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The impact of ecological civilization construction on the resilience of green technology innovation: evidence based on double dual machine learning

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Can the accelerated development of ecological civilization promote the sustainable development of green innovation?This paper investigates the effects of ecological civilization demonstration zones (ECDZs) on green innovation resilience. Based on a sample of 237 prefecture-level cities across 31 provinces in China from 2011 to 2021, our double dual machine learning and spatial difference-in-differences model indicates that ECDZs significantly enhance urban green innovation resilience. Our findings also reveal a spatial spillover effect of ECDZ—the development of ECDZs in one city significantly improves the resilience of green innovation in neighboring cities. The spatial spillover effect reaches its maximum in the fifth year. Our analysis of the underlying mechanisms suggests that ECDZs promote urban green innovation resilience through the advancement of digitalization, green consciousness, and new quality productivity. We also conduct an analysis of heterogeneity based on geographical locations and levels of policy support, and the results show that the impact of ECDZs on urban green innovation resilience is mainly observed in western, inland, and strongly policy-supported regions. The findings of this study provide crucial insights and valuable guidance for developing national environmental conservation policies and programs.

KEYWORDS

ecological civilization demonstration zones, green innovation resilience, double machine learning, spatial difference-in-differences model, China

1 Introduction

As the challenges of climate change and resource depletion become increasingly severe, global environmental issues are becoming more urgent. Pursuing a path of sustainable development has become crucial for ensuring the stable functioning of the global economy. At present, China, the United States, India, the European Union, and Russia are the primary contributors to global greenhouse gas emissions. China is the largest emitter, accounting for around 28% of global emissions (Yan et al., 2024), followed by the United States (approximately 15%), India (7%), and the European Union (6%). Despite worldwide efforts to curb emissions, global greenhouse gas levels continue to rise. Actively engaging in international climate change negotiations, fulfilling the commitments outlined in the Paris Agreement, and reducing greenhouse gas emissions present significant challenges for nations worldwide (Zheng et al., 2022). To achieve the "carbon reduction" goal of a sustainable future, countries worldwide are actively strengthening the sustainable development of green technology innovation (Hu and Xu, 2023). In this context, green innovation resilience has become a key pillar of global sustainable development. By enhancing the resilience of green innovation, countries around the world can more effectively address environmental changes, improve economic sustainability, and drive breakthroughs and applications in green technology (Roper and Tapinos, 2016). This not only helps mitigate the global climate crisis but also promotes the optimization of economic structures, enhances energy security, and improves social welfare. Green innovation resilience also can stimulate international cooperation and drive significant progress in addressing shared ecological challenges (Jin and Chen, 2024). In summary, the research and practice of green innovation resilience are essential not only for achieving global sustainable development but also for building a more harmonious and prosperous future.

According to Article six of the Paris Agreement, countries are encouraged to adopt environmental policies, such as ecological civilization demonstration zones (ECDZs), for national development. ECDZs are a significant measure to develop ecological civilization and achieve sustainable green development. To notably enhance the ecological environment, the Chinese government has strategically decided to actively promote the development of green ecology. Consequently, since their inception, China's ECDZs have garnered considerable attention both domestically and internationally due to their impact on industrial structure, energy composition, and efforts in energy conservation and emission reduction (Wang et al., 2021; Lv et al., 2022; Jie et al., 2023). However, research on the influence of ECDZs on green innovation resilience remains limited. With issues like energy shortages, environmental pollution, and climate change becoming increasingly prominent, studying green innovation resilience from an environmental development perspective is particularly crucial (Hu et al., 2020). Green innovation itself usually focuses on the development and application of new technologies, products or processes to achieve environmental sustainability (Karimi Takalo et al., 2021). Green innovation resilience focuses more on how systems adapt and respond to environmental changes (such as climate change, resource depletion, ecological degradation, etc.) and external shocks over the long term. Green innovation resilience requires not only technological innovations themselves, but also the ability of these innovations to function flexibly and stably in different social, economic, and ecological contexts. Studying the resilience of green innovation can help build more resilient ecosystems and ensure that green innovation continues to work in the face of increasing global uncertainty and complexity. Therefore, with the increasingly severe global energy crisis, climate change and public health challenges, the construction of ecological civilization, as the core strategy to promote green development, plays a vital role. This study not only provides theoretical support for enhancing the global green innovation capacity and adaptability, but also promotes the leapfrog development of technological innovation in environmental protection, health and resilience, providing a strong guarantee for the global society to achieve green transformation and long-term prosperity.

In this research, we aim to address the following important research questions:

RQ1: How does China's ecological civilization influence green innovation resilience?
RQ2: What are the mechanisms through which ecological civilization influences green innovation resilience?
RQ3: Is there heterogeneity across different regions in the impact of ecological civilization on green innovation resilience?

Answers to these questions not only contributes to China's future policy formulation in sustainable development but also provides valuable insights and guidance for other countries seeking to develop environmental policies to enhance global green innovation resilience.

In the field of environmental policy, the establishment of ECDZs represents the convergence of regional and environmental strategies. Domestic and international academic research on ECDZs primarily focuses on ecological protection and economic growth. Specifically, the environmental impact of environmental policies encompasses various factors, including effects on control of air pollution (Liu et al., 2022), ecological resources (Thiers et al., 2018; Keenan et al., 2019), economic growth (Xiao et al., 2022), low-carbon technologies (Sun et al., 2023), and industrial structure (Fanti and Buccella, 2017; Yu et al., 2017; Li M. et al., 2022). Regarding innovation, most researchers confirm the positive impact of environmental policies on technological innovation (Brunel, 2019; Yang et al., 2022; Qin et al., 2021). However, some scholars hold different views on this issue (Mahmoud and Rousselière, 2022). Nevertheless, there is a general consensus that the establishment of ECDZs can significantly enhance regional innovation. This consensus is supported by various aspects of innovation, including eco-efficiency (Czyżewski et al., 2020; Liang et al., 2018), technology clustering effects (Tao, 2018), the Innovation Development Index (Udeagha and Nicholas, 2023), and other relevant dimensions. Most existing literature predominantly examines the relationship between the establishment of ECDZs, environmental protection, and technological innovation.

In economics, resilience should be regarded as a key concept when studying the spatial economy's response to fluctuations in external environments (Reggiani et al., 2002). Currently, resilience measurement is divided into two main approaches: comprehensive index evaluation and single-indicator measurement (Lloyd et al., 2013; Seymour et al., 2020). For measuring green innovation resilience, single-indicator methods, such as evaluating the sensitivity index of core indicators before and after an impact (Martin, 2012; Yuan et al., 2022; Zhao et al., 2024), offer greater comparability. Regarding core indicators of green innovation, most scholars focus on green innovation efficiency or green total factor productivity (Zhao et al., 2023). The comprehensive index evaluation approach involves constructing a resilience index system, which is commonly used to assess economic and ecological resilience. The academic community currently identifies four key aspects of resilience: "recovery capacity," "disturbance," "systemic," and "adaptive capacity." Regarding the measurement of urban resilience, some scholars have established an urban resilience evaluation system based on the perspective of social ecosystem (SES), integrating economy, environment, society and infrastructure into a unified research framework (Luo et al., 2022). In addition, some scholars focus on the "resilience and recovery potential", "adaptation and flexibility potential" and "innovation and upgrading potential" to construct the evaluation of economic and ecological resilience (Liang et al., 2020; Huang et al., 2023). Building on the research of these scholars, this paper defines green innovation resilience as the ability to withstand risks and threats, maintain ongoing green innovation, and restore, sustain, and expand green innovation through continuous improvement and progress.

In summary, the existing literature extensively explores the impacts of ECDZs on ecological protection and technological innovation from various perspectives. The measurement of green innovation resilience also provides different standards, laying a solid foundation for this research and offering valuable insights. Nonetheless, previous studies often overlook the impact of ECDZs on green innovation resilience. This paper aims to address this gap by conducting a series of analyses to explore and expand upon the mechanisms and heterogeneity involved, to understand the strategies that link ECDZs with urban green innovation resilience within the framework of environmental policy. Based on these findings, we will further refine and improve research models and methods. Ultimately, to enrich and expand the existing body of research, this paper explores the environmental policy effects of ECDZs from the perspective of green innovation resilience.

Contrary to earlier studies, the marginal contributions of this paper can be categorized into four dimensions. (1) While most scholars have focused on the impact of ECDZs construction on ecological conservation and technological innovation, this paper uniquely examines the direct and spillover effects of ECDZs from the perspective of green innovation resilience. (2) Regarding the measurement of green innovation resilience, this paper optimizes the existing indicator system by comprehensively constructing a green innovation resilience based on three aspects: resistance capacity, sustainable capacity, and diffusion capability. Additionally, it employs a combination weighting method to calculate the green innovation resilience. (3) To avoid model bias and the challenges of high-dimensional data common in traditional econometric approaches (Chernozhukov et al., 2018), and to enhance the credibility of the findings, this paper employs the double machine learning (DML) approach. The method utilizes machine learning algorithms to make predictions in a high-dimensional and non-parametric setting to assess the effects of ECDZ policy impacts. (4) When analyzing the influencing mechanism of ECDZs on green innovation resilience, we explore the perspectives of digital technology embedding effect, environmental focusing effect, and productivity enhancement effect. Accordingly, we consider digitization, green consciousness, and new quality productivity as mediating variables. This approach aims to reveal how ECDZs influence urban green innovation resilience, providing pathways that maximize support for environmental policy impacts. The research structure of this paper is shown in Figure 1.

2 Theoretical analysis and hypotheses

ECDZs aims to explore new paths of sustainable development through systematic ecological protection, efficient use of resources and environmental governance. They serve as important experimental areas for promoting sustainable development and environmental innovation (Li et al., 2024). Green innovation resilience refers to the capacity to sustain stable and sustainable development in green innovation despite various environmental, economic, and social pressures and challenges (Luo et al., 2021). According to Porter's hypothesis, the green and low-carbon demands of environmental policies raise production costs in polluting industries, driving them to upgrade technologies and adopt green innovation practices (Zheng et al., 2022). The influence of ecological civilization demonstration zones on urban green innovation resilience is primarily reflected in three key aspects. First of all, based on the optimization effect of innovation resource allocation (Zhang et al., 2022), the demonstration zone effectively gathers innovation resources, such as talent, technology and capital. This efficient allocation of resources makes the development and application of green technology more rapid and effective, and improves the resilience and adaptability of green innovation. Secondly, the implementation of ECDZs also includes the introduction and promotion of environmental protection technologies, green products and services based on product demonstration effects (Liu et al., 2024). This encourages enterprises to prioritize environmentally friendly products in their production and consumption processes, thereby increasing public awareness and acceptance of green products. The product demonstration effect stimulates enterprise innovation and market competition, and this incentive effect makes more enterprises willing to invest resources in green innovation, and enhances the resilience of green innovation. Finally, based on the agglomeration effect, ecological civilization demonstration zones promote the concentration of innovative technologies and the competition in the green innovation market to a certain extent (Wang et al., 2021). This agglomeration effect makes it easier for knowledge and technology to spread and share among different subjects, promoting the rapid development of green technology and the diffusion of innovation. The spillover effect of knowledge and technology improves the adaptability of green innovation, which can help enterprises and research institutions acquire and apply cutting-edge technologies more quickly in the face of new environmental challenges, and promote the continuous upgrading of green innovation results. Based on the above analysis, Hypothesis 1 is proposed:

Hypothesis 1: The construction of ECDZs can significantly enhance urban green innovation resilience.

The positive spillover effect refers to the way in which the construction of ECDZs disseminates internal green innovation capabilities and development experiences to surrounding areas through various channels, such as knowledge spillover, resource allocation, and technology diffusion, thereby enhancing the green innovation resilience of neighboring cities. This positive spillover effect can strengthen the overall environmental adaptability and sustainable development capacity of the region, providing technical support, resource sharing, and policy demonstration effects for the green transformation of adjacent areas (Yu and Wang, 2021). In the context of the "dual carbon" goals, strong government support for green environmental projects and increased attention from investors in green initiatives serve as robust guarantees for the realization of these effects. The green development experience, environmental protection technology, and sustainable development concepts accumulated in the ECDZs can be transmitted to neighboring cities through the flow of talent, information exchange, and cooperative projects,

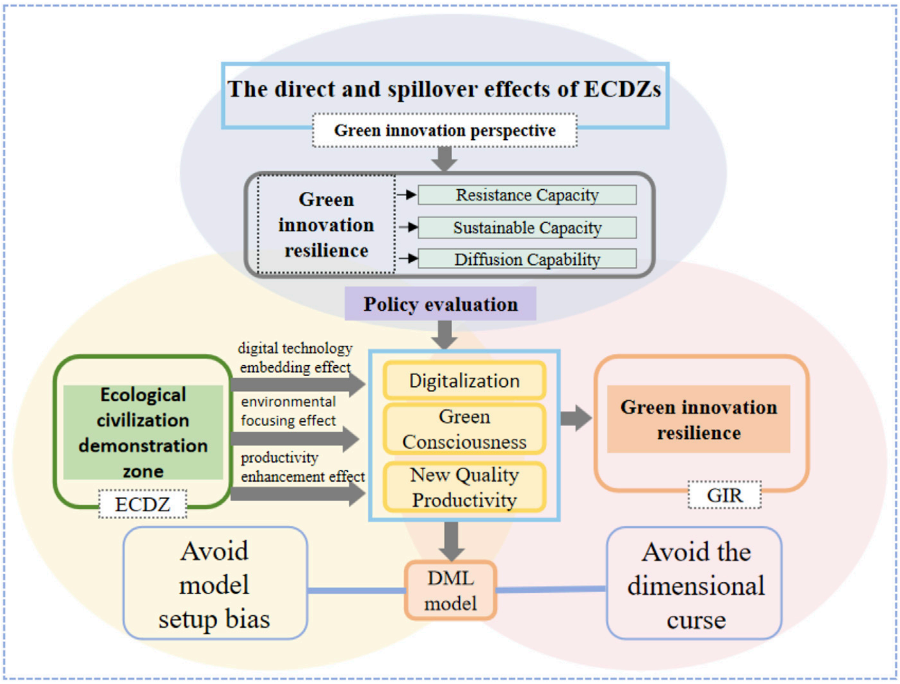

FIGURE 1
Research structure.

resulting in a "knowledge spillover effect". This effect promotes the formation of green innovation networks between the demonstration zone and neighboring cities. Such networked cooperation facilitates the complementarity of strengths among cities, accelerates the dissemination and application of knowledge, and thereby enhances the green development resilience of the entire region. In addition, the establishment of ECDZs has attracted substantial ecological resources, funds, and talents, which contribute to the reorganization and optimization of green innovation in neighboring cities, creating a "resource allocation effect". This effect promotes the efficient use and sharing of resources between the demonstration zones and surrounding areas, fostering a synergistic development effect within the region. Finally, the green technologies and industrial models developed in the ECDZs can generate a "technology diffusion effect" in neighboring cities through market mechanisms and policy support. This diffusion not only elevates the technological capabilities of neighboring cities in green industries, but also enhances their capacity to manage green innovation risks and drive sustainable development (Zhang et al., 2022). In summary, ECDZs drive regional green innovation resilience and sustainable development through knowledge spillover, resource allocation, and technology diffusion, forming an interconnected green innovation network that supports the green transformation of neighboring cities and the broader region. Hypothesis 2 is proposed:

Hypothesis 2: The construction of ECDZs can significantly enhance the green innovation resilience of neighboring cities.

As significant experimental platforms for promoting green development and constructing ecological civilization, ECDZs exhibit a digital technology embedding effect. Digital technology refers to the technological system involving the processing, storage, transmission, and management of data using computer, communication, software, and network technologies (Volkoff et al., 2007). These demonstration zones actively introduce and apply digital technologies to improve environmental management, resource efficiency, and service effectiveness. This includes the construction of intelligent monitoring and control systems, the application of data analysis and forecasting, and the establishment and utilization of digital platforms aimed at optimizing the management and protection of the ecological environment. In the process of achieving deep integration with environmental development, digital technologies enable the efficient and comprehensive use of various innovative resources to maximize their effective value (Wen et al., 2019). At the same time, the advance of digitalization has facilitated the transformation of low-carbon industries and technologies (Li et al., 2021). Technologies such as big data analytics, the Internet of Things, and artificial intelligence provide new platforms and tools for the research and application of green technologies. With a data-driven approach, environmental issues can be identified and addressed more quickly, driving innovation in the areas of clean energy, circular economy, emission reduction, and energy conservation. Moreover, digitization is crucial for improving the efficiency of urban management (Zhang and Liu, 2022). Digital technologies enhance environmental monitoring, resource utilization, and management efficiency in the production process. Intelligent monitoring systems can collect environmental data in real-time, accurately assess resource utilization efficiency, and promote the sustainable development of green innovation. Based on the above analysis, Hypothesis 3a is proposed:

Hypothesis 3a: The construction of ECDZs can promote urban green innovation resilience by enhancing digitalization.

From the perspective of the environmental focusing effect, green consciousness in demonstration zones can accelerate urban greening. As pioneers in environmental protection and sustainable development, ECDZs generally establish more stringent and advanced standards in environmental management. Their environmental policies and management measures provide important references for other regions and countries in formulating regulations, and they promote the improvement of national and even global environmental standards. Additionally, by strengthening green consciousness, ECDZs can enhance their technological innovation capabilities and become more competitive in the green market (Dennett and Roy, 2015). By precisely aligning high-quality innovation resources with green products, they accelerate the resilient development of green innovation. Academics believe that green consciousness plays a key role in driving green innovation (Quan et al., 2019). Strict green consciousness compels regions to improve production processes and technologies, thereby reducing pollutant emissions and resource consumption. To meet environmental standards, regions must invest in the development of cleaner production, energy conservation, and pollution control technologies, which in turn promotes the improvement of green innovation resilience. Based on the above analysis, Hypothesis 3b is proposed:

Hypothesis 3b: The construction of ECDZs can promote urban green innovation resilience by strengthening green consciousness.

In addition to digitalization and green consciousness, new quality productivity is pivotal in influencing urban green innovation resilience within ECDZs. Unlike traditional production methods reliant on extensive resource inputs and high consumption, new quality productivity achieves breakthroughs through disruptive technologies, ensuring efficient and high-quality output. In the digital era, it signifies greater integration and novel implications, indicative of future development directions (Wang et al., 2024). From the standpoint of enhancing productivity, ECDZs can elevate productivity standards while speeding up innovation processes. From the effects of enhancing productivity, ECDZs can improve productivity quality while accelerating innovation speed. The establishment of these zones inevitably involves improvements in infrastructure and advancements in information and communication technology, significantly enriching channels for information exchange. This enhancement facilitates the refinement of production and transaction processes (Hendriks, 1999), enhances transparency in relevant information, broadens the scope of information search, accelerates information transmission speed, and effectively mitigates information asymmetry issues. Consequently, these improvements enhance the speed and quality of production and transaction activities (Hardy, 1980). At the same time, the enhancement of new quality productivity facilitates the emergence of efficient new organizational structures (Yin, 2024). This optimization not only improves internal production efficiency and resource utilization within enterprises but also enhances collaboration with external partners. Through refined division of labor and collaborative operations, businesses can accelerate the research and commercial application of green technologies more swiftly. This transformation enables traditional industries to transition towards high value-added, low-carbon green sectors, and injects new momentum into the promotion of green innovation resilience. Based on the above analysis, Hypothesis 3c is proposed:

Hypothesis 3c: The construction of ECDZs can promote urban green innovation resilience by through enhancing new quality productivity.

3 Research design

3.1 Model setting

3.1.1 Double machine learning model

Building on the work of Chernozhukov et al. (2018), this study employs dual machine learning (DML) methods to empirically analyze the effects of "ecological civilization demonstration zones" (ECDZs) as quasi-natural experiments. Compared to traditional multiple linear regression models, DML offers distinct advantages in model estimation and variable selection. It effectively handles nonlinear data, addresses model specification errors, and overcomes the limitations of linear assumptions in traditional causal inference models. Additionally, by integrating multiple machine learning and regularization algorithms, DML automatically selects key factors influencing green innovation, resulting in accurate predictions. This approach helps mitigate estimation bias caused by dimensionality issues, multicollinearity, and constraints of primary control variables, while ensuring the accuracy of causal inference in high-dimensional settings (Cao et al., 2024). Therefore, this study uses the release date of the "ecological civilization" demonstration city document as the impact point and applies DML to analyze the effect of these zones on green innovation. For specific models, refer to Equations 1, 2.

$$GIR_{i,t+1} = \theta_0 ECDZs_{it} + f_0(X_{it}) + U_{it}, E(U_{it}|X_{it}, ECDZs_{it} = 0) \tag{1}$$

$$ECDZs_{it} = m_0(X_{it}) + V_{it}, E(V_{it}|X_{it}) = 0 \tag{2}$$

In the equation: subscript i denotes the identifier for each city (i = 1,2, ... ,237), subscript t denotes the identifier for each year (t = 2011,2014, ... ,2021), $GIR_{i,t+1}$ represents urban green innovation resilience; $ECDZs_{it}$ is the policy dummy variable for the "ECDZs," where ECDZs = 1 if city i implements a policy pilot in year t, otherwise ECDZs = 0. The coefficient and significance of θ_0 are the main focus of this study; a significant positive coefficient indicates that ECDZs promote urban green innovation. X_{it} denotes the set of control variables influencing green innovation, which are covariates affecting the explained variable through a functional form estimated by machine learning algorithms. U_{it} represents the error term, with a conditional mean of 0. To avoid regularization bias arising from direct estimation of Equation 1, we introduce an auxiliary Equation 2, where m_0 is the regression function of the policy dummy variable on the control variables; V_{it} represents the error term with a conditional mean of 0. The specific steps are as follows: first, we use a machine learning model to estimate parameter $\hat{m}_0$ in Equation 2 for m_0, thereby obtaining the residual estimates $V_{it} = ECDZs_{it} - \hat{m}_0(X_{it})$; next, apply machine learning algorithms to estimate f_0; finally, treat the residuals as instrumental variables and regress Equation 1 to calculate the unbiased estimates of the coefficients. Finally, we treat V_{it} as the instrumental variable for $ECDZs_{it}$, and incorporate it into Equation 1 for regression, thereby calculating the unbiased estimate of θ_0.

3.1.2 Spatial difference-difference model

This paper analyzes the relationship between ECDZs and green innovation resilience by constructing the spatial weight matrix of geographical distance. The geographical distance here refers to the reciprocal Euclidean distance between the center of mass of two prefecture-level cities, that is, expressed by the inverse distance. As shown in Equation 3.

$$W = \begin{bmatrix} 0 & \frac{1}{d_{12}} & \cdots & \frac{1}{d_{1n}} \\ \frac{1}{d_{21}} & 0 & \cdots & \frac{1}{d_{2n}} \\ \vdots & \vdots & \vdots & \vdots \\ \frac{1}{d_{n1}} & \frac{1}{d_{n2}} & \cdots & 0 \end{bmatrix} \tag{3}$$

Where d_{ij} represents the distance between the center of mass of region i and j.

To estimate the spatial spillover effect ECDZs construction on the resilience of urban green innovation, this paper extends the traditional model to a spatial Durbin model, incorporating both the spatial lag and spatial error terms of the explanatory variables. The resulting spatial difference model is as shown in Equation 4:

$$\begin{aligned} GIR_{it} = \gamma_0 + \rho W_{ij} \times GIR_{it} + \beta_1 ECDZs_{it} + \beta_2 W_{ij} \times ECDZs_{it} \\ + \gamma_1 X_{it} + \gamma_2 W_{ij} \times X_{it} + city_i + time_i + e_{it} \end{aligned} \tag{4}$$

Where j represents each prefecture-level city unit, W_{ij} is the element in the spatial weight matrix, $W_{ij} \times GIR_{it}$ is the spatial lag term of the explained variable, $W_{ij} \times ECDZS_{it}$ is the spatial lag term of the pilot policy variable of "ecological civilization", $\gamma_2 W_{ij} \times X_{it}$ is the spatial lag term of the control variable, ρ and β_2 is the spatial correlation coefficient. Spatial lag model and spatial error model can be regarded as special forms of spatial durbin model. When $\beta_2 = \gamma_2 = 0$, the model is a spatial lag model. When $\rho = \beta_2 = \gamma_2 = 0$, the model is a spatial error model.

3.2 Variable selection

3.2.1 Dependent variable

The dependent variable is the green innovation resilience (GIR). This paper constructs and optimizes the existing index system to develop the green innovation resilience. Among them, resistance refers to the organization's ability to effectively identify, respond to and mitigate the impact of risks in the face of external threats and uncertainties, so as to ensure that green innovation activities are not subjected to major impacts. Sustainability refers to the ability of an organization to maintain the stability and growth of innovation activities over a long period of time and ensure that its innovation benefits can continue to be generated when it carries out green innovation (Xie et al., 2019). Diffusion capacity refers to an organization's ability to promote its green innovation from within to the broader market and society level (Long et al., 2019).

3.2.1.1 Indicator system

The index system consists of three dimensions: resistance capacity, sustainable capacity, and diffusion capability. Resistance capacity includes indicators such as R&D expenditure, number of R&D personnel, green patent applications, and green patent grants. Sustainable capacity includes R&D sustainability and green patent sustainability. Following the methodology of He and Zhou (2017), R&D sustainability is calculated by comparing R&D expenditure and personnel for green patents across different periods. Similarly, green patent sustainability is measured by the total continuity of patent applications and grants. Diffusion capability includes indicators such as forest coverage rate, *per capita* park green area, and foreign direct investment.

3.2.1.2 The weight of indicators

This paper proposes an optimized combinatorial weighting model to determine the weights of each index. First, subjective and objective weighting methods are applied to calculate the weights separately. These weights are then optimized and combined based on the principle of minimizing deviation, achieving a balance between subjective and objective weight coefficients. The subjective weighting method employs the Analytic Hierarchy Process (AHP), while the objective weighting method utilizes the entropy method and the coefficient of variation.

Firstly, standardizing the evaluation criteria.

Positive indicators, refer to Equation 5:

$$Pij = \frac{v_{ij} - \min_{1 \le j \le n}\left(V_{ij}\right)}{\max_{1 \le j \le n}\left(v_{ij}\right) - \min_{1 \le j \le n}\left(v_{ij}\right)} \tag{5}$$

Negative indicators, refer to Equation 6:

$$Pij = \frac{\max_{1 \le j \le n}\left(V_{ij}\right) - V_{ij}}{\max_{1 \le j \le n}\left(v_{ij}\right) - \min_{1 \le j \le n}\left(v_{ij}\right)} \tag{6}$$

Then, based on the weights obtained from AHP, Entropy method, and Coefficient of Variation method, the weights are optimized as follows. Step 1: Let the weight vector obtained from the AHP is $\theta = (\theta_1, \theta_2, ..., \theta_n)^T, 0 \le \theta_i \le 1$ and $\sum_{i=1}^{n} \theta_i = 1$. The weight vector obtained from the entropy method is $\mu = (\mu_1, \mu_2, ..., \mu_n)^T, 0 \le \mu_i \le 1$ and $\sum_{i=1}^{n} \mu_i = 1$ And from the coefficient of variation method is $Y = (Y_1, Y_2, ..., Y_n)^T, 0 \le Y_i \le 1$ and $\sum_{i=1}^{n} Y_i = 1$. α, β and δ respectively represent the weighting coefficients θ, μ and γ, forming the optimized weight vector model:

$$W = \alpha \times \theta + \beta \times \mu + \delta \times \gamma \tag{7}$$

α, β, and δ satisfy the following:

$$\alpha \ge 0,\ \beta \ge 0,\ \delta \ge 0,\ \alpha + \beta + \delta = 1 \tag{8}$$

TABLE 1 Evaluation system for green innovation resilience.

Primary indicators	Secondary indicators	Tertiary indicators	Weight
Green Innovation Resilience (GIR)	Resistance capacity (0.636)	R&D expenditure	0.15
		number of R&D personnel	0.06
		green patent applications	0.314
		green patent grants	0.112
	Sustainable capacity (0.204)	R&D sustainability	0.108
		green patent sustainability	0.096
	Diffusion capability (0.160)	forest coverage rate	0.081
		per capita park green area	0.054
		foreign direct investment	0.025

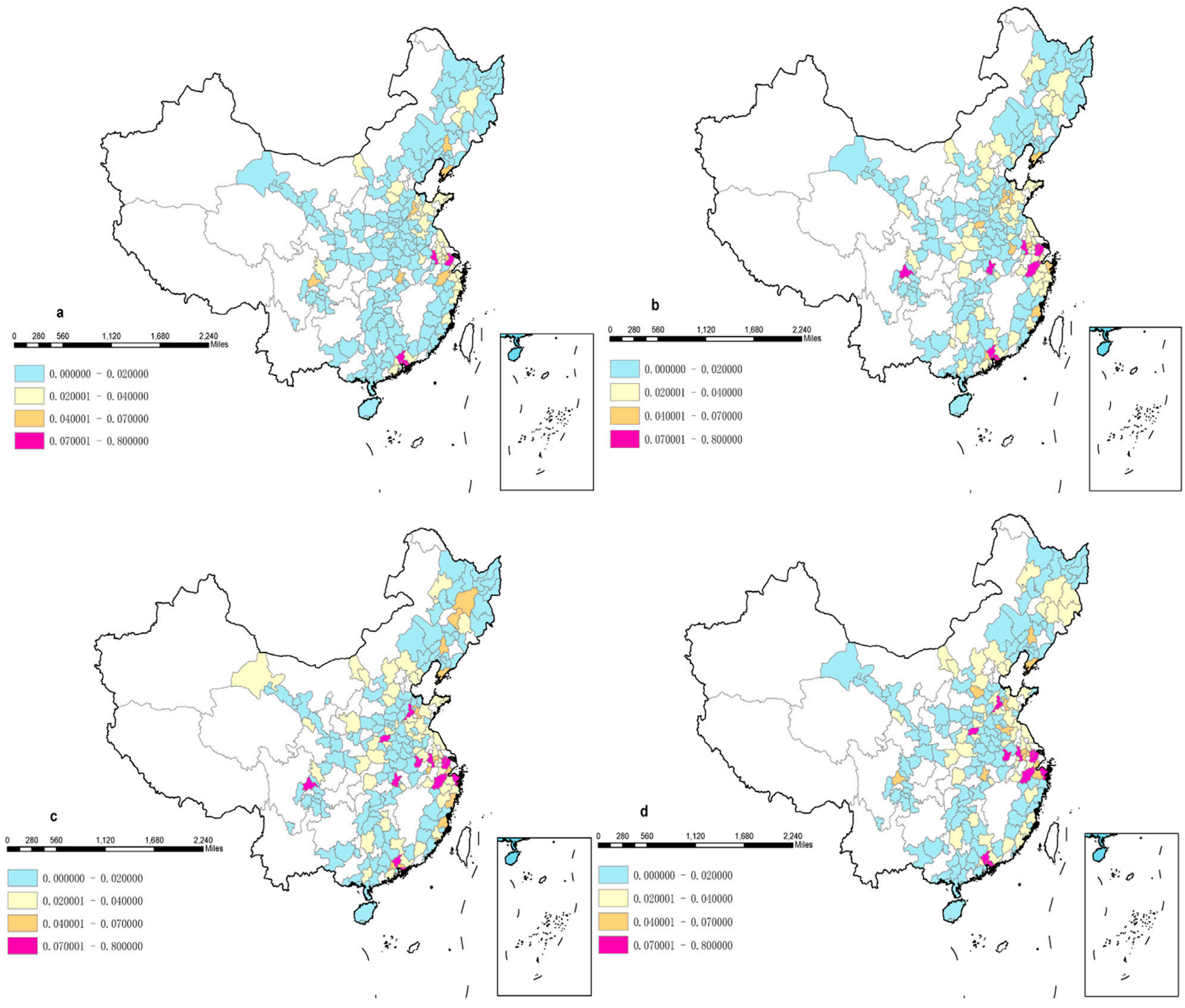

FIGURE 2
The changing pattern of green innovation resilience in 2012 **(A)**, 2015 **(B)**, 2018 **(C)** and 2021 **(D)**.

TABLE 2 Descriptive statistical results.

Variable	Full sample		Treatment group		Control group	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
GIR	0.0215	0.0279	0.0339	0.0345	0.0185	0.0252
did	0.1323	0.3389	0.6818	0.4662	0.0000	0.0000
agg	0.0236	0.0088	0.0269	0.0107	0.0228	0.0080
coa	10.0096	3.1649	9.9655	3.1782	10.0202	3.1624
hc	0.1768	0.0401	0.1652	0.0412	0.1796	0.0393
inno	0.2049	0.7349	0.3077	0.7198	0.1801	0.7365
sc	1.0465	0.5893	1.1170	0.5690	1.0295	0.5929
lnpgdp	10.7456	0.5647	10.8792	0.6058	10.7134	0.5497

Step 2: Assuming only AHP and Entropy Method weights are considered, with weight coefficients α' and β' respectively, as per Formula 6, the subjective weighted attribute value of criterion x_i under indicator y_i is $\alpha' Z_{ij}\theta_{ij}$, and the objective weighted attribute value is $\beta' Z_{ij}\theta_{ij}$. The difference between these two is $\alpha' Z_{ij}\theta_{ij} - \beta' Z_{ij}\theta_{ij}$. Therefore, the deviation of criterion x_i's subjective and objective evaluation values from decision information is:

$$d_i = \sum_{j=1}^{n} \left(\alpha' z_{ij}\theta_{ij} - \beta' z_{ij}u_{ij}\right)^2, 1 \le j \le m \tag{9}$$

Obviously, the smaller the value of d_i, the closer the evaluation object's subjective and objective decision information under the evaluation criteria. Therefore, based on the principle of minimizing the deviation of subjective and objective decision information, we establish the combined weight optimization model:

$$\left\{ \begin{array}{l} mina = \sum_{i=1}^{n} d_i = \sum_{i=1}^{m}\sum_{j=1}^{n} \left(\alpha' z_{ij}\theta_{ij} - \beta' z_{ij}u_{ij}\right)^2 \\ s.t.\alpha' + \beta' = 1, \alpha' \ge 0, \beta' \ge 0 \end{array} \right\} \tag{10}$$

After obtaining α' and β', derive the ratio of α to β based on $\alpha'/\beta'/\alpha/\beta$. Similarly, obtain the α/δ and β/δ. Use Formula 8 to determine the optimal combination of the three sets of weight coefficients. Finally, substitute these three sets of weight coefficients into Formula 7 to compute the combined weight W. The specific evaluation framework and weights are as follows in Table 1. The calculation results of green innovation resilience in individual years are shown in Figure 2.

3.2.2 Explanatory variables

In this study, whether city i is a demonstration zone of ecological civilization in t years is taken as a policy grouping dummy variable (did), where did = treat*time. This paper is based on 100 pilot demonstration zones for ecological civilization announced in batches across the country in 2014–2015, including 47 prefecture-level cities, 4 provinces and 49 districts, counties, special zones or river basins. Considering that there may be differences in the policies of demonstration zones in different provinces and cities, 47 prefecture-level cities corresponding to districts and counties were excluded and selected as the experimental group with corresponding treat = 1, and the remaining 190 prefecture-level cities as the control group with treat = 0. According to the establishment time of the pilot city, the time dummy variable time is created. time = 1 after 2014 or 2015; otherwise, time = 0.

3.2.3 Control variables

(1) Innovation talent agglomeration (agg). It is defined in this study as the number of individuals engaged in six major industries per ten thousand people as shown in Equation 11 (Zhang et al., 2021). This measurement is based on existing literature, which typically includes metrics such as the proportion of employed individuals with a bachelor's degree or higher, talent location entropy, and talent density.

$$agg = \frac{(L1 + L2 + L3 + L4 + L5 + L6) \times 10000}{L} \tag{11}$$

Here, agg denotes innovation talent agglomeration, L represents the urban resident population, and L1 to L6 represent employees in the financial software and information technology services industry, education industry, cultural, sports, and entertainment industry, scientific research and technical services industry, as well as leasing and business services industry.

(2) Industrial agglomeration (coa). This study uses the adjusted E-G index to measure the synergistic agglomeration between manufacturing and service industries (Chen et al., 2016), calculated as follows shown in Equation 12.

$$\left\{ \begin{array}{l} SA_{is} = (L_{is}/L_i)/(L_s/L) \\ HA_{ih} = (L_{ih}/Li)/(L_h/L) \end{array} \right\} \tag{12}$$

In the equation, SA_{is} and HA_{ih} represent the location quotients of productive service industries (s) and manufacturing industries (h) in region i. L_{is} and HA_{ih} denote the regional employment in productive service industries and high-tech industries, respectively, while L_s and L_h represent national employment totals in productive service industries and high-tech industries. L_i and L represent total employment in each region and nationwide.

TABLE 3 Results of VIF value calculation.

Variable	agg	Lnpgdp	Inno	coa	sc	hc	did	Mean VIF
VIF	1.91	1.58	1.55	1.51	1.45	1.22	1.08	1.47
1/VIF	0.522	0.631	0.64	0.66	0.69	0.82	0.92	

TABLE 4 Benchmark regression results.

Variables	(1) GIR	(2) GIR	(3) GIR
ECDZs	0.0090***	0.0111***	0.0130***
	(0.0015)	(0.0032)	(0.0027)
Linear term	Yes	Yes	Yes
Quadratic term	No	No	Yes
Time fixed effects	No	Yes	Yes
Urban fixed effects	No	Yes	Yes
Observations	2,607	2,607	2,607

Notes: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. Values in parentheses are robust standard errors. Same below.

TABLE 5 Robustness checks.

Variables	(1) Instrumental variable	(2) Sample period 2012-2021	(3) Province-time interaction	(4) Excluding other policy disturbances
	GIR	GIR	GIR	GIR
ECDZs	0.0672***	0.0101***	0.0096***	0.0086***
	(0.0175)	(0.0033)	(0.0032)	(0.0026)
Linear term	Yes	Yes	Yes	Yes
Quadratic term	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes	Yes
Observations	2,607	2,370	2,607	2,607

Notes: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. Values in parentheses are robust standard errors.

The synergistic agglomeration index for productive service industries and manufacturing industries is constructed accordingly in Equation 13.

$$\text{coa} = [1 - |SA - HA|/(SA + HA)] + |SA + HA| \tag{13}$$

(3) Innovation index (inno). The innovation index is a comprehensive indicator that measures a city's competitiveness in innovation, influencing urban GIR. We utilize the Urban Innovation index of China's Urban and Industrial Innovation Power Report (Kou and Liu, 2017) as a three-level index to measure the level of innovation. The report aims at the difference in the number of patents of different age groups in valid invention patents each year, by calculating the average value of patents of each age group, and combining the weighting at the city level, the final innovation index is obtained.

(4) Economic development level (lnpgdp). The economic development level significantly affects urban GIR (Hu et al., 2020). It is measured using the natural logarithm of *per capita* GDP.

(5) Industrial Structure (sc). Industrial structure denotes the composition and interrelationships among various industrial sectors. It is quantified by the logarithm of the ratio of value added from secondary and tertiary industries to GDP.

(6) Human Capital (hc). Human capital significantly impacts the development capacity of urban GIR (He et al., 2023). It is measured by the ratio of education expenditure to fiscal expenditure.

3.3 Data sources

This study treats the establishment of ECDZs as a quasi-natural experiment, using data spanning 2011 to 2021 from 237 Chinese cities. Cities that established ecological civilization demonstration zones are categorized as the experimental group, while those that did not are the control group. Data for calculating the green innovation resilience, such as the number of green patent applications, are obtained from the china national research data sharing platform (CNRDS) and the green patent database. Additional data sources include the China Urban Statistical Yearbook and the china statistical yearbook. Missing data are addressed through interpolation. The descriptive statistical results of each variable are shown in Table 2.

4 Empirical results

4.1 Multicollinearity test

In order to further determine whether there is a multicollinearity problem between the variables selected in this paper, in statistical analysis, the variance inflation factor (VIF) is usually used to evaluate the degree of multicollinearity between the independent variables in the regression model. As can be seen from Table 3, the highest VIF value is 1.91, the lowest is 1.04, and the mean value is 1.08, all of which are less than 10, that is, the model established in this paper does not have the problem of multicollinearity.

4.2 Baseline regression

This study employs a sample split ratio of 1:4 and utilizes the LASSO algorithm to predict and solve both the main and auxiliary regressions. Table 2 presents the policy effects of "ecological civilization" on green innovation resilience estimated using a dual machine learning model. In Column (1) of Table 4, primary control variables are adjusted across the entire sample period. Given potential autocorrelation of disturbance terms in panel data across individual and time dimensions, robust standard errors and regression coefficients may exhibit significant biases. Column (2) further incorporates time and city fixed effects. The results in Column (2) of Table 4 reveal that the regression coefficient for the ECDZs is significantly positive and passes statistical significance tests, indicating that the construction of ECDZs promotes regional green innovation resilience. Column (3) in Table 4 introduces controls for quadratic terms of control variables. The direction and significance of the "ecological civilization" policy remain unchanged, providing initial evidence of the driving impact of ECDZs on green innovation resilience and supporting Hypothesis 1.

4.3 Endogeneity test

In order to obtain the causal identification effect of ECDZs on the resilience of green innovation, it is necessary to deal with the possible endogenous problems: first, the result bias caused by missing variables in the model. Although this paper controls a series of important factors affecting the resilience of green innovation at the city level on the basis of reference to existing studies, it inevitably leads to omissions. Second, the problem of reverse causality. The increased resilience of green innovation may also in turn affect the selection of ECDZs. In this paper, the daily air quality data of each city is obtained through the China Air Quality online detection and analysis platform, and the daily air quality data is sorted into annual statistical data to measure the average annual air quality index of each city. The air quality index (AQI) is used as an instrumental variable, which satisfies the hypothesis of externality and correlation of the instrumental variables. Table 5 Column (1) reports the regression results of the instrumental variables of ECDZs affecting the resilience of green innovation. The results show that, on the basis of alleviating the endogenous problems by using panel instrumental variables, ECDZs still has a significant promoting effect on GIR.

4.4 Robustness test

4.4.1 Event analysis method

To determine if the model results follow a consistent trend before and after the intervention, this study uses the event analysis method to perform pre- and post-tests on the impact of ECDZs on green innovation resilience. Virtual variables d are introduced to substitute for the policy implementation, before and after its enactment. Specifically, d_3 denotes the 3 years preceding policy implementation, d_2 indicates the 2 years prior, and so on. The model is specifically constructed as follows shown in Equation 14.

$$
\begin{aligned}
GIR_{i,t+1} = \theta_0 d\_3_{it}/d\_2_{it}/d\_1_{it}/d0_{it}/d1_{it}/d2_{it}/d3_{it} + f0\,(xit) + Uit,\\
E\left(U_{it}\middle|X_{it},d\_3_{it}/d\_2_{it}/d\_1_{it}/d0_{it}/d1_{it}/d2_{it}/d3_{it}\right) = 0\\
d\_3_{it}/d\_2_{it}/d\_1_{it}/d0_{it}/d1_{it}/d2_{it}/d3_{it} = m_0\\
(X_{it}) + V_{it}, E\,(V_{it}|X_{it}) = 0
\end{aligned}
\tag{14}
$$

To determine whether the establishment of ECDZs has a pre- and post-implementation effect on the promotion of green innovation resilience, Figure 3 presents the time-varying coefficients of variable d from Equation 1 with a 95% confidence interval. It is evident that before the establishment, the coefficients of variable d are moderate and not significant (from d_3 to d_1). However, in the first to third years after the establishment of the ECDZs (from d0 to d3), these zones significantly enhance green innovation resilience in their respective cities. This suggests that the positive effect of ECDZs on urban green innovation resilience can persist for at least 3 years, showing a significant change in the trend of green innovation resilience before and after the establishment. Therefore, the impact of ECDZs on promoting green innovation resilience is robust.

4.4.2 Adjustment of sample period

To further validate the reliability of the conclusions, this study adjusts the research period by selecting sample data from 2012 to 2021 for regression analysis. The results, presented in Column (2) of Table 5, indicate that the ECDZs continue to exhibit a significant positive trend on the GIR.

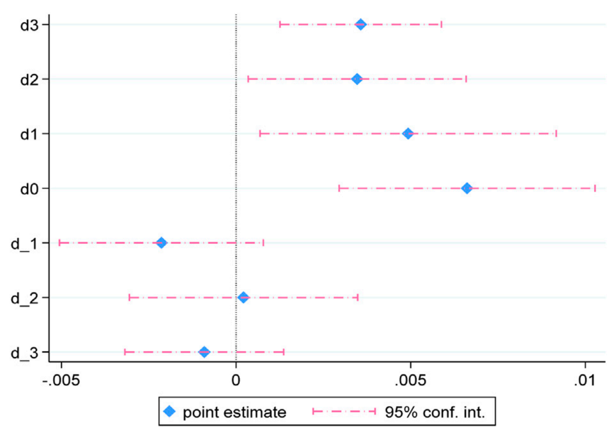

FIGURE 3
Pre- and post-implementation test.

4.4.3 Considering province-time interaction fixed effects

Provinces hold a crucial position in China's administrative structure. Since cities within the same province often share similarities in policy environment, history, culture, and geographical characteristics, this paper incorporates province-time interaction fixed effects in the baseline regression to account for temporal variations across provinces. The results in Column (3) of Table 5 indicate that, even after considering the interaction between cities within the same province, the impact of ECDZ on GIR remains significantly positive at the 1% level, further confirming the original conclusion.

4.4.4 Excluding other policy disturbances

This study addresses concerns regarding potential interference from concurrent policies when assessing the impact of ECDZs on GIR. To ensure accurate estimation of policy effects, the study controls for similar policies implemented during the same period. After 2015, alongside the launch of ECDZs, two significant concurrent policies emerged: the establishment of "National New Zones" (zone1) and the creation of "National Big Data Comprehensive Experimental Zones" (zone2). As a result, dummy variables for these policies, labeled zone1 and zone2, are included in the regression analysis. The results in Column (4) of Table 5 show that, even after accounting for these concurrent policies, the policy effect of ECDZs remains both significant and unchanged, highlighting the robustness of the study's findings.

4.4.5 Resetting the DML model

To minimize potential bias in the dual machine learning model, this study implemented several adjustments. Firstly, we modified the sample splitting ratios. Following the method of CHERNOZHUKOV et al., the sample was randomly divided into 5 groups in the baseline regression. For robustness testing, we adjusted the sample partition ratio from 1:4 to 1:2 and 1:7. The results are presented in Columns (1) and (2) of Table 6. Secondly, we replaced the machine learning algorithms. To assess robustness, the random forest algorithm was replaced with lasso regression and gradient boosting. Additionally, a partial linear model based on dual machine learning was constructed in the baseline regression, using subjective model settings. To examine the influence of these settings on the study's conclusions, a more generalized dual machine learning interaction model was employed. The adjustments made in the primary and auxiliary regressions are outlined below shown in Equation 15.

$$\begin{aligned} GIR_{i,t+1} &= g\left(ECDZs_{it}, X_{it}\right) + U_{it} \\ ECDZs_{it} &= m\left(X_{it}\right) + V_{it} \end{aligned} \tag{15}$$

The estimated coefficients of the interactive model are shown in Equation 16.

$$\hat{\theta}_1 = E\left[g\left(ECDZs_{it} = 1, X_{it}\right) - g\left(ECDZs_{it} = 0, X_{it}\right)\right] \tag{16}$$

Columns (1) to (5) in Table 6 indicate that variations in sample splitting ratios, machine learning algorithms, and model estimation forms in the DML model do not impact the conclusion that ECDZs promote GIR. These variations only slightly alter the magnitude of policy effects, which sufficiently demonstrates the robustness of the original conclusion.

4.5 Mechanism testing

This study confirms that ECDZs notably enhance urban GIR through empirical analysis. It further investigates the specific pathways through which ECDZs exert their influence. The theoretical analysis presented earlier suggests that ECDZs impact GIR through three primary pathways: digitalization, green consciousness, and new quality productivity. To validate these mechanisms, the medium effect two-step method is adopted (Jiang, 2022).

4.5.1 Enhancing digitalization

To investigate the mediating role of digitalization (DIG), Using Python, we calculated the natural logarithm of the frequency of the term "digitalization" in Baidu search indexes from 2011 to 2021 as an indicator of urban-level digitalization (Li X. et al., 2022). In Table 7, Column (1) examines the impact of DIG, controlling for time, urban fixed effects, and other variables in both linear and quadratic terms. The regression coefficient for DIG is 0.2048, indicating statistical significance. This suggests that ECDZs enhance urban GIR through digitalization, implying that digitalization partially mediates the effect of ECDZs on GIR. Moreover, it underscores how the digital platforms of demonstration zones provide a scientific basis and real-time feedback for green innovation resilience, assisting innovators in accurately identifying environmental issues and solutions, thereby advancing the development and application of green innovation resilience. Hypothesis H3a is supported.

4.5.2 Strengthening green consciousness

Next, Columns (2) in Table 7 present the tests examining the mechanism of green consciousness (GC). This study utilizes Python software to extract vocabulary related to the environment from government work report texts (Chen and Chen, 2018). Specifically, these terms include environmental protection, energy consumption, conservation, pollution, discharge emission reduction, ecology, low-

TABLE 6 Results of resetting the DML model.

Variables	(1) Sample 1:2	(2) Sample 1:7	(3) Lassso regression	(4) Gradient promotion	(5) Interacitve model
	GIR	GIR	GIR	GIR	GIR
ECDZs	0.0118***	0.0095***	0.0100***	0.0092***	0.0098***
	(0.0024)	(0.0026)	(0.0012)	(0.0011)	(0.0004)
Linear term	Yes	Yes	Yes	Yes	Yes
Quadratic term	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	2,607	2,607	2,607	2,607	2,607

Notes: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. Values in parentheses are robust standard errors.

TABLE 7 Empirical results of mediation effect.

Variables	(1)DIG	(2)GC	(3)NQP
ECDZs	0.2048**	0.2120***	0.2612***
	(0.0878)	(0.0594)	(0.0675)
Linear term	Yes	Yes	Yes
Quadratic term	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes
Observations	2,607	2,607	2,607

Notes: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. Values in parentheses are robust standard errors.

carbon practices, green initiatives, air quality, sulfur dioxide, chemical oxygen demand, carbon dioxide, PM2.5, and PM10. Subsequently, the frequency of these relevant terms plus one is logged as a proxy variable for environmental concern. The regression coefficient for ER is statistically significant at the 1% level, with a coefficient of 0.2120. This finding suggests that ECDZs influence urban GIR partly through heightened green consciousness, implying that green consciousness act as a mediating factor in the relationship between ECDZs and GIR. Furthermore, this underscores how demonstration zones can stimulate the advancement and adoption of green technology innovations by establishing environmental standards, emission limits, energy efficiency requirements, and other measures. It supports hypothesis H3b.

4.5.3 Enhancing new quality productivity

Finally, Column (2) in Table 7 presents the results of the examination of the new quality productivity (NQP) mechanism using the DDML method. In this paper, we use Python to segment the government work reports and extract the frequencies of 46 keywords related to "new quality productivity." The log-transformed frequencies of these keywords are used to measure new quality productivity. These keywords include new quality productivity, artificial intelligence, technological innovation, technological reform, scientific development, innovation momentum, disruptive technology, breakthrough technology, among others. Regression results show that the coefficient of ECDZs' impact on NQP is significant at the 1% level, with a value of 0.2612. This indicates that ECDZs influence urban GIR through enhancing new quality productivity, suggesting that new quality productivity serves as a partial mediator in the impact of ECDZs on GIR. Furthermore, this underscores that in demonstration zones, the promotion of new quality productivity encourages enterprises and research institutions to adopt environmentally friendly, energy-saving, and low-carbon new technologies and processes. These technologies not only enhance production efficiency but also reduce resource consumption, driving the development of green innovation resilience. Hypothesis H3c is supported.

4.6 Heterogeneity analysis

4.6.1 Regional heterogeneity

Based on the Ministry of Transport's "Announcement on the Release of the National Major Port Directory," this study categorizes sample cities into coastal and inland for grouped regression analysis, as presented in Columns (1) and (2) of Table 8. The findings show that, compared to coastal cities, ECDZs have a significantly stronger impact on promoting GIR in inland cities, with a coefficient of 0.0154. This underscores the role of ECDZs in leveraging the "borderlessness" feature to reduce physical spatial constraints in fostering green innovation resilience. However, the influence of ECDZs on GIR in coastal cities is not statistically significant, possibly due to the limited demonstration effect of successful green technology innovations within the zones on nearby coastal cities. This suggests that green technologies developed within demonstration zones may face constraints in technological adaptability, limiting their direct applicability to the specific environmental and economic conditions of surrounding coastal cities.

Furthermore, this study examines how ECDZs influence GIR differently across the eastern, central, and western regions. The analysis stratifies the sample accordingly, as detailed in Columns (3),

TABLE 8 Heterogeneity test results for different regions.

Variables	(1) Coastal	(2) Inland	(3) East	(4) Median	(5) West	(6) Strong policy support	(7) Weak policy support
	GIR	GIR	GIR	GIR	GIR	GIR	GIR
ECDZs	−0.0026	0.0154***	0.0032	0.0110***	0.0115***	0.0120*	0.0099***
	(0.0081)	(0.0025)	(0.0075)	(0.0009)	(0.0023)	(0.0062)	(0.0014)
Constant	−0.0012	0.0003	0.0007	0.0001	−0.0000	0.0006	0.0002
	(0.0026)	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0006)	(0.0001)
Linear term	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quadratic term	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	176	2,431	1,012	913	682	1,001	1,606

Notes: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. Values in parentheses are robust standard errors.

(4), and (5) of Table 8. Compared to the eastern region, ECDZ policies exhibit more significant effects in the central and western regions. Specifically, in the western region, the coefficient for ECDZs is 0.0115 at the 1% significance level, indicating a stronger promotion of GIR in western cities. This disparity may stem from greater developmental disparities and heightened pressures related to resources and environmental constraints in the western region, as compared to the more developed eastern regions. Therefore, governmental policies in the western region are likely more targeted and supportive, thereby facilitating the quicker adoption and implementation of green innovation resilience initiatives.

4.6.2 Policy support heterogeneity

In addition, considering the diverse approaches taken by different cities in promoting green development and implementing low-carbon measures, there exist varying intensities of policy support. Environmental policy support is notably stronger in low-carbon pilot cities compared to non-pilot cities. We categorize low-carbon pilot cities as having strong policy support and non-pilot cities as having weak policy support, conducting grouped regression analysis as shown in Columns (6) and (7) of Table 8. The regression results indicate that ECDZs play a significantly larger role in enhancing GIR in cities with strong policy support relative to those with weak policy support. This is likely because the ecological civilization concept promotes environmental protection and sustainable development, with cities receiving strong policy support often setting clear environmental goals and commitments, such as legal regulations, emission reduction targets, environmental tax incentives, and green financing. These measures provide explicit direction and support for green innovation resilience. Furthermore, cities with strong policy support typically make substantial investments in funds and resources, thereby encouraging and supporting enterprises and research institutions in innovating within green technologies and environmental protection. This approach can accelerate the implementation and market adoption of green innovation resilience.

TABLE 9 Test results of Moran index.

Year	Variables	I	E (I)	Sd (I)	z	p
2011	GIR	0.076	−0.004	0.006	12.881	0
2012	GIR	0.074	−0.004	0.006	12.47	0
2013	GIR	0.074	−0.004	0.006	12.295	0
2014	GIR	0.066	−0.004	0.006	11.066	0
2015	GIR	0.067	−0.004	0.006	11.164	0
2016	GIR	0.063	−0.004	0.006	10.488	0
2017	GIR	0.052	−0.004	0.006	8.904	0
2018	GIR	0.051	−0.004	0.006	8.825	0
2019	GIR	0.046	−0.004	0.006	7.975	0
2020	GIR	0.035	−0.004	0.006	6.528	0
2021	GIR	0.07	−0.004	0.006	11.606	0

5 Spatial difference-difference model

5.1 Moran index test

Before conducting spatial econometric analysis, we examined the spatial correlation of GIR among cities. Using an distance spatial weight matrix, we computed the Moran's I index for GIR (Zhong et al., 2024), as shown in Table 9. The results indicate a significant positive spatial clustering of GIR across Chinese cities from 2011 to 2021.

5.2 Model selection

To select the optimal empirical model, LM test, Wald test, and LR test were conducted sequentially, using the geographical distance

TABLE 10 Model selection results.

	type	Statistical value	P-Value
LM test	LM error	85.24	0.000
	Robust LM error	53.36	0.000
	LM lag	30.27	0.000
	Robust LM lag	28.55	0.000
LR test	Likelihood-rato test (Assumption:sar nested in sdm)	47.06	0.000
	Likelihood-rato test (Assumption:sem nested in sdm)	2000.10	0.000
Wald test	Wald Test for SEM	9.47	0.0236
	Wald Test for SAR	24.85	0.000
Hausman	chi2 (7)	417.01	0.000

matrix as the spatial weight matrix. The LM test primarily determines whether the OLS model should incorporate spatial factors. Table 10 demonstrates that all LM tests passed at a 1% significance level. Additionally, the results from the robust LM test suggest that the econometric model should include spatial factors, validating the acceptance of SAR and SEM models. To further refine model selection, Wald and LR tests were performed on the spatial Durbin model (SDM) to assess whether the differential spatial Durbin model should be used. The test results indicate that the Chi-square value for the SDM model is significantly higher than those for SAR and SEM, with a P-value of 0.000, implying that the SDM model cannot be simplified into the SEM or SAR models. Therefore, the SDM model is chosen as the best measurement model.

5.3 Spatial difference-in-differences results

This paper adopts the fixed-effect SDM to explore the spatial effects of environmental policies on the resilience of green innovation. In the spatial econometric model, the regression coefficient of explanatory variables cannot directly reflect the degree of influence on the explained variables. Therefore, in order to further analyze the spatial spillover effect, it is necessary to decompose the estimated results of the SDM model, and then obtain the overall effect of ECDZs on the resilience of green innovation, and subdivide it into direct effects and indirect effects. The regression results in Table 11 show that, after controlling for factors affecting urban economic and environmental compatibility, however, when the fixed effects of city and year are included, the estimated coefficient of WECDZs is statistically significant at the 1% level, with a value of 0.0595. This indicates that ECDZs construction has a positive spillover effect on the resilience of green innovation in neighboring cities. These regression results support hypothesis H3 proposed in this paper, showing that ECDZs significantly promote the resilience of green innovation in neighboring cities. It is further demonstrated that the construction of ECDZs not only has a positive impact on the pilot cities themselves, but also promotes the resilience of green innovation in neighboring cities through knowledge spillover, resource allocation and technology diffusion. This shows that ECDZs construction is able to cross administrative boundaries and have a radiating effect on a wider regional scale. In addition to policy effects, control variables also have expected outcomes. The concentration of innovative talents (agg) can enhance the regional technology research and development ability and the allocation

TABLE 11 Results of spatial difference-in-differences regression.

Variables	(1) GIR	(2) GIR	(3) GIR
	Direct	Indirect	Total
ECDZs	0.0119***	0.0398***	0.0516***
	(0.0010)	(0.0119)	(0.0121)
agg	0.2046***	−1.1245**	−0.9199*
	(0.0551)	(0.5398)	(0.5375)
coa	0.0005	0.0003	0.0009
	(0.0005)	(0.0009)	(0.0010)
inno	0.0111***	0.0002	0.0113**
	(0.0007)	(0.0048)	(0.0047)
human	0.0182	−0.2058**	−0.1876**
	(0.0138)	(0.0906)	(0.0874)
sc	0.0027***	−0.0163***	−0.0135**
	(0.0008)	(0.0059)	(0.0058)
lnpgdp	0.0027	0.0146*	0.0173**
	(0.0017)	(0.0078)	(0.0069)
WECDZs		0.0595***	
		(0.0166)	
rho		0.1995***	
		(0.0635)	
Observations	2,607	2,607	2,607
R-squared	0.4020	0.4020	0.4020

Notes: ***, **, and * indicate significance levels at 1%, 5%, and 10%, respectively. Values in parentheses are robust standard errors.

efficiency of innovation resources, and has a positive and significant impact on the improvement of green innovation resilience. Regions with a higher innovation index (inno) tend to have a better ability to translate green technologies and concepts into practical applications, contributing to the formation and improvement of the green industry chain. The optimization of industrial structure helps to improve the overall resilience of green innovation. With the upgrading of industrial structure (sc), capital, technology and human resources in the region will flow more to green technology-intensive industries. This reallocation of resources is conducive to the further innovation and application of green technology.

5.4 Parallel trend test of spatial difference-in-differences model

To ensure the accuracy of the estimated results, the differential model requires that both the treatment and control groups meet the parallel trend assumption. This assumption posits that, in the absence of ECDZs, the trends in green innovation resilience should be similar over time in both pilot and non-pilot cities. This hypothesis is tested using dynamic effect analysis in this study. Specifically, 2014 is considered the base year, prior to the implementation of the first set of pilot policies. The interaction between the policy pilot area and the year, along with its spatial lag term, is incorporated into the regression model as explanatory variables. This approach aims to evaluate both the parallel trend assumption and the dynamic effects of the policy in local and surrounding areas. The specifications of the model are outlined as follows.

$$GIR_{it} = \gamma_0 + \sum_{t=2011}^{2021} \alpha_t ECDZs_{it} + \sum_{t=2011}^{2021} \beta_t W \times ECDZs_{it} + \gamma X_{it} + City_i + Time_i + e_{it} \tag{17}$$

Where, ECDZs is the interaction term between the policy pilot area and the year, WECDZs is the spatial lag term between the policy pilot area and the year, α_t represents the size of the local policy effect in each year, β_t represents the size of the neighboring policy effect in each year, that is, the neighborhood effect of the policy in each year.

Figure 4 displays the estimated neighborhood effect of the pilot policy with a 95% confidence interval. The test results for the dynamic effect of neighboring policies show that the coefficient of dummy variables before policy implementation was not significant, indicating no notable difference in GIR between pilot and non-pilot areas prior to the first batch of pilot policies, which supports the parallel trend hypothesis. Starting from the second year of policy implementation, the coefficient of policy dummy variable is significantly positive at least at the level of 10%, indicating that the implementation of the first and second batch of pilot policies significantly promotes the resilience of green innovation in neighboring places, and there is a certain “lag” in the policy effect of ECDZs on neighboring places, which may be due to the “cumulative effect” of green innovation resilience. Green innovation resilience itself is a relatively complex dynamic process, often requires a certain period of policy support and resource

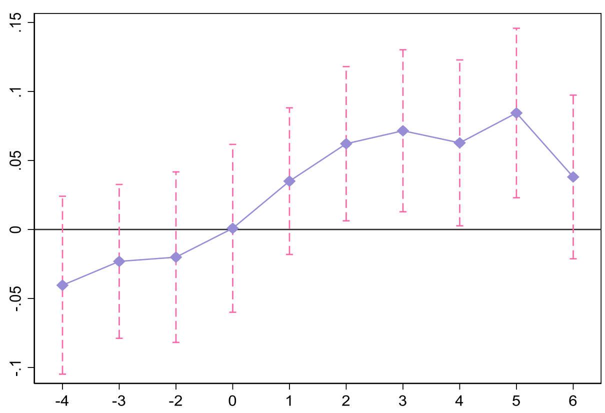

FIGURE 4
Parallel trend test of policy spatial effect.

investment to gradually form a significant effect. Capital investment, technology introduction and institutional innovation in the initial stage of policy implementation may take one to 2 years to translate into actual green innovation results and have spillover effects on neighboring regions. In the sixth year of the implementation of the policy, the dummy variable coefficient was not significant, indicating that the pilot policy only had a promoting effect on the resilience of green innovation in the neighborhood in the short term, and the effect of the policy gradually weakened with the passing of time. This may be because with the gradual deepening of the implementation of ecological civilization construction, the policy’s support for green industries has increased after 2019, for example, increasing subsidies and incentives for green energy (such as solar energy, wind energy, electric vehicles, etc.), and promoting the research and development and industrialization of green technology, especially in energy conservation and emission reduction, environmental protection equipment manufacturing. In addition, in 2018, the reform of the Environmental Protection Tax Law provided more direct economic incentives for the construction of ecological civilization. Since then, China has issued a series of green finance policies in 2019 to support green industry development and green project financing, and further promote the construction of a green innovation system. The superposition of the mandatory and demonstration effects of relevant environmental policies promotes the improvement of the spatial spillover effects of ECDZs.

6 Conclusion and policy recommendations

6.1 Conclusion

This study, based on panel data spanning 2011 to 2021 from 237 prefecture-level cities in China, employs double machine learning model and spatial difference-in-differences model to assess how establishing ECDZs impacts urban green innovation resilience. The findings reveal that: firstly, ECDZs significantly boost urban green innovation resilience, a result confirmed through rigorous robustness tests. This underscores the effectiveness of environmental policies in encouraging businesses and institutions to adopt greener technologies and practices, thereby fostering green innovation resilience. Secondly, The construction of ECDZs has a spatial spillover effect on the green innovation resilience of neighboring cities, and this neighborhood effect reaches its maximum in the fifth year. Thirdly, the study examines how ECDZs influence urban green innovation resilience through several mechanisms: digital technology embedding, environmental focus, and productivity enhancement effects driven by environmental policies. Finally, the impact of ECDZs varies across different geographical and policy contexts. While less pronounced in eastern and coastal regions, it is notably stronger in western and inland areas. Furthermore, under varying policy supports, ECDZs prove more effective in promoting green innovation resilience in low-carbon pilot cities compared to non-pilot cities. This suggests that digitization, green consciousness, and new quality productivity collectively serve as crucial intermediaries in this process.

6.2 Policy recommendations

Urban green innovation resilience in China hinges on expediting the establishment of ECDZs and cultivating a conducive environment for green initiatives. As a testing ground for environmentally friendly and low-carbon technologies, ECDZs significantly promote urban green innovation resilience. Therefore, the government can effectively promote green innovation resilience by supporting the development of eco-civilization demonstration cities. Cities that have established ECDZs should further encourage businesses within these regions to increase their environmental investments in green technology research and development. The focus should be on nurturing ECDZs to become leaders in urban green innovation resilience, making them models and pioneers of demonstration cities. Additionally, establishing a framework of cooperation and synergy between the model city and its neighbors is essential to promote collective green development throughout the region.

China's various regions should establish closer cross-border cooperation mechanisms. Specifically, governments can enhance the resilience of green innovation by promoting cooperation between ECDZs demonstration cities and neighboring cities to form regional linkage effects of green technology transfer and innovation. The results of this study show that the construction of ECDZs has a significant positive spillover effect on the resilience of green innovation in neighboring cities. Therefore, policymakers should pay special attention to the spillover effects of such policies, and give full play to the exemplary and leading role of "ecological civilization" demonstration cities. Specifically, local governments can promote the joint development of ECDZs cities and neighboring cities in the field of green technology by establishing closer cross-border cooperation mechanisms. Demonstration cities are encouraged to share their successful experience and technological achievements with neighboring cities, jointly carry out major scientific and technological research projects, and jointly enhance their ability to cope with green innovation challenges in the region. In addition, the government can also promote cross-regional industrial chain collaboration, promote the complementary advantages and resource sharing between different cities, and form a cluster effect of green industries in the region. By developing and implementing a more strategic and collaborative top-level design, local governments can ensure that green technology innovation can achieve universal and sustainable development on a wider scale, and promote the overall improvement of regional green innovation resilience.

Strengthening digitalization, enhancing green consciousness, and fostering new quality productivity can enhance the green technology environment in ECDZs, thereby boosting green innovation resilience capacity. Digitization plays a crucial role in improving management and service levels within ECDZs. Technologies such as big data, artificial intelligence, and the Internet of Things enable real-time monitoring, analysis, and management of the environment, leading to improved resource efficiency, optimized production processes, and reduced pollution emissions. Additionally, it is crucial for demonstration zones to enforce strict environmental laws, regulations, and standards, overseeing and regulating the environmental practices of enterprises and organizations to ensure the sustainable development of the ecosystem. Furthermore, new quality productivity, driven by principles of technological innovation and sustainable development, supports green industries such as new energy, energy conservation, environmental protection, and biopharmaceuticals, thereby promoting new economic growth opportunities. Therefore, the development of ECDZs requires comprehensive utilization of digital tools, rigorous enforcement of green consciousness, and the cultivation and promotion of new quality productivity. These measures are essential to achieve the dual goals of ecological environmental protection and high-quality economic development, effectively demonstrating the coordinated progress of technological innovation and environmental protection.

The environmental policy impact of ECDZs on urban green innovation resilience is different, and regions should make full use of their comparative advantages. With the goal of fostering the stable and sustainable capacity of green innovation resilience, they should seriously consider the common and unique characteristics of urban development. The western and central regions should prioritize promoting the construction and upgrading of new infrastructure, while simultaneously increasing support for high-tech green industries. These regions should seize national policy opportunities, prioritize support, accelerate environmental innovation, and gradually narrow the developmental gap with eastern and central regions. At the same time, mainland cities should fully utilize the benefits of national high-tech zone policies to uphold and elevate high standards in green innovation resilience. For regions with weaker green innovation resilience, especially coastal and non-low-carbon pilot cities, strong policy support is crucial for addressing areas where the environmental impact of ECDZs is less significant.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

CL: Conceptualization, Data curation, Formal Analysis, Investigation, Supervision, Writing–original draft. SZ: Conceptualization, Data curation, Methodology, Project administration, Writing–original draft. BY: Formal Analysis, Investigation, Project administration, Software, Validation, Writing–review and editing.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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