

Article

Has the Healthy City Pilot Improved Ecological Resilience in China? Evidence from a Quasi-Natural Experiment

Kebei Shi ¹, Tongping Li ^{1,*} and Xuyang Li ²¹ School of Economics and Management, China University of Geosciences, Wuhan 430078, China; shikebei@cug.edu.cn² School of Economics and Trade, Henan University of Technology, Zhengzhou 450001, China

* Correspondence: litongping@cug.edu.cn

Abstract

Enhancing ecological resilience and human well-being is key to achieving the global Sustainable Development Goals (SDGs). Within the framework of the Healthy China strategy, this paper treated China's Healthy City pilot (HCP) policy as a quasi-natural experiment and systematically investigated its impact on ecological resilience, the underlying transmission mechanisms, and heterogeneity. Based on panel data from 286 prefecture-level cities spanning 2011–2023 and employing a spatial difference-in-differences (SDID) model, the empirical results showed that: Spatial correlation analysis indicated a significantly positive spatial correlation in urban ecological resilience across Chinese cities. The baseline regression results showed that the HCP policy significantly improved urban ecological resilience, with the resilience index increasing by 18.1% on average compared with non-pilot cities. The SDID results indicated that the policy generated positive spatial spillover effects on urban ecological resilience, and that policy effects were influenced by geographically neighboring cities. Mechanism tests showed that the Healthy City Pilot policy significantly promoted urban technological innovation and facilitated the transformation of the energy consumption structure, both of which played important roles in enhancing urban ecological resilience. Heterogeneity analysis revealed that the policy had stronger effects in eastern and northeastern cities than in central and western cities, and that large cities benefited more than small and medium-sized cities, mainly due to differences in regional location, development foundations, environmental governance capacity and policy implementation conditions.

Keywords: healthy city; ecological resilience; technological innovation; energy consumption structure



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1. Introduction

Against the backdrop of increasingly severe global environmental problems, the stability and recovery capacity of ecosystems have become a focus of research. As the most complex social-ecological systems, cities have been continuously subjected to various external and internal shocks and disturbances since their formation [1]. Since the reform and opening-up, China's economy has experienced rapid growth for more than four decades. Urban prosperity and development have improved people's living standards and quality of life, but they have also brought about ecological vulnerability and sudden risks. For instance, the 2023 North China floods led to the emergency relocation of 1.6 million people, with direct economic losses reaching 95.811 billion yuan. Such shocks are highly uncertain, yet they are an inherent manifestation of the objective laws of social and natural

development and cannot be completely avoided [2]. Against this background, “ecological resilience” has attracted widespread attention. Resilience here refers to the capacity of an ecosystem to maintain its key characteristics and functions under natural or anthropogenic risk shocks, to recover from disturbances, and to gradually enhance its functionality [3]. Specifically, urban ecological resilience refers to a city’s ability to respond, adapt, and react to ecological emergencies in order to mitigate ecological disasters and recover rapidly from them. At present, building urban ecological resilience has undoubtedly become a core element in promoting sustainable development.

With the acceleration of urbanization, urban ecosystems are confronted with numerous challenges. Large-scale urban construction and expansion continuously encroach upon natural ecological space, damaging the structural integrity of ecosystems and weakening their self-regulation and resistance capacities, which has led many cities to face the coexistence of ecological fragility and urban decline [4]. The Chinese government has been exploring scientifically sound solutions to the environmental problems brought about by extensive development and, in 2016, implemented the “Healthy China 2030” Planning Outline to promote the building of healthy cities and achieve the goal of “Healthy China.” The National Patriotic Health Campaign Committee launched the Healthy City pilot program, designating 38 cities (pilot cities include: Baotou, Dalian, Changchun, Daqing, Suzhou, Wuxi, Zhenjiang, Hangzhou, Ningbo, Tongxiang, Ma’anshan, Xiamen, Yichun, Jinan, Weihai, Yantai, Zhengzhou, Yichang, Zixing, Zhuhai, Nanning, Qionghai, Chengdu, Luzhou, Guiyang, Yuxi, Lhasa, Baoji, Jinchang, Golmud, Yinchuan, Karamay, Tangshan (Qi-an’an District), Tianjin (Heping District), Beijing (Xicheng District), Shanghai (Jiading District), Chongqing (Hech-uian District), and Linfen (Houma City), among other pilot cities, totaling 38 cities, with 15 in the eastern region, 9 in the central region, 11 in the western region, and 3 in the northeastern region) as the first batch of pilot cities. Healthy city construction must be committed to providing people with clean air, safe drinking water, a safe and abundant food supply, a clean sanitary environment, sufficient green space, and so forth [5]. The National Healthy City Evaluation Indicator System (for details, see National Healthy City Evaluation Indicator System (2018 Edition)) includes rigid constraints such as the “Air Health Index” and the “harmless treatment rate of domestic waste.” These indicators cannot be attained through simple end-of-pipe treatment; instead, they require profound transformations in urban production technologies and energy use patterns. At the same time, technological innovation provides technical support for the energy transition (e.g., energy storage and smart grids), forming a positive “technology–energy” cycle that can reduce chronic ecological pressure, enhance early warning and restoration capabilities, and promote urban ecological resilience.

An increasing number of studies have focused on the HCP policy [6–9], and scholars have examined it from multiple dimensions, yielding abundant research findings. As an environmental policy with fiscal incentives and performance evaluation, its environmental effects have been widely recognized [10], yet quantitative assessments of its policy effects remain relatively rare. Can the HCP policy genuinely serve to improve urban ecological resilience? If so, to what extent? Do spatial spillover effects exist? And what are the underlying operational mechanisms or core driving forces? To date, there is still a lack of in-depth and systematic analysis addressing these questions both domestically and internationally. Therefore, this paper treated China’s HCP policy as a quasi-natural experiment and employed a spatial difference-in-differences model to evaluate the impact of the Healthy City Pilot policy on urban ecological resilience.

2. Literature Review and Hypotheses

2.1. Literature Review

This section focuses on the literature concerning the Healthy City pilot and urban ecological resilience. Research on ecological resilience began relatively early and has developed into a fairly comprehensive research system, which can be broadly divided into the following three categories: (1) Studies on the measurement and spatiotemporal patterns of ecological resilience: The measurement of ecological environmental resilience has evolved from single indicators to multi-level, multi-dimensional indicator systems. Specific indicator selection often adopts the “Pressure–State–Response” (PSR) dimensions [11], the “Resistance–Recovery–Adaptability” dimensions [12], “Scale–Density–Morphology” [13], and so on. For comprehensive indicator methods, the entropy weight method [14] and the TOPSIS method [15] are frequently employed. Spatiotemporal distribution analysis commonly uses spatial autocorrelation [16], kernel density estimation [17], and other methods widely applied in regional ecological resilience assessment. With the rapid development of intelligent technologies, remote sensing and GIS techniques also provide precise geospatial data support for analyzing the spatial distribution of urban ecological resilience [18]. (2) Exploration of coupling and adaptation relationships: This includes the relationships between ecological resilience and urbanization [13], ecological resilience and ecological risk [19], ecological resilience and urban renewal, among others. (3) Analysis of influencing factors and mechanisms of ecological environmental resilience: Studies have examined the effects of the policy environment [6], climate change [20], and urban green infrastructure construction [21] on ecological resilience, using methods such as the grey relational model [11], geographically and temporally weighted regression (GTWR) [22], and exploratory spatiotemporal data analysis [23].

With regard to studies on the impact of the HCP policy on the ecological environment, the literature has concentrated on the different effects of healthy city construction on the ecological environment. For example, Yue et al. [24] employed a systematic sampling method to select 15 pilot cities and found that healthy city construction can significantly increase per capita green space area, enhance the capacity for domestic waste and sewage treatment, and markedly improve the urban environment. Guo and Zhang [5] found that the HCP policy can improve air quality through urban innovation and green infrastructure. Hao et al. [25] applied an interaction model and the synthetic control method to evaluate the HCP policy and found that it can improve healthy city performance by reducing pollution emissions and can effectively alleviate urban ecological environmental pressures.

It is evident that the existing literature provides a solid foundation for this study, yet several gaps remain (see Table 1). First, from a research perspective, existing studies have examined the environmental impacts of other pilot policies and development models in cities but have not yet paid sufficient attention to the impact of the HCP policy on ecological resilience. Second, in terms of empirical strategies, the existing literature either uses interviews and case analysis to descriptively analyze the policy effects of the Healthy City pilot or employs the synthetic control method to evaluate the construction progress of individual pilot cities; few studies have comprehensively investigated the ecological resilience effects and spatial spillover effects of the Healthy City pilot. Third, regarding mechanism discussions, the existing literature provides inadequate explanations of the intrinsic mechanisms through which the pilot policy operates, and in particular, there is a lack of discussion on the specific pathways through which urban construction affects ecological resilience.

Table 1. Summary of the related literature.

Theme	Representative Studies	Methods	Findings	Research Gaps
The measurement and spatiotemporal patterns of ecological resilience	[11–18]	Entropy method, TOPSIS, spatial autocorrelation, GIS	Ecological resilience is usually measured by multidimensional indicators and shows spatial heterogeneity.	Limited causal evidence on policy impacts.
Coupling relationships and influencing factors of ecological resilience	[6,13,19–23]	Coupling models, grey relational analysis, GTWR	Urbanization, ecological risk, climate change, and green infrastructure affect ecological resilience.	The mechanisms through which urban policies shape ecological resilience are still insufficiently examined.
Environmental Effects of the HCP	[5,24,25]	Systematic sampling; interaction models; synthetic control method; econometric models	The policy improves green space, pollution control, air quality, and urban health performance.	Little attention has been paid to ecological resilience and spatial spillovers.

In view of this, based on data from 286 major cities spanning 2011–2023, this paper used the SDID method to examine the impact of the HCP policy on the ecological environment and its spatial spillover effects. Compared with the existing literature, the marginal contributions of this paper were as follows: First, by constructing an ecological resilience indicator that integrates ecology and economics into the framework for measuring urban ecological resilience, this study provided a more comprehensive assessment of cities' adaptive and recovery capacities in the face of environmental changes and pressures. Specifically, it evaluated ecosystem quality using indicators such as the Normalized Difference Vegetation Index (NDVI), forest coverage rate, and water area, thereby offering reference for related research. Second, it systematically evaluated the impact of the Healthy City pilot on ecological resilience at the city level, extending from single environmental indicators to a composite indicator, thereby further broadening the research perspective on the HCP policy. Third, this study integrated both temporal and spatial dimensions, accounted for spatial spillover effects, and provided a more in-depth investigation of the driving mechanisms of urban ecological resilience.

2.2. Research Hypotheses

Based on the general connotation of ecological resilience and building on existing research, this paper draws on the structural analysis of urban ecological resilience by Canavera-Herrera [26] and others, and decomposes urban ecological resilience into three layers. The first is the basic layer, namely the ecological quality layer, which measures the natural and social foundational conditions of a city's ecological environment, such as the Normalized Difference Vegetation Index (NDVI), forest coverage rate, water area, and garden green space area. The higher the ecosystem quality, the lower the likelihood of environmental conflict and the higher the level of resilience. The second is the processing layer, namely the environmental governance layer, which reflects the treatment and feedback of urban governance authorities regarding the urban environment, such as the harmless treatment rate of domestic waste, centralized treatment rate of wastewater treatment plants, and green coverage rate of built-up areas. The better the governance, the higher the ecological resilience. The third is the perception layer, namely the emission pressure layer, which reflects the pressures and disturbances faced by the urban ecological environment,

i.e., negative indicators such as industrial wastewater discharge, industrial sulfur dioxide emissions, and industrial smoke and dust emissions. The greater the pressure, the lower the ecological resilience.

This study further analyzes the impact of the Healthy City Pilot policy on urban ecological resilience from three perspectives: the direct effect, the spatial effect, and the underlying mechanism pathways (see Figure 1).

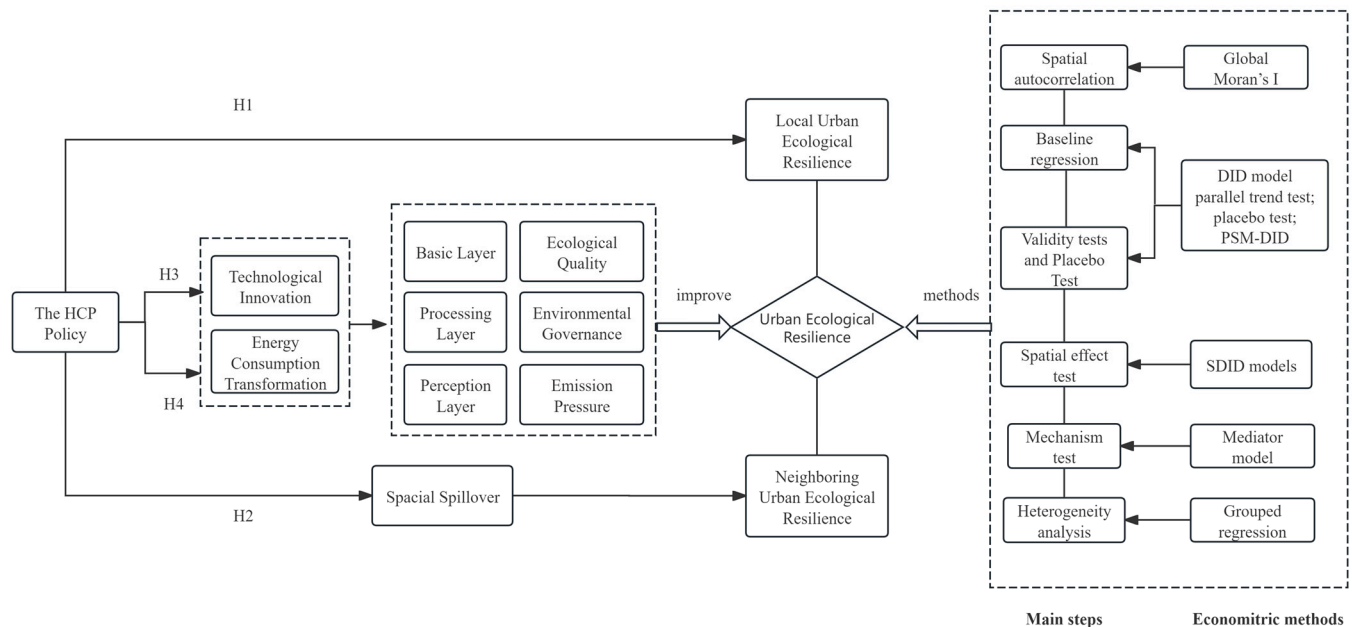


Figure 1. Mechanisms and econometric strategies. Dashed boxes indicate grouped mechanism components and econometric-method modules.

2.2.1. Direct Effects of the HCP Policy

The HCP Policy is expected to directly enhance the overall ecological resilience of cities. Introduced by the central government, this environmental initiative incorporates financial incentives and rigorous performance assessment mechanisms. This policy framework exerts performance pressure on local governments, compelling them to set explicit environmental targets and implement emission-reduction measures. Consequently, it can improve overall urban environmental quality and strengthen cities' ecological resilience. Specifically: (1) The construction of healthy cities can improve the ecological quality dimension of urban resilience. The pilot policy identifies a livable environment as a core objective. Accordingly, it may strengthen cities' ecological-quality resilience by improving living conditions, ensuring the harmless treatment of household waste, and increasing the availability of community green spaces. (2) The construction of healthy cities can improve the resilience of urban environmental governance. Pilot cities have expanded broadband Internet infrastructure and actively promoted new-generation information technologies, including big data and artificial intelligence (AI). These efforts directly enhance environmental governance resilience by enabling rapid responses to ecological shocks and improving governance efficiency. (3) The construction of healthy cities can mitigate urban emission pressures. The pilot policy reduces emission pressures through emission-control measures, thereby enhancing urban resilience to environmental stress. Based on the above analysis, the following hypothesis is proposed:

H1. Implementation of the HCP Policy directly enhances the ecological resilience of cities.

2.2.2. Spatial Effects of the Healthy City Pilot Policy

Urban ecological resilience exhibits clear spatial dependence. Ecological environmental quality, pollution emissions, energy use efficiency, green technological innovation, and environmental governance capacity are not confined to a single city; rather, they may be transmitted across cities through industrial linkages, population mobility, and technological diffusion. Specifically, the experience accumulated by pilot cities in health governance, ecological environmental improvement, and green development may provide neighboring cities with opportunities for policy learning and governance imitation. The diffusion of technological innovation and green production practices can also help surrounding cities improve their environmental governance efficiency. Therefore, the Healthy City Pilot policy may not only enhance the ecological resilience of pilot cities themselves but also affect surrounding cities through demonstration and diffusion effects, accelerating intercity imitation and cooperation and generating positive effects on neighboring cities. Accordingly, the following hypothesis is proposed:

H2. *The impact of the Healthy City Pilot policy on urban ecological resilience may generate positive spatial spillover effects.*

2.2.3. Transmission Mechanisms

This study elaborates on the transmission mechanisms through which the HCP Policy affects urban ecological resilience from two perspectives: technological innovation and energy consumption. The detailed analysis is presented below.

The HCP Policy has the potential to stimulate technological innovation. According to Porter's Hypothesis, well-designed environmental regulations can stimulate technological innovation [27]. The environmental assessment mechanisms embedded in the policy can incentivize innovation among enterprises and local governments. These mechanisms encourage industrial transformation, adoption of cleaner production technologies, and achievement of energy conservation and emission reduction goals, thereby mitigating environmental pollution and ultimately improving urban ecological resilience. Moreover, the development of healthy cities may enhance technological innovation through investments in infrastructure such as internet connectivity, big data, and artificial intelligence. Enhanced technological capacity facilitates the seamless integration of ecological information across multiple platforms, broadening data scope and accelerating processing speed. Consequently, it enhances governmental responsiveness to shocks, reduces uncertainty in ecological planning and decision-making, and strengthens urban ecological resilience.

H3. *Implementation of the HCP Policy enhances urban ecological resilience by driving technological innovation.*

Pilot cities may also strengthen urban ecological resilience by optimizing their energy consumption structure. The primary impetus for energy transition is not technological advancement alone but a strategic necessity for sustainable social development. Accordingly, the initial driving force of energy transition is policy-driven rather than innovation-led [28]. Coal remains the dominant fuel source for global electricity production and contributes substantially to pollution emissions from energy generation [29]. It also constitutes a major share of China's energy consumption. The energy structure significantly affects ecological balance, posing serious threats to socioeconomic development and public health [30]. Therefore, reducing coal consumption and increasing the share of clean energy are top priorities in building healthy cities [5]. Emission-reduction targets and assessment mechanisms within the pilot policy prompt local governments and enterprises to transform energy consumption structures, thereby enhancing urban ecological resilience.

H4. *Implementation of the HCP Policy enhances urban ecological resilience by promoting transformation of the energy consumption structure.*

3. Materials and Methods

3.1. Policy Background

The Healthy City initiative constitutes an important practice under the Healthy China strategy. China began to explore Healthy City development in the 1990s. Beijing's Dongcheng District and Shanghai's Jiading District launched pilot projects in 1994, and Suzhou was designated as China's first Healthy City project pilot in 2001. In October 2016, the State Council issued the "Healthy China 2030" Planning Outline, which emphasized the integration of health into urban planning, construction, and management. In November 2016, the National Patriotic Health Campaign Committee issued the Notice on Launching Healthy City Pilot Work and identified the first batch of 38 pilot cities. Since ecological environment-related indicators, including air quality, green space systems, and the water environment, account for a relatively high proportion of the Healthy City evaluation system, the policy has both public health and ecological governance implications. This study regarded the Healthy City Pilot policy as a quasi-natural experiment. Given that the national pilot policy was formally launched in 2016, this study defined 2016 as the policy implementation year, took the first batch of pilot cities as the treatment group, and treated non-pilot cities as the control group. A difference-in-differences model was constructed to evaluate the local effect of the policy on urban ecological resilience, and a spatial difference-in-differences model was further employed to examine its spatial spillover effects.

3.2. Data Sources

In consideration of the completeness and accessibility of data, this study utilized the panel data of 286 Chinese cities spanning from 2011 to 2023 as the research sample (data for Hong Kong, Macao, and Taiwan of China were not available). Among these, there were 35 pilot cities (data for the pilot cities of Tongxiang, Zixing, and Golmud were incomplete), and 251 non-pilot cities. The indicator data were sourced from the China City Statistical Yearbook and the statistical yearbooks of various prefecture-level cities. For some missing values, the linear interpolation method and the method of filling with the average value of adjacent years were employed.

3.3. Variables and Measurement

3.3.1. Dependent Variable

The dependent variable in this study was the urban ecological resilience index, which measured a city's capacity to maintain or restore its ecological functions and system stability when confronted with external shocks such as natural disasters, climate change, resource constraints, and long-term environmental shifts. It encompassed the quality of the urban ecosystem (capacity to withstand shocks), environmental governance capacity (ability to recover rapidly after disturbances), development capacity (sustained growth under stress), and ecological endowment (natural resources and overall ecosystem health). Following the studies of Guo and Liu [31] and Chu Erming [14], the index was divided into three subdimensions: ecological quality resilience, environmental governance resilience, and emission pressure resilience, each quantified by 13 third-level indicators (Table 2). Because the indicators exert both positive and negative effects on the overall resilience index, all variables were normalized, and the entropy weighting method was applied to determine indicator weights and compute the comprehensive ecological resilience index for each city.

Table 2. Urban Ecological Resilience Measurement Index System.

Primary Indicators	Secondary Indicators	Tertiary Indicators	Unit	Indicator Attribute
Urban ecological resilience (UERI)	Ecological Quality Resilience Index (EQR)	Forest coverage area	hectare	positive
		Water Area	hectare	positive
		Garden and Green Space Area	hectare	positive
		Normalized Difference Vegetation Index	%	positive
		Proportion of Days with Air Quality at or Better than Grade II	%	positive
		Atmospheric PM _{2.5} Concentration	µg/m ³	negative
	Environmental Governance Resilience Index (GCR)	Harmless Treatment Rate of Municipal Solid Waste	%	positive
		Centralized Treatment Rate of Municipal Wastewater by Sewage Treatment Plants	%	positive
		Green Coverage Rate in Built-up Areas	%	positive
		Built-up Area	km ²	positive
	Emission Pressure Resilience Index (PCR)	Industrial Sulfur Dioxide (SO ₂) Emissions	t	negative
		Industrial Smoke and Dust Emissions	t	negative
		Industrial Wastewater Discharge	ten thousand t	negative

3.3.2. Independent Variable

The: core explanatory variable in this study was the interaction term between a city-level dummy variable indicating the implementation of the HCP Policy and a time dummy variable. National pilot cities were designated as the treatment group, assigned a value of 1, while non-pilot cities served as the control group, assigned a value of 0. For pilot cities, the variable equaled 1 from the year of policy implementation onward and 0 in all preceding years. For non-pilot cities, the time dummy variables remained 0 for all years.

3.3.3. Control Variable

Following the studies of Guo and Zhang [5] and Huo et al. [32], four meteorological indicators—average temperature, relative humidity, wind speed, and cumulative precipitation—were selected. Meteorological data were obtained from the China Daily Surface Climate Data Set (V3.0) provided by the China Meteorological Data Service Center. This dataset contains comprehensive daily records, including precipitation, wind speed, and humidity, covering cities nationwide. The inverse distance weighting (IDW) method was applied to interpolate meteorological station data and generate a national

raster map. The resulting raster was then aggregated and statistically analyzed according to administrative divisions to produce annual city-level meteorological data.

Drawing on the studies of Shi Dachuan et al. [33], Guo and Zhang [5], Chu Erming et al. [14], and Shi Dan and Li Shaolin [34], four key influencing factors were selected as control variables: (1) Economic development level, measured by the logarithm of real GDP. Nominal GDP was converted to real GDP using 2011 as the base year, and its logarithm was taken to represent each city's level of economic development. (2) Degree of openness to external investment, measured by the ratio of actual foreign investment to GDP. (3) Financial development level, represented by the ratio of total financial institution deposits at year-end to GDP. (4) Population density, expressed as the logarithm of the ratio between the permanent resident population of each prefecture-level city and its administrative area. The city-level data were primarily obtained from the China City Statistical Yearbook. Descriptive statistics for the main variables are presented in Table 3, with missing data imputed using linear interpolation.

Table 3. Descriptive statistics results of the variables.

Variable Type	Variable Names	Variable Descriptions	Sample Size	Mean	Standard Deviation	Minimum	Maximum
Explained Variable	<i>UERI</i>	Urban Eco-Environmental Resilience Index	3718	0.236	0.0783	0.0354	0.609
	<i>EQR</i>	Ecological Quality Resilience Index	2681	0.110	0.0374	0.0431	0.405
	<i>GCR</i>	Environmental Governance Resilience Index	3176	0.0262	0.0187	0.00352	0.170
	<i>PCR</i>	Emission Pressure Resilience Index	2430	0.154	0.00824	0.0653	0.161
Key Explanatory Variable	<i>DID</i>	Interaction Term of Policy Implementation City Dummy Variable and Time Dummy Variable	3718	0.0710	0.257	0	1
Control Variable	lnGDP	Logarithm of Real GDP (in ten thousand yuan)	3691	7.446	0.925	4.896	10.59
	<i>FDI</i>	Ratio of Actually Utilized Foreign Direct Investment to Regional Gross Domestic Product	3090	0.012	0.620	0	0.12
	<i>FD</i>	Ratio of Total Deposits and Loans of Financial Institutions to Regional Gross Domestic Product	3425	1.074	0.620	0.132	7.451
	lnPD	Logarithm of Regional Permanent Resident Population per Urban Area	3425	5.712	1.015	1.653	9.089
	RH	Annual Mean Relative Humidity	3712	0.00844	0.00295	0.00252	0.0163
	Wind	Annual Mean Wind Speed (m/s)	3718	5.098	0.867	2.64	7.669
	Temp	Annual Mean Air Temperature (°C)	3712	14.82	5.166	−1.612	25.95
	Rain	Annual Total Precipitation (mm)	3712	1011	490.7	45.24	2542

3.4. Methods

3.4.1. Global Spatial Autocorrelation

This study used the global Moran's I index as a measure of global spatial autocorrelation to examine the spatial dependence of the ecological resilience index across 286 Chinese cities. The global Moran's I is expressed as follows:

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

where n denotes the number of cities; x_i and x_j represent the ecological resilience indices of cities i and j , respectively; $S^2 = \sum_{i=1}^n (x_i - \bar{x})^2 / n$ is the sample variance; and w_{ij} is the spatial weight matrix element. This study used an inverse squared distance spatial weight matrix for the analysis.

3.4.2. Difference-in-Differences (DID) Model

The DID model has been widely applied in economics due to its advantages in addressing endogeneity and measuring policy impacts. The basic specification of the DID model is expressed as follows:

$$y_{it} = \alpha_0 + \alpha_1 DID + \alpha_2 Control + \eta_t + \mu_i + \varepsilon_{it} \quad (2)$$

In Equation (1), y denotes the dependent variable y_{it} ; $post$ is a dummy variable identifying whether a city belongs to the experimental group ($post = 1$) or the control group ($post = 0$); and $time$ indicates whether the policy has been implemented ($time = 0$ before intervention, $time = 1$ after intervention). DID represents the interaction term between the two dummy variables—pilot city and policy period—such that $DID = 1$ for treatment group observations after the policy intervention, and 0 otherwise. The coefficient α_1 of DID captures the average treatment effect, reflecting the impact of the HCP Policy on ecological environmental resilience. $Control$ denotes a set of control variables, including climate factors (temperature, humidity, precipitation, and wind speed) and socio-economic factors (economic development level, openness, financial development, and population density). η_t and μ_i denote time and city fixed effects, respectively, while ε represents the random error term.

3.4.3. Validity Test: Parallel Trend Test

Satisfying the “parallel trend” assumption is a prerequisite for using the difference-in-differences (DID) method. That is, the treatment group and the control group must have the same trend before the policy implementation, because the same trend implies that the post-policy trend of the control group can be used as a counterfactual for the treatment group (i.e., the trend that the treatment group would have followed if not affected by the policy). If the parallel trend assumption is violated, the DID method would overestimate or underestimate the policy effect. To ensure the validity of our DID estimates, we conducted a parallel trend test between the treatment and control groups. This paper followed the method of Beck [35].

3.4.4. Robustness Tests

(1) Placebo test:

To further test whether our results were driven by unobserved factors, we conducted a placebo test by randomly assigning the pilot cities. Specifically, we randomly selected 38 cities out of the 286 cities as the treatment group, assuming that these 38 cities implemented the Healthy City Pilot policy, while the remaining cities served as the control group.

This random sampling ensured that the constructed independent variable has no effect on the urban ecological resilience scores. In other words, any significant finding would indicate bias in our regression results. A total of 500 random samplings were conducted, and benchmark regressions were performed for each.

(2) Propensity Score Matching-Difference-in-Differences (PSM-DID) Estimation:

Although the Difference-in-Differences (DID) method can estimate the average treatment effect of the policy, the policy implementation does not constitute a strict natural experiment and may still be subject to sample selection bias. To improve the robustness of the regression results and account for inter-city heterogeneity, this study further employed the PSM-DID approach for robustness testing. First, the Propensity Score Matching (PSM) method was used to identify a more comparable control group for the treatment cities. Specifically, the probability of a city being selected as a pilot city is estimated using the control variables from the benchmark model (via Logit estimation). Kernel matching was then applied to match treatment and control cities, retaining the optimal control group that exhibits the smallest possible pre-policy differences from the treatment group. Next, the study re-estimated the impact of the HCP policy on urban ecological resilience using the DID method.

3.4.5. Spatial Difference-in-Differences (SDID) Model

A key assumption for the validity of the DID approach is the stable unit treatment value assumption. However, in the presence of spatial interactions, the treatment effect for one city may be affected by whether neighboring cities are also treated. The spatial difference-in-differences model can account for potential spatial dependence among variables, control for omitted factors with spatial influence, and further decompose the average treatment effect into direct effects, spatial spillover effects, and total effects. Following the framework of Dubé et al. [36], this study constructed three types of SDID models.

The spatial autoregressive difference-in-differences model (SAR-SDID) is specified as:

$$y_{it} = \rho W y_{it} + \alpha_1 DID + \alpha_2 Control + \mu_i + \varepsilon_{it} \quad (3)$$

The spatial error difference-in-differences model (SEM-SDID) is specified as:

$$\begin{aligned} y_{it} &= \alpha_1 DID + \alpha_2 Control + \mu_i + \mu_{it} \\ \mu_{it} &= \lambda W \mu_{it} + \varepsilon_{it} \end{aligned} \quad (4)$$

The spatial Durbin difference-in-differences model (SDM-SDID) is specified as:

$$y_{it} = \rho W y_{it} + \alpha_1 DID + \beta W DID + \alpha_2 Control + \mu_i + \varepsilon_{it} \quad (5)$$

where the variables are defined as in Equation (1). W denotes the spatial weight matrix. This study constructed the spatial relationship among 286 Chinese cities using an inverse squared distance spatial weight matrix.

3.4.6. Mechanism Analysis

We analyzed the mechanism of HCP policy's impact on urban ecological resilience based on the theoretical analysis in the previous section, referring to the study of Jiang Ting [37] to estimate the impact of HCP policy on the mechanisms. The following econometric model was established:

$$Mediator_{it} = \beta_0 + \beta_1 DID_{it} + \beta_2 Control_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (6)$$

$$Y_{it} = \gamma_0 + \gamma_1 Mediator_{it} + \gamma_2 DID_{it} + \gamma_3 Control_{it} + \mu_i + \eta_t + \varepsilon_{it} \quad (7)$$

In this context, *Mediator* denotes the mediating variables, specifically technological innovation and the energy consumption structure. The rest of the variables are defined in Equation (2). If the HCP policy influences ecological resilience, the estimated coefficients β_1 , γ_1 , and γ_2 in Equations (6) and (7) are expected to be statistically significant. Following Jiang Ting's [37] recommendation, this study primarily focused on β_1 .

3.4.7. Grouped Regression

(1) Urban Regional Heterogeneity

The impact of implementing the Healthy City pilot policy on urban ecological resilience may vary across regions. This variation may arise not only from regional disparities in economic and social development but also from differing ecological and environmental foundations. To examine these potential differences, the sample cities were grouped into eastern, northeastern, central, and western regions.

(2) City-Scale Grouped Regression

Owing to differences in city size, the degree of production factor agglomeration, the level of ecological and environmental infrastructure, and the likelihood of sudden ecological or environmental shocks all vary across cities. Consequently, the impact of the Healthy City pilot policy on urban ecological resilience may exhibit heterogeneity. To test for this heterogeneity, the study divided the sample into large and medium–small cities for grouped regression, following the Notice on Adjusting the Standards for Classifying City Sizes issued by the State Council in 2014.

We plot the mechanisms and econometric strategies of this paper in Figure 1.

4. Results and Discussion

4.1. Spatial Autocorrelation Analysis

The estimated global Moran's I values for the ecological resilience of 286 Chinese cities were all positive and statistically significant, indicating a significant positive spatial autocorrelation (Table 4). Specifically, cities with high (low) ecological resilience tended to be surrounded by cities with similarly high (low) resilience, demonstrating a spatial pattern of "high–high" and "low–low" clusters.

Table 4. Spatial Autocorrelation Test.

Year	I
2011	0.199 ***
2012	0.189 ***
2013	0.146 ***
2014	0.172 ***
2015	0.190 ***
2016	0.184 ***
2017	0.174 ***
2018	0.162 ***
2019	0.155 ***
2020	0.148 ***
2021	0.143 ***
2022	0.133 ***
2023	0.131 ***

Notes: *** denotes statistical significance at the 1% level.

4.2. Benchmark Regression Analysis

Based on Model (1), the baseline regression results of the impact of healthy city construction on ecological resilience are reported in Table 5. To address potential heteroscedasticity, standard errors were clustered at the city level, and all regressions controlled for year fixed effects and city fixed effects. Column (1) of Table 5 presents the regression results after including control variables. The coefficient of the DID term is significantly positive, with an estimated value of 0.0177 at the 5% significance level. This indicates that the HCP policy significantly improves the urban ecological resilience index. Since DID is the interaction term between the pilot city dummy and the post-policy time dummy, its coefficient captures the average treatment effect of the policy. Specifically, the estimated coefficient suggests that the HCP policy increases the urban ecological resilience index by approximately 0.0173 index points on average. Relative to the sample mean of the dependent variable, this effect is equivalent to approximately 18.1% of the mean. This finding supports Hypothesis 1, which states that implementation of the HCP Policy directly enhances the ecological resilience of cities.

Table 5. Baseline Regression Results.

Variables	(1) <i>UERI</i>	(2) <i>EQR</i>	(3) <i>GCR</i>	(4) <i>PCR</i>
<i>DID</i>	0.0173 *** (4.517)	0.0051 *** (6.888)	0.0051 *** (11.584)	0.0031 *** (6.397)
<i>lnGDP</i>	0.0205 * (1.814)	0.0087 *** (3.094)	0.0106 *** (8.004)	−0.0053 *** (−23.383)
<i>FDI</i>	−0.1993 *** (−2.656)	0.0130 (0.822)	−0.0132 (−1.501)	−0.0040 (−0.378)
<i>lnPD</i>	−0.0005 (−0.145)	0.0000 (0.031)	0.0008 ** (2.170)	0.0007 *** (2.991)
<i>FD</i>	0.0034 (1.372)	0.0043 *** (5.747)	0.0013 *** (4.353)	0.0000 (0.112)
<i>Wind</i>	0.0109 ** (2.166)	0.0003 (0.336)	0.0002 (0.334)	0.0000 *** (3.942)
<i>RH</i>	14.3165 *** (4.567)	2.6761 *** (4.030)	0.7924 ** (2.189)	0.4360 (1.053)
<i>Temp</i>	−0.0058 ** (−2.423)	−0.0015 *** (−2.834)	0.0004 (1.357)	0.0003 (1.158)
<i>Rain</i>	−0.0000 (−0.417)	0.0000 *** (4.099)	−0.0000 (−1.159)	0.0000 (0.810)
<i>_Cons</i>	0.0321 (0.342)	0.0401 * (1.772)	−0.0704 *** (−6.385)	0.1537 *** (9.248)
Year Fixed Effects	Y	Y	Y	Y
City Fixed Effects	Y	Y	Y	Y
Observations	3093	2390	2857	2292
Adjust R ²	0.446	0.340	0.384	0.189

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses. The same notation applies to subsequent tables/results.

Columns (2), (3), and (4) of Table 5 report the baseline regression results of the Healthy City pilot policy on the three sub-dimensions of the ecological resilience index: ecological quality resilience, environmental governance resilience, and emission pressure resilience, respectively. The treatment effect coefficients were all significantly positive. It was observed that the regression coefficients of healthy city construction on the ecological quality resilience index (EQR), the environmental governance resilience index (GCR), and the emission pressure resilience index (PCR) were all significantly positive at the 1% level, with values of 0.0051, 0.0051, and 0.0031, respectively. This fully demonstrated that healthy

city construction is sensitive to changes in the various dimensions of urban ecological resilience. Regarding the control variables, Column (1) of Table 5 shows that GDP ($\ln gdp$) significantly improved urban ecological resilience at the 10% level, suggesting that the more economically developed a city was, the higher its ecological resilience index. The coefficient of actual foreign direct investment utilization (FDI) is negative, possibly because foreign direct investment to some extent relocates high-pollution industries into the country, thereby inhibiting the improvement of ecological resilience. The coefficient of population density ($\ln PD$) is negative but insignificant, which may have been due to the increased burden that higher population density places on the urban ecological environment. The coefficient of financial development (FD) is positive but insignificant; the development of the financial sector can promote urbanization and industrial upgrading, but the investment and financing process may also bring negative environmental externalities.

4.3. Parallel Trends Test

The results indicated that, prior to the implementation of the HCP Policy, the coefficients representing differences between the control and experimental groups fluctuated around zero (Figure 2). This suggested that both groups shared a similar growth trend and are therefore comparable, satisfying the parallel-trend condition. Before policy implementation, the estimated coefficients of the period-specific interaction terms were statistically insignificant. After implementation, these coefficients exhibited an upward trend and became significant in later periods, confirming that the parallel-trend assumption held. In summary, the HCP Policy satisfied the parallel-trend assumption.

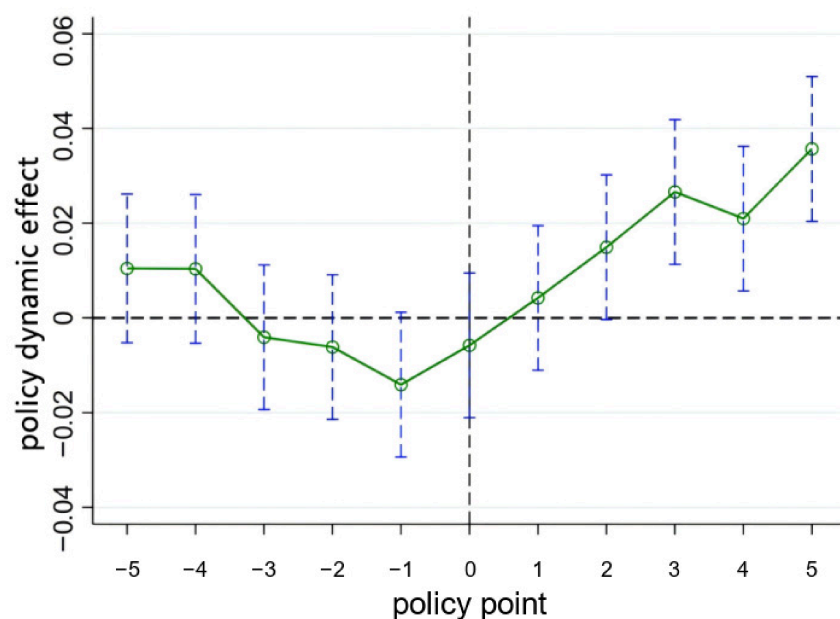


Figure 2. Parallel Trend Assumption Test.

4.4. Robustness Test

4.4.1. Placebo Test

Figure 3 presents the mean of the regression coefficients obtained from 500 random allocations. The results showed that the mean of all estimated coefficients was approximately zero. Additionally, the distributions of the 500 estimated coefficients and their corresponding p -values were plotted, as shown in Figure 3. The distributions were centered around zero, and most p -values exceeded 0.1. Meanwhile, the true estimate of urban ecological environmental resilience appeared as a clear outlier in the placebo test. These

findings suggested that the estimated effects are unlikely to be driven by unobservable factors and, to some extent, confirmed the robustness of the benchmark regression results.

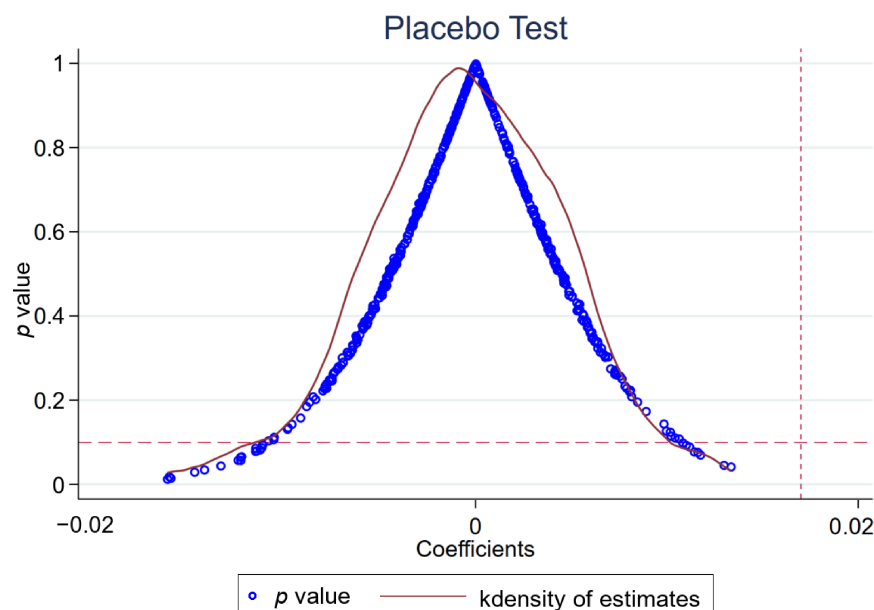


Figure 3. Placebo Test for Urban Ecological Resilience. The dashed horizontal line indicates $p = 0.1$, and the dashed vertical line indicates the benchmark estimate.

4.4.2. PSM-DID

Table 6 reports the balance test results after matching. Next, the study re-estimated the impact of the HCP policy on urban ecological resilience using the DID method. Table 7 presents the PSM-DID estimation results.

Table 6. Post-Propensity Score Matching (PSM) Balance Test.

Variables	Pre-Matched		Mean		%Decrease		T Test		V(T)/
	Post-Matched		Treatment Group	Control Group	%Deviation	Deviation	t	$p > t$	V(C)
<i>lnGDP</i>	U		8.425	7.339	121		23.57	0.000	1.44 *
	M		8.330	8.229	6.0	90.6	1.49	0.136	1.01
<i>lnPD</i>	U		6.234	5.725	−49.6		9.49	0.000	1.18
	M		6.155	6.017	28.0	43.5	1.47	0.141	0.49 *
FDI	U		0.024	0.015	146.7		10.59	0.000	2.10 *
	M		0.023	0.022	11.1	92.4	0.64	0.520	1.43 *
FD	U		1.435	1.012	30.8		12.46	0.000	1.57 *
	M		1.497	1.396	−2.5	92.0	0.19	0.851	0.94
Wind	U		5.318	5.049	29.8		5.72	0.000	1.34 *
	M		5.284	5.251	3.6	87.9	0.51	0.610	1.80 *
RH	U		0.008	0.009	−10.3		−1.84	0.066	0.91
	M		0.008	0.008	−0.7	93.9	−0.10	0.942	1.10
Temp	U		14.88	15.007	−2.6		−0.46	0.648	0.78 *
	M		14.878	14.972	−1.9	26.0	−0.27	0.785	1.02
Rain	U		938.09	1045.8	−23.2		−4.03	0.000	0.80 *
	M		947.87	947.99	−0.0	99.9	−0.00	0.997	1.11

Notes: * denotes statistical significance at the 10% level.

Table 7. Test results of PSM-DID.

Variables	(1) <i>UERI</i>	(2) <i>EQR</i>	(3) <i>GCR</i>	(4) <i>PCR</i>
<i>DID</i>	0.0124 * (1.672)	0.0038 * (1.703)	0.0046 *** (2.716)	0.0029 ** (2.349)
Cons	0.0195 (0.161)	0.0188 (0.516)	−0.0834 *** (−4.173)	0.1547 *** (6.645)
Control Variable	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
City Fixed Effects	Y	Y	Y	Y
Observations	3006	2348	2781	2211
Adjust R ²	0.507	0.425	0.447	0.284

Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Standard errors are reported in parentheses.

The study conducted a robustness test of the model using the Propensity Score Matching–Difference-in-Differences (PSM-DID) approach, and the results remained consistent with the main findings. The PSM-DID results further confirmed that China’s HCP policy exerted a significant positive effect on ecological resilience, ecological quality resilience, environmental governance resilience, and emission pressure resilience in pilot cities.

4.4.3. Eliminate the Influence of Other Relevant Policies During the Same Period

During the policy implementation period, other environmental initiatives may have influenced the estimation results. Policy reform in China is a complex and dynamic process, often accompanied by multiple concurrent economic policies and government regulations, which may confound the identification of the HCP policy’s effects. To enhance the robustness of the results, this study sought to control for the potential influence of other concurrent policies. In addition to the HCP policy, the Ecological Civilization Pilot Zone policy launched in 2013 may also have affected the pilot regions. To mitigate potential policy interference, this study excluded Guizhou, Jiangxi, and Fujian provinces from the Difference-in-Differences (DID) analysis. The regression results indicated that, after excluding regions affected by concurrent policies, the coefficient of the DID variable remained statistically significant (Table 8). Therefore, the benchmark regression results remained robust.

Table 8. Robustness test by excluding contemporaneous relevant policies.

Variables	(1) <i>UERI</i>	(2) <i>EQR</i>	(3) <i>GCR</i>	(4) <i>PCR</i>
<i>DID</i>	0.0181 *** (4.420)	0.0055 *** (6.953)	0.0050 *** (10.583)	0.0034 *** (8.129)
Cons	0.0803 (0.813)	0.0284 (1.181)	−0.0723 *** (−6.146)	0.1387 *** (10.034)
Control Variable	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
City Fixed Effects	Y	Y	Y	Y
Observations	2808	2193	2586	2073
Adjust R ²	0.440	0.347	0.367	0.321

Notes: *** denotes statistical significance at the 1% level. Standard errors are reported in parentheses.

4.4.4. Adding Control Variables

Table 9 reports the robustness test results obtained by gradually adding control variables. Column (1) controlled only for year and city fixed effects, and the coefficient of *DID*

was 0.0177, significant at the 1% level. Column (2) further included socioeconomic control variables, and the coefficient remained positive and significant at the 1% level. Column (3) added climatic control variables, and the coefficient of *DID* was still significantly positive. Overall, the estimated coefficients of *DID* remained positive and statistically significant across all specifications, indicating that the positive effect of the HCP policy on urban ecological resilience is not sensitive to the inclusion of different control variables. This confirmed the robustness of the baseline results.

Table 9. Robustness Test: Adding Control Variables.

Variables	(1) <i>UERI</i>	(3) <i>UERI</i>	(3) <i>UERI</i>
<i>DID</i>	0.0177 *** (4.868)	0.0170 *** (4.422)	0.0189 *** (3.329)
lnGDP		0.0236 ** (2.118)	
<i>FDI</i>		0.1914 *** (3.106)	
lnPD		−0.0153 *** (−12.597)	
<i>FD</i>		0.0030 (1.207)	
Wind			0.0125 *** (5.511)
RH			11.1703 *** (3.898)
Temp			−0.0035 *** (−6.714)
Rain			−0.0000 (−0.669)
_cons	0.2531 *** (124.524)	0.0516 *** (6.118)	0.2037 *** (30.006)
Year Fixed Effects	Y	Y	Y
City Fixed Effects	Y	Y	Y
Observations	3718	3093	3712
Adjust R ²	0.679	0.470	0.528

Notes: ** and *** denote statistical significance at the 5% and 1% levels, respectively. Standard errors are reported in parentheses.

4.5. Policy Effect Analysis Based on the Spatial Difference-in-Differences Model

4.5.1. Regression Results of the SDID Model

Table 10 reports the regression results of the spatial models based on the inverse squared distance spatial weight matrix. To examine the spatial effects of the HCP policy on urban ecological resilience, this study estimated the spatial autoregressive difference-in-differences model (SAR-SDID), the spatial error difference-in-differences model (SEM-SDID), and the spatial Durbin difference-in-differences model (SDM-SDID). As shown in Table 10, the estimated policy effects, represented by the coefficients of *DID*, were significantly positive at the 1% level in all three spatial models, consistent with the baseline DID results. This indicated that, after controlling for spatial dependence, the conclusion that the HCP policy improved urban ecological resilience remained valid.

Table 10. Results of the Spatial Difference-in-Differences Models.

Variables	(1) SAR-SDID W	(2) SEM-SDID W	(3) SDM-SDID W
<i>DID</i>	0.0468 *** (11.731)	0.0447 *** (11.324)	0.0502 *** (12.470)
$W \times DID$			0.0129 (0.747)
$W \times \mu$		0.0037 *** (42.750)	
$W \times y$	0.6563 *** (19.678)		0.8900 *** (46.370)
Year Fixed Effects	Y	Y	Y
City Fixed Effects	Y	Y	Y
Observations	3718	3718	3718

Notes: *** denotes statistical significance at the 1% level. Standard errors are reported in parentheses.

Specifically, first, in the SAR-SDID model, the coefficient of DID was 0.0468 and significant at the 1% level. In the SEM-SDID model, the coefficient was 0.0447 and also significant at the 1% level. In the SDM-SDID model, the coefficient was 0.0502 and remained significant at the 1% level. These results suggested that the positive effect of the HCP policy on local urban ecological resilience is robust across different spatial model specifications. Second, the estimated spatial dependence terms further indicated that urban ecological resilience exhibited clear spatial dependence. In the SAR-SDID model, the coefficient of $W \times y$ is 0.6563 and significant at the 1% level. In the SDM-SDID model, the coefficient of $W \times y$ is 0.8900 and also significant at the 1% level. This finding confirmed a significant positive spatial association in urban ecological resilience. In the SEM-SDID model, the coefficient of $W \times \mu$ is 0.0037 and significant at the 1% level, indicating that unobserved factors not fully captured by the model also exhibit spatial dependence. Third, in the SDM-SDID model, the coefficient of $W \times DID$ is 0.0129 but was not statistically significant, suggesting that the direct effect of neighboring cities' HCP policy implementation on local ecological resilience is not obvious. However, in the spatial Durbin model, the coefficient of a single spatially lagged explanatory variable cannot fully capture the spatial spillover effect of the policy. Therefore, direct, indirect, and total effect decompositions are further required.

4.5.2. Decomposition of the Spatial Effects of the HCP Policy

Table 11 reports the effect decomposition results of the SDM-SDID model based on the inverse squared distance spatial weight matrix. First, the direct effect of the HCP policy was significantly positive, indicating that the policy significantly improved ecological resilience in pilot cities. Second, the spatial spillover effect was positive and significant at the 10% level, suggesting that the HCP policy not only enhanced local urban ecological resilience but also generated positive spillover effects on neighboring cities. Pilot cities may transmit policy experience, technological diffusion, and factor mobility to surrounding cities, thereby promoting improvements in ecological resilience in neighboring areas. Third, the total effect of the HCP policy was positive and significant at the 5% level, indicating that the policy significantly promoted urban ecological resilience overall. The total effect is larger than the direct effect, suggesting that the policy impact is not confined to pilot cities but also involves spatial diffusion effects. These findings generally supported Hypothesis 2.

Table 11. Direct, Spatial Spillover, and Total Effects of the SDM-SDID Model.

Effect Type	Variables	W	
		Coefficient	p-Value
Direct effect	<i>DID</i>	0.0537	0.000
Spatial spillover effect	<i>DID</i>	0.2956	0.081
Total effect	<i>DID</i>	0.3492	0.042

4.6. Analysis of the Mechanism of the Pilot Policy for Healthy Cities

4.6.1. Technological Innovation

Policymakers must strengthen pollution control and emission reduction to improve the urban ecological environment. Government agencies and enterprises can mitigate pollution through technological innovation and industrial transformation to achieve environmental objectives. Enhancing technological innovation contributes to the sustainable development of cities and the restoration of ecosystems. The HCP policy emphasizes innovation and environmental health as core objectives, aligning closely with the essence of the Porter Hypothesis.

This study employed the logarithm of the total number of patent applications (*Tec*) as a proxy variable for urban technological innovation to test the proposed mechanism. The data were obtained from the National Intellectual Property Administration of China. The regression results are presented in Table 12. Column (1) of Table 12 reports the estimated effect of the HCP policy on urban technological innovation. The estimated coefficient β_1 was 0.183 and statistically significant at the 1% level, indicating that the policy significantly promoted urban technological innovation. Column (2) presents the baseline regression including technological innovation as a mediating variable. The results suggested that the HCP policy improved the urban ecological resilience index through the mediating role of technological innovation, thereby supporting Hypothesis 2.

Table 12. Mechanism test.

Variables	(1) <i>Tec</i>	(2) <i>UERI</i>	(3) <i>Energy</i>	(4) <i>UERI</i>
<i>DID</i>	0.1830 *** (5.756)	0.0189 *** (4.931)	0.0084 ** (2.405)	0.0153 *** (4.149)
<i>Tec</i>		0.0090 *** (3.959)		
<i>Energy</i>				0.0006 (0.028)
Cons	−0.9598 (−1.229)	0.0407 (0.435)	0.0989 (1.132)	0.0588 (0.638)
Control Variable	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
City Fixed Effects	Y	Y	Y	Y
Observations	3093	3093	2987	2987
Adjust R ²	0.827	0.449	0.610	0.473

Notes: ** and *** denote statistical significance at the 5% and 1% levels, respectively. Standard errors are reported in parentheses.

4.6.2. Energy Consumption

The primary objective of the HCP policy is to improve environmental quality and promote public health. Accordingly, increasing the share of clean energy consumption constitutes a key policy component. In the context of China's policy practices, this approach aligns with global energy transition patterns, emphasizing accelerated coal phase-out, re-

duced oil dependence, and the use of natural gas as a transitional energy source. To test this mechanism, we employed the ratio of natural gas consumption to total energy consumption from clean energy sources as a proxy variable representing the energy consumption structure. Compared with raw coal and crude oil, natural gas produces lower pollutant emissions; hence, a higher proportion of natural gas reflects a more optimized energy consumption structure.

The data were primarily drawn from the China City Statistical Yearbook, provincial and municipal statistical yearbooks, and social statistical bulletins. Missing values were supplemented using interpolation methods. Columns (3) and (4) of Table 12 report the estimation results for the mechanism through which the HCP policy promoted the upgrading of the energy consumption structure and its subsequent impact on urban ecological resilience. Column (3) presents the regression results of the HCP policy on the urban energy structure, with a coefficient (β_1) of 0.008, significant at the 5% level, indicating that the policy significantly optimized the urban energy consumption structure. Column (4) reports the results of the baseline regression with energy consumption included as an additional variable. The results demonstrated that the HCP policy enhanced urban ecological resilience by optimizing the energy consumption structure, thereby verifying Hypothesis 3.

4.7. Heterogeneity Analysis

4.7.1. Urban Regional Heterogeneity

The regression results in Table 13 showed that the HCP policy had a significant positive effect on urban ecological resilience in eastern and northeastern cities, indicating stronger policy effects in these regions. This heterogeneity may be explained by differences in development foundations, fiscal capacity, industrial structure, and environmental governance conditions. Eastern cities generally had stronger economic foundations, greater fiscal resources, more advanced infrastructure, and higher levels of technological innovation, which enabled them to implement the HCP policy more effectively and translate policy interventions into improvements in ecological resilience. In northeastern cities, the long-standing concentration of traditional heavy industries generated relatively high environmental pressure and ecological vulnerability. As a result, policy interventions aimed at improving environmental governance and urban resilience may have generated larger marginal effects. By contrast, the policy effects in central and western cities were not statistically significant, possibly because these regions were still undergoing industrialization and may have faced increasing pollution pressures associated with industrial transfer, which could have partially offset the positive effects of the HCP policy.

Table 13. Heterogeneity analysis by city location (region).

Variables	(1) <i>UERI</i> Eastern Region	(2) <i>UERI</i> Northeastern Region	(3) <i>UERI</i> Central Region	(4) <i>UERI</i> Western Region
<i>DID</i>	0.0281 *** (5.029)	0.0229 * (1.814)	−0.0016 (−0.182)	0.0114 (1.463)
Cons	0.0333 (0.106)	0.8451 *** (2.683)	−0.7875 *** (−3.734)	−0.0574 (−0.215)
Control Variable	Y	Y	Y	Y
Year Fixed Effects	Y	Y	Y	Y
City Fixed Effects	Y	Y	Y	Y
Observations	963	375	962	793
Adjust R ²	0.473	0.431	0.555	0.393

Notes: *** and * denote statistical significance at the 1% and 10% levels, respectively. Standard errors are reported in parentheses.

4.7.2. Heterogeneity of City Scale

As shown in Table 14, the HCP policy had a significantly positive effect on ecological resilience in large cities, while its effect in medium-sized cities was negative at the 10% significance level. This size-based heterogeneity may have been related to differences in factor agglomeration, fiscal capacity, infrastructure conditions, and exposure to ecological risks. Medium and small cities usually had weaker factor agglomeration, more limited fiscal resources, and lower levels of infrastructure and governance capacity. The relatively high investment required for Healthy City construction may therefore have weakened its net effect in these cities. In contrast, large cities had larger populations, higher factor agglomeration, stronger fiscal capacity, and more complex ecological and environmental pressures. These conditions increased both the demand for resilience improvement and the capacity to implement policy measures. Consequently, the HCP policy was more effective in enhancing ecological resilience in large cities.

Table 14. Heterogeneity analysis by city size.

Variables	(1) <i>UERI</i> Large Cities	(2) <i>UERI</i> Medium and Small Cities
<i>DID</i>	0.0379 *** (6.887)	−0.0108 * (−1.774)
Cons	0.2017 (0.755)	−0.0092 (−0.092)
Control Variable	Y	Y
Year Fixed Effects	Y	Y
City Fixed Effects	Y	Y
Observations	778	2291
Adjust R ²	0.378	0.483

Notes: *** and * denote statistical significance at the 1% and 10% levels, respectively. Standard errors are reported in parentheses.

5. Conclusions and Policy Recommendations

Using panel data from 286 Chinese prefecture-level cities spanning 2011–2023, this study treated the National Healthy City pilot policy as a quasi-natural experiment and evaluated its impact on urban ecological resilience from both temporal and spatial perspectives. The main conclusions are as follows: (1) The spatial correlation analysis indicated that urban ecological resilience displayed a significantly positive spatial autocorrelation among Chinese cities, suggesting that it is not independent of administrative boundaries [38–40]. (2) The baseline regression results showed that the HCP policy significantly enhances urban ecological resilience. Compared with non-pilot cities, the ecological resilience index of pilot cities increased by an average of 18.1%, and the policy effect was more pronounced for ecological quality resilience and environmental governance resilience than for emission pressure resilience [41,42]. (3) The SDID results further demonstrated that the HCP policy has positive spatial spillover effects, indicating that pilot construction can influence neighboring cities through spatial interaction, policy learning, factor mobility, and regional environmental governance linkages. (4) The mechanism tests showed that Healthy City construction improves urban ecological resilience by promoting technological innovation and optimizing the energy consumption structure, with the technological innovation channel playing a relatively stronger role [43,44]. (5) The heterogeneity analysis revealed that the policy effect is stronger in eastern and northeastern cities than in central and western cities, and that large cities benefited more than small and medium-sized cities, highlighting

the importance of local fiscal capacity, governance capacity, industrial structure, and urban scale in shaping policy outcomes [45].

These findings offer valuable policy implications for the coordinated promotion of Healthy City construction and the enhancement of urban ecological resilience. Based on these findings, the following policy recommendations are proposed:

First, strengthen spatial monitoring and regional coordination mechanisms for ecological resilience. Because the empirical results show significant spatial correlation and positive spillover effects, Healthy City construction should move beyond city-by-city implementation and establish a cross-regional ecological-resilience monitoring network. Pilot cities can jointly build data-sharing platforms for air quality, green space, water environment, energy consumption, and public health risks, and neighboring cities should coordinate early warning, emergency response, and pollution-control actions. This will help transform spatial spillovers from passive diffusion into organized regional governance effects [45,46].

Second, deepen the Healthy City pilot program and incorporate ecological resilience into performance evaluation. Building on the experience of existing pilot projects, the scope of Healthy City construction should be further expanded while avoiding purely symbolic implementation. Local governments should include ecological quality, environmental governance capacity, emission pressure, and public health co-benefits in assessment systems, so that the policy can promote not only health-supportive environments but also long-term urban adaptive capacity.

Third, create institutional channels for intercity policy learning and spillover transformation. The positive spatial spillover effect suggests that pilot cities can serve as regional demonstration nodes. Therefore, provincial and metropolitan-area governments should encourage paired assistance, joint training, shared technical standards, and collaborative environmental enforcement between pilot and non-pilot cities. Cross-city cooperation can reduce duplicated investment, improve governance consistency, and help surrounding cities absorb the management experience and technological resources generated by pilot construction [47].

Fourth, stimulate green technological innovation and accelerate the clean transformation of the energy structure. The mechanism results indicate that technological innovation and energy-structure optimization are important channels through which the HCP policy enhances ecological resilience. Governments should support industry–university–research collaboration, environmental monitoring technologies, low-carbon production processes, and digital governance platforms. At the same time, pilot cities should expand clean-energy infrastructure, improve incentives for renewable energy and low-emission technologies, and set binding targets for energy intensity and carbon emissions, while recognizing that energy transitions require sustained investment and phased implementation.

Fifth, adopt differentiated policy packages according to region and city scale. For eastern cities, the priority is to consolidate technological and financial advantages and strengthen regional spillovers. For northeastern cities, Healthy City construction should be linked with industrial upgrading and ecological restoration in traditional industrial bases. For central and western cities, fiscal transfers, ecological compensation, and targeted capacity building are necessary to prevent environmental pressure from offsetting policy benefits. Large cities should use digital monitoring, ecological infrastructure, and emergency-response systems to manage complex urban risks, whereas medium and small cities should emphasize low-cost, nature-based, and community-oriented governance measures rather than excessive hardware investment.

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