of the production sector's industrial structure, the moderating roles of the household sector's deposit balances and insurance cost in the impacts of the CPU on the UCR, and the heterogeneity of their correlations across cities and risk levels.

The possible contributions of this paper are as follows. First, this study investigates the climate risk levels of 274 Chinese cities using a systematic and scientific climate risk assessment framework and their spatial and temporal evolution. Second, cities with high population density and economic concentration face higher climate risks and are more vulnerable to policy impacts, but the relationship between CPU and climate risk has yet to be investigated in previous studies, so we fill this research gap. Third, this study identifies the driving mechanisms of UCR from a new theoretical perspective, assisting policymakers in improving climate risk management, developing appropriate climate policies, and promoting sustainable development goals.

2. Theoretical analysis

CPU refers to the degree of ambiguity and unpredictability in government policies and regulations addressing climate change mitigation and adaptation that result from potential policy or regulatory changes (Kyselá et al., 2019; Wen et al., 2022). Extreme weather events and long-term climate change frequently render cities unable to respond promptly and effectively, resulting in the accumulation and exacerbation of risks due to frequent changes or ambiguous climate policies. On the one hand, CPU may result in frequent adjustments to energy policies (Lee et al., 2021) and uncertainty in emission reduction targets (Atsu & Adams, 2021), affecting network relationships between clean and brown energy (Banerjee et al., 2024), reducing cities' ability to prevent and respond to climate change, and influencing climate risk levels. On the other hand, CPU also has impacts on the world's population's critical energy infrastructure (Mishra & Sadhu, 2023), and a chain of events triggered by disruptions in critical services such as electricity, natural gas, and heat will inevitably result in social dysfunctions, exacerbating the climate risk that cities are already facing (Leal et al., 2024; Rübbelke & Vögele, 2011). Building upon this analysis, the study proposes the following hypothesis:

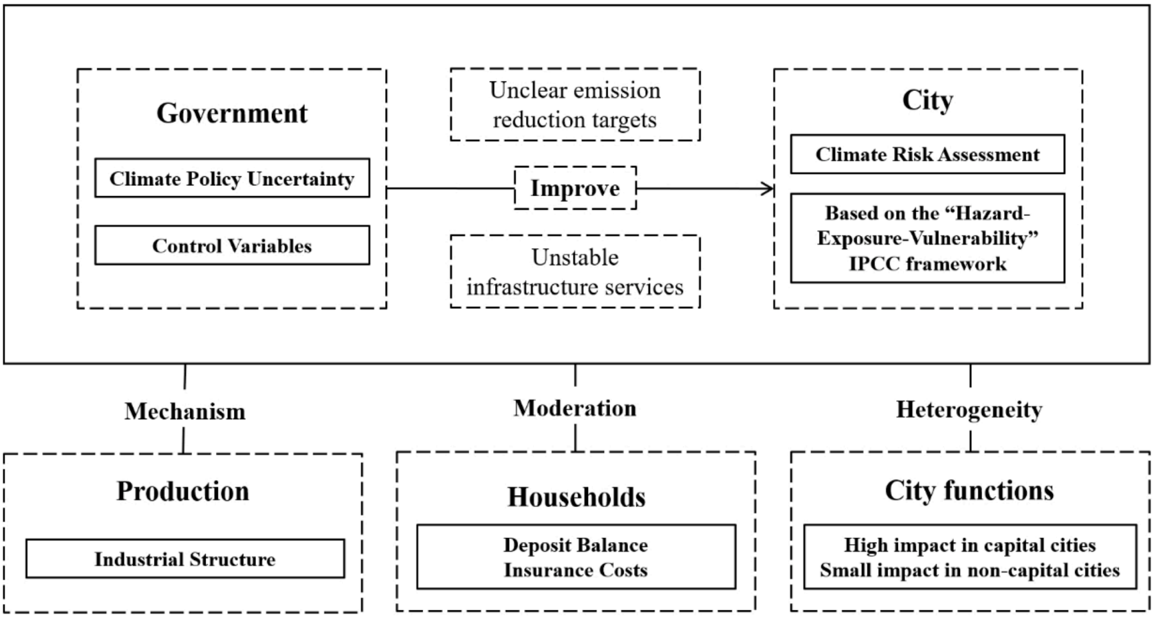

Fig. 1. Theoretical research framework.

H1. ***Climate policy uncertainty increases the level of urban climate risk.***

CPU influences the industrial restructuring of productive sectors, which raises the level of UCR. The output structure, consumption structure, or employment structure of an industry or sector can be used to quantify the process of industrial restructuring (Herrendorf et al., 2014), which refers to the redistribution of economic activity across sectors (Kuznets & Murphy, 1966). The guidance and intervention of relevant policies can be used as a forcing mechanism to promote industrial structure adjustment (Yuan & Xie, 2014). As the CPU increases, it becomes more difficult for high-carbon emitting industries to transition to low-carbon or green industries (Zhang & Qi, 2011), increasing cities' vulnerability to climate change. Therefore, the following hypothesis is proposed:

H2. ***Climate policy uncertainty exacerbates the level of urban climate risk through the industrial structure of the productive sector.***

When faced with uncertainty caused by policy changes, the household sector tends to engage in various economic behaviors to respond to potential risks, such as increasing deposit balances (Aaberge et al., 2017; Shen & Xie, 2012) and insurance expenditures (Mills, 2005; Xiang et al., 2023). The increase in deposit balances and insurance purchases reflects households' concerns about future uncertainty, prompting them to prioritize saving over consumption to mitigate potential economic risks associated with climate change, such as property loss or income reduction caused by sudden climate disasters (Calel et al., 2020). This behavior reflects the household sector's risk management strategies in the face of CPU, exacerbating the positive correlation between CPU and UCR. Therefore, the following hypothesis is formulated:

H3. ***Deposit balances and insurance cost of the household sector exacerbate the positive correlation between climate policy uncertainty and the level of urban climate risk.***

As provincial centers, capital cities typically have higher population densities, economic activity, and infrastructure development (Yang et al., 2013), making them more vulnerable and risk-exposed to CPU. Simultaneously, they frequently serve as political hubs, wielding significant power over resource allocation and policy formulation, shaping urban development (Yu & Lu, 2005). Furthermore, capital cities are typically distinguished by more complex industrial structures, particularly in traditional industries that produce significant emissions and consume significant amounts of energy. These industries may be more affected by transformation and upgrading, rendering them more vulnerable to changes in climate policies (Fan et al., 2019). Therefore, compared to non-capital cities, capital cities may be more sensitive to CPU, potentially affecting their climate risk levels. The next hypothesis is thus proposed as follows:

H4. ***Climate policy uncertainty has a greater impact on the level of climate risk in capital cities than in non-capital cities.***

Fig. 1 summarizes the theoretical analysis framework of the impact of CPU on UCR, suggesting that CPU exacerbates the level of UCR through the industrial structure of the productive sector, the deposit balances and insurance cost of the household sector exacerbate the positive correlation between CPU and UCR, and CPU has a greater impact on climate risk levels in capital cities than in non-capital cities.

3. Methodology and data

3.1. Method for measuring UCR

3.1.1. Indicator system for evaluating UCR

UCR refers to the potential negative impacts of climate change on natural and socioeconomic systems. The IPCC (2012, 2014) introduced the H-E-V adaptation decision-making framework based on climate risk assessment. This framework considers the following factors: (1) Hazard (hazard of disaster-caused) is the frequency and intensity of extreme weather or climate events; (2) Exposure (exposure of disaster-vector) is the population, economic, and social wealth exposed to the hazard; (3) Vulnerability (vulnerability of disaster-environment) describes the sensitivity or vulnerability of system exposed to specific hazards. UCR assessment aims to analyze past, current, and future climate risk information and identify high-risk areas (Muis et al., 2015), which can be used to inform decision-making for climate risk mitigation measures and assess their effectiveness (Meyer et al., 2009). Scholars and research institutions extensively use the H-E-V framework because of its comprehensive and clear assessment content, demonstrating strong operability (Wu et al., 2024; Zhang et al., 2019; Zheng et al., 2016). Based on the above analysis, this study develops a UCR measurement index system based on the H-E-V assessment framework, which includes

Table 1
Indicator system for evaluating UCR.

Primary Indicator	Secondary Indicator		Unit	Type	Interpretation
Hazard of disaster-caused	HD1	Average annual number of days with high temperature	day	+	Hazard of high temperatures
	HD2	Average annual number of days with low temperature	day	+	Hazard of low temperatures
	HD3	Average annual number of days of heavy rain	day	+	Hazard of heavy rainfall
Exposure of disaster-vector	ED1	Total population	10,000	+	Exposure of population vector
	ED2	Gross domestic product	billion yuan	–	Exposure of wealth vector
	ED3	Ratio of agriculture in GDP	%	+	Exposure of industry vector
Vulnerability of disaster-environment	VD1	Ratio of construction land	%	+	Vulnerability of development intensity
	VD2	Ratio of household dependency	%	+	Vulnerability of vulnerable population
	VD3	Ratio of urban to rural income	%	+	Vulnerability of social equity

nine indicators, as shown in Table 1.

3.1.2. Entropy weight method

This study employs the entropy weight method (Zhu et al., 2020) to calculate the weight of each indicator, an objective evaluation method based on evaluation indicators. When the difference between the values of an evaluation object in a specific indicator is greater, the indicator is considered more important and has a higher weight value. The method is highly operable and effectively reflects the implied information from the data, preventing unclear analysis due to negligible differences in the selected indicators, thus comprehensively reflecting various types of information. The precise procedure for calculating is as follows.

Suppose there are n evaluation objects, m evaluation indicators, and x_{ij} represents the beginning data of the indicator j in the evaluation object i. The original evaluation indicator matrix X is as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \tag{1}$$

1) The data for every indicator were first standardization due to the varied unit of the indicators (positive indications were handled according to eq. (2), and negative indicators were dealt with in accordance with eq. (3)).

$$y_{ij} = \frac{x_{ij} - x_{min}}{x_{max} - x_{min}} \tag{2}$$

$$y_{ij} = \frac{x_{max} - x_{ij}}{x_{max} - x_{min}} \tag{3}$$

Where x_{ij} is the value of the indicator j in the object i; y_{ij} is the standardized value of the indicator j in the object i; x_{max} is the maximum value of the indicator j; x_{min} is the minimum value of the indicator j. The matrix Y following the standardization procedure is:

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1m} \\ y_{21} & y_{22} & \cdots & y_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ y_{n1} & y_{n2} & \cdots & y_{nm} \end{bmatrix} \tag{4}$$

2) Calculate the weight of indicators based on the value of the evaluation object i within the indicator j:

$$P_{ij} = y_{ij} \Big/ \sum_{i=1}^{n} y_{ij} \tag{5}$$

3) Calculate the entropy of indicator j:

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^{n} P_{ij} \ln P_{ij} \tag{6}$$

4) Calculate the coefficient of difference for the indicator j:

$$G_j = 1 - E_j \tag{7}$$

5) Calculate the weight of the indicator j:

$$w_j = \frac{G_j}{\sum_{j=1}^{m} G_j} \tag{8}$$

6) Calculate the composite score of evaluation object i:

$$UCR_i = 100 \times \sum_{j=1}^{m} w_j z_{ij} \tag{9}$$

Where UCR_i is the climate risk score of each city, and the larger the value, the higher the likelihood of the city experiencing climate risk; on the contrary, the lower the climate risk of the city.

3.2. Empirical models

This study explores the impact of climate policy uncertainty in the government sector on urban climate risk (Imai & Kim, 2021). The econometric model specification is as follows:

$$UCR_{i,t} = \alpha_0 + \alpha_1 CPU_{i,t} + \sum_{k=2}^{8} \alpha_k Control_{i,t} + \varepsilon_i + \theta_t + \mu_{i,t} \tag{10}$$

where i and t represent the city and the year, respectively, $UCR_{i,t}$ and $CPU_{i,t}$ represent the urban climate risk level and climate policy uncertainty of city i in period t, respectively. $Control_{i,t}$ denotes the control variable, ε_i and θ_t represent the individual city effect and time fixed effect, and $\mu_{i,t}$ represents the random disturbance term.

This study uses the industrial structure of the production sector as the mechanism variable based on Eqn (11) and (12) and employs Romano and Wolf (2005) stepwise test to examine the causal pathways through which climate policy uncertainty impacts urban climate risk. The following is the econometric model:

$$IS_{i,t} = \beta_0 + \beta_1 CPU_{i,t} + \sum_{k=2}^{8} \beta_k Control_{i,t} + \varepsilon_i + \theta_t + \mu_{i,t} \tag{11}$$

$$UCR_{i,t} = \gamma_0 + \gamma_1 CPU_{i,t} + \gamma_2 IS_{i,t} + \sum_{k=3}^{9} \gamma_k Control_{i,t} + \varepsilon_i + \theta_t + \mu_{i,t} \tag{12}$$

where $IS_{i,t}$ denotes the industrial structure of city i at time t, γ_1 represents the direct impact effect, and $\beta_1\gamma_2$ denotes the indirect impact effect .

This study introduces moderating variables and interaction terms between the core explanatory variables and the moderating variables, with the aim of examining the moderating effects on the link between uncertainty about climate policy and urban climate risk in terms of household deposit balances and insurance costs. The following is the econometric model:

$$UCR_{i,t} = \delta_0 + \delta_1 CPU_{i,t} + \delta_2 M_{i,t} + \delta_3 CPU_{i,t} \times M_{i,t} + \sum_{k=4}^{10} \delta_k Control_{i,t} + \varepsilon_i + \theta_t + \mu_{i,t} \tag{13}$$

where $M_{i,t}$ denotes the moderating variables, including deposit balances and insurance costs in the household sector. and δ_3 denotes the size of the moderating effect.

3.3. Variables and data

3.3.1. Variables

Based on the aforementioned theoretical studies, this study selects industrial structure as mechanism variable, with household deposit balance and insurance expenditure as moderating variables. When constructing the model, this study includes seven control variables to reduce estimation bias caused by omitted variables, allowing for a more accurate depiction of the impact of CPU on the UCR and ensuring robustness and scientific validity of the model results.

Table 2
Variable description.

Variables		Description	Unit	Data source
Explained variable	UCR	Urban climate risk		Calculated based on the entropy weight method
Explanatory variable	CPU	Climate policy uncertainty		Ma et al. (2023)
Mechanism variable	IS	Industrial structure	%	China Urban City Statistical Yearbook
Moderator variables	HDB	Household deposits balance	10 billion yuan	China Statistical Yearbook, Provincial Statistical Yearbooks
	IC	Insurance cost	billion yuan	China Insurance Yearbook
Control variables	IL	Industrialization level	%	China Statistical Yearbook, Provincial Statistical Yearbooks
	SWUR	Solid waste utilization rate	%	China Urban Construction Statistical Yearbook
	GC	Greening coverage	10,000 hectares	China Urban City Statistical Yearbook
	TEC	Total electricity consumption	billion kw·h	China Energy Statistical Yearbook
	WSPC	Water supply production capacity	million m^3	China Urban Construction Statistical Yearbook
	AGPC	Artificial gas production capacity	million m^3	China Urban Construction Statistical Yearbook
	UCHA	Urban centralized heat area	million m^2	China Urban Construction Statistical Yearbook

Specifically, the industrialization level reflects the economic development mode and industrialization process of cities, and cities with higher industrialization usually face greater environmental pressure and higher climate risks. Solid waste utilization rate reflects cities' waste treatment capacity and environmental governance level, and cities with lower waste management levels are more susceptible to climate change-induced environmental risks. Greening coverage rate is crucial to urban climate regulation and mitigation of extreme weather events, and it can influence cities' climate adaptation capacity; Electricity consumption, water supply capacity, gas production capacity, and urban heating area—all of which reflect the efficiency and sustainability of urban energy use—play an important role in climate risk management. Table 2 shows detailed descriptions and data sources for each variable.

3.3.2. Data

The indicators in this study are based on data from the China Statistical Yearbook, China City Statistical Yearbook, China Urban Construction Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China Insurance Yearbook, and Provincial Statistical Yearbooks. Data on climate extremes (maximum temperature, minimum temperature, cumulative precipitation) are sourced from the National Meteorological Science Data Center. CPU data from Chinese climate policy uncertainty index calculated by Ma et al. (2023), using a deep learning algorithm (the MacBERT model) based on 1755,826 articles published in six Chinese mainstream newspapers from 2000 to 2022.

Table 3 displays descriptive statistics for variables. There are 3014 sample sizes; the explained Variable, UCR, have mean and standard deviation of 6.773 and 2.759, and the main explanatory variable, CPU, has a mean and standard deviation of 1.417 and 0.583. It can be seen there is a significant difference between the maximum and minimum values, indicating that UCR and CPU fluctuated during the sample period.

4. Empirical results

4.1. Measurement results of UCR

This study uses the entropy weight approach to calculate the UCR levels of various cities from 2011 to 2021, as shown in Fig. 2. It shows that value of UCR was 6.692 in 2011, since then, amid year-by-year fluctuations, it had grown to 7.325 by 2021. The trends in UCR levels across the country's three major regions are generally consistent, with the east coast having the highest average value, followed by the west and central areas. This study uses the standard deviation grading method to visualize UCR levels from 2011, 2014, 2018, and 2021 in geospatial space, with ArcGIS software used for a more intuitive and accurate analysis of changes in the spatiotemporal pattern of UCR levels. Fig. 3 clearly shows a significant spatial imbalance in the UCR levels of Chinese cities, whereas the UCR levels of individual cities remain unchanged.

Table 3
Descriptive Statistics.

VARIABLE	Obs	Mean	Std. dev.	Min	Max
UCR	3014	6.773	2.759	2.338	31.464
CPU	3014	1.417	0.583	0.001	4.057
IS	3014	87.925	7.711	50.110	105.924
HDB	3014	20.991	31.802	0.877	438.900
IC	3014	10.387	19.061	0.307	252.693
IL	3014	38.226	12.709	1.461	100.000
SWUR	3014	78.382	23.133	23.133	100.000
GC	3014	0.432	0.722	0.001	8.745
TEC	3014	15.659	21.124	0.111	258.070
WSPC	3014	0.881	1.811	0.016	31.989
AGPC	3014	0.423	3.327	0.001	52.940
UCHA	3014	27.679	67.807	0.001	721.629

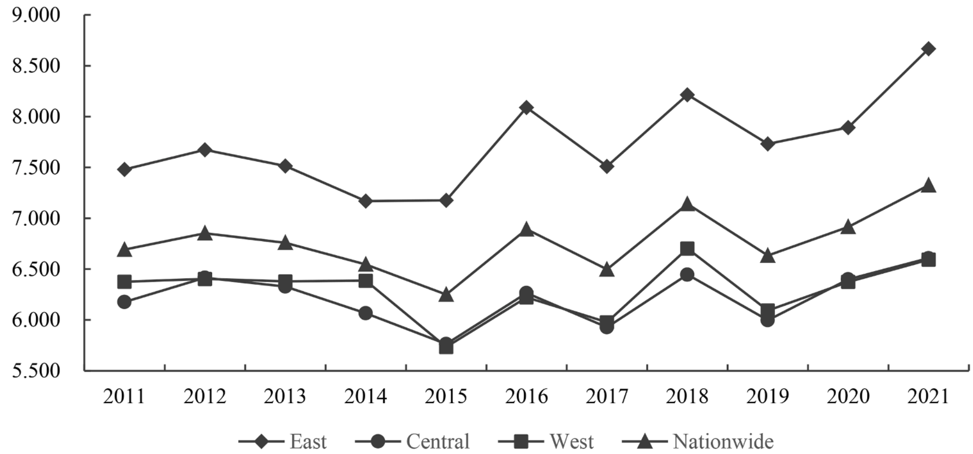

Fig. 2. Measurement results of UCR
Note: The region mean values are calculated at the average mean for each city.

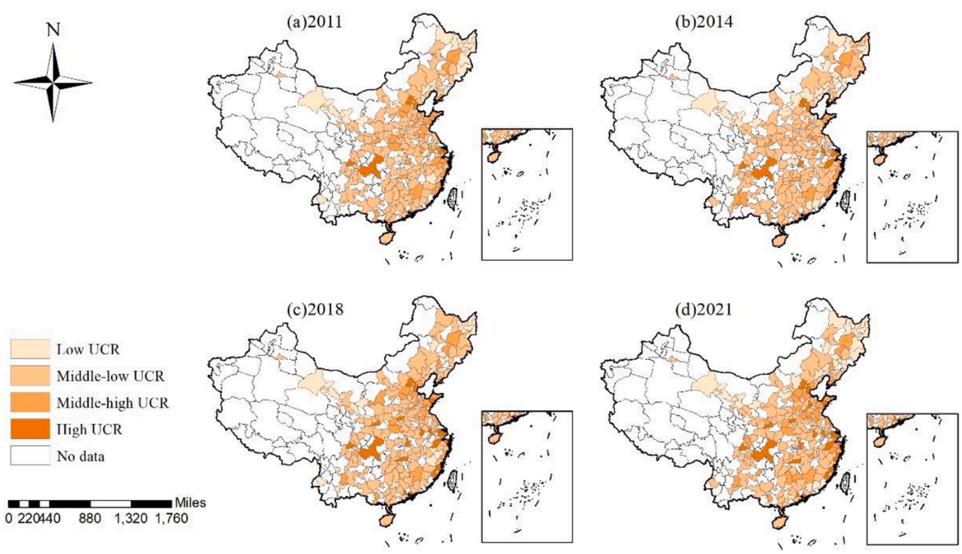

Fig. 3. Distribution of UCR.

4.2. Baseline regression analysis

Considering different CPU in each city may have different effects on UCR, this study estimates panel data from 2011 to 2021 using mixed OLS models, random effects models, and fixed effects models, respectively. Furthermore, the VIF values are all <10, indicating that the variables used in this study are not multicollinear, and the two-way fixed effects model outperforms the mixed regression and random effects models, according to the Hausman test. Table 4 shows the results of the baseline regressions using the various models, where the first column shows the coefficients estimated using the mixed OLS model, the second column shows the coefficients estimated using the random effects model, the third column shows the results of the regressions controlling only for city fixed effects, the fourth column shows the results of the regressions controlling only for year fixed effects, and the fifth column summarizes the regression results by controlling for two-way fixed effects for the city and year, with control variables added to each model. Table 4 shows that CPU has a significant positive effect on UCR across all estimation models, with each one-unit increase in CPU increasing the UCR index by 0.096 units and being statistically significant at the 1 % level. These results suggest that as CPU increases, the lack of clear policy guidelines for local governments and businesses to respond to climate change exacerbates the level of climate risk in cities as actors' expectations of future climate governance become ambiguous, and they adopt a wait-and-see attitude toward environmental governance and climate adaptation investments, impeding the introduction of green technologies and long-term infrastructure investment. Therefore, the empirical results verify H1, which states that CPU exacerbates the level of UCR.

4.3. Endogeneity test

To address the potential issue of reverse causality or endogeneity of omitted variables, this study uses the first-order lagged term of the CPU index as an instrumental variable for the instrumental variable method estimation, which is based on the benchmark regression of the panel fixed-effects model. The instrumental variable was chosen logically because the lagged one-period CPU significantly impacts the current-period CPU but does not directly affect the UCR in this period. At the same time, changes in policies or regulations, rather than the level of UCR directly affecting the CPU, satisfy the requirements of relevance and endogeneity. The test statistic for instrumental variable non-identification is significantly positive, indicating a strong rejection of the original "instrumental variable non-identification" hypothesis. Furthermore, the F-statistic value for the weak instrumental variable test is greater than 10, rejecting the original "instrumental variable is a weak

Table 4
Baseline regression results.

VARIABLES	(1) OLS	(2) RE	(3) FE1	(4) FE2	(5) FE3
CPU	0.362***	0.145***	0.112***	0.335***	0.096***
	(4.121)	(3.448)	(3.149)	(3.841)	(2.737)
IL	−0.011***	−0.001	0.006	−0.016***	0.001
	(−6.288)	(−0.358)	(1.574)	(−9.194)	(0.290)
SWUR	0.010***	−0.000	−0.003**	0.009***	−0.003**
	(5.591)	(−0.216)	(−2.353)	(5.403)	(−2.230)
GC	0.283	−0.558***	−0.793***	0.204	−0.830***
	(0.849)	(−2.942)	(−5.199)	(0.579)	(−4.461)
TEC	0.052***	0.024***	0.008**	0.059***	0.011**
	(10.667)	(2.595)	(2.002)	(11.281)	(2.209)
WSPC	0.738***	0.519**	0.191*	0.710***	0.198*
	(3.980)	(2.232)	(1.895)	(3.671)	(1.941)
AGPC	−0.040***	−0.008	−0.095	−0.039***	−0.098
	(−10.351)	(−0.167)	(−1.054)	(−10.208)	(−1.032)
UCHA	−0.005***	0.005	0.002	−0.004***	0.003
	(−5.768)	(1.227)	(0.924)	(−5.978)	(1.154)
Constant	4.476***	6.140***	6.641***	4.704***	6.855***
	(18.951)	(28.594)	(29.069)	(21.601)	(27.919)
City fixed			YES		YES
Year fixed				YES	YES
Observations	3014	3014	3014	3014	3014
R-squared	0.709		0.211	0.722	0.295

Note: The values in parentheses indicate the t-value of each coefficient. ***, **and*mean significance at the1, 5 and 10 % levels, respectively.

Table 5
Endogeneity test results.

VARIABLES	2SLS	2SLS	2SLS	2SLS
CPU	0.957***	0.755***	0.798***	0.478**
	(5.450)	(2.766)	(4.690)	(2.404)
Constant	3.633***	4.181***	4.076***	4.836***
	(14.353)	(8.699)	(14.664)	(12.731)
Control variables	YES	YES	YES	YES
City fixed		YES		YES
Year fixed			YES	YES
Observations	2740	2740	2740	2740
R-squared	0.701	0.922	0.722	0.937

Note: The values in parentheses indicate the t-value of each coefficient. ***, **and*mean significance at the1, 5 and 10 % levels, respectively.

instrumental variable" hypothesis. These indicate that the selection of instrumental variables is both reasonable and effective. The regression results in Table 5 show that all the regression coefficients of CPU are significantly positive and pass the 5 % significance level test, implying that the effect of CPU on UCR remains significant even when reverse causality is considered, further validating Hypothesis 1.

Table 6
Robustness test results.

VARIABLES	(1) OLS	(2) RE	(3) FE1	(4) FE2	(5) FE3
ER	−1.028***	−0.018	0.314**	−1.432***	0.276**
	(−4.512)	(−0.165)	(2.390)	(−6.191)	(1.992)
Constant	5.721***	6.117***	6.280***	5.960***	6.348***
	(36.722)	(36.703)	(28.058)	(75.895)	(29.323)
Control variables	YES	YES	YES	YES	YES
City fixed			YES		YES
Year fixed				YES	YES
Observations	3014	3014	3014	3014	3014
R-squared	0.696		0.088	0.717	0.182

Note: The values in parentheses indicate the t-value of each coefficient. ***, **and*mean significance at the1, 5 and 10 % levels, respectively.

4.4. Robustness test

This study conducts robustness tests to determine the reliability of benchmark regression mode results. This study substitutes the intensity of environmental regulation (ER) for the CPU as the core independent variable in the previous baseline regression model for testing. Referencing the study of Dong and Wang (2019), ER is calculated based on the standardized value of pollutant emissions and economic output indicators of each city. Under China's top-down management model, the level of UCR can be significantly influenced by both the intensity of ER and CPU, which are both components of government behavior. Therefore, this study replaces the independent variables and regresses the baseline model once more. Table 6 shows the results, demonstrating that the baseline regression results are still significant at the 5 % level. It suggests that the baseline regression results obtained in this study are reliable and robust and that variations in selecting the core independent variables have no impact on the conclusions.

5. Further analysis

5.1. Mechanism analysis

The aforementioned theoretical analyses suggest that the production sector will prioritize secondary and tertiary industries that are less dependent on climate policy, influencing the level of UCR. That is because CPU has a greater impact on agriculture, known for being "weather-dependent." Therefore, this study selects the industrial structure (IS) as the mechanism variable and confirms the effect of CPU on UCR by estimating Eqs. (11) and 12. The results show that CPU has a significant effect on IS, while IS has a significant effect on the level of UCR. This study provides three different estimation results for the robustness test: one for the control year, one for the control city, and one for both the control year and the city, as shown in Table 7. The results of the two-way fixed effects show that the coefficients of CPU and IS are significant at the 5 % level, thus verifying Hypothesis 2, which states that CPU exacerbates UCR by affecting the IS of the productive sector. Specifically, as CPU increases, it becomes more challenging to transform the city's industrial structure toward a greener, lower-carbon future, increasing the cumulative effect of climate risk. It suggests that rational industrial restructuring is critical for mitigating the adverse effects of CPU and lowering UCR.

Table 7
Influence mechanism results.

VARIABLES	(1) IS	(2) UCR	(3) IS	(4) UCR	(5) IS	(6) UCR
CPU	0.294***	0.108***	2.245***	0.312***	0.228**	0.091**
	(3.154)	(3.019)	(13.499)	(4.618)	(2.483)	(2.580)
IS		0.014*		0.010		0.021***
		(1.783)		(0.929)		(2.650)
Constant	86.621***	5.431***	69.303***	4.004***	84.113***	5.096***
	(112.195)	(7.722)	(89.862)	(4.242)	(94.074)	(7.271)
Control variables	YES	YES	YES	YES	YES	YES
City fixed	YES	YES			YES	YES
Year fixed			YES	YES	YES	YES
Observations	3014	3014	3014	3014	3014	3014
R-squared	0.023	0.212	0.434	0.722	0.141	0.297

Note: The values in parentheses indicate the t-value of each coefficient. ***, **and*mean significance at the1, 5 and 10 % levels, respectively.

Table 8
Moderation analysis results.

VARIABLES	(1) UCR	(2)	(3)	(4)	(5)	(6)
CPU	0.095***	0.156**	0.076***	0.086***	0.154**	0.065**
	(3.386)	(2.630)	(2.805)	(3.002)	(2.773)	(2.314)
HDB	0.027***	0.075***	0.035***			
	(5.845)	(17.795)	(5.990)			
CPU_HDB	0.009***	−0.005*	0.008***			
	(8.737)	(−2.141)	(6.935)			
IC				0.019***	0.082**	0.026***
				(2.874)	(3.121)	(3.638)
CPU_IC				0.014***	−0.007	0.012***
				(4.089)	(−1.275)	(3.509)
Constant	6.078***	4.675***	6.425***	6.548***	5.011***	6.864***
	(25.937)	(36.755)	(31.945)	(29.992)	(27.130)	(30.494)
Control variables	YES	YES	YES	YES	YES	YES
City fixed	YES		YES	YES		YES
Year fixed		YES	YES		YES	YES
Observations	3014	3014	3014	3014	3014	3014
R-squared	0.322	0.851	0.420	0.307	0.806	0.407

Note: The values in parentheses indicate the t-value of each coefficient. ***, **and*mean significance at the1, 5 and 10 % levels, respectively.

5.2. Moderation analysis

Using Eq. (13), this study further estimates the moderating effects of deposit balances and insurance spending of the household sector on the relationship between CPU and UCR. Table 8 shows the regression results of the two-way fixed-effects model with moderating effects included, demonstrating the continued impact of CPU on UCR, which is consistent with the baseline model and robustness estimation. Meanwhile, the impacts of the household deposit balance (HDB) moderator effect variable (the interaction of CPU and HDB) and the insurance cost (IC) moderator effect variable (the interaction of CPU and IC) on the UCR are significantly positive, indicating that as the HDB and IC increase, so does the impact of CPU on the UCR, which can be explained in terms of the risk-averse behavior of the household sector. In the face of CPU, the household sector typically reacts to potential future risks by increasing savings and purchasing insurance. However, this defensive economic behavior reduces consumer demand in society, limiting cities' economic vitality and weakening their ability to allocate funds and resources in response to climate risks. The economic behavior of the household sector has a significant positive moderating effect on the impact of the CPU and UCR, thus verifying H3.

5.3. Heterogeneity analysis

This section begins with the functional position of the city and divides it into provincial capital cities and non-provincial capital cities for sub-sample regression to investigate their heterogeneity, taking into account the fact that provincial capital cities and ordinary prefecture-

Table 9
Heterogeneity analysis: non-capital cities and capital cities.

VARIABLES	(1) Non-capital cities	(2)	(3)	(4) Capital cities	(5)	(6)
CPU	0.086**	0.312***	0.073**	0.351***	0.244*	0.325**
	(2.372)	(3.803)	(1.986)	(3.669)	(2.025)	(2.772)
Constant	6.469***	4.839***	6.729***	7.596***	2.950***	5.870***
	(28.517)	(22.488)	(28.269)	(5.339)	(6.057)	(3.540)
Control variables	YES	YES	YES	YES	YES	YES
City fixed	YES		YES	YES		YES
Year fixed		YES	YES		YES	YES
Observations	2739	2739	2739	275	275	275
R-squared	0.165	0.718	0.260	0.595	0.702	0.639

Note: The values in parentheses indicate the t-value of each coefficient. ***, **and*mean significance at the1, 5 and 10 % levels, respectively.

Table 10
Heterogeneity analysis: quantile regression method.

VARIABLES	q25	q50	q75
CPU	0.148***	0.210***	0.128*
	(3.347)	(4.197)	(1.940)
Constant	4.156***	4.550***	5.558***
	(29.739)	(34.241)	(32.942)
Control variables	YES	YES	YES
Observations	3014	3014	3014
R-squared	0.243	0.337	0.468

Note: The values in parentheses indicate the t-value of each coefficient. ***, **and*mean significance at the1, 5 and 10 % levels, respectively.

level cities exhibit a certain degree of distinction. The two-way fixed-effects model yielded an estimated coefficient of 0.073 for non-capital cities and 0.325 for provincial capital cities (Table 9). Both coefficients are significant at the 5 % level, indicating that the CPU has a greater influence on provincial capital cities than non-capital cities. It is primarily because the provincial capital cities typically house the provincial governments, which, as the province's political center, is responsible for administration, policy formulation, and decision implementation. Consequently, the capital cities respond more strongly to policy uncertainty, confirming its policy-leading role and verifying H4.

Different degrees of CPU can also have different effects on UCR. This study uses the quantile regression method to investigate the various CPU locations and their diverse impact on UCR at the 0.25, 0.5, and 0.75 quantiles, which can improve model estimation accuracy, prevents extreme values from influencing estimation results, and produces more comprehensive results. Table 10 shows a positive correlation between CPU and UCR at each quantile point, with a significant impact at the 10 % level, confirming the significant robustness of the results. Specifically, as the quantile points increase, the regression coefficients grow initially and then drop. We can conclude that cities with middle UCR have the greatest impact from the CPU, while cities with lower or higher UCR have limited influence. That could be because cities with a medium level of risk are currently going through a period of industrial restructuring and climate risk management, making them more vulnerable to the effects of the CPU, and increases the likelihood of fluctuations in the social and economic systems, accumulating additional potential risks.

5.4. Discussion

This study constructs a theoretical framework for the impact of CPU on UCR, and empirically tests the impact of CPU on UCR and its mechanism. The results show that CPU significantly increases the level of UCR, and reveal the specific impact mechanism through the industrial structure of the production sector and the economic behavior of the household sector. This finding provides a new understanding of the causes of UCR, especially urban risk management in the context of uncertainty, with important theoretical and practical implications.

Compared with previous studies, the findings of this study are consistent with Han et al. (2025) and Almulhim and Cobbina (2024), pointing out the key role of policies in urban climate change response and resilience building. Zhang et al. (2024) assessed the effectiveness of local governments' policies in enhancing urban resilience, and the results showed that different policy sets have synergies or conflicts in enhancing urban resilience, echoing the findings of this study. Furthermore, by incorporating the productive and household sectors into the theoretical framework, this study conducts a more comprehensive mechanism analysis, revealing how CPU affect the level of UCR through the complex relationships in the urban economic and social systems, which bridges the gap between the theoretical and mechanism-level analysis of existing studies. Future research could explore how governments mitigate the impact of CPU on UCR by optimizing policy design and improving governance capacity.

6. Conclusion and policy implications

Based on theoretical analysis, this study uses panel data of 274 cities from 2011 to 2021 in China to investigate the impact of CPU on the level of UCR using multidimensional empirical tests. The results show that: (1) There is a significant spatial imbalance in the level of UCR across cities in China, and climate policy uncertainty significantly increases the level of urban climate risk. (2) Climate policy uncertainty affects the level of urban climate risk through the industrial structure of the production sector. (3) Deposit balances and insurance cost of the household sector exacerbate the positive relationship between climate policy uncertainty and urban climate risk. (4) Climate policy uncertainty has a greater impact on climate risk in capital cities than in non-capital cities, and climate policy uncertainty has the most significant impact in cities with medium level of climate risk and limited impact in cities with lower or higher levels.

Based on the findings of this study, the following policy recommendations are proposed. (1) The government should fully consider the impact of climate policy uncertainty when developing and implementing climate policies, as well as include climate policy uncertainty in the scope of policy effect assessment and regulation. Simultaneously, improving coordination among various climate policy-making departments is critical to ensuring the secure operation of city. (2) Coordinate industrial structural adjustment, pollution control, and ecological protection in response to climate change, emphasize the role of climate policy pathways, and promote the transformation and upgrading of industrial development to lay a solid foundation for reducing risk and promoting the long-term development of city. (3) Actively engage in media publicity and guidance, strengthen policy education to address climate change, improve positive policy publicity and reporting, and avoid transmitting uncertain information to raise public awareness of climate policies.

CRediT authorship contribution statement

Hanying Zhang: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Jing Liu:** Supervision, Project administration, Funding acquisition, Conceptualization. **Qing Guo:** Writing – review & editing, Software, Methodology, Data curation. **Xuan Zhang:** Writing – original draft, Data curation. **Xiangdong Hu:** Supervision, Project administration.

Declaration of competing interest

This manuscript has not been published or presented elsewhere in part or in entirety and is not under consideration by another journal. We have read and understood your journal's policies, and we believe that neither the manuscript nor the study violates any of these. We declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. There are no other conflicts of interest to declare.

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Data availability

Data will be made available on request.

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