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The Impact of the Digital Economy on Urban Ecological Resilience: Empirical Evidence from China's Comprehensive Big Data Pilot Zone Policy

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Abstract: The present study examines the effects of China's comprehensive big data pilot zone policy on urban ecological resilience. This is achieved through the utilization of a quasi-natural experiment, employing panel data from 217 prefecture-level cities in China spanning the years 2010 to 2021. The research revealed that China's extensive policy on big data pilot zones has a notable and favorable influence on the ecological resilience of urban areas. This impact is both constant and subject to variation across different regions. The aforementioned impact is attained by means of progressions in industrial structure and the introduction of innovative green technologies. Furthermore, the strategy exerts a beneficial impact on the ecological resilience of urban areas in adjacent regions by means of spatial spillover effects.

Keywords: digital economy; China's comprehensive big data pilot zone; ecological resilience; difference in differences

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1. Introduction

Over the past few decades, China's economy has expanded roughly and developed effectively. This resource-dependent mode of production has led to increasingly prominent environmental problems, seriously weakening the carrying capacity of the environment, reducing the regional ecological resilience, and posing a major threat to China's ecological security [1]. The Chinese government, in its report to the 20th National Congress, underscored the importance of integrating carbon reduction, green expansion, pollution reduction, and economic growth to improve China's ecological environment. In 2023, General Secretary Xi Jinping explicitly indicated in the Conference on Environmental and Ecological Protection that "we must continue to fight a good battle against pollution in depth; adhere to the precise and scientific treatment of pollution in accordance with the law; maintain the strength, extend the depth, expand the breadth, and deeply promote the three major defence wars of blue sky, blue water, and clean soil". To address the conflict between economic advancement and ecological conservation within the framework of high-level urban development and to improve cities' ecological resilience, a prompt resolution is necessary [2]. The China big data comprehensive pilot area policy is a unique policy pilot area created by the state to utilize data as a central component, foster scientific and technical innovation, and expedite the advancement of industrial digitization and digital industrialization, serving a significant purpose. The implementation of a series of industrial support policies, data resource opening policies, talent support policies, infrastructure construction policies and innovation support policies, and other policies and measures in a specific area aims at data flow driving capital flow, technology flow, talent flow convergence and circulation, the development of digital technologies, digital industries, digital business forms, and digital models. The establishment of the China big data comprehensive pilot zone aims to optimize the benefits of big data and its many uses while facilitating the integration of the digital economy in various sectors. This initiative also presents a significant opportunity to enhance urban ecological environments and strengthen urban ecological resilience.

Ecological resilience refers to the ability of ecosystems to maintain stability, functionality, and restoration when subjected to external disturbances and damage [3] and represents the continuity of relationships within ecosystems [4]. With the continuous development of ecological resilience theory, scholars have emphasized the ability of ecosystems to achieve transformation and development by adjusting their structure and changing their path from an evolutionary perspective [5]. Studies on ecological resilience have focused mostly on the aspects of measurement and influencing factors. To measure ecological resilience, Wang S et al. (2022) constructed a three-dimensional system including scale, density, and morphology to assess the relationship between urbanization and ecological resilience [6]. In their study, Li and Wang (2023) conducted an assessment of the diversity and convergence of ecological resilience in urban areas of China, focusing on three distinct dimensions: resistance, adaptation, and resilience [7]. In addition to natural factors, such as vegetation, soil, water, and climate [8], driving factors include social factors, such as industrial transformation, scientific and technological innovation [9], population density [10], urbanization [11], and environmental regulation [12].

The digital economy is environmentally friendly with characteristics of low consumption and low pollution [13]. Data are widely recognized as crucial factors in production [14]. They play a direct role in various aspects of research, production, distribution, exchange, and consumption by integrating digital services with technology, industry, and the market. This integration has led to significant transformations in the real economy, thereby stimulating high-quality economic growth in China [15]. Utilizing the data within the comprehensive big data pilot zone policy is a novel approach for China to attain environmentally sustainable and high-quality advancements, thereby capitalizing on the advantageous position of the digital economy [16]. According to Li and Wang (2022), the advancement of the digital economy and the reduction of urban carbon emissions can be facilitated by the enhancement of technical progress, the rectification of flawed resource allocation, and the optimization of industrial structure [17]. Lyu Y and colleagues (2023) assert that the expansion of the digital economy is accountable for the rise in green total factor productivity [18]. Due to the aforementioned factors, the digital economy greatly contributes to enabling the green transformation of China's manufacturing sector [19], enhances regional eco-efficiency [20], empowers China's ecological civilization construction [21], and reconciles economic growth and the ecological environment [22], thus enhancing urban ecological resilience [23]. Subsequent research has demonstrated that the digital economy impacts urban ecological resilience through various channels, including economic growth [24], scientific and technological advancement, transformation of the industrial structure [25], environmental regulation [26], and resource allocation optimization [27].

According to the literature, experts widely concur on the positive impact of the digital economy on the environment. However, there are variations in the specific areas of research that fall under the green effect category. Most scholars have studied the impacts from a single level, such as pollutant emissions, green total factor productivity, or environmental governance, while a few scholars have focused on ecological resilience. Ecological resilience is a systematic concept with more multidimensional measurement criteria, and most studies on ecological resilience take it as an independent object for measurement and differential research. Therefore, in contrast to prior research, this study adopts an environmental economics approach by focusing on a particular policy within the digital economy, namely China's big data comprehensive pilot zone, and regards it as a quasi-natural experiment. The study of the relationship between the two helps to comprehensively strengthen the ecosystem's resistance, resilience, and recovery. This study's novel contributions are evident in the following aspects. First, the integration of the national big data comprehensive pilot zone and urban ecological resilience within a research framework expands the scope of investigating the environmental advantages associated with the digital economy. Second, this study utilizes a mathematical model to examine the ecological restoration capabilities of China's big data comprehensive pilot zone. This approach addresses a theoretical void in the existing literature. Third, in terms of heterogeneity analysis, the sample is categorized not only by the layout of the comprehensive pilot zones but also by the degree of ecological environmental pollution, thus making the research conclusions more precise. Fourth, with regards to the mechanism of action, the internal logic by which the pilot zone policy influences the ecological resilience of a city is clarified through the two paths of green technological innovation and the advancement of the industrial structure. Fifth, from a spatial perspective, this study utilizes a spatial econometric model to investigate the impact of the policy on urban ecological resilience at the "local neighborhood" level. The aim is to establish a foundation for coordinating regional development efforts.

2. Theoretical Analysis and Research Hypothesis

2.1. Mathematical Model Analysis

This study utilizes research from Hu Zongyi and Li Yi (2020) and Yan Zhijun et al. (2022) to investigate the effects of establishing a comprehensive big data pilot zone on the ecological resilience of urban areas [28,29]. The analysis is conducted through the development of a straightforward two-sector economic model. It is assumed that there are two sectors in the economy, the polluting sector x and the clean sector y, with corresponding outputs q_x and q_y, respectively. The implementation of the big data comprehensive pilot zone strategy has a substantial influence on the polluting industry, while the clean industry remains relatively unaffected. For simplicity, this paper assumes that labour (l) and capital (k) are input factors, and the production functions of the two sectors are as follows:

$$q_y = l_y^{\alpha_2} k_y^{\beta_2}$$

where α_1, α_2, β_1, and $\beta_2 \in (0, 1)$ denote the shares of labour and capital inputs in the two sectors, and the total factor inputs are $l_x + l_y = \bar{l}$ and $k_x + k_y = \bar{k}$. The polluting sector produces a certain amount of polluting emissions e during the production process, which is included in the production function to obtain:

$$q_x = e^{\varepsilon}\left(l_x^{\alpha_1} k_x^{\beta_1}\right)^{1-\varepsilon}, 0 < \varepsilon < 1$$

From the above, the expression of the profit maximization function for the polluting and clean sectors is:

$$Max\ \ \pi_x = p_x q_x - c_x = p_x e^{\varepsilon}\left(l_x^{\alpha_1} k_x^{\beta_1}\right)^{1-\varepsilon} - wl_x - rk_x - Te$$

$$Max\ \pi_y = p_y q_y - c_y = p_y l_y^{\alpha_2} k_y^{\beta_2} - wl_y - rk_y$$

where p_x and p_y denote the prices of products in the polluting and clean sectors, respectively; w denotes the price of labour; r denotes the price of capital; and T is the amount of penalties per unit of polluting emissions. The size of the T-value is closely related to the policy, thanks to the use of advanced technologies and data analysis that enable more precise monitoring and assessment of the extent and impact of pollution emissions. It is set according to the condition of profit maximization for polluting sector x:

$$w = p_x \alpha_1 (1-\varepsilon)\left(\frac{e}{q_x}\right)^{\varepsilon} \frac{q_x}{l_x}$$

$$r = p_x \beta_1 (1-\varepsilon)\left(\frac{e}{q_x}\right)^{\varepsilon} \frac{q_x}{k_x}$$

$$p_x \varepsilon \left(\frac{q_x}{e}\right)^{1-\varepsilon} = T$$

Similarly, for the clean sector y, the profit maximization condition is:

$$w = p_x \alpha_2 \frac{q_y}{l_y}$$

$$r = p_y \beta_2 \frac{q_y}{k_y}$$

In summary, the combined conditions for profit maximization in both sectors are as follows:

$$p_x \alpha_1 (1-\varepsilon) \left(\frac{e}{q_x} \right)^{\varepsilon} \frac{q_x}{l_x} = p_y \alpha_2 \frac{q_y}{l_y}$$

$$p_x \beta_1 (1-\varepsilon) \left(\frac{e}{q_x} \right)^{\varepsilon} \frac{q_x}{k_x} = p_y \beta_2 \frac{q_y}{k_y}$$

$$p_x \varepsilon \left(\frac{q_x}{e} \right)^{1-\varepsilon} = T$$

To observe the changes in the variables caused by the implementation of the policy, the natural logarithms of both sides of the equation are taken, and the differentiation operation at time t is performed via the following equation:

$$\varepsilon \hat{e} + (1-\varepsilon)\hat{q}_x - \hat{l}_x = \hat{q}_y - \hat{l}_y$$

$$\varepsilon \hat{e} + (1-\varepsilon)\hat{q}_x - \hat{k}_x = \hat{q}_y - \hat{k}_y$$

$$\hat{e} = \hat{q}_x - \frac{1}{1-\varepsilon}\hat{T}$$

In the above equation, $\hat{X} = \frac{d\ ln\ X}{dt}$. Since this study does not address consumer utility maximization, p is considered an exogenous variable and does not change in the short run. Furthermore, the following can be obtained from $l_x + l_y = \bar{l}$ and $k_x + k_y = \bar{k}$:

$$\theta_{l_x} \hat{l}_x + \theta_{l_y} \hat{l}_y = 0$$

$$\theta_{k_x} \hat{k}_x + \theta_{k_y} \hat{k}_y = 0$$

where $\theta_{l_x} = \frac{l_x}{l}$, $\theta_{l_y} = \frac{l_y}{l}$, $\theta_{k_x} = \frac{k_x}{k}$, and $\theta_{k_y} = \frac{k_y}{k}$ indicate the share of labour and capital factor inputs in the polluting and clean sectors, respectively.

In this paper, the same treatment is applied to $q_x = l_x^{\alpha_1} k_x^{\beta_1}$ and $q_y = l_y^{\alpha_2} k_y^{\beta_2}$. To simplify the analysis, it is assumed that there exists at least one fixed-input factor of production in the short term, and the system of parallel equations yields the expression for the polluting sector x:

$$\hat{l}_x = -\frac{\theta_{l_y}}{\theta_{l_x}(1-\alpha_2) + \theta_{l_y}(1-\alpha_1)} \frac{\varepsilon}{1-\varepsilon} \hat{T} < 0$$

$$\hat{k}_x = -\frac{\theta_{ky}}{\theta_{k_x}(1-\beta_2) + \theta_{k_y}(1-\beta_1)} \frac{\varepsilon}{1-\varepsilon} \hat{T} < 0$$

$$\hat{q}_x = -\alpha_1 \frac{\theta_{l_y}}{\theta_{l_x}(1-\alpha_2) + \theta_{l_y}(1-\alpha_1)} \frac{\varepsilon}{1-\varepsilon} \hat{T} = -\beta_1 \frac{\theta_{k_y}}{\theta_{k_x}(1-\beta_2) + \theta_{k_y}(1-\beta_1)} \frac{\varepsilon}{1-\varepsilon} \hat{T} < 0$$

$$\hat{e} = -\left(\frac{\alpha_1 \theta_{l_y}}{\theta_{l_x}(1-\alpha_2) + \theta_{l_y}(1-\alpha_1)} + \frac{1}{\varepsilon}\right) \frac{\varepsilon}{1-\varepsilon} \hat{T} = -\left(\frac{\beta_1 \theta_{k_y}}{\theta_{k_x}(1-\beta_2) + \theta_{k_y}(1-\beta_1)} + \frac{1}{\varepsilon}\right) \frac{\varepsilon}{1-\varepsilon} \hat{T} < 0$$

Similarly, the expression for the clean sector y is:

$$\hat{l}_y = \frac{\theta_{l_x}}{\theta_{l_x}(1-\alpha_2) + \theta_{l_y}(1-\alpha_1)} \frac{\varepsilon}{1-\varepsilon} \hat{T} > 0$$

$$\hat{k}_y = \frac{\theta_{kx}}{\theta_{k_x}(1-\beta_2)+\theta_{k_y}(1-\beta_1)}\frac{\varepsilon}{1-\varepsilon}\hat{T} > 0$$

$$\hat{q}_y = \alpha_2\frac{\theta_{l_x}}{\theta_{l_x}(1-\alpha_2)+\theta_{l_y}(1-\alpha_1)}\frac{\varepsilon}{1-\varepsilon}\hat{T} = \beta_2\frac{\theta_{k_x}}{\theta_{k_x}(1-\beta_2)+\theta_{k_y}(1-\beta_1)}\frac{\varepsilon}{1-\varepsilon}\hat{T} > 0$$

This policy of the comprehensive big data pilot zone will result in an increase in the sewage tax paid by the polluting sector and an increase in the penalties imposed by the government, i.e., $\hat{T} > 0$. Combined with the above formula, when the policy is put into action, it can shift labour and capital from highly polluting industries to cleaner ones, signalling a shift in economic development towards more environmentally friendly and sustainable sectors. This, in turn, enhances production capacity in the clean sector, fosters the green transition of the local economy, and enhances the ecological resilience of the city. Meanwhile, increasing taxes and punishments for polluting industries leads to a decrease in pollution emissions, showing that implementing a complete big data pilot zone policy helps enhance urban ecological resilience. Furthermore, there are two aspects of the pollution reduction and abatement effects of the construction of the pilot zone: $\frac{\alpha_1\theta_{1_y}}{\theta_{1_x}(1-\alpha_2)+\theta_{1_y}(1-\alpha_1)}$ and $\frac{1}{\varepsilon}$. The former indicates the industrial cleaning and upgrading effect; the larger the factor output elasticities α_1 and α_2 are, the faster the factor transfer speed is, and the parameter β is the same, which indicates that the construction of the pilot zone has a noteworthy effect on industrial structure. The latter term denotes the impact of technological innovation, and technological innovation and the value of ε have a negative correlation. The construction of the pilot zone stimulates technological innovation, leading to decreased pollution control costs, the promotion of environmental behaviour, and improvements to the city's ecological resiliency.

2.2. Theoretical Analysis

The environmental Kuznets curve theory suggests that technological and structural effects are key factors in reducing the pollution of the ecological environment. With digital technology and data elements as the core, China's comprehensive pilot zone for big data accelerates the formation of interregional innovation and cooperation networks and links upstream and downstream industries. This supports the integration of innovation and industrial chains and induces a gradual change from a high-energy-consuming and high-polluting economic development mode to a cleaner and more sustainable model of economic development in the region, thus enhancing ecological resilience. In addition, the establishment of a pilot zone can strengthen multifaceted monitoring, response, management, and governance systems; gradually realize digital ecological environmental governance; and promote improvements in pollution control capacity to protect the ecological environment and enhance ecological resilience. Therefore, this paper proposes Hypothesis 1.

Hypothesis 1: *China's comprehensive big data pilot zone is positively related to urban ecological resilience.*

The construction of a pilot zone not only effectively expands the spillover of green technological knowledge but also fully exploits the green driving role of data elements [30]. On the one hand, the use of big data to collect ecological and environmental information can establish a unified ecological and environmental data system and break the information dilemma of urban environmental governance, thus improving the intensity of urban environmental regulation [31]. External drivers of enterprises' green technological innovation come from strong environmental regulation [32], and a higher intensity of environmental regulation stimulates enterprises' environmental protection initiative to carry out green technological innovation. In addition, as far as the enterprise is concerned, green technological innovation has the risks of large investment, a long cycle, and an uncertain external environment, while the comprehensive big data pilot zone policy can break through the information asymmetry barriers of the enterprise, increase the predictability of the market to alleviate the constraints of enterprise financing [33], reduce the production cost of traditional production methods [34], and enhance risk-bearing enterprise initiatives [35], prompting enterprises to take the initiative to make environmental protection decisions, stimulating corporate investment in green innovation, and accelerating the transformation of green innovation results. In turn, enterprises that take the lead in completing green transformation will occupy a competitive advantage due to their ecological advantages, and, at the same time, force high-polluting enterprises to engage in green innovation and green production, which will enhance overall green innovation in the region. On the other hand, the policy can help realize the upgrading and iteration of green technology and green innovation by coordinating, managing, and applying data resources to address the inefficiency and unnecessary loss of green innovation resources in the process of matching supply and demand. Green technology innovation has the potential to decrease the utilization of natural resources, achieve efficient and circular use of resources, promote the transformation of consumption, production, and lifestyles, thus reducing pressure on the ecological environment [36], and fundamentally protect the adaptability, resistance, and recovery of the ecosystem.

The comprehensive big data pilot zone policy supports the coordination of the relationships among the energy structure, market structure, and industrial structure, thereby gradually restructuring the regional industrial structure [37]. Firstly, its development accelerates the reasonable flow of production factors, and, with the flow of production factors to high-efficiency sectors, the utilization efficiency of regional industrial resources improves, which is a favourable condition for the advanced industrial structure [38]. Secondly, the pilot zone is conducive to the coordinated development of traditional industries and emerging industries. The data characteristics of the digital economy can give rise to a series of digital-intensive industries and realize digital industrialization. In addition, the permeability and sharing of the digital economy can force the digital transformation of traditional low-end industries and realize industrial digitization. An advanced industrial structure is an important guarantee for realizing urban ecological resilience. In the process of industrial restructuring, the dominant industries in the area shift towards being capital-intensive and knowledge-intensive while decreasing the presence of high-pollution and high-energy-consuming industries. This transition promotes the environmental friendliness and ecological sustainability of industries. Therefore, this paper puts forwards Hypothesis 2.

Hypothesis 2: *Green technology innovation and industrial structure upgrading mediates the relationship between China's big data comprehensive pilot zone and urban ecological resilience, respectively.*

The established pilot zone policy is able to transcend geographical limitations through data elements and information communication, realizing the linkage of economic activities across regions and time and space. The unique spatial geographic characteristics of the policy make it possible to overcome barriers to the dissemination of knowledge, technology and factors in the process of influencing ecological resilience. Through learning and imitation, neighbouring regions may likewise promote the innovation and application of green technology, optimize the industrial layout, and enhance the efficiency of energy use to improve the ecological environment and enhance ecological resilience. There is an obvious spatial spillover effect. Therefore, this paper proposes Hypothesis 3.

Hypothesis 3: *China's comprehensive big data pilot zone is positively related to urban ecological resilience in neighbouring regions.*

Through theoretical analyses, this paper draws the mechanism framework as shown in Figure 1.

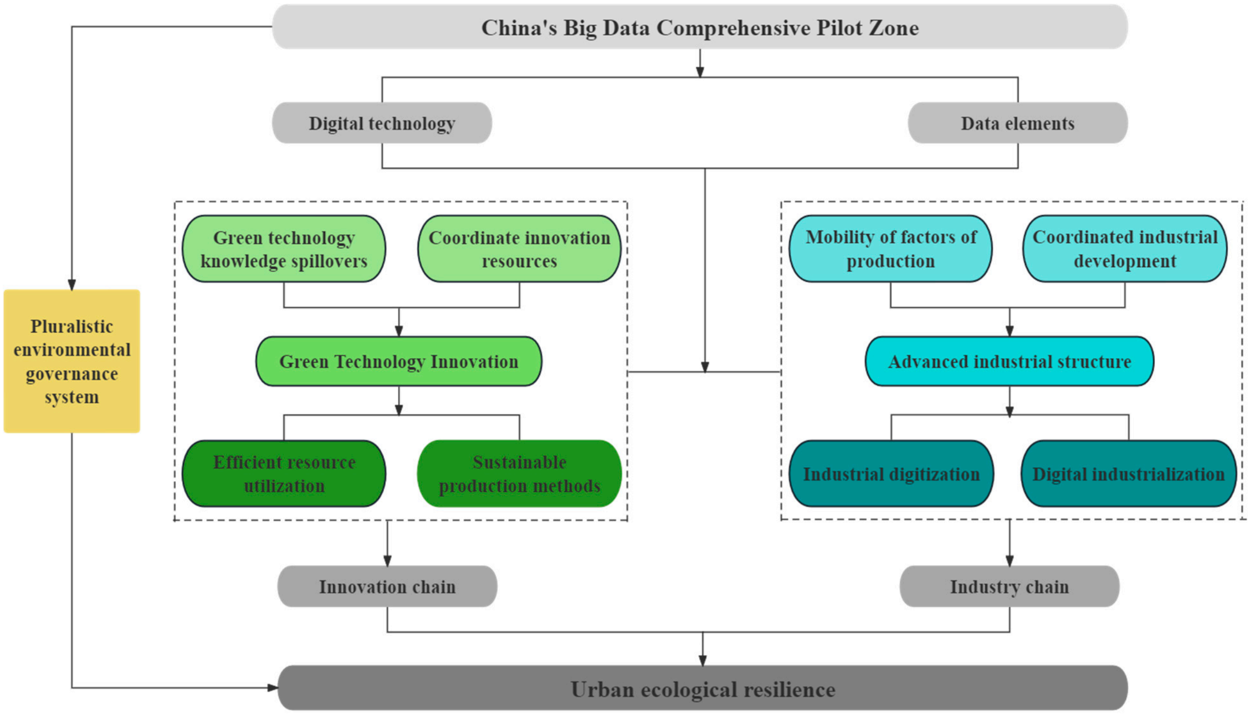

Figure 1. Theoretical analysis framework.

3. Study Design

3.1. Model Setting

This study treats the policy as a quasi-natural experiment and utilizes a difference-in-difference approach. Quasi-natural experiments are a method of research which attempts to assess the impact of policies or behaviours by modelling the effects of randomization in a non-randomized way. To analyse whether the policy significantly improved urban ecological resilience, the differences between big data comprehensive pilot zone cities and non-pilot cities were compared via the following model:

$$ER_{it} = \alpha + \beta Big\_data_{it} + X'_{it}\lambda + \mu_i + \delta_t + \varepsilon_{it}$$

where ER_{it} represents the level of urban ecological resilience. Big_data_{it} is a policy variable, while X_{it} is the control variable. μ_i represents the fixed influence of the city, δ_t represents the fixed effect of time, and ε_{it} represents the random error term. This research focuses on the coefficients of the policy variables, which quantify the overall impact of implementing the national big data comprehensive pilot zone policy on urban ecological resilience.

3.2. Variable Selection

3.2.1. Explained Variables

The explanatory variable in this paper is ecological resilience (ER_{it}), which refers to the ability of an ecosystem to maintain its functionality and stability when it suffers from various external disturbances. In this paper, the indicators are selected by Peng et al. (2023) and Shi et al. (2023) [39,40]. First, the resistance index reflects the ability of urban ecosystems to maintain their structure and function when subjected to external pressures and disturbances, and urban ecosystems with greater resistance are able to reduce the impact of external disturbances on the system. This study focuses on the characterization of the pressure and disturbance caused by human production activities on the environment through the three wastes. Second, the adaptability index reflects the ability of urban ecosystems to make corresponding adjustments or adaptations in the face of external changes, and more adaptable urban ecosystems can help cities effectively cope with a variety of changing situations and maintain ecosystem stability. In this paper, the rate of harmless treatment of domestic waste and the rate of urban sewage treatment are selected to characterize the environmental purification power of the ecosystem, and the level of industrialization is used to characterize the factors that undermine the stability of the ecosystem. Finally, the resilience index reflects the ability of ecosystems to rebuild and repair quickly after damage or disaster, and highly resilient urban ecosystems can quickly restore their original ecological functions, reduce ecosystem losses and recovery time, and guarantee the long-term healthy operation of urban ecosystems. In this paper, three greening indicators are selected to characterize the internal sustainable restoration power of the ecosystem, and the government's attention to environmental conservation exemplifies its external governance authority over the ecosystem. The establishment of the indicator system can assist in assessing the resilience and flexibility of urban ecosystems while dealing with external pressures, alterations, and disasters in a thorough manner. It can also serve as a crucial reference point for sustainable urban growth. Specific indicators are constructed as follows in Table 1.

Table 1. Urban ecological resilience evaluation system.

Measurement Dimensions	Basic Indicators	Measurement Method	Unit of Measure	Indicator Properties
Resistance	Industrial wastewater discharge	-	Tons	Negative
	Industrial sulphur dioxide emissions	-	Tons	Negative
	Industrial smoke and dust emissions	-	Tons	Negative
Adaptability	Nonhazardous treatment rate of domestic waste	(Amount of domestic waste treated harmlessly/total domestic waste) × 100%	%	Positive
	Urban sewage treatment rate	(Sewage treatment capacity/total sewage discharges) × 100%	%	Positive
	Industrialization level	(Secondary industry output/GDP) × 100%	%	Negative
Recovery	Greening coverage in built-up areas	(Green area/built-up area) × 100%	%	Positive
	Green space per capita in parks	Green area of parks/urban resident population	Square metres/person	Positive
	Area of landscaped green space	-	Hectares	Positive
	Government environmental attention	(Eco-friendly word frequency/total word frequency of government work report) × 100%	%	Positive

In this paper, the above 10 basic indicators are selected to measure the ecological resilience. The specific calculation process for the integrated ecological resilience index is as follows:

Data Standardization

Since there are very large indicators, very few indicators, positive indicators, and negative indicators used to measure urban ecological resilience, the data must be standardized to facilitate scientific accuracy and comparability before the empirical analysis.

Positive indicators:

$$x'_{ij} = \frac{x_{ij} - Min(x_j)}{Max(x_j) - Min(x_j)}$$

Negative indicators:

$$x'_{ij} = \frac{Max(x_j) - x_{ij}}{Max(x_j) - Min(x_j)}$$

where x_{ij} is the primary data, x'_{ij} is the extreme differential standardized data, $Min(x_j)$ is the minimum value of the primal data, and $Max(x_j)$ is the maximum value of a primary number.

Entropy Value Method

This work utilizes the entropy weight approach to handle the explanatory variables.

$$P_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x_{ij}} \qquad (i = 1,2,3,\ldots,n; j = 1,2,3,\ldots,m)$$

$$e_j = -\frac{1}{\ln n}\sum_{i=1}^{n} P_{ij} \ln P_{ij}, 0 \le e_j \le 1 \qquad (j = 1,2,3,\ldots,m)$$

$$w_j = \frac{1 - e_j}{\sum_{j=1}^{m}(1 - e_j)}$$

$$Score_i = \sum_{i=1}^{n} w_j x_{ij} \qquad (i = 1,2,3,\ldots,m; j = 1,2,3,\ldots,n)$$

In this study, $Score_i$ is the final comprehensive score of ecological resilience, where P_{ij} represents the proportion of the value of the jth indicator of the ith city to the sum of the corresponding indicator values of all cities. The entropy of the jth indicator is written as e_j, while the weight of the jth indicator is denoted as w_j.

3.2.2. Core Explanatory Variables

In this research, the primary explanatory variable is China's comprehensive big data pilot zone policy (Big_data_{it}). If city i becomes a pilot zone in year t, it is assigned a value of 1; otherwise, it is assigned a value of 0. According to the pilot list released by the relevant authorities in turn and the availability of city data, the experimental group in this paper is the 51 prefecture-level cities in the pilot list. The first sample of the experimental group includes 4 prefecture-level cities, and the second sample includes 47 prefecture-level cities. The policy starting points are set to 2015 and 2016. The remaining 166 prefectural-level cities not included in the list serve as the comparison group. Figure 2 illustrates the spread of policy implementation throughout China's big data comprehensive pilot area. The portion of the figure depicted in dark yellow represents the initial set of big data comprehensive pilot zones, while the portion represented in light yellow represents the subsequent set of big data comprehensive pilot zones.

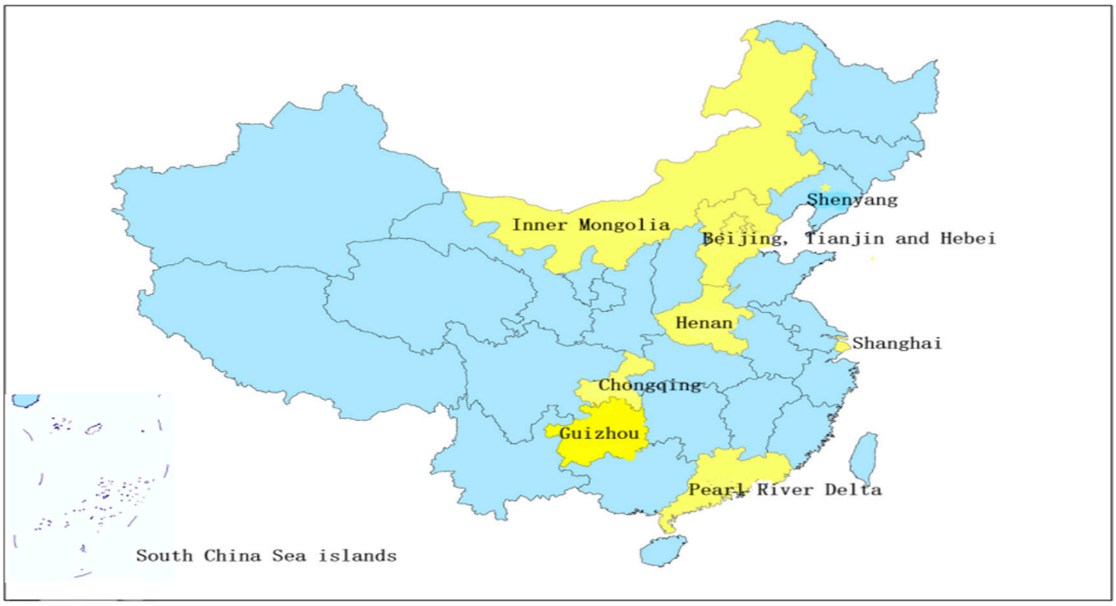

Figure 2. Distribution map of comprehensive big data pilot zones.

The specific sample distribution is shown in Table 2 below:

Table 2. Sample distribution.

Treatment Group	Control Group
Beijing Shanghai Chongqing Tianjin	
Hebei province (11) Shanxi province (0)	Hebei province (0) Shanxi province (4)
Inner Mongolia (9) Liaoning province (1)	Inner Mongolia (0) Liaoning province (10)
Jilin province (0)	Jilin province (6)
Heilongjiang province (0)	Heilongjiang province (5)
Jiangsu Province (0) Shandong Province (0)	Jiangsu Province (12) Shandong Province (12)
Anhui Province (0) Fujian Province (0)	Anhui Province (7) Fujian Province (9)
Zhejiang province (0) Yunnan Province (0)	Zhejiang province (11) Yunnan Province (7)
Jiangxi Province (0) Hubei Province (0)	Jiangxi Province (10) Hubei Province (10)
Henan Province (17) Hunan Province (0)	Henan Province (0) Hunan Province (11)
Guangdong Province (5) Guangxi Province (0)	Guangdong Province (6) Guangxi Province (11)
Guizhou Province (4) Gansu Province (0)	Guizhou Province (0) Gansu Province (9)
Sichuan Province (0) Xinjiang Province (0)	Sichuan Province (11) Xinjiang Province (1)
Shaanxi Province (0) Ningxia Province (0)	Shaanxi Province (8) Ningxia Province (4)
	Hainan Province (2)

3.2.3. Control Variables

In order to mitigate the issue of biased outcomes resulting from omitted variables and in accordance with previous research [41–43], the present study has chosen the following control variables: ① population density (lnpop); ② level of science and technology (tech); ③ level of urbanization (urban); ④ degree of financial development (fd); ⑤ degree of openness to the outside world (open); and ⑥ degree of government intervention (govern). The control variables are measured and the units are shown in Table 3.

Table 3. Description of control variables.

Control Variables	Notation	Unit of Measure	Measurement Method
Population density	lnpop	10,000 persons/km^2	ln (total population/land area of administrative districts)
Level of science and technology	tech	-	Science and technology expenditures/local public budget expenditures
Level of urbanization	urban	-	The urban population/the total population
Degree of financial development	fd	-	Balance of loans from financial institutions at the end of the year/GDP
Degree of openness to the outside world	open	-	FDI/GDP
Degree of government intervention	govern	-	General public budget expenditure/GDP

3.2.4. Mediating Variables

This article further analyses two ways in which China's big data comprehensive pilot zone affects urban ecological resilience, namely, green technological innovation and industrial structure advancement [44,45]. The mediating variables are measured and the units are shown in Table 4.

Table 4. Description of mediating variables.

Intermediary Variables	Notation	Unit of Measure	Calculation Method
Green technological innovation	gi	10,000 persons/item	Number of green patents granted/total population
Industrial structure advancement	indus	-	Tertiary industry value added/secondary industry value added

3.3. Data Sources and Description

The panel data used in the study were obtained from various relevant statistical yearbooks in China. To maintain the integrity and uniformity of the sample data, cities with significant missing data are omitted. The remaining cities were filled with the least amount of missing data using linear interpolation. The primary statistical data of this work are displayed in Table 5.

Table 5. Descriptive statistics.

Variables	Obs	Mean	Std. Dev.	Min	Max
ER	2604	0.116	0.082	0.043	0.849
Big_data	2604	0.119	0.324	0	1
lnpop	2604	5.755	0.934	0.683	7.809
tech	2604	0.017	0.017	0.001	0.166
urban	2604	0.557	0.150	0.181	1
fd	2604	2.475	1.194	0.588	12.569
open	2604	0.018	0.018	0.000	0.229
govern	2604	0.194	0.090	0.044	0.704
gi	2604	0.747	1.599	0	24.422
indus	2604	1.049	0.610	0.175	5.350

4. Empirical Analysis

4.1. Benchmark Regression Analysis

Table 6 presents the findings of the benchmark regressions that examined the impact of the pilot zone strategy on urban ecological resilience. The regression results, which gradually incorporate control variables, are displayed in columns (1)–(7). The study's findings indicate that the coefficient estimate for the effect of the national big data comprehensive pilot zone policy on urban ecological resilience is statistically significant at the 1% level. Even after accounting for other variables, this significance remains strong. The inclusion of the control variables gradually increases the coefficient estimate to 0.012, indicating a 1.2 percent improvement in urban ecological resilience due to the implementation of the big data pilot zone. The findings of this study provide support for Hypothesis 1.

Table 6. Benchmark regression results.

Variables	Explanatory Variable: *ER*						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Big_data	0.012 ***	0.011 ***	0.011 ***	0.012 ***	0.012 ***	0.012 ***	0.012 ***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
lnpop		−0.004 **	−0.004 **	−0.004 *	−0.004 *	−0.004 *	−0.004 *
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
tech			0.082 *	0.070	0.079 *	0.080 *	0.076
			(0.045)	(0.046)	(0.047)	(0.047)	(0.048)
urban				−0.044 ***	−0.044 ***	−0.044 ***	−0.044 ***
				(0.011)	(0.011)	(0.011)	(0.011)
fd					0.001	0.001	0.001 *
					(0.001)	(0.001)	(0.001)
open						−0.027	−0.023
						(0.038)	(0.038)
govern							−0.010
							(0.012)
Constant	0.115 ***	0.140 ***	0.139 ***	0.159 ***	0.156 ***	0.157 ***	0.158 ***
	(0.000)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	2604	2604	2604	2604	2604	2604	2604
R-squared	0.964	0.964	0.964	0.964	0.964	0.964	0.964

*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses indicate robust standard errors.

Regarding the empirical results, the estimated coefficient of population density (lnpop) on urban ecological resilience is significantly negative, indicating that population density adversely affects urban ecological resilience, possibly because high population density requires the utilization of more natural resources, and the overuse of resources destroys the resilience and regeneration of ecosystems. Furthermore, high population density leads to high emissions of waste gas, wastewater, and waste solids, making the whole ecosystem vulnerable and reducing its adaptive capacity to external changes and disturbances and undermining its ecological resilience. High emissions make the entire ecosystem fragile, reducing its ability to adapt to external changes and disturbances and undermining ecological resilience. The estimated coefficient of the effect of the urbanization level (urban) on urban ecological resilience is significantly negative, indicating that the urbanization process damages urban ecological resilience. This may be because large-scale land development and construction encroach upon ecological land, such as farmland, forestland, and grassland, which destroys the foundation of the ecological environment and reduces the adaptability and stability of ecosystems. On the other hand, industrialization and transportation accompanying urbanization further contribute to negative impacts on environmental protection and environmental degradation. Industrialization and transportation cause environmental pollution, affecting ecological health and destroying ecosystem resilience. The estimated coefficient on the level of finance (fd) is significantly positive, indicating that it enhances urban ecological resilience and that the dynamic financial market continues to drive green finance and sustainable investment, which provides financial support for low-carbon, environmentally friendly, and sustainable development projects. Such green investment behaviours can help promote the sustainable development of the ecological environment and the stable and healthy functioning of ecosystems, which enhances ecological resilience.

4.2. Robustness Tests

4.2.1. Parallel Trend Test

In order to conduct research using the double-difference approach, it is essential to subject both the experimental and control groups to a parallel trend test. This test evaluates the consistency between the two groups by utilizing the list of pilot zone policies as the dividing criterion and the year of policy implementation as the boundary. To ensure the reliability of the regression results, it is crucial that both groups exhibit minimal differences prior to policy implementation. The parallel trend test is conducted using event study methodology, with the model structured in the following manner:

$$ER_{it} = \alpha + \sum_{k=-4}^{6} \beta_k Big\_data_{it} + \gamma X'_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

In this paper, the double difference model is used to test the parallel trend, and, since the big data comprehensive pilot zone began to be implemented in 2015, 2015 is selected as the time boundary to analyse the ecological effect of the big data comprehensive pilot zone from 2011 to 2021. In the formula, Big_data_{it} is the policy variables, β_k is the impact coefficient of the big data comprehensive pilot zone on ecological resilience in different years, and the value range of k is set to $-4 \leq \text{k} \leq 6$. The other variables are assigned the same meanings as in the previous regression equation.

Figure 3 illustrates the parallel trend test, with the *y*-axis representing the estimated coefficient β value and the *x*-axis representing the relationship between policy implementation and the base year of 2015. The column associated with the value x = 0 represents the year of policy implementation, specifically 2015. Prior to the introduction of the policy, the coefficient β value exhibited fluctuations around zero and did not demonstrate statistical significance, suggesting a lack of meaningful distinction between the experimental and control groups. From 2015 onwards, the coefficient estimate consistently increases and reaches a value close to 0.01 by 2017, thereby passing the significance test, which indicates the ecological effectiveness of the program. The conducted parallel trend test has yielded positive results. In Figure 3, it can be observed that the implementation of the complete pilot zone of the big data policy has a temporal lag in its ability to augment urban ecological resilience.

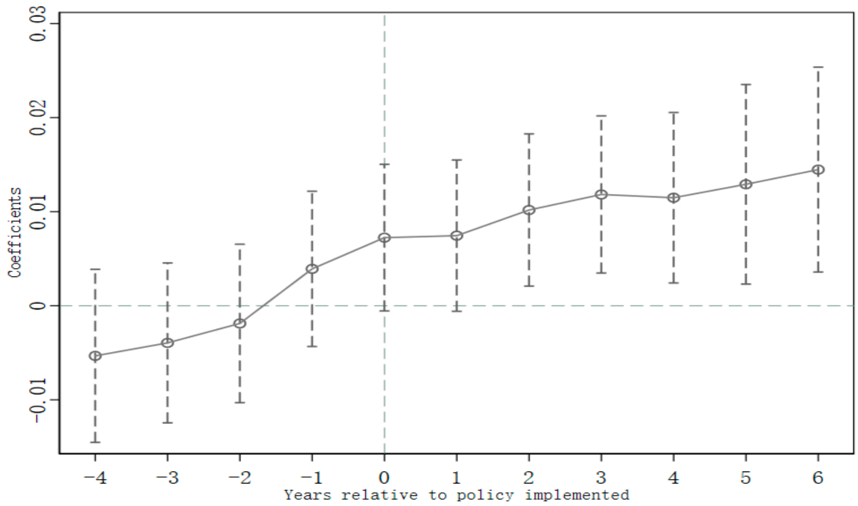

Figure 3. Parallel trend test.

4.2.2. Placebo Test

To eliminate the interference of other factors related to the national big data comprehensive pilot zone policy on the benchmark regression results, a placebo test is conducted by means of the replacement test of randomly generated experimental groups. The specific operation method was as follows. A random construction of the dummy variable for the counterfactual experimental group and a temporal dummy variable for the counterfactual policy shock is performed. The sample of 217 prefecture-level cities is then subjected to 1000 iterations. The policy shock is randomly set at different times, and cities in each sample are randomly taken as the experimental group for the placebo test. The process is repeated 1000 times to generate the counterfactual coefficients, as shown in Figure 4.

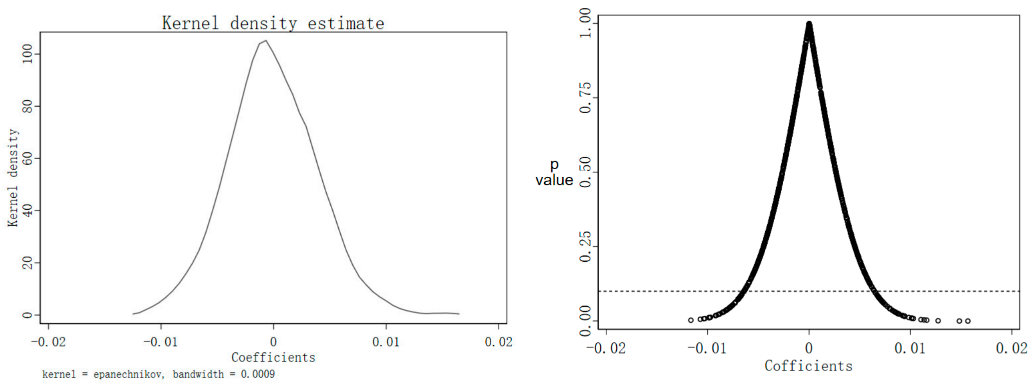

Figure 4. Placebo test.

The left panel shows the kernel density curve of the placebo test coefficient estimates, which can be seen to be approximately normally distributed, with the coefficient estimates centrally distributed at approximately 0, indicating that the regression coefficients are unbiased estimators. The black hollow circles in the right figure indicate the p-values corresponding to the pseudo-estimated coefficients, and the horizontal dashed line represents the horizontal line of 0.1. It can be seen from the figure that most of the p-values are above the horizontal dashed line, i.e., most of the p-values are greater than 0.1. Therefore, the randomly generated counterfactual experimental group affected by the national big data comprehensive pilot zone policy does not indicate a policy effect on urban ecological resilience, and the placebo test is passed.

4.2.3. Propensity Score Matching Double-Difference Model Estimation

The PSM-DID model is used to address any selection bias in the pilot policy by conducting robustness tests on the baseline regression results. This work utilizes one-to-four nearest-neighbour matching, radius matching, and kernel matching techniques. Subsequently, the double-difference model is employed for estimation based on the matching findings. Figure 5 displays the results of the balance test for radius matching; the left graph shows that the data after matching are all within 10% bias, and the right figure is a bar chart of the common support domain, indicating that the matching effect is better. Other matching methods also successfully passed the balancing test.

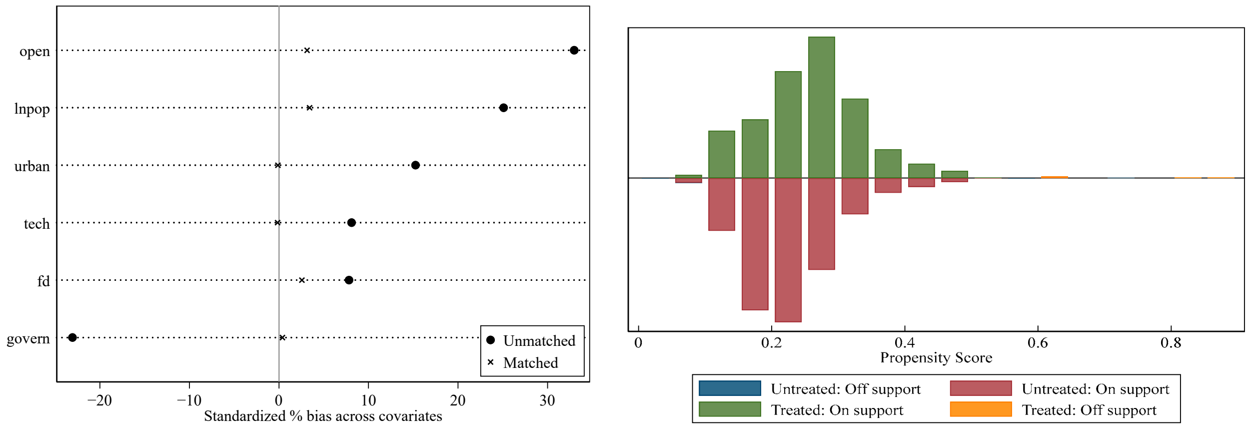

Figure 5. Radius matching.

Table 7 displays the expected results of the balance test after matching. The results show that the calculated coefficients are consistently positive regardless of the matching method utilized, indicating that selection bias does not impact the results.

Table 7. PSM–DID robustness test results.

Variables	Explanatory Variable: *ER*		
	(1) Nearest Neighbour Matching	**(2) Radius Matching**	**(3) Kernel Matching**
Big_data	0.010 ***	0.012 ***	0.012 ***
	(0.002)	(0.002)	(0.002)
Constant	0.183 ***	0.157 ***	0.157 ***
	(0.017)	(0.013)	(0.013)
Control	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	1375	2594	2598
R-squared	0.977	0.964	0.964

*** represents significance at the 1% levels. Values in parentheses indicate robust standard errors.

4.2.4. Endogeneity Test

This research uses the number of landline telephones per 100 persons in 1984 (tele) and the degree of topographic relief (rdls) as instrumental variables for the double-difference term Big_data. One aspect to consider is that the level of topographic relief and the quantity of landline telephones per 100 individuals in 1984 were external factors that did not influence ecological resilience. Conversely, the level of topography and slope can influence the progress of digital infrastructure, while the rate of fixed telephone calls per 100 individuals in 1984 can affect the digital economy. As a result, both factors are important in implementing the comprehensive big data pilot zone policy. The instrumental variables meet the criteria of both exogeneity and correlation, allowing them to be included in the regression instead of the big data comprehensive pilot zone policy. This allows the original model error term and endogenous variable correlation to be eliminated.

The study uses the interaction terms T-tele and T-rdls between instrumental variables and time dummy variables of each year as instrumental variables in the empirical analysis to show changes over time [46]. Below is the building block of the instrumental variable model.

$$ER_{it} = \xi_0 + \xi_1 Big\_data_{it} + \xi_2 X'_{it} + \varepsilon_{it}$$

$$Big\_data_{it} = \xi_0^1 + \xi_1^1 IV_{it} + \xi_2^1 X'_{it} + \mu_i + \delta_t + \varepsilon_{it}^1$$

$$ER_{it} = \xi_0^2 + \xi_1^2 Big\_data_{it} - hat + \xi_2^2 X'_{it} + \mu_i + \delta_t + \varepsilon_{it}^2$$

where the parameters ξ_1, ξ_1^1, and ξ_1^2 denote the OLS estimation, first-stage IV estimation, and second-stage IV estimation, respectively. The results of the instrumental variable estimation are shown in Table 8.

Table 8. Endogeneity test.

Variables	First-Stage Regression		Second-Stage Regression	
	(1) T-tele	(2) T-rdls	(3) T-tele	(4) T-rdls
Big_data			0.064 ***	0.027 ***
			(0.010)	(0.006)
T-tele	0.589 ***			
	(0.027)			
T-rdls		0.844 ***		
		(0.032)		
Constant	−0.035	−0.492 ***	−0.092 ***	−0.104 ***
	(0.039)	(0.052)	(0.020)	(0.022)
Control	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Underidentification test			292.479	182.609
			[0.000]	[0.000]
Weak instruments test			5277.556	2417.831
			{16.38}	{16.38}
Observations	2604	2604	2604	2604
R-squared	0.684	0.504	0.792	0.798

Note: *** denote significance at the 1%. Values in parentheses indicate robust standard errors. Under identification tests were performed using the Kleibergen–Paap rk LM statistic, with p values in [ ]; and the weak instruments test adopts the Donald Wald-F statistic, with the Stock–Yogo test 10% level critical value in { }.

The regression outcomes of the endogeneity test utilizing the two instrumental variables are presented in Table 8. The initial-stage regression findings for the instrumental variables are presented on the left side of Table 8. The instrumental variables T-tele and T-rdls have estimated coefficients of 0.589 and 0.844, respectively. These coefficients are statistically significant at the 1 per cent level. The results of the second-stage regression of the instrumental variables are displayed on the right side of Table 8. The instrumental variables T-tele and T-rdls have estimated coefficients of 0.064 and 0.027, respectively, and both values have been found to be statistically significant. Furthermore, it can be observed that both coefficients surpass the previous benchmark regression coefficient of 0.012. This suggests that the inclusion of instrumental variables in the model leads to larger absolute values for the estimated coefficients of the policy variables derived from the instrumental variables approach, as compared with the previous model. Failure to consider the endogeneity issue may result in an underestimation of the favourable influence of the big data comprehensive pilot zone on urban ecological resilience.

4.2.5. Other Robustness Tests

Table 9 displays the outcomes of further robustness tests. In order to mitigate the influence of non-random sample data on the model estimation outcomes, the explanatory variables in columns (1), (2), and (3) of Table 9 are subjected to 1% two-sided shrinkage, 1% two-sided truncation, and elimination of the municipality samples, respectively. In addition, this paper incorporates lagged one-period urban ecological resilience into the model for the full-sample regression analysis, taking into account the potential serial autocorrelation and inertial correlation of the explanatory variables. The results may be found in column (4) of Table 9. Given that this article covers the period from 2010 to 2021, it is possible that the "Broadband China" pilot policy and the smart city pilot policy may intersect with the policy outlined in this paper. Consequently, this overlap could have an impact on the outcomes of the model. Hence, the model incorporates additional policies, as indicated in column (5) of Table 9. The aforementioned regression findings exhibit statistically significant positive associations, hence substantiating the robustness of the conclusions drawn in this study.

Table 9. Other robustness tests.

Variables	**Explanatory Variable: *ER***				
	(1) Shrinkage 1%	**(2) Truncated 1%**	**(3) Excluding Municipalities**	**(4) Lag One Phase**	**(5) Exclusion of Other Policies**
Big_data	0.008 ***	0.009 ***	0.005 ***	0.004 ***	0.012 ***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Broadband					0.005 ***
					(0.001)
Smartcity					0.001
					(0.002)
L.ER				0.628 ***	
				(0.055)	
Constant	0.149 ***	0.148 ***	0.141 ***	0.068 ***	0.152 ***
	(0.013)	(0.013)	(0.012)	(0.010)	(0.013)
Control	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	2604	2552	2556	2387	2604
R-squared	0.956	0.934	0.954	0.979	0.964

*** represents significance at the 1% levels. Values in parentheses indicate robust standard errors.

4.3. Heterogeneity Analysis

This paper takes these four regions as the standard for regressing the subsamples for the heterogeneity test by geographic location. As shown in Table 10, the comprehensive big data experimental zone policy has a significant positive effect on the ecological resilience of the eastern, central, and western regions, and the effect is greatest in the eastern region. However, this policy is detrimental to the ecological resilience of cities in the northeast. One potential explanation for this disparity is that the eastern region encompasses a greater number of extensive big data pilot zones, such as Beijing–Tianjin–Hebei, the Pearl River Delta, and Shanghai municipality, where highly developed economies, high administrative levels, and cross-regional characteristics allow for all-encompassing, high-level, and large-scale diffusion and radiation effects that boost policy effectiveness. In addition, the eastern region provides a good foundation for enhancing urban ecological resilience through the use of cutting-edge innovative technologies, strong resource allocation capacity, and good green infrastructure. Shenyang, the only comprehensive big data pilot zone in the northeast region, is located in the centre of Liaoning Province and the southern part of the northeast region. Although it is the political, economic, cultural, and transportation centre of the northeast region, Shenyang has not yet given full play to its radiating and driving role in enhancing urban ecological resilience. In addition, the northeast region belongs to the agricultural and animal husbandry border zone and forest border zone, the ecological chain is weak, and the foundation of its ecological resilience has been damaged by the overutilization of natural resources, such as soil, forestland, and water resources. Moreover, as an old industrial base that relies on abundant coal and iron resources, the northeast region is characterized by heavy industry, which results in a large volume of three-waste emissions that seriously affect its ecological environment and reduce its ecological resilience.

Table 10. Geographic location heterogeneity.

Variables	Explanatory Variable: *ER*			
	(1) East	**(2) Centre**	**(3) West**	**(4) Northeast**
Big_data	0.022 ***	0.011 ***	0.018 ***	−0.049 ***
	(0.004)	(0.002)	(0.003)	(0.010)
Constant	0.503 ***	0.158 ***	0.106 ***	−0.502
	(0.104)	(0.026)	(0.014)	(0.542)
Control	YES	YES	YES	YES
City FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Observations	852	708	780	264
R-squared	0.984	0.836	0.884	0.787

*** represents significance at the 1% levels. Values in parentheses indicate robust standard errors.

China's two major river basins have complex and diverse geomorphological and natural conditions. With the advancement of industrialization and urbanization, frequent human activities have caused severe environmental and climatic pollution and ecosystem degradation in these two river basins, and their ecological security is seriously challenged. Therefore, the samples from the Yangtze River Economic Belt and the Yellow River Basin are used for regression estimations, and the results, as shown in columns (1) and (2) of Table 11, indicate that the comprehensive big data pilot zone policy has a significant effect on the ecological resilience of the two watersheds and that the ecological resilience of the Yangtze River Economic Belt is greater than that of the Yellow River Basin. In terms of ecological conditions, the Yangtze River Economic Belt is located in eastern China, where the climate is mild and humid and water resources are abundant, which is conducive to ecosystem stability. In contrast, the Yellow River Basin is located in an arid and semiarid climate zone in northern China, where water resources are scarce and the ecological environment is poor. In terms of economic structure, the Yangtze River Economic Zone has relatively balanced economic development and a diversified industrial structure that does not rely on a single resource. In contrast, the Yellow River Basin region has a single industrial structure, and excessive development and utilization resulting from a high degree of resource dependence has caused serious ecological and environmental problems. As a result, the poorer ecological foundation of the Yellow River Basin has led to slower policy effects. In addition, the Yangtze River economy possesses more economically developed city clusters with a more developed level of digital economic development, more rapid industrial structure transformation, and more cutting-edge technological innovation than does the Yellow River Basin, which results in a more pronounced enhancement of ecological resilience.

Table 11. Heterogeneity of the two river basins.

Variables	Explanatory Variable: *ER*	
	(1) Yangtze River Economic Belt	**(2) Yellow River Basin**
Big_data	0.050 ***	0.004 **
	(0.007)	(0.002)
Constant	0.180 ***	0.111 ***
	(0.062)	(0.012)
Control	YES	YES
City FE	YES	YES
Year FE	YES	YES
Observations	1020	888
R-squared	0.970	0.877

, * represent significance at the 5% and 1% levels, respectively. Values in parentheses indicate robust standard errors.

The study categorizes the entire sample into resource cities and non-resource cities. Resource cities are then further classified into growing, mature, declining, and regenerating cities for regression analysis. The statistical analysis reveals that there is no substantial enhancement effect observed on the ecological resilience of declining and regenerating cities, while, according to the findings shown in Table 12, it is evident that the big data comprehensive pilot zone exerts a significant impact on the ecological resilience of growing cities, mature cities, and non-resource cities. In resource cities, growing cities and mature cities refer to cities in which resource development and utilization are in the rising and stable stages, respectively, and big data technology can realize the fine management and intelligent planning of resources in growing and mature cities, and realize the rational allocation and effective utilization of resources. Through real-time monitoring of resource conditions and forecasting changes in resource demand, cities can better plan and manage resource development, avoid overdevelopment and waste, and improve the efficiency of resource use, thus enhancing the ecological resilience of growing and mature cities. Declining cities typically experience resource depletion, sluggish economic growth, and significant ecological and environmental challenges, necessitating the implementation of comprehensive environmental governance and resource integration. While the establishment of a comprehensive big data pilot zone has the potential to enhance resource utilisation efficiency by providing data support, it necessitates significant capital investment, system integration, and administrative governance to effectively address the economic challenges faced by recessionary cities. The constraints and challenges faced by comprehensive big data pilot zones in enhancing the ecological resilience of declining cities are more complex due to the overlap of multiple ecological, social, and economic problems, resulting in the possibility that declining cities may not be able to make full use of big data technologies to enhance ecological resilience. Regenerative cities are urban states in which resource cities achieve regeneration through systematic urban renewal and transformation. This process requires a long period of time and a large amount of investment, while the construction of a big data pilot zone requires considerable time and cost, and regenerative cities may not be able to obtain relevant support quickly. In addition, regenerative cities usually take environmental protection and ecological construction as an important goal, and therefore usually have a lower level of ecological pollution and a better ecological foundation. Big data integrated pilot zones cannot significantly enhance the ecological resilience of regenerative cities. Column (5) of Table 12 shows that the big data policy enhances the ecological resilience of non-resource cities more than resource cities. Non-resource cities have the advantage of diversified economic structures, environmental conservation consciousness, urban planning and management, and technological innovation and scientific and technological support, on which a comprehensive big data pilot zone can strengthen this synergy and improve the ecological resilience of cities.

Table 12. Resource endowment heterogeneity.

Variables	**Explanatory Variable: *ER***				
	(1) Growing City	**(2) Mature City**	**(3) Declining City**	**(4) Regenerative City**	**(5) Non-Resource City**
Big_data	0.009 *	0.005 **	0.004	0.003	0.015 ***
	(0.005)	(0.002)	(0.003)	(0.004)	(0.003)
Constant	0.367 *	−0.276 **	0.067 ***	−0.091	0.233 ***
	(0.190)	(0.125)	(0.010)	(0.099)	(0.017)
Control	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	120	504	240	144	1596
R-squared	0.838	0.765	0.685	0.841	0.969

*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses indicate robust standard errors.

5. Further Analysis

5.1. Analysis of Mediating Effects

The following equations further explore the possible impact of the above policy on urban ecological resilience, as shown in the following intermediary effect model:

$$ER_{it} = \alpha_1 + \beta_1 Big\_data_{it} + \gamma_1 X'_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

$$Med_{it} = \alpha_2 + \beta_2 Big\_data_{it} + \gamma_2 X'_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

$$ER_{it} = \alpha_3 + \beta_3 Big\_data_{it} + cMed_{it} + \gamma_3 X'_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

In the above equation, Med_{it} is the mediating variable and c is its estimated coefficient. If the estimated coefficients β_1, β_2, β_3 and c in this equation are significant, the existence of a mediating effect can be proven. The mediating variables are industrial structure advancement (*indus*) and green technology innovation (*gi*).

The aforementioned findings illustrate the results of the mechanism validation regarding the impact of green technology innovation. The first column of Table 13 demonstrates that the implementation of the comprehensive big data pilot zone policy has a substantial impact on the advancement of urban green technology innovation. The second column of Table 13 demonstrates that the calculated coefficients for both policy variables and green technology innovation exhibit a statistically significant positive relationship. This suggests that the policy has a beneficial impact on urban ecological resilience by fostering the development of green technology innovation. In order to exclude other policy interference, columns (3) and (4) of Table 13, controlling for a range of variables, include both smart city construction and broadband China policy in the model for testing, and the results are each significantly positive, i.e., indicating the robustness of the mediating effect.

Table 13. Analysis of mediating effects.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	gi	***ER***	***gi***	***ER***	***indus***	***ER***	***indus***	***ER***
Big_data	0.444 ***	0.010 ***	0.448 ***	0.010 ***	−0.031 *	0.012 ***	−0.030 *	0.012 ***
	(0.093)	(0.002)	(0.092)	(0.002)	(0.017)	(0.002)	(0.017)	(0.002)
Smartcity			0.547 ***	0.003 **			0.040 **	0.005 ***
			(0.066)	(0.001)			(0.017)	(0.001)
Broadband			−0.062	0.001			−0.005	0.001
			(0.064)	(0.002)			(0.017)	(0.002)
gi		0.004 ***		0.004 ***				
		(0.001)		(0.001)				
indus						0.010 ***		0.010 ***
						(0.002)		(0.002)
Constant	2.722 ***	0.147 ***	2.245 ***	0.143 ***	0.159	0.156 ***	0.125	0.150 ***
	(0.847)	(0.014)	(0.845)	(0.014)	(0.160)	(0.012)	(0.163)	(0.012)
Control	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	2604	2604	2604	2604	2604	2604	2604	2604
R-squared	0.795	0.965	0.802	0.966	0.893	0.965	0.894	0.965

*, **, *** represent significance at the 10%, 5%, and 1% levels, respectively. Values in parentheses indicate robust standard errors.

The findings of the mechanism validation pertaining to the impact of industrial structure are presented above. The data presented in columns (5) of Table 13 indicates that the big data comprehensive pilot zone strategy does not promote the progress of the industrial structure. Column (7) of Table 13 is an empirical test of the effect of the big data comprehensive pilot zone policy on the advancement of the industrial structure by controlling for some economic factors and further controlling for other policy variables that may affect the industrial structure. The results show that its estimated coefficient is −0.030, indicating that the policy still hinders the advanced industrial structure. Excluding the impact of relevant economic factors and other policies, this may be because the comprehensive big data pilot zone policy is a strategy and has led to excessive concentration of resources, structural misallocation in the labour market, and fundamental changes in traditional production modes, business models, etc., and the value chain. These impacts cause profound changes and challenges for traditional industries regarding digital transformation and affect the advancement of industrial structure. In addition, the big data policy usually involves high and new technologies and focuses on technological innovation and application practices, thus generating technological barriers, restricting cooperation and synergistic development between traditional and high-tech industries, and preventing effective articulation and collaboration between industrial chains, which may lead to limitations on the advancement of the industrial structure. The sixth column of Table 13 demonstrates that the calculated coefficients for both policy variables and industrial structure advancement exhibit a statistically significant positive relationship. This suggests that the advancement of industrial structures plays a crucial role in enhancing urban ecological resilience. Similarly, column (8) of Table 13 shows the mediating effect test after controlling for economic factors and other policies, and the obtained results align with the findings shown in column (6) of Table 13. The robustness of this mechanism for the advancement of the industrial structure has been verified.

Therefore, Hypothesis 2 of this research is confirmed.

5.2. Analysis of Spatial Effects

The purpose of this section is to investigate the spillover effect of the comprehensive big data pilot zone policy on ecological resilience. This is performed by establishing a double-difference spatial Durbin model (SDMDID) and incorporating spatial elements to decompose the consequences. The equation that establishes the model is as follows:

$$ER_{it} = \alpha + \rho W \times ER_{it} + \beta Big\_data_{it} + \gamma X'_{it} + \lambda_1 W \times Big\_data_{it} + \lambda_2 W \times X'_{it} + \mu_i + \delta_t + \varepsilon_{it}$$

where W is a binary adjacent spatial weight matrix, with $W \times ER_{it}, W \times Big\_data_{it}$ and $W \times X'_{it}$ representing the spatial lag term of urban ecological resilience, big data policy, and control variable, respectively.

5.2.1. Spatial Correlation Analysis

This paper used ArcGIS software 10.8.1 to visualize and analyse the ecological toughness of China's cities in 2010, 2014, 2018, and 2021, and the results are shown in Figure 6. The minimum values of the ecological toughness of the cities in 2010, 2014, 2018, and 2021 were 0.043058, 0.056607, 0.066113, and 0.073275, respectively, and the maximum values were 0.641738, 0.683787, 0.740655, and 0.848814, respectively. On the whole, China's ecological toughness has gradually improved, and the areas with higher ecological toughness are mainly municipalities and some cities along the coastal belt. In addition, according to the four-year spatial distribution map of ecological toughness, China's ecological toughness level exhibited a clustering pattern, and most of the cities with relatively high ecological toughness levels were provincial core cities, while their development pattern tended to gradually diffuse from core cities to peripheral cities. In addition, as far as 2021 is concerned, 166 cities are located at the mean value of ecological resilience (0.1321992), which shows that the level of ecological resilience in China is relatively unbalanced.

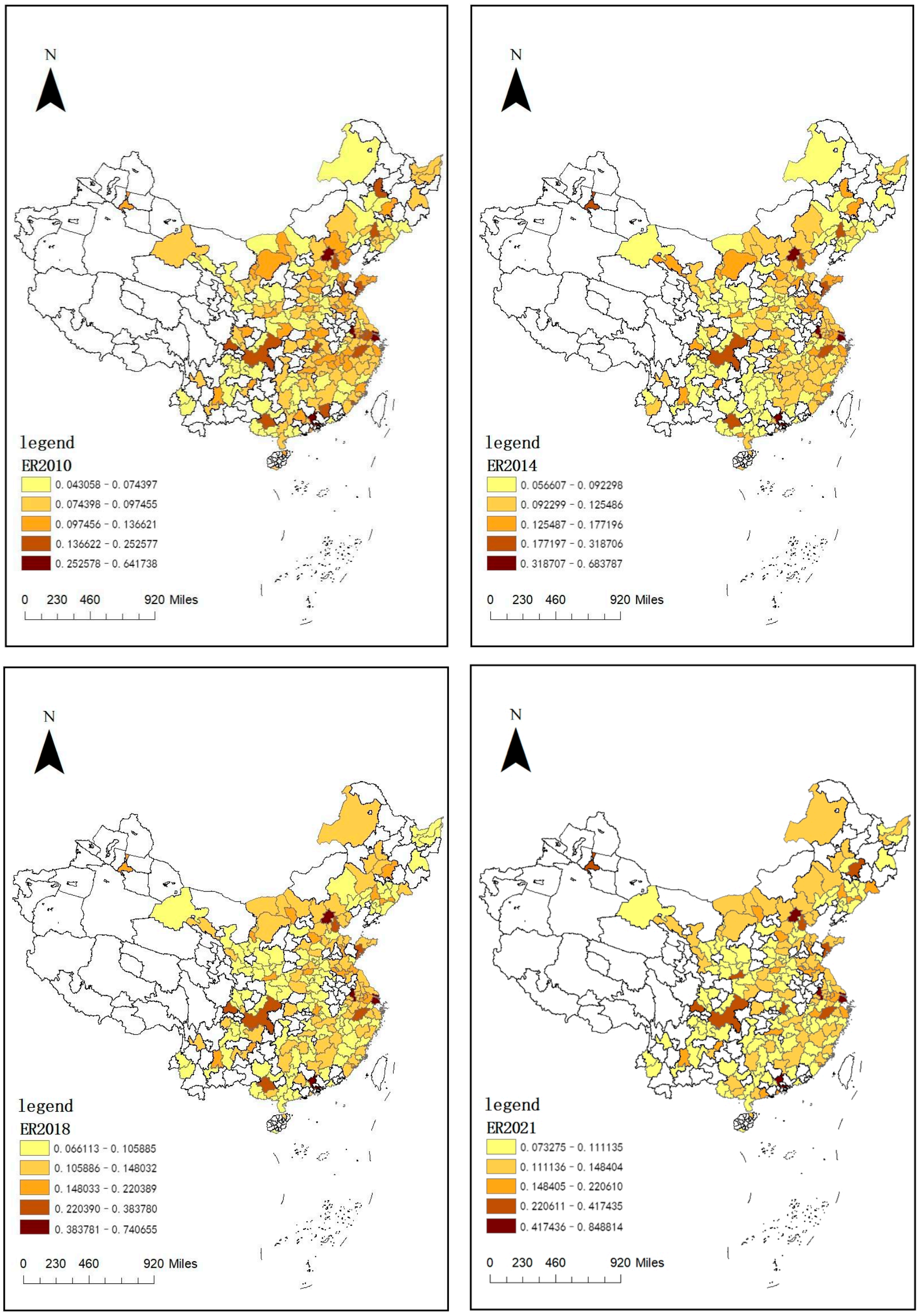

Figure 6. Spatial distribution of ecological resilience.

5.2.2. Global Spatial Correlation Test

Table 14 presents the findings indicating that the Moran indices for urban ecological resilience and the pilot zone policy have values exceeding zero, hence implying a spatial association between these two variables. Therefore, the implementation of the pilot zone affects urban ecological resilience not only within the pilot region but also in neighbouring regions.

Table 14. Global Moran index values.

Year	ER	Big_data
	Moran's I	Moran's I
2015	0.028	0.735
2016	0.020	0.634
2017	0.028	0.634
2018	0.020	0.634
2019	0.009	0.634
2020	0.007	0.634
2021	0.012	0.634

5.2.3. Analysis of Spatial Econometric Models

The results shown in Table 15 indicate that both the LR test and the Wald test yield statistically significant rejections of the initial hypothesis. This finding provides strong evidence for the suitability of the spatial Durbin model in the context of this research. The analysis of the urban ecological resilience spillover impact of the comprehensive big data pilot zone policy takes into account the double fixed effects of time and location, as indicated by the findings of the Hausman test.

Table 15. SDMDID model applicability test.

Type of Test	Statistical Value
LR_spatial_lag	232.08 ***
LR_spatial_error	270.24 ***
Wald_spatial_lag	234.85 ***
Wald_spatial_error	256.72 ***
Hausman test	267.41 ***

*** represent significance at the 1% levels.

The direct effects observed in column (3) of Table 16 align with the findings derived from the preceding benchmark regression analysis. The column (4) of Table 16 demonstrates a statistically significant positive spatial spillover effect, suggesting that the establishment of a big data policy can have an ecological effect on adjacent regions. The reason is that the neighbouring cities can change their production structure, improve energy efficiency, and eliminate backward production capacity through imitation and learning, thereby enhancing their own urban ecological resilience. Therefore, hypothesis 3 of this paper can be argued.

Table 16. Estimates of spatial measures and decomposition of spatial effects.

Variables	Explanatory Variable: *ER*			
	(1) Main	(2) LR_Direct	(3) LR_Indirect	(4) LR_Total
Bigdata	0.015 ***	0.015 ***	0.003 ***	0.018 ***
	(0.002)	(0.002)	(0.001)	(0.002)
rho	0.183 ***	—	—	—
	(0.025)			
sigma2_e	0.000 ***	—	—	—
	(0.000)			
Control	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2604	2604	2604	2604
R-squared	0.239	0.239	0.239	0.239
Number of id	217	217	217	217

*** represent significance at the 1% levels. Values in parentheses indicate robust standard errors.

6. Conclusions and Policy Recommendations

The present research investigates the policy variable of China's big data comprehensive pilot zone, employing data collected from 217 prefecture-level cities over the period from 2010 to 2021. This study aims to thoroughly analyse the methods by which the digital economy contributes to the promotion of urban ecological resilience. First, the enforcement of a comprehensive big data pilot zone significantly enhances urban economic resilience, and the conclusions are robust after excluding sample municipalities, lagging individual explanatory variables by one period, deleting extreme values, eliminating the interference of other policies, and addressing endogeneity issues. Second, the big data pilot zone's influence on improving urban eco-resilience varies across different regions. Specifically, the big data comprehensive pilot zone can significantly affect the urban agglomerations in east, central, and west China, the two major river basin urban agglomerations, the growing and mature urban agglomerations, and the non-resource-based urban agglomerations. It also significantly inhibits urban ecological resilience in the northeast. Third, green technological innovation and advanced industrial structure are both important channels for enhancing urban ecological resilience. Fourth, China's big data comprehensive pilot zone has the potential to bolster the ecological resilience of nearby cities through a radiation-induced impact.

The aforementioned conclusions of this study provide relevant policy insights.

First, to promote the strong expansion and creative application of the big data sector, government oversight of the present pilot zones is of paramount importance. This entails making timely adjustments to policies and support measures, as well as continuously optimizing the development environment of these zones. Furthermore, there is a need to aggressively broaden the extent of the comprehensive pilot zone for big data, fully harness its ecological impact, and bolster the ecological resilience of the urban area. The government should prioritize creating additional pilot zones in a radial manner. This will create an inter-regional linkage effect and multiply the ecological effect. Specifically, the government needs to carefully select sites for planning comprehensive big data pilot zones, choosing areas with strong development potential and infrastructure conditions. Priority should be given to cities or regions with convenient transport, well-developed information and communication infrastructure, and more developed electronic information industries to ensure the development conditions and environment of the pilot zone. It is imperative for the government to clarify the positioning and functional orientation of the comprehensive pilot zone. Additionally, it is crucial to establish the development targets, leading industry orientations, development priorities, and other pertinent components of the pilot zone. In addition, the government needs to formulate relevant policy support measures to provide a favourable policy environment and policy incentives for the comprehensive big data pilot zone. This includes tax incentives, research project funding policies, industrial development support policies, etc., to attract enterprises and organizations to actively participate in the development of the pilot zone.

Second, each locality's unique circumstances should guide the execution of the policy for the creation of comprehensive big data pilot zones. The implementation of big data pilot zones in cities located in the northeastern region of China has the potential to yield substantial reductions in their ecological impacts. Therefore, for these cities, the first step should be to enhance its policy direction and prioritize the augmentation of ecological restoration in the northeastern region to fortify its ecological chain. Based on this conclusion, it is recommended to leverage the data benefits to enhance the monitoring and oversight of ecological degradation during resource development and utilization in the northeast region. Additionally, industries in the northeast can adopt environmentally sustainable practices by harnessing the green technology impact of the comprehensive big data pilot zone. The combined effects of ecological restoration, ecological regulation, and economic transformation are conducive to the sound development of the northeast. The big data pilot zone policy can strengthen the ecological resilience of the city clusters in the Yellow River Basin and the growing and maturing city clusters in resource cities. However, the role of these zones is relatively weak. Therefore, for this kind of city with richer resource endowment, the government should fully execute the resource management function of the big data policy and collect real-time data information of all kinds of resources, including resource supply and demand, market price, environmental indicators, etc., in order to establish a comprehensive resource database. Through the data analysis and mining function of big data technology, the resource data can be deeply analysed and mined to identify the potential value, potential bottlenecks, and potential risks of resource utilization, provide a basis for decision-making on resource allocation, and achieve rational allocation and efficient use of resources, thus reducing resource waste and environmental pollution, which can effectively protect and improve the ecological environment. Concurrently, governments should strengthen soil and water protection, vegetation restoration, and water quality management in resource-endowed cities in order to block the vicious cycle of urban ecology. In addition, for the declining and regenerating cities, the ecological resilience of the comprehensive pilot zone on big data will not be significantly enhanced. The government can establish an ecological compensation mechanism to reward enterprises and individuals in these cities that have made outstanding contributions to the ecological environment and resource protection so as to incentivise them to actively participate in ecological environmental protection by transforming their industrial structure. At the same time, governments should strengthen environmental supervision of declining and regenerating cities, strictly enforce the law, increase penalties, promote green business operations by enterprises, and reduce environmental violations. The government should also combine the ecological compensation work and environmental regulation work, increase the financial support and introduction of science and technology, focusing on the transformation of declining cities to regenerative cities, and ultimately stimulate the latecomer ecological advantages of highly polluted cities.

Third, the industrial structure should be deeply adjusted, and green technological innovation should be vigorously promoted to ensure the ecological effect of comprehensive big data experiments. The presence of digital infrastructure is essential for the robust growth of a comprehensive big data zone, accelerating information sharing and cooperation between data elements and traditional industries through the construction of data sharing platforms, industrial Internet platforms, and so on. Industry data standards and sharing mechanisms should be established, information barriers should be overcome, and the in-depth integration of cross-industry data should be promoted, thereby forcing spontaneous technological innovation and in-depth reform of traditional industries, empowering traditional industries to break through development bottlenecks, and realizing new momentum for green development. Additionally, they should provide support for investigating fundamental environmentally friendly technological advancements, initiate green innovation alliances through government-led or industry organizations to bring together enterprises, research institutes, colleges and universities, and other relevant parties, encourage cross-border cooperation and innovation, and promote cross-innovation between different fields. Furthermore, green innovation technology incubation bases should be established to provide innovative enterprises with technical support, financial support, and market docking services to promote the incubation and transfer of green technologies and accelerate the in-depth integration of green innovation technologies with industrial development. This would expedite the process of transitioning to environmentally friendly practices and promoting sustainable growth in both the agricultural and industrial sectors, while also achieving ecological progress in urban industries.

Fourth, when providing capital support for comprehensive pilot zones for big data through financial means, the government should support the design of policies for synergistic regional development, so as to strengthen the spatial effect of comprehensive pilot zones for big data. The government should summarise and promote the experience of various types of demonstration zones in a timely manner, establish a sound evaluation mechanism, set up an information-sharing platform, strengthen exchanges and cooperation, and form a batch of replicable experience and practices and institutional results. First of all, the government needs to make timely assessments of the construction experience of various types of demonstration zones, including the assessment of their effects and impacts on economic development, social management, ecological environment, and other aspects. Through assessment, the government can identify the successes and shortcomings of the demonstration zones in a timely manner, providing a basis for further summarisation and promotion. The establishment of an assessment mechanism can also help the government better understand the characteristics and actual situation of various types of demonstration zones, providing reference and lessons for the construction of other regions. Moreover, it is imperative for the government to provide a platform that facilitates the flow of information. The government can take advantage of the comprehensive big data pilot zones' own strengths to establish an information sharing platform to integrate and collate the successful experiences, typical cases, and key technologies of the various types of demonstration zones and share them openly with the society. By utilizing the information sharing platform, the government can effectively distribute the knowledge and accomplishments derived from the establishment of demonstration zones. This enables a broader city to comprehend and derive insights from these zones' experiences, thereby fostering regional development and advancement. Finally, the government should strengthen communication and cooperation. The government can invite relevant persons in charge of the demonstration zones and experts and scholars to share their experiences and insights by organising various seminars, symposiums, and learning and exchange activities, so as to promote the exchange of experiences and cooperation between regions. The government can also actively support co-operation projects and cross-regional co-operation between demonstration zones, promote resource sharing and complementary advantages between demonstration zones, achieve the goal of win–win co-operation, and provide more experience and reference for the construction of other regions. On this basis, lower-level cities can facilitate the movement of factors and information, implement tailored measures, and support the advancement of big data. This will help to establish a network of interconnections and exploit the advantageous spatial spillover phenomenon. Ultimately, this will enhance the ecological resilience of cities.

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References

1. Zhao, L.; Sun, Z. Evolution and Spatial Convergence Characteristics of Synergistic Development of Economic Development Quality and Ecological Resilience in Coastal Zone Cities. *Econ. Geogr.* **2023**, *43*, 119–129+240.
2. Dong, Y.; Zhou, Y. Systems Thinking for Technology-Enabled Urban Resilience Governance. *Southeast Acad. Res.* **2022**, 85–97. [CrossRef]
3. Capdevila, P.; Stott, I.; Oliveras Menor, I.; Stouffer, D.B.; Raimundo, R.L.G.; White, H.; Barbour, M.; Salguero-Gómez, R. Reconciling resilience across ecological systems, species and subdisciplines. *J. Ecol.* **2021**, *109*, 3102–3113. [CrossRef]
4. Jiang, W.; Wu, J.; Xu, J. Research on the Coupled and Coordinated Relationship between Urban Ecological Resilience and Economic Development Level--Taking Jiangsu Province as an Example. *Resour. Dev. Mark.* **2023**, *39*, 299–308+318.
5. Wang, S.; Niu, J. Spatial and temporal evolution of urban ecological resilience in the Yellow River Basin and its influencing factors. *Acta Ecol. Sin.* **2023**, *43*, 8309–8320.
6. Wang, S.; Cui, Z.; Lin, J.; Xie, J.; Su, K. The coupling relationship between urbanization and ecological resilience in the Pearl River Delta. *J. Geogr. Sci.* **2022**, *32*, 44–64. [CrossRef]
7. Li, G.; Wang, L. Study of regional variations and convergence in ecological resilience of Chinese cities. *Ecol. Indic.* **2023**, *154*, 110667. [CrossRef]
8. Chen, T.; Li, Y.L. Urban design strategies of urban water environment orientation based on perspective of ecological resilience. *Sci. Technol. Rev.* **2019**, *37*, 26–39.
9. Yan, X.; Tu, J. Spatio-temporal evolution and driving factors of eco-efficiency in resource-based cities in the Yellow River basin. *J. Nat. Resour.* **2021**, *36*, 223–239. [CrossRef]
10. Zhu, Q.; Xie, C.; Liu, J.B. The impact of population agglomeration on ecological resilience: Evidence from China. *Math. Biosci. Eng.* **2023**, *20*, 15898–15917. [CrossRef]
11. Xu, Y.; Li, G.; Cui, S.; Xu, Y.; Pan, J.; Tong, N.; Xu, J.; Zhu, Y. Retrospect and Prospect of Resilience Science: From Ecological Theory to Urban Practice. *Acta Ecol. Sin.* **2018**, *38*, 5297–5304.
12. Lu, W.; Qin, Z.; Yang, S. Heterogeneity effects of environmental regulation policy synergy on ecological resilience: Considering the moderating role of industrial structure. *Environ. Sci. Pollut. Res.* **2024**, 1–19. [CrossRef] [PubMed]
13. Li, Z.; Li, N.; Wen, H. Digital economy and environmental quality: Evidence from 217 cities in China. *Sustainability* **2021**, *13*, 8058. [CrossRef]
14. Yang, D. Fully grasp the rich connotation and practical value of the digital economy. *Jiangsu Soc. Sci.* **2023**, 114–121. [CrossRef]
15. Hong, Y.; Ren, B. Connotation and approach to the deep integration of the digital economy and the real economy. *China Ind. Econ.* **2023**, *2*, 5–16. [CrossRef]
16. Ren, S.; Li, L.; Han, Y.; Hao, Y.; Wu, H. The emerging driving force of inclusive green growth: Does digital economy agglomeration work? *Bus. Strategy Environ.* **2022**, *31*, 1656–1678. [CrossRef]
17. Li, Z.; Wang, J. The dynamic impact of digital economy on carbon emission reduction: Evidence city-level empirical data in China. *J. Clean. Prod.* **2022**, *351*, 131570. [CrossRef]
18. Lyu, Y.; Wang, W.; Wu, Y.; Zhang, J. How does digital economy affect green total factor productivity? Evidence from China. *Sci. Total Environ.* **2023**, *857*, 159428. [CrossRef]
19. Li, Z.; Zhang, Y.; Zhao, Z. Digital Economy and Industrial Green Transformation—Mediating and Threshold Effects Based on Science and Technology Innovation. *J. Ind. Technol. Econ.* **2023**, *42*, 3–16.
20. Yang, Y.; Liang, Q. Digital economy, environmental regulation and green eco-efficiency—Empirical evidence from 285 cities in China. *Front. Environ. Sci.* **2023**, *11*, 1113293. [CrossRef]
21. Chen, W.; Li, B.; Yang, T. Digital Technology Enabling the Construction of Ecological Civilization: Theoretical Basis, Role Mechanism and Path of Realization. *Contemp. Econ. Res.* **2023**, 99–109. [CrossRef]
22. Jiang, Y.; Liu, M.; Yang, C. Mechanisms of digitalization driving economic growth in harmony with ecological development.China Population. *Resour. Environ.* **2023**, *33*, 171–181.
23. Liu, D.; Yang, K.; Sun, S. Spatio-temporal Dynamic Characteristics of Digital Economy and Urban Ecological Resilience and its Coupling Coordination: An Empirical Analysis in the Pearl River Delta Region. *West Forum Econ. Manag.* **2023**, *34*, 1–14, 99.
24. Yue, Y.; Ma, Y. Digital Economy Development and Regional Environmental Quality Improvement—Evidence from Provincial Panel Data. *Chin. J. Environ. Manag.* **2023**, *15*, 94–104.
25. Tang, Y.; Wang, Y. Impact of digital economy on ecological resilience of resource-based cities: Spatial spillover and mechanism. *Environ. Sci. Pollut. Res.* **2023**, *30*, 41299–41318. [CrossRef]
26. Chen, W.; Chang, Q. Has Big Data Empowered Green Innovation in Enterprises-A Quasi-Natural Experiment Based on a National Big Data Comprehensive Pilot Zone. *Financ. Econ.* **2022**, 76–92.
27. Guo, B.; Wang, Y.; Zhang, H. Has the development of digital economy improved urban air quality—A quasi-natural experiment based on a national-level comprehensive big data pilot zone. *J. Guangdong Univ. Financ. Econ.* **2022**, *37*, 58–74.
28. Hu, Z.; Li, Y. Evaluation of Pollution Abatement Effect of Environmental Information Disclosure. *Stat. Res.* **2020**, *37*, 59–74.
29. Yan, Z.; Zhang, B.; Hu, L. Can Environmental Information Disclosure Improve Total Factor Energy Efficiency?—A Quasi-Natural Experiment from the Disclosure of Regulatory Information on Urban Pollution Sources. *China Popul. Resour. Environ.* **2022**, *32*, 67–75.

30. Lyu, Y.; Xiao, X.; Zhang, J. Does the digital economy enhance green total factor productivity in China? The evidence from a national big data comprehensive pilot zone. *Struct. Change Econ. Dyn.* **2024**, *69*, 183–196. [CrossRef]
31. Shi, D.; Sun, G. Research on the Mechanism of the Impact of Big Data Development on Total Factor Productivity of Manufacturing Enterprises. *Financ. Trade Econ.* **2022**, *43*, 85–100.
32. Hou, J.; Kang, W.; Bai, W. Digital economy, environmental regulation and regional green innovation performance. *Inq. Econ. Issues* **2023**, *44*, 177–190.
33. Ren, Y.; Liu, Y.; Hu, Z.; Li, H. The Impact of Big Data Development and Intellectual Property Protection on Enterprises' Green Technology Innovation. *China Popul. Resour. Environ.* **2023**, *33*, 157–167.
34. Sun, Q. Research on the Triple Path of Green Technology Innovation of Enterprises Empowered by Digital Economy. *Acad. J. Zhongzhou* **2023**, 26–32. [CrossRef]
35. Cui, J.; Yong, Y.; Wang, S. State-level Big Data Comprehensive Pilot Zones and Enterprise Green Technology Innovation. *Inq. Econ. Issues* **2023**, *44*, 37–59.
36. Ma, S.; Wei, W.; Li, J. Has the digital economy improved the ecological environment? Empirical evidence from China. *Environ. Sci. Pollut. Res.* **2023**, *30*, 91887–91901. [CrossRef] [PubMed]
37. Shi, D. Evolution of industrial development trends under the conditions of the digital economy. *China Ind. Econ.* **2022**, 26–42. [CrossRef]
38. Zhang, Y.; Ran, C. Effect of digital economy on air pollution in China? New evidence from the "National Big Data Comprehensive Pilot Area" policy. *Econ. Anal. Policy* **2023**, *79*, 986–1004. [CrossRef]
39. Peng, W.; Cao, X. Spatial and Temporal Differentiation of Ecological Resilience and Its Influencing Effect under the Role of Urban Renewal—The Case of Changzhutan Urban Agglomeration. *Econ. Geogr.* **2023**, *43*, 44–52.
40. Shi, C.; He, X. The effect of environmental regulation on urban ecological resilience: A case study of city clusters in the middle reaches of the Yangtze River. *J. Shaanxi Norm. Univ. (Nat. Sci. Ed.)* **2023**, *51*, 56–71.
41. Wang, W.; Yang, X.; Cao, J.; Bu, W.; Dagestani, A.A.; Adebayo, T.S.; Dilanchiev, A.; Ren, S. Energy internet, digital economy, and green economic growth: Evidence from China. *Innov. Green Dev.* **2022**, *1*, 100011. [CrossRef]
42. Huang, L.; Zhang, H.; Si, H.; Wang, H. Can the digital economy promote urban green economic efficiency? Evidence from 273 cities in China. *Ecol. Indic.* **2023**, *155*, 110977. [CrossRef]
43. Zhao, P.; Guo, J.; Wang, Y. How does the digital economy affect green development?—Evidence from 284 cities in China. *Sustainability* **2023**, *15*, 11596. [CrossRef]
44. Xiao, Y.; Wu, S.; Liu, Z.Q.; Lin, H.J. Digital economy and green development: Empirical evidence from China's cities. *Front. Environ. Sci.* **2023**, *11*, 1124680. [CrossRef]
45. Kong, L.; Li, J. Digital economy development and green economic efficiency: Evidence from province-level empirical data in China. *Sustainability* **2022**, *15*, 3. [CrossRef]
46. Niu, Z.; Cui, B. Network Infrastructure Construction and Air Pollution Control: A Quasi-Natural Experiment from the "Broadband China" Strategy. *China J. Econ.* **2021**, *8*, 153–180.