

## Article

# Green Industrial Park Policy and Urban Resilience in China: Evidence from Double Machine Learning

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## Abstract

As industrial green transformation advances and urban risks become more complex, this study explores the relationship between China's national green industrial park policy and urban resilience. The empirical analysis draws on panel data for 293 Chinese cities at the prefecture level or above between 2011 and 2024 and uses a Double/Debiased Machine Learning (DML) framework to flexibly account for observed city characteristics and possible nonlinear relationships. A positive association is observed between the green industrial park policy and the composite urban resilience measure, with this pattern remaining broadly consistent under a range of robustness and sensitivity analyses. Positive coefficients are also obtained across all four resilience components; however, the empirical support is comparatively stronger for the ecological and infrastructure components than for their economic and social counterparts. The pathway results are compatible with potential roles for environmental governance investment, residents' income, and new-quality productive forces. Differences in the estimated relationships are more pronounced when cities are grouped by resource dependence and industrial-base characteristics, whereas the east–central–west classification does not yield statistically significant between-group variation. By shifting attention from park-specific environmental performance to broader resilience outcomes at the city level, this study extends the scope of green industrial park policy assessment. Given the assumptions underlying the empirical design, the reported coefficients represent conditional relationships rather than conclusive causal evidence.

**Keywords:** green industrial park policy; urban resilience; double machine learning; policy evaluation; heterogeneity analysis



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## 1. Introduction

Amid rapid urbanization, intensifying climate change impacts, and growing urban disaster risks, cities are increasingly exposed to interconnected shocks arising from extreme weather, public health emergencies, energy price volatility, supply chain disruptions, and ecological degradation. These risks can cascade across economic, social, ecological, and infrastructure systems, placing greater pressure on public services, environmental governance, and infrastructure maintenance. Strengthening the ability of cities to absorb disturbances, preserve core functions, and adjust to evolving conditions has therefore become a key concern in sustainable urban development.

This concern is also reflected in the United Nations 2030 Agenda, especially SDG 11, which emphasizes inclusive, safe, resilient, and sustainable urban development [1]. Related initiatives, including Making Cities Resilient 2030 (MCR2030), further emphasize

the importance of integrated planning, institutional capacity, technical support, and local resilience strategies [2]. Urban resilience has therefore emerged as an important lens for explaining how cities cope with uncertainty while maintaining development under multiple forms of risk.

Industrial development is closely connected to this issue. Industrial parks concentrate production activities, energy use, infrastructure, technological resources, and environmental pressures, and their development patterns may be linked to broader changes in urban systems through industrial linkages, employment, environmental governance, and infrastructure provision. The international eco-industrial park framework developed jointly by UNIDO, the World Bank Group, and GIZ highlights resource efficiency, cleaner production, industrial symbiosis, sustainable park management, and improvements in environmental, social, and economic performance [3]. These principles suggest that the relevance of industrial park green transformation may extend beyond park-level environmental performance to broader urban development conditions.

China has incorporated green industrial park development into its green manufacturing policy framework. Under the Green Industrial Development Plan (2016–2020), the Ministry of Industry and Information Technology (MIIT) promoted green industrial parks through improved resource utilization, infrastructure upgrading, waste recycling, industrial linkages, and public service platforms [4]. The subsequent Notice on Promoting the Development of the Green Manufacturing System set out a standardized recognition process involving self-assessment, third-party evaluation, provincial recommendation, expert appraisal, and public announcement [5].

Against this background, the green industrial park policy offers an appropriate context for assessing the link between industrial green transformation and broader changes in urban resilience. Given the close connections between industrial parks and urban economic activity, environmental governance, infrastructure, employment, and innovation, policy implementation may have broader implications for urban systems. Accordingly, the analysis focuses on the association between China's national green industrial park policy and urban resilience and further investigates dimension-specific relationships, potential pathways, and heterogeneity across cities with different structural conditions.

## 2. Related Literature

### 2.1. Urban Resilience: Concept, Measurement, and Determinants

The concept of urban resilience has gradually expanded beyond post-disturbance recovery to encompass adaptation, adjustment, and transformation [6,7]. In urban studies, resilience is generally viewed as a multidimensional property of complex systems, with particular attention to diversity, redundancy, connectivity, adaptive planning, and interactions among social, ecological, infrastructural, and institutional components [8–10].

Empirical research has translated this multidimensional understanding into composite resilience indices covering economic, social, ecological, and infrastructure dimensions [11,12]. Other studies show that resilience also varies with cities' economic foundations, regional conditions, and industrial structures [13,14]. Together, these studies provide a well-established basis for conceptualizing and measuring urban resilience and for explaining differences across cities.

Much of this literature, however, concentrates on internal urban characteristics. The role of external policy interventions has received less attention, particularly whether green-oriented industrial policies are associated with changes in comprehensive urban resilience. This gap motivates a closer connection between urban resilience research and studies of industrial green transformation and policy evaluation.

## 2.2. Green Industrial Parks and the Effects of Green Transition Policies

Industrial parks are important spatial carriers of industrial production, resource allocation, and technological activity, yet conventional development models often involve intensive resource and energy use. Research on eco-industrial parks therefore emphasizes industrial symbiosis, inter-firm resource exchange, recycling, and environmental management as important means of improving resource efficiency and reducing environmental pressures [15–17].

China's green manufacturing framework extends these ideas through the development of national-level green industrial parks, which place greater emphasis on resource and energy efficiency, environmental management, green production, and technology application. Empirical evidence generally links eco-industrial park development and related green industrial policies with improvements in regional economic performance, green development, technological innovation, industrial upgrading, and environmental governance [18,19].

Recent studies have also begun to consider resilience-related outcomes. Evidence suggests that green industrial park development is associated with greater industrial-chain resilience, with innovation and industrial restructuring identified as relevant factors [20]. Industrial-chain resilience, however, focuses mainly on how industrial systems maintain continuity, adjust after disruptions, and evolve over time, while urban resilience encompasses interactions across economic, social, ecological, and infrastructure systems.

Existing research has documented the environmental, technological, and industrial implications of green industrial park development, yet its broader relevance to urban systems remains less clear. Less is known about how green industrial park policies are related to comprehensive urban resilience, including variation across resilience dimensions, potential pathways, and cities with different structural conditions.

Research on urban resilience and green industrial parks has developed largely along separate lines. Urban resilience studies have focused mainly on cities' internal characteristics, with less attention to green-oriented industrial policies. Studies of green industrial parks, meanwhile, have concentrated on resource efficiency, pollution control, technological innovation, industrial upgrading, and park- or industry-level performance, leaving broader urban-system outcomes less explored. In addition, limited evidence is available on the potential pathways linking green industrial park policies to urban resilience or on how these relationships vary across cities with different structural conditions.

To address these gaps, the empirical investigation links city-level policy exposure with a multidimensional measure of urban resilience. Rather than relying only on the composite index, the analysis separately considers the economic, social, ecological, and infrastructure dimensions. The sample covers 293 Chinese cities at the prefecture level or above during 2011–2024, and Double/Debiased Machine Learning (DML) is used to accommodate a rich set of covariates and flexible nonlinear specifications. Environmental governance investment, residents' income, and new quality productive forces are further examined as potential pathways, while formal between-group tests are used to assess whether the estimated relationships differ by resource endowment, industrial foundation, and geographic region.

### 3. Theoretical Analysis and Research Hypotheses

#### 3.1. Green Industrial Park Policy and Urban Resilience

Urban resilience refers to the capacity of urban systems to maintain core functions, adapt to changing conditions, and adjust or transform in response to external disturbances [10]. Previous research associates differences in urban resilience with economic foundations, innovation capacity, industrial structure, and governance quality [21]. Accordingly, policies related to industrial transformation, resource allocation, and governance capacity may also be relevant to urban resilience.

The green industrial park policy is designed to promote greener production systems, more efficient resource and energy use, and stronger environmental governance. Improved innovation capacity can strengthen cities' ability to adapt to external shocks [22]. Given the close connections between industrial parks and host cities, the policy may relate to broader urban-system changes involving industrial upgrading, green technological innovation, and environmental governance. Such changes may be linked to greater economic adjustment capacity, stronger urban adaptability, and lower ecological risks. Accordingly, H1 is formulated as follows:

**Hypothesis 1 (H1).** *The green industrial park policy is expected to be positively associated with urban resilience.*

#### 3.2. Environmental Governance Investment Pathway

Green industrial park policies incorporate green development requirements, environmental performance evaluation, and resource-use efficiency into park construction and operation. By strengthening green access requirements, environmental management, and pollution-prevention standards, these policies may encourage park enterprises and local governance entities to devote more resources to environmental governance [19]. Existing research also suggests that well-designed environmental regulation can stimulate corporate environmental innovation and improve environmental performance [23]. The policy may therefore increase investment in energy conservation, environmental protection, pollution control, and resource recycling. Such investment may improve ecological conditions and enhance urban capacity to respond to environmental risks and pressures. Previous studies show that environmental regulation can promote industrial upgrading and regional green transformation through technological innovation [24], while sound ecological governance and environmental management can enhance regional capacity to respond to environmental pressures [25]. Environmental governance investment may therefore serve as a potential pathway linking the green industrial park policy to urban resilience. We propose:

**Hypothesis 2 (H2).** *Environmental governance investment constitutes a potential pathway linking the green industrial park policy to urban resilience.*

#### 3.3. Residents' Income Level Pathway

Urban resilience relies on the stable functioning of industrial and infrastructure systems as well as on residents' economic resources and capacity to cope with risks. Existing studies indicate that socioeconomic conditions and access to resources are important determinants of risk response capacity, while greater economic security strengthens the adaptability of individuals and communities facing external shocks [26]. Thus, higher residents' income may provide an important micro-level foundation for urban resilience.

By promoting green production and industrial restructuring, the green industrial park policy may facilitate regional industrial development and reshape labor demand. Studies on green transition and labor markets show that green transformation induces employment restructuring and labor reallocation across industries and occupations [27]. Evidence from China further suggests that the policy is positively associated with regional green development through advances in green technology and adjustments in industrial structure [19].

These changes may improve employment opportunities and residents' income, thereby strengthening household economic buffers and urban risk-coping capacity. This study therefore examines whether residents' income level represents a potential pathway linking the green industrial park policy to urban resilience. We thus propose:

**Hypothesis 3 (H3).** *Residents' income level constitutes a potential pathway linking the green industrial park policy to urban resilience.*

### 3.4. New Quality Productive Forces Pathway

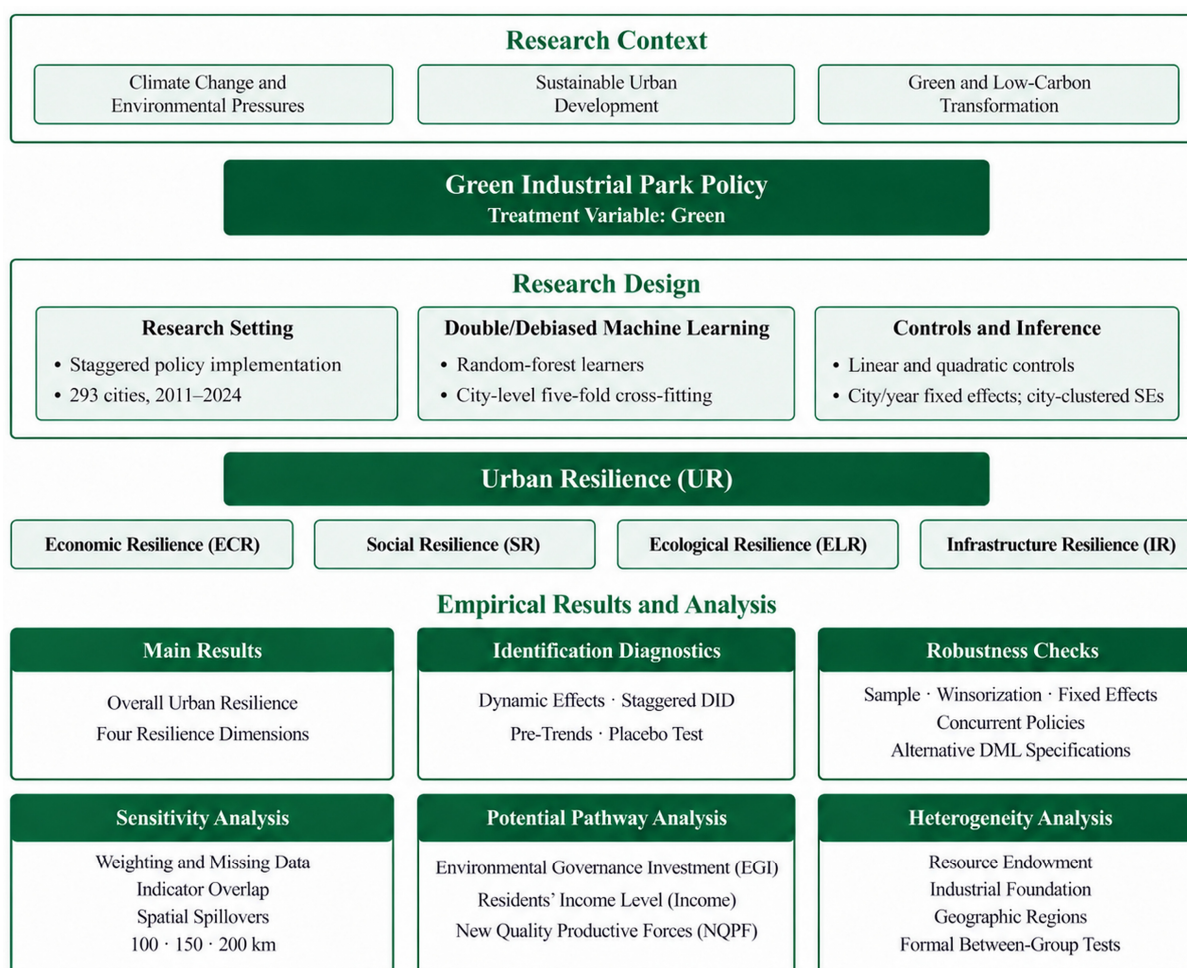
To support a shift toward greener production modes and enhance industrial innovation capacity, the green industrial park policy may improve regional factor allocation by advancing enterprise green transformation, encouraging green technology adoption, and optimizing industrial development models. Existing research shows that national green industrial parks can strengthen urban industrial-chain resilience through advances in green technology and adjustments in industrial structure, providing support for a possible innovation-related link between the policy and urban resilience [20].

New quality productive forces are primarily rooted in technological innovation and may improve production efficiency through digital and green transitions and the more efficient combination of production factors. Previous research indicates that green innovation can improve firms' sustainable development capacity [28], while digital technology adoption can strengthen organizational capabilities and adaptability to environmental change [29]. Within China's institutional context, further evidence suggests that new quality productive forces may enhance resilience at both the enterprise and urban-system levels through stronger innovation capacity and improved resource allocation [30].

Accordingly, the green industrial park policy may foster new quality productive forces through technological upgrading, digital transformation, and innovation-resource agglomeration, thereby strengthening urban systems' adaptive and recovery capacities under external shocks. This study measures new quality productive forces using indicators of emerging-industry development, digital infrastructure, artificial intelligence enterprise agglomeration, and innovation-resource supply, and examines whether it represents a potential pathway linking the green industrial park policy to urban resilience. We thus propose:

**Hypothesis 4 (H4).** *New quality productive forces constitute a potential pathway linking the green industrial park policy to urban resilience.*

Building on the preceding theoretical analysis and empirical identification strategy, this study develops a unified theoretical and analytical framework. Figure 1 presents its overall structure.



**Figure 1.** Theoretical and empirical framework for the relationship between green industrial park policy and urban resilience.

## 4. Research Design

### 4.1. Model Specification

The empirical analysis examines how urban resilience relates to the green industrial park policy. Differences in urban resilience may reflect economic conditions, industrial structure, innovation capacity, infrastructure provision, and governance quality. Policy exposure, city characteristics, and urban resilience may also be related in nonlinear ways. When numerous controls and nonlinear terms are included, conventional parametric specifications may be vulnerable to functional-form misspecification and may have difficulty handling high-dimensional covariates. To flexibly capture observable city-level characteristics and their potential nonlinear effects, Double/Debiased Machine Learning (DML) is used to estimate the conditional relationship between policy exposure and urban resilience.

Systematically developed by Chernozhukov et al. (2018) [31], DML uses machine-learning methods to approximate nuisance functions for the outcome and treatment equations given the covariates. Orthogonalization and cross-fitting reduce the extent to which nuisance-model prediction errors, regularization, and in-sample overfitting propagate into estimation of the target parameter. Unlike traditional parametric models, DML avoids stringent ex-ante assumptions regarding the specific functional forms linking controls to outcome and treatment variables. It can therefore flexibly characterize underlying nonlinear associations and variable interactions and has seen broad application in economic policy evaluation and causal analysis [32].

Several potential pathways may underlie the association between the green industrial park policy and urban resilience, such as environmental governance investment, industrial restructuring, technological innovation diffusion, and resource-allocation optimization. These mechanisms likely involve nonlinearities and complicated interactions among variables, which cannot be fully captured by conventional linear models. DML fits auxiliary functions via machine learning and isolates the variation in the policy variable unexplained by observable city characteristics through residualization and orthogonalization, allowing us to estimate the conditional association between policy exposure and urban resilience.

Drawing on the partial linear DML framework of Chernozhukov et al. (2018) [31], this study specifies the model as follows:

$$UR_{it} = \theta Green_{it} + g(X_{it}) + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

$$Green_{it} = m(X_{it}) + \mu_i + \lambda_t + v_{it} \quad (2)$$

where  $UR_{it}$  represents the urban resilience index for city  $i$  in year  $t$ .  $Green_{it}$  is the policy-treatment indicator, taking the value 0 before a city first appears on the official national-level green industrial park list released by the Ministry of Industry and Information Technology and 1 from the first year of inclusion onward.  $X_{it}$  represents the control-variable set, including both linear and quadratic terms for each city-level covariate.  $\mu_i$  and  $\lambda_t$  account for city and year fixed effects, respectively.  $g(X_{it})$  and  $m(X_{it})$  denote unknown functions linking the covariates to urban resilience and policy exposure.  $\varepsilon_{it}$  and  $v_{it}$  are disturbance terms for the two equations, while  $\theta$  is the policy coefficient of interest.

Estimation begins by removing city-specific means from the outcome, treatment, and continuous control variables, while year effects remain in the transformed specification. Machine-learning methods are then fitted to the transformed outcome and treatment conditional on the controls, and out-of-sample predictions are used to obtain the residuals:

$$\hat{U}_{it} = \widetilde{UR}_{it} - \hat{E}(\widetilde{UR}_{it} | \widetilde{X}_{it}, \lambda_t) \quad (3)$$

$$\hat{V}_{it} = \widetilde{Green}_{it} - \hat{E}(\widetilde{Green}_{it} | \widetilde{X}_{it}, \lambda_t) \quad (4)$$

Here, the tilde indicates that a variable has undergone within-city transformation.  $X_{it}$  denotes the continuously measured control variables and their quadratic terms after the same within-city transformation, and  $\lambda_t$  represents year fixed effects. It should be noted that the quadratic terms of control variables are calculated from the original variables before within-city transformation at the city level, and their form is given by:

$$\widetilde{X}_{it}^2 = X_{it}^2 - \overline{X_i^2},$$

rather than  $(X_{it} - \overline{X_i})^2$ . Finally, the residuals of the outcome variable  $\widetilde{U}_{it}$  are regressed on the residuals of the treatment variable  $\widetilde{V}_{it}$ . The parameter of interest,  $\theta$ , is recovered from the orthogonalized partial score. This procedure reduces the first-order impact of estimation errors arising from auxiliary models on the target parameter.

This study adopts a partially linear DDML model and uses random forest as the baseline learner for both the outcome and treatment equations. Random forest, originally proposed by Breiman [33], improves the fitting capacity for nonlinear relationships and variable interactions by assembling multiple decision trees, which makes it suitable for prediction tasks with numerous control variables. This study implements random forest through the pystacked framework (version 0.7.5) in Stata/MP 18.0, using the default hyperparameter settings of the program. The baseline model adopts five-fold cross-fitting ( $k = 5$ ), and the corresponding ratio of validation samples to training samples is approximately

1:4. Notably, sample splitting is performed by city rather than by individual city–year observations. All annual observations of the same city are assigned to the same fold. In each cross-fitting round, roughly 80% of cities are used to train the outcome and treatment equations, and the remaining 20% of cities generate out-of-sample predictions. Therefore, observations from the same city do not appear in both the training and validation samples, achieving city-level separation between training and validation sets.

To limit sensitivity to a particular sample split, city-level five-fold cross-fitting is performed in five repetitions, with the median estimate retained. The random seed is fixed at 42 for reproducibility. Considering potential serial dependence among repeated observations within the same city over time, this study conducts statistical inference using city-level clustered standard errors. Sensitivity to alternative DML settings is evaluated by using three- and eight-fold cross-fitting instead of the baseline five-fold scheme and by substituting LassoCV, gradient boosting, and support vector machines for random forest.

It should be noted that DML can flexibly control observable city characteristics and their nonlinear effects, yet it cannot automatically eliminate time-varying unobservable factors that affect both policy selection and urban resilience. Identification of the policy parameter depends on the assumption that, conditional on the included controls and city and year fixed effects, no additional unobserved factors jointly determine policy implementation and urban resilience. Therefore, this study interprets  $\theta$  as a conditional policy coefficient estimated under the above assumptions. Pre-policy trends, post-policy dynamic changes, and alternative timing tests are used as supplementary identification diagnostics rather than as independent causal evidence.

#### 4.2. Variable Definitions

##### 4.2.1. Dependent Variable

Urban resilience (UR) is used as the outcome variable in the empirical analysis. Drawing on studies of Chinese cities, urban resilience is operationalized through four components: economic, social, ecological, and infrastructure resilience [12]. Economic resilience captures the capacity of the local economy to sustain basic functioning and adjust its structure when confronted with external shocks. Social resilience concerns the ability of residents and social security systems to absorb risks and disturbances. Ecological resilience refers to ecosystem stability and recovery under environmental pressure. Infrastructure resilience concerns whether systems such as water supply, roads, drainage, gas supply, public transportation, and information and communication infrastructure can maintain essential services and recover promptly.

Regarding the measurement of urban resilience, most existing studies employ the indicator-system-based comprehensive evaluation approach [12,13]. A single measure is insufficient to represent the multidimensional complexity of urban systems. A multidimensional indicator system instead captures urban resilience across different cities and years through representative indicators reflecting its core dimensions. This multidimensional design better serves the study's focus on overall urban resilience rather than on any single efficiency measure. Accordingly, drawing on the basic framework of previous studies on urban resilience measurement and related research by Zhang and Yao (2023) [34], Shi and Jin (2025) [35], Lu et al. (2025) [36], and Chu et al. (2023) [37], Accordingly, urban resilience is assessed through four dimensions: economic, social, ecological, and infrastructure resilience.

Specifically, economic resilience mainly captures the ability of the urban economy to sustain growth, stabilize income, and provide fiscal support in response to external shocks. Economic resilience is operationalized using measures of regional economic output, consumer-market activity, and fiscal support, including per capita gross regional product, total retail sales of consumer goods, and relevant fiscal expenditure indicators. Social

resilience captures the buffering capacity of urban public service provision, employment security, and social security systems against risks and shocks, its measurement combines indicators of public-service resources, social protection, and employment conditions, including the volume of books in public libraries, number of physicians, participation in basic employee pension and medical insurance, total employment, wages of on-the-job employees, and average number of on-the-job employees. Infrastructure resilience reflects the supporting capacity of urban transportation, municipal, and energy infrastructure for economic and social operations, measured by per capita road area, gas penetration rate, and drainage pipeline length. Ecological resilience captures how urban ecosystems maintain stability under environmental stress while supporting pollution control and resource availability. Relevant indicators include green coverage rate of built-up areas, harmless treatment rate of domestic garbage, and urban wastewater treatment rate. The indicator system is presented in Table 1.

**Table 1.** Urban resilience indicator system and corresponding weights.

| Criterion Layer           | Indicator                                                    | Properties | Weight | Pre-Policy Fixed Weight |
|---------------------------|--------------------------------------------------------------|------------|--------|-------------------------|
| Economic Resilience       | Registered urban unemployed population                       | —          | 0.0017 | 0.0020                  |
|                           | Per capita gross regional product                            | +          | 0.0571 | 0.0610                  |
|                           | Proportion of the tertiary industry in GDP                   | +          | 0.0152 | 0.0186                  |
|                           | Fixed asset investment                                       | +          | 0.1165 | 0.0977                  |
|                           | Total retail sales of consumer goods                         | +          | 0.2834 | 0.3771                  |
|                           | Fiscal expenditure on science and technology                 | +          | 0.3976 | 0.3405                  |
|                           | Fiscal expenditure on education                              | +          | 0.1285 | 0.1031                  |
| Social Resilience         | Book collections of public libraries                         | +          | 0.1796 | 0.2018                  |
|                           | Number of physicians                                         | +          | 0.0803 | 0.0762                  |
|                           | Participants in basic employee pension insurance             | +          | 0.1391 | 0.1501                  |
|                           | Participants in basic employee medical insurance             | +          | 0.1495 | 0.1396                  |
|                           | Year-end employed population                                 | +          | 0.1314 | 0.1317                  |
|                           | Total wages of on-the-job employees                          | +          | 0.1981 | 0.1800                  |
|                           | Average number of on-the-job employees                       | +          | 0.1220 | 0.1206                  |
| Ecological Resilience     | Annual average concentration of inhalable particulate matter | —          | 0.0009 | 0.0017                  |
|                           | Industrial wastewater discharge                              | —          | 0.0010 | 0.0014                  |
|                           | Centralized wastewater treatment rate                        | +          | 0.0047 | 0.0077                  |
|                           | Harmless treatment rate of domestic garbage                  | +          | 0.0038 | 0.0081                  |
|                           | Green coverage rate of built-up areas                        | +          | 0.0048 | 0.0082                  |
|                           | Granted green utility model patents                          | +          | 0.3945 | 0.4039                  |
|                           | Granted green invention patents                              | +          | 0.5903 | 0.5691                  |
| Infrastructure Resilience | Length of drainage pipelines                                 | +          | 0.3998 | 0.4062                  |
|                           | Gas penetration rate                                         | +          | 0.0061 | 0.0095                  |
|                           | Per capita road area                                         | +          | 0.0549 | 0.0598                  |
|                           | Per capita daily domestic water consumption                  | +          | 0.0645 | 0.0685                  |
|                           | Number of internet users                                     | +          | 0.2585 | 0.2574                  |
|                           | Number of mobile phone subscribers                           | +          | 0.2161 | 0.1985                  |

Note: The symbols “+” and “—” indicate positive and negative indicators, respectively. The reported weights are calculated within each dimension. Owing to rounding, the displayed weights may not sum exactly to one. The four dimensions are assigned equal weights of 25% when constructing the composite urban resilience index.

For indicator preprocessing, the raw data are first standardized according to indicator attributes. For positive indicators, normalization is performed using the following formula:

$$x_{ijt}^+ = \frac{x_{ijt} - x_j^{\min}}{x_j^{\max} - x_j^{\min}} \quad (5)$$

For negative indicators, the normalization formula is shown below:

$$x_{ijt}^- = \frac{x_j^{\max} - x_{ijt}}{x_j^{\max} - x_j^{\min}} \quad (6)$$

where  $x_{ijt}$  denotes the observed value of indicator  $j$  for city  $i$  in year  $t$ , while  $x_j^{\max}$  and  $x_j^{\min}$  are the corresponding maximum and minimum values over the full set of city–year observations; and  $x_{ijt}^+$  and  $x_{ijt}^-$  denote the normalized values of positive and negative indicators, respectively. For each indicator, the maximum and minimum are determined using the full set of city–year observations over 2011–2024 rather than being recalculated annually. This ensures a consistent normalization benchmark across different years and improves the intertemporal comparability of urban resilience indicators.

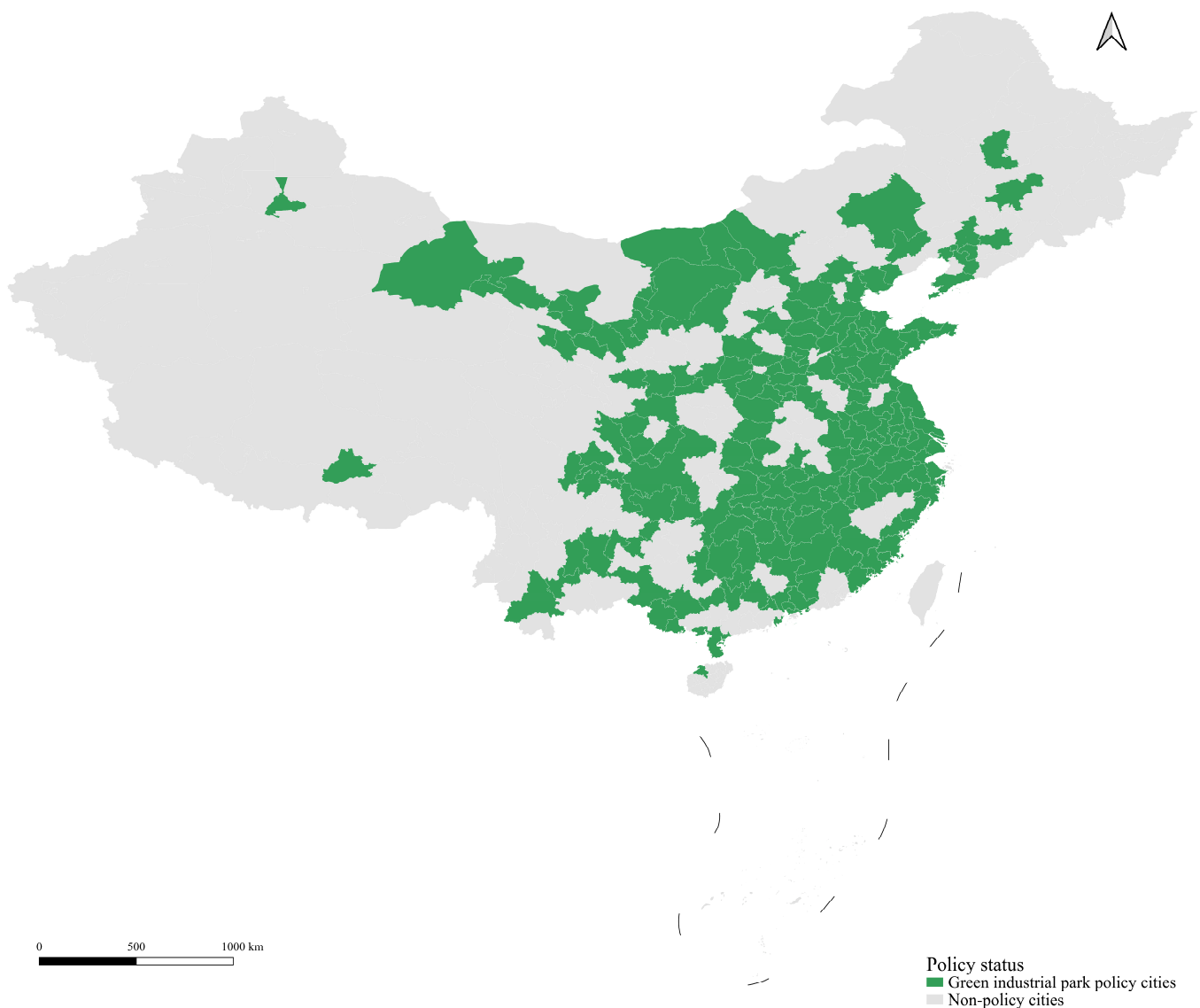
After normalization, all city–year observations over 2011–2024 are combined into a single evaluation matrix. Information entropy, difference coefficients, and indicator weights are then computed for the full sample rather than recalculated separately by year. Entropy weighting is performed separately for the economic, social, ecological and infrastructure dimensions, with the weights within each dimension normalized to sum to one. The corresponding economic (ECR), social (SR), ecological (ELR), and infrastructure (IR) resilience indices are subsequently obtained. The four dimensional scores are then combined using equal weights, so that each contributes 25% to the overall urban resilience index.

To improve comparability across cities and years and facilitate the interpretation of subsequent empirical results, the overall resilience index and its four component indices are rescaled linearly to a 0–10 range [38]. Higher values correspond to greater urban resilience. This mapping only changes the measurement scale and preserves the relative rankings of city–year observations.

As a sensitivity analysis of the weighting scheme, fixed indicator weights are additionally derived from the 2011–2016 pre-policy sample. These fixed weights are subsequently applied to the full 2011–2024 sample to reconstruct the urban resilience index. Table 1 reports both the full-panel entropy weights and the pre-policy fixed weights, while the corresponding DML estimates are presented in the subsequent sensitivity analysis.

#### 4.2.2. Core Explanatory Variable

The national-level green industrial park policy indicator (Green) is used as the principal explanatory variable. Policy status is identified from the official national-level green industrial park list released by the Ministry of Industry and Information Technology and linked to a city panel comprising 293 Chinese cities, all at the prefecture level or higher. The Green variable is defined according to the year when each city was first included in this official list. Specifically, Green is coded as 1 from the first year in which city  $i$  is covered by the policy and remains 1 thereafter; otherwise, it equals 0. The full sample consists of 201 policy-exposed cities and 92 non-exposed cities. Figure 2 presents the spatial distribution of cities implementing the national-level green industrial park policy within the sample.



**Figure 2.** Spatial distribution of cities implementing the national-level green industrial park policy in the sample (2024).

#### 4.2.3. Control Variables

To account for socioeconomic conditions related to urban resilience, this study draws on prior research on urban resilience, green development, and environmental policy evaluation and selects openness, population density, urbanization level, human capital, government intervention, financial development, and transportation development as control variables in light of city-level data availability. Specifically, openness (*open*) is calculated as total import and export volume divided by regional GDP; population density (*ipd*) is expressed as the natural logarithm of resident population per unit of administrative area; urbanization level (*urb*) is represented by the share of urban residents in the total population; human capital (*hcl*) is proxied by regular higher education enrollment relative to the total population; government intervention (*gov*) is measured using local fiscal expenditure as a share of regional GDP; financial development (*fin*) is represented by financial-institution loan balances relative to regional GDP; and transportation development is captured by the natural logarithms of highway passenger volume (*pass*) and freight volume (*fre*), respectively. To allow for nonlinearities, the specification also contains quadratic terms for the

controls. City and year fixed effects are further included to account for time-invariant city characteristics and shocks common across years.

#### 4.2.4. Potential Pathway Variables

Three potential pathways are examined in relation to the green industrial park policy and urban resilience: environmental governance investment (EGI), residents' income (Income), and new quality productive forces (NQPF). EGI is measured by the natural logarithm of energy-saving and environmental protection expenditure as a proxy for local governments' fiscal input in environmental governance, while Income is measured as the natural logarithm of urban residents' per capita disposable income.

Existing empirical studies generally adopt multidimensional indicator systems to measure new quality productive forces, although no unified measurement framework has yet emerged. Cao (2024) [39] measures digital new quality productive forces across the dimensions of digital labor, digital labor objects, and digital means of production, while Chen et al. (2026) [40] develop a city-level index organized around three dimensions: high-quality labor, advanced means of labor, and new objects of labor. Given city-level data constraints, NQPF is measured using four indicators: employees in emerging industries, total telecommunications business volume, artificial intelligence enterprises, and regular higher education institutions. These indicators represent emerging-industry development, digital infrastructure, intelligent technology application, and innovation-resource support, respectively. These indicators are aggregated using the entropy method. The measurement methods and specific indicators of the potential pathway variables are summarized in Table 2.

**Table 2.** Measurement and indicator composition of the potential pathway variables.

| Variables | Dimension                               | Indicator                                                                  | Properties | Processing Method |
|-----------|-----------------------------------------|----------------------------------------------------------------------------|------------|-------------------|
| EGI       | Environmental Governance Capacity       | Government expenditure on energy conservation and environmental protection | +          | Natural Logarithm |
| Income    | Economic Resource Accumulation Capacity | Per capita disposable income of urban residents                            | +          | Natural Logarithm |
| NQPF      | Emerging Industry Development           | Number of employees in emerging industries                                 | +          | Entropy Method    |
|           | Digital Infrastructure Conditions       | Total telecommunications business volume                                   | +          |                   |
|           | Intelligent Technology Application      | Number of artificial intelligence enterprises                              | +          |                   |
|           | Innovation Resource Support             | Number of regular higher education institutions                            | +          |                   |

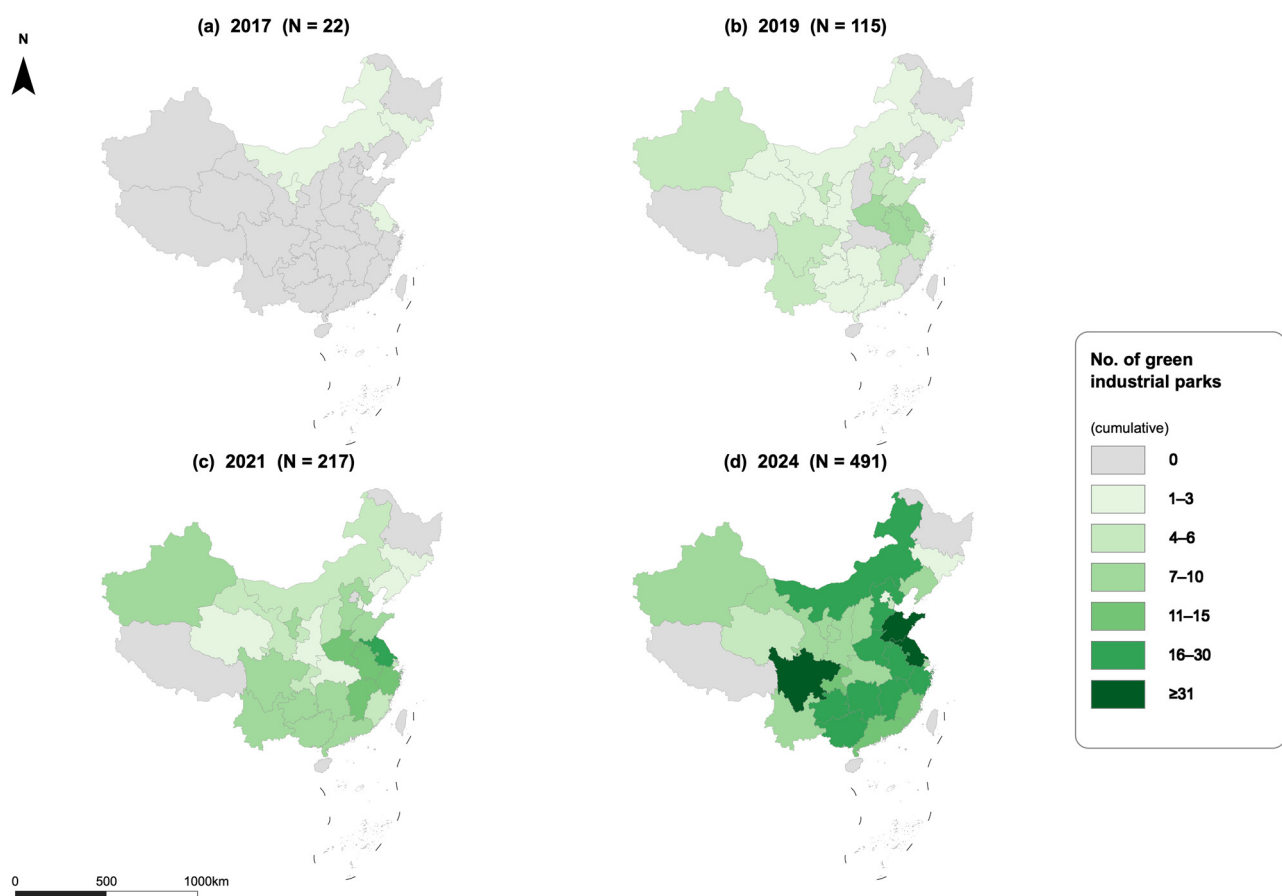
Note: The “+” symbols indicate positive indicators.

These variables correspond to three theoretical pathways. The policy's emphasis on green production, pollution control, and resource efficiency may promote EGI; industrial green transformation and upgrading may be associated with higher Income; and technological upgrading, digital transformation, and innovation-resource agglomeration may contribute to NQPF. These changes may, in turn, strengthen the capacity of urban systems to cope with external shocks and adjust to changing conditions. Accordingly, this study further examines these three potential pathways.

#### 4.2.5. Data Sources and Descriptive Statistics

Considering the policy rollout, data availability for urban resilience indicators, and the completeness of city-level controls, the analysis covers 293 Chinese cities of prefecture rank or higher over 2011–2024. The initial dataset contains 4102 city–year observations. After variable matching and the removal of observations with missing values on key variables, 4019 observations remain in the final sample. The policy indicator is constructed from the official national-level green industrial park list issued by the Ministry of Industry and Information Technology of the People’s Republic of China (MIIT). Policy information is matched to the city panel according to each park’s location and official approval year.

National-level green industrial parks were designated in successive batches rather than simultaneously, resulting in staggered policy timing across cities. To visualize this progressive policy rollout, Figure 3 presents the temporal evolution and spatial distribution of national-level green industrial parks from 2017 to 2024.



**Figure 3.** Evolution of the number and spatial distribution of national-level green industrial parks (2017–2024). Note: Values represent the cumulative number of national-level green industrial parks in each province, municipality, and autonomous region; gray areas indicate regions without such parks in the corresponding year. Park information for 2017–2024 is obtained from the Ministry of Industry and Information Technology of China. The map uses the Standard Map Service of the Ministry of Natural Resources of China (GS(2024)) with an Albers Equal Area projection.

Figure 3 shows that the number of national-level green industrial parks rose from 22 in 2017 to 491 in 2024, reflecting a marked expansion in policy coverage. The distribution of certified parks also differs markedly across regions.

For urban resilience measurement, the underlying indicators are compiled primarily from the China City Statistical Yearbook, provincial and municipal statistical yearbooks,

and other city-level statistical publications. Additional variables are obtained from the China City Statistical Yearbook, China Urban Construction Statistical Yearbook, China Environmental Statistical Yearbook, China Science and Technology Statistical Yearbook, and public databases maintained by the National Bureau of Statistics of China.

For the pathway variables, information on emerging-industry employment, telecommunications business volume, and regular higher education institutions is compiled from successive editions of the China City Statistical Yearbook, China Labor Statistical Yearbook, and relevant provincial yearbooks. The artificial intelligence enterprise count is derived from corporate registration records in Tianyancha, which has been widely adopted in existing studies to construct indicators of new quality productive forces [41]. Environmental governance investment draws on data from the China Environmental Statistical Yearbook and local statistical yearbooks [37]. Data on urban residents' per capita disposable income come from the China City Statistical Yearbook and the China Household Survey Yearbook [12].

For missing values in the basic urban resilience indicators, this paper first supplements the raw data using municipal statistical yearbooks, provincial statistical yearbooks, and official statistical bulletins. The statistical definitions and time-series patterns of each original indicator are then checked, and values identified as unreasonable or isolated abnormal jumps are treated as missing observations. A stratified imputation strategy is adopted for the remaining missing observations after data supplementation. First, linear interpolation is applied only to inner-series gaps where valid observations are available in the adjacent years within the same city and the continuous missing period is limited to one year [42,43]. To reduce potential distortion of temporal variation and avoid mixing information across the policy transition, interpolation is not performed when the interval spans the policy implementation year. Second, single-year gaps at either endpoint of a city's time series are filled using the nearest valid observation for the same city. Third, random forest models are used to predict and impute the remaining missing values. The green industrial park policy variable is excluded from the prediction model, and five-fold cross-validation is conducted at the city level to prevent observations from the same city from appearing in both the training and validation samples. Separate labels are retained for observations generated by within-city linear interpolation, endpoint imputation, and model-based prediction. Table 3 reports the missing rate of each basic urban resilience indicator and the proportions of observations processed using the different imputation approaches.

**Table 3.** Missing-data treatment for urban resilience indicators.

| Indicator                                 | Missing (%) | Within-City Linear Interpolation (%) | Endpoint Imputation (%) | Model Prediction (%) |
|-------------------------------------------|-------------|--------------------------------------|-------------------------|----------------------|
| Registered urban unemployment             | 37.18       | 0.29                                 | 0.39                    | 36.49                |
| Per capita GRP                            | 1.93        | 0.88                                 | 0.15                    | 0.90                 |
| Tertiary industry share                   | 1.54        | 0.59                                 | 0.10                    | 0.85                 |
| Fixed-asset investment                    | 8.39        | 0.02                                 | 5.80                    | 2.56                 |
| Retail sales of consumer goods            | 1.93        | 0.88                                 | 0.15                    | 0.90                 |
| Fiscal science and technology expenditure | 1.56        | 0.63                                 | 0.12                    | 0.80                 |
| Fiscal education expenditure              | 1.56        | 0.63                                 | 0.12                    | 0.80                 |

Table 3. Cont.

| Indicator                                     | Missing (%) | Within-City Linear Interpolation (%) | Endpoint Imputation (%) | Model Prediction (%) |
|-----------------------------------------------|-------------|--------------------------------------|-------------------------|----------------------|
| Public library collections                    | 2.41        | 1.15                                 | 0.17                    | 1.10                 |
| Physicians                                    | 1.54        | 0.59                                 | 0.12                    | 0.83                 |
| Basic employee pension insurance participants | 8.73        | 6.39                                 | 1.24                    | 1.10                 |
| Basic employee medical insurance participants | 9.85        | 6.56                                 | 1.22                    | 2.07                 |
| Year-end employment                           | 10.90       | 0.15                                 | 4.44                    | 6.31                 |
| Wages of on-the-job employees                 | 13.58       | 0.37                                 | 2.39                    | 10.82                |
| Average number of on-the-job employees        | 16.19       | 0.20                                 | 0.68                    | 15.31                |
| PM2.5 concentration                           | 1.85        | 0.00                                 | 0.17                    | 1.68                 |
| Industrial wastewater discharge               | 38.59       | 1.07                                 | 0.51                    | 37.01                |
| Wastewater treatment rate                     | 2.93        | 1.19                                 | 0.15                    | 1.58                 |
| Domestic garbage treatment rate               | 3.02        | 0.95                                 | 0.15                    | 1.93                 |
| Green coverage rate of built-up areas         | 2.49        | 0.88                                 | 0.12                    | 1.49                 |
| Granted green utility model patents           | 0.00        | 0.00                                 | 0.00                    | 0.00                 |
| Granted green invention patents               | 0.00        | 0.00                                 | 0.00                    | 0.00                 |
| Drainage pipeline length                      | 2.93        | 0.88                                 | 0.17                    | 1.88                 |
| Gas penetration rate                          | 0.73        | 0.02                                 | 0.00                    | 0.71                 |
| Road area per capita                          | 0.63        | 0.00                                 | 0.00                    | 0.63                 |
| Daily domestic water consumption per capita   | 0.66        | 0.02                                 | 0.00                    | 0.63                 |
| Internet users                                | 24.57       | 1.54                                 | 0.83                    | 22.21                |
| Mobile phone subscribers                      | 9.36        | 6.12                                 | 1.22                    | 2.02                 |
| All indicator-level observations              | 7.59        | 1.18                                 | 0.76                    | 5.65                 |

Notes: Indicators are presented in the order listed in Table 1, with full definitions and corresponding dimensions provided therein. The imputation proportion of each indicator is calculated based on 4102 city-year observations. The statistics in the final row are derived from 110,754 indicator-level observations, equal to the product of 27 indicators and 4102 city-year samples. Owing to rounding errors, the sum of within-city linear interpolation rate, endpoint imputation rate and random-forest imputation rate for each indicator may slightly deviate from its missing rate. A total of 1312 indicator-level missing observations are filled via within-city linear interpolation, and none of these interpolations span the policy implementation year. The random forest algorithm is adopted for model-based imputation. Five-fold cross-validation is conducted by city, and the green industrial park policy variable is excluded from the predictor set.

Table 3 shows that missingness is generally limited across most urban resilience indicators. Nevertheless, due to changes in statistical definitions and the suspension of official data release, registered urban unemployment, industrial wastewater discharge and internet subscribers suffer from substantial missing values, with missing rates of 37.18%, 38.59% and 24.57%, respectively. Because a high proportion of imputed values may attenuate actual temporal variation and introduce measurement bias, this study further eliminates the three indicators with a missing rate exceeding 20%, recalculates entropy weights and reconstructs the urban resilience index to test the robustness of core findings. In addition, to avoid disturbances to empirical results caused by linear interpolation, this paper drops all city-year samples containing any within-city linearly interpolated observations and re-estimates the baseline model to evaluate whether the results are sensitive to interpolation.

In terms of data preprocessing, population density, highway passenger traffic, highway freight traffic, environmental governance investment and residents' income level are transformed into natural logarithms to reduce variable skewness and improve estimation stability. The baseline regression does not apply winsorization to the urban resilience index, policy variable or control variables. In the robustness analysis, the urban resilience index and policy variable remain unchanged, while continuous controls are winsorized

separately at the 1st–99th and 5th–95th percentiles. Table 4 reports the descriptive statistics for all variables.

**Table 4.** Variable definitions and descriptive statistics.

| Variable Type      | Variable Name                       | Definition and Symbol                                                                                                                  | Mean   | Std. Dev. | Min   | Max    |
|--------------------|-------------------------------------|----------------------------------------------------------------------------------------------------------------------------------------|--------|-----------|-------|--------|
| Dependent Variable | Urban Resilience                    | Composite index based on four dimensions and linearly rescaled to 0–10 (UR)                                                            | 0.600  | 0.883     | 0.000 | 10.000 |
| Treatment Variable | Green Industrial Park Policy        | Takes the value of 1 in and after the year when a city obtains its first national-level green industrial park, and 0 otherwise (Green) | 0.216  | 0.412     | 0.000 | 1.000  |
| Pathway Variables  | New Quality Productive Forces       | Composite index constructed from four indicators of new quality productive forces (NQPF)                                               | 0.037  | 0.067     | 0.000 | 0.754  |
|                    | Environmental Governance Investment | Natural logarithm of government expenditure on energy conservation and environmental protection (EGI)                                  | 11.348 | 0.929     | 7.122 | 15.338 |
|                    | Income Level                        | Natural logarithm of per capita disposable income of urban residents (Income)                                                          | 10.367 | 0.352     | 9.315 | 11.435 |
| Control Variables  | Population Density                  | Natural logarithm of the ratio of permanent resident population to administrative area (ipd)                                           | 5.674  | 1.086     | 0.358 | 9.106  |
|                    | Openness Level                      | Ratio of total import and export volume to regional GDP (open)                                                                         | 0.182  | 0.285     | 0.000 | 2.547  |
|                    | Human Capital Level                 | Share of students enrolled in regular higher education institutions in the total population (hcl)                                      | 0.020  | 0.021     | 0.000 | 0.163  |
|                    | Financial Development Level         | Financial-institution RMB loan balances relative to regional GDP (fin)                                                                 | 1.160  | 0.647     | 0.132 | 5.527  |
|                    | Government Intervention             | Local general public budget expenditure relative to regional GDP (gov)                                                                 | 0.217  | 0.123     | 0.056 | 1.492  |
|                    | Urbanization Level                  | Ratio of urban population to municipal permanent resident population (urb)                                                             | 0.575  | 0.151     | 0.088 | 1.000  |
|                    | Highway Passenger Transport         | Natural logarithm of highway passenger traffic volume (pass)                                                                           | 7.914  | 1.298     | 1.792 | 12.737 |
|                    | Highway Freight Transport           | Natural logarithm of highway freight volume (fre)                                                                                      | 9.021  | 0.962     | 3.664 | 13.225 |

Notes: Descriptive statistics are calculated using the common estimation sample of 4019 city–year observations. Values are reported before the within-city transformation used to account for city fixed effects. Owing to rounding, the reported minimum values of some variables may appear as zero.

## 5. Empirical Results and Analysis

### 5.1. Baseline Results for Urban Resilience

This study applies a Double/Debiased Machine Learning model to estimate the association between the green industrial park policy and urban resilience, with random forest used for the outcome and treatment equations. To account for time-invariant city heterogeneity, this study conducts within-city demeaning of outcome variables, treatment variables and time-varying control variables, and incorporates year fixed effects. In the cross-fitting stage, five-fold sample splitting is conducted by city to ensure that all annual observations of the same city are assigned to the same fold and avoid the mixing of samples from the same city in the training set and validation set. This study repeats the cross-fitting five times, reports the median estimate across the five repetitions, and uses city-clustered standard errors. The regression results are shown in Table 5.

**Table 5.** Baseline estimation results.

| Treatment Variable       | (1) UR               | (2) UR               |
|--------------------------|----------------------|----------------------|
| Green                    | 0.116 ***<br>(0.033) | 0.094 ***<br>(0.032) |
| Linear Controls          | Yes                  | Yes                  |
| Quadratic Controls       | No                   | Yes                  |
| Year Fixed Effects       | Yes                  | Yes                  |
| City Fixed Effects       | Yes                  | Yes                  |
| City-Level Cross-Fitting | Yes                  | Yes                  |
| N                        | 4019                 | 4019                 |

Notes: Five-fold cross-fitting is implemented at the city level so that all yearly observations for the same city remain in a single fold. The procedure is repeated five times, and the median estimate is retained. Parentheses contain city-clustered standard errors. \*\*\* correspond to the 1% significance levels.

Column (1) includes city and year fixed effects together with the linear city-level covariates. The policy estimate in Column (1) is 0.116 (city-clustered SE = 0.033;  $p < 0.01$ ). This estimate suggests a positive association between policy implementation and urban resilience conditional on the observed covariates and fixed effects. Column (2) additionally includes quadratic terms for the city-level covariates to accommodate possible nonlinear relationships. The policy estimate in Column (2) is 0.094 (city-clustered SE = 0.032;  $p < 0.01$ ). Although the coefficient declines after adding the quadratic terms, its sign and statistical significance remain unchanged.

Subject to the conditional identification assumptions discussed in Section 4.1, the estimates remain consistent with a positive association between the green industrial park policy and urban resilience, thereby supporting Hypothesis H1.

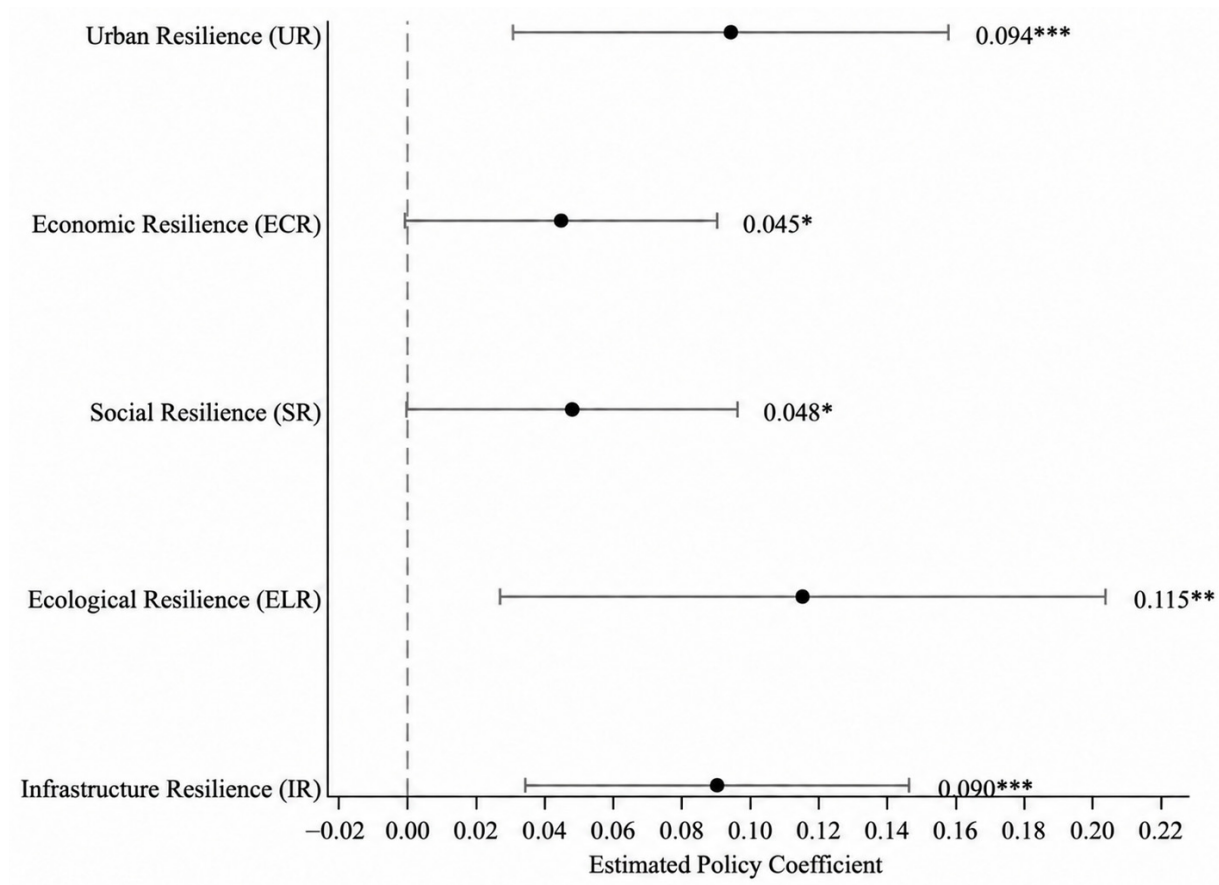
### Dimension-Specific Estimates for Urban Resilience

Table 6 further reports the estimated relationships between the green industrial park policy and different dimensions of urban resilience, and the corresponding estimation results are illustrated in Figure 4. Positive coefficients are obtained for all four dimensions. Specifically, the coefficients for economic resilience (ECR) and social resilience (SR) are 0.045 and 0.048, respectively. The ECR and SR estimates are 0.045 and 0.048, respectively, with both significant at the 10% level. The ELR estimate is 0.115 ( $p < 0.05$ ), while the IR estimate is 0.090 ( $p < 0.01$ ).

**Table 6.** Estimated relationships between the green industrial park policy and urban resilience dimensions.

| Treatment Variable       | ECR                | SR                 | ELR                 | IR                   |
|--------------------------|--------------------|--------------------|---------------------|----------------------|
| Green                    | 0.045 *<br>(0.023) | 0.048 *<br>(0.025) | 0.115 **<br>(0.045) | 0.090 ***<br>(0.029) |
| Linear Controls          | Yes                | Yes                | Yes                 | Yes                  |
| Quadratic Controls       | Yes                | Yes                | Yes                 | Yes                  |
| Year Fixed Effects       | Yes                | Yes                | Yes                 | Yes                  |
| City Fixed Effects       | Yes                | Yes                | Yes                 | Yes                  |
| City-Level Cross-Fitting | Yes                | Yes                | Yes                 | Yes                  |
| N                        | 4019               | 4019               | 4019                | 4019                 |

Notes: Standard errors clustered at the city level are shown in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.



**Figure 4.** Estimated coefficients of the green industrial park policy across urban resilience dimensions. Notes: The dots show the median DML estimates obtained from five cross-fitting repetitions, while the horizontal lines denote 95% confidence intervals. Standard errors clustered at the city level are shown in parentheses. \*, \*\*, and \*\*\* denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Overall, the green industrial park policy is positively associated with all four dimensions of urban resilience, although the strength of statistical evidence varies across dimensions. The statistical evidence is relatively stronger for infrastructure and ecological resilience, whereas the economic and social resilience estimates are only marginally significant and should be interpreted cautiously. It should also be noted that each sub-dimensional

index is separately rescaled to the 0–10 range. Therefore, coefficient magnitudes should not be used to directly rank the estimated relationships across dimensions.

For economic resilience, the estimate is positive and is statistically distinguishable from zero at the 10% level. The comparatively limited statistical support nevertheless remains consistent with a positive association for the economic resilience dimension. Green production requirements, cleaner production upgrading, and technological improvement may encourage firms to adjust production modes and improve resource allocation, thereby supporting the adaptive capacity of the local economy.

Social resilience presents a somewhat different pattern. The estimated coefficient is likewise positive and reaches the 10% significance level, providing only modest evidence of a positive association in the social dimension. Green industrial development may contribute to employment opportunities and improvements in residents' economic conditions. At the same time, social resilience is shaped by a wider set of factors, including public service provision, social security, labor-market conditions, and demographic characteristics, which may make its response to the policy less direct and more complex.

The ecological resilience finding is more directly related to the policy's core green-development objectives. Pollution control, cleaner production, resource conservation, and environmental governance are all central components of green park development. Improvements in these areas may be closely related to environmental governance capacity and resource-use efficiency, which may help explain the stronger evidence for ecological resilience.

Infrastructure resilience exhibits the strongest statistical support, with the estimated coefficient reaching the 1% significance threshold. This result accords with the policy's focus on wastewater treatment, solid-waste disposal, energy management, and resource-recycling facilities. Improvements in these systems may support the reliability and adaptive capacity of urban infrastructure when cities face external disturbances.

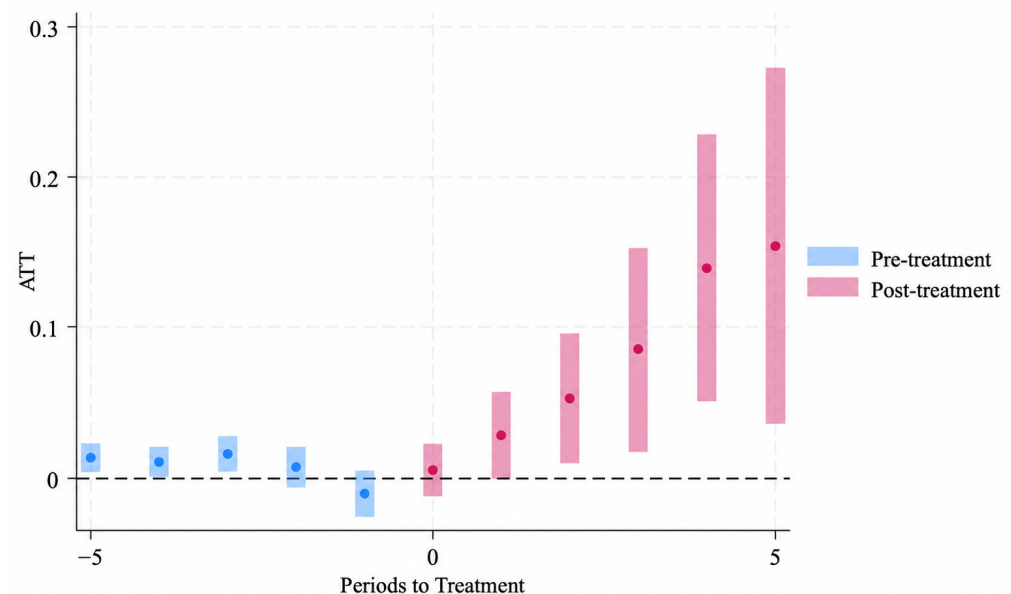
## 5.2. Dynamic Patterns and Identification Diagnostics

Given that the national-level green industrial park policy was rolled out sequentially across different cities, the conventional two-way fixed-effects event-study model may yield biased estimates when cities adopt the policy at different times and treatment effects vary over time. Following Callaway and Sant'Anna (2021) [44], this study employs a staggered difference-in-differences estimator suited to phased policy adoption to examine pre-policy trends and post-policy dynamics. Treatment cohorts are defined according to the year when a city first obtained a national-level green industrial park, and cities that had not yet adopted the policy in the corresponding year serve as the control group. The model incorporates the same pre-policy city-level characteristics as the baseline specification, with city-clustered standard errors.

The policy features clear staggered implementation. Among the 293 cities in the sample, 92 cities had not received a national-level green industrial park by 2024. The numbers of newly treated cities from 2017 to 2024 are 18, 40, 20, 25, 18, 21, 30 and 29, respectively. A staggered DID estimator is therefore used to accommodate variation in policy adoption timing.

Figure 5 reports event-time average treatment effects for a window extending five periods on either side of policy adoption. The estimate for the adoption year is 0.006 and does not attain statistical significance. In the first period following adoption, the estimate becomes positive and reaches marginal significance, after which it rises progressively. Specifically, the coefficients for post-policy periods 1–5 are 0.029, 0.053, 0.085, 0.140, and 0.154, respectively. The period-1 estimate reaches the 10% significance level, whereas the estimates for periods 2–5 are significant at the 5% level or stronger. Across the post-policy periods, the average estimate is 0.078 ( $p < 0.01$ ). Taken together, the estimates point to a

delayed response that becomes more pronounced following policy adoption. The positive association between policy adoption and urban resilience is limited in the adoption year but becomes more pronounced in subsequent periods.



**Figure 5.** Dynamic estimates and pre-trend diagnostics for the green industrial park policy. Notes: The figure reports event-time average treatment effects estimated using the Callaway–Sant’Anna staggered DID approach. Treatment timing is defined by the first year in which a city receives a national-level green industrial park designation, while cities not yet treated in a given year serve as the comparison group. Dots denote estimated average treatment effects and vertical lines represent 95% confidence intervals; standard errors are clustered at the city level.

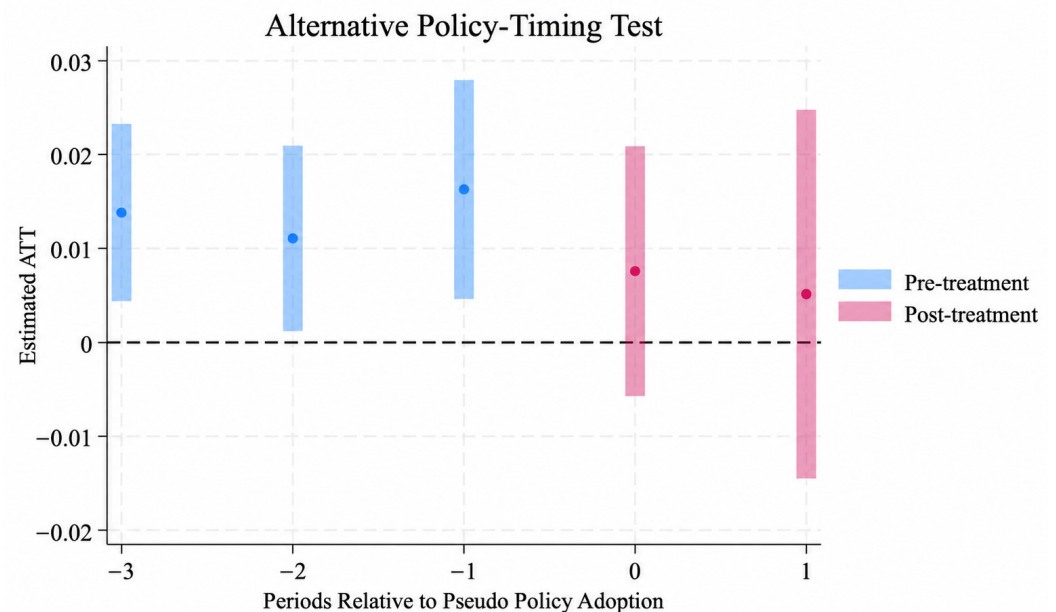
Nevertheless, the pre-policy estimates require cautious interpretation. The coefficients for the first two leads are statistically insignificant, suggesting no meaningful differential changes in the two periods immediately preceding treatment. However, the coefficients for leads 3–5 are significantly positive, while the mean estimate across the pre-policy periods is 0.008 ( $p < 0.01$ ). The joint pre-trend test yields ( $\chi^2(68) = 125.231$ ,  $p < 0.001$ ), indicating that the pre-policy coefficients are not jointly equal to zero.

Significant early pre-policy coefficients may reflect long-run divergence in developmental trajectories between treated and control cities, or could stem from policy anticipation and selective screening of green industrial parks. This study therefore interprets the event-study results mainly as supplementary evidence on dynamic patterns and identification diagnostics rather than as standalone causal evidence. The increase in post-policy coefficients over time is consistent with a lagged and cumulative dynamic pattern, although causal interpretation remains contingent on the underlying identification assumptions.

To further verify whether the post-policy results can be mechanically replicated before the actual policy rollout, this study conducts a placebo test by shifting each city’s treatment time two years backward to construct fictitious adoption years. To avoid contamination from the actual policy adoption period, the estimation sample retains only never-treated cities and observations of treated cities prior to their actual policy adoption; cities that had not yet reached the fictitious treatment year form the control group.

As illustrated in Figure 6, the average post-placebo estimate is 0.006 and is statistically insignificant ( $p = 0.410$ ). The estimated coefficients in the fictitious adoption year and the first post-placebo period are 0.008 and 0.005; the corresponding  $p$ -values are 0.264 and 0.609, and neither estimate is statistically significant at conventional levels. After artificially moving the policy starting time two years earlier, no significant placebo effect

emerges. This offers supplementary evidence that the positive post-policy dynamic pattern documented for the true adoption date cannot be mechanically reproduced under an earlier fictitious timing.



**Figure 6.** Placebo test with policy timing shifted two years backward. Note: Fictitious treatment years are set two years before the actual adoption year for each treated city. To avoid contamination from the actual policy adoption period, the sample consists of never-treated cities and pre-treatment observations of treated cities, with cities that have not yet reached the fictitious treatment year as controls. Dots denote estimated average treatment effects and vertical lines represent 95% confidence intervals; standard errors are clustered at the city level.

Even so, pre-placebo coefficients remain significantly positive, and the average pre-policy estimate reaches 0.014 ( $p < 0.001$ ), consistent with the early pre-treatment divergence shown in Figure 6. Although the placebo test detects no significant post-placebo effect, concerns regarding persistent long-term developmental gaps between treated and control cities cannot be completely eliminated.

Overall, staggered DID estimation yields a clear post-policy dynamic profile: the estimated coefficient is insignificant in the adoption year, turns positive approximately one year afterwards, and rises steadily in subsequent periods. No statistically significant post-placebo estimates are identified when the policy is dated two years in advance. Nonetheless, the joint pre-trend test rejects strict parallel trends, and several early pre-policy coefficients are significant. The results are thus regarded as supplementary dynamic evidence and identification diagnostics. The baseline DML estimates remain conditional on the included observable controls, fixed effects, and the other identifying assumptions discussed above; accordingly, the conclusions are interpreted cautiously.

### 5.3. Robustness Checks

To assess the stability of the baseline findings, several robustness checks are conducted. These include modifying the research sample, winsorizing continuous control variables, adding province-by-year fixed effects, controlling for concurrent policies, using alternative fold settings for cross-fitting, and replacing the baseline machine-learning algorithm. The corresponding results are reported in Tables 7 and 8.

**Table 7.** Robustness check results.

| Variable                               | (1)                      | (2)                  |                      | (3)                         | (4)                                 |                      |                      |
|----------------------------------------|--------------------------|----------------------|----------------------|-----------------------------|-------------------------------------|----------------------|----------------------|
|                                        | Adjusted Sample          | Winsorization        |                      | Province-Year Fixed Effects | Controlling for Concurrent Policies |                      |                      |
|                                        | Excluding Partial Cities | 1%Wins               | 5%Wins               |                             |                                     |                      |                      |
| Green                                  | 0.079 **<br>(0.034)      | 0.090 ***<br>(0.031) | 0.125 ***<br>(0.035) | 0.054 **<br>(0.024)         | 0.096 ***<br>(0.032)                | 0.092 ***<br>(0.033) | 0.093 ***<br>(0.032) |
| Controlling for Smart-City Policy      | -                        | -                    | -                    | -                           | Yes                                 | No                   | Yes                  |
| Controlling for Low-Carbon City Policy | -                        | -                    | -                    | -                           | No                                  | Yes                  | Yes                  |
| Linear Controls                        | Yes                      | Yes                  | Yes                  | Yes                         | Yes                                 | Yes                  | Yes                  |
| Quadratic Controls                     | Yes                      | Yes                  | Yes                  | Yes                         | Yes                                 | Yes                  | Yes                  |
| Year Fixed Effects                     | Yes                      | Yes                  | Yes                  | Yes                         | Yes                                 | Yes                  | Yes                  |
| City Fixed Effects                     | Yes                      | Yes                  | Yes                  | Yes                         | Yes                                 | Yes                  | Yes                  |
| City-Level Cross-Fitting               | Yes                      | Yes                  | Yes                  | Yes                         | Yes                                 | Yes                  | Yes                  |
| Province-year fixed effects            | No                       | No                   | No                   | Yes                         | No                                  | No                   | No                   |
| N                                      | 2775                     | 4019                 | 4019                 | 3957                        | 4019                                | 4019                 | 4019                 |

Notes: Column (1) modifies the research sample by excluding Beijing and cities located in provinces with fewer than five or more than twenty national-level green industrial parks. Column (2) applies winsorization to the continuous controls using the 1st–99th and 5th–95th percentile ranges; the urban resilience index and policy variable are not winsorized. Column (3) accounts jointly for city effects and province-by-year effects. Because province-by-year fixed effects fully absorb observations from provincial units containing only one city, the high-dimensional fixed-effects procedure drops 62 singleton observations, leaving 3957 city–year observations across 289 cities. Column (4) controls for the smart-city pilot policy and the low-carbon city pilot policy separately and jointly. All specifications include linear and quadratic terms for the control variables. Cross-fitting is conducted by city using five folds and repeated five times, with the median estimate across repetitions reported. Parentheses contain standard errors clustered by city. \*\*, and \*\*\* correspond to significance levels of 5%, and 1%, respectively.

**Table 8.** Robustness checks with alternative DML specifications.

| Variable                 | (1)                             |                      | (2)                                     |                      |                      |
|--------------------------|---------------------------------|----------------------|-----------------------------------------|----------------------|----------------------|
|                          | Alternative Cross-Fitting Folds |                      | Alternative Machine Learning Algorithms |                      |                      |
|                          | Kfolds = 3                      | Kfolds = 8           | LassoCV                                 | GradBoost            | SVM                  |
| Green                    | 0.112 ***<br>(0.038)            | 0.100 ***<br>(0.033) | 0.110 ***<br>(0.027)                    | 0.103 ***<br>(0.028) | 0.085 ***<br>(0.025) |
| Linear Controls          | Yes                             | Yes                  | Yes                                     | Yes                  | Yes                  |
| Quadratic Controls       | Yes                             | Yes                  | Yes                                     | Yes                  | Yes                  |
| Year Fixed Effects       | Yes                             | Yes                  | Yes                                     | Yes                  | Yes                  |
| City Fixed Effects       | Yes                             | Yes                  | Yes                                     | Yes                  | Yes                  |
| City-Level Cross-Fitting | Yes                             | Yes                  | Yes                                     | Yes                  | Yes                  |
| N                        | 4019                            | 4019                 | 4019                                    | 4019                 | 4019                 |

Notes: Column (1) keeps random forest unchanged while using three- and eight-fold city-level cross-fitting instead of the baseline five-fold setting. Column (2) keeps five-fold city-level cross-fitting unchanged and replaces the baseline random forest learner with LassoCV, gradient boosting, and support vector machines, respectively. All yearly observations from the same city are assigned to a single fold. City fixed effects are removed through within-city demeaning. Each specification is repeated five times, with the median estimate retained across repetitions. Parentheses contain standard errors clustered by city. \*\*\* correspond to the 1% significance levels.

### 5.3.1. Adjusted Sample

Given the uneven provincial distribution of national-level green industrial parks, some provinces host only a small number of such parks and therefore have relatively limited policy coverage. Meanwhile, provinces such as Jiangsu, Shandong, Sichuan, and Anhui have a relatively large number of national-level green industrial parks, which may disproportionately influence the full-sample estimates. To assess the sensitivity of the baseline results to the uneven provincial distribution of green industrial parks and sample concentration, this study adjusts the sample set by excluding cities under the jurisdiction of Beijing Municipality, Jilin, Heilongjiang, Hainan and Xizang (provinces with fewer than

five parks), as well as Jiangsu, Shandong, Sichuan and Anhui (provinces with more than 20 parks). The model is re-estimated on the restricted sample, with the results presented in Column (1) of Table 7. The policy estimate is 0.079 ( $p < 0.05$ ). Although smaller than the baseline estimate, it remains positive and statistically distinguishable from zero. This suggests that the baseline finding is not driven by a limited number of provinces with unusually low or high policy coverage.

### 5.3.2. Winsorization of Continuous Variables

Economic and social control variables at the city level may be affected by extreme values, and individual outlying observations could affect the estimated relationship. Since the urban resilience index has been standardized with a clear value range, the outcome variable UR and the treatment variable Green remain unchanged in this study. Winsorization is applied only to the continuous controls, using the 1st–99th and 5th–95th percentile ranges. Specifically, observations above the upper percentile and below the lower percentile are replaced with the corresponding percentile values, and the quadratic terms are recalculated based on the winsorized linear terms. The DML model is then re-estimated, and Column (2) of Table 7 presents the results. The policy estimate is 0.090 under the 1% winsorization scheme and 0.125 under the 5% scheme, with both estimates significant at  $p < 0.01$ . Relative to the baseline estimates, the magnitudes of the coefficients change slightly after winsorization, while the coefficients remain positive and statistically significant. These results suggest that extreme observations do not materially alter the baseline finding and that the positive relationship between the green industrial park policy and urban resilience remains robust.

### 5.3.3. Province-Year Fixed Effects

Cities in the same province often share similar policy environments, industrial foundations, resource endowments, and governance conditions. Meanwhile, different provinces may face divergent economic development conditions, industrial policies, and environmental governance requirements in the same period. Controlling only for city and year fixed effects may not fully capture time-varying provincial factors. Therefore, province-by-year interaction fixed effects are additionally included to account for common shocks that vary across provinces over time, such as provincial industrial policies, environmental regulation, and macroeconomic conditions.

Specifically, the outcome, policy, and control variables are jointly residualized with respect to city and province-by-year fixed effects, after which the DML model is estimated using the resulting residuals. The results are presented in Column (3) of Table 7. The policy estimate is 0.054 (city-clustered SE = 0.024;  $p < 0.05$ ). The coefficient is lower than the baseline estimate, suggesting that time-varying provincial factors may account for part of the baseline association. Nevertheless, the estimate remains positive and statistically significant after the inclusion of the more stringent province-by-year fixed effects.

It should be noted that province-year fixed effects fully absorb observations belonging to provincial units containing only a single city. The high-dimensional fixed-effect estimation procedure automatically drops 62 singleton observations. This robustness test finally employs 3957 city–year observations and 289 cities.

### 5.3.4. Controlling for Concurrent Policies

The baseline estimates of this study may be contaminated by other concurrent urban policies. During the sample period, China successively launched location-targeted policies such as the smart-city pilot program and the low-carbon city pilot program. These policies may affect urban resilience through channels including digital infrastructure improvement, low-carbon transition, enhanced environmental governance capacity and optimized public

services. Moreover, their implementation timing and geographical distribution partially overlap with the green industrial park policy. Omitting these policies may bias the estimated association for the green industrial park policy.

Accordingly, dummy variables are constructed for the smart-city policy (Smart-City) and the low-carbon city pilot policy (Low-Carbon). These two indicators are entered into the DML model separately and jointly to assess whether the estimated relationship is sensitive to concurrent policies. Column (4) of Table 7 presents the corresponding estimates. The estimated coefficient is 0.096 when only the smart-city policy is included, 0.092 when only the low-carbon city pilot policy is controlled for, and 0.093 when both policies enter the model simultaneously. All three estimates are statistically significant at  $p < 0.01$  and remain close to the baseline value of 0.094. This pattern suggests that neither concurrent policy appears to account for the baseline association to a substantial extent.

### 5.3.5. Alternative Double Machine Learning Specifications

Sensitivity to alternative DML settings is assessed along two dimensions: alternative cross-fitting fold schemes and alternative machine-learning learners. The baseline specification uses random forest as the auxiliary learner with five-fold cross-fitting conducted by city. First, the cross-fitting folds are adjusted to three and eight, changing the validation-to-training sample ratio from the baseline 1:4 to 1:2 and 1:7, respectively. Second, with city-level five-fold cross-fitting held fixed, random forest is replaced in turn by LassoCV, gradient boosting (GradBoost), and support vector machine (SVM).

The results in Table 8 show that the policy coefficients remain positive and significant at the 1% level across the alternative fold settings and machine-learning algorithms. Although the magnitudes vary across specifications, the overall pattern remains stable, indicating that the baseline findings are not sensitive to a particular DML specification.

## 5.4. Sensitivity Analysis

### 5.4.1. Weighting Scheme and Missing-Data Treatment

The construction of a composite urban resilience index relies on indicator normalization rules, weighting schemes and missing-value processing strategies, leaving a certain degree of arbitrariness in measurement results. When entropy weights are calculated using the full-period sample, post-policy changes in the dispersion of underlying indicators may affect the resulting indicator weights. Consequently, the measurement framework of the urban resilience index incorporates post-policy sample information. Meanwhile, structural missingness and linear interpolation may smooth time-series fluctuations in the original indicators and affect the estimated relationship. To address these measurement limitations, this paper conducts sensitivity analysis along three dimensions: weighting windows, indicators with high missing rates, and linearly interpolated observations.

Regarding weighting specifications, this paper calculates fixed entropy weights exclusively based on the pre-policy sample from 2011 to 2016. These pre-policy weights are subsequently used throughout the 2011–2024 city-year sample, thereby limiting the extent to which post-policy changes in indicator dispersion can influence the outcome through the weighting scheme. Using the pre-policy fixed weights produces an estimate in Column (1) of Table 9 that is similar to the baseline result, suggesting limited sensitivity to post-policy changes in indicator dispersion and the corresponding weighting adjustments.

**Table 9.** Sensitivity analysis of urban resilience measurement.

| Variable                 | (1) UR               | (2) UR               | (3) UR                |
|--------------------------|----------------------|----------------------|-----------------------|
| Green                    | 0.092 ***<br>(0.032) | 0.093 ***<br>(0.031) | 0.108 ***<br>(0.034)  |
| Specification            | Fixed Weights        | Indicator Exclusion  | Observation Exclusion |
| Linear Controls          | Yes                  | Yes                  | Yes                   |
| Quadratic Controls       | Yes                  | Yes                  | Yes                   |
| Year Fixed Effects       | Yes                  | Yes                  | Yes                   |
| City Fixed Effects       | Yes                  | Yes                  | Yes                   |
| City-Level Cross-Fitting | Yes                  | Yes                  | Yes                   |
| N                        | 4019                 | 4019                 | 3314                  |

Notes: The dependent variable in all columns is the urban resilience index (UR). Column (1) uses fixed entropy weights estimated from the pre-policy sample for 2011–2016. Column (2) reconstructs UR after excluding three indicators with relatively high missing rates: registered urban unemployment, industrial wastewater discharge, and internet users. Column (3) excludes city–year observations containing at least one linearly interpolated indicator. Parentheses report standard errors clustered at the city level, while \*\*\* correspond to the 1% significance thresholds.

Three indicators, namely the number of registered urban unemployed persons, industrial wastewater discharge and internet users, suffer from high missing rates, and periods of structural missingness may coincide with policy implementation. This paper drops these three indicators and reconstructs the urban resilience index. The estimate reported in Column (2) of Table 9 remains positive and statistically significant, indicating that the baseline finding is not primarily attributable to indicators with relatively high missing rates.

To explore how linear interpolation affects the estimates, this paper excludes city–year observations in which at least one underlying indicator is imputed using linear interpolation. This procedure reduces the valid sample size from 4019 to 3314. Nevertheless, the policy coefficient in Column (3) of Table 9 is still significantly positive, indicating that excluding observations involving linear interpolation does not materially alter the baseline result. Overall, the policy coefficients remain positive and statistically significant across all three sensitivity checks, providing further support for the stability of the baseline result under alternative weighting windows, indicator composition, and interpolation treatment.

#### 5.4.2. Indicator Overlap with Policy Targets

The composite urban resilience index partly depends on the composition of its underlying indicators. Several indicators used in this study, including granted green invention patents, granted green utility model patents, and wastewater treatment rate, are closely related to the objectives of the green industrial park policy. Their direct responses to policy implementation may therefore create measurement overlap between policy targets and the urban resilience index.

To assess whether such overlap drives the baseline results, this study sequentially reconstructs the urban resilience index by excluding policy-related indicators. First, the two green patent indicators are excluded, after which the index is renormalized, reweighted, reaggregated, and remapped to the 0–10 range. Column (1) of Table 10 yields a policy estimate of 0.062 ( $p < 0.05$ ). The centralized wastewater treatment rate is subsequently excluded as well. In Column (2), the corresponding estimate is 0.069 ( $p < 0.05$ ). Both specifications use the same 4019 city–year observations.

**Table 10.** Estimation results after excluding policy-related indicators.

| Variable                 | (1) UR                            | (2) UR                                      |
|--------------------------|-----------------------------------|---------------------------------------------|
| Green                    | 0.062 **<br>(0.027)               | 0.069 **<br>(0.027)                         |
| Specification            | Excluding Green Patent Indicators | Further Excluding Wastewater Treatment Rate |
| Linear Controls          | Yes                               | Yes                                         |
| Quadratic Controls       | Yes                               | Yes                                         |
| Year Fixed Effects       | Yes                               | Yes                                         |
| City Fixed Effects       | Yes                               | Yes                                         |
| City-Level Cross-Fitting | Yes                               | Yes                                         |
| N                        | 4019                              | 4019                                        |

Notes: Both columns use a reconstructed urban resilience index (UR) based on the corresponding alternative indicator set. Column (1) removes the two green patent indicators. Column (2) further excludes the centralized wastewater treatment rate. Both alternative indices are restandardized, reweighted, and rescaled to 0–10. Parentheses report standard errors clustered at the city level, while \*\* correspond to the 5% significance thresholds.

Although both estimates are below the baseline value, they remain positive and statistically significant. This pattern suggests that direct overlap between policy objectives and resilience indicators does not fully account for the baseline result. Because indicator exclusion also changes entropy weights and the distribution of the reconstructed index, differences in coefficient magnitude across the two specifications should not be interpreted as differences in policy strength. Overall, these results provide additional evidence that the baseline finding is stable to alternative indicator compositions.

#### 5.4.3. Spatial Spillover Sensitivity

Potential spatial spillovers of the green industrial park policy may arise in nearby cities through industrial linkages, labor mobility, technology diffusion, and environmental-governance cooperation. If untreated neighboring cities are also affected by the policy, treating them as fully unaffected control units may contaminate the control group. To assess whether this issue affects the baseline findings, this paper calculates intercity distances from the geographic coordinates of city centers. Using thresholds of 100 km, 150 km, and 200 km separately, it identifies whether each city–year observation has neighboring cities that implemented the green industrial park policy in the same year. While retaining all treated observations, this paper excludes untreated city–year observations that have at least one treated neighboring city within the corresponding distance threshold in the same year. The within-city demeaning procedure and DML estimation are then repeated using the remaining sample. The corresponding results are reported in Table 11.

For the 100 km, 150 km, and 200 km thresholds, the corresponding policy estimates are 0.097, 0.116, and 0.113, with each remaining statistically significant. With the exclusion radius extended to 200 km, the coefficient still reaches the 5% significance level. The direction and magnitude of the estimates remain broadly stable across the three distance thresholds, suggesting that the baseline finding is unlikely to be mainly attributable to contamination of the control group by neighboring policy exposure. It should be noted that this test is intended to examine the sensitivity of baseline estimates to potential spatial spillovers and does not directly establish whether spatial spillovers exist or determine their direction or magnitude.

**Table 11.** Spatial spillover sensitivity test.

| Variable                 | (1) 100 km           | (2) 150 km           | (3) 200 km          |
|--------------------------|----------------------|----------------------|---------------------|
| Green                    | 0.097 ***<br>(0.032) | 0.116 ***<br>(0.040) | 0.113 **<br>(0.047) |
| Linear Controls          | Yes                  | Yes                  | Yes                 |
| Quadratic Controls       | Yes                  | Yes                  | Yes                 |
| Year Fixed Effects       | Yes                  | Yes                  | Yes                 |
| City Fixed Effects       | Yes                  | Yes                  | Yes                 |
| City-Level Cross-Fitting | Yes                  | Yes                  | Yes                 |
| N                        | 3582                 | 3253                 | 3064                |

Notes: Untreated city–year observations located within the specified distance of a treated city in the same year are excluded. Estimation uses five-fold city-level cross-fitting. Parentheses report standard errors clustered at the city level, while \*\*, and \*\*\* correspond to the 5%, and 1% significance thresholds, respectively.

### 5.5. Potential Pathway Analysis

Earlier estimates indicate that urban resilience is positively related to green industrial park policy exposure at conventional significance levels, while the potential pathways underlying this relationship remain underexplored. Leveraging the strengths of the double-debiased machine learning (DML) method in accommodating high-dimensional covariates and possible nonlinearities [31], this paper examines the potential pathways linking the green industrial park policy to urban resilience within the DML framework. Following the general logic of conventional mediation analysis [45] and the pathway analysis approach proposed by Zhang and Li (2023) [38], the analysis focuses on three potential pathways: environmental governance investment, residents' income level and new quality productive forces.

Taking each pathway variable as the outcome variable, this paper estimates the association between the green industrial park policy and each potential pathway variable. The model specification is presented as follows:

$$M_{it} = a_m \text{Green}_{it} + g_{1m}(X_{it}) + \mu_i + \lambda_t + v_{it} \quad (7)$$

In this equation,  $M_{it}$  denotes the  $m$ -th potential pathway variable, including environmental governance investment (EGI), residents' income level (Income), and new quality productive forces (NQPF);  $a_m$  captures the relationship between the green industrial park policy and the corresponding pathway variable;  $g_{1m}(X_{it})$  represents the high-dimensional nonparametric function fitted via machine learning;  $\mu_i$  and  $\lambda_t$  represent city-specific and year-specific fixed effects, respectively, while  $v_{it}$  is the error term in the equation. A statistically significant  $a_m$  with the theoretically expected sign is taken as empirical support for an association between policy exposure and the corresponding pathway variable.

On this basis, this paper incorporates both the green industrial park policy variable and the corresponding pathway variable as target variables into the DML model, and jointly estimates their conditional relationships with urban resilience:

$$UR_{it} = \theta_m \text{Green}_{it} + b_m M_{it} + g_{2m}(X_{it}) + \mu_i + \lambda_t + \xi_{it} \quad (8)$$

where  $b_m$  captures the conditional relationship between the  $m$ -th pathway variable and urban resilience after accounting for both the green industrial park policy and other covariates;  $\theta_m$  reflects the conditional relationship between the green industrial park policy and

urban resilience conditional on the corresponding pathway variable and remaining covariates;  $g_{2m}(X_{it})$  stands for the high-dimensional nonparametric function fitted by machine learning methods; and  $\xi_{it}$  denotes the random disturbance term.

Equations (7) and (8) adopt the DML estimation procedure described above. This paper employs random forests to fit the conditional expectations for the outcome, policy, and pathway variables with respect to high-dimensional covariates. City-level de-meaning is applied to absorb city fixed effects, and five-fold cross-fitting is implemented at the city level, guaranteeing that all yearly observations from the same city are placed in a single fold. Cross-fitting is repeated five times, and the median estimate across repetitions is reported, and statistical inference relies on city-clustered standard errors.

Given that environmental governance investment, residents' income level and new quality productive forces may themselves respond to policy implementation, while the current design cannot completely exclude post-treatment confounding or reverse causality, the resulting evidence is therefore interpreted as being consistent with the proposed pathways rather than as establishing causal mediation.

Table 12 reports the results of the potential pathway analysis. Overall, the green industrial park policy is positively associated with environmental governance investment, residents' income level and new quality productive forces, although statistical significance differs across the three pathways. In the joint DML model, after accounting for the policy variable and other covariates simultaneously, all three pathway variables exhibit significant positive relationships with urban resilience. These results broadly accord with the proposed theoretical pathways.

**Table 12.** Results of the potential pathway analysis.

| Variable                 | (1) EGI            | (2) UR               | (3) Income           | (4) UR               | (5) NQPF            | (6) UR                |
|--------------------------|--------------------|----------------------|----------------------|----------------------|---------------------|-----------------------|
| Green                    | 0.065 *<br>(0.037) | 0.093 ***<br>(0.033) | 0.027 ***<br>(0.007) | 0.089 ***<br>(0.031) | 0.005 **<br>(0.002) | 0.042 **<br>(0.017)   |
| EGI                      |                    | 0.049 **<br>(0.023)  |                      |                      |                     |                       |
| Income                   |                    |                      |                      | 0.302 **<br>(0.140)  |                     |                       |
| NQPF                     |                    |                      |                      |                      |                     | 10.294 ***<br>(1.129) |
| Linear Controls          | Yes                | Yes                  | Yes                  | Yes                  | Yes                 | Yes                   |
| Quadratic Controls       | Yes                | Yes                  | Yes                  | Yes                  | Yes                 | Yes                   |
| Year Fixed Effects       | Yes                | Yes                  | Yes                  | Yes                  | Yes                 | Yes                   |
| City Fixed Effects       | Yes                | Yes                  | Yes                  | Yes                  | Yes                 | Yes                   |
| City-Level Cross-Fitting | Yes                | Yes                  | Yes                  | Yes                  | Yes                 | Yes                   |
| N                        | 4019               | 4019                 | 4019                 | 4019                 | 4019                | 4019                  |

Notes: Columns (1), (3), and (5) estimate the policy–pathway relationship; columns (2), (4), and (6) jointly estimate the policy and corresponding pathway variable for urban resilience. The baseline policy coefficient is 0.094 (SE = 0.032). All specifications contain both linear and quadratic control terms and year fixed effects; city effects are removed through within-city transformation, and five-fold cross-fitting is implemented at the city level with five repetitions. The median across the five repetitions is retained, and parentheses contain standard errors clustered by city. \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively.

#### 5.5.1. Environmental Governance Investment

Columns (1)–(2) of Table 12 report the results for environmental governance investment (EGI). The green industrial park policy is positively associated with EGI and reaches

the 10% significance level. In the joint DML model, EGI shows a positive and statistically significant relationship with urban resilience, while the policy coefficient remains near its baseline value. This pattern accords with the environmental-governance orientation of the green industrial park policy.

This pattern is consistent with the environmental-governance orientation of the green industrial park policy. Requirements related to environmental access, cleaner production, centralized pollution treatment, and full-process environmental supervision may encourage greater environmental governance investment. Centralized wastewater treatment, collaborative solid-waste disposal, energy-environmental monitoring, resource recycling, and green infrastructure may help reduce environmental risks, improve resource-use efficiency, and improve the ability of urban systems to adjust to disturbances.

Consistent with the variable definition adopted in this study, EGI mainly reflects local government financial resources devoted to energy conservation, emission reduction, and environmental governance. Existing research suggests that environmental regulation can provide an important governance foundation for strengthening ecosystem resilience [46]. Green governance investment may also improve regional ecological quality and sustainable development by promoting green technology adoption and enhancing environmental management capacity [19,47]. These mechanisms provide a plausible explanation for the positive conditional association between EGI and urban resilience reported in Table 12.

#### 5.5.2. Residents' Income Level

Household economic resources and risk-bearing capacity constitute an important micro-level foundation for the stable operation of urban socioeconomic systems. Existing research reveals that economic development fundamentals, industrial structure, and innovation capacity are key conditions shaping urban economic resilience [38]. Meanwhile, as an important reflection of economic development outcomes, residents' income level is closely associated with improved economic welfare, enhanced risk-coping capacity, and strengthened social adaptability of residents [48]. Accordingly, residents' income level may serve as a potential transmission pathway between the green industrial park policy and urban resilience.

Columns (3)–(4) of Table 12 report the corresponding estimates. The green industrial park policy shows a positive and statistically significant association with residents' income level. In the joint DML model, Income also shows a positive and statistically significant relationship with urban resilience, while the policy coefficient remains positive and significant, although its magnitude is slightly below the baseline value. These results are consistent with Hypothesis H3 and provide suggestive support for residents' income as a potential pathway.

A plausible explanation is that green industrial park development may promote technological upgrading, digital transformation, and industrial restructuring, thereby improving production efficiency and increasing demand for skilled labor. Green industrial transition may shift labor demand toward skilled, knowledge-intensive, and higher-quality employment and increase workers' earnings [49]. Higher income, in turn, can strengthen households' financial buffers and consumption-smoothing capacity, mitigate the effects of external shocks on livelihoods and human-capital investment, and thereby enhance social adaptability and urban resilience [50].

#### 5.5.3. New Quality Productive Forces

New quality productive forces may represent a potential pathway linking the green industrial park policy to technological progress, optimized production modes, and improved factor allocation. Columns (5)–(6) of Table 12 show a positive and statistically significant

association between the green industrial park policy and NQPF. In the joint DML model, NQPF also shows a positive and statistically significant relationship with urban resilience, while the policy coefficient remains positive and significant but is smaller than the baseline estimate. Taken together, these findings support H4 and offer suggestive evidence that NQPF may constitute a potential pathway.

A plausible explanation is that green industrial park development may promote equipment renewal, process upgrading, digital transformation, and the agglomeration of innovative factors, including capital, technology, data, and human capital. Public technical platforms, digital management systems, and industry–university–research cooperation may further facilitate knowledge diffusion and technological absorption, thereby improving factor allocation efficiency and innovation capacity.

Existing research suggests that new quality productive forces may support urban economic resilience through digital innovation, industrial agglomeration, and improvements in human-capital structure [51]. By improving factor allocation efficiency, enhancing industrial-chain coordination, and mitigating resource misallocation, new quality productive forces may also help urban industrial systems absorb external disturbances more effectively [52]. These mechanisms provide a plausible explanation for the positive conditional relationship between NQPF and urban resilience.

### 5.6. Heterogeneity Analysis

Cities vary considerably in resource dependence, industrial foundations, and regional development conditions. These initial conditions may influence how the green industrial park policy is associated with urban resilience. To examine whether the baseline findings differ across city types, grouped estimations are conducted along three dimensions: resource endowments, industrial development foundations, and regional location.

#### 5.6.1. Resource Endowment Heterogeneity

Resource-based cities have historically depended on extractive industries and primary resource processing. Although such activities can boost economic growth, they tend to create a narrow industrial structure, deepen path dependence and accumulate ecological pressure, which limits the adaptive capacity of urban systems. In comparison, non-resource-based cities tend to exhibit broader industrial diversification and greater mobility of production factors, which may place them in a more favorable position to benefit from green transition policies. To examine heterogeneity across different resource endowments, this paper classifies the sample cities into resource-based and non-resource-based groups using the classification provided in the National Sustainable Development Plan for Resource-Based Cities (2013–2020) [53].

Column (1) of Table 13 reports the corresponding estimates. For resource-based cities, the policy estimate is 0.025 and does not reach conventional significance levels. By contrast, the estimate for non-resource-based cities is 0.138 ( $p < 0.01$ ). The formal between-group comparison yields a difference of  $-0.113$  ( $p = 0.014$ ), defined as the resource-based estimate minus the non-resource-based estimate, indicating a significantly weaker association for resource-based cities. Thus, although the point estimate for resource-based cities is positive, the available evidence does not establish a statistically significant positive relationship for this group. The significant between-group difference suggests that resource dependence may partly weaken the positive association between the green industrial park policy and urban resilience.

**Table 13.** Results of the heterogeneity analysis.

| Variable                 | (1)                   |                           | (2)                        |                                | (3)                              |                     |                     |
|--------------------------|-----------------------|---------------------------|----------------------------|--------------------------------|----------------------------------|---------------------|---------------------|
|                          | Resource-Based Cities | Non-Resource-Based Cities | Old Industrial Base Cities | Non-Old Industrial Base Cities | Eastern Region                   | Central Region      | Western Region      |
| Green                    | 0.025<br>(0.027)      | 0.138 ***<br>(0.045)      | 0.044 *<br>(0.025)         | 0.120 ***<br>(0.042)           | 0.148 **<br>(0.067)              | 0.055 **<br>(0.026) | 0.089 **<br>(0.042) |
| Linear Controls          | Yes                   | Yes                       | Yes                        | Yes                            | Yes                              | Yes                 | Yes                 |
| Quadratic Controls       | Yes                   | Yes                       | Yes                        | Yes                            | Yes                              | Yes                 | Yes                 |
| Year Fixed Effects       | Yes                   | Yes                       | Yes                        | Yes                            | Yes                              | Yes                 | Yes                 |
| City Fixed Effects       | Yes                   | Yes                       | Yes                        | Yes                            | Yes                              | Yes                 | Yes                 |
| City-Level Cross-Fitting | Yes                   | Yes                       | Yes                        | Yes                            | Yes                              | Yes                 | Yes                 |
| N                        | 1519                  | 2500                      | 1313                       | 2706                           | 1402                             | 1382                | 1235                |
| Formal Difference Test   | −0.113; $p = 0.014$   |                           | −0.076; $p = 0.041$        |                                | $\chi^2(2) = 2.68$ ; $p = 0.262$ |                     |                     |

Notes: Subgroup effects are estimated using full-sample interaction DML models. The reported contrasts are calculated by subtracting the estimates for non-resource-based cities from those for resource-based cities and those for non-old-industrial-base cities from those for old-industrial-base cities. Geographic heterogeneity is evaluated using a joint Wald test; pairwise test  $p$ -values are 0.127 (central vs. eastern), 0.444 (western vs. eastern), and 0.506 (central vs. western). Each model uses 4019 observations, city-level five-fold cross-fitting, and five repetitions; median estimates are reported. Parentheses report standard errors clustered at the city level. \*, \*\*, and \*\*\* correspond to the 10%, 5%, and 1% significance thresholds, respectively.

This discrepancy may largely stem from the long-term development path dependence formed in resource-based cities. Drawing on Unruh’s (2000) “carbon lock-in” theory [54], fossil-fuel-based development models create self-reinforcing mechanisms through technological systems, industrial structures and institutional arrangements, trapping regional economies within high-carbon development trajectories. Resource-based cities, which rely heavily on resource extraction and processing, are also characterized by relatively rigid, specialized, and low-end industrial structures that may reduce their ability to absorb external economic shocks; empirical evidence further identifies industrial structure as an important determinant of economic resilience in China’s resource-based cities [55]. More recent evidence shows that dependence on resource-based industries is significantly associated with lower urban resilience and that this effect operates partly through inhibited industrial structural upgrading and hindered green technological innovation [56].

Against this background, the relatively lower estimated coefficient observed in resource-based cities may reflect the structural constraints associated with long-term resource dependence. Although the green industrial park policy may promote green upgrading, resource-use efficiency, and industrial restructuring, translating these changes into broader resilience gains may be more difficult where industrial structures remain strongly resource-dependent and adjustment capacity is constrained. By contrast, the relatively more diversified industrial foundations of non-resource-based cities may provide greater room for green technology diffusion, industrial restructuring, and the reallocation of innovative resources, thereby facilitating a stronger positive relationship between green industrial park development and urban resilience. These structural differences provide a plausible explanation for the observed between-group heterogeneity.

### 5.6.2. Industrial Foundation Heterogeneity

Urban industrial foundations may shape the relationship between green transition policies and resilience-related outcomes in different ways. On the one hand, a well-developed manufacturing system and mature industrial-chain networks may facilitate green technol-

ogy diffusion, inter-firm production collaboration, and resource recycling. On the other hand, long-established heavy-industry structures, fixed-asset lock-in, and industrial path dependence may increase the costs of industrial restructuring and green transition. Accordingly, the sample is grouped into old-industrial-base and non-old-industrial-base cities using the classification in the National Plan for the Adjustment and Renovation of Old Industrial Bases (2013–2022) [57], which allows comparison of the estimated relationship across different industrial foundations.

The corresponding results are reported in Table 13. For old-industrial-base cities, the policy estimate is 0.044 ( $p < 0.10$ ), while the corresponding estimate for non-old-industrial-base cities is 0.120 ( $p < 0.01$ ). The formal between-group comparison yields a difference of  $-0.076$  ( $p = 0.041$ ), calculated as the old-industrial-base estimate less the non-old-industrial-base estimate. Although both group estimates are positive, the between-group test shows a significantly smaller association for old-industrial-base cities. Thus, the estimated positive association is more pronounced among non-old-industrial-base cities.

One possible explanation lies in differences in the transition conditions associated with cities' industrial foundations. Existing research on old industrial areas emphasizes that long-established industrial structures and development trajectories may generate path dependence and lock-in, thereby constraining regional restructuring and the creation of new development paths [56,57]. In particular, established technological systems, production networks, and institutional arrangements may increase the difficulty of restructuring traditional industrial systems and adapting to new development trajectories [58,59]. Empirical evidence on China's old industrial bases also reveals that regional economic resilience is closely linked to industrial restructuring and innovation enhancement, whereas traditional industrial systems tend to exhibit strong adjustment inertia when confronted with external shocks [60].

From this perspective, the smaller estimated coefficient for old industrial base cities may reflect the greater adjustment costs associated with transforming established industrial systems. Green transition in these cities may rely more heavily on the gradual retrofitting and restructuring of existing production systems, such as equipment renewal, process upgrading, and improvements in environmental governance, which may require a longer adjustment period. In comparison, legacy industrial structures may impose weaker constraints on non-old-industrial-base cities, leaving greater scope for green technology adoption, industrial restructuring, and the reallocation of innovative resources. These structural differences provide a plausible interpretation of the observed between-group heterogeneity.

### 5.6.3. Regional Heterogeneity

Because Chinese regions differ substantially in industrial structure, development stage, and factor-allocation conditions, the association between the green industrial park policy and urban resilience may also differ across regions. To examine this issue, the sample cities were grouped into eastern, central, and western regions following the National Bureau of Statistics classification, and we estimated the policy coefficient for each group separately. Column (3) of Table 13 presents the regional estimates.

The policy estimates for the eastern, central, and western regions are 0.148, 0.055, and 0.089, respectively, with each significant at  $p < 0.05$ . Thus, positive and statistically significant estimates are obtained for all three regions. Numerically, the point estimate is highest in the eastern region, followed by the western and central regions. Nevertheless, numerical differences in point estimates across groups do not necessarily imply statistically significant heterogeneity in the estimated coefficients. Formal pairwise comparisons yield  $p = 0.127$  for central versus eastern,  $p = 0.444$  for western versus eastern, and  $p = 0.506$  for central versus western; none of these differences is statistically significant at conventional

levels. The joint Wald test likewise does not reject equality of the three regional coefficients ( $\chi^2(2) = 2.68$ ,  $p = 0.262$ ). Therefore, despite numerical differences across regions, the evidence does not indicate statistically significant regional heterogeneity in the estimated policy coefficients.

Even so, regional development conditions may help explain the observed numerical differences among point estimates. Eastern regions generally possess sound industrial systems, strong factor-agglomeration capacity and solid innovation foundations, which facilitate the adoption of green technologies and industrial upgrading. Existing literature also confirms that disparities in urbanization levels and spatial development conditions are correlated with urban ecological resilience [25]. Central regions feature a relatively robust manufacturing base and serve as key destinations for industrial relocation from eastern China. Their geographical location, cost advantages and industrial foundations attract manufacturing capital and related investment [61]. Nevertheless, several central cities still host a large share of traditional industries, implying relatively high adjustment costs for equipment renewal and industrial upgrading. Western regions also enjoy considerable potential for green transition. In cities with weak industrial foundations, the construction of green industrial parks may simultaneously promote production-technology improvement, infrastructure upgrades and the adoption of green production modes. Prior research documents that eco-industrial parks strengthen industrial-chain resilience and generate positive effects in central and western China [62]. At the same time, insufficient industrial supporting capacity and a shortage of innovation resources may constrain the sustained release of policy benefits.

In summary, formal between-group tests provide statistical evidence supporting heterogeneity driven by resource endowments and industrial foundations: the estimated coefficients in resource-based cities and old industrial base cities are significantly lower than those in their respective reference groups. In contrast, although the estimated coefficients are significantly positive across eastern, central and western regions, the between-group differences fail to achieve statistical significance. This suggests that the estimated relationship between the green industrial park policy and urban resilience varies with cities' existing development foundations and transition capacities, while statistical evidence for geographical regional heterogeneity remains limited.

## 6. Discussion

This study extends green industrial park policy evaluation beyond park-level environmental and green development performance to the broader urban-system level. Existing studies have mainly examined eco-industrial parks in relation to resource-use efficiency, pollution abatement, and green development performance [63]. The present analysis extends this perspective by considering urban resilience as a multidimensional outcome involving economic, social, ecological, and infrastructure subsystems [10]. Green industrial park development may therefore be associated with broader urban-system conditions, including environmental management, infrastructure provision, economic adjustment, and social conditions.

The variation across resilience dimensions may reflect differences in how closely each subsystem is connected to the functions of green industrial parks. Ecological governance, resource recycling, pollution control, and infrastructure upgrading correspond closely to the operational objectives of green industrial development and may therefore be more directly connected to changes associated with park construction and management. Economic and social resilience, in contrast, depend on a broader set of conditions and may adjust more gradually. Social resilience, for example, is shaped by employment, income, public services, social security, demographic conditions, and local fiscal capacity. Industrial restructuring

may also involve labor reallocation, skill mismatches, and short-term adjustment costs, which may delay improvements in social outcomes.

The pathway analysis points to several dimensions through which the relationship between green industrial parks and urban resilience may operate. Environmental governance investment is related to local capacity for pollution control and ecological management, while higher residents' income may strengthen households' ability to absorb economic shocks and maintain consumption and welfare. New quality productive forces may matter through technological upgrading, digitalization, and the concentration of innovation resources. These interpretations align with earlier research highlighting the roles of governance capacity, economic foundations, and innovation capacity for urban resilience [64]. At the same time, these relationships should be viewed as plausible pathways rather than established causal mechanisms.

Differences across city types also suggest that the relationship between green industrial transformation and resilience-related outcomes depends partly on the broader urban context. Resource-based cities and old industrial base cities often face constraints associated with long-standing industrial specialization, heavier dependence on traditional sectors, and higher adjustment costs during structural transformation [25]. Such conditions may help explain why the relationship between green industrial development and resilience-related outcomes varies across cities. By comparison, broad eastern, central, and western classifications may conceal substantial variation in local industrial structures and transition conditions. Resource endowments and industrial foundations may therefore provide a more useful basis for interpreting heterogeneity than regional location alone.

## 7. Conclusions and Policy Implications

### 7.1. Main Research Conclusions

The empirical analysis uses panel data covering 293 Chinese cities at the prefecture level or above from 2011 to 2024. Double/Debiased Machine Learning (DML) is employed to estimate the conditional relationship between national-level green industrial park policy exposure and urban resilience. The results indicate a statistically significant positive association between policy implementation and comprehensive urban resilience, and this relationship remains robust across a range of robustness and sensitivity checks.

The dimension-specific estimates are positive for economic, social, ecological, and infrastructure resilience, although the strength of statistical evidence varies across dimensions. Evidence is relatively stronger for ecological and infrastructure resilience, whereas the results for economic and social resilience are comparatively weaker.

The potential pathway results are broadly consistent with the roles of environmental governance investment, residents' income, and new quality productive forces. These findings should be interpreted as empirical evidence consistent with the proposed pathways rather than as estimates of strict causal mediation effects.

Heterogeneity is more evident across cities with different resource endowments and industrial foundations. The estimated coefficients are lower in resource-based cities and old industrial base cities than in non-resource-based cities and non-old industrial base cities, while no statistically significant differences are identified across eastern, central, and western regions.

These results should be interpreted cautiously. The DML estimates are conditional on observable city-level characteristics and city and year fixed effects, while the staggered DID diagnostics reject strict parallel trends over the full pre-treatment period. Accordingly, the staggered DID results serve as supplementary dynamic evidence rather than independent causal identification, while the main estimates are interpreted as conditional empirical associations rather than definitive causal effects.

## 7.2. Policy Implications

These findings suggest several directions for the further implementation and refinement of green industrial park policy.

- (1) Place environmental governance and infrastructure operation at the center of post-designation park development. Ecological and infrastructure resilience show relatively stronger statistical evidence. Subsequent efforts could therefore focus more on pollution control, energy and water conservation, wastewater and solid-waste treatment, environmental monitoring, and the operation and maintenance of municipal infrastructure in and around the parks. Continued investment and performance evaluation after designation should also be strengthened to avoid weak operational efficiency after construction is completed.
- (2) Strengthen economic adjustment capacity, employment, and public-service support alongside park development. The estimates for economic and social resilience are positive but only marginally significant at the 10% level, indicating comparatively weaker evidence for these two dimensions. Green industrial park development could therefore be accompanied by measures that support technological upgrading and productivity improvement of local firms, while also strengthening vocational training, employment services, and assistance for workers affected by industrial restructuring. Complementary efforts to stabilize employment and income and improve access to medical care, pension services, and other basic public services may further strengthen the connection between industrial transformation and broader urban resilience.
- (3) Differentiate support according to cities' own structural conditions rather than relying mainly on broad regional classifications. Policy design should give greater attention to resource dependence, industrial legacies, technological capacity, and local innovation conditions when determining support priorities. Resource-based cities and old industrial base cities could receive greater support for technological upgrading of traditional industries, equipment renewal, cleaner production, and the application of green technologies, while other cities could adjust their policy priorities according to their industrial structure, technological capacity, and innovation base.

## 7.3. Research Limitations and Future Research Directions

Although the analysis provides a comprehensive examination of the link between the green industrial park policy and urban resilience, several limitations should be acknowledged.

First, the empirical identification strategy is constrained by the research design. The DML approach flexibly controls for observable urban characteristics and potential nonlinear relationships but cannot fully eliminate bias arising from time-varying unobserved factors. Moreover, the staggered DID analysis does not support strict parallel trends over the entire pre-policy window. The dynamic estimates should therefore be interpreted as supplementary identification diagnostics rather than as standalone causal evidence.

Second, the analysis is conducted primarily at the city level and cannot capture micro-level responses at the park and firm levels. The binary policy indicator identifies whether and when a city first became exposed to the national-level green industrial park policy, but it does not measure differences in policy intensity, the number or scale of green industrial parks, industrial composition, or operational quality. The estimated relationship therefore reflects policy adoption rather than a dose–response relationship. Future research could combine city-, park-, and firm-level data and construct more refined measures of policy exposure and implementation intensity.

Third, the pathway analysis provides evidence consistent with the proposed roles of environmental governance investment, residents' income, and new quality productive forces, but it does not establish strict causal mediation. Likewise, although the heterogeneity

analysis identifies significant between-group differences related to resource endowments and industrial foundations, the factors underlying these differences—such as industrial path dependence, innovation capacity, and technological absorptive capacity—are not directly tested.

Fourth, the spatial analysis relies mainly on sensitivity tests that exclude untreated observations located near treated cities. These tests help assess whether the baseline estimates are sensitive to potential spatial interference, but they do not identify the existence, direction, or magnitude of spatial spillover effects.

Future research could further examine policy intensity, underlying pathways, sources of heterogeneity, and spatial spillovers using more detailed micro-level data and stronger identification strategies. Longer time-series data could also be used to investigate the longer-term evolution of the estimated relationship and the responses of different dimensions of urban resilience.

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