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Spatial-temporal evolution analysis of the impact of climate change adaptation policy on industry chain resilience

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The impact of climate change on the supply chain industry has emerged as a critical challenge for urban development. Existing literature primarily focuses on policies and measures for restoring the industrial economy, but overlooks the impact of climate change adaptation policy (CCAP) on the urban industrial chain resilience (ICR). Using panel data from 278 prefecture-level cities in China from 2000 to 2022, this study analyzes whether CCAP enhances the spatial heterogeneity of ICR. Additionally, the study develops an analytical framework to examine the mechanisms through which CCAP influences ICR, considering the levels of science and technology and GDP per capita. The results indicate that: (1) CCAP positively influences ICR improvement. (2) The effect of CCAP on ICR enhancement is mediated by rural revitalization and the digital economy, while excluding the impacts of Broadband China and Smart City policies. (3) CCAP directly enhances urban ICR and exerts a positive spatial spillover effect on the ICR of neighboring cities. This study offers insights into the sustainable development of urban industrial chains and the effectiveness of environmental policies in climate adaptation.

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Introduction

Under the threat of climate change, both individuals and organizations within the urban ICR often exhibit insufficient risk awareness and inadequate resource accumulation. Consequently, governments need to facilitate urban adaptation through targeted public policies and tools (Beretić et al., 2024). CCAP tools are specifically designed to achieve policy goals by altering target behaviors or addressing underlying issues (Ma et al., 2025). Research on ICR is crucial for advancing urban industrial development in the context of climate change (Hoque & Uddin, 2025). Can CCAP enhance the resilience of urban industrial chains? What are the mechanisms and pathways through which these policies improve the urban of ICR? This paper seeks to address these questions and summarize relevant empirical findings, which hold significant theoretical and practical implications for enhancing the resilience of the circulation industry chain and fostering a dual-cycle development model under CCAP.

CCAP typically encompasses a broad array of interventions aimed at reducing vulnerability and enhancing the adaptive capacity of social, economic, and ecological systems (Ferreira, 2024; Puig et al., 2025). The content of these policies can be categorized into the following dimensions: (1) Infrastructure and Urban Planning (Birchall & Bonnett, 2021). Development of climate-resilient infrastructure, green urban spaces, and water-sensitive urban design to reduce the physical impacts of climate-related events (e.g., flood defenses, cooling networks). (2) Resource Management (Schoenefeld et al., 2022). Adaptive management of natural resources such as water, soil, and biodiversity to buffer the ecological consequences of climate change. (3) Sectoral Adaptation (Goodwin et al., 2025). Promotion of adaptive practices in agriculture (e.g., drought-resistant crops), industry (e.g., climate-proofing supply chains), and public health (e.g., heat early-warning systems). (4) Institutional Mechanisms (Benischke et al., 2025). Establishment of national adaptation plans (NAPs), risk assessment frameworks, multi-level governance platforms, and financial instruments (e.g., green bonds, climate insurance). (5) Data, Monitoring, and Learning Systems (Kumar et al., 2024; Liu, Chen, et al., 2025b). Integration of climate modeling, impact forecasting, and knowledge-sharing platforms to support evidence-based policymaking and continuous improvement. Such measures aim to reduce both direct exposure and indirect systemic vulnerability, particularly in complex industrial systems that are sensitive to environmental and infrastructural disruptions.

From the perspective of macro-policy analysis, this paper first establishes an ICR index system and employs the HHI method to calculate the ICR indices for 278 Chinese cities from 2000 to 2022. Secondly, this study uses the construction of CCAP pilot cities as a quasi-natural experiment and applies the SDM-DID method to evaluate whether the implementation of CCAP policies has improved urban ICR levels. Meanwhile, spatial-temporal evolution analysis is applied to examine the spillover effects of CCAP on ICR and to identify heterogeneity factors, such as technological advancement and GDP per capita. Thirdly, this paper investigates the mechanism through which the rural revitalization index and digital economy level act as mediating variables influencing the relationship between CCAP and ICR. Finally, the effects of the Smart City policy and the Broadband China policy were controlled in terms of methods. The uniqueness of the experimental results was ensured by eliminating the possible influence of other policies on ICR. The data demonstrate that: (1) CCAP positively and directly impacts urban ICR and exerts a positive spatial spillover effect on the ICR of neighboring cities. (2) The rural revitalization index and digital economy level directly and positively contribute to the improvement of urban

ICR. The study further demonstrates that the positive impact of CCAP on ICR is independent of Smart City policies and the Broadband China policy. (3) Science and technology levels and GDP per capita have heterogeneous effects on ICR in neighboring cities. Cities with higher levels of science and technology exhibit a stronger improvement effect on the ICR of neighboring cities compared to those with lower levels. Similarly, cities with higher GDP per capita have a greater positive impact on the ICR of neighboring cities compared to those with lower GDP per capita.

Literature review and model hypothesis

ICR in the process of supply chain development. The term “resilience” originates from physics, emphasizing the ability of a system to return to its original state after an external impact. In the early 21st century, the concept of resilience was introduced into economics, where it refers to an economy’s ability to recover to its pre-shock state after experiencing external shocks. Relevant studies have primarily focused on economic resilience (Briguglio et al., 2006; Eichengreen et al., 2024). ICR refers to the ability of an industrial chain to positively respond to internal and external pressures, maintain dynamic balance, restore to its pre-impact state in an orderly manner, and achieve transformation and upgrading during dynamic evolution (Ivanov, 2021).

Unlike the supply chain, the industrial chain is primarily an economic concept. Since the 21st century, with increasingly sophisticated policies supporting industrial chain development, the membership relationships, network structures, and geographical distributions of industrial and supply chains have become more complex (Ellram, 1991). This complexity has significantly heightened the risk of disruptions caused by external uncertainties. This development has underscored the urgency of enhancing ICR by strengthening domestic market participants and optimizing structural frameworks, thereby emphasizing the need for research into the internal structure and resilience mechanisms of industrial chains (Chen et al., 2025). According to previous studies, strategies for improving supply chain resilience focus on three key capacities: the ability to manage potential sudden risks, the capacity for rapid response during disruptions, and the ability to restore and rebuild the chain (Gasser et al., 2021). These studies indicate that supply chain resilience management primarily addresses the ability of stakeholders to handle potential risks or uncertainties under conventional market conditions. It does not, however, account for risks associated with climate change or extreme weather events that stakeholders are unable to manage.

Theoretical research emphasizes the conceptual definition and pathways for improvement (Palmisano & Godfrid, 2025). A literature review reveals that ICR is a core objective of industrial chain modernization. It includes industry diversification, rapid repair and replacement capabilities following shocks, and the ability to respond to shocks promptly. Building on the concept of ICR, many scholars have explored pathways to enhance resilience from various perspectives, including integrating resilience with safety improvement and focusing on specific industrial chains. For instance, research has examined resilience in specific industrial chains, such as the manufacturing industry (Wieland & Durach, 2021), the shipbuilding industry (Wan et al., 2022), and the automobile industry (Castro-Vincenzi, 2022).

Empirical research primarily focuses on measuring industrial chain resilience and analyzing its impact mechanisms (Cheng et al., 2022). Scholars have adopted economic resilience research methods as a practical approach to identifying the risks of “chain breaks” and ensuring the security and stability of industrial chains. Scholars have proposed constructing a multidimensional

evaluation index system (Tong et al., 2020). Methods such as the comprehensive evaluation approach, the industrial diversification index (Yazdanparast et al., 2021), and regional innovation capacity have been employed to measure ICR (Razak et al., 2023). Based on measurements of ICR, scholars have examined the influence mechanisms of factors such as industrial agglomeration and the digital economy on resilience (Shashi et al., 2020).

The influencing mechanism of CCAP on ICR. Policymakers often perceive a negative correlation between the development of industrial or supply chains and environmentally sustainable development policies (Waqar et al., 2025). To date, academic analyses of sustainable development policies and industrial chains have remained constrained by a binary perspective opposing the environment and the economy from a scientific perspective. ICR serves as a crucial dynamic indicator for supply chains or industrial chains to achieve sustainable development goals. In summary, enhancing the ICR level is a key measure for adapting to climate change and mitigating its impacts on industry.

From a theoretical and empirical standpoint, the influence of CCAP on ICR operates through several interconnected mechanisms: (1) Risk Reduction and Vulnerability Mitigation. CCAP functions as a proactive risk management tools that reduce industrial exposure to climate-related hazards (Palliyaguru et al., 2014). For instance, improved land use planning and disaster-prevention infrastructure lowers the probability of production halts and logistic bottlenecks, thereby safeguarding supply chain continuity. (2) Capacity Building and Flexibility Enhancement. By fostering adaptive capacities—such as technological innovation, organizational learning, and diversification of supply sources—CCAP increases the ability of industrial actors to anticipate, absorb, and recover from shocks (Brix, 2019). This aligns with resilience theories emphasizing redundancy, modularity, and adaptive flexibility as core attributes (Karman, 2020). (3) Institutional Coordination and Adaptive Governance. CCAP facilitates cross-sectoral coordination and multi-level governance, enabling more agile and integrated responses to emergent climate threats (Liu, Fang, et al., 2025a). The adaptive governance framework underlines the importance of iterative learning, stakeholder engagement, and policy feedback mechanisms in enhancing the resilience of socio-technical systems (Liu, Fang, et al., 2025b). (4) Integration into Strategic Planning and Industrial Policy. By embedding adaptation objectives into industrial policy frameworks, governments can incentivize private sector compliance, promote green innovation, and support the restructuring of vulnerable sectors toward more climate-resilient models (Kameoka et al., 2004). This fosters a shift from reactive responses to anticipatory resilience-building strategies (Xu, 2022). Accordingly, this paper proposes the following research hypotheses:

Hypotheses 1: CCAP has a positive effect on ICR.

Existing studies suggest that rural revitalization, as a key component of CCAPs, enhances ICR through several mechanisms. Firstly, rural revitalization improves agricultural and ecosystem resilience, ensuring the stability of agricultural production and the reliability of supply chains (Birchall & Bonnett, 2021; Olazabal et al., 2024). Secondly, infrastructure development and the promotion of green energy projects in rural areas not only improve local production conditions but also provide more robust support for industrial chains, thereby enhancing their capacity to cope with climate-related risks (Xu et al., 2024). Additionally, rural revitalization fosters agricultural technological innovation and the application of green technologies, which not only bolster the climate adaptability of the agricultural sector but also provide necessary technological support for other segments of the industrial chain, thereby

promoting green transformation within the entire supply chain (Tao et al., 2024). On the social capital and governance front, rural revitalization strengthens local governance capabilities and enhances the coordination mechanisms among social organizations, enabling more effective responses to climate-induced challenges (Ye & Jiang, 2025). Finally, rural revitalization promotes regional economic coordination, mitigating the disproportionate impacts of climate change on specific regions and enhancing the flexibility and spatial distribution of industrial chains (Lu et al., 2024). In summary, rural revitalization provides an effective intermediary mechanism between CCAP and ICR, its impact extending beyond enhancing agricultural resilience to encompass regional economic development, social governance, and various other dimensions, thereby laying a foundation for the long-term stability and sustainability of industrial chains. This study proposes the following research hypotheses:

Hypotheses 2: CCAP enhances urban ICR by affecting the level of rural revitalization.

Existing research indicates that the digital economy significantly enhances the flexibility and responsiveness of ICR through data-driven, intelligent decision-making and collaborative platform construction (Schoenefeld et al., 2022; Suprayitno et al., 2024). Specifically, digital technologies, through real-time monitoring, big data analytics, and intelligent decision-support systems, enable enterprises to rapidly adjust production plans and optimize supply chain management in response to climate-related risks (Kuang et al., 2024). Furthermore, the digital economy promotes the innovation of green technologies and the widespread adoption of low-carbon production models, improving resource efficiency and effectively reducing carbon emissions, thus enhancing the environmental adaptability of ICR (Tian et al., 2024). Additionally, the digital economy fosters inter-industry and inter-regional information sharing and collaboration, which strengthens the synergistic effects and risk diversification within the ICR, further increasing its overall resilience (Niu et al., 2024). Finally, through climate risk forecasting, big data modeling, and smart decision-making, the digital economy improves the foresight and strategic adaptability of ICR in the face of CCAP, thereby providing robust support for their sustainable development (Song et al., 2024). Therefore, the digital economy not only provides technological support for the effective implementation of CCAP but also significantly enhances the risk resilience and long-term sustainability of ICR (Xia et al., 2025). This study proposes the following research hypotheses:

Hypotheses 3: CCAP enhances urban ICR by affecting the level of the digital economy.

Mechanisms for the impact of CCAP on ICR. To explore how CCAP affects urban ICR, it is critical to consider not only direct effects but also the spatial dimension of policy diffusion and inter-city interactions. As urban economic systems are highly interconnected, environmental policies implemented in one city can influence industrial dynamics in neighboring regions. This section draws upon spatial spillover theory, institutional diffusion frameworks, and regional policy feedback mechanisms to propose the following hypotheses.

From the perspective of spatial political economy and policy externalities, cities often operate within broader regional systems, where adaptation policies in one locality may influence resource flows, infrastructure resilience, and environmental risks in adjacent areas (Anselin, 2003; Verhoef & Nijkamp, 2004). Given the spatially diffusive nature of industrial supply chains, CCAP in one city can reduce regional vulnerabilities and strengthen cross-border industrial coordination, thereby enhancing ICR in surrounding cities. Moreover, institutional isomorphism suggests

that neighboring governments may emulate successful adaptation strategies (Asmare et al., 2019; Carrico, 2021), reinforcing positive spillover effects.

Hypotheses 4: CCAP has a positive spatial spillover effect on ICR.

That is, the implementation of CCAP in each city will enhance the ICR of its neighboring cities through mechanisms such as supply chain interdependence, infrastructure connectivity, and intergovernmental learning.

However, regional heterogeneity in economic capacity, policy coordination, and administrative boundaries may moderate these spillover effects. According to spatial segmentation theory and policy threshold effects (Feng et al., 2022), certain cities may act as “spatial intercepts” that limit the transmission of policy benefits due to institutional misalignment or infrastructural bottlenecks (Liu, Chen, et al., 2025a).

Hypotheses 5: CCAP has a spatial intercept limitation on the spillover effect of ICR.

In other words, the magnitude and direction of CCAP’s spatial spillovers on ICR may be constrained by administrative discontinuities, governance disparities, or sectoral mismatches, leading to uneven policy diffusion across city networks.

These hypotheses provide a theoretical foundation for subsequent spatial econometric modeling, enabling us to empirically examine the regional dynamics of adaptation policy and industrial resilience.

Spatial DID model construction

Spatial auto-correlation models. Since ICR is influenced by variations in regional environments and resource endowments, its impact across regions exhibits both similarities and differences. Consequently, it is essential to investigate the spatial dependence of ICR at both global and national scales. This study adopts method, referencing the global Moran’s I as a standard for measuring spatial dependence (Chen, 2013). The derivation formula is presented as follows:

$$Moran's\ I = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{S^2 \sum_{i=1}^n \sum_{j=1}^n w_{ij}} \tag{1}$$

In Eq. (1), x_i and x_j represent the ICR indices of city i and city j , respectively. \bar{x} denotes the average ICR, n is the total number of cities, and S^2 represents the variance. When the calculated value falls within the range (0,1], it indicates a positive correlation between ICR and spatial effects. When the value is 0, it indicates that the spatial effect is random. When the calculated value falls within the range [-1,0), it indicates a negative correlation between ICR and spatial effects. The formula for the first-order inverse distance matrix is as follows:

$$W_{ij} = \begin{cases} \frac{1}{d} (i \neq j) \\ 0 (i = j) \end{cases} \tag{2}$$

Formula (2) denotes the first-order inverse distance matrix and denotes the spherical distance between cities.

Spatial DID model. The comparison of the effects of implementing CCAP in Chinese pilot cities versus not implementing these policies serves as a quasi-natural experiment, providing empirical evidence on whether CCAP enhances ICR. The standard DID model is specified as follows:

$$ICR_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 Treat + \beta_3 Policy + \sum \gamma_i C_{it} + \varphi_{it} \tag{3}$$

In Eq. (3), i represents the city, t represents the time, and ICR_{it} denotes the ICR of city i in year t . DID_{it} is a dummy variable

($DID_{it} = Treat * Policy$), constructed for the period 2000–2022. It is assigned a value of 1 if the city is a CCAP pilot city, and otherwise it is assigned a value of 0. $Policy$ represents the year of policy implementation; it is assigned a value of 1 if the city has implemented the CCAP pilot city and 0 otherwise. Based on this, to control for the effects of time and individual characteristics across different periods, the M-DID model is constructed as follows:

$$ICR_{it} = \beta_0 + \beta_1 DID_{it} + \sum \gamma_i C_{it} + \mu_i + \sigma_t + \varphi_{it} \tag{4}$$

In Eq. (4), μ_i and σ_t represent individual and time fixed effects, respectively. As previously mentioned, ICR exhibits spatial autocorrelation. CCAP often focuses resources on cities with higher risks or more developed economies, for instance, by strengthening infrastructure construction and upgrading industrial technologies (Luo et al., 2023). Adjacent regions may be marginalized due to the “siphon” effect of resources and policies, resulting in weakened risk resistance capabilities in the upstream and downstream of the ICR (Krisanski et al., 2021). This resource crowding-out mechanism resulting from the concentrated implementation of policies will, in theory, have a spatial spillover effect on the impact of CCAP on ICR (Saupe et al., 2019). Incorporating this feature, the study integrates spatial autocorrelation factors into the reference model and constructs the SDM-DID model based on the M-DID framework (Andrienko et al., 2003).

$$ICR_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 W DID_{it} + \rho W c g_{it} + \sum \gamma_i C_{it} + W \sum \gamma_i C_{it} + \mu_i + \sigma_t + \varphi_{it} \tag{5}$$

To examine the spatial effects of the CCAP pilot city policy on the ICR of a city, this study introduces a set of new control variables based on formula (5) and uses the model to test H4. ICR_{it} represents the ICR value of city i in period t . C_{it} represents the control variable. μ_i represents the influence of the city level on ICR. σ_t represents the influence on the time dimension of ICR. φ_{it} represents the error term. Finally, a spatio-temporal analysis model based on the SDM-DID framework is developed, with the reference weight matrix defined as a first-order inverse distance matrix (Atluri et al., 2018).

$$ICR_{it} = \beta_0 + \sum_{s=25}^{400} \delta_s N_{it}^s + \sum \gamma_i C_{it} + \mu_i + \sigma_t + \varphi_{it} \tag{6}$$

In formula (6), s represents the spherical distance between cities. If a CCAP pilot city is located within the specified spatial range $i(s - 25, s]$ from another city, $N_{it}^s = 1$; otherwise, $N_{it}^s = 0$. The coefficient of N_{it}^s reflects the effect of the CCAP on the ICR of neighboring cities after its implementation.

Variable selection

Dependent variables. In this study, ICR is defined as the capacity to respond positively to external environmental pressures and climate change, restoring the pre-impact state while maintaining dynamic balance. Simultaneously, ICR enables the transformation and upgrading of the chain during dynamic evolution (Jia et al., 2021). This paper employs the industrial diversification index and urban innovation capability index to represent ICR, as system diversity functions as an automatic stabilizer to disperse risks and resist shocks. Industrial diversity mitigates risks and absorbs shocks by fostering functional and resource complementarity within systems, while continuously enhancing the sharing of labor, resources, technology, and information. To sustain the system’s emergence over time, this study focuses on enhancing adaptability and innovation as starting points for improving ICR.

Construction of ICR index system. To better illustrate the dependent variables, this paper defines ICR in terms of the system's adaptability and innovation capabilities. The Hirschman-Herfindahl Index (HHI) is employed to measure the diversification index, as shown in formula (7). In prior research, HHI has been widely used to measure the degree of industrial concentration. A higher HHI indicates a lower degree of industrial diversification and weaker system resilience to withstand, recover from, and integrate following shocks, and vice versa.

$$HHI = \sum_i^N S_i^2 \quad (7)$$

In this paper, the industrial diversification level (*Indiv*) is defined as the toughness of the industrial chain, as shown in formula (8).

$$Indiv = \frac{1}{HHI} = 1 / \sum_i^N S_i^2 \quad (8)$$

In Eq. (8), S_i represents the proportion of the output value of industry i relative to the total subsistence value of the region. Higher industrial diversification strengthens ICR and promotes urban economic development. Considering data availability, this study adopts methods proposed by previous scholars (Biesbroek, 2021; Suprayitno et al., 2024), setting $i = 1, 2, 3$.

Core explanatory variables. The core explanatory variable of this study is DID, a dummy variable representing the pilot cities under the CCAP. This study conceptualizes CCAP as a policy cluster initiated by the Notice on Launching Climate-Adaptive City Construction issued in 2017. This initiative designated 28 cities as pilot zones to experiment with innovative approaches for green urban transformation and climate resilience. The policy has played a pivotal role in incentivizing local governments to optimize their industrial structures. Moreover, it aligns closely with the strategic objectives of the 2015 Sponge City initiative, reflecting an integrated policy framework for urban ecological transition. Accordingly, this paper collectively refers to these interrelated policies as CCAP. From an empirical standpoint, a rigorous assessment of CCAP's implementation outcomes is vital for promoting sustainable and low-carbon urban development.

This research uses the interaction term of the CCAP city pilot construction as the primary independent variable in the MDID model. Between 2000 and 2022, CCAP, as a policy measure for urban pilot construction, was selectively implemented at various time points in 278 cities nationwide. The variables *Treat* and *Post* represent policy group and time dummy variables, respectively, corresponding to cities participating in the CCAP. *Treat* equals 1 if the city meets the conditions of the CCAP. Otherwise, *treat* equals 0. *Post* equals 1 if the year is greater than or equal to the policy implementation year. Otherwise, *post* equals 0. Therefore, CCAP can be regarded as a quasi-natural experiment.

Control variables. This study includes the following main control variables:

Energy Consumption (EC) refers to the total amount of energy utilized by a system, organization, or region for production, operation, and daily life within a specified temporal and spatial scope. In the present study, the scope of EC encompasses both primary energy sources (e.g., coal, oil, natural gas, hydropower, wind power, and solar energy) and secondary energy sources derived from conversion processes (e.g., electricity, heat, and refined petroleum products). At the urban scale, EC is defined as the aggregate energy consumption within the administrative boundary of a prefecture-level city, with the EC index obtained from the *China City Statistical Yearbook*. Previous studies have indicated that ER represents a city's total energy consumption, referring to the quantity of various energy types consumed by all societal sectors

and households during the reporting period (Pérez-Lombard et al., 2008). Total energy consumption is calculated as: terminal energy consumption + processing and conversion loss - recycled utilization + transmission and distribution loss (Chen & Chen, 2011; Emenike & Falcone, 2020). Energy consumption is usually measured in physical units and converted to standard coal equivalents based on calorific value (Jiang et al., 2025).

Urbanization Level (UL) refers to the degree to which population, land use, and economic activities are concentrated in urban areas within a given spatial and temporal scope. It is a key indicator reflecting the transformation from rural to urban societies, as well as the structural evolution of human settlements and regional development. UL fundamentally shapes a city's industrial structure (Zhang et al., 2025), infrastructural resilience (Tian & Hou, 2024), and institutional capacity (Zheng et al., 2025), all of which critically mediate the effectiveness of CCAP (Zhang et al., 2025). Highly urbanized cities are more likely to implement adaptation measures efficiently and enhance ICR through better resource mobilization and governance mechanisms (Zhang et al., 2024). Therefore, controlling for urbanization allows for a more accurate estimation of the net impact of CCAP by mitigating potential confounding effects arising from heterogeneity in urban development contexts (Lin et al., 2022). In this study, UL is primarily measured by the proportion of the urban population to the total population, expressed as a percentage. To ensure robustness, additional indicators such as the built-up area ratio and the share of secondary and tertiary industries in GDP are also considered, following common practices in urban studies. UL index is obtained from the *China City Statistical Yearbook*.

Education Spending (ES) refers to the total financial resources allocated to the education sector within a specific spatial and temporal scope. It includes government fiscal expenditures on education, such as investments in primary, secondary, and higher education, as well as expenditures on educational infrastructure, personnel, and public services. ES serves as a critical indicator of a government's commitment to human capital accumulation and social development. ES reflects the human capital investment and innovation potential of a city, both of which are crucial for enhancing adaptive capacity and industrial flexibility (Hicken & Simmons, 2008). Cities with higher education investment tend to possess a more skilled workforce and stronger R&D capabilities (Su et al., 2021), enabling industries to better absorb shocks and adjust to climate-related policy shifts (Humbatova & Hajiyeve, 2019). Therefore, controlling for ES helps isolate the true effect of CCAP by accounting for variations in endogenous resilience-building capacities across cities (Sun et al., 2019). In this study, the indicator of ES is derived from the *China City Statistical Yearbook*, which provides standardized and authoritative statistical data at the prefecture-level city scale. ES is measured as the total fiscal expenditure on education within a given administrative unit.

Capital Productivity (CPR) refers to the ratio of economic output to capital input, which reflects the efficiency of capital utilization in the production process. It is commonly expressed as GDP or value added per unit of fixed asset investment or capital stock, thereby serving as a proxy for evaluating investment efficiency and capital allocation effectiveness. In empirical studies, CPR is commonly measured by GDP (or value added) per unit of fixed asset investment or capital stock. Alternative approaches employ capital-output ratios, where lower values indicate higher capital productivity. CPR reflects the efficiency with which capital inputs are transformed into economic outputs (Cui & Du, 2025), directly influencing industrial adaptability and supply chain flexibility (Romer, 1990). Cities with higher CPR are typically more capable of absorbing policy-induced costs and reallocating resources in response to climate adaptation measures (Feng et al., 2024). Higher output indicates greater investment efficiency (Benlemlih & Bitar, 2018; Jun, 2003; Wang et al., 2025). In this

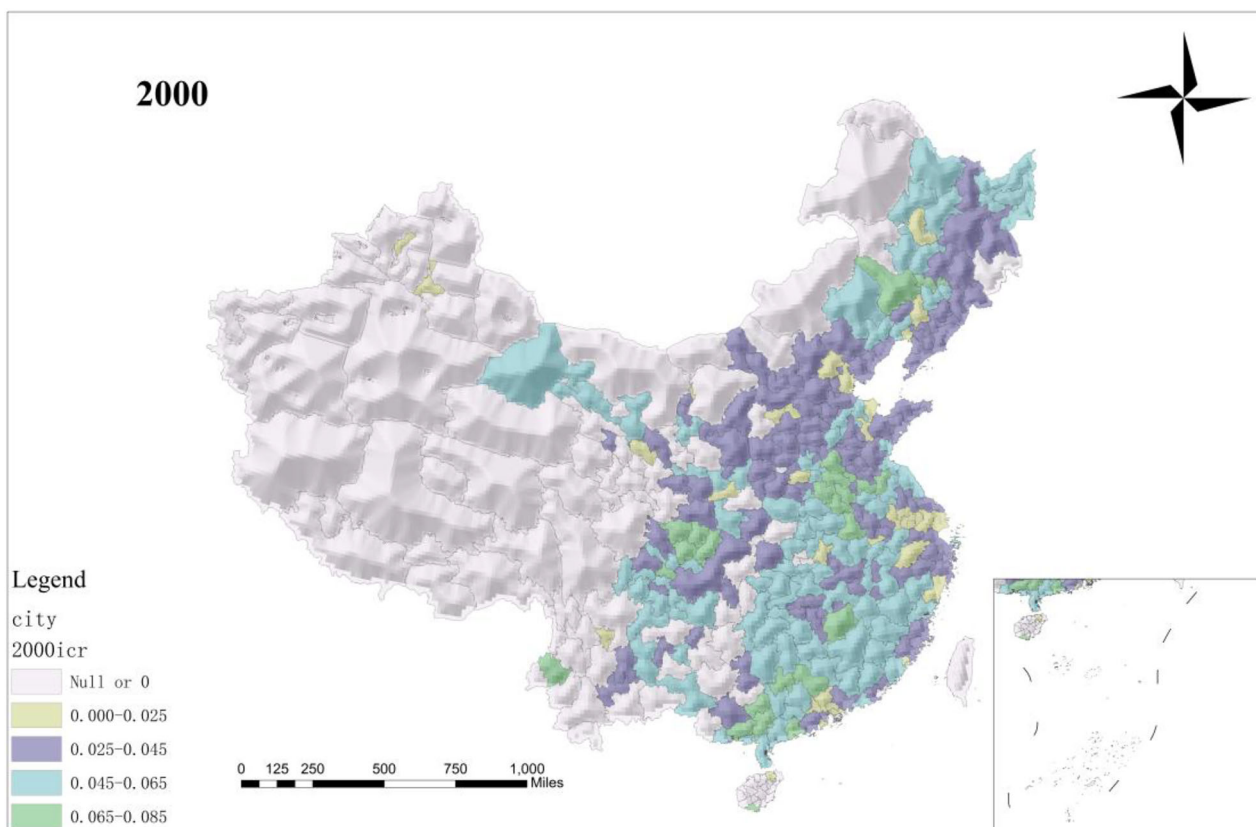


Fig. 1 ICR in 2000.

study, the CPR indicator is obtained from the *China City Statistical Yearbook*, which provides standardized statistical data on GDP and fixed asset investment at the prefecture-level city scale.

Environmental Regulation (ER) refers to the set of institutional arrangements, laws, policies, and administrative measures implemented by governments to prevent, control, and mitigate environmental pollution and ecological degradation. ER aims to balance economic development with environmental protection by influencing the behavior of firms, industries, and individuals through regulatory instruments. ER reflects the stringency of local environmental governance, which can independently shape industrial transformation dynamics and supply chain stability (Rosič et al., 2009; Su et al., 2025; Xia et al., 2022). Cities with stricter ER may experience higher compliance costs or technological upgrading, both of which can affect the responsiveness and ICR to CCAP (Zavitsas et al., 2018). Therefore, controlling for ER allows researchers to isolate the specific contribution of adaptation policies from broader regulatory pressures that simultaneously influence industrial performance (Li et al., 2025). In this study, the ER indicator is obtained from the *China Environmental Statistical Yearbook* and the *China City Statistical Yearbook*. These sources provide standardized statistical information on environmental governance, including industrial pollution control investment, fiscal expenditure on environmental protection, sewage treatment rate, and the revenues from pollution discharge fees or environmental taxes.

Empirical results

Spatial-temporal evolution analysis results of ICR. In this study, the ICR index from 2000 to 2022 is divided into four periods, each spanning seven years. The years 2000, 2007, 2014, and 2022 are selected for visual analysis of the spatial evolution of ICR. The results are presented in Fig. 1 through 4.

As shown in Fig. 1, in 2000, the average ICR of cities in the eastern region ranged from 0.045 to 0.065, while cities in the Beijing-Tianjin-Hebei region and the central region exhibited slightly lower ICR values, ranging from 0.025 to 0.045. Overall, cities in the western region exhibit lower ICR values. As shown in Fig. 2, the ICR value of certain cities in the eastern region decreased in 2007 compared to 2000, with the ICR value in some eastern coastal cities declining from 0.045–0.065 to 0.025–0.045. Like 2000, the ICR value in the western region remained relatively low in 2007. As shown in Fig. 3, the ICR values of cities in the eastern region decreased in 2014 compared to 2000, with many cities experiencing a decline from 0.045–0.065 to 0.025–0.045. Additionally, the ICR values of certain cities in the Yellow River Basin declined to 0.00–0.025. Like previous years, the ICR values in the western region remained low. As shown in Fig. 4, the spatial-temporal evolution of the ICR index in 2022 indicates that cities in Northeast China, particularly in the three eastern provinces, exhibit the highest ICR growth rates. Additionally, cities in the estuary region of the Yellow River Basin and those in the middle and lower reaches of the Yangtze River show relatively high ICR growth rates, generally exceeding those of other cities nationwide, with values ranging from 0.45 to 0.65.

The Moran's I test. Previous studies have demonstrated that ICR values differ across regions due to resource mobility and energy sharing (Malik & Ford, 2024; Pietrapertosa et al., 2018). Prior to measuring the SDM-DID model of CCAP's impact on ICR, this study conducted a spatial correlation analysis of the ICR values for 278 selected cities from 2000 to 2022 using models (1) and (2). The Moran's I values are presented in Table 1.

As can be seen from Table 1, all the p-values of Moran's I are significant from 2000 to 2022, which proves that the ICR values between regions have obvious autocorrelation. This test result

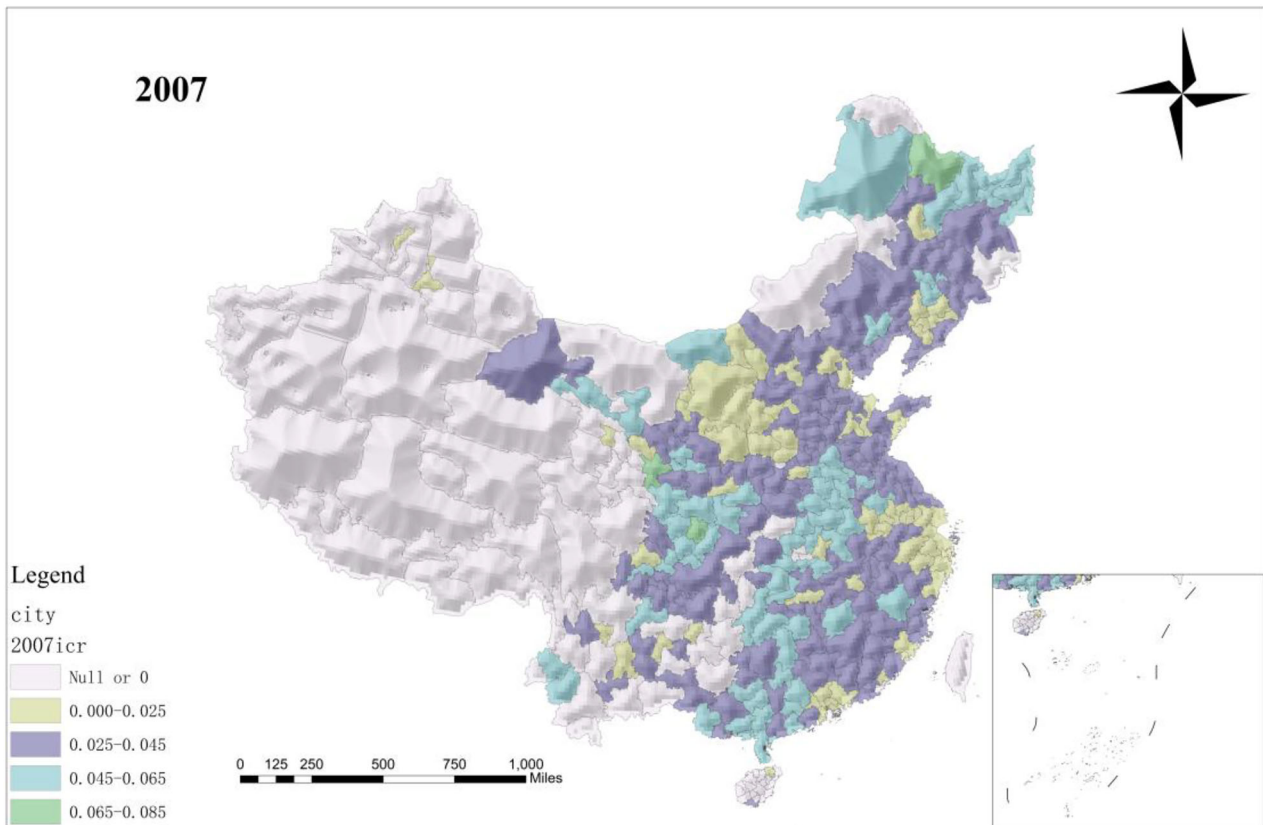


Fig. 2 ICR in 2007.

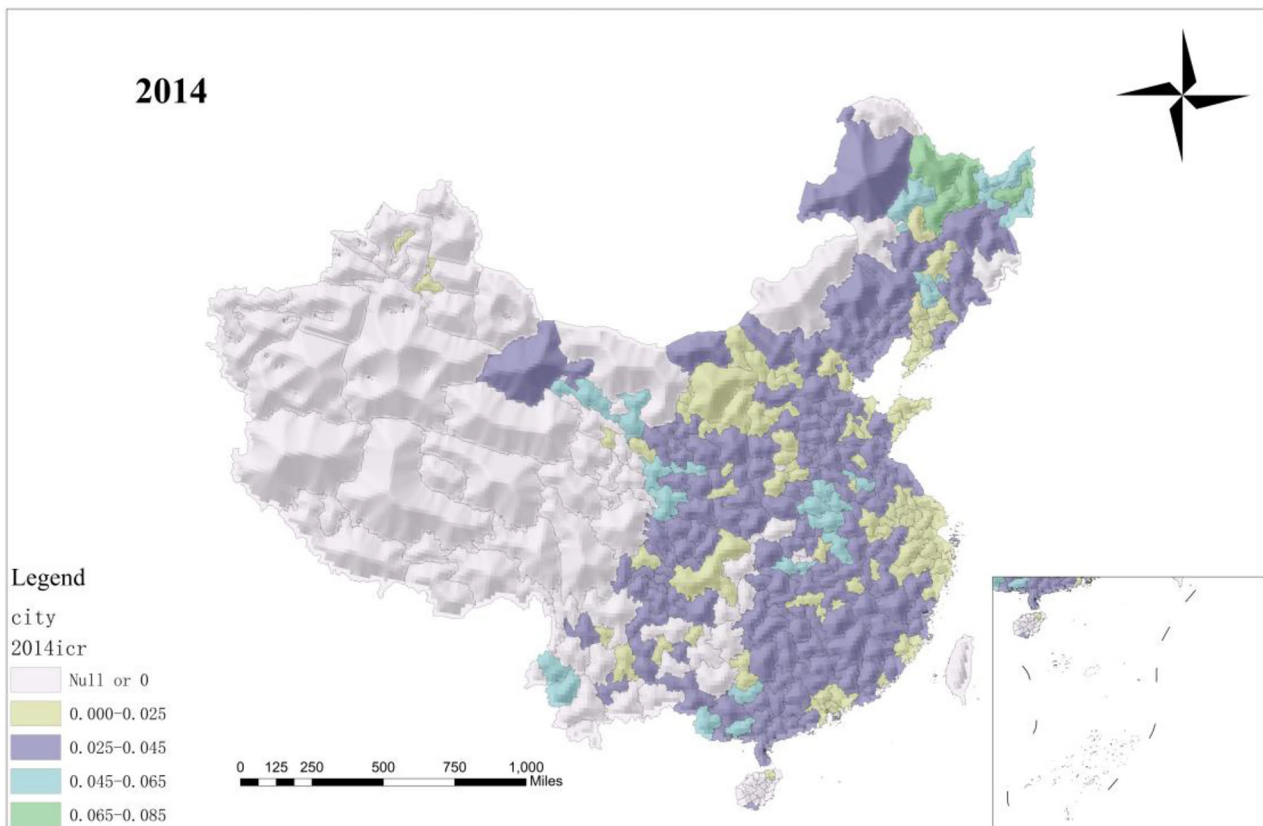


Fig. 3 ICR in 2014.

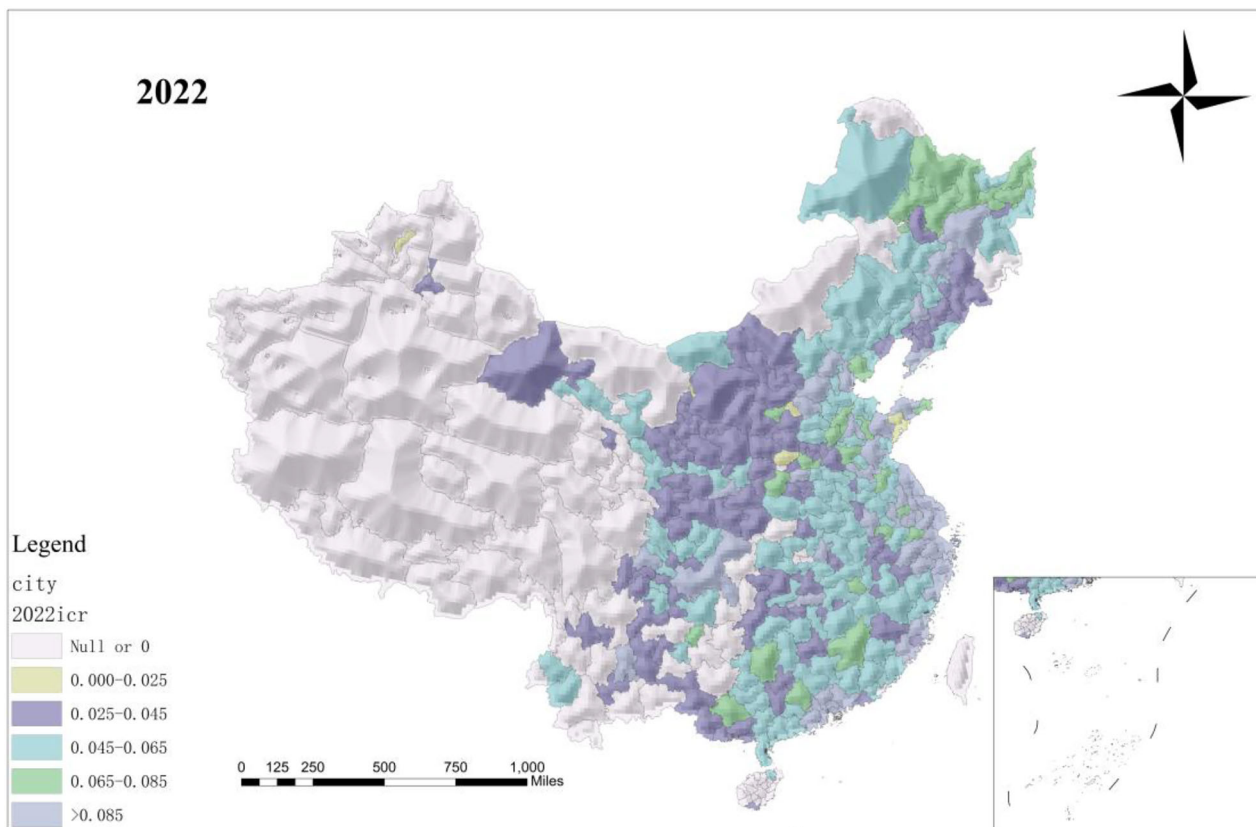


Fig. 4 ICR in 2022.

Table 1 Moran's I value.

Year	I	E(I)	Sd(I)	Z	P-value
2000	0.046	-0.004	0.006	7.985	0.000
2001	0.046	-0.004	0.006	7.998	0.000
2002	0.055	-0.004	0.006	9.439	0.000
2003	0.059	-0.004	0.006	10.117	0.000
2004	0.070	-0.004	0.006	11.823	0.000
2005	0.074	-0.004	0.006	12.454	0.000
2006	0.074	-0.004	0.006	12.541	0.000
2007	0.083	-0.004	0.006	13.855	0.000
2008	0.084	-0.004	0.006	14.156	0.000
2009	0.075	-0.004	0.006	12.717	0.000
2010	0.070	-0.004	0.006	11.810	0.000
2011	0.072	-0.004	0.006	12.195	0.000
2012	0.074	-0.004	0.006	12.603	0.000
2013	0.077	-0.004	0.006	13.061	0.000
2014	0.088	-0.004	0.006	14.814	0.000
2015	0.093	-0.004	0.006	15.700	0.000
2016	0.094	-0.004	0.006	15.856	0.000
2017	0.062	-0.004	0.006	11.087	0.000
2018	0.073	-0.004	0.006	12.884	0.000
2019	0.066	-0.004	0.006	11.902	0.000
2020	0.069	-0.004	0.006	12.249	0.000
2021	0.066	-0.004	0.006	11.753	0.000
2022	0.065	-0.004	0.006	11.636	0.000

supports the adoption of SDM-DID model to carry out follow-up research.

Spatial overflow distance analysis. This study uses the CCAP pilot city as the center and defines the origin as the pilot city. Distances are expanded outward in 25 km increments ($S = 25$),

with measurements taken at $S = 25, S = 50, S = 75, \dots, S = 400$ to evaluate the spatial spillover degree at different distances. The calculation formula is provided in model (6), and the regression results for the spatial spillover effect distances are presented in Fig. 5.

As shown in Fig. 5, the influence of ICR values in areas adjacent to CCAP pilot cities follows a pattern of “enhanced - weakened - enhanced - weakened - steady.” Specifically, the ICR effects of CCAP on areas surrounding the pilot cities are as follows: (1) A significant positive spatial spillover effect is observed within the range of 0–25 km. (2) A significant negative spatial spillover effect is observed within the range of 25–50 km. (3) A significant positive spatial spillover effect is observed within the range of 50–75 km. (4) A positive spillover effect exists within the range of 75–100 km, but its intensity diminishes. (5) ICR exhibits a negative spatial spillover effect within the distance of 100–150 km from CCAP pilot cities. (6) The spatial spillover effect of CCAP on ICR remains relatively stable in areas beyond 150 km from pilot cities.

The observed pattern—where CCAP exhibits a positive effect on ICR within 0–25 km, a negative effect within 25–50 km, and a renewed positive impact beyond 75 km—aligns well with the theoretical framework of agglomeration economies and spatial externalities.

Specifically, cities located within 0–25 km of CCAP pilot areas tend to benefit from the spillover effects of green infrastructure development, the clustering of environmentally-friendly industrial enterprises, and improvements in green transportation systems. These developments collectively enhance the regional industrial environment and facilitate the upgrading of local supply chains, thereby increasing the ICR of nearby cities.

However, in the 25–50 km range, a siphoning effect becomes evident. CCAP pilot cities, often prioritized in terms of policy

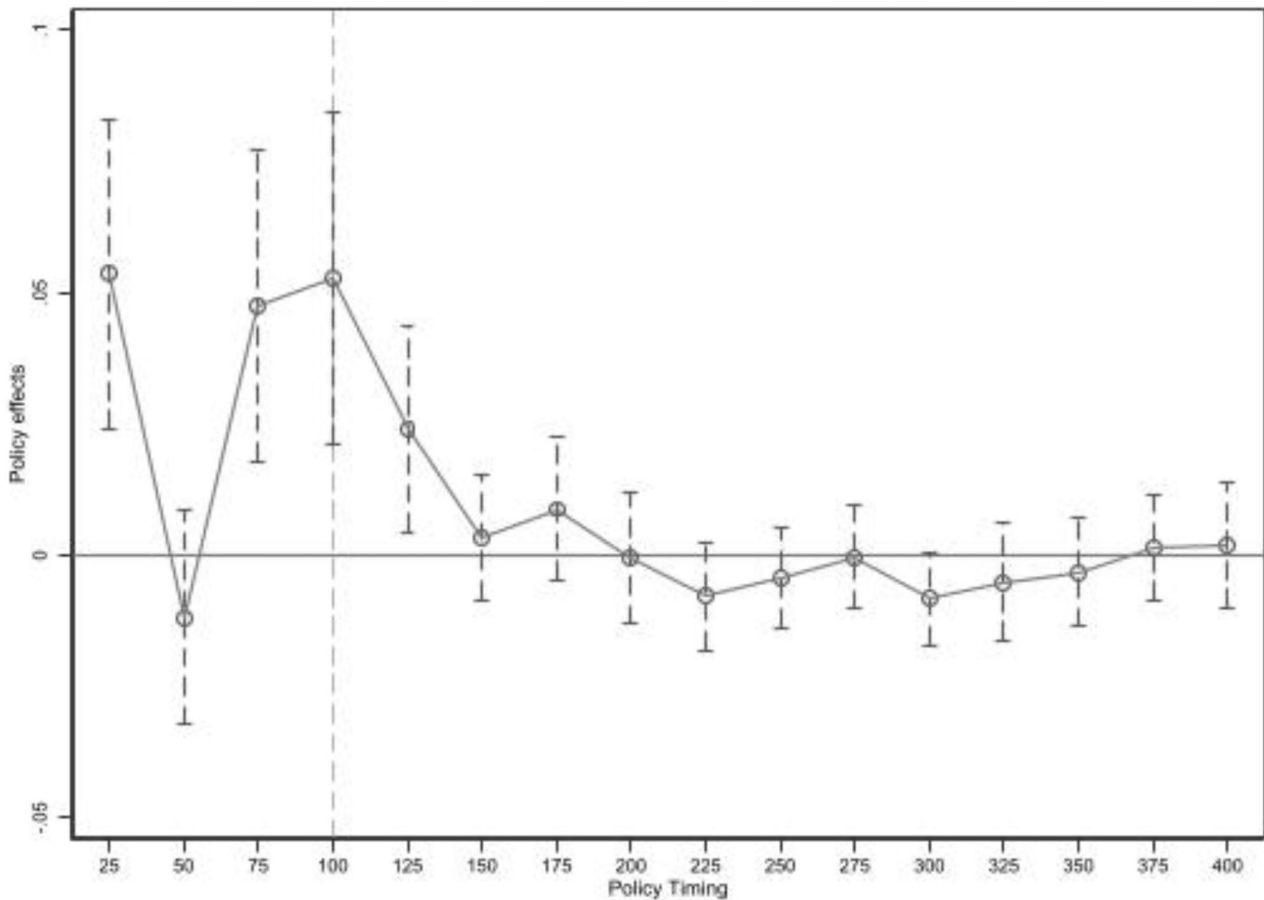


Fig. 5 Results of spatial spillover distance.

incentives, fiscal transfers, and environmental investment, may draw resources—such as talent, capital, and infrastructure—away from adjacent non-pilot cities. This competitive imbalance can suppress industrial upgrading in these surrounding areas, resulting in a relative decline in ICR.

At distances between 75–100 km, the negative externalities associated with resource competition begin to dissipate. Instead, broader network effects—such as supply chain reorganization, policy emulation, and environmental standard diffusion—become dominant, leading to a secondary increase in ICR.

Finally, the influence of CCAP becomes negligible or even vanishes beyond a certain distance threshold. As shown in Fig. 5, the farther a city is from the CCAP pilot zone, the weaker the spatial policy externality becomes, indicating a geographical limitation in the diffusion of climate adaptation benefits.

These findings underscore the nonlinear and distance-sensitive nature of CCAP’s spatial spillover, which has important implications for regional coordination and multi-scale climate governance strategies.

Benchmark regression results

The regression results of M-DID model. In this study, formula (4) serves as the baseline regression model for M-DID, with the variables EC, UL, ER, ES, and CPR controlled. A total of 6394 observations from 2000 to 2022 are analyzed, using the policy effect of CCAP on ICR as the test basis. A quasi-natural experiment based on M-DID is conducted, and the results are presented in Table 2.

Table 2 The regression results of M-DID.	
VARIABLES	ICR
DID	0.039*** (2.65)
EC	-0.038*** (-5.38)
UL	0.128** (2.34)
ER	-0.000*** (-3.99)
ES	0.028*** (3.70)
CPR	0.018* (1.84)
Constant	0.913*** (3.78)
Observations	6394
Time fixed effects	YES
City fixed effects	YES
Number of id	278
R-squared	0.307

Robust t-statistics in parentheses.
***p < 0.01, **p < 0.05, *p < 0.1.

The regression results of SDM-DID. In this study, formula (5) served as the benchmark regression model for SDM-DID, following the same approach as applied for M-DID. The variables EC, UL, ER, ES, and CPR were controlled, and the results are presented in Table 3.

As shown in Table 3, CCAP significantly improves the ICR index of a city. However, the relationship is weak, with a reported value of only 0.042. Secondly, the implementation of CCAP policy in pilot cities exhibits a positive spillover effect on the ICR index of neighboring cities. Thirdly, EC and ER exhibit stronger inhibitory effects, as the implementation of environmental regulations and related policies increases urban ICR’s dependence on government interventions, thereby weakening the ICR index. Conversely, UL and ES significantly enhance the positive spillover effect of CCAP on neighboring areas of ICR cities, potentially indicating that free market competition contributes to improving the ICR index and spatial spillover effects (Buurman & Babovic, 2016; Suhaeb et al., 2024).

Heterogeneity Test

Scientific and technological level. Previous studies have highlighted that the improvement of urban ICR is influenced by various factors, with the Tech level being closely associated with the ICR index (Carlson et al., 2024; Liu & Chen, 2024). To specifically identify the impact of Tech as a heterogeneity factor on CCAP and ICR mechanisms, the average value of the Tech index in 2014 was used to distinguish heterogeneous groups.

In Table 4, the first group represents less than Tech’s average in 2014, and this group of data is named “Low-Tech”. The second group represents more than the average value of Tech in 2014, and this group of data is named “High-Tech”. The regression results of heterogeneity test are shown in Table 4. The results of heterogeneity test with Tech as the grouping standard show that High-Tech helps to enhance the influence of CCAP on ICR, and meanwhile, the spatial spillover is also improved.

Gross regional product per capita. GPP refers to the total economic output of a region divided by its average resident population over a specific period. GPP reflects the average economic value generated per person in a region and serves as a key indicator of regional economic development (Dubovik et al., 2024). Previous studies have identified the GPP index as a significant factor influencing the implementation of regional environmental policies (Li et al., 2022). Regions with higher per capita GPP possess greater financial resources to optimize supply chains, leading to stronger ICR. Therefore, to investigate the potential heterogeneity of GPP on the mechanism, this study used the average GPP value in 2014 as the criterion for classifying high and low groups, as shown in Table 5.

As shown in Table 5, High-GPP regions are more effective in improving the ICR level in cities during the implementation of CCAP. Meanwhile, the heterogeneity test results for High-GPP indicate a stronger spatial spillover effect. This suggests that in regions with higher GPP, CCAP-induced improvements in ICR positively influence neighboring cities. In contrast, in low-GPP regions, the heterogeneity of the influence mechanism is weaker, and the spatial spillover effect on ICR in neighboring cities is limited.

Table 3 The regression results of SDM-DID.

VARIABLES	Main	Wx	Spatial	Variance
DID	0.042*** (17.46)	0.355*** (7.76)		
EC	-0.039*** (-15.89)	0.022* (1.65)		
UL	0.123*** (18.26)	-0.077* (-1.67)		
ER	-0.000*** (-2.80)	-0.000*** (-2.76)		
ES	0.028*** (10.23)	-0.093*** (-3.65)		
CPR	0.017*** (5.67)	0.026 (1.13)		
Time fixed effects	YES	YES		
City fixed effects	YES	YES		
Rho			0.918*** (55.42)	
Sigma2_e				0.001*** (56.31)
R-squared	0.106	0.106	0.106	0.106

Robust t-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1.

Table 4 Heterogeneity test result of Tech.

	Low-Tech				High-Tech			
	Main	Wx	Spatial	Variance	Main	Wx	Spatial	Variance
DID	0.005*** (4.81)	-0.060*** (-3.64)			0.052*** (9.34)	0.252*** (3.95)		
EC	-0.007*** (-6.72)	0.015*** (2.74)			-0.075*** (-10.01)	0.090** (2.22)		
UL	0.008*** (2.68)	-0.013 (-0.55)			0.286*** (16.05)	-0.373*** (-4.77)		
ER	-0.000*** (-2.66)	-0.000 (-1.49)			-0.000 (-0.71)	0.000 (0.43)		
ES	0.012*** (9.29)	-0.072*** (-7.25)			0.042*** (6.34)	-0.205*** (-4.52)		
CPR	0.001 (0.53)	0.030*** (3.73)			0.020** (2.24)	0.116** (2.06)		
Time fixed effects	YES	YES			YES	YES		
City fixed effects	YES	YES			YES	YES		
Rho			0.125 (1.30)				0.676*** (12.43)	
Sigma2_e				0.000*** (46.61)				0.002*** (31.84)
R-squared	0.032	0.032	0.032	0.032	0.085	0.085	0.085	0.085

Robust t-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1.

Table 5 Heterogeneity test result of GPP.

	Low-GPP				High-GPP			
	Main	Wx	Spatial	Variance	Main	Wx	Spatial	Variance
DID	0.004*** (3.79)	-0.035** (-2.33)			0.061*** (12.24)	0.191*** (4.20)		
EC	-0.005*** (-5.13)	0.011** (2.12)			-0.057*** (-9.29)	0.004 (0.13)		
UL	0.001 (0.16)	0.046 (1.55)			0.127*** (11.60)	-0.034 (-0.63)		
ER	-0.000* (-1.91)	-0.000 (-0.99)			-0.000 (-1.12)	-0.001** (-2.41)		
ES	0.009*** (6.49)	-0.048*** (-4.69)			0.027*** (4.82)	-0.138*** (-3.61)		
CPR	0.001 (1.05)	0.054*** (5.25)			0.048*** (5.66)	-0.152*** (-3.70)		
Time fixed effects	YES	YES			YES	YES		
City fixed effects	YES	YES			YES	YES		
rho			0.464*** (5.60)				0.721*** (15.83)	
sigma2_e				0.000*** (44.11)				0.002*** (34.76)
R-squared	0.003	0.003	0.003	0.003	0.193	0.193	0.193	0.193

Robust t-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1.

The influence mechanism of CCAP on ICR

Rural Revitalization Index. Rural Revitalization Index (RRI) encompasses five dimensions: industrial revitalization, ecological livability, rural culture and civilization, effective governance, and prosperity. It consists of 5 primary indicators, 14 secondary indicators, and 34 tertiary indicators. It aims to gradually develop and establish a universally applicable evaluation system for rural revitalization. The influence mechanism by which CCAP enhances ICR via RRI.

Therefore, the following empirical tests are conducted to verify H2. RRI is used to gauge the level of rural revitalization. This index reflects the degree of urban-rural integration, infrastructure, and basic public service levels in both urban and rural regions. The indicator system for the rural revitalization strategy, based on the overall requirements of these dimensions of indicators, promotes the revitalization of rural industries, talents, the environment, and other aspects, accelerates the pace of agricultural modernization, develops rural industries, and builds beautiful, ecological, and livable rural areas. Referring to the research of Xu et al., the indicators for rural revitalization are calculated from five dimensions: prosperous industries, pleasant living environment, civilized rural customs, effective governance, and prosperous life (Xu, 2022). The detailed analysis results are presented in Table 6.

Table 6 Influence mechanism analysis of RRI.

VARIABLES	RRI			
	Main	Wx	Spatial	Variance
DID	0.185*** (14.99)	1.425*** (5.94)		
EC	-0.070*** (-5.62)	0.070 (1.01)		
UL	0.004 (0.12)	-1.312*** (-5.49)		
ER	-0.000 (-0.79)	0.001 (0.65)		
ES	0.035** (2.44)	0.195 (1.48)		
CPR	0.125*** (8.06)	-0.594*** (-5.08)		
Time fixed effects	YES	YES		
City fixed effects	YES	YES		
Rho			-0.640*** (-4.62)	
Sigma2_e				0.025*** (56.40)
R-squared	0.005	0.005	0.005	0.005

Robust t-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1.

Digital Economy Level. Digital Economy Level (DEL) refers to taking data resources as the key production factors and modern information networks as the main carrier to improve efficiency and optimize economic structure through the effective use of information and communication technologies (Suprayitno et al., 2024). It covers e-commerce, mobile payment, cloud computing, Internet of Things, artificial intelligence, and other fields, and promotes the intellectualization and networking of productivity (Liu, Yuan, et al., 2025). Some studies have pointed out that the development of DEL has promoted the integration of traditional industries and science and technology information technology, and after science and technology empowers industrial industries, the supply chain structure has been updated, and the ability to

cope with climate risks and resist natural disasters has been enhanced (Zhang et al., 2021).

Therefore, to verify H3, CCAP enhances urban ICR by affecting the level of DEL. In this study, the level of internet development is employed as the core variable to construct the regional DEL (Pan et al., 2022; Xia et al., 2024). The internet development dimension encompasses multiple indicators, including the Level of Internet Adoption (Internet Penetration Rate Per 100 Individuals), Relevant Professionals (The share of Personal Engaged in Computer Services and Software), Associated Outputs (Telecommunications Services Per Person) and The Rate of Mobile Phone Adoption (Mobile Phone Subscriber Density Per 100 Individuals). To quantify the overall DEL, this

Table 7 Influence mechanism analysis of DEL.

VARIABLES	DEL			
	Main	Wx	Spatial	Variance
DID	0.017*** (17.35)	0.103*** (5.54)		
EC	-0.007*** (-6.73)	0.004 (0.80)		
UL	0.004 (1.37)	-0.087*** (-4.74)		
ER	-0.000 (-0.17)	-0.000 (-0.06)		
ES	0.004*** (3.54)	-0.001 (-0.10)		
CPR	0.010*** (8.68)	-0.040*** (-4.48)		
Time fixed effects	YES	YES		
City fixed effects	YES	YES		
Rho			-0.246** (-2.00)	
Sigma2_e				0.000*** (56.52)
R-squared	0.001	0.001	0.001	0.001

Robust t-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1.

Table 8 Robustness test results of M-DID.

VARIABLES	Main	Wx	Spatial	Variance
M-DID	0.029*** (15.05)	0.027*** (8.43)		
EC	-0.023*** (-14.62)	-0.018*** (-6.97)		
UL	0.078*** (15.17)	0.023*** (3.09)		
ER	-0.000*** (-3.57)	-0.000 (-1.52)		
ES	0.011*** (5.07)	0.025*** (7.23)		
CPR	0.014*** (6.32)	-0.009** (-2.53)		
Time fixed effects	YES	YES		
City fixed effects	YES	YES		
Rho			0.498*** (51.28)	
Sigma2_e				0.001*** (54.20)
R-squared	0.018	0.018	0.018	0.018

Robust t-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1.

study applies the entropy-weighted TOPSIS method, which integrates and weights the aforementioned factors to generate a comprehensive composite index. The following empirical tests are made as Table 7.

Empirical test
Robustness test

Traditional robustness test. To verify the reliability of CCAP’s influence mechanism on ICR, this study conducted robustness tests on the empirical results, and the findings are reported below. Table 8 presents the robustness regression results of the traditional DID model. The table indicates that the M-DID result of CCAP on ICR is positive, with a value of 0.029. Furthermore, the

Table 9 Robustness test results of first-order inverse matrix.

VARIABLES	Main	Wx	Spatial	Variance
SDM-DID	0.038*** (16.78)	0.019** (2.02)		
EC	-0.035*** (-14.05)	0.016*** (3.19)		
UL	0.121*** (18.50)	-0.077*** (-4.74)		
ER	-0.000** (-2.48)	-0.000** (-2.53)		
ES	0.031*** (11.47)	-0.033*** (-4.70)		
CPR	0.015*** (5.16)	-0.002 (-0.22)		
Time fixed effects	YES	YES		
City fixed effects	YES	YES		
Rho			0.629*** (33.67)	
Sigma2_e				0.001*** (55.64)
R-squared	0.025	0.025	0.025	0.025

Robust t-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1.

small regression coefficient suggests that the findings from the traditional regression model are robust.

Inverse matrix robustness test. Additionally, a second robustness test was performed on the influence mechanism of CCAP on ICR by altering the matrix weights, with the results presented in Table 9. The robustness test results of the first-order inverse matrix indicate that the regression coefficient of CCAP on the SDM-DID of ICR is 0.038, and it is positive. These results suggest that: (1) The effect of CCAP on ICR is both positive and significant. (2) CCAP exhibits a positive spatial spillover effect on ICR. (3) The small variation in the regression coefficient confirms the robustness of the findings.

Control the impact of other policies on ICR. Smart City Policy (SCP) aims to develop more scientific and efficient urban management while enhancing the quality of life. Supported by information and communication technologies, SCP improves urban operational efficiency and public services through transparent information acquisition, secure data transmission, and effective scientific processing. It aims to create a new form of urban development by establishing a low-carbon urban ecosystem (Huang et al., 2023). With the rapid advancement of science and technology, smart city policies have emerged as a hallmark of modern urban information development. Therefore, it is essential to account for and control the influence of SCP on ICR when analyzing the impact mechanism of CCAP on ICR. The experimental results are presented in Table 10.

Broadband China Policy (BCP) facilitates the informatization of the urban industrial chain. Represented by “Internet Plus”, BCP has created new growth opportunities for the development of digital economies of scale within urban ICR, driven by the mutual promotion of future industries and technological innovation (Wang et al., 2024). Within this policy context, BCP contributes to the development of the urban industrial economy. To ensure the accuracy of CCAP’s SDM-DID quasi-natural experiment results on ICR, further measures were taken. At the conclusion of the quasi-natural experiment, this study conducted an empirical test to control the impact of BCP. The results are presented in Table 11.

Table 10 Control the influence of SCP.

VARIABLES	SCP			
	Main	Wx	Spatial	Variance
SCP	0.001 (0.60)	-0.058*** (-3.24)		
DID	0.042*** (17.56)	0.388*** (8.28)		
EC	-0.038*** (-15.81)	0.024* (1.76)		
UL	0.123*** (18.36)	-0.112** (-2.37)		
ER	-0.000*** (-2.77)	-0.001*** (-2.92)		
ES	0.029*** (10.30)	-0.096*** (-3.77)		
CPR	0.017*** (5.63)	0.018 (0.79)		
Time fixed effects	YES	YES		
City fixed effects	YES	YES		
Rho			0.916*** (53.71)	
Sigma2_e				0.001*** (56.30)
R-squared	0.098	0.098	0.098	0.098

Robust t-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1.

Table 11 Control the influence of BCP.

VARIABLES	BCP			
	Main	Wx	Spatial	Variance
BCP	0.020*** (12.04)	0.099*** (4.68)		
DID	0.039*** (16.47)	0.250*** (5.28)		
EC	-0.036*** (-15.12)	0.003 (0.26)		
UL	0.118*** (17.70)	0.022 (0.48)		
ER	-0.000*** (-2.86)	-0.000** (-2.47)		
ES	0.024*** (8.68)	-0.110*** (-4.32)		
CPR	0.015*** (4.98)	0.032 (1.43)		
Time fixed effects	YES	YES		
City fixed effects	YES	YES		
Rho			0.915*** (53.33)	
Sigma2_e				0.001*** (56.32)
R-squared	0.101	0.101	0.101	0.101

Robust t-statistics in parentheses ***p < 0.01, **p < 0.05, *p < 0.1.

Placebo test. To further assess the robustness of our results, we conducted a placebo test as part of our robustness checks. Specifically, we employed a permutation test to randomize the core explanatory variable, DID, thereby examining the sensitivity of our findings to random variations. This method constructs a series of “pseudo-datasets” that retain the original sample’s covariate distributions but, by design, cannot reflect the actual policy effect.

In the empirical implementation, we utilized Stata’s permute command, setting the number of repetitions to 500. In each

iteration, we randomly permuted the DID variable, then re-estimated the spatial difference-in-differences model (SDM). To ensure that the observed results were solely attributable to the randomization of the DID variable rather than differences in model specification, we kept other control variables (such as EC, UL, ER, ES, and CPR) and the spatial weight matrix (based on the first-order inverse distance matrix) unchanged.

Figure 6 demonstrates that the test results fluctuated within the range of (-0.01, 0.01), confirming that the study successfully passed the placebo test. This process generated 500 virtual estimates under a “no policy intervention” scenario, forming a distribution of pseudo-estimates. By comparing the real estimate against this distribution, we can assess whether the empirical results are driven by random factors, thus providing additional verification of the robustness of our main findings.

Parallel trend test. Before applying the MDID model to evaluate the impact of the CCAP on ICR and its underlying mechanisms, it is critical to verify the assumption of parallel trends. Specifically, to ensure the reliability of the results, it is essential to confirm that the ICR trends in the treatment group (pilot cities) and the control group (non-pilot cities) are similar prior to the implementation of the CCAP. According to the parallel trends assumption, the two groups should exhibit consistent trends over time before the policy intervention. If this assumption is violated, any estimated policy effects may be biased due to pre-existing differences, leading to inaccurate conclusions.

To address this, we performed a parallel trend test based on Eq. (9), with the results presented in Fig. 7. The test results show that, prior to the implementation of CCAP, there were no significant differences in ICR levels between pilot and non-pilot cities. This suggests that, before the policy intervention, the ICR trends for both groups were broadly similar, in line with the parallel trends assumption. Furthermore, in the year of implementation, the ICR effects remained comparable across both groups, further supporting the notion of parallel trends and indicating that the policy did not generate significant immediate effects in the short term.

$$ICR_{i,t+1} = \alpha + \sum_{k=-7, k \neq 1}^4 \beta_k Policy_{i,t+k} + \gamma Controls_{i,t} + \varphi Controls_{i,t} + \tau_t + \varphi_i + \varepsilon_{t+1} \tag{9}$$

Where denotes the ICR of the city at time. indicates policy treatment variables. refers to control variables. and denotes individual fixed effects and time fixed effects, respectively. stands for the error term.

It is worth noting that in the year when the policy was implemented, CCAP showed a significant positive impact on ICR, with the regression coefficient fluctuating upward. Although positive effects began to emerge in the first year after implementation, these effects were not sustainable. On the contrary, over time, they persist and gradually intensify, which indicates the medium-term dynamic impact of this policy.

The results of the Propensity Score Matching Test. Propensity Score Matching is conducted to reduce selection bias in observational studies by matching treated and control units with similar characteristics, thereby approximating random assignment and improving the validity of causal effect estimates. Figure 8 shows the results of the PSM test.

Conclusions and policy recommendations

Main conclusions and research contributions. The main contents of this paper are as follows: First, the study develops an ICR

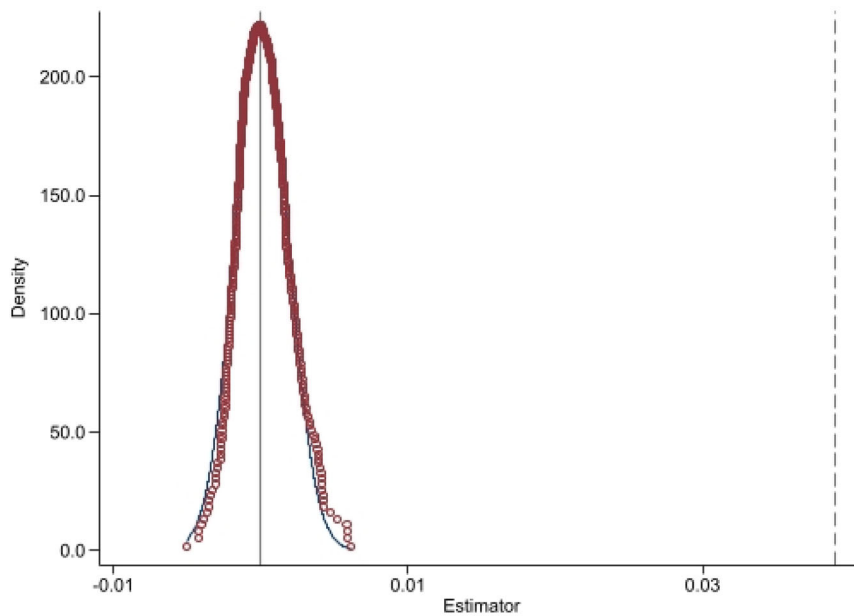


Fig. 6 Results of placebo test.

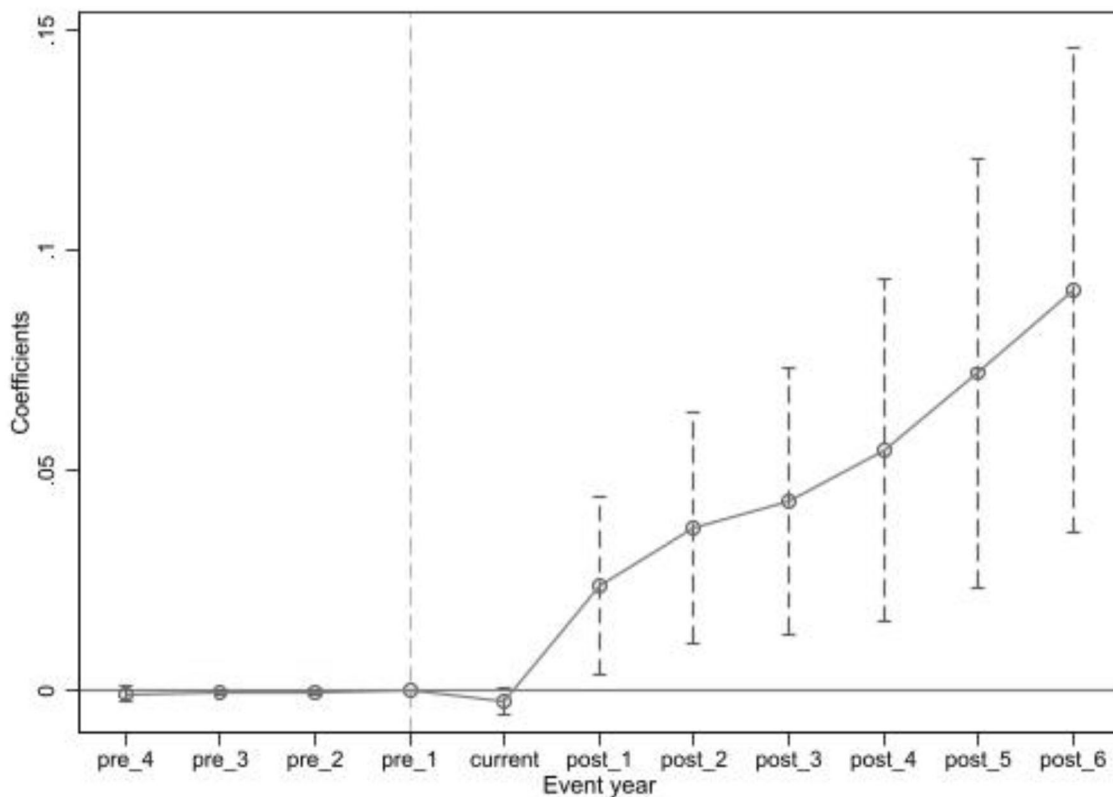


Fig. 7 Results of parallel trend test.

index system and applies the HHI method to measure the ICR index of 278 Chinese cities from 2000 to 2022. Secondly, the study considers CCAP pilot city construction as a quasi-natural experiment and applies the SDM-DID method to evaluate whether the implementation of CCAP improved the ICR levels of cities. Additionally, spatial-temporal evolution analysis was employed to evaluate the spillover effects between CCAP and ICR, as well as to identify heterogeneity factors, such as the level of science and technology and GPP. Thirdly, the paper

investigates the influence mechanism of the RRI and DEL as mediating variables affecting the relationship between CCAP and ICR. Finally, the paper controls the SCP and the BCP as potential influencing factors on CCAP's impact on ICR.

The main findings of this paper are as follows: (1) CCAP positively and directly enhances urban ICR while exerting a positive spatial spillover effect on the ICR of neighboring cities. (2) The RRI and the level of the DEL directly and positively influence the enhancement of urban ICR. The study further

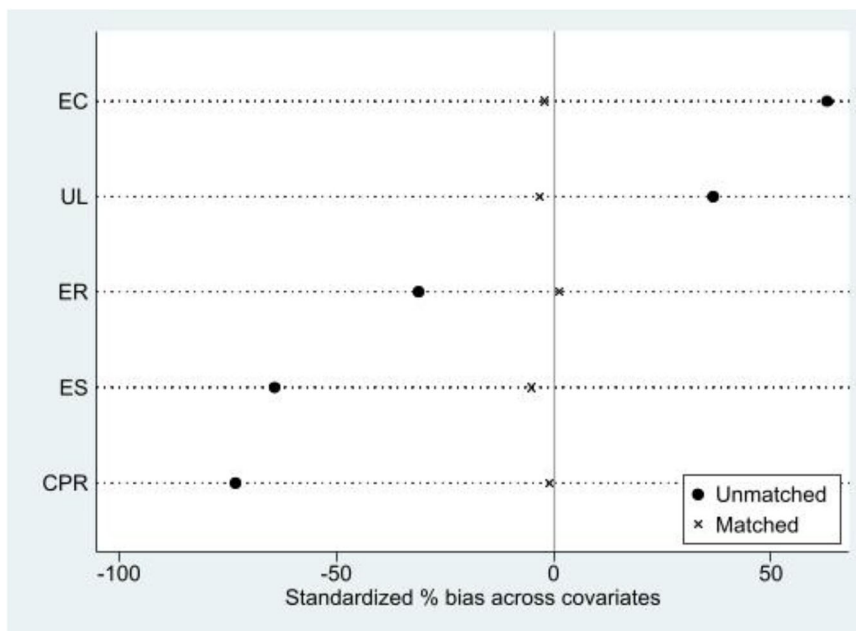


Fig. 8 The results of propensity score matching test.

confirms that the impact of CCAP on improving ICR is independent of smart city policies and the BCP. (3) The level of Tech and GPP exhibits heterogeneous effects on ICR in neighboring cities. Compared to cities with lower levels of science and technology, those with higher levels exhibit a greater enhancement effect on the ICR of neighboring cities. Similarly, cities with higher GPP exert a stronger impact on the ICR of neighboring cities compared to those with lower GPP.

This study offers several key contributions to the existing literature on CCAP and ICR:

First, although the DID method is well-established in policy evaluation research, its application to assess the causal relationship between CCAP and ICR remains limited. By leveraging DID, this study identifies the temporal dynamics of policy effects and provides robust empirical evidence on the effectiveness of CCAP in enhancing ICR—an area that has received scant attention in prior empirical studies.

Second, the study introduces a novel spatial perspective by quantifying the spatial spillover distance of CCAP’s effects on ICR. While previous research has acknowledged the possibility of spatial externalities, few have attempted to systematically measure the spatial decay or transmission range of such policy effects. By doing so, this research enriches the spatial econometric literature and provides actionable insights for regional policy coordination and spatial governance.

Third, in contrast to most existing studies that rely on provincial-level panel data, this study adopts a more granular dataset at the prefecture-level city scale, covering 278 Chinese cities over a 23-year period. This refined spatial resolution allows for a more precise assessment of localized policy effects and spillover mechanisms. As a result, the study not only confirms the direct impact of CCAP on ICR within cities but also reveals the heterogeneous spillover patterns across neighboring urban areas.

Policy recommendations. Building upon the empirical findings, this study proposes the following targeted and practical policy recommendations:

Integrate CCAP with context-specific rural and digital strategies to enhance ICR. This study confirms that CCAP improves ICR

through two key mediating channels: rural revitalization and digital economy development. Therefore, policy design should emphasize the coordinated implementation of CCAP with regionally differentiated strategies: In rural areas, CCAP should be embedded within rural revitalization plans by investing in climate-resilient agricultural supply chains, green infrastructure, and decentralized clean energy systems. Local governments should also strengthen financial and technical support for rural SMEs to upgrade their production processes in line with adaptation goals. In urban areas, digital infrastructure and platforms (e.g., IoT-enabled logistics, AI-based supply chain monitoring) should be prioritized to amplify CCAP effectiveness. Policies such as tax incentives or innovation grants can be used to promote digital adaptation technologies in high-emission industries. Importantly, CCAP should not function as a standalone policy but should be interlocked with spatially differentiated development strategies, enhancing its systemic contribution to ICR across diverse regions.

Tailor CCAP design based on regional technological capacity and economic development levels. The study identifies heterogeneous effects: regions with High-Tech and High-GPP derive greater benefits from CCAP in terms of both direct and spillover effects on ICR. Policymakers should therefore: Prioritize CCAP pilot expansion in high-tech cities to accelerate innovation diffusion through supply chains. Encourage cross-regional partnerships between High-Tech/High-GPP and low-resource cities via inter-city technology transfer programs and joint industrial clusters, reducing resilience gaps. Introduce adaptive subsidies or differentiated investment models based on local absorptive capacity and resilience thresholds.

Manage spatial spillover and siphoning effects through coordinated regional planning. The study finds that CCAP generates positive spatial spillovers within a moderate distance (0–25 km), but may cause resource siphoning in nearby regions (25–50 km) and loses efficacy beyond 100 km. To address these dynamics: Adjacent non-pilot cities should be supported through shared infrastructure investments (e.g., regional logistics hubs, interoperable industrial data platforms) to capture spillover benefits. Talent and

capital siphoning can be mitigated by creating cross-jurisdictional labor mobility agreements and equitable financing frameworks to prevent over-concentration of resources in pilot zones. Establish a climate-adaptive urban network system—with dynamic feedback mechanisms—that facilitates data sharing, emergency response coordination, and industrial cooperation across regions. These recommendations aim to ensure that CCAP not only strengthens resilience locally but also promotes balanced and regionally integrated industrial adaptation.

Limitations and future research. Despite its novel contributions, this study has several limitations. First, the measurement of CCAP intensity and ICR relies on proxy indicators derived from policy documents and statistical data, which may not fully capture the multidimensional and dynamic nature of resilience, particularly firm-level adaptation strategies. Second, although spatial econometric techniques and robustness checks were applied, potential endogeneity—such as reverse causality or omitted variable bias—cannot be entirely ruled out. Cities with stronger resilience may be more capable of implementing effective CCAP, complicating causal inference. Third, the analysis of underlying mechanisms is limited to macro-level mediators such as RRI and DEL. Important meso-level factors, including local governance capacity and institutional variations in policy implementation, remain unexamined.

Building upon the limitations identified in this study, several avenues merit further exploration. First, future research should refine the measurement of ICR by incorporating micro-level data, such as firm-level surveys, supply chain disruptions, and real-time adaptation behaviors. This would enable a more nuanced understanding of how resilience manifests across sectors and regions. Second, addressing endogeneity more robustly—through quasi-experimental designs, instrumental variable approaches, or natural experiments—could strengthen causal claims regarding the impact of CCAP. Third, unpacking the heterogeneous components of adaptation policy is essential. Disaggregated analysis of specific tools (e.g., climate risk insurance, ecological compensation, infrastructure retrofitting) would help identify which instruments are most effective under different local conditions. Fourth, future work should investigate the role of institutional capacity, policy learning, and multi-level governance in mediating the implementation and effectiveness of CCAP. These meso-level mechanisms are critical but remain understudied. Finally, comparative studies across countries or regions with differing governance regimes and climate vulnerabilities would enhance external validity and contribute to a globally relevant theory of adaptation-resilience linkages. By integrating macro-, meso-, and micro-level perspectives, future research can offer a more comprehensive and policy-relevant account of how cities build resilient industrial systems in the face of climate uncertainty.

Data availability

Data is provided within the manuscript or supplementary information files.

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Author contributions

Weirong Fang: conceptualization, methodology, validation, investigation, and formal analysis
Huifang Liu: Project administration, Methodology, Validation, Investigation
Chenggang Zhang: Formal analysis, resources, data organization, and writing the original manuscript. All authors have read and agreed to the published version of the manuscript.

Competing interests

The authors declare no competing interests.

Ethics approval

The present study does not involve any human participants, animals, or identifiable personal data. The research is entirely based on secondary data obtained from publicly available sources, including official statistical yearbooks and government databases. No primary data collection, surveys, interviews, experiments, or interventions involving individuals or organizations were conducted. In accordance with established academic publishing standards and ethical guidelines, studies relying solely on publicly accessible secondary data do not require approval from an institutional ethics committee.

Informed consent

This paper does not contain any studies with human participants performed by the author.

Additional information

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