

Article

Sci-Tech Finance and Sustainable Urban Transition: Evidence from Pollution–Carbon Reduction Synergy and Green Growth in Chinese Cities

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Abstract

Reconciling pollution–carbon reduction with green growth is a central challenge for sustainable urban transition, yet the role of innovation-oriented financial policy in this process remains insufficiently understood. This study uses China's sci-tech finance pilot policy (STFP) as a quasi-natural experiment and applies a multi-period difference-in-differences model to panel data for 284 prefecture-level cities from 2008 to 2023. The baseline results show that STFP significantly reduces the pollution–carbon synergistic pressure index (PCSP) and improves the green growth efficiency index (GGEI). Specifically, the policy reduces PCSP by approximately 8.10% and increases GGEI by 0.0350 units. These conclusions hold after a series of robustness and endogeneity tests. Mechanism analysis reveals that STFP works through three pathways: stimulating green industrial entrepreneurship, promoting green and digital technological innovation, and inducing the agglomeration of capital, talent, and technology factors. Heterogeneity analysis shows that the policy effect is more pronounced in large cities, cities with stronger collaborative governance capacity, and cities with better innovation environments. Spatial analysis reveals that STFP significantly reduces PCSP in neighboring cities, but has no significant spatial spillover effect on GGEI. Further analysis shows that STFP strengthens the coordinated improvement of pollution–carbon reduction and green growth. Policy-interaction analysis indicates that the Zero-Waste City pilot enhances the effect of STFP, whereas green finance policy exhibits a marginal substitution effect. This study provides city-level evidence on how sci-tech finance can serve as an institutional instrument for coordinating environmental governance and green growth in sustainable urban transition.

Keywords: sci-tech finance; sustainable urban transition; pollution–carbon synergy; green growth efficiency; spatial spillover; Zero-Waste City pilot

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1. Introduction

Global climate change, environmental pollution, and ecological degradation are profoundly affecting the sustainability of economic and social development. Green and low-carbon transition has therefore become an important strategic choice for countries seeking to respond to climate risks and reshape their development models [1]. For China, the

“dual carbon” goals and the construction of a Beautiful China require not only a reduction in carbon emission intensity, but also a more coordinated governance system that integrates pollution control, ecological restoration, and high-quality economic development. The report of the 20th National Congress of the Communist Party of China explicitly calls for “coordinated efforts to reduce carbon emissions, cut pollution, expand green development, and promote growth.” The 2024 Central Economic Work Conference further emphasized the need to “coordinate carbon reduction, pollution reduction, green growth, and accelerate the comprehensive green transformation of economic and social development.” These policy signals indicate that China’s environmental governance is shifting from single-pollutant control toward a systematic governance stage that coordinates pollution reduction, carbon reduction, ecological greening, and economic growth. Against this background, cities, as the core spatial carriers of socioeconomic activities, resource and energy consumption, and environmental policy implementation, are not only key areas where pollutants and carbon emissions are concentrated, but also crucial actors in promoting green and low-carbon transition and achieving coordinated governance [2]. Therefore, how to promote urban green and low-carbon transition has become an important issue for China in advancing high-quality development and ecological civilization.

More specifically, urban green transition is not a simple aggregation of pollution control, carbon mitigation, ecological greening, and economic growth, but a systematic governance process in which multiple objectives are mutually embedded and mutually constrained. Pollutants and carbon emissions share common sources in energy consumption, industrial production, and transportation activities, and coordinated governance can help reduce policy implementation costs and improve the efficiency of environmental governance [3,4]. In practice, however, pollution–carbon reduction and green growth do not always move in the same direction. Environmental regulation may increase firms’ compliance costs in the short term; ecological restoration and green infrastructure construction require sustained investment; and economic growth depends on the efficient allocation of resources and factors. Therefore, the key to urban green transition lies not merely in reducing pollution or lowering carbon emissions, but in building a coordinated governance capacity that simultaneously accounts for environmental quality, ecological welfare, and development performance. As an institutional arrangement that connects technological innovation with financial resources, sci-tech finance can, to some extent, alleviate financing constraints, risk mismatches, and insufficient long-term investment in the green transition, thereby providing important support for cities to move from single-objective environmental governance toward multi-objective coordinated governance [5,6]. Accordingly, sci-tech finance policy may become an important policy instrument for promoting the coordinated transition of pollution–carbon reduction and green growth.

Existing studies on urban pollution–carbon reduction, green growth, and sci-tech finance can be summarized into three strands. First, research on pollution–carbon co-governance has gradually shifted from single-pollutant control or isolated carbon mitigation toward the joint control of air pollutants and carbon emissions. Existing studies have developed indicators of synergistic governance efficiency and co-benefits, examined the effects of green finance, environmental regulation, and low-carbon policies on coordinated governance performance, and further explored their spatial dependence and regional disparities [7–9]. However, most studies focus on pollution–carbon governance performance itself, while its integration with green growth under an innovation-oriented financial policy framework remains insufficiently examined.

Second, regarding green growth efficiency and broader green development performance, green total factor productivity and green inclusive growth are commonly used to capture the coordination between economic growth and ecological improvement. Evi-

dence suggests that the digital economy and data element allocation can enhance urban green development by improving resource allocation, stimulating green technological innovation, and strengthening ecological governance investment. Artificial intelligence has also been found to increase industrial output while reducing pollution emissions, with positive spatial spillovers on green total factor productivity in neighboring regions [10,11]. More recent work further shows that the dual-pilot policy combining low-carbon city pilots and sci-tech finance pilots can generate synergistic gains in urban green total factor productivity beyond the effect of a single policy [12]. Nevertheless, this strand of literature mainly emphasizes the measurement, driving factors, and policy determinants of green growth efficiency. It has not fully explained whether green growth improvement can occur simultaneously with the alleviation of pollution–carbon pressure. Therefore, a more integrated framework is needed to examine whether cities can achieve both environmental pressure reduction and green growth improvement under the same policy shock.

Third, the role of sci-tech finance and financial development in green transition has also received increasing attention. Existing evidence indicates that green finance, digital finance, and financial technology can promote green innovation, improve energy efficiency, and reduce carbon emissions by easing financing constraints, mitigating information asymmetry, and optimizing resource allocation. Sci-tech finance policies, by integrating financial services with technological innovation, have also been shown to support industrial upgrading, resource allocation optimization, and low-carbon transformation [5,6,13]. However, the environmental effect of sci-tech finance is not necessarily uniform across cities. Sci-tech finance can support emission reduction and green growth by expanding long-term capital supply, lowering financing barriers for green innovation, and improving the allocation of technological resources. Yet its effectiveness may depend on whether financial resources are matched with local innovation capacity, industrial foundations, and policy implementation conditions. Recent evidence suggests that sci-tech finance affects carbon emissions through innovation, structural adjustment, and scale expansion, and the final environmental outcome depends on the relative strength of these channels [5]. In addition, when financial support is misallocated, absorbed by short-term projects, or repeatedly targeted at similar policy areas, its green benefits may be weakened by resource mismatch, regional absorptive-capacity constraints, or policy overlap [14]. Therefore, whether sci-tech finance can consistently promote sustainable urban transition remains an empirical question that requires further investigation.

Despite these advances, three gaps remain in the literature. First, in terms of measurement and outcome integration, existing studies have mainly examined the effects of financial or technological policies on single environmental outcomes, such as carbon emissions, energy efficiency, green innovation, or green total factor productivity. Less attention has been paid to whether an innovation-oriented financial policy can simultaneously alleviate pollution–carbon pressure and improve green growth efficiency within a unified sustainable urban transition framework [5,9]. This leaves unresolved whether pollution–carbon reduction and green growth are parallel policy outcomes or whether they can be jointly promoted by the same institutional intervention. Second, in terms of mechanism testing, the mechanisms through which sci-tech finance supports urban sustainability remain insufficiently clarified. Prior research has largely emphasized financing constraints, green innovation, or carbon reduction, but has not fully explained how sci-tech finance transforms financial support into green industrial entrepreneurship, technological upgrading, and the agglomeration of capital, talent, and technology factors. Thus, the internal process through which sci-tech finance converts financial resources into industrial, technological, and factor-based support for sustainable urban transition still requires clearer empirical evidence. Third, in terms of spatial spillovers and policy-combination effects, the spatial and policy-combination effects of sci-tech finance are still underex-

plored. Although some studies have examined the joint effects of sci-tech finance and other green policies, limited evidence exists on whether sci-tech finance generates spillover effects across cities or forms complementary or substitutive relationships with other urban sustainability pilots, such as the Zero-Waste City pilot, the Low-Carbon City pilot, and green finance policy [12,15]. This is particularly important because urban green transition is shaped not only by a single policy, but also by cross-city diffusion and the interaction among multiple policy instruments.

To address these gaps, this study takes the Pilot Program for Promoting the Integration of Science, Technology, and Finance as a quasi-natural experiment and uses panel data for 284 Chinese prefecture-level cities from 2008 to 2023 to examine whether and how sci-tech finance accelerates sustainable urban transition. The main research question is: Can sci-tech finance simultaneously reduce pollution–carbon pressure and improve green growth efficiency? To answer this question, this study identifies the policy effect using a multi-period difference-in-differences model, evaluates its impacts on the pollution–carbon synergistic pressure index and the green growth efficiency index, and further examines three secondary questions: Through which mechanisms does sci-tech finance work? Do its effects vary across different types of cities? Does it generate spatial spillovers or interact with other urban sustainability policies?

This study contributes to the literature in three ways. The central innovation of this paper lies in constructing an integrated evaluation framework that jointly considers pollution–carbon synergistic pressure and green growth efficiency. First, it provides new evidence on sci-tech finance as an institutional instrument for sustainable urban transition. Unlike studies focusing on single outcomes such as carbon reduction, energy efficiency, or green innovation, this study jointly examines pollution–carbon pressure, green growth efficiency, and their coordinated improvement, thereby offering a more integrated assessment of how innovation-oriented financial policy supports urban environmental governance and green development. Second, this study reveals the internal pathways through which sci-tech finance promotes urban sustainability. By constructing a mechanism framework of “green industrial entrepreneurship–technological innovation–factor agglomeration,” it explains how financial support is transformed into green industrial carriers, technological upgrading, and innovation-resource concentration. Third, based on this integrated evaluation framework, this study extends the policy evaluation of sci-tech finance by incorporating urban heterogeneity, spatial externalities, and policy interactions. It identifies the urban conditions under which sci-tech finance works more effectively, tests whether its effects spill over to neighboring cities, and compares its complementary or substitutive relationships with other sustainability-oriented pilot policies. These findings provide policy-relevant evidence for designing integrated financial, technological, and environmental governance strategies for sustainable cities.

2. Theoretical Framework and Research Hypotheses

2.1. Direct Impact of Sci-Tech Finance on Sustainable Urban Transition

Sci-tech finance policy provides sustained financial support and institutional incentives for urban green and low-carbon transition by linking scientific and technological resources with financial capital. By improving the accessibility and allocation efficiency of financial resources, sci-tech finance helps ease the financing constraints that restrict green and innovation-oriented activities. With stronger financial support, cities are better able to promote technological upgrading, adjust industrial development patterns, and improve ecological governance capacity. In particular, sci-tech finance helps shift urban industrial development from resource-intensive and emission-intensive expansion toward technology-driven, cleaner, and higher-value-added activities. These changes can weaken

the dependence of urban growth on high-emission and high-pollution activities, thereby reducing pollution–carbon synergistic pressure and improving green growth efficiency.

First, sci-tech finance policy can facilitate the low-carbon restructuring of urban industries. Traditional energy-intensive sectors often rely on resource inputs and scale expansion, which may lead to path dependence in pollution and carbon emissions. By using policy tools such as green credit subsidies, risk compensation, and intellectual property pledge financing, sci-tech finance pilots channel financial resources into green R&D and cleaner production, thereby supporting enterprise green transformation and the clustering of low-carbon industries [6]. Meanwhile, sci-tech finance improves the matching efficiency between financial resources and industrial demand, guides capital toward strategic emerging industries such as renewable energy, and promotes the upgrading of traditional industries toward higher value-added and lower-emission activities [16]. As the focus of urban industrial development shifts from high-emission sectors to low-carbon sectors, the dependence of economic growth on energy consumption and pollutant emissions gradually declines, providing a structural foundation for the synergy between pollution reduction, carbon reduction, and green growth.

Second, sci-tech finance policy can improve urban energy efficiency. Energy consumption is a common source of both pollutant emissions and carbon emissions; therefore, inefficient energy use may simultaneously intensify environmental pollution and carbon pressure. Existing evidence suggests that sci-tech finance can improve urban energy efficiency through technological innovation, industrial upgrading, and financial development, thereby reducing carbon emissions and associated pollutants generated by energy use [17]. By improving the match between financial resources and energy-efficiency improvement needs, sci-tech finance also helps adjust the structure of energy supply and consumption and reduce the energy intensity of economic output [18]. As energy intensity declines, fossil-fuel-related carbon emissions and co-emitted pollutants are reduced simultaneously, strengthening the synergistic effect of pollution and carbon reduction.

Finally, sci-tech finance policy can strengthen urban ecological governance and the provision of green public goods. The coordination between pollution–carbon reduction and green growth depends not only on changes in firms' production behavior, but also on sustained public governance inputs in pollution treatment, ecological restoration, and green space construction. Sci-tech finance pilots can extend beyond the production side by supporting urban greening, public services, and green infrastructure, thereby improving urban ecological governance capacity and green welfare [19]. Moreover, by integrating financial technology, environmental information, and green project evaluation, sci-tech finance can improve the identification, financing, and supervision of green public projects. This helps guide capital toward pollution-control facilities, low-carbon infrastructure, ecological restoration projects, and other public goods related to urban sustainability. With the improvement of pollution control facilities, the expansion of ecological space, and the enhancement of green public-service provision, urban environmental carrying capacity and residents' green welfare can be enhanced simultaneously. This ecological improvement may further increase urban attractiveness and green growth potential, thereby strengthening the joint improvement of pollution–carbon reduction and green growth. Based on the above analysis, this paper proposes the following hypothesis:

H1. *The sci-tech finance pilot policy reduces urban pollution–carbon synergistic pressure and improves green growth efficiency.*

2.2. Analysis of Influence Mechanism

2.2.1. Green Industrial Entrepreneurship Mechanism

Entrepreneurial activity can reshape urban industrial structures through firm entry, market competition, and business model renewal, and thus serves as an important force for green transition and high-quality growth. Green industrial entrepreneurship refers to the creation and expansion of business entities in green-related sectors, such as environmental protection, energy conservation, clean energy, resource recycling, pollution control, ecological restoration, and green technology services, which provide industrial carriers for sustainable urban transition. The formation of green industrial entrepreneurship depends on technological capabilities, institutional conditions, and stable financial support. In particular, green business models usually require sustained R&D investment and long-term financing to move from opportunity identification and incubation to market expansion [20]. Sci-tech finance pilot policy, by linking technological resources with financial capital, can provide more stable financial support for innovation-oriented entrepreneurs and guide entrepreneurial activities toward green and low-carbon sectors [21]. At the same time, risk compensation and credit enhancement mechanisms reduce the potential losses faced by financial institutions when supporting green entrepreneurial projects. This increases the willingness of financial capital to enter green technology development and green business model incubation, thereby strengthening green industrial entrepreneurship.

Sci-tech finance can also improve the direction and efficiency of financial resource allocation. Relying on sci-tech finance service platforms and specialized project-screening mechanisms, financial institutions can better identify the technological potential, environmental performance, and growth prospects of green start-ups, which helps channel green capital into environmentally friendly sectors [22]. As financial resources gradually shift from high-pollution and energy-intensive sectors to green industries, green start-ups can obtain more favorable market-entry conditions and a stronger growth environment. In addition, fintech and big data technologies reduce the cost of green identification and enable more targeted financial services for green industries, thereby improving financial allocation efficiency and enhancing the endogenous expansion capacity of the urban green industrial system [23]. The increase in green industrial entrepreneurship can expand the supply of green products, green technologies, and environmental governance services. It also facilitates the diffusion of cleaner production, energy-saving, and carbon-reduction technologies within urban industrial systems. As green industries expand, they can further drive the transformation of traditional sectors, thereby promoting the coordinated improvement of pollution and carbon reduction and green growth. Based on the above analysis, this paper proposes the following hypothesis:

H2. *Sci-tech finance pilot policy reduces urban pollution–carbon synergistic pressure and improves green growth efficiency by enhancing green industrial entrepreneurship.*

2.2.2. Technological Innovation Mechanism

Innovation provides a sustained driving force for urban green transition by expanding the production technology frontier and improving resource allocation efficiency. In the context of sci-tech finance policy, technological innovation mainly operates through two related channels: green technological innovation and digital technological innovation.

On the one hand, green technological innovation is a key carrier linking innovation-driven development with the green economy. It helps cities break resource and environmental constraints and promotes the transition toward cleaner and low-carbon growth [24]. However, green R&D is often characterized by large upfront investment, high technological uncertainty, and delayed returns, making it difficult for firms to rely solely on

internal funds. Sci-tech finance pilot policy can ease financing constraints for green R&D by expanding sci-tech credit supply, improving risk-sharing mechanisms, and strengthening the institutional environment for green innovation [25]. With stronger financial support, firms are more capable of improving production processes, upgrading equipment, and raising energy efficiency, thereby enabling the simultaneous control of pollutant emissions and greenhouse gas emissions at the production stage. Moreover, sci-tech finance can facilitate the commercialization of green innovation outcomes, allowing firms to obtain economic returns from green product development and clean production transformation, which further strengthens their incentives for continuous innovation [12]. In this way, sci-tech finance transforms financial support into cleaner production capacity and environmental governance capability, thereby improving urban pollution reduction, carbon reduction, and green growth synergy.

On the other hand, digital technological innovation can further strengthen the enabling role of sci-tech finance in urban green transition. By promoting the integration of financial capital and technological resources, sci-tech finance policy improves firms' digital infrastructure and enhances their capacity for digital technology adoption and R&D, thereby supporting breakthroughs in digital technologies [26]. It can also increase the share of patient capital and provide long-term financial support for digital R&D and iterative upgrading. Through joint R&D and knowledge spillovers, sci-tech finance enhances firms' learning capacity and promotes digital technological innovation [27]. As digital innovation advances, firms and urban governance departments can rely on data collection, intelligent analysis, and real-time feedback to identify sources of pollution and carbon emissions more accurately, and to optimize energy allocation, production scheduling, and environmental supervision dynamically. The diffusion of digital technologies also accelerates the digital transformation of traditional industries and the wider application of green technologies, shifting pollution and carbon reduction from end-of-pipe treatment toward full-process coordinated governance [28,29]. Based on the above analysis, this paper proposes the following hypothesis:

H3a. *Sci-tech finance promotes pollution–carbon reduction and green growth by stimulating green technological innovation.*

H3b. *Sci-tech finance promotes pollution–carbon reduction and green growth by stimulating digital technological innovation.*

2.2.3. Factor Agglomeration Mechanism

Innovation factor agglomeration can provide sustained support for urban green transition by reducing matching costs, strengthening knowledge spillovers, and improving resource allocation efficiency. Under sci-tech finance policy, this effect is mainly reflected in the agglomeration of venture capital, talent, and technology.

First, sci-tech finance pilot policy can strengthen the incentives for venture capital to flow into green and low-carbon sectors. By providing government-backed credibility, R&D funds, and risk-sharing arrangements, sci-tech finance can leverage social capital toward green innovation activities and form a capital agglomeration effect, thereby offering continuous financial support for green technology R&D and industrial application [30]. Since clean technology projects attract venture capital not only through financing demand but also through expected market returns and policy certainty, sci-tech finance can improve green project identification, stabilize innovation expectations, and increase the willingness of venture capital to enter green and low-carbon fields [25,31].

Second, sci-tech finance policy can enhance the spatial attraction of high-skilled talent by improving the urban innovation ecosystem. Pilot cities usually develop clearer institu-

tional arrangements around emerging industries, research platforms, and talent-support policies, which create more R&D positions, entrepreneurial opportunities, and scientific resources, thereby attracting R&D, digital, and green technology talent [32]. The policy signal released by sci-tech finance pilots can further strengthen high-skilled human capital mobility, especially in fields such as environmental technology, renewable energy, and big data [6]. Talent agglomeration increases the density of knowledge exchange, technological absorption capacity, and cross-sector collaboration, making it easier to match green and digital technologies with urban environmental governance needs.

Finally, sci-tech finance can accelerate the transformation of scientific research outcomes into industrial applications and promote the diffusion of new technologies across firms, industries, and regions, thereby strengthening technological factor agglomeration [16]. Through the joint agglomeration of venture capital, talent, and technology, sci-tech finance transforms financial support into stronger green innovation capacity and low-carbon industrial development capacity. This process helps cities improve pollution and carbon reduction and green growth in a more coordinated way.

Although venture capital, talent, and technology represent different types of production factors, this study treats them as sub-mechanisms within the broader factor-agglomeration effect rather than as three isolated channels. The reason is that sci-tech finance does not only attract a single factor, but also improves the matching and co-location of financial capital, human capital, and technological resources around green and innovation-oriented activities. Venture capital provides risk-bearing financial support, talent offers knowledge and managerial capacity, and technology supplies innovation assets and application scenarios. Their simultaneous agglomeration can generate complementarities, improve resource-allocation efficiency, and strengthen the capacity of cities to promote pollution-carbon reduction and green growth. Therefore, this paper proposes the following hypothesis:

H4. *Sci-tech finance pilot policy reduces urban pollution-carbon synergistic pressure and improves green growth efficiency by facilitating the agglomeration of venture capital, talent, and technology.*

Figure 1 summarizes the theoretical framework through which sci-tech finance affects pollution-carbon reduction and green growth. Specifically, the sci-tech finance pilot policy promotes green industrial entrepreneurship by easing financing constraints for green start-ups and improving green project incubation, thereby supporting green industrial expansion. It also stimulates technological innovation by promoting green technological innovation and accelerating digital technological innovation, which further facilitates smart green transformation. In addition, sci-tech finance strengthens factor agglomeration by attracting capital, talent, and technology, thereby improving resource allocation efficiency. These pathways are not isolated from each other. Factor agglomeration provides the resource basis for technological innovation, technological innovation supports the formation and expansion of green industrial entrepreneurship, and green industrial entrepreneurship serves as the industrial carrier through which innovation resources and technological progress are translated into pollution-carbon reduction and green growth. Thus, the framework clarifies both the direct effects of the three mechanisms and their sequential transmission logic.

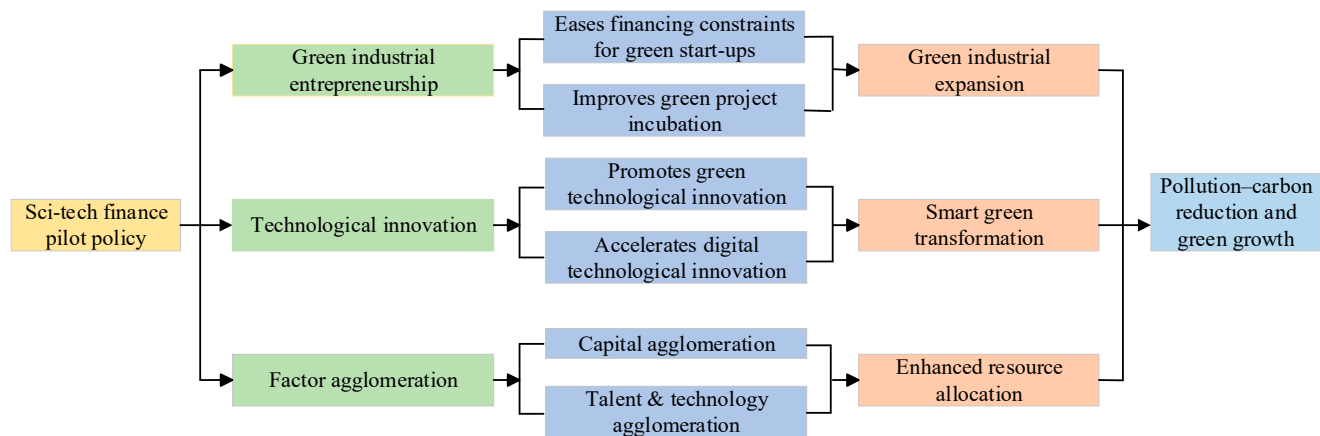


Figure 1. Theoretical framework of sci-tech finance, pollution-carbon reduction, and green growth.

3. Research Design

3.1. Model Setting

3.1.1. Benchmark Regression Model

The sci-tech finance pilot policy provides a quasi-natural experiment for identifying the effect of innovation-oriented financial intervention on urban pollution-carbon reduction and green growth efficiency. Following the standard multi-period difference-in-differences framework, pilot cities are treated as the treatment group and non-pilot cities as the control group. The benchmark model is specified as follows:

$$Y_{it} = a_0 + a_1STFP_{it} + \gamma Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes the dependent variable of city i in year t , including the pollution-carbon synergistic pressure index (PCSP) and the green growth efficiency index (GGEI). $STFP_{it}$ is the sci-tech finance pilot policy variable, indicating whether city i is affected by the sci-tech finance pilot policy in year t . $Control_{it}$ denotes the set of control variables. μ_i and λ_t represent city-fixed effects and year-fixed effects, respectively. ε_{it} is the random disturbance term. Standard errors are clustered at the city level.

3.1.2. Mechanism Model

Following Jiang [33], this study further examines the channels through which the sci-tech finance pilot policy affects pollution-carbon reduction and green growth efficiency. Specifically, we construct the following mechanism model:

$$Media_{it} = \beta_0 + \beta_1STFP_{it} + \gamma Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

where $Media_{it}$ denotes the mechanism variable of city i in year t . β_1 captures the effect of the sci-tech finance pilot policy on the mechanism variable. Other variables are defined as in Equation (1).

3.1.3. Spatial Effects Model

Sci-tech finance may affect not only local pollution-carbon reduction and green growth, but also neighboring cities through policy demonstration, factor mobility, technological diffusion, industrial linkages, and cross-regional environmental governance. If spatial dependence is ignored, the estimated policy effect may be biased, and the spatial externalities of the sci-tech finance pilot policy cannot be properly identified. Therefore, following Zhou, Ning, Huang, Zhou, Shi and Qin [13], this paper constructs a Spatial Autoregressive Difference-in-Differences model (SAR-DID) to examine the spatial spillover effects of the sci-tech finance pilot policy. A row-standardized inverse-squared geographic

distance matrix is used to characterize the spatial linkages among cities. The model is specified as follows:

$$Y_{it} = \rho \sum_{j \neq i}^N w_{ij} Y_{jt} + STFP_{it} \beta + X_{it} \gamma + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

where Y_{it} denotes the PCSP or GGEI of city i in year t . $STFP_{it}$ is the sci-tech finance pilot policy variable. w_{ij} denotes the element of the spatial weight matrix. $\sum_{j \neq i}^N w_{ij} Y_{jt}$ is the spatially lagged dependent variable, which captures the spatial dependence and feedback effects of PCSP or GGEI across cities. X_{it} represents the set of control variables, while μ_i and λ_t denote city and year fixed effects, respectively. ε_{it} is the random disturbance term. The coefficient ρ captures the spatial dependence of the dependent variable, and β measures the policy effect of the sci-tech finance pilot policy.

In this SAR-DID framework, the spatial spillover effect is generated by the spatial transmission and feedback mechanism associated with the spatially lagged dependent variable. Therefore, following the spatial effect decomposition approach, the estimated policy effect is decomposed into direct, indirect, and total effects. The direct effect measures the average impact of STFP on the local city, the indirect effect measures the spillover impact transmitted to neighboring cities through the spatial weight matrix, and the total effect is the sum of the direct and indirect effects.

3.2. Variable Selection

3.2.1. Explanatory Variable

The core explanatory variable is the sci-tech finance pilot policy (STFP). China implemented two batches of pilot programs for promoting the integration of science, technology, and finance in 2011 and 2016. Following the phased implementation of the policy, STFP is assigned a value of 1 for a city in the year when it becomes a pilot city and in all subsequent years, and 0 otherwise. The complete list of treated cities and their corresponding treatment years is reported in Appendix A Table A2.

3.2.2. Dependent Variables

The dependent variables include the pollution–carbon synergistic pressure index (PCSP) and the green growth efficiency index (GGEI).

First, following the measurement logic of Shi et al. [34], this paper constructs PCSP by multiplying carbon dioxide emissions by PM2.5 concentration, which respectively capture carbon emission pressure and air pollution pressure. The specific formula is as follows:

$$PCSP_{it} = \ln(CO_{2it} \times PM2.5 + 1) \quad (4)$$

where CO_{2it} represents the carbon dioxide emissions of city i in year t , and $PM2.5_{it}$ represents the annual average PM2.5 concentration of city i in year t . Since the original product term is highly skewed and sensitive to extreme values, it is further processed using logarithmic transformation and 1% winsorization. After this treatment, the skewness and kurtosis of PCSP decrease from 3.344 and 21.559 to −0.299 and 2.795, respectively, indicating that the distributional characteristics of the variable are substantially improved and more suitable for regression analysis.

Second, green growth efficiency reflects the improvement of economic growth quality under resource and environmental constraints. Following Zhang et al. [35], this study uses green total factor productivity (GTFP) to proxy urban green growth efficiency, denoted as GGEI. This measure is appropriate because GTFP captures desirable economic output while incorporating resource inputs and undesirable emissions, thereby reflecting whether cities achieve growth in a greener and more efficient manner.

Based on the global production frontier, the GML index can be expressed in a simplified form as follows:

$$GML_t^{t+1} = \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})}$$

where x , y , and b denote inputs, desirable output, and undesirable outputs, respectively, and $\vec{D}^G(\cdot)$ denotes the global directional distance function. A value greater than 1 indicates an improvement in green growth efficiency, while a value less than 1 indicates a decline.

The SBM-GML model is adopted because it incorporates both desirable and undesirable outputs into the production framework, allows non-radial adjustment of input and output slacks, and avoids the base-period dependence problem by constructing a global production frontier. In this framework, undesirable outputs are treated as outputs that should be reduced; therefore, lower industrial wastewater, exhaust gas, and smoke/dust emissions under the same level of inputs and desirable output indicate higher green growth efficiency. In terms of city-level measurement, energy input is measured by total energy consumption, while pollutant emissions are measured by industrial wastewater emissions, industrial exhaust gas emissions, and industrial smoke/dust emissions. Therefore, the SBM-GML model is suitable for measuring intertemporal changes in urban green growth efficiency under resource and environmental constraints. The measurement framework of GGEI is reported in Table 1.

Table 1. Measurement framework for green growth efficiency index.

Category	Indicator	Measurement
Input	Labor input	Number of employed persons at year-end
	Capital input	Capital stock
	Energy input	Total energy consumption
	Urbanization input	Built-up area of the city
Output	Desirable output	Real GDP
	Undesirable outputs	Industrial wastewater, exhaust gas and smoke/dust emissions

Note: All indicators are measured at the city-year level. Monetary variables are adjusted to constant prices where applicable. Energy input and pollutant emissions are consistently measured across cities and years.

3.2.3. Mechanism Variables

Guided by the theoretical analysis, this paper examines three transmission channels: green industrial entrepreneurship, technological innovation, and innovation factor agglomeration. First, green industrial entrepreneurship is measured by the number of newly established green industrial firms per 10,000 people, denoted as $Gine$ [36]. Green firms are identified according to the Green and Low-Carbon Transformation Industry Guidance Catalogue (2024 version) and the Industrial Classification for National Economic Activities (GB/T 4754–2017) [37], covering energy-saving and carbon-reduction, environmental protection, resource recycling, green energy, ecological protection, green infrastructure upgrading, and green services. Second, technological innovation includes green technological innovation and digital technological innovation. Green technological innovation (GTI) is measured by the number of green invention patent applications per 10,000 people [38], as green patents are widely regarded as direct and observable outputs of environmentally oriented technological activities and are commonly used to capture green innovation performance in sustainable manufacturing [39]. Digital technological innovation (DTI) is measured by the logarithm of digital economy patent applications [40]. Third, innovation factor agglomeration is captured from three dimensions: venture capital, tal-

ent, and technology. Following Hou and Shi [41], venture capital agglomeration (Capital) is measured by the ratio of venture capital investment to GDP. Following Huang, Liu, Tian, Liu, Wang and Zhang [16], talent agglomeration (Talent) is proxied by the employment share in information transmission, computer services and software, scientific research, and technical services, which are closely related to R&D, digital technology, and green technology applications and therefore can reflect the local concentration of high-skilled innovation-oriented talent. Technological agglomeration (Tech) is measured by a composite index, calculated as 0.5 times the ratio of government expenditure on science and technology to total fiscal expenditure plus 0.5 times standardized per capita patent applications.

3.2.4. Control Variables

To reduce omitted-variable bias, this paper controls for a set of city-level covariates that may affect urban green and low-carbon co-governance performance. These include economic development (lnGDP), measured by the logarithm of per capita GDP; wage level (lnWage), measured by the logarithm of employee wages; financial development (Loan), measured by the ratio of year-end financial institution loans to GDP; openness (Open), measured by the logarithm of per capita foreign direct investment; education expenditure (Edu), measured by the share of education expenditure in fiscal expenditure; and environmental protection support (Env), measured by the share of energy conservation and environmental protection expenditure in fiscal expenditure.

3.3. Data Sources

This study uses panel data for 284 prefecture-level cities in China from 2008 to 2023. Green patent data and digital patent data are obtained from the CNRDS database. Green industrial firm data are obtained from the Qiyuan Social Science Big Data Platform (CBDPS). Other socioeconomic, environmental, fiscal, financial, and control-variable data are mainly collected from the China City Statistical Yearbook, the EPS database, and the CSMAR database. All variables are matched at the city-year level according to administrative codes. Monetary variables are denominated in RMB and are processed into logarithmic or ratio indicators according to the definitions of each variable. For ratio variables, the numerator and denominator are kept in consistent statistical units before calculation. Missing values are supplemented using city statistical reports and linear interpolation where appropriate. To reduce the influence of extreme values, all continuous variables are winsorized at the 1% and 99% levels. Descriptive statistics are reported in Table 2.

Table 2. Descriptive statistical analysis.

Variable Name	Observation	Mean	SD	Min	Max
PCSP	4544	20.62	1.097	17.79	22.88
GGEI	4544	1.062	0.122	0.691	1.634
STFP	4544	0.134	0.341	0.000	1.000
lnGDP	4544	10.55	0.659	8.167	12.46
lnWage	4544	10.42	1.949	8.885	12.68
Loan	4544	1.012	0.613	0.075	9.227
Open	4544	9.345	2.851	0.000	14.70
Edu	4544	0.178	0.047	0.001	0.876
Env	4544	0.029	0.017	0.002	0.193

4. Empirical Results and Analyses

4.1. Benchmark Regression

Benchmark regression results are reported in Table 3. Columns (1) and (2) use the pollution–carbon synergistic pressure index (PCSP) as the dependent variable, while columns (3) and (4) use the green growth efficiency index (GGEI) as the dependent variable. This setting allows us to examine whether the sci-tech finance pilot policy affects the environmental and growth dimensions of sustainable urban transition separately. The coefficients of STFP in columns (1) and (2) are significantly negative at the 1% level, indicating that the policy effectively reduces urban pollution–carbon synergistic pressure. After adding control variables, the coefficient remains negative at -0.0845 . Since PCSP is log-transformed, the percentage effect is calculated as $\exp(\beta) - 1$; thus, $\exp(-0.0845) - 1 = -0.0810$, suggesting that treated cities experience an average reduction of approximately 8.10% in pollution–carbon synergistic pressure. This finding implies that sci-tech finance helps alleviate the combined environmental burden of air pollution and carbon emissions.

Columns (3) and (4) show that the coefficients of STFP are significantly positive when GGEI is used as the dependent variable. In column (4), the coefficient is 0.0350, suggesting that the policy also improves urban green growth efficiency. Overall, the benchmark results indicate that STFP contributes to both pollution–carbon reduction and green growth, thereby providing preliminary empirical support for the role of sci-tech finance in accelerating sustainable urban transition.

Table 3. Baseline regression analysis.

	(1) PCSP	(2) PCSP	(3) GGEI	(4) GGEI
STFP	−0.0935 *** (0.0338)	−0.0845 *** (0.0321)	0.0398 *** (0.0082)	0.0350 *** (0.0076)
lnGDP		−0.0300 (0.0496)		−0.0922 *** (0.0150)
lnWage		0.0011 (0.0020)		−0.0049 ** (0.0019)
Loan		−0.0754 *** (0.0236)		0.0093 (0.0092)
Edu		−0.9086 *** (0.1682)		0.0437 (0.0578)
Env		0.5538 (0.4061)		0.0557 (0.1436)
Open		−0.0070 ** (0.0034)		0.0013 (0.0019)
Constant	20.6335 *** (0.0045)	21.2244 *** (0.5307)	1.0575 *** (0.0011)	2.0525 *** (0.1627)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R ²	0.9739	0.9747	0.2518	0.2684
N	4544	4544	4544	4544

Note: Standard errors clustered at the city level are reported in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively. The control variables included in columns (2) and (4) are those defined in Section 3.2.4. The complete list of treated cities and treatment years is reported in Appendix A Table A2, and the descriptive statistics of the dependent variables are reported in Table 2.

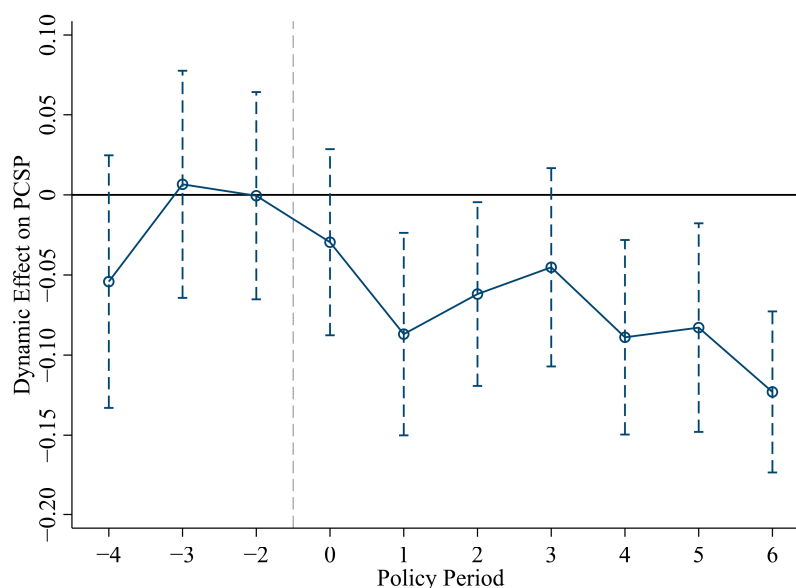
4.2. Robustness Test

4.2.1. Parallel Trend Test

Satisfying the parallel trends assumption is a prerequisite for the validity of the multi-period DID model. Specifically, in the absence of sci-tech finance policy, pilot and non-pilot cities should have followed comparable pre-policy trends in PCSP and GGEI. To examine this assumption, this paper adopts a dynamic DID specification based on the event-study approach [42], taking the year immediately before policy implementation as the benchmark period.

Figure 2 presents the results of the parallel trend test. Before the implementation of the sci-tech finance pilot policy, the estimated coefficients fluctuate around zero, and their confidence intervals generally include zero, indicating no systematic pre-policy difference between the treatment and control groups. After policy implementation, the coefficients for PCSP are generally negative, suggesting a reduction in pollution–carbon synergistic pressure. In contrast, the coefficients for GGEI gradually turn positive in the post-policy periods, indicating an improvement in urban green growth efficiency. These findings support the parallel trends assumption and confirm the validity of the multi-period DID estimation.

In addition to visual inspection, we further conduct joint significance tests for the pre-treatment coefficients. The p -values are 0.4774 for PCSP and 0.1388 for GGEI, respectively, indicating that the pre-treatment coefficients are jointly insignificant. Therefore, there is no evidence of systematic differences in pre-policy trends between the treated and control cities before the implementation of the sci-tech finance pilot policy. Moreover, because the sci-tech finance pilot policy was implemented in different batches, we further use the Callaway and Sant’Anna staggered DID estimator to address potential bias arising from heterogeneous treatment timing. The detailed results are reported in Supplementary Material S1, Table S1.



(a) Dynamic effect on PCSP

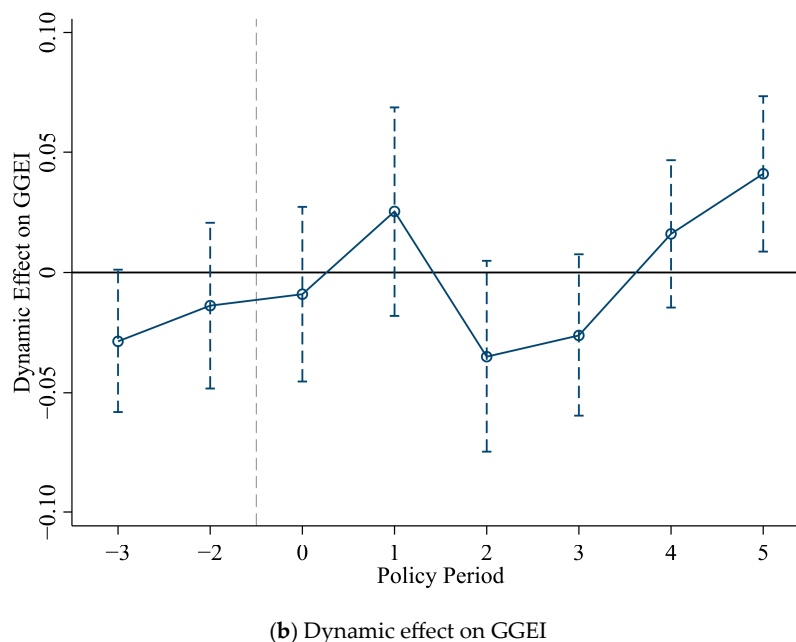


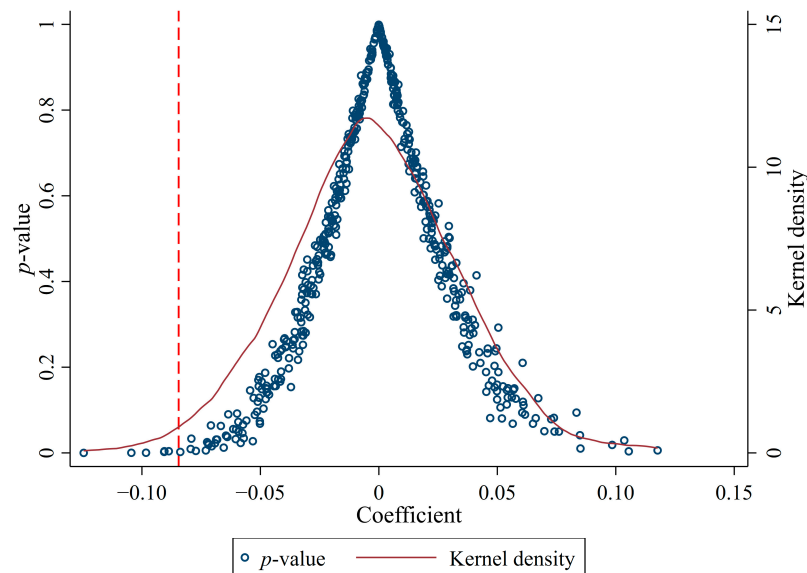
Figure 2. Parallel trend test and dynamic policy effects. Panel (a) reports the dynamic effect of the sci-tech finance pilot policy on pollution–carbon synergistic pressure (PCSP), and Panel (b) reports the dynamic effect on green growth efficiency index (GGEI). The dots represent the estimated coefficients of the event-time indicators, and the vertical dashed bars indicate the 95% confidence intervals based on robust standard errors clustered at the city level. The year immediately before policy implementation is omitted and used as the reference period. Negative coefficients for PCSP indicate a reduction in pollution–carbon synergistic pressure, while positive coefficients for GGEI indicate an improvement in urban green growth efficiency index.

4.2.2. Placebo Test

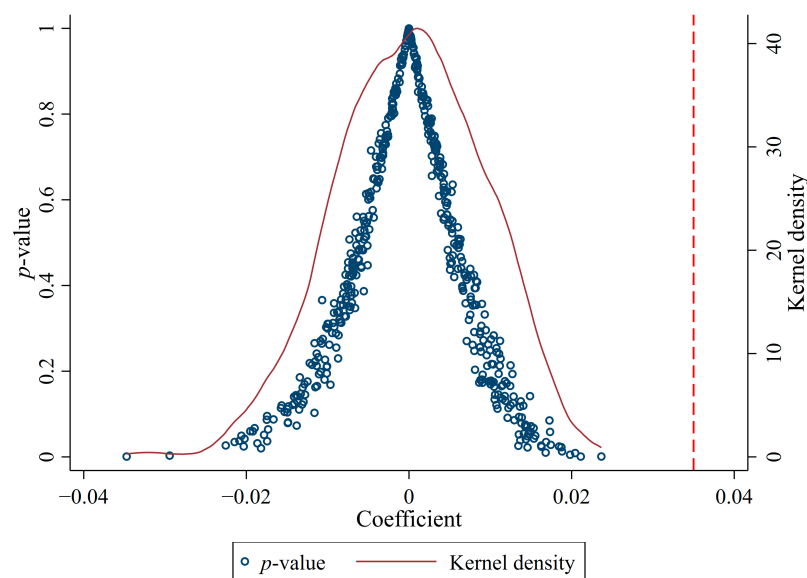
To further rule out the possibility that the benchmark results are driven by random policy shocks, this paper conducts a placebo test, following Ye et al. [43]. Specifically, pilot cities and policy implementation years are randomly reassigned, and the regression is repeated 500 times. If the estimated effects are not caused by random factors, the placebo coefficients should be concentrated around zero and clearly separated from the benchmark estimates.

Figure 3 reports the placebo test results. The simulated coefficients are mainly distributed around zero, while the benchmark estimates are located in the tails of the simulated distributions. For PCSP, the benchmark coefficient lies on the left side of the placebo distribution, indicating a significant reduction in pollution–carbon synergistic pressure. For GGEI, the benchmark coefficient lies on the right side, indicating a significant improvement in green growth efficiency. These results suggest that the estimated effects of STFP on PCSP and GGEI are unlikely to be driven by randomly assigned policy shocks, thereby strengthening the credibility of the benchmark findings.

The red dashed vertical line represents the true estimated coefficient, while the scatter points and kernel density curve show the distribution of placebo estimates. We further calculate the empirical pseudo- p -value as the proportion of placebo coefficients whose absolute values are greater than or equal to the absolute value of the true estimated coefficient. The empirical pseudo- p -values are 0.0240 for PCSP and 0.0000 for GGEI, respectively, indicating that the true estimated effects are unlikely to be generated by random policy assignment.



(a) Placebo test for PCSP



(b) Placebo test for GGEI

Figure 3. Placebo test. Note: Panel (a) reports the placebo test for PCSP, and Panel (b) reports the placebo test for GGEI. The blue hollow dots indicate the estimated coefficients and p -values from 500 random placebo simulations, and the red solid curve shows the kernel density distribution of the placebo coefficients. The red dashed vertical line represents the benchmark estimated coefficient based on the actual sci-tech finance pilot policy. The simulated coefficients are mainly distributed around zero, while the actual coefficient lies outside the main distribution range, indicating that the estimated policy effects are unlikely to be caused by random assignment or omitted shocks. The red dashed vertical line denotes the true estimated coefficient.

4.2.3. Propensity Score Matching

Although the multi-period DID model identifies the policy effect of sci-tech finance, the selection of pilot cities may not be completely random. Observable differences between pilot and non-pilot cities may therefore lead to potential sample selection bias. To address this concern, this paper adopts a PSM-DID approach. Specifically, the propensity

score is estimated using the main control variables, including $\ln GDP$, $\ln Wage$, $Loan$, Edu , Env , and $Open$, and kernel matching is used to construct a comparable control group under the common support condition. We further check the covariate balance before and after matching, and the detailed balance diagnostics are reported in Supplementary Material S2, Table S2. The results show that the differences in observable characteristics between pilot and non-pilot cities are substantially reduced after matching.

The results are reported in columns (1) and (2) of Table 4. After kernel matching, the coefficient of STFP for PCSP is -0.0727 and significant at the 10% level, indicating that the sci-tech finance pilot policy continues to reduce pollution–carbon synergistic pressure. The coefficient of STFP for GGEI is 0.0297 and significant at the 1% level, suggesting that the policy also improves urban green growth efficiency. Overall, the PSM-DID results are consistent with the benchmark regressions, indicating that the main findings are not driven by observable differences between pilot and non-pilot cities.

Table 4. Robustness tests.

Variables	PSM-DID		Excluding Policy Shocks		Excluding Municipalities	
	(1) PCSP	(2) GGEI	(3) PCSP	(4) GGEI	(5) PCSP	(6) GGEI
STFP	-0.0727^* (0.0381)	0.0297^{***} (0.0089)	-0.0745^{**} (0.0341)	0.0296^{***} (0.0082)	-0.0790^{**} (0.0320)	0.0345^{***} (0.0078)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4347	4347	4544	4544	4468	4468
R ²	0.9735	0.2652	0.9749	0.2551	0.9747	0.2675

Notes: Robust standard errors clustered at the city level are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.2.4. Excluding Confounding Policy Shocks

During the sample period, several urban pilot policies related to green transformation and environmental governance may overlap with the implementation of the sci-tech finance pilot policy. The low-carbon city, zero-waste city, and smart city pilot policies may affect urban environmental performance through carbon reduction, waste governance, resource recycling, digital governance, and infrastructure upgrading. Specifically, the low-carbon city pilot policy was implemented in several batches, mainly in 2010, 2012, and 2017; the smart city pilot policy was launched in several batches from 2013 onward; and the zero-waste city pilot policy was launched in 2019. Based on the official pilot lists, this paper constructs city-year dummy variables for these three types of pilot policies, with each dummy equal to 1 for pilot cities from the approval year onward and 0 otherwise. To alleviate concerns that the benchmark results are confounded by these concurrent policy shocks, this paper further controls for these three types of pilot policies.

The results are reported in columns (3) and (4) of Table 4. After controlling for low-carbon city pilots, zero-waste city pilots, and smart city pilots, the coefficient of STFP remains negative for PCSP and positive for GGEI, with statistical significance broadly consistent with the benchmark results. This suggests that the estimated effects of sci-tech finance policy on reducing PCSP and improving GGEI are not driven by overlapping urban pilot policies.

4.2.5. Excluding Municipalities

Municipalities directly under the central government may differ from ordinary prefecture-level cities in administrative status, policy resources, fiscal capacity, and development patterns. To avoid the possibility that the benchmark results are driven by these

special cities, this paper further excludes Beijing, Tianjin, Shanghai, and Chongqing from the sample and re-estimates the baseline model.

The results are reported in columns (5) and (6) of Table 4. After excluding the four municipalities, the coefficient of STFP remains negative for PCSP and positive for GGEI, and the significance levels are broadly consistent with the benchmark results. This indicates that the estimated effects of sci-tech finance policy are not driven by the special administrative and economic characteristics of municipalities.

4.2.6. Province-by-Year Fixed Effects

To further control for province-level time-varying shocks, this paper includes province-by-year fixed effects in the baseline specification. This setting helps absorb unobserved shocks that vary across provinces over time, such as province-specific environmental regulation, industrial policy adjustments, and regional development strategies. After introducing province-by-year fixed effects, the identification of STFP mainly comes from differences between pilot and non-pilot cities within the same province and year, rather than from cross-province variation.

The results are reported in columns (1) and (2) of Table 5. After controlling for province-by-year fixed effects, the coefficient of (STFP) remains significantly negative for PCSP and significantly positive for GGEI. This indicates that the benchmark findings are not driven by province-level time-varying factors, further confirming the robustness of the estimated policy effects.

Table 5. Additional robustness tests.

Variables	Province-Year Fixed Effects		Double Machine Learning		(5) Coupling Coordination Index
	(1) PCSP	(2) GGEI	(3) PCSP	(4) GGEI	
STFP	−0.0946 *** (0.0347)	0.0283 ** (0.0114)	−0.0747 *** (0.0237)	0.0944 *** (0.0334)	0.0106 ** (0.0053)
Controls	Yes	Yes	Yes	Yes	Yes
Quadratic terms	No	No	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Province-year FE	Yes	Yes	No	No	No
N	4544	4544	4544	4544	4544
R-squared	0.9812	0.4450			0.8623

Notes: Robust standard errors clustered at the city level are reported in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

4.2.7. Double Machine Learning

Traditional linear regressions may be affected by functional-form misspecification when the relationships between control variables and the outcome variables are nonlinear. To address this concern, this paper further adopts a double machine learning approach [44]. Specifically, the neural network algorithm is used to estimate the nuisance functions, and five-fold cross-fitting is applied to reduce overfitting bias. The estimation is implemented in Stata 17, and the main tuning parameters follow the default settings of the implemented package. In addition, both the linear and quadratic terms of the control variables are included to better capture potential nonlinear effects.

The results are reported in columns (3) and (4) of Table 5. The coefficient of STFP remains significantly negative for PCSP and significantly positive for GGEI. Compared with the benchmark estimate, the DML coefficient for GGEI is larger, which may be because the DML specification flexibly captures nonlinear relationships between city-level covariates and green growth efficiency. Therefore, the DML result should be interpreted

as additional robustness evidence rather than as a replacement for the benchmark estimate. Overall, the direction and statistical significance remain consistent with the baseline findings, indicating that the main conclusions are robust to nonlinear model specifications.

4.2.8. Alternative Construction of the Pollution–Carbon Indicator

To further examine whether the baseline result is sensitive to the construction of the pollution–carbon indicator, this paper further replaces the original PCSP with a pollution–carbon coupling coordination index. Following Zhang, Deng, Yan, Feng and Sun [9], the alternative index is constructed based on the coupling coordination model. Specifically, the carbon-reduction subsystem includes carbon emissions and carbon intensity, while the pollution-reduction subsystem includes PM2.5 concentration, PM2.5 intensity, and NOx intensity. Since all indicators represent environmental pressure, they are treated as negative indicators and transformed into positive indicators before aggregation. The final index ranges from 0 to 1, with a larger value indicating a higher level of coordinated pollution and carbon reduction.

The result is reported in column (5) of Table 5. After replacing the dependent variable with the pollution–carbon coupling coordination index, the coefficient of STFP is 0.0106 and is significant at the 5% level. This indicates that the sci-tech finance pilot policy significantly improves the coordinated level of pollution and carbon reduction. Therefore, the baseline conclusion remains robust after using an alternative construction of the pollution–carbon indicator.

4.3. Endogeneity Test

To further alleviate potential endogeneity arising from the non-random selection of pilot cities, this paper conducts an instrumental-variable estimation following Zhou, Ning, Huang, Zhou, Shi and Qin [13] and Li, Ding and Guo [32]. Specifically, the spherical distance from each city to Hangzhou is used as an instrument for the sci-tech finance pilot policy. This instrumental-variable strategy has also been adopted in recent studies on sci-tech finance policy evaluation and digital–green coordinated development. Hangzhou is one of China’s representative centers of e-commerce, digital finance, and technology-finance innovation. Cities closer to Hangzhou are more likely to be affected by financial-resource diffusion, policy learning, and technology-finance networks, and therefore have a higher probability of being selected as sci-tech finance pilot cities. This supports the relevance condition of the instrument. Since the distance to Hangzhou is time-invariant, its level effect is absorbed by city fixed effects in the fixed-effects IV specification, while the identifying variation comes from cross-city differences in distance-based policy exposure. Regarding the exclusion restriction, geographical distance is exogenously given and does not vary with cities’ current environmental performance. Moreover, a shorter distance to Hangzhou does not necessarily imply lower pollution–carbon synergistic pressure or higher green growth efficiency. Therefore, the distance to Hangzhou is expected to affect PCSP and GGEI mainly through its influence on the sci-tech finance pilot policy. Nevertheless, the IV results are interpreted as supplementary endogeneity evidence rather than as the sole basis for causal identification.

Table 6 reports the instrumental variable estimates. Columns (1) and (3) present the first-stage results for the PCSP and GGEI specifications, while columns (2) and (4) report the corresponding second-stage estimates. The coefficients of Distance to Hangzhou are significantly negative in both first-stage regressions, indicating that cities farther from Hangzhou are less likely to be selected as sci-tech finance pilot cities, which is consistent with theoretical expectations. The first-stage F-statistic is 17.69, exceeding the conventional threshold of 10. The Kleibergen–Paap rk LM statistics are also significant, rejecting

the null hypothesis of underidentification. These results indicate that the instrument is relevant and that weak-instrument concerns are not serious. After addressing potential endogeneity, the second-stage coefficient of STFP remains significantly negative for PCSP and significantly positive for GGEI, further supporting the robustness of the main conclusions.

Table 6. Instrumental variable estimation.

Variables	PCSP		GGEI	
	First Stage	Second Stage	First Stage	Second Stage
	(1) STFP	(2) PCSP	(3) STFP	(4) GGEI
IV	−0.0058 *** (0.0014)		−0.0058 *** (0.0014)	
STFP		−0.2005 *** (0.0721)		0.3226 *** (0.0850)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4532	4532	4532	4532
First-stage F-statistic	17.69			
Kleibergen–Paap rk LM	14.93 ***			

Notes: Robust standard errors clustered at the city level are reported in parentheses. *** denotes significance at the 1% level.

4.4. Mechanism Analysis

Based on the preceding theoretical analysis, the sci-tech finance pilot policy may affect sustainable urban transition through three channels: green industrial entrepreneurship, technological innovation, and innovation factor agglomeration. Following the mechanism-test logic commonly used in the DID literature, this section replaces the dependent variable with each mechanism variable to examine whether the policy significantly promotes these channels. The results are reported in Table 7.

Table 7. Mechanism test results..

Variables	(1) Gine	(2) GTI	(3) DTI	(4) Capital	(5) Talent	(6) Tech
STFP	0.0967 *** (0.0139)	0.0862 *** (0.0119)	0.1724 ** (0.0854)	0.2820 *** (0.0568)	0.0093 *** (0.0022)	0.7072 *** (0.0946)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	4544	4544	4544	4544	4544	4544
R ²	0.8454	0.8252	0.9457	0.4263	0.7423	0.8685

Notes: Robust standard errors clustered at the city level are reported in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

4.4.1. Green Industrial Entrepreneurship Effect

Column (1) of Table 7 reports the result for green industrial entrepreneurship. The coefficient of STFP is 0.0967 and significant at the 1% level, indicating that the sci-tech finance pilot policy significantly increases the entry of green industrial firms. This finding suggests that sci-tech finance improves the entrepreneurial environment for green industries by expanding financing channels, lowering entry barriers, and strengthening market expectations for green development. The growth of green industrial firms can enlarge the

supply of clean production services, energy-saving technologies, pollution-control solutions, ecological restoration services, and resource-recycling activities. It also intensifies market competition in green sectors and encourages traditional firms to adopt cleaner production modes. Therefore, green industrial entrepreneurship provides an important industrial foundation for reducing pollution and carbon emissions while supporting green growth. Accordingly, the result is consistent with Hypothesis 2 and provides supportive evidence for the green industrial entrepreneurship channel.

4.4.2. Technological Innovation Effect

Columns (2) and (3) of Table 7 report the results for technological innovation. The coefficient of STFP is 0.0862 for GTI and significant at the 1% level, while the coefficient for DTI is 0.1724 and significant at the 5% level. These results indicate that sci-tech finance promotes both green technological innovation and digital technological innovation. Green technological innovation directly improves cleaner production processes, energy-saving equipment, end-of-pipe treatment technologies, and low-carbon production capacity, thereby reducing pollution and carbon emissions at the production stage. Digital technological innovation further enhances data collection, environmental monitoring, intelligent regulation, and resource allocation efficiency, enabling firms and governments to identify emission sources more accurately and improve the precision of environmental governance. The joint advancement of GTI and DTI therefore helps shift urban green transformation from single pollution control to full-process coordinated governance, providing technological support for pollution reduction, carbon reduction, and green growth. For example, Gao et al. [45] show that digital twin technology and distributed model predictive control can coordinate electricity, heating, and gas networks under a dynamic carbon trading mechanism, thereby improving real-time energy optimization and reducing carbon emissions. More broadly, recent process-level studies also show that digital monitoring, intelligent optimization, and low-carbon energy-system integration can improve production efficiency and reduce carbon emissions in specific industrial links [46,47]. These studies provide micro-level industrial evidence for the broader mechanism through which digital and green technologies contribute to pollution-carbon reduction. Accordingly, the results are consistent with Hypotheses 3a and 3b and provide supportive evidence for the technological innovation channel.

4.4.3. Factor Agglomeration Effect

Columns (4)–(6) of Table 7 report the results for innovation factor agglomeration. The coefficients of STFP on Capital, Talent, and Tech are 0.2820, 0.0093, and 0.7072, respectively, and all are significant at the 1% level. These results indicate that the sci-tech finance pilot policy significantly promotes the agglomeration of venture capital, talent, and technological resources. Venture capital agglomeration provides long-term financial support for green innovation and low-carbon industrialization, reducing the financing uncertainty faced by technology-based firms. Talent agglomeration increases the density of knowledge exchange and strengthens firms' capacity to absorb and apply green and digital technologies. Technological agglomeration accelerates the transformation of scientific achievements and promotes knowledge spillovers across firms and industries. Through the joint concentration of capital, talent, and technology, sci-tech finance improves the efficiency of innovation resource allocation and enhances cities' capacity for coordinated green transformation. Accordingly, the results are consistent with Hypothesis 4 and provide supportive evidence for the factor-agglomeration channel.

Overall, the mechanism results show that the sci-tech finance pilot policy promotes the coordinated improvement of pollution and carbon reduction and green growth efficiency by activating green industrial entrepreneurship, stimulating green and digital tech-

nological innovation, and gathering key innovation factors. Relative to these sample means, the estimated coefficients suggest that the effects of STFP on the proposed mechanism variables are economically meaningful. These findings provide empirical support for the proposed mechanism hypotheses.

4.5. Heterogeneity Analysis

The effect of sci-tech finance may vary across cities because the transformation of financial support into green and low-carbon outcomes depends on local market scale, governance capacity, and innovation conditions [24,48]. Therefore, following the logic that city characteristics shape policy absorption and implementation efficiency, this paper examines the heterogeneous effects of STFP from the perspectives of city-scale, collaborative governance capacity and innovation environments.

4.5.1. City-Scale Heterogeneity

Cities with different population sizes differ substantially in market capacity, factor concentration, industrial foundation, and policy absorption capacity, which may lead to heterogeneous effects of sci-tech finance. To examine this issue, this paper classifies cities with a year-end total population below one million as smaller cities and the remaining cities as larger cities. The results are shown in Figures 4 and 5.

For PCSP, the estimated coefficient of STFP in larger cities is -0.0904 and is significantly negative at the 1% level, while the coefficient in smaller cities is 0.0455 and statistically insignificant. This indicates that the pollution–carbon reduction effect of sci-tech finance is mainly reflected in larger cities. For GGEL, the estimated coefficient of STFP in larger cities is 0.0335 and is significantly positive at the 1% level, while the coefficient in smaller cities is 0.0856 and is significantly positive at the 5% level. These results suggest that sci-tech finance improves green growth efficiency in both larger and smaller cities, but the policy effect in larger cities is more statistically stable. Overall, larger cities show a more balanced effect in reducing pollution–carbon pressure and improving green growth efficiency.

This may be because larger cities usually have deeper financial markets, stronger industrial foundations, more abundant innovation resources, and more complete green infrastructure, which help transform sci-tech financial support into green investment, technological application, and industrial upgrading. In contrast, smaller cities may have a stronger marginal response in green growth efficiency, but their limited financial supply, insufficient innovation carriers, and weaker green project reserves constrain the conversion of sci-tech finance into pollution–carbon reduction outcomes.

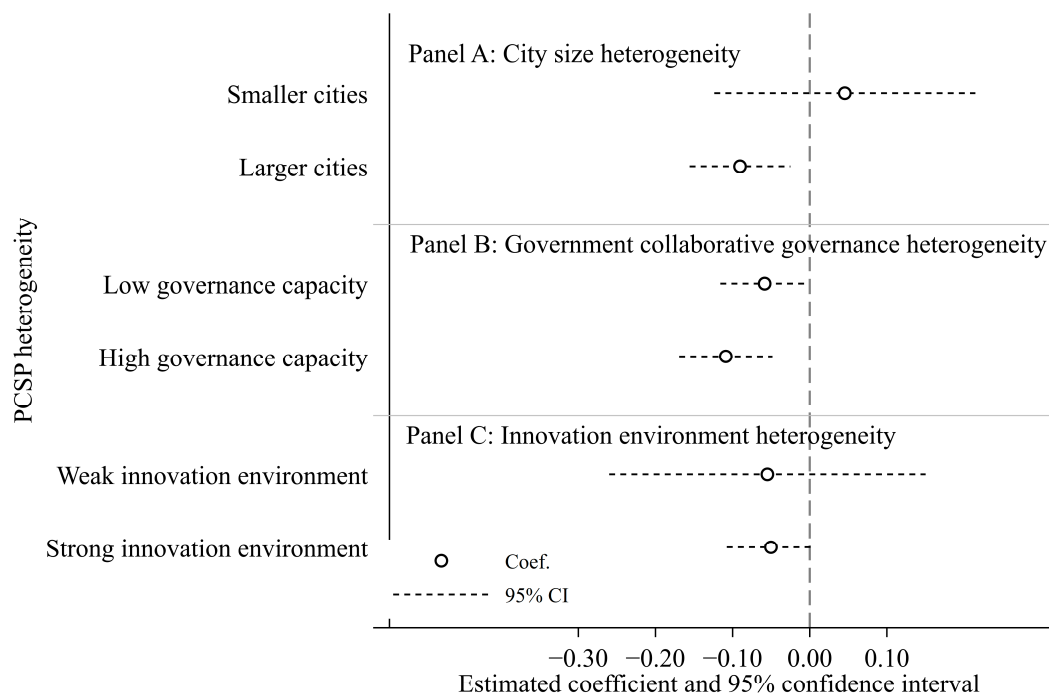


Figure 4. Heterogeneous effects of STFP on PCSP.

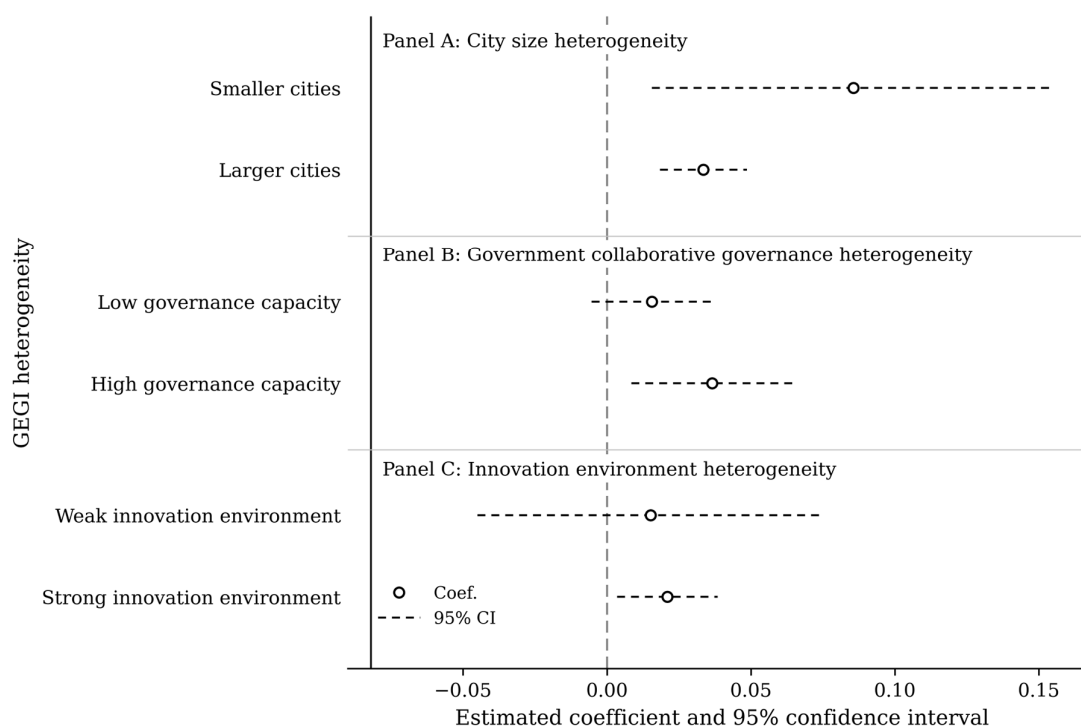


Figure 5. Heterogeneous effects of STFP on GEGI.

4.5.2. Government Collaborative Governance Heterogeneity

Effective governance can strengthen low-carbon transition by improving policy enforcement and enhancing the allocation efficiency of financial resources [48]. Since sci-tech finance involves finance, science and technology, environmental protection, industry, and

fiscal authorities, local collaborative governance capacity may further shape its policy effect. This paper measures collaborative governance capacity using the ratio of collaborative-governance-related keywords in government work reports to total word frequency. The keywords include “complementary advantages,” “collaborative governance,” “win-win cooperation,” and “resource sharing.” A higher value indicates stronger collaborative governance capacity. The results are shown in Figures 4 and 5.

For PCSP, the estimated coefficient of STFP in cities with stronger collaborative governance capacity is -0.1088 and is significantly negative at the 1% level, while the coefficient in cities with weaker collaborative governance capacity is -0.0584 and is significantly negative at the 5% level. For GGEI, the estimated coefficient of STFP in cities with stronger collaborative governance capacity is 0.0365 and is significantly positive at the 5% level, while the coefficient in cities with weaker collaborative governance capacity is 0.0156 and is statistically insignificant. These results indicate that stronger collaborative governance capacity enhances both the pollution–carbon reduction effect and the green growth effect of sci-tech finance.

This finding indicates that the effectiveness of sci-tech finance depends not only on financial resource supply, but also on the ability of local governments to coordinate policy instruments and guide resources toward green innovation and industrial transformation. Cities with stronger collaborative governance can reduce departmental fragmentation, improve project screening, and enhance the linkage among financial support, technological innovation, and environmental governance. By contrast, weak collaborative governance may result in fragmented implementation and lower resource allocation efficiency, thereby weakening the policy effect.

4.5.3. Innovation Environment Heterogeneity

Sci-tech finance is essentially an innovation-oriented financial policy, and its effectiveness may depend on the local innovation environment. This paper uses the city innovation index from the China City and Industry Innovation Power Report released by Fudan University as a proxy for the urban innovation environment. Cities are divided into strong and weak innovation environment groups according to whether their annual innovation index is above the annual median.

The results are shown in Figures 4 and 5. The results show that the policy effect is stronger in cities with a better innovation environment. In these cities, STFP significantly reduces PCSP and improves GGEI, indicating that a sound innovation environment enhances the conversion of sci-tech financial support into green and low-carbon outcomes. This may be because cities with stronger innovation environments have better innovation networks, higher technology absorption capacity, and more mature channels for commercializing research outcomes. These conditions help financial resources flow more accurately to projects with technological potential and environmental benefits. In contrast, in cities with weaker innovation environments, limited innovation carriers and insufficient high-quality projects may weaken the actual effect of financial support. These findings suggest that the innovation environment is an important condition for amplifying the pollution–carbon reduction and green growth effects of sci-tech finance.

4.6. Spatial Spillover Effects

Before estimating the spatial model, this paper first examines spatial dependence using Global Moran’s I based on the row-standardized inverse squared geographic distance matrix. Appendix A Table A1 shows that PCSP exhibits persistent and significant positive spatial autocorrelation during 2008–2023, with Moran’s I ranging from 0.272 to 0.310 and all p -values below 0.001 . By contrast, the spatial correlation of GGEI is weaker and less stable. These results indicate that pollution–carbon synergistic pressure is more spatially

clustered than green growth efficiency, providing a stronger basis for further examining the spatial spillover effect of PCSP.

Table 8 shows that the local and indirect effects of STFP on PCSP are significantly negative. Since a lower PCSP indicates lower pollution–carbon synergistic pressure, the negative indirect effect implies that sci-tech finance generates a positive spatial spillover in substantive terms. That is, the policy not only reduces local pollution–carbon pressure, but also alleviates pollution–carbon pressure in geographically connected cities through policy demonstration, technology diffusion, and cross-city environmental governance.

For GGEI, the direct effect of STFP is significantly positive, whereas the indirect effect is statistically insignificant. This indicates that sci-tech finance improves local green growth efficiency, but does not generate a clear spillover effect on neighboring cities. The difference between PCSP and GGEI suggests that pollution–carbon governance is more likely to diffuse across cities, while green growth efficiency depends more on local industrial foundations, innovation capacity, and resource absorption conditions.

Table 8. Spatial spillover effect decomposition results..

Variables	(1) PCSP				(2) GGEI			
	Main	Direct	Indirect	Total	Main	Direct	Indirect	Total
STFP	−0.0670 *** (0.0151)	−0.0699 *** (0.0163)	−0.2224 *** (0.0597)	−0.2923 *** (0.0741)	0.0643 *** (0.0244)	0.0652 *** (0.0251)	−0.0006 (0.0034)	0.0647 *** (0.0249)
rho	0.7705 *** (0.0263)				−0.0084 (0.0504)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4544	4544	4544	4544	4544	4544	4544	4544

Notes: Robust standard errors clustered at the city level are reported in parentheses. *** denotes significance at the 1% level.

4.7. Further Analysis: Synergy Effects

This section further examines whether sci-tech finance promotes synergy from two dimensions: outcome coordination and policy complementarity. First, because PCSP is a pressure index, lower values indicate better pollution-carbon reduction performance. Therefore, PCSP is normalized and reverse-coded, and the transformed indicator is multiplied by GGEI to construct an outcome synergy index. A larger value indicates stronger joint improvement in pollution-carbon reduction and green growth efficiency. Second, this paper examines whether STFP forms complementary or substitutive relationships with other urban environmental pilot policies. Following the policy-interaction framework, DDD terms are constructed by interacting STFP with the Zero-Waste City pilot, the Low-Carbon City pilot, and the green finance policy. Since the dependent variables are positively oriented, a significantly positive DDD coefficient indicates a complementary policy effect.

Column (1) of Table 9 reports the outcome synergy result. The coefficient of STFP is 0.0358 and significant at the 1% level, indicating that the sci-tech finance pilot policy significantly enhances the joint improvement of pollution-carbon reduction and green growth efficiency. This result suggests that STFP not only affects individual environmental or growth dimensions, but also strengthens their coordinated improvement.

For policy interactions, the Zero-Waste City pilot has a significantly positive DDD coefficient, supporting a clear “1 + 1 > 2” complementary effect. The Low-Carbon City interaction is positive but insignificant. In contrast, the STFP-green finance interaction is

significantly negative, indicating a marginal substitution effect rather than policy complementarity.

The marginal substitution effect between STFP and green finance policy may stem from overlaps in implementing entities, service scopes, and capital investment directions. Sci-tech finance is mainly implemented through science-and-technology departments, financial institutions, and local governments, with a focus on supporting technology-based firms, R&D activities, and the commercialization of scientific achievements. Green finance policy mainly guides financial institutions to allocate capital to green credit, environmental protection, clean energy, pollution control, and low-carbon projects. Although the two policies differ in their primary objectives, they both target green technology firms, clean production projects, and low-carbon industrial transformation. Under the constraints of limited local financial resources and qualified green project reserves, such policy overlap may lead to repeated targeting, competition for similar financial resources, and marginal resource crowding-out, thereby weakening the additional effect of policy combination. In addition, differences in project-screening standards, policy evaluation criteria, and administrative coordination procedures may generate implementation frictions, further reducing the marginal synergy between the two financial policies.

By contrast, the Low-Carbon City pilot focuses more on carbon-emission targets, industrial restructuring, energy conservation, and administrative governance, rather than direct financial-resource allocation. Therefore, its interaction with STFP may operate through more indirect and longer-term channels, which helps explain why the STFP–Low-Carbon City interaction is positive but statistically insignificant.

Table 9. Synergy effects between outcome dimensions and pilot policies.

Variables	(1) Outcome Synergy	(2) Zero-Waste City	(3) Low-Carbon City	(4) Green Finance Policy
DDD		0.0342 *** (0.0114)	0.0134 (0.0114)	−0.2085 ** (0.0940)
STFP	0.0358 *** (0.0081)	0.0255 *** (0.0082)	0.0281 *** (0.0089)	0.0368 *** (0.0096)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	4544	4544	4544	4544
R ²	0.9149	0.9037	0.9088	0.9150

Note: Each policy-interaction regression includes STFP, the corresponding policy variable, their interaction term, control variables, city fixed effects, and year fixed effects. The reported DDD coefficient refers to the interaction between STFP and the corresponding policy DID variable. *** and ** denote significance at the 1% and 5% levels, respectively.

5. Research Conclusions and Policy Recommendations

5.1. Conclusions

From the perspective of sustainable urban transition, this paper takes the sci-tech finance pilot policy as a quasi-natural experiment and uses panel data of Chinese prefecture-level cities from 2008 to 2023 to examine its policy effect, mechanisms, heterogeneity, spatial spillovers, and policy synergy. The main conclusions are as follows: (1) Sci-tech finance significantly reduces pollution–carbon synergistic pressure and improves green growth efficiency. This conclusion remains robust after parallel trend tests, placebo tests, PSM-DID, and double machine learning estimation. (2) The mechanism analysis reveals that sci-tech finance promotes urban green transformation through three channels: green industrial entrepreneurship, technological innovation, and innovation factor agglomeration. Specifically, the policy increases the entry of green industrial firms, promotes green

and digital technological innovation, and strengthens the agglomeration of venture capital, talent, and technological resources. (3) The heterogeneity analysis shows that the effect of sci-tech finance is more pronounced in larger cities, cities with stronger government collaborative governance capacity, and cities with better innovation environments. This indicates that market scale, administrative coordination, and innovation conditions are important factors shaping the effectiveness of sci-tech finance. (4) The spatial spillover results indicate that sci-tech finance has a positive spatial spillover effect on PCSP, while its spillover effect on GGEI is not significant. In other words, sci-tech finance in pilot cities contributes to reducing pollution–carbon synergistic pressure in neighboring cities, but its effect on green growth efficiency is mainly reflected within local cities. (5) The policy-interaction results show that the Zero-Waste City pilot forms a significant “ $1 + 1 > 2$ ” complementary effect with sci-tech finance, whereas the Low-Carbon City pilot does not generate a statistically significant additional effect. In contrast, the interaction between sci-tech finance and green finance policy is significantly negative, suggesting a marginal substitution effect rather than policy complementarity.

5.2. Policy Recommendations

First, the policy evaluation system for sci-tech finance should be improved. Local governments should move beyond single indicators such as carbon reduction or economic growth and incorporate the joint performance of pollution reduction, carbon reduction, and green growth into policy assessment. In practice, pilot cities should establish project-level evaluation criteria covering technological potential, expected emission-reduction benefits, green growth value, and commercialization feasibility. Financial resources should be directed toward projects that simultaneously generate environmental benefits and long-term economic returns, so that sci-tech finance can better serve the coordinated transition of pollution–carbon reduction and green growth.

Second, differentiated implementation strategies should be adopted across cities with different scales and governance capacities. Larger cities should play a leading role in green technology diffusion, green project incubation, and regional demonstration by relying on their stronger financial markets, industrial foundations, and innovation resources. Smaller cities should focus on improving basic financial service capacity, expanding qualified green project reserves, and strengthening local innovation carriers. For cities with weaker collaborative governance capacity, coordination mechanisms among finance, science and technology, environmental protection, industry, and fiscal departments should be strengthened. Joint project-screening platforms, interdepartmental information sharing, and coordinated subsidy arrangements can be established to improve the conversion efficiency of sci-tech financial support.

Third, the key transmission mechanisms of sci-tech finance should be strengthened. Local governments should improve green entrepreneurship services, reduce financing barriers for green industrial firms, and support the marketization of green and digital technologies. Financial institutions should develop credit products, guarantee tools, and risk-compensation mechanisms suitable for long-cycle and high-risk innovation projects. Meanwhile, pilot cities should attract venture capital, skilled talent, and technological resources through innovation platforms, industry–university–research cooperation, and green project databases. These measures can strengthen the pathways of green industrial entrepreneurship, technological innovation, and factor agglomeration.

Fourth, regional coordination and policy combinations should be enhanced according to the spatial spillover and policy-interaction results. Since sci-tech finance has a significant spatial spillover effect on pollution–carbon synergistic pressure, pilot cities should strengthen cross-city cooperation in pollution–carbon governance, green technology transfer, environmental information sharing, and joint project financing. A “leading

cities helping neighboring cities” mechanism can be established to promote the diffusion of capital, technology, and governance experience. In terms of policy combinations, sci-tech finance should be closely linked with Zero-Waste City construction, especially in source reduction, resource recycling, clean production, and green infrastructure investment. The coordination with Low-Carbon City pilots should focus on longer-term links between financial support, industrial restructuring, and energy-efficiency improvement. For green finance policy, local governments should avoid repeated project targeting and resource crowding-out by clarifying policy boundaries, differentiating funding priorities, and improving coordination among financial instruments.

The findings also have comparative implications for other countries pursuing green transition. For economies seeking to coordinate environmental governance and green growth, the Chinese experience suggests that innovation-oriented financial policy can be an effective instrument when financial resources are linked with technological innovation, green entrepreneurship, and local industrial upgrading. However, the applicability of this policy logic may depend on country-specific institutional conditions. In countries with more market-oriented financial systems, similar policy effects may require stronger green information disclosure, risk-sharing mechanisms, and public–private cooperation to guide capital toward green and technological projects. In developing economies with weaker financial infrastructure or limited innovation capacity, the priority may be to build project-screening platforms, strengthen local innovation carriers, and improve coordination among financial, industrial, and environmental authorities. Therefore, the broader lesson is not to replicate China’s sci-tech finance pilot model mechanically, but to adapt innovation-oriented financial instruments to each country’s financial structure, governance capacity, and stage of green transition.

5.3. Limitations and Future Research

Although this study provides city-level evidence on the effect of sci-tech finance on pollution–carbon reduction and green growth, several limitations remain. First, due to data availability, this paper mainly evaluates urban-level policy effects and cannot fully capture firm-level behavioral responses, such as changes in green investment, financing structure, and technology adoption. Second, although the event-study results support the parallel trends assumption, the DID design may still be affected by potential anticipatory responses or pre-treatment spillovers. Local governments, financial institutions, or firms may adjust their behavior before formal pilot approval due to policy expectations or learning from nearby pilot candidates. Non-pilot cities may also be indirectly affected through regional policy learning, factor mobility, or green technology diffusion. Although the placebo tests and insignificant pre-treatment coefficients help reduce this concern, such potential anticipation and diffusion effects cannot be completely ruled out. Third, although this study examines spatial spillovers and policy interactions, the longer-term dynamic effects of sci-tech finance and its coordination with other sustainability-oriented policies require further investigation. Future research can use micro-level enterprise data, longer observation periods, and more refined policy-interaction designs to further examine how sci-tech finance affects firms’ green transformation decisions and how different policy instruments can be better coordinated to promote sustainable urban transition.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18147045/s1>. Supplementary Material S1: Modern Staggered DID Robustness Check [49]. Table S1. Robustness check using the Callaway and Sant’Anna estimator. Supplementary Material S2: PSM-DID Balance Diagnostics. Table S2. Covariate balance test before and after propensity score matching.

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Appendix A

Table A1. Global Moran's I statistics.

Year	Moran's I of PCSP	p-Value	Moran's I of GGEI	p-Value
2008	0.281	0.000	−0.002	0.754
2009	0.280	0.000	0.008	0.493
2010	0.286	0.000	0.004	0.534
2011	0.282	0.000	0.049	0.002
2012	0.282	0.000	0.046	0.000
2013	0.298	0.000	0.005	0.221
2014	0.293	0.000	0.070	0.000
2015	0.299	0.000	0.066	0.000
2016	0.292	0.000	0.056	0.000
2017	0.283	0.000	−0.001	0.812
2018	0.298	0.000	0.006	0.581
2019	0.310	0.000	−0.022	0.242
2020	0.310	0.000	0.062	0.000
2021	0.287	0.000	0.038	0.023
2022	0.278	0.000	−0.012	0.519
2023	0.272	0.000	0.034	0.036

Note: This table is prepared for the annual Global Moran's I results based on the row-standardized inverse squared geographic distance matrix.

Table A2. Treated cities and treatment years of the sci-tech finance pilot policy.

First Batch (2011; 41 Cities)	Second Batch (2016; 9 Cities)
Beijing, Tianjin, Shanghai, Nanjing, Wuxi, Xuzhou, Changzhou, Suzhou, Nantong, Lianyungang, Huai'an, Yangzhou, Zhenjiang, Taizhou, Suqian, Hangzhou, Wenzhou, Huzhou, Hefei, Bengbu, Wuhu, Wuhan, Changsha, Guangzhou, Foshan, Dongguan, Chongqing, Chengdu, Mianyang, Xi'an, Baoji, Tianshui, Weinan, Tongchuan, Shangluo, Qingyang, Pingliang, Longnan, Dalian, Qingdao, Shenzhen	Zhengzhou, Xiamen, Ningbo, Jinan, Nanchang, Guiyang, Yinchuan, Baotou, Shenyang

Note: The treatment year refers to the year from which the STFP variable takes the value of 1 for each treated city. Cities not listed in this table are treated as non-pilot cities during the sample period.

Appendix A Table A3 reports the sensitivity test based on an alternative economic-geographic spatial weight matrix. Compared with the baseline inverse squared geographic distance matrix, the economic-geographic matrix further incorporates economic linkages between cities and therefore captures a broader spatial interaction structure. The results show that the main conclusions remain robust. For PCSP, the direct effect, indirect effect, and total effect of STFP are all significantly negative, indicating that sci-tech finance not only reduces local pollution–carbon synergistic pressure but also generates a positive spillover effect through economic-geographic linkages. For GGEI, the direct effect of STFP remains significantly positive, while the indirect effect is statistically insignificant. This is consistent with the baseline finding that the green growth effect of sci-tech finance is mainly reflected locally and does not form a stable spillover effect on neighboring cities.

Table A3. Sensitivity test using the economic-geographic spatial weight matrix.

Variables	(1) PCSP				(2) GGEI			
	Main	Direct	Indirect	Total	Main	Direct	Indirect	Total
STFP	−0.0707 *** (0.0174)	−0.0705 *** (0.0178)	−0.1075 *** (0.0365)	−0.1780 *** (0.0355)	0.0549 ** (0.0260)	0.0560 ** (0.0266)	0.0342 (0.0539)	0.0902 * (0.0519)
rho	0.0333 (0.0300)				0.0246 (0.0308)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	4544	4544	4544	4544	4544	4544	4544	4544
Within R ²	0.0436	0.0436	0.0436	0.0436	0.0015	0.0015	0.0015	0.0015

Notes: This table reports the spatial effect estimates based on the economic-geographic spatial weight matrix. Robust standard errors are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

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