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Climate Risk and Public Service Provision in Large Cities: The Moderating Role of Digital Governance

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Abstract

Against the backdrop of intensifying climate change and deepening digital governance, public service systems in large cities face increasingly severe and complex challenges. Based on multi-source heterogeneous data from large cities in China, this study empirically examines the relationship between climate risk and public service provision and its underlying mechanisms using two-way fixed effects models, mediation models, and threshold regression models. Findings indicate that, first, both physical and transition climate risks are significantly and negatively associated with public service provision. Second, the mediation analysis suggests that physical climate risk is linked to public service provision mainly through entrepreneurial vitality, whereas transition climate risk is linked to public service provision through knowledge spillovers and industrial upgrading. Third, this negative association is more pronounced in coastal cities and cities with larger population scales. Finally, open public data and AI-related development are associated with a partial attenuation of these negative relationships. Therefore, urban policymakers should closely monitor multiple climate-risk pathways, strengthen climate-adaptive governance with data resources and AI technologies, and incorporate differentiated climate vulnerabilities into land-use zoning, green infrastructure planning, and the spatial distribution of critical public services so as to enhance urban resilience.

Keywords: climate risk; public service provision; large cities; digital governance

1. Introduction

In recent years, extreme weather events and slow-onset environmental pressures have begun reshaping the global risk landscape with unprecedented scope and intensity [1,2]. Continuous assessments by the Intergovernmental Panel on Climate Change (IPCC) and the UN 2030 Agenda for Sustainable Development (SDGs) indicate that climate risk has transcended the singular realm of environmental science. It has evolved into a core variable that threatens the sustainable development of human society and induces systemic crises [3]. As the world's largest developing country, China faces particularly severe climate challenges. In 2024, for instance, extreme weather and natural disasters affected over 94.13 million people nationwide, causing direct economic losses of 401.11 billion RMB. These staggering statistics not only reflect substantial macroeconomic tolls but also expose the profound vulnerability of critical urban infrastructure to extreme shocks, directly leading to supply chain disruptions and a sharp decline in the stability of public service provision [4,5]. With its high complexity and destructive power, climate risk poses a systemic threat to social governance in the modernization process. Consequently, the

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Chinese government has placed a high priority on climate adaptation and risk management. From integrating adaptation concepts into macro-level top design via the National Climate Change Adaptation Strategy 2035, to promoting the transition toward risk-driven early warning models in the Action Plan for Enhancing Meteorological Disaster Risk Early Warning Capabilities (2025–2027), constructing a forward-looking, proactive, and efficient climate risk management framework has become a central agenda for enhancing national climate resilience and ensuring sustainable development.

Against this macro backdrop, large cities—complex giant systems with highly concentrated populations, capital, and critical infrastructure—constitute key spatial nodes for absorbing risk shocks and exploring adaptive governance. High-density built environments and highly interconnected urban networks give rise to significant cascading effects, making local climate disturbances highly susceptible to evolving into systemic failures of public service systems [6,7]. The urban resilience literature provides an important theoretical foundation for understanding these challenges. Urban resilience is commonly understood as the capacity of urban systems to absorb disturbances, reorganize resources, and maintain essential functions under external shocks [8]. Related studies have emphasized that resilience is multidimensional, involving social, economic, institutional, infrastructural, and community capacities [9]. From this perspective, public service provision is a key dimension of urban resilience because education, healthcare, transportation, communication, and social security systems directly determine whether cities can maintain service continuity during and after climate-related disruptions. Recent climate assessments of cities, settlements, and key infrastructure further show that urban climate risk emerges from the interaction between climate hazards, infrastructure exposure, governance capacity, and social vulnerability [10]. However, existing studies on urban resilience have paid relatively more attention to infrastructure robustness, disaster recovery, and community adaptation, while the fiscal, industrial, and knowledge-based channels through which climate risk affects public service provision remain insufficiently examined. Traditional literature frequently analyzes the drivers of public service provision using classical frameworks: scale, technology, and structural effects. Specifically, regarding scale effects, traditional urban economics posits that the agglomeration of population and economic activities generates significant economies of scale, thereby improving per capita supply efficiency and the spatial coverage of public services by amortizing high fixed infrastructure costs [11,12]. Regarding the effects of technology, existing studies emphasize that advances in information technology and digital government can dismantle bureaucratic information silos. By reducing administrative transaction costs and mitigating information asymmetry, technology reshapes the delivery process and optimizes the precision of public good allocation [13,14]. Structurally, classical public economics and polycentric governance theories suggest that fiscal decentralization, flattened governance architectures, and industrial upgrading can more flexibly align with heterogeneous local preferences, driving a systemic leap in public service quality from both the institutional and factor-supply sides [15,16].

Previous research has emphasized that mitigation and adaptation should not be treated as isolated policy domains, because climate policies may generate both synergies and trade-offs across development objectives [17]. At the urban scale, mitigation measures may bring long-term environmental and resilience co-benefits, but they may also create short- to medium-term adjustment pressures for cities with carbon-intensive economic structures [18]. These pressures may affect fiscal capacity, industrial restructuring, innovation incentives, and ultimately the ability of local governments to sustain public service provision. However, at the dual intersection of intensifying climate change and digital governance transformation, these existing theoretical perspectives fall short in fully capturing the novel, complex constraints facing public service systems in large cities. Specifically, the

current literature requires deepening in three critical areas. First, studies on climate risk and urban systems have mainly emphasized physical hazards, infrastructure damage, disaster recovery, and economic losses, while less attention has been paid to how different dimensions of climate risk are associated with the continuity of public service provision [19,20]. Second, although the distinction between physical and transition climate risks has been widely discussed in climate-finance and sustainability research, it has rarely been incorporated into city-level analyses of public service systems. This limits our understanding of whether precipitation-related physical risk and carbon-related structural transition pressure are linked to public service provision through different economic and governance-related channels. Third, existing studies on digital governance and smart cities have often emphasized administrative efficiency, service delivery, or technological empowerment, but have provided relatively limited quantitative evidence on whether digital-governance-related conditions shape the relationship between climate risk and public service provision [21,22]. These gaps motivate this study to examine climate risk, public service provision, and digital governance within an integrated urban resilience framework.

To bridge these theoretical gaps, this study utilizes multi-source heterogeneous panel data from large Chinese cities to systematically examine the relationship between climate risk and public service provision and its underlying mechanisms. This study focuses on the following core questions: (1) How are physical and transition climate risks associated with urban public service provision capacities? (2) Are the associations between different types of climate risk and public service provision consistent with differentiated mechanism channels? (3) Under different geographical locations and city-scale characteristics, what asymmetric spatial heterogeneity do these climate shocks exhibit? (4) Can digital governance capacity—proxied in this study by open public data and AI-related development—condition the relationship between climate risk and public service provision? These indicators are used as observable city-level proxies for the theoretical constructs examined in this study, and their definitions, data sources, and measurement boundaries are further explained in Section 3.3.

The contributions of this paper are reflected in three main aspects. First, this study brings the distinction between physical and transition climate risks into the analysis of urban public service provision. Rather than treating climate risk as a homogeneous external pressure, it examines whether precipitation-related physical risk and carbon-related structural transition pressure are associated with public service provision through different mechanism channels. This helps extend climate-risk research from general economic and infrastructure outcomes to the continuity of multidimensional public service systems. Second, this study links climate risk to public service provision through three city-level channels: entrepreneurial vitality, knowledge spillovers, and industrial structure upgrading. These channels connect climate-related pressures with the fiscal, innovation, and structural conditions that support public service provision. In this sense, the study provides a more specific empirical framework for understanding how urban resilience is shaped not only by infrastructure robustness and disaster recovery, but also by the economic and knowledge conditions underlying public service capacity. Third, this study incorporates digital governance into the climate risk–public service relationship as a conditional governance capacity. By operationalizing digital governance through AI-related development and public data openness, the analysis examines whether technological and institutional digital conditions are associated with differences in the climate risk–public service relationship. This provides empirical evidence on the role of digital governance in urban climate adaptation while also recognizing that such effects depend on broader institutional and technological conditions. In addition, the analysis of coastal–inland differences and city-scale heterogeneity connects the findings to land-use planning concerns, including

risk-sensitive zoning, climate-adaptive infrastructure layout, and the spatial allocation of critical public service facilities.

The remainder of this paper is structured as follows: Section 2 elaborates on the theoretical foundation and research hypotheses; Section 3 details the research design and data sources; Section 4 reports the empirical results and robustness checks; Section 5 further explores the moderating role of digital governance; and Section 6 concludes with policy implications.

2. Theoretical Analysis and Research Hypotheses

2.1. Physical Climate Risk, Entrepreneurial Vitality, and Public Service Provision

Based on Complex Adaptive Systems (CAS) theory, the shock of physical climate risk on urban public service systems is not limited to direct physical destruction; rather, it generates profound cascading effects through the coupling relationships among subsystems [23,24]. This study posits that entrepreneurial vitality may serve as an important mechanism channel linking physical climate risk and the sustainable provision of public services. Specifically, physical climate risk suppresses entrepreneurial activities primarily through three mechanisms:

First, direct asset losses, supply chain disruptions, and elevated barriers to entry in factor markets resulting from extreme weather events significantly increase startups' sunk costs and survival constraints. Such immediate and tangible shocks directly reduce the feasibility of entrepreneurial activities [25,26]. Second, the frequent occurrence of climate disasters exacerbates macroeconomic uncertainty and induces risk aversion among investors and potential entrepreneurs, thereby dampening the willingness to allocate capital to long-cycle, high-risk entrepreneurial projects [27,28]. Furthermore, in the face of sudden climate shocks, local governments are often compelled to divert substantial fiscal resources toward emergency response and post-disaster reconstruction. This reactive surge in expenditure exerts a "crowding-out effect" on special budgets originally earmarked for incubating innovation and subsidizing entrepreneurship, subsequently weakening the government's ability to maintain a healthy entrepreneurial ecosystem [29].

As the core micro-foundation of urban economic resilience, the decline of entrepreneurial vitality may weaken the material and technological support for public service provision [30,31]. On the one hand, the contraction of entrepreneurial activities directly weakens momentum in urban economic growth and reduces new job opportunities, fundamentally eroding the local tax base [32]. On the other hand, startups are typically vital participants in the innovation of public service delivery models; a decline in their vitality restricts the effective penetration of social capital and emerging technologies into the public service sector [33,34].

Hypothesis 1. *Physical climate risk is negatively associated with public service provision, with urban entrepreneurial vitality serving as a mechanism channel.*

2.2. Climate Transition Risk, Knowledge Spillovers, and Public Service Provision

Climate transition risk is characterized primarily by policy uncertainty, technological paradigm shifts, and shifts in market preferences during the transition toward a low-carbon economy [35,36]. In empirical research, however, different indicators may capture different aspects of this broader transition process. In this study, the empirical measure mainly reflects the structural adjustment pressure associated with carbon-intensive development patterns. This study further examines whether carbon-related structural transition pressure is negatively associated with public service provision through its relationship with the creation, application, and spillover of knowledge. According to Real Options Theory, the

tightening of environmental regulations and the dynamic adjustment of carbon market policies significantly elevate the "wait option" value of irreversible investments by micro-entities [37,38]. This compels enterprises to prioritize resource allocation toward short-term compliance or low-risk adaptive projects, thereby generating a "delayed investment" effect on frontier knowledge-creation activities with long-term positive externalities [39,40]. Simultaneously, the restructuring of industrial chains and the adjustment of spatial layouts driven by the low-carbon transition frequently lead to structural fractures in existing regional knowledge flow networks [41,42]. Faced with the complex systemic risks of the transition period, enterprises tend to adopt defensive, inward-looking knowledge management strategies (e.g., technology hoarding and reducing open innovation cooperation), which substantially weaken the external spillover effects of knowledge.

As a critical factor in urban governance innovation, the fracturing of knowledge spillover networks constrains public service provision from dual perspectives: technological empowerment and macroeconomic resources. On the one hand, the obstructed spillover of cutting-edge digital technologies and green governance experience exacerbates the "knowledge friction" between the public and private sectors [43,44]. This not only significantly increases transaction costs for governments seeking to acquire external expertise but also impedes the integration of innovative elements into critical urban service networks. The direct consequence is that the public supply side becomes constrained by "technology lock-in," thereby increasing the costs of upgrading climate-adaptive infrastructure—such as smart early-warning systems and sponge cities—to digitalization and low-carbonization [45,46]. On the other hand, as the core engine driving regional total factor productivity (TFP) growth, the attenuation of knowledge spillovers drags down the city's overall innovation momentum. This, in turn, weakens local fiscal extraction capacities, imposing hard budget constraints on the continuous expansion of basic public services [1,47]. Accordingly, this study proposes the second research hypothesis:

Hypothesis 2. *Climate transition risk is negatively associated with public service provision, with urban knowledge spillovers serving as a mechanism channel.*

2.3. Climate Transition Risk, Industrial Structure Upgrading, and Public Service Provision

Beyond knowledge spillovers, carbon-related structural transition pressure may also be linked to public service provision through its association with urban industrial restructuring. Cities with higher carbon emission intensity often have stronger dependence on carbon-intensive production systems, which may face greater adjustment burdens during the low-carbon transition. One possible channel is that such cities may encounter more difficulty reallocating capital, labor, and technological resources toward emerging low-carbon and service-oriented sectors. This significantly elevates the decision-making risks associated with long-term capital formation, such as green technology research and development (R&D) and low-carbon infrastructure [48,49]. Consequently, it becomes difficult for emerging green industries to cross the "valley of death" swiftly to achieve economies of scale and close the innovation loop, thereby delaying their leading role in advancing the industrial structure [50]. On the other hand, regulatory misalignments during the transition period (e.g., short-term, radical carbon reduction campaigns) frequently disrupt existing market equilibria and exacerbate cross-industry distortions in factor allocation. This leads to structural mismatches and circulation lags for credit capital and highly skilled labor that would otherwise flow into emerging industries [51–53].

The stagnation of the industrial structure upgrading process may place pressure on the public service provision system: First, obstructed industrial upgrading implies insufficient tax contributions from high-value-added industries. Compounded by the struggling transi-

tion of traditional high-carbon industries, this directly weakens local governments' fiscal extraction capacity, thereby compressing the fiscal space for investment in essential public services such as education and healthcare [54,55]. Second, a lagging industrial structure impedes the urban economy's smooth transition to a knowledge-intensive model. This weakens the societal demand signals for novel public services, such as digital infrastructure and intellectual property protection. Meanwhile, lacking fiscal support, the supply side struggles to respond effectively to these diverse demands [56]. Third, the coexistence of the phase-out crisis in traditional industries and the insufficient labor-absorption capacity of emerging industries is highly prone to induce structural unemployment and regional developmental imbalances. This compels the government to passively increase rigid expenditures on social assistance and unemployment benefits, which further crowd out forward-looking investments aimed at enhancing the long-term quality of public services [57–59]. Accordingly, this study proposes the third research hypothesis:

Hypothesis 3. *Climate transition risk is negatively associated with public service provision, with industrial structure upgrading serving as a mechanism channel.*

3. Research Design

3.1. Data Sources

The sample selection for this study adheres to the Notice on Adjusting the Criteria for Categorizing City Sizes issued by the State Council of China, which defines "large cities" objectively as those with an urban resident population exceeding one million. After comprehensively considering the consistency of statistical calibers due to administrative division adjustments and the availability of key indicator data, samples with severe data deficiencies were excluded. Ultimately, 99 major cities in China were selected as the research subjects. Based on this, a city-level balanced panel dataset spanning 2008 to 2019 was constructed, comprising 1188 observations.

Regarding data sources, the urban macroeconomic and social indicators used in this study were primarily extracted from the China City Statistical Yearbook over the years and provincial/municipal statistical communiqués. Micro-level enterprise registration and innovation data were retrieved from the National Enterprise Credit Information Publicity System and the database of the China National Intellectual Property Administration (CNIPA). Regarding missing-data treatment, missing observations in the panel were limited and scattered. Before interpolation, missing values mainly appeared in the control variable Den and in a very small number of indicators within the dependent variable evaluation system, such as the number of hospitals per capita. Core explanatory variables, mediating variables, digital-governance variables, and control variables other than Den did not require interpolation. To preserve the balanced panel structure, linear interpolation was applied only to isolated or intermittent missing observations along the time dimension within the same city. It was not used to fill long consecutive gaps, missing values at the beginning or end of a city's time series, or missing values across different cities. Appendix A Table A3 summarizes the distribution of missing values and the corresponding treatment.

3.2. Model Construction

3.2.1. Baseline Regression Model

To estimate the relationship between climate risk and urban public service provision while accounting for major sources of unobserved heterogeneity, this study constructs a two-way fixed effects (TWFE) model. This specification controls for time-invariant city

characteristics and common year-specific shocks. The specific baseline regression model is specified as follows:

$$pub_{it} = \alpha + \beta_1 cr_{it} + \beta Controls_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (1)$$

where i denotes the city and t denotes the year. pub_{it} represents urban public service provision, cr_{it} represents climate risk, and $Controls_{it}$ represents a set of control variables. γ_i denotes city fixed effects, δ_t denotes year fixed effects, and ε_{it} is the random error term. The TWFE framework does not fully eliminate the possibility of bias from unobserved time-varying confounders. For example, differences across cities in development intensity, fiscal adjustment, industrial restructuring, or governance capacity may evolve over time and may be related to both climate-risk exposure and public service provision. All panel regressions are estimated with city and year fixed effects. Unless otherwise specified, statistical inference is based on robust standard errors clustered at the city level, which helps account for heteroskedasticity and within-city serial correlation over time.

3.2.2. Mediation Effect Model

To examine whether the data are consistent with the proposed mechanism channels linking climate risk and urban public service provision, this study adopts the causal steps approach proposed by Baron and Kenny (1986) [60]. The models are set as follows:

$$M_{it} = \beta_0 + \beta_1 cr_{it} + \beta_2 Controls_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (2)$$

$$pub_{it} = \gamma_0 + \gamma_1 cr_{it} + \gamma_2 M_{it} + \gamma_3 Controls_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (3)$$

where M_{it} represents the mediating variable. The testing logic is as follows: First, test whether the total effect is significant based on Model (1). Second, examine the coefficient of the core explanatory variable on the mediating variable based on Model (2). Finally, incorporate both the core explanatory variable and the mediating variable simultaneously into Model (3). If β_1 and γ_2 are both significant, and the absolute value of γ_1 decreases compared to α_1 or its significance level drops, it indicates the presence of a partial mediation effect. In addition, the mediated proportion is calculated as the ratio of the indirect effect to the total effect to provide a more intuitive interpretation of the magnitude of each mediation channel.

3.3. Variables and Data Description

3.3.1. Dependent Variable: Public Service Provision (Pub)

Public service provision is a multidimensional concept that reflects the capacity of cities to provide basic services and maintain service accessibility for residents. Drawing on existing studies and considering the availability and consistency of city-level statistical data, this study constructs an evaluation system from four dimensions: education and culture, healthcare, social security and employment, and transportation and communication [61,62]. These dimensions cover both welfare-oriented public services and infrastructure-supported service accessibility, thereby providing a comprehensive representation of urban public service provision during the sample period. The system includes 14 basic indicators, as shown in Table 1.

To avoid the weight bias inherent in subjective weighting methods, this study adopts the entropy-weighting method. By using information entropy to assign weights to each indicator objectively, the comprehensive index of public service provision for each city is

ultimately calculated. Specifically, each indicator is first normalized using the min–max method. For positive indicators, the normalized value is calculated as:

$$x'_{ijt} = \frac{x_{ijt} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (4)$$

Table 1. Evaluation indicator system for urban public service provision.

Primary Indicator	Secondary Indicator	Tertiary Indicator	Weight
Public service provision	Education and cultural services	Number of universities per capita	0.114
		Student-teacher ratio in primary schools	0.049
		Public library collections per 100 persons	0.035
		Student-teacher ratio in secondary schools	0.042
	Healthcare services	Number of hospitals per capita	0.096
		Number of hospital and clinic beds per capita	0.053
		Number of doctors per capita	0.054
	Social security services	Coverage rate of basic pension insurance for urban employees	0.042
		Coverage rate of basic medical insurance for urban employees	0.035
		Coverage rate of unemployment insurance for urban employees	0.059
	Transportation and communication services	Per capita urban road area	0.050
		Number of telephones per capita	0.067
		Number of households with broadband internet access per 10,000 persons	0.105
		Per capita postal volume	0.200

For negative indicators, the normalized value is calculated as:

$$x'_{ijt} = \frac{\max(x_j) - x_{ijt}}{\max(x_j) - \min(x_j)} \quad (5)$$

where x'_{ijt} denotes the original value of indicator j for city i in year t. After normalization, the entropy value and information utility value of each indicator are calculated, and the final weight is determined according to the relative information contribution of each indicator. The entropy weight reflects the degree of variation and information provided by each indicator across cities and years, rather than a normative judgment about the substantive importance of each public service dimension. To examine the sensitivity of the results to the weighting structure, an equal-weighting scheme is further used in the robustness analysis.

3.3.2. Core Explanatory Variables

Physical Climate Risk (Cpr): Drawing on Sun et al. (2023) [63], this study uses Geographic Information System (GIS) technology to process raster and vector data and

construct a city-level indicator of the annual frequency of rainstorms. Specifically, utilizing high-resolution ($0.1^\circ \times 0.1^\circ$) annual rainstorm raster data from the China Science Data platform spanning 2001 to 2019, and adhering to the rainstorm criteria defined by the China Meteorological Administration (i.e., precipitation events meeting single-hour precipitation $\geq$ 16 mm, continuous 12 h precipitation $\geq$ 30 mm, or continuous 24 h precipitation $\geq$ 50 mm), the annual frequency of rainstorms for each city is calculated. We use this indicator because precipitation-related extreme events are among the most direct and disruptive physical climate hazards for large urban public service systems, particularly in terms of infrastructure interruption, transport disruption, and emergency service pressure. At the same time, this measure should be interpreted as a precipitation-related proxy for physical climate risk rather than a complete representation of all physical climate hazards faced by cities. Other relevant hazards—such as heat waves, droughts, typhoons, and non-rainfall flooding—are not fully captured by this indicator and therefore remain important directions for future refinement.

Transition Climate Risk (Ctr): Following Ciccarelli & Marotta (2024) [64], this study adopts carbon emission intensity (i.e., carbon dioxide emissions per unit of GDP) as the measurement indicator. Cities with higher carbon-emission intensity face greater pressure for economic structural adjustment and greater risk exposure when confronting mandatory national low-carbon transitions and tightening environmental regulations. This indicator primarily reflects the degree of structural exposure to decarbonization costs and transition-related adjustment burdens at the city level. The empirical results associated with this variable should therefore be interpreted mainly as evidence on the public-service implications of carbon-related structural transition pressure. Because carbon emission intensity may also reflect industrial structure, energy efficiency, development stage, and local energy mix, it should be understood as a proxy for carbon-related transition pressure.

3.3.3. Mediating Variables

Given the long time span of the panel and the need for consistent city-level comparability, the mediating variables in this study are measured using observable proxies that are broadly available across large cities.

Urban Entrepreneurial Vitality (Vit): Using the Chinese Industrial and Commercial Enterprise Registration Database, this study compiles newly registered enterprise data for the sample cities. To reduce scale-related measurement bias, the number of newly registered enterprises per 100 persons is used as a proxy for urban entrepreneurial vitality. This indicator mainly reflects the intensity of market entry and the overall activeness of entrepreneurial activity at the city level.

Knowledge Spillovers (Kno): This study uses the number of authorized patents per capita in the current year as a proxy for regional knowledge spillovers. At the city level, patent authorization data provide a measurable representation of innovation output and knowledge-related activity, and are widely used in empirical research on regional innovation and spillover effects.

Industrial Structure Upgrading (Indu): The ratio of tertiary-industry value-added to secondary-industry value-added is used to measure the broad direction of urban industrial structure upgrading. This indicator captures the extent to which the local economy is shifting toward more service-oriented production patterns and is commonly used in city-level studies of structural transformation.

3.3.4. Control Variables

To account for relevant city-level factors that may be associated with public service provision, this study includes the following control variables: Economic Development

Level (Eco), measured by the natural logarithm of the city's per capita GDP, to control for economic scale effects. Population Density (Den): Measured by the natural logarithm of the number of permanent residents per square kilometer to control for the congestion effects of spatial agglomeration. Fiscal Revenue (Rev): Measured by the natural logarithm of local general public budget revenue to reflect the government's intervention capacity. Urban Infrastructure Level (PI): Represented by the proportion of infrastructure construction investment to GDP to control for foundational hardware support. Technological Level (Tech): Measured by the proportion of science and technology expenditure to local general public budget expenditure to control for the potential driving effects of the innovation environment. The descriptive statistics of the main variables are shown in Table 2.

Table 2. Descriptive statistics of main variables.

Variable Name	Symbol	Mean	Std. Dev.	Min	Max
Public service provision	Pub	0.156	0.069	0.064	0.534
Physical climate risk	Cpr	0.017	0.01	0.000	0.046
Transition climate risk	Ctr	0.043	0.03	0.004	0.366
Entrepreneurial vitality	Vit	1.358	1.408	0.161	14.544
Knowledge spillovers	Kno	0.188	0.322	0.001	3.071
Industrial structure	Indu	1.020	0.546	0.139	5.168
Artificial intelligence level	Ai	5.537	1.602	1.099	9.991
Public data openness	Open	0.105	0.307	0.000	1.000
Economic development level	Eco	6.234	3.791	0.957	46.775
Population density	Den	0.390	0.265	0.056	1.506
Fiscal revenue	Rev	14.673	1.032	12.138	18.087
Urban infrastructure level	PI	0.027	0.031	0.000	0.387
Technological level	Tech	0.003	0.003	0.000	0.023

4. Empirical Results

4.1. Baseline Regression

Table 3 reports the baseline regression results for the relationship between climate risk and public service provision. As shown in Column (2) of Table 3, the estimated coefficient of Cpr on Pub is −0.261, which is statistically significant at the 5% level. This suggests that higher physical climate risk is associated with a lower level of public service provision in large cities. Column (4) demonstrates that the coefficient of Ctr is −0.083, significant at the 1% level. The coefficient of transition climate risk is also significantly negative, indicating that greater transition-related adjustment pressure is associated with weaker public service provision.

4.2. Robustness Checks

To examine the robustness of the baseline regression results, this study conducted a series of robustness checks across four dimensions: omitted variables, measurement substitution, extreme value interference, and sample selection bias. The results are summarized in Table 4.

4.2.1. Adding Omitted Control Variables

Considering that regional financial resource endowments and local fiscal expenditure preferences may simultaneously affect a city's climate adaptation capacity and public service investments, this study further incorporated the regional financial development level (rfinancial, total loans and deposits/GDP) and the proportion of fiscal education expenditure (reduction, education expenditure/general public budget expenditure) into the baseline model. Columns (1) and (2) of Table 4 show that after introducing these

potential omitted variables, the signs and significance levels of the coefficients for both physical and transition climate risks remain substantively unchanged.

Table 3. Baseline regression results of climate risk on public service provision.

	(1)	(2)	(3)	(4)
Variable	**Pub**	**Pub**	**Pub**	**Pub**
Cpr	−0.191 *	−0.261 **		
	(−1.68)	(−2.41)		
Ctr			−0.114 ***	−0.083 ***
			(−3.86)	(−2.89)
Eco		0.003 ***		0.003 ***
		(9.57)		(8.97)
Den		0.000		0.001
		(0.12)		(0.24)
Rev		−0.002		−0.003
		(−0.58)		(−1.03)
PI		−0.002		−0.007
		(−0.13)		(−0.36)
Tech		1.935 ***		2.050 ***
		(5.46)		(5.81)
Constant	0.131 ***	0.141 ***	0.135 ***	0.161 ***
	(52.12)	(3.55)	(53.83)	(3.96)
FE	YES	YES	YES	YES
N	1188	1188	1188	1188
R^2	0.555	0.608	0.560	0.609

Note: *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. City-clustered robust t-statistics are reported in parentheses.

4.2.2. Replacing the Measurement of the Core Explanatory Variable

To examine whether the results are sensitive to single-indicator measurement, this study substituted the proxy variable for physical climate risk from "rainstorm frequency" to "rainstorm intensity level" (Cpr1) for re-estimation. The results in Column (3) indicate that after replacing the frequency feature with the intensity feature, the negative association between physical risk and public service provision remains statistically significant.

4.2.3. Extreme-Value Treatment

Macroeconomic panel data may contain anomalous observations driven by unanticipated external shocks. Therefore, this study Winsorized all continuous variables at the 1st and 99th percentiles. As shown in Columns (4) and (5), after eliminating the influence of extreme values, the model estimation results are highly consistent with the baseline findings.

4.2.4. Excluding Samples with Special Administrative Levels

The four directly administered municipalities (Beijing, Shanghai, Tianjin, and Chongqing) enjoy special national policy advantages in fiscal autonomy, resource allocation capacity, and public facility construction standards. Mixing them with ordinary prefecture-level cities in the regression might induce sample selection bias. This study re-estimated the model after excluding these municipality samples. The results in Columns (6) and (7) show that the estimated negative associations remain broadly consistent within the sample of ordinary large cities.

Table 4. Robustness test.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Variable	**Adding Controls**	**Adding Controls**	**Replacing IV**	**Winsorization**	**Winsorization**	**Excluding Municipalities**	**Excluding Municipalities**	**Equal-Weighting**	**Equal-Weighting**
Cpr	−0.265 **			−0.190 *		−0.251 **		−0.123 *	
	(−2.45)			(−1.91)		(−2.38)		(−1.71)	
Ctr		−0.081 ***			−0.095 **		−0.076 ***		−0.057 **
		(−2.80)			(−2.42)		(−2.75)		(−2.44)
Cpr1			−0.002 **						
			(−2.00)						
Eco	0.003 ***	0.003 ***	0.003 ***	0.004 ***	0.004 ***	0.003 ***	0.002 ***	0.003 ***	0.002 ***
	(9.39)	(8.84)	(9.30)	(11.96)	(11.00)	(8.94)	(8.39)	(4.69)	(10.17)
Den	0.001	0.001	0.001	−0.001	−0.001	0.001	0.001	−0.003	−0.003
	(0.18)	(0.29)	(0.16)	(−0.23)	(−0.32)	(0.18)	(0.32)	(−0.60)	(−1.04)
Rev	−0.001	−0.002	−0.001	−0.006 **	−0.007 **	−0.002	−0.003	0.001	0.000
	(−0.36)	(−0.84)	(−0.44)	(−2.26)	(−2.56)	(−0.79)	(−1.21)	(0.38)	(0.15)
PI	−0.005	−0.009	−0.003	0.017	0.016	0.001	−0.003	0.002	0.002 *
	(−0.25)	(−0.45)	(−0.17)	(0.74)	(0.72)	(0.07)	(−0.16)	(1.53)	(1.86)
Tech	1.926 ***	2.040 ***	1.988 ***	1.812 ***	1.889 ***	2.172 ***	2.277 ***	−0.008	0.022
	(5.43)	(5.78)	(5.62)	(4.92)	(5.15)	(6.30)	(6.63)	(−0.04)	(0.19)
rfinancial	0.002	0.001	0.002						
	(1.45)	(1.17)	(1.57)						
reducation	−0.070	−0.030	−0.069						
	(−0.49)	(−0.21)	(−0.48)						
Constant	0.130 ***	0.151 ***	0.130 ***	0.195 ***	0.210 ***	0.148 ***	0.165 ***	0.145 ***	0.159 ***
	(3.21)	(3.64)	(3.21)	(5.33)	(5.63)	(3.86)	(4.24)	(3.21)	(4.92)
FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
N	1188	1188	1188	1188	1188	1140	1140	1188	1188
R^2	0.609	0.609	0.608	0.649	0.649	0.619	0.620	0.711	0.712

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

4.2.5. Alternative Weighting Scheme for the Public Service Provision Index

To examine whether the baseline results depend on the specific weighting structure used to construct the public service provision index, this study further recalculates the dependent variable using an equal-weighting scheme across the underlying indicators. Compared with the entropy-weighting method, the equal-weighting approach assigns the same importance to each indicator and therefore provides a useful benchmark for testing the sensitivity of the results to alternative conceptions of service adequacy. The re-estimation results show that the signs, significance levels, and overall patterns of the core explanatory variables remain substantively unchanged. This suggests that the main findings are not driven by the particular weighting rule adopted in the baseline index construction.

4.3. Mechanism Analysis

Table 5 reports the results of the mediation effect analysis. Column (1) of Table 5 shows that the regression coefficient for physical climate risk is −13.957, significant at the 1% level, indicating that physical climate risk is negatively associated with urban entrepreneurial vitality. Column (2) further demonstrates that entrepreneurial vitality is positively associated with public service provision. Together, these results suggest that physical climate risk is associated with lower public service provision through weaker entrepreneurial vitality, which is consistent with Hypothesis 1. One possible interpretation is that precipitation-related physical shocks may weaken market entry and entrepreneurial activity by increasing disruption, uncertainty, and adjustment pressure for local economic actors. In this sense, the estimated results are consistent with a sequential association among physical climate risk, entrepreneurial vitality, and public service provision.

Column (3) of Table 5 reveals that the regression coefficient of transition climate risk is −0.635, significant at the 1% level. Combined with Column (4)—where the coefficient of knowledge spillovers on public service provision is 0.056 and significant at the 1% level—the results suggest that greater transition-related adjustment pressure is associated with weaker knowledge spillovers and reduced support for public service provision. This pattern is consistent with the view that carbon-related structural transition pressure may constrain knowledge diffusion and innovation continuity in large cities. Thus, Hypothesis 2

is verified. One possible interpretation is that cities with stronger carbon-dependent development structures may face greater friction in resource reallocation, innovation continuity, and intersectoral coordination during the low-carbon transition. Such frictions may, in turn, weaken the generation, diffusion, and practical application of knowledge within urban systems.

Table 5. Regression results of mediation effects.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	**Vit**	**Pub**	**Kno**	**Pub**	**Indu**	**Pub**
Cpr	−13.957 ***	−0.104				
	(−3.37)	(−1.06)				
Vit		0.011 ***				
		(15.66)				
Ctr			−0.635 ***	−0.047 *	−0.604 **	−0.076 ***
			(−2.68)	(−1.85)	(−1.97)	(−2.66)
Kno				0.056 ***		
				(17.29)		
Indu						0.012 ***
						(4.07)
Constant	−2.873 *	0.174 ***	1.185 ***	0.094 ***	2.455 ***	0.132 ***
	(−1.88)	(4.83)	(3.53)	(2.60)	(5.65)	(3.24)
Controls	YES	YES	YES	YES	YES	YES
FE	YES	YES	YES	YES	YES	YES
N	1188	1188	1188	1188	1188	1188
R^2	0.563	0.681	0.475	0.694	0.650	0.615

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

Column (5) of Table 5 shows that the regression coefficient of transition climate risk is −0.604, significant at the 1% level. Meanwhile, Column (6) demonstrates that the coefficient of industrial structure upgrading on public service provision is 0.012, also significant at the 1% level. These results are consistent with Hypothesis 3, suggesting that greater transition-related adjustment pressure is associated with weaker public service provision through slower industrial structure upgrading. One possible interpretation is that cities with stronger carbon-related adjustment pressure may encounter greater difficulty in balancing short-term economic stability with long-term industrial restructuring. Under such conditions, resource reallocation toward emerging sectors may proceed more slowly, which can weaken the industrial basis supporting improvements in public service provision. Overall, the empirical findings of this study are broadly consistent with existing studies on the effects of climate risk on entrepreneurial activities and socio-economic system stability [65,66]. Building on this literature, this study provides two additional perspectives. First, it offers city-level empirical evidence that entrepreneurial vitality may serve as an important channel linking precipitation-related physical climate risk and public service provision. This extends the discussion of climate risk from direct physical disruption and economic loss to the market vitality conditions that support urban public service capacity. Second, the study distinguishes the mechanism patterns associated with physical and transition climate risks. While physical risk is mainly linked to entrepreneurial vitality, carbon-related structural transition pressure is more closely associated with knowledge spillovers and industrial structure upgrading. This distinction complements prior studies that treat climate risk as a homogeneous shock and provides a more differentiated framework for understanding climate-adaptive urban governance.

Table A2 further reports the decomposition of the mediation effects. The mediated proportion of entrepreneurial vitality in the relationship between physical climate risk and

public service provision is approximately 58.8%, indicating that the entrepreneurial vitality channel accounts for a substantial share of the estimated total association. For transition climate risk, the mediated proportions through knowledge spillovers and industrial structure upgrading are approximately 42.8% and 8.7%, respectively. These results suggest that the knowledge-spillover channel explains a larger share of the estimated transition-risk effect than the industrial-structure channel.

4.4. Heterogeneity Analysis

To enhance the reproducibility of the heterogeneity analysis, the classification criteria are clarified as follows. In the spatial heterogeneity analysis, coastal cities are defined as sample cities located in China's coastal provincial-level regions, including Liaoning, Hebei, Tianjin, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Guangdong, Guangxi, and Hainan. Cities outside these coastal provincial-level regions are classified as inland cities. For city-scale heterogeneity, this study does not further divide the sample into additional "large" and "small" city groups. According to the State Council's city-size classification standard, cities with an urban resident population of 1–5 million are classified as large cities, those with 5–10 million as extra-large cities, and those with more than 10 million as super-large cities. Since all sample cities have an urban resident population exceeding one million, they fall into the categories of large, extra-large, or super-large cities. Therefore, city scale is measured by the logarithm of urban resident population and is introduced as a time-varying continuous variable interacted with the climate-risk variables. This interaction specification avoids arbitrary threshold selection, preserves within-sample variation in city size, and directly examines whether the climate-risk association changes with city scale. The heterogeneity results are reported in Table 6.

Table 6. Results of heterogeneity analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
Variable	**Coastal**	**Inland**	**Coastal**	**Inland**	**Pub**	**Pub**
Cpr	−0.334 **	−0.006			1.255 ***	
	(−2.19)	(−0.04)			(3.11)	
Ctr			−0.268 ***	0.003		1.277 ***
			(−4.31)	(0.11)		(11.99)
City scale × Cpr					−0.686 ***	
					(−4.04)	
City scale × Ctr						−0.064 ***
						(−13.10)
Controls	YES	YES	YES	YES	YES	YES
Constant	0.026	0.081 **	0.083	0.080 **	0.082 **	0.089 **
	(0.35)	(2.05)	(1.12)	(2.00)	(2.09)	(2.35)
FE	YES	YES	YES	YES	YES	YES
N	696	492	696	492	1188	1188
R^2	0.594	0.668	0.603	0.668	0.604	0.653

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

In the spatial dimension, the sample was divided into coastal and inland cities based on China's regional characteristics. Columns (1)–(4) of Table 6 show that for large coastal cities, the regression coefficient of physical climate risk is −0.334 (significant at the 5% level), and the regression coefficient of transition risk is −0.268 (significant at the 1% level). In contrast, the coefficients of both types of risk are not statistically significant in the inland-city sample. These results provide descriptive evidence that the estimated climate risk–public service relationship may differ between coastal and inland cities. Several contextual factors may help explain this regional pattern. First, coastal cities may face a

"double exposure" pattern: they are more likely to confront compounded physical climate risks, such as typhoons and sea-level rise, while also bearing greater pressure from the global low-carbon transition [67]. Second, the economic structure of coastal cities is typically more outward-oriented. Consequently, climate shocks are more easily transmitted through channels such as suppressed market vitality and disrupted supply chain resilience, which, in turn, weaken the fiscal foundation supporting public services [68,69]. Third, inland cities may comparatively benefit from a higher proportion of central fiscal transfers, creating a fiscal buffer capacity that offsets, to some extent, the direct shocks from climate risks [8,70].

At the city-scale, Columns (5)–(6) of Table 6 show that the coefficients for the interaction terms between both types of climate risk (physical and transition) and city scale are significantly negative. This suggests that the negative association between climate risk and public service provision becomes stronger as city scale increases. Possible explanations for this phenomenon are twofold. On the one hand, under the shock of extreme climate events, the highly integrated and interconnected infrastructure systems (e.g., transportation and energy networks) of large-scale cities are more prone to "cascading failures," thereby potentially amplifying climate-related disruptions [7,71]. On the other hand, the more complex industrial structures and social networks of large cities entail higher adjustment costs and greater difficulties in coordinating governance during the adaptation to a low-carbon transition, placing additional pressure on the public service system [72].

This finding challenges the traditional perception that "economies of scale inevitably enhance risk resistance capacity" [73,74]. It highlights the importance of building more resilient and adaptive urban governance systems in large, extra-large, and super-large cities to support the stable provision and quality of critical public services.

5. Further Analysis: The Moderating Role of Digital Governance

Digital governance is introduced in this study not merely as a standalone policy instrument, but as a governance capacity that conditions how climate-related shocks are translated into public service outcomes. In this sense, digital governance may operate as a moderating mechanism because it affects the timeliness of information acquisition, the efficiency of cross-departmental coordination, and the adaptability of public decision-making under risk. At the same time, we acknowledge that digital governance can also function as a broader policy lever in urban adaptation. Critical studies of smart urbanism have shown that big data and real-time urban technologies may generate new governance risks, including technocratic decision-making, technological lock-in, privacy concerns, and uneven power relations in urban management [75]. In the public sector, AI applications may also face challenges related to transparency, accountability, fairness, implementation capacity, and institutional oversight [76]. If these issues are not properly addressed, digital tools may reinforce existing inequalities across districts, social groups, or cities with different administrative and fiscal capacities. Therefore, the role of digital governance in this study should be understood not as automatic technological empowerment, but as a conditional governance capacity whose effectiveness depends on institutional safeguards, data quality, transparency, and inclusive access.

To capture this dual character in an empirically tractable manner, this study operationalizes digital governance through two complementary city-level dimensions. The first is AI-related development, which reflects the technological infrastructure and intelligent analytical capacity that may strengthen risk sensing, prediction, and resource allocation. The second is public data openness, which reflects the institutionalized capacity for information sharing, interdepartmental coordination, and collaborative governance. For analytical convenience, these two dimensions are further interpreted as "hard resilience" and "soft resilience," respectively.

5.1. The Non-Linear Moderation of "Hard Resilience": A Threshold Effect Test Based on Artificial Intelligence

To empirically examine the moderating effect of "hard resilience," this study draws on Wang et al. (2022) [77]. It uses Chinese industrial and commercial enterprise registration data to quantify the AI industry's development at the city level. Specifically, enterprises whose business scope includes core AI technologies (e.g., chips, image recognition, natural language processing) are defined as AI enterprises, and a city-level panel dataset is constructed from 2008 to 2019. The natural logarithm of the annual number of AI enterprises in a city is used as a proxy to measure urban "hard resilience" (Ai). This measure captures the local AI-related industrial base and technological application potential. Given the potential nonlinearity, the panel threshold regression model proposed by Hansen (1999) [78] is employed for analysis. The threshold regression is estimated using the xthreg command in Stata/MP 17.0. In this framework, the threshold values are not specified manually; instead, they are endogenously estimated from the sample through a grid-search procedure that identifies the threshold points associated with the lowest residual sum of squares. Taking a double-threshold model as an example, the model is specified as follows:

$$pub_{it} = \alpha + \beta_1 cr_{it} \times I(q_{it} \leq \varphi) + \beta_2 cr_{it} \times I(q_{it} > \varphi) + \beta_k Controls_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (6)$$

where q_{it} is the threshold variable. If the expression within the parentheses is true, I takes the value of 1; otherwise, it takes the value of 0.

Table 7 reports the results of the panel threshold regression. Column (1) of Table 7 shows that when the urban AI level is below 6.373, the coefficient of physical climate risk is significantly negative (coefficient = −0.396, significant at the 1% level). When the AI level is between 6.373 and 8.290, the coefficient is no longer statistically significant. However, when the AI level exceeds 8.290, the coefficient turns positive and becomes statistically significant (coefficient = 1.378, significant at the 1% level). Similarly, Column (2) shows that when the AI level is below 6.599, the coefficient of transition climate risk is significantly negative (coefficient = −0.062, significant at the 5% level). After crossing the 6.599 threshold, the coefficient becomes positive and statistically significant (coefficient = 0.251, significant at the 1% level). Furthermore, when the AI level surpasses the second threshold of 8.398, the positive coefficient becomes larger (coefficient = 0.942, significant at the 1% level).

The above results suggest that the moderating role of AI in the relationship between climate risk and public service provision is non-linear. More specifically, the estimated coefficients are consistent with a pattern in which the moderating role of AI-related development remains limited at relatively low levels of development, becomes more visible after the first threshold is crossed, and strengthens further at higher levels of AI-related capacity. One possible interpretation is that the effectiveness of AI depends not only on the presence of digital technologies themselves, but also on a set of complementary conditions, including data infrastructure, implementation capacity, cross-departmental coordination, and the degree of integration between digital tools and governance processes. When AI-related development remains at a relatively low level, these complementary conditions may still be insufficient, so the attenuation associated with AI-related development remains limited. After the first threshold is crossed, AI-related capacities may begin to contribute more substantially to risk sensing, resource coordination, and adaptive response. At higher levels of development, the interaction between digital infrastructure, analytical capacity, and governance integration may become stronger, making the resilience-enhancing role of AI more visible in the empirical results. At the same time, the observed threshold pattern may also partly reflect measurement limitations in the AI indicator, differences in sample composition across cities, or other unobserved factors correlated with both AI development and governance capacity [79].

Table 7. Results of panel threshold regression analysis.

	(1)	(2)
Variable	**Pub**	**Pub**
Cpr(Ai ≤ 6.373)	−0.396 ***	
	(0.099)	
Cpr(6.373 < Ai ≤ 8.290)	0.163	
	(0.113)	
Cpr(Ai > 8.290)	1.378 ***	
	(0.162)	
Ctr(Ai ≤ 6.599)		−0.062 **
		(0.028)
Ctr(6.599 < Ai ≤ 8.398)		0.251 ***
		(0.047)
Ctr(Ai > 8.398)		0.942 ***
		(0.095)
Constant	−0.117 ***	−0.092 ***
	(0.019)	(0.022)
Controls	YES	YES
FE	YES	YES
N	1188	1188
R^2	0.614	0.607

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

These results suggest that the moderating role of AI-related development may be threshold-dependent. From a policy perspective, this implies that fragmented or low-intensity digital deployment may not be sufficient to generate visible resilience gains, whereas more integrated and sustained investment may be more likely to strengthen adaptive governance capacity [80]. Substantively, since the AI variable is measured on a logarithmic scale of AI-related enterprises, the estimated thresholds can be understood as empirical markers of different stages of AI-related industrial accumulation and digital governance capacity. Cities below the lower threshold generally have a relatively weak AI-related industrial base, and the supporting conditions for AI-enabled climate adaptation may not yet be fully developed. Cities between the two thresholds may have begun to accumulate more visible AI-related resources and application capacity, allowing AI to play a more apparent buffering role. Cities above the higher threshold are more likely to have a stronger AI ecosystem, better data-processing capacity, and a more developed digital governance infrastructure.

5.2. The Linear Moderation of "Soft Resilience": An Interaction Effect Test Based on Open Public Data

To explore the role of "soft resilience" in mitigating climate-related shocks in large cities, this study further analyzes the moderating effect of open public data policies on the relationship between climate risk and public service provision. Regarding variable measurement, drawing on the methodology of Lv et al. (2026) [81], this study defines city-level open public data as a binary dummy variable (Open). Specifically, if a city has established a government-led open public data platform and this platform has been integrated into the national government data-sharing and exchange system, Open equals 1; otherwise, it equals 0. Based on this, this study constructs a moderating effect model incorporating the interaction terms between the climate risk variables and open public data (Cpr × Open and Ctr × Open), specified as follows:

$$pub_{it} = \alpha + \beta_1 cr_{it} + \beta_2 (cr_{it} \times Open_{it}) + \beta Controls_{it} + \gamma_i + \delta_t + \varepsilon_{it} \quad (7)$$

Table 8 reports the results of the moderating effect analysis. Columns (1)–(2) show that the coefficient of the interaction term between open public data and physical climate risk is 0.342, which is significant at the 1% level. Additionally, the coefficient of the interaction term between open public data and transition climate risk is 0.025, significant at the 1% level. This indicates that public data openness is associated with an attenuation of the negative relationship between climate risk and urban public service provision. This pattern may be related to several governance functions associated with data openness. First, the open sharing of multi-source data—such as meteorological, geospatial, and governmental data—may help urban policymakers identify risk exposure points, assess vulnerabilities, and simulate transmission pathways. This may support more timely coordination and allocation of emergency resources [82,83]. Second, the unimpeded flow of critical data (e.g., carbon emissions and energy consumption) across different departments and administrative levels helps dismantle information silos and promotes policy synergy, effectively reducing institutional friction and coordination costs within large cities [84,85]. Third, open data platforms provide standardized channels for market participants, social organizations, and the public to access authoritative, timely risk information. This transparency helps stabilize market expectations, maintain socio-economic order, and stimulate the active engagement of diverse stakeholders in climate adaptation and mitigation actions [86,87]. Open public data platforms are often introduced as part of broader digital-government reforms. In this sense, the Open variable may capture not only the presence of a data platform, but also related institutional conditions such as administrative transparency, interdepartmental coordination, and digital infrastructure readiness. This variable captures the institutional presence of an open-data platform, but it does not directly measure platform quality, dataset coverage, usage intensity, or actual governance performance. The moderating role of open public data should therefore be understood as part of a broader digital-governance environment.

Table 8. Results of moderating effect analysis.

	(1)	(2)
Variable	**Pub**	**Pub**
Cpr	−0.271 **	
	(−2.52)	
Cpr × Open	0.342 ***	
	(3.67)	
Ctr		−0.070 **
		(−2.45)
Ctr × Open		0.025 ***
		(4.93)
Constant	0.145 ***	0.162 ***
	(3.67)	(4.04)
Controls	YES	YES
FE	YES	YES
N	1188	1188
R^2	0.613	0.617

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

This finding is consistent with the policy emphasis on accelerating the cultivation of the data factor market outlined in China's 14th Five-Year Plan for the Development of the Digital Economy. It suggests the potential value of data openness as one component of broader digital governance capacity for enhancing urban climate resilience.

6. Conclusions and Policy Implications

6.1. Research Conclusions

This study examines the relationship between climate risk and public service provision in large Chinese cities and explores the potential mechanism channels and moderating role of digital governance. By employing econometric models such as two-way fixed effects, mediation effects, and panel threshold regression, a systematic empirical analysis was conducted. The main conclusions are as follows:

First, physical and transition climate risks are significantly and negatively associated with public service provision, but the estimated mechanism patterns differ across risk types. The results are consistent with the view that physical risk is linked to public service provision partly through entrepreneurial vitality, while transition-related adjustment pressure is associated with weaker knowledge spillovers and slower industrial upgrading. This pattern suggests that climate risk should not be treated as a single homogeneous pressure, but as a multidimensional source of disruption connected to urban economic, innovation, and governance conditions.

Second, the estimated associations show spatial heterogeneity. The negative relationship between climate risk and public service provision is more pronounced in coastal cities and cities with larger population scales. This suggests that climate-related pressures may interact with geographic exposure, infrastructure density, industrial structure, and governance complexity, leading to differentiated public service vulnerabilities across urban contexts.

Third, digital governance, reflected here in AI-related development and public data openness, may condition the relationship between climate risk and public service provision. AI-related development shows a non-linear threshold pattern, suggesting that its resilience-enhancing role becomes more visible after cities accumulate stronger digital and technological capacities. Public data openness is also associated with a weaker negative relationship between climate risk and public service provision. These findings suggest that digital governance may contribute to urban climate resilience, although its role depends on technological, institutional, and governance conditions.

6.2. Policy Implications

Synthesizing the empirical findings, this study derives several policy implications for climate-adaptive public service governance in large Chinese cities. These implications are primarily grounded in the sample of 99 large Chinese cities during 2008–2019. Therefore, their applicability to other countries or regions should be interpreted with caution. Nevertheless, the empirical patterns examined in this study may offer conditional reference points for other rapidly urbanizing contexts that face similar pressures of climate adaptation, low-carbon transition, public service expansion, and digital governance transformation.

First, policymakers may consider differentiated adaptation strategies based on heterogeneous climate-risk pathways. For large Chinese cities, policy design can distinguish between precipitation-related physical risks and carbon-related structural transition pressure, rather than relying on one-size-fits-all climate responses. To address physical risks, priority should be given to investing in smart infrastructure capable of real-time monitoring and response, such as sensor-deployed flood control systems and sponge cities. Additionally, exploring and promoting parametric catastrophe insurance linked to climate thresholds can provide rapid payouts and emergency credit to affected market entities, thereby safeguarding micro-level entrepreneurial vitality. To address transition risks, regional climate transition innovation cooperation centers should be established, mandating the participation of leading high-carbon enterprises and linking them with research institutions to unclog knowledge spillover channels. Simultaneously, modular green skills

training programs should be rolled out to ensure the smooth transition of the labor force during industrial restructuring.

Second, an asymmetric resource-tilt mechanism based on dynamic risk assessments should be established to strengthen high-risk areas. For coastal cities and larger-scale cities in the sample, the results suggest greater sensitivity of public service provision to climate risk. This implies that risk-sensitive resource allocation and spatial planning may be particularly important for cities with higher exposure, denser infrastructure networks, and more complex public service systems. In particular, high-resolution climate-risk assessments should be embedded into urban master planning, land-use approval, and major infrastructure siting decisions. For highly exposed urban areas, planners should avoid the excessive concentration of critical public service facilities, guide new development away from high-risk zones where appropriate, and strengthen the spatial integration of blue-green infrastructure, sponge-city systems, emergency shelters, and resilient transport networks. In this way, land-use planning can serve as a forward-looking instrument for reducing exposure, redistributing vulnerability, and enhancing the continuity of public service provision under climate stress.

Third, the threshold results suggest that digital-governance capacity is more likely to support climate-adaptive public service provision when data infrastructure, application scenarios, and institutional coordination are jointly developed. To strengthen institutional "soft resilience" and support the use of AI-related technologies, cities may clarify responsibilities for cross-departmental data sharing and improve institutional arrangements for data governance. Policymakers should lead the development of national or regional climate resilience data standards to ensure interoperability across systems. This will encourage the private sector to contribute high-granularity commercial and mobility data under the premise of guaranteed security, leveraging data flows to drive the adaptive allocation of public service systems and the low-cost training of AI early-warning models.

More specifically, the findings of this study also carry direct implications for land-use planning. Since climate risk does not affect all urban spaces equally, land-use regulation should move beyond efficiency-oriented allocation and incorporate resilience-oriented spatial governance. In high-risk coastal and large-scale cities, the siting of schools, hospitals, elderly care facilities, transport hubs, and other essential public services should take climate exposure into account more explicitly. At the same time, local governments should use zoning tools and development intensity controls to reduce the clustering of vulnerable populations and critical facilities in hazard-prone areas, while expanding the coverage of green buffers, drainage corridors, sponge-city infrastructure, and other nature-based solutions. Such planning adjustments can help transform the paper's empirical findings into spatial strategies for safeguarding the continuity and equity of public service provision under climate change.

6.3. Limitations and Future Prospects

Although this study has conducted a meaningful exploration of the intersection of climate risk and public services, there remain limitations that require further exploration in future research. First, there are limitations in the measurement of physical climate risk. In this study, physical climate risk is proxied by the annual frequency of rainstorms, which captures an important dimension of precipitation-related extreme events but does not fully represent the broader spectrum of urban physical climate hazards, such as heat waves, droughts, typhoons, and compound flooding. Although we conduct a robustness test by replacing rainstorm frequency with rainstorm intensity, this still remains within the domain of precipitation-related risk. Future research could construct a more comprehensive multi-hazard physical climate risk index, develop richer transition-risk

measures incorporating carbon-intensive employment, environmental regulation intensity, energy-structure dependence, and policy uncertainty, and strengthen causal identification through policy shocks, instrumental variables, or other quasi-experimental designs when suitable data are available. Another limitation concerns potential spatial dependence and cross-city spillover effects. Climate risk, public service provision, and urban development are spatially embedded processes. Extreme weather events may affect neighboring cities through infrastructure networks, commuting patterns, supply chains, and emergency-resource coordination. Future research could extend the analysis by constructing spatial weight matrices and applying spatial panel models, spatial Durbin models, or spatially weighted climate-risk indicators to examine whether climate risk and public service provision exhibit significant spatial spillover effects. In addition, the public service provision index is constructed from available city-level statistical indicators and entropy weights. Although the equal-weighting robustness check shows broadly consistent results, the index remains an empirical approximation of multidimensional public service capacity. Future research could incorporate resident preferences, expert weights, service accessibility data, or sub-dimensional indices to further refine the measurement of public service provision.

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Appendix A

Table A1. Panel unit root test results.

Variable	Test Form	LLC Statistic	LLC *p*-Value	IPS Statistic	IPS *p*-Value
Public service provision	First difference	−14.4254	0	−10.0449	0
Rainstorm frequency	Level	−11.704	0	−7.1773	0
Carbon emission intensity	Level	−12.4534	0	−3.7101	0.0001
Entrepreneurial vitality	First difference	−8.9933	0	−6.6316	0
Knowledge spillovers	First difference	−10.8916	0	−10.1529	0
Economic development level	First difference	−12.4923	0	−7.5625	0
Population density	Level	−37.8113	0	−6.6943	0
Fiscal revenue level	Level	−7.6486	0	−1.8505	0.0321
Urban infrastructure level	Level	−18.8167	0	−4.9432	0
Technological input level	First difference	−13.3884	0	−8.2254	0

Notes: LLC denotes the Levin–Lin–Chu panel unit root test, and IPS denotes the Im–Pesaran–Shin panel unit root test. The null hypothesis is that the panel contains a unit root.

Table A2. Decomposition of mediation effects.

Pathway	Total Effect	Direct Effect	Indirect Effect	Bootstrap 95% CI	Mediated Proportion
Cpr → Vit → Pub	−0.261	−0.104	−0.154	[−0.305, −0.009]	58.80%
Ctr → Kno → Pub	−0.083	−0.047	−0.036	[−0.066,−0.001]	42.80%
Ctr → Indu → Pub	−0.083	−0.076	−0.007	[−0.084, −0.005]	8.70%

Table A3. Distribution and treatment of missing values.

Variable	Role in Model	Missing-Value Pattern Before Interpolation	Treatment
Den	Control variable	Very limited, isolated city-year gaps	Linear interpolation within the same city
Number of hospitals per capita	Indicator in dependent-variable system	Very limited, isolated city-year gaps	Linear interpolation within the same city
Other public-service indicators	Indicators in dependent-variable system	Rare and scattered missing entries	Linear interpolation within the same city
Cpr	Core explanatory variable	No missing values requiring interpolation	Not interpolated
Ctr	Core explanatory variable	No missing values requiring interpolation	Not interpolated
Mediating variables	Mechanism variables	No missing values requiring interpolation	Not interpolated
Digital-governance variables	Moderation variables	No missing values requiring interpolation	Not interpolated
Control variables other than Den	Control variables	No missing values requiring interpolation	Not interpolated

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