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How Do Green Transformation Policies for Industrial Parks Affect Urban Green Total-Factor Energy Efficiency? Evidence from National-Level Green Industrial Parks

Sifan Geng [1], Xianzhong Mu [1,]* and Liang Xie [2,]*

[1] College of Materials Science and Engineering, Beijing University of Technology, Beijing 100124, China; gengsf2024@163.com

[2] School of Business Administration, China University of Petroleum (Beijing) at Karamay, Karamay 834000, China

* Correspondence: mu_bjutredps@163.com (X.M.); bjutxie@163.com (L.X.)

Abstract

As the growth poles of regional development, industrial parks realize green transformation, which boosts green development in host cities while potentially generating impacts on neighboring cities. Drawing on the construction practices of national green industrial parks, this paper utilizes China's city-level panel data spanning 2007–2023 and employs the multi-period DID model and spatial DID model to empirically examine the impacts, transmission mechanisms, and spatial spillover effects of the industrial park green transformation policy on urban green total-factor energy efficiency (GTFEE). The findings indicate that green industrial park construction boosts urban GTFEE by approximately 11.6%, with industrial agglomeration, green technological innovation, and optimized capital allocation serving as its mediating channels. Heterogeneity analysis reveals that green industrial park construction generates stronger improvements in GTFEE for cities in eastern and western China, as well as those with abundant green industrial parks, advanced green finance, ample general higher education institutions, and underdeveloped digital infrastructure. Compared with national-level industrial parks, provincial ones transformed into green industrial parks exert a stronger positive effect on GTFEE. From a spatial perspective, green industrial park construction hinders the improvement in GTFEE in neighboring cities, and the negative spillover effect is more prominent for those that also build such parks.

Keywords: green total-factor energy efficiency; green transformation of industrial parks; green industrial parks; spatial spillover effects; multi-period DID; super-efficiency SBM; China

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1. Introduction

Faced with intensifying resource constraints and mounting pressure from global climate governance, improving energy efficiency has become a global consensus and policy orientation [1]. In recent years, China has vigorously implemented energy policies aimed at improving energy efficiency and advancing green development, achieving remarkable results. The *Global Energy Review 2026* released by the International Energy Agency (IEA) reports that the share of coal-fired generation in China declined to 55% in 2025, down from 70% a decade ago (https://iea.blob.core.windows.net/assets/df903e1c-49c6-4757-8cbf-6fbcfe7611a0/GlobalEnergyReview2026.pdf (accessed on 8 April 2026)). Nevertheless, China's coal-dominated energy consumption structure remains unchanged, and it still faces prominent pressure from both total carbon emissions and energy intensity [2]. According to data from the National Bureau of Statistics of China, coal consumption increased by 0.1% in 2025, accounting for 51.4% of total national energy consumption (https://www.stats.gov.cn/sj/zxfbhjd/202602/t20260228_1962662.html (accessed on 9 April 2026)). Therefore, improving green total-factor energy efficiency (GTFEE) remains a key approach for China to alleviate resource and environmental constraints and achieve the dual carbon targets.

Green industrial development is pivotal to the enhancement of GTFEE across China. Industrial sectors dominate national energy consumption and pollutant emissions, among which industrial parks constitute the primary source. To advance industrialization, China has actively built industrial parks to leverage their economic benefits, including attracting foreign investment, creating jobs, promoting industrial upgrading, and boosting output. Nevertheless, this development pattern has also triggered extensive energy consumption alongside surging pollutant and carbon emissions, bringing severe ecological and environmental problems. Previous studies have documented that industrial parks account for over 60% of China's aggregate GDP [3]. Meanwhile, these parks maintain substantial energy consumption and greenhouse gas emissions, accounting for 70% and 72% of the national aggregate volumes, respectively [4]. This development model featuring high energy consumption and heavy emissions represents a critical constraint on nationwide green and sustainable industrial and regional growth.

Against this backdrop, China proposed the active development of a green manufacturing system under *Made in China 2025*. National-level green industrial parks (hereinafter referred to as "green industrial parks") serve as a key component of this system, aiming to advance the green, low-carbon and circular development of traditional industrial parks [5]. Later, competent departments released multiple policies to promote the development of green industrial parks. In July and September 2016, the Ministry of Industry and Information Technology (MIIT) issued the *Industrial Green Development Plan (2016–2020)* and the *Notice on Launching the Construction of the Green Manufacturing System*, which clarified the definition, evaluation criteria and implementation procedures of green industrial parks. In 2022, the *Action Plan for Industrial Carbon Peaking* further stressed the development of a green manufacturing system and promoted the construction of green industrial parks focusing on the improvement of green and low-carbon industrial chains, efficient utilization of energy and resources, and supply of green electricity. By 2023, China had officially accredited eight batches of green industrial parks, with a total of 375 parks covering 167 cities. Compared with other industrial park green transition policies, the green industrial park initiative features the largest number of projects, widest geographical coverage, and the most comprehensive policy implications. Thus, exploring green industrial park development in China is of great significance for understanding the industry-led green transition in developing economies. Against China's national green development agenda, this study takes green industrial park construction as a quasi-natural experiment to systematically investigate the impacts of the industrial park green transition policy on urban GTFEE. It also provides empirical references for advancing the green transformation of traditional industrial parks, improving the green manufacturing system and achieving regional energy conservation and emission reduction.

2. Literature Review

Improving energy efficiency is crucial for achieving urban sustainability and high-quality economic development. Existing studies on energy efficiency mainly focus on measurement methods and influencing factors. In terms of energy efficiency measurement, it can be divided into single-factor and total-factor categories. Single-factor energy efficiency is measured merely by the ratio of economic output to energy input, ignoring the substitution and complementarity between energy input and other inputs such as labor and capital [6]. In contrast, GTFEE takes into account not only conventional production inputs such as labor and capital, but also adverse environmental impacts including pollutant emissions from energy consumption. It thus fully reflects the nexus between energy utilization and environmental protection. At present, the measurement methods for GTFEE mainly include the stochastic frontier parametric approach and data envelopment analysis (DEA). Compared with the stochastic frontier approach, DEA requires no estimation of costs or production functions, thus eliminating associated estimation errors [7]. It also accommodates complex production systems with multiple inputs and outputs, thus being widely applied. However, the model assumes proportional cuts in inputs or undesirable outputs alongside proportional rises in desirable outputs [6], conflicting with actual production practices. Therefore, some scholars adopt the slacks-based measure (SBM) model, a slack-based DEA model, to estimate the total-factor energy efficiency of China's industrial sectors [8]. This model can address non-radial slacks of both inputs and outputs, namely the excess of unit inputs or the shortage of unit outputs. In terms of the influencing factors of energy efficiency, scholars have further explored the impacts of government intervention [9], foreign trade [10], urbanization [11], financial development [12] and technological progress [13] on energy efficiency. In recent years, numerous scholars have also noted the important role of environmental regulation in improving energy efficiency. Some scholars argue that environmental regulation exerts a positive linear effect on the energy efficiency [14], while others identify its non-linear effect [15].

Beyond national environmental regulations, governments have enacted effective industrial policies that advance green transformation in industrial parks while delivering high-quality regional economic growth. The existing literature on green transformation policies for industrial parks mainly focuses on the implementation effects of three policy instruments: national eco-industrial parks (NEDPs), circular economy parks, and low-carbon industrial parks. Some scholars adopt case studies to dissect the mechanisms through which traditional industrial parks undergo circular renovation to realize intra-park cleaner production, industrial symbiosis, and sustainable development [16–19]. Others build evaluation models to explore development paths and influencing factors for high-quality development of NEDPs, circular renovation of industrial parks, and energy conservation and emission reduction in low-carbon industrial parks [20–24]. In addition, the prior literature confirms the favorable impacts of such park development on regional carbon mitigation and improved urban metabolic efficiency [25–29], and identifies agglomeration effects, technological progress and environmental regulations as its key transmission channels. Notably, these industrial parks mitigate adverse environmental externalities imposed on neighboring regions mainly via constructing internal circular systems and implementing end-of-pipe pollution control. In contrast, green industrial parks place greater emphasis on green technology spillovers, green standard guidance and green industry cultivation, aiming to foster deeply coordinated development with host cities and surrounding regions [30]. This indicates that green park construction should not merely focus on internal optimization within park boundaries but also prioritize integrated development with host cities to holistically boost resource utilization efficiency and factor integration capacity, thereby advancing regional green development.

However, extant research on the environmental effects of green industrial park construction is relatively limited. Most relevant studies mainly focus on the park scale, while systematic analyses of its environmental impacts on host cities and regions are insufficient. At the park level, there is no consistent consensus among scholars on the environmental impacts of green industrial park construction. Yu et al. [31] find that green park construction facilitates the decoupling of economic growth from resource consumption and environmental degradation. By contrast, some scholars contend that sound production practices fail to translate into expected eco-economic benefits [5]. Specifically, the green economic efficiency of China's green industrial parks has not reached the optimal level, featuring extensive energy use and slack undesirable outputs, alongside a temporal trend of initial inhibition followed by improvement. At the city level, Xian et al. [30] document that green industrial park construction improves urban air quality by encouraging enterprises to develop green management systems and pursue green technological innovation, yet the study ignores the effects of resource allocation within this mechanism. In addition, the construction of green industrial parks exerts spillover effects on neighboring cities. On the one hand, such parks may raise the stringency of environmental regulations in host cities, creating cross-regional disparities in regulatory intensity that trigger cross-border pollution transfer and the pollution haven effect [32]. On the other hand, green industrial parks may deliver demonstration and driving effects to boost environmental quality in surrounding areas. Nevertheless, few existing studies explore the environmental effects of green industrial park construction from the perspective of spatial spillovers.

The extant literature has generated abundant insights into green transformation policies of industrial parks, yet some research gaps persist. First, numerous studies assess the environmental effects of industrial policies covering NEDPs, low-carbon pilot parks and industrial park circular renovation at park and regional scales, whereas green industrial parks have attracted limited research attention. Only few studies estimate the environmental impacts of green industrial parks at the park level but fail to reach consistent conclusions, and studies examining this issue from a regional perspective are far scarcer. Second, most studies focus on the local effects of green industrial park construction and overlook the spatial interactions among cities, resulting in insufficient investigations into its cross-regional spatial spillover effects. Third, extant studies confirm that agglomeration and technological progress effects serve as functional channels through which the green transition of industrial parks improves environmental quality, yet they largely ignore the influence of resource allocation effects triggered by factor mobility.

Based on the above, this study regards the construction of green industrial parks as a quasi-natural experiment, and comprehensively and systematically estimates the impact effect, mechanism of action and spatial spillover effect of the green transformation of industrial parks on the GTFEE. Relative to the extant literature, the potential marginal contributions of this study reside in the following respects: (1) Based on a manually sorted list of green industrial parks, this paper empirically examines the impact of green industrial park construction on urban GTFEE, enriching research on the environmental effect evaluation of green transformation policies for industrial parks. Meanwhile, multiple methods including PSM-DID, heterogeneous treatment effect tests and endogeneity tests are adopted to verify the robustness of the baseline results. (2) To capture spatial effects, this paper further constructs a spatial difference-in-differences (SDID) model to thoroughly investigate the spatial spillover effects of green industrial park construction on different types of neighboring regions, addressing the insufficient identification of spatial externalities arising from the green transformation of industrial parks. (3) This paper examines the mechanisms through which green industrial parks affect urban GTFEE from three perspectives: industrial agglomeration, green technological innovation, and resource allocation. In addition, it identifies heterogeneous efficiency enhancement effects of such parks across three dimensions, geographic location, park characteristics, and regional development endowments, thereby expanding and deepening theoretical and empirical research regarding energy efficiency gains from the green transformation of industrial parks.

3. Policy Background and Theoretical Mechanisms

3.1. Policy Background

To accelerate the green transformation and upgrading of traditional manufacturing industries, the MIIT successively issued the *Industrial Green Development Plan (2016–2020)*, the *Implementation Guidelines for the Green Manufacturing Project (2016–2020)*, and the *Notice on Launching the Construction of the Green Manufacturing System* in 2016. These documents clarified the development goals, evaluation criteria and application procedures for green industrial parks. Green industrial parks are industrial parks that pursue green, low-carbon and circular development. They serve as platforms gathering manufacturing enterprises and infrastructure featuring green philosophies and requirements, and emphasize integrated management and collaborative linkages among on-site factories. The construction of such parks aims to play an exemplary leading role, improve the efficiency of regional resource and energy use, cut pollutant emissions, and advance the green and low-carbon transition of the industrial sector. The newly formulated *General Principles for the Evaluation of Green Industrial Parks* specifies that its evaluation indicator system consists of five dimensions: industrial development, energy utilization, resource utilization, infrastructure and ecological environment. The system not only covers indicators related to energy use, resource use and ecological environment, but also incorporates content concerning industrial development and infrastructure construction, such as green factories, green microgrids and digital development. In this way, it effectively guides industrial parks to achieve clean, efficient and circular energy use as well as intensive and economical utilization of resources.

At the implementation stage, the development of green industrial parks adopts standardized and hierarchical procedures. To begin with, all parks complete self-assessment based on green manufacturing system criteria. Those green industrial parks with qualified assessment results may commission MIIT-endorsed third-party assessors to conduct on-site verification and issue comprehensive assessment reports. Eligible parks may submit the *Self-evaluation Report on Green Parks* and the *Third-party Evaluation Report on Green Parks* to the competent provincial authorities. Next, competent provincial authorities assess and verify the submitted documents in accordance with local implementation plans, and select outstanding parks for recommendation to MIIT. Finally, through expert appraisal, public announcement and random on-site sampling, MIIT determines the official list of national-level green industrial parks and puts in place a dynamic supervision system. It conducts unscheduled inspections: parks failing to maintain relevant standards will be delisted, while those passing three consecutive checks will be exempt from inspection for five years.

Between 2017 and 2023, MIIT issued eight rounds of green industrial park lists (see Table 1). In total, 375 parks have obtained the official qualification of national-level green industrial parks. In terms of temporal trends, the count of green industrial parks increased amid fluctuations between 2017 and 2022, followed by a substantial surge in 2023. This may be attributed to the issuance of the *Implementation Plan for Carbon Peaking in the Industrial Sector* by relevant government authorities in July 2022. The plan strives to build a green manufacturing system, so as to accelerate the green and low-carbon transformation of industry and achieve carbon peaking in the industrial sector. In terms of quantity and spatial pattern of park distribution, green industrial parks show obvious geographical imbalance. In terms of total quantity, the number is the largest in the eastern region, followed by the west, with the central region being the smallest. Specifically, there are 147 green industrial parks in eastern China, accounting for 39.2%; 102 in central China, taking up 27.2%; and 126 in western China, making up 33.6%. As illustrated in Figure 1, green industrial parks in eastern and western regions feature stronger spatial agglomeration. Most cities host more than two green industrial parks, with core cities exhibiting particularly pronounced agglomeration effects. By contrast, the layout in central China is relatively scattered. Most cities have only one to two green industrial parks, with a generally low number per city and weak regional agglomeration.

Table 1. Timeline of green industrial park construction.

Year	Batch	Number of GIPs Established	Cumulative Total
2017	First	24	24
2018	Second	22	46
2018	Third	34	80
2019	Fourth	39	119
2020	Fifth	53	172
2021	Sixth	52	224
2022	Seventh	47	271
2023	Eighth	104	375

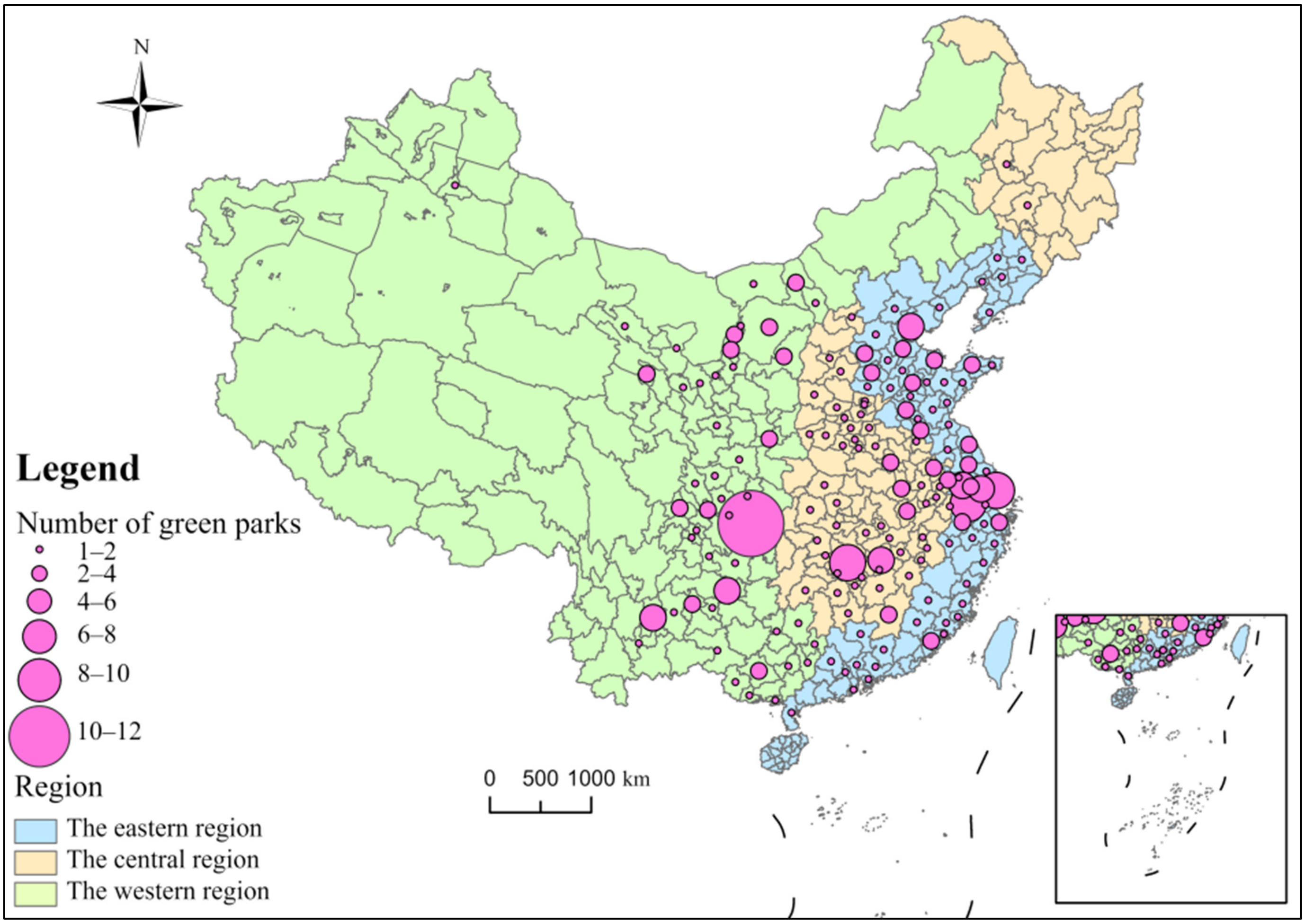

Figure 1. Quantity distribution of green industrial parks by city. Note: This map is based on the standard map downloaded from the Standard Map Service website of the Ministry of Natural Resources of China (Map Approval No. GS(2024)0650), with no modifications made to the map boundaries.

3.2. Theoretical Mechanism

3.2.1. Direct Effects of Green Industrial Park Construction on Urban GTFEE

The concept of green, low-carbon and circular development of green industrial parks runs through the whole process of industrial development, infrastructure construction, energy and resource utilization, and ecological environmental protection, thereby influencing the urban GTFEE in economic, environmental and social dimensions. For economic performance, guided by the philosophy of green development, green industrial parks encourage resident enterprises to develop green products, support leading industries to build green factories, and push flagship firms to establish green supply chains, to raise the utilization efficiency of energy and resources. For environmental protection, green industrial park construction promotes energy transition as well as the establishment of inter-industry circular and symbiotic systems. Within the parks, renewable energy is promoted and industrial green microgrids are built to lower dependence on fossil fuels, which helps enhance regional energy efficiency and optimize natural resource allocation [33]. Meanwhile, based on the sharing of public infrastructure, parks leverage ecological and environmental information management platforms to boost inter-enterprise by-product exchange, cascaded energy utilization and collaborative waste disposal [31]. This enables systematic management of energy consumption and environmental governance. For social benefits, green industrial park construction requires raising the share of green buildings in public and industrial buildings. This initiative reduces overall energy use and carbon emissions of park buildings, continuously improves the production and living environment, strengthens regional talent appeal and brand competitiveness, and underpins long-term regional sustainable development.

3.2.2. Indirect Effects of Green Industrial Park Construction on Urban GTFEE

The construction of green industrial parks represents a new type of production relation compatible with the formation and development of green productivity, while GTFEE reflects the development level of green productivity. Green productivity effectively improves GTFEE through industrial layout adjustment, revolutionary technological breakthroughs and the optimal allocation of production factors. From the perspective of industrial agglomeration, parks attract related enterprises to settle down via preferential policies and green infrastructure, thereby improving the industrial chain. From the technological perspective, revolutionary technological breakthroughs foster the development of advanced green technologies for energy conservation and carbon reduction. From the perspective of factor allocation, shifting factors to high-productivity sectors optimizes allocation. Based on the above analysis, this paper attempts to theoretically explain how green industrial park construction influences GTFEE from three channels: industrial agglomeration, technological innovation, and optimal factor allocation effects.

Green industrial park construction increases policy support and promotes the green upgrading of infrastructure to attract related enterprises to cluster. It further improves regional energy efficiency through agglomeration externalities. Green industrial parks generate excess “policy rents” through diversified incentive policies such as fiscal subsidies and tax preferences. These policy benefits attract enterprises to voluntarily cluster in the parks. Meanwhile, green industrial park construction demands green-oriented infrastructure. By deploying green microgrids and building energy and carbon digital management centers and other new green infrastructure, parks can effectively reduce enterprises’ costs for energy-saving and carbon-reduction renovation, improve green production efficiency, and drive the agglomeration and development of green industries. From the classical agglomeration perspective, Marshallian externality theory holds that the clustering of production factors within cities reduces expenses of goods transportation, labor matching and knowledge dissemination via intermediate input sharing, labor pool effect and knowledge spillover effect, thereby improving regional GTFEE.

According to the Porter Hypothesis, moderate environmental regulation drives green technological innovation among enterprises due to innovation compensation effects. For green industrial parks, competent government authorities have introduced environmental incentives for pilot parks. They prioritize funding for energy saving, emission reduction and technological innovation in these areas, which undoubtedly amplifies the innovation compensation effect of environmental regulation and steers firms toward green technological innovation. Technological innovation, especially green technological innovation, is regarded as the fundamental driver for improving GTFEE [34]. In the long run, technological progress, especially green-oriented innovation, serves as an effective means to address environmental pollution [35].

With technology remaining unchanged, the flow of production factors from low-productivity sectors to high-productivity ones also helps improve energy efficiency [36]. The original intention of establishing industrial parks is to integrate various resources and realize their optimal allocation across different locations [37]. The evaluation and assessment system for green industrial park construction requires raising the proportion of high-tech and green industries within the parks. Accordingly, faced with environmental regulation and industrial transformation pressures, park enterprises will readjust factor allocation in pursuit of long-term economic gains, guiding factors to shift from polluting and inefficient sectors to clean and efficient ones. This mitigates regional resource misallocation. Existing studies indicate that factor misallocation exerts a significant negative impact on energy efficiency and environmental efficiency [38]. Specifically, capital misallocation can deprive high-efficiency and green-oriented firms lacking sufficient funds to introduce advanced technologies and equipment, thereby hampering their energy-saving and emission-reduction performance [39].

3.2.3. Spatial Spillover Effect of Green Industrial Park Construction on Urban GTFEE

Given regional interactions, local policy implementation and government activities may influence the economic and social development of neighboring cities. On the one hand, driven by various economic linkages such as regional agglomeration externalities and interregional competition effects, local cities can generate radiation and driving effects, while neighboring cities tend to learn and imitate. Consequently, local policy shocks exert positive influences on the development of adjacent cities. On the other hand, industrial policies and measures also shape spatial resource allocation. They attract technology, talent and capital to concentrate within the region, generating a siphon effect that drains resources from peripheral areas to central regions. Such direct government intervention and artificial market segmentation may trigger rent-seeking behaviors that hinder specialized division of labor and effective competition, thereby curbing the improvement of GTFEE in neighboring cities.

Neighboring cities of green industrial park-hosting cities can be divided into two groups: cities without green industrial parks and those with similar green industrial park construction. Both local and adjacent cities with green industrial parks need to achieve the green transformation of industrial parks through equipment upgrading, technological innovation and industrial chain improvement. If the two regions establish sound cooperative relationships, the imitation effect will become more evident, whereas if administrative barriers make them focus solely on their own development, vicious competition will be triggered and the resource siphon effect will be exacerbated. For cities that have not built green industrial parks, if neighboring areas launch green industrial parks, they can receive the radiation effect through learning and imitation, and may also face pollution transfer.

Based on the above analysis, this paper proposes that:

Hypothesis 1. *The green transformation of industrial parks can improve urban GTFEE.*

Hypothesis 2. *The green transformation of industrial parks can improve urban GTFEE by promoting industrial agglomeration, green technological innovation, and factor allocation optimization.*

Hypothesis 3. *The green transformation of industrial parks exerts spatial spillover effects on neighboring cities. Compared with adjacent cities without green industrial parks, green industrial park construction generates stronger negative spatial spillovers on adjacent cities that also develop such parks.*

4. Methodology and Data

4.1. Research Method

This study aims to explore the impact of green industrial park construction on urban GTFEE. Since green industrial parks were established in batches at different times, this paper adopts the multi-period DID model. The model is specified as Equation (1):

$$\ln GTFEE_{it} = \alpha + \beta GP\mathrm{ark}_{it} + \theta \ln X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (1)$$

where $GTFEE_{it}$ denotes the green total-factor energy efficiency of city i in year t. $GPark_{it}$ denotes the policy dummy, which takes the value of 1 in the approval year and all subsequent years for cities approved to establish green industrial parks, and 0 otherwise. Considering that a city may establish multiple green industrial parks during the sample period, we take the time of its first green industrial park approval as the policy shock point. X_{it} represents a set of control variables. μ_i and ν_t represent the city and year fixed effects, respectively, and ε_{it} is the standard error clustered at the city level.

4.2. Variables and Data Sources

4.2.1. Dependent Variable

The core dependent variable of this study is urban GTFEE. Following Shi and Li [36], this study establishes the indicator system for GTFEE. The input factors for GTFEE mainly include capital, labor and energy consumption. The desirable output variable covers real GDP, while the undesirable outputs include industrial sulfur dioxide, industrial smoke (dust), and industrial wastewater. Detailed definitions of variables are presented in Supplementary S1. The super-efficiency SBM model is adopted to measure GTFEE.

4.2.2. Control Variables

To mitigate omitted variable bias as much as possible, we select six control variables following Li et al. and Yang et al. [40,41]. ① Population density ($popu$), measured as the ratio of the total population at year-end to administrative area: cities with higher population density have advantages in energy consumption and energy-saving potential compared with sparsely populated cities [42], which may help improve GTFEE. ② Economic development level ($pgdp$), represented by per capita GDP: during industrialization and urbanization, most cities in China still rely on extensive growth driven by industrial expansion, which may impede GTFEE improvement. ③ Financial development (fin), proxied by the ratio of total deposits and loans of financial institutions at year-end to GDP: cities with well-established financial institutions can broaden firms' financing channels and ease corporate financial constraints, which may help reduce energy consumption [12]. ④ Degree of openness (fdi), measured as the ratio of actually utilized foreign capital to GDP: FDI-induced spillovers along industrial chains exert positive effects on energy-saving technologies in China's industrial sector [10], which may help improve regional GTFEE. ⑤ Urbanization rate (urb), measured by the proportion of urban population in the total population: a higher urbanization rate can effectively reduce urban energy intensity by improving GTFEE in the transportation sector, transforming residents' consumption patterns and raising the utilization efficiency of public infrastructure [43]. ⑥ Government intervention (gov), measured as the ratio of local general budgetary expenditure to GDP: excessive government intervention distorts factor prices and leads to inefficient resource allocation [9], restraining energy efficiency growth.

4.3. Sample Selection and Data Sources

This study uses a balanced panel dataset covering 278 prefecture-level and above cities from 2007 to 2023 as the research sample. China launched the construction of economic development zones in 1984, and their expansion accelerated around 2000. Nevertheless, such expansion was accompanied by excessive construction, irrational structural layout and cut-throat competition among local governments. To tackle these problems, the Chinese government rolled out a nationwide rectification initiative covering all types of development zones in 2003. Numerous industrial parks that violated regulations or failed to meet approval criteria were revoked and consolidated, and this work was largely completed by the end of 2006. To exclude confounding disturbances stemming from the development zone rectification, we set 2007 as the initial year of our sample period. Among the 278 cities, 167 cities with established green industrial parks constitute the treatment group, while the remainder form the control group. The spatial distribution of the two groups is presented in Supplementary S2.

Data are sourced from the *China City Statistical Yearbook*, *China Energy Statistical Yearbook*, prefectural statistical yearbooks, and municipal economic and social development statistical bulletins. Nighttime light data are retrieved from the websites of the National Geophysical Data Center and the Earth Observation Group. For partial missing values, this paper adopts linear interpolation for data imputation. All continuous variables are log-transformed to alleviate potential heteroskedasticity. Descriptive statistics for variables are presented in Supplementary S3.

5. Empirical Results

5.1. Baseline Regression Results

Table 2 reports the baseline regression results of the impact of green industrial park construction on urban GTFEE. Column (1) only includes the explanatory variable. Columns (2) to (4) report the estimation results after sequentially adding city fixed effects, year fixed effects and control variables. All results indicate that the coefficient of *GPark* is significantly positive. Taking Column (4) as an example, cities with green industrial parks exhibit an 11.6% increase in GTFEE compared with those without such parks, which verifies Hypothesis 1.

Table 2. Baseline regression results.

Variable	(1) lnGTFEE	(2) lnGTFEE	(3) lnGTFEE	(4) lnGTFEE
GPark	0.119 *** (0.020)	0.298 *** (0.030)	0.119 *** (0.035)	0.116 *** (0.035)
lnpopu				0.306 (0.191)
lnpgdp				−0.127 (0.101)
lnfin				0.101 (0.086)
lnfdi				5.852 (5.344)
lnurb				0.215 ** (0.093)
lngov				−0.153 *** (0.068)
City	NO	YES	YES	YES
Year	NO	NO	YES	YES
N	4726	4726	4726	4726
R^2	0.005	0.429	0.711	0.714

Note: The standard errors in parentheses are based on city-level clustering. ** and *** indicate significance at the 5% and 1% levels, respectively.

5.2. Parallel Trend Test

The validity of DID estimates depends on the parallel-trend assumption for treated and control groups. Accordingly, this paper adopts an event-study specification to test this assumption.

$$\ln GTFEE_{it} = \alpha + \beta_k \sum_{k=-5}^{k=5} G\mathrm{Park}(k) + \theta \ln X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{2}$$

where *GPark* (k) denotes a set of dummy variables. *GPark* (-5) to *GPark* (-1) correspond to the 1st to 5th periods before the construction of the green industrial park; *GPark* (0) denotes the period in which green industrial parks are launched; *GPark* (1) to *GPark* (5) represent the 1st to 5th periods after green industrial park implementation. Other variables follow the definitions in Equation (1). To avoid multicollinearity, we take the year prior to policy implementation as the benchmark period. Figure 2 presents event-study plots, with full regression results in Supplementary S4. All coefficients use 95% confidence intervals. Prior to green industrial park construction, cities in the treatment and control groups exhibit no statistically significant disparities in GTFEE, thereby validating the parallel-trend assumption.

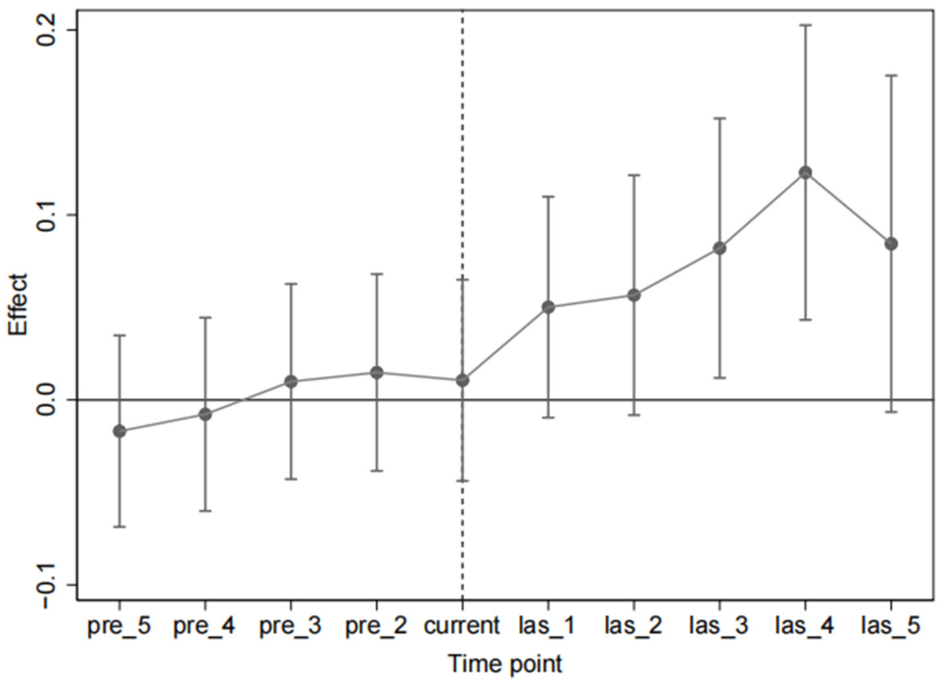

Figure 2. Parallel trend test results.

5.3. Robustness Test

① Placebo Test. To further eliminate the impact of unobserved random factors on policy evaluation, we conduct a placebo test [36]. The specific procedure is as follows: We randomly select 167 cities as the treatment group and randomly assign a policy implementation year to each selected city. This process is repeated 500 times, yielding 500 sets of policy dummy variables ($GPark^{random}$). We then replace $GPark$ in Equation (1) with $GPark^{random}$ for regression, and obtain 500 estimated coefficients β^{random}. Figure 3 illustrates the corresponding results. The estimated coefficients β^{random} of the pseudo policy variables are mostly distributed around zero, which differ markedly from the coefficient of 0.116 for the real policy variable $GPark$. This indicates that the baseline findings are not accidental. In addition, most p-values are greater than 0.1, indicating that the coefficients of most pseudo policy variables in the placebo test are statistically insignificant. To sum up, the improvement in urban GTFEE driven by green industrial park construction is not caused by other unobserved random factors, confirming the validity of our baseline findings.

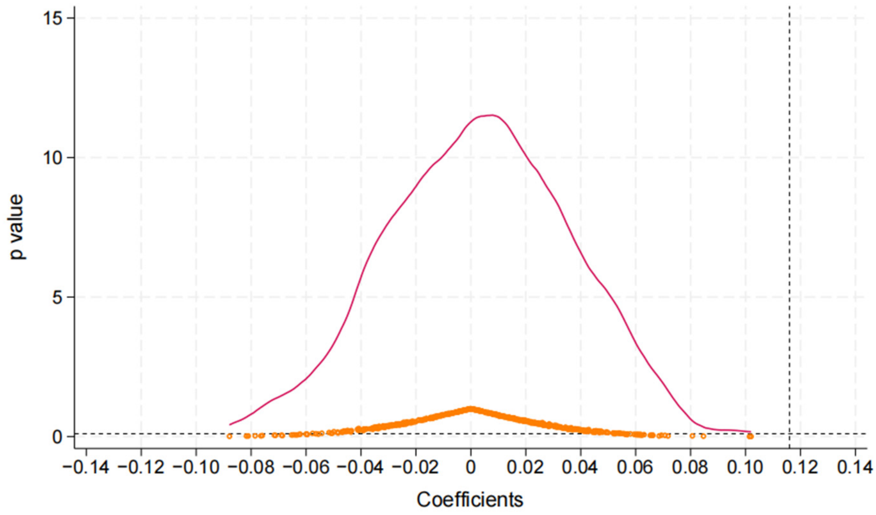

Figure 3. Placebo test results.

② Replace the explained variable. Existing studies suggest that modeling industrial urban energy consumption solely based on nighttime light data leads to overestimated statistical parameters [44]. To ensure the reliability of estimation results, we follow the approach of Gao and Yuan [45] and re-estimate total urban energy consumption by integrating nighttime light data and industrial structure data for subsequent regression analysis. Column (1) of Table 3 indicates that after replacing the dependent variable, the estimated coefficient remains significantly positive, which confirms the robustness of the findings.

Table 3. Robustness tests.

Variable	(1) Replace the Explained Variable	(2) PSM–DID	(3) Sun and Abraham	(4) Eliminate the Impact of Outliers	(5) Replace the Explanatory Variable	(6) Accounting for Anticipatory Effects	(7) First-Stage Regression of the IV Estimation	(8) Second-Stage Regression of the IV Estimation
GPark	0.092 *** (0.011)	0.078 ** (0.031)	0.282 *** (0.059)	0.100 *** (0.033)	0.112 *** (0.035)	0.104 *** (0.032)		0.217 ** (0.062)
anticipatory effects						0.041 (0.027)		
IV1							0.465 *** (0.018)	
KP LM statistic							193.726 ***	
KP-F statistic							193.646 <16.38>	
Control	YES	YES	YES	YES	YES	YES	YES	YES
City	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
N	4726	3516	4726	4658	4726	4726	4726	4726
R^2	0.808	0.726	0.723	0.717	0.714	0.694	0.572	0.731

Note: Figures within < > are critical values for the 10% significance level. ** and *** indicate significance at the 5% and 1% levels, respectively.

③ Use the multi-period PSM–DID model for estimation. Green industrial park construction may not constitute a fully randomized experiment, implying the existence of selection bias. To improve the robustness of the research, we adopt multi-period PSM-DID to mitigate the sample self-selection issue. Specifically, we take population density, economic development level, financial development level, degree of openness, urbanization and government intervention as matching variables, and set GTFEE as the outcome variable. We then match the data via kernel density matching and obtain the propensity score matched data for the period 2007–2023. Column (2) reveals that the coefficient sign and significance of *GPark* remain basically the same as those in the baseline regression. See the Supplementary S5 for the balance test results.

④ Account for heterogeneous treatment effects. Given that green industrial parks were constructed at different timings, which may induce heterogeneous treatment effects, this paper further adopts the approach proposed by Sun and Abraham (2021) for robustness checks [46]. The regression results in Column (3) show that the average treatment effect is significantly positive at the 1% statistical level, demonstrating that the baseline regression results of this paper are highly robust to potential bias arising from heterogeneous treatment effects.

⑤ Exclude the four provincial-level municipalities: Beijing, Shanghai, Tianjin and Chongqing. These cities are home to large interest groups with strong political influence. Their development often benefits from various policy dividends, tilted factor resources and institutional preferences beyond industrial park policies. To avoid bias in the baseline estimation results caused by data of the four municipalities throughout the sample period, we re-run the regression after excluding the observations of these four cities from the sample. The results in Column (4) confirm the robustness of the benchmark regression.

⑥ Replace the explanatory variable. The MIIT implements dynamic supervision over green industrial parks and revokes the qualifications of unqualified parks (according to successive circulars titled *Notice on Announcing the List of Green Manufacturing Entities* issued by the General Office of the MIIT, Taixing Economic and Technological Development Zone was removed from the green park list in 2018; three green industrial parks were also removed off the green manufacturing list in 2022, namely Laicheng Industrial Park in Shandong, Liuyang High-tech Industrial Development Zone and Futian Free Trade Zone). By 2023, four industrial parks had their official certifications revoked. To eliminate the impact of park qualification revocation on GTFEE, this paper excludes decertified parks from the sample and reruns regression estimations. The results in Column (5) show that there is no obvious change in the magnitude and statistical significance of the coefficient.

⑦ Accounting for anticipatory effects. The establishment of a green industrial park requires a period of preparation. Therefore, following the approach of Song et al. [47], we add a dummy variable for the year prior to the establishment of green industrial parks to Equation (1). The corresponding results are shown in Column (6). The coefficient of *GPark* remains significantly positive, and anticipatory effects exert no significant impact on urban GTFEE.

⑧ Mitigate endogeneity problems. The approval and establishment of green industrial parks may be affected by various latent confounding factors, which would bias the estimation results of the DID model. Accordingly, this paper constructs two instrumental variables to conduct endogeneity tests. First, following Liao [48], we construct an instrumental variable (IV1) for the establishment of green industrial parks, which is the interaction term between the historical industrial land share and the annual newly added number of green industrial parks in each prefecture-level city. The construction of industrial parks relies heavily on urban land planning and land supply conditions. Meanwhile, as a historical endowment, the base-year share of industrial land barely exerts a direct influence on contemporaneous GTFEE. Considering that historical land use data is time-invariant, this paper further incorporates the annual number of newly built green industrial parks in

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each city as an exogenous variable along the time dimension. Columns (7) and (8) show that the KP LM statistic rejects the null hypothesis of underidentification, and the KP-F statistic eliminates weak instrument concerns, confirming the validity of our instrumental variable. Second, we employ the instrumental variable method put forward by Duflo and Pande (2007) [49] to further validate the credibility of our findings. Detailed procedures and regression outputs are available in the Supplementary S6. All the above results demonstrate that after accounting for potential endogeneity issues, green industrial parks still significantly improve urban GTFEE, which confirms the robustness of the baseline regression results.

⑨ Rule out interference from contemporaneous policies. During the sample period adopted in this paper, five major policies were implemented that may affect urban GTFEE, including the Carbon Emissions Trading pilot policy (CET), Low-Carbon City pilot policy (LCC), New Energy Demonstration City pilot policy (NEDC), Comprehensive Financial Demonstration City for Energy Conservation and Emission Reduction pilot policy (ESER), and Smart City pilot policy (SMC). To eliminate the confounding effects of these policies, we add dummy variables for each of the above policies to Equation (1) for re-estimation. Columns (1)–(5) of Table 4 indicate consistent and robust results when the above policies are excluded.

Table 4. Robustness tests: Ruling out interference from contemporaneous policies.

Variable	(1) Exclude CET	(2) Exclude LCC	(3) Exclude NEDC	(4) Exclude ESER	(5) Exclude SMC
GPark	0.121 *** (0.035)	0.114 *** (0.035)	0.115 *** (0.035)	0.116 *** (0.035)	0.116 *** (0.034)
CET	0.157 ** (0.073)				
LCC		0.028 (0.038)			
NEDC			0.026 (0.050)		
ESER				0.016 (0.082)	
SMC					0.003 (0.045)
Control	YES	YES	YES	YES	YES
City	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES
N	4726	4726	4726	4726	4726
R^2	0.716	0.714	0.714	0.714	0.714

Note: ** and *** indicate significance at the 5% and 1% levels, respectively.

6. Mechanism Analysis

Based on the foregoing theoretical analysis, the construction of green industrial parks improves urban GTFEE through three channels: industrial agglomeration effect, green technological innovation effect and factor allocation effect. To further examine these transmission channels, this paper constructs a mediating effect model for mechanism examination following Lu et al. [50]. The model specification is shown in Supplementary S7.

6.1. Industrial Agglomeration Effect Test

This paper uses the number of employees per unit area to measure the level of industrial agglomeration ($lnAgg$). As shown in Column (1) of Table 5, the significantly positive coefficient on $GPark$ reveals that green industrial park construction has remarkably improved industrial agglomeration in host cities. The coefficient of $lnAgg$ in Column (2) is significantly positive, indicating that industrial agglomeration helps improve GTFEE. The coefficient of $GPark$ in Column (3) is significantly positive yet smaller than that in the baseline regression. This indirectly verifies the existence of the industrial agglomeration effect. The magnitude of this channel effect is calculated to be 0.00345 (0.010×0.345), accounting for 2.974% (0.00345/0.116) of the total effect. That is, the construction of green industrial parks elevates the level of urban industrial agglomeration and thereby improves urban GTFEE.

Table 5. Industrial agglomeration effect.

Variable	(1) lnAgg	(2) lnGTFEE	(3) lnGTFEE
GPark	0.010 ** (0.002)		0.114 *** (0.020)
lnAgg		0.345 *** (0.122)	0.344 *** (0.119)
Control	YES	YES	YES
City	YES	YES	YES
Year	YES	YES	YES
N	4726	4726	4726
R^2	0.932	0.713	0.715

Note: ** and *** indicate significance at the 5% and 1% levels, respectively.

6.2. Green Technology Innovation Effect Test

This paper adopts the number of urban green invention patent applications to characterize the level of urban green technology innovation ($lnTech$). As reported in Column (1) of Table 6, the coefficient on $GPark$ is positive and statistically significant at the 1% level, implying that the green industrial park construction can effectively stimulate enterprises in pilot cities to carry out green technology innovation. The coefficient of $lnTech$ in Column (2) is significantly positive, which demonstrates that green technological innovation effectively boosts GTFEE. The coefficient of $GPark$ in Column (3) stands at 0.112, lower than the coefficient in the baseline regression, indirectly confirming the existence of the green technological innovation effect. The magnitude of this channel effect is calculated to be 0.005 (0.072 $\times$ 0.066), accounting for 4.310%(0.005/0.116) of the total effect.

Table 6. Green technology innovation effect.

Variable	(1) lnTech	(2) lnGTFEE	(3) lnGTFEE
GPark	0.072 *** (0.025)		0.112 *** (0.020)
lnTech		0.066 *** (0.010)	0.064 *** (0.010)
Control	YES	YES	YES
City	YES	YES	YES
Year	YES	YES	YES
N	4726	4726	4726
R^2	0.933	0.714	0.717

Note: *** indicate significance at the 1% levels, respectively.

6.3. Factor Allocation Effect Test

Following Lei et al. [51], we first calculate the relative price distortion coefficients of capital and labor. After subtracting one and taking absolute values, we derive the capital mismatch index ($Kmis$) and labor mismatch index ($Lmis$). Higher values imply greater factor misallocation.

Columns (1)—(3) of Table 7 present the estimation results for the capital allocation effect. $GPark$ is significantly negative, implying green industrial parks markedly mitigate urban capital misallocation. This may stem from local governments prioritizing the introduction of capital-intensive enterprises to pursue short-term economic growth, which results in excessive capital concentration in low-end industries and creates industrial structural lock-in. The construction of green industrial parks guides capital flows from high-pollution and low-efficiency sectors to clean and efficient counterparts by introducing high-tech enterprises and green factories, thereby alleviating capital misallocation and unlocking structural dividends. The coefficient of lnKmis in Column (2) is significantly negative, revealing that mitigating capital misallocation serves as a vital driver for the improvement of GTFEE. The coefficient of *GPark* in Column (3) is smaller than that in the baseline regression. The magnitude of this channel effect is calculated to be 0.003 ($-0.186 \times (-0.018)$), accounting for 2.586% (0.003/0.116) of the total effect. This indicates that the construction of green industrial parks can improve GTFEE by alleviating capital misallocation.

Table 7. Factor allocation effect.

Variable	**(1) lnKmis**	**(2) lnGTFEE**	**(3) lnGTFEE**	**(4) lnLmis**	**(5) lnGTFEE**	**(6) lnGTFEE**
GPark	−0.186 ** (0.042)		0.110 *** (0.020)	0.012 (0.082)		0.116 *** (0.035)
lnKmis		−0.018 ** (0.007)	−0.016 ** (0.007)			
lnLmis					0.016 (0.011)	0.016 (0.011)
Control	YES	YES	YES	YES	YES	YES
City	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	4726	4726	4726	4726	4726	4726
R^2	0.704	0.711	0.713	0.665	0.712	0.715

Note: ** and *** indicate significance at the 5% and 1% levels, respectively.

Columns (4)–(6) present the results for the labor allocation effect. *GPark* is positive but statistically insignificant, indicating that the green industrial parks fail to effectively alleviate urban labor misallocation. A possible explanation is that the development of green industrial parks is accompanied by the rise of emerging industries and the phase-out of outdated industries. This leads to an imbalance between labor supply and demand in the short run, which hinders the optimal allocation of regional labor resources [37].

7. Extended Analysis

7.1. Heterogeneity Test

7.1.1. Geographic Location Heterogeneity

China covers a vast territory, and cities in different geographic regions differ substantially in economic and social characteristics. Accordingly, the energy efficiency improvement effect of green industrial parks may vary across cities in different regions. Table 8 reports the regression results stratified by geographical heterogeneity. The results reveal that green industrial park construction significantly improves GTFEE in eastern and western cities, and such beneficial effect is stronger in the west, whereas no meaningful effect emerges in central China.

Table 8. Heterogeneity across geographic regions.

Variable	**(1) The Eastern Region**	**(2) The Central Region**	**(3) The Western Region**
GPark	0.098 * (0.053)	0.070 (0.049)	0.156 ** (0.063)
Control	YES	YES	YES
City	YES	YES	YES
Year	YES	YES	YES
N	1683	1700	1343
R^2	0.748	0.753	0.710

Note: * and ** indicate significance at the 10% and 5% levels, respectively.

The eastern region has a solid industrial base and sound green governance system. Its GTFEE is relatively high, with little marginal room for GTFEE improvement from green industrial park construction. Western regions possess distinctive natural and environmental advantages for green low-carbon development. With powerful national policy backing, they can speed up local green transformation via the development of green industrial parks. By contrast, most indigenous enterprises in central China are heavy industrial and high energy-consuming firms with heavy fossil energy dependence, weakening the positive contribution of green technological innovation to environmental efficiency [52]. Meanwhile, this region suffers from an obvious unbalanced distribution of city sizes, which hinders cross-regional factor mobility and triggers resource misallocation, particularly capital misallocation [53]. Consequently, the GTFEE enhancement effect of green industrial park construction has not yet materialized in central China.

7.1.2. Park Quantity and Rank Heterogeneity

To explore the impact of green industrial park quantity on local GTFEE, we follow Liu et al. [54] and replace the original core explanatory variable with the number of green industrial parks. Table 9 Column (1) reports the results. The quantity of green industrial parks shows a significant positive impact on local GTFEE. Furthermore, we classify cities into three categories to examine the heterogeneity in park number: zero-park cities, cities with seven or fewer parks, and cities with over seven parks. Columns (2)–(4) present the results of grouped regressions. Cities with seven or fewer parks show significant economic growth relative to zero-park cities, though the statistical significance is modest. Notably, cities with more than seven green industrial parks achieve a stronger improvement in energy efficiency than those with seven or fewer. Meanwhile, cities with more than seven green industrial parks exhibit significantly higher energy efficiency than those without green industrial parks. The above results confirm that when the number of green parks within a city surpasses a certain threshold, the beneficial effect of green industrial parks on GTFEE will be markedly strengthened.

Table 9. Heterogeneity in quantity and administrative level of green industrial parks.

Variable	(1) Park Quantity	(2) Seven or Fewer Parks vs. Without Parks	(3) More than Seven Parks vs. Seven or Fewer Parks	(4) More than Seven Parks vs. Without Parks	(5) National-Level Industrial Parks	(6) Provincial-Level Industrial Parks
GPark	0.072 ***	0.056 **	0.644 ***	0.777 ***	0.061 ***	0.093 ***
	(0.022)	(0.029)	(0.225)	(0.238)	(0.020)	(0.032)
Control	YES	YES	YES	YES	YES	YES
City	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
N	4726	4658	2856	1938	3451	2754
R^2	0.716	0.771	0.780	0.766	0.764	0.760

Note: ** and *** indicate significance at the 5% and 1% levels, respectively.

Given that most green industrial parks are upgraded from national or provincial industrial parks, we conduct two separate group analyses to explore the impacts of green industrial parks at different administrative levels on GTFEE. First, for the group consisting of green industrial parks upgraded from national-level industrial parks, we identify 203 cities that host national-level industrial parks. Among them, the 115 cities whose national-level industrial parks have been upgraded to green industrial parks constitute the treatment group, while the remaining cities form the control group. Next, for the group consisting of green industrial parks upgraded from provincial industrial parks, we reconstruct the analytical sample. Within the full sample, we exclude all cities with green industrial parks upgraded from national or municipal industrial parks. The final sample consists of 162 cities. Among them, provincial-level industrial parks in 51 cities have been upgraded to green industrial parks. The results in Columns (5) and (6) show that green industrial parks upgraded from either national-level or provincial-level industrial parks can improve urban GTFEE, and the impact is more pronounced for those upgraded from provincial-level industrial parks. Wang and Liu [55] draw similar conclusions. A possible explanation is that, compared with national-level industrial parks, provincial counterparts are set up largely to cater to local government competition. Accordingly, provincial-level industrial park policies are better tailored to local realities and enjoy strong implementation adaptability. The technological spillovers, industrial agglomeration optimization, and environmental governance dividends brought about by their green transformation can spread more rapidly across the entire region.

7.1.3. Regional Development Characteristics Heterogeneity

The level of human, capital and physical resources in a city exerts a crucial impact on the energy efficiency improvements of green industrial parks. In particular, against the trend of integrated green and digital development, and close university–industry cooperation, targeted capital allocation and new infrastructure construction exert profound impacts on regional innovation quality, factor allocation and technological upgrading, thereby affecting regional energy efficiency. Accordingly, this section examines the heterogeneous effects of green industrial park construction on the improvement of urban GTFEE from the perspective of urban characteristics including industry–university–research collaboration, green finance and digital infrastructure. Following Wang and Liu [56], this paper adopts the green finance index to measure the development level of green finance. The level of urban industry–university–research cooperation is measured by the number of regional general institutions of higher education [57]. Meanwhile, digital infrastructure is quantified by the proportion of keywords linked to new digital infrastructure [58]. Specifically, cities are divided into two groups according to the annual medians of green finance, university quantity and digital infrastructure level: the top half belongs to the high group, and the bottom half to the low group.

Table 10 reports the estimation results. Columns (1) to (2) show that green industrial parks significantly improve urban GTFEE in both high- and low-green-finance groups, with a larger promoting effect observed for cities with advanced green finance development. This indicates that a higher level of green finance helps strengthen the improvement effect of green industrial parks on urban GTFEE. Columns (3)–(4) indicate that green industrial parks exert a significantly positive impact on GTFEE in regions abundant in universities, whereas no significant effect is observed in regions with fewer higher education institutions. This indicates that close cooperation between enterprises, universities and research institutions helps boost the energy efficiency gains of green industrial parks. Columns (5) and (6) show that green industrial parks effectively improve urban GTFEE in both high- and low-digital-infrastructure groups, with a more pronounced effect in the low group. One plausible explanation is that the network effects of digital infrastructure can break sectoral barriers and information silos, facilitate the integration and sharing of resources, and provide solid support for green industrial park construction and the improvement of regional energy efficiency. Nevertheless, digital infrastructure itself carries no inherent green attributes, and its rapid expansion is accompanied by substantial energy consumption arising from data transmission, storage, computation, and data center operation [59]. Therefore, in regions with advanced digital infrastructure, the energy efficiency gains generated by green industrial parks are largely offset by the high energy consumption inherent to such infrastructure. This suggests that China has not yet achieved a pattern of coordinated development between digitalization and greenization.

Table 10. Heterogeneity of regional development characteristics.

Variable	(1) High Green Finance	(2) Low Green Finance	(3) High Number of Regular Universities	(4) Low Number of Regular Universities	(5) High Digital Infrastructure	(6) Low Digital Infrastructure
GPark	0.141 ***	0.106 **	0.073 *	0.066	0.074 *	0.132 ***
	(0.052)	(0.041)	(0.040)	(0.058)	(0.043)	(0.043)
Control	YES	YES	YES	YES	YES	YES
City	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES
Chow test	5.74 (0.003)		23.5 (0.000)		11.56 (0.000)	
N	2334	2351	2668	2050	2355	2353
R^2	0.692	0.739	0.761	0.720	0.720	0.739

Note: The Chow test F-statistic is adopted for inter-group difference tests; *p*-values are shown in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

7.2. Spatial Spillover Effect Test

As spatial carriers of enterprise agglomeration and highlands for policy institutions, green industrial parks can boost the urban GTFEE of host cities, while possibly generating impacts on surrounding cities. However, under the Stable Unit Treatment Value Assumption, the conventional DID model can only capture the policy effects on independent individual units, ignoring the impacts of policy shocks on surrounding regions, which is inconsistent with practical realities. Therefore, following the research of Liu et al. [60], this paper constructs an SDID model to evaluate the spatial spillover effects of green industrial park construction, which, to a certain extent, mitigates the estimation bias caused by the neglect of spatial correlations across regions in the conventional DID model. Given the geographic interactions among regions, this paper establishes an SDID model based on the n-th order nearest neighbor matrix:

$$\ln GTFEE_{it} = \alpha + (\beta + \gamma W^n) GPark_{it} + \rho W^n \times \ln GTFEE_{it} + \theta \ln X_{it} + \mu_i + \nu_t + \varepsilon_{it} \tag{3}$$

$$\begin{aligned} \ln GTFEE_{it} = \alpha + \beta GPark_{it} + \gamma_1 W^n_{TT} \times GPark_{it} + \gamma_2 W^n_{NTT} \times GPark_{it} \\ + \rho W^n \times \ln GTFEE_{it} + \theta \ln X_{it} + \mu_i + \nu_t + \varepsilon_{it} \end{aligned} \tag{4}$$

In Equation (3), W^n denotes the n-th order nearest-neighbor spatial weight matrix. For city i, its neighbors are defined as the n geographically closest regions. The element takes a value of 1 if two regions are neighbors, and 0 otherwise. $W^n \times lnGTFEE$ is the spatial lag of GTFEE, while $W^n \times GPark$ stands for the spatial lag of green industrial parks. β refers to the average direct treatment effect of green industrial parks on local GTFEE. γ denotes the spatial spillover effect of green industrial parks, namely the average indirect treatment effect.

Given potentially heterogeneous spillover effects of green park construction on adjacent treated and control groups, this study follows Chagas et al. [61] to decompose the spatial weight matrix. The matrix W^n is divided into four parts: W^n_{TT} (impacts within the treatment group), W^n_{NTT} (impacts from the treatment group to the control group), W^n_{TNT} (impacts from the control group to the treatment group), and W^n_{NTNT} (impacts within the control group). The calculations show that only the terms $W^n_{TT} \times GPark$ and $W^n_{NTT} \times GPark$ are kept in Equation (4). Full formula derivations appear in Supplementary S8. γ_1 and γ_2 capture the average indirect treatment effects on neighboring cities of the treatment group and the control group, respectively (*GPark_TT*, *GPark_NTT*). To verify result robustness, we re-estimate the model with adjacency and economic–geographic weight matrices, with results reported in Supplementary S9.

Table 11 presents the estimation results derived from the spatial DID model. We consider eight nearest-neighbor matrices of the 2nd through 9th order and determine the optimal matrix based on AIC and BIC [61]. As the two criteria are minimized at the 5th order, our analysis centers on the results in Column (4). *GPark* captures the average direct treatment effect in cities hosting green industrial parks. The significantly positive coefficient suggests that green industrial parks exert a prominent promoting effect on regional GTFEE. The estimation results of *GPark_NTT* and *GPark_TT* reveal that the construction of green industrial parks is not conducive to the improvement in GTFEE in surrounding regions. The underlying reasons can be summarized into the following two aspects. First, the green attributes of park construction require substantial financial support and professional talent for initial operation and long-term maintenance. Second, pilot regions may provide policy support including fiscal subsidies, tax incentives and talent introduction schemes to smoothly advance the construction of green industrial parks, which further intensifies the siphon effect of production factors on surrounding areas. Compared with *GPark_NTT*, *GPark_TT* is more significant. A possible explanation is that regions with green industrial parks engage in excessive competition and fall into a prisoner's dilemma.

Table 11. Test for spatial spillover effects of green industrial parks.

Variable	(1) W2	(2) W3	(3) W4	(4) W5	(5) W6	(6) W7	(7) W8	(8) W9
GPark	0.124 ***	0.148 ***	0.100 ***	0.099 ***	0.099 ***	0.121 ***	0.101 ***	0.107 ***
	(0.024)	(0.026)	(0.026)	(0.027)	(0.027)	(0.028)	(0.029)	(0.029)
GPark_TT	−0.031 **	−0.037 ***	−0.018 *	−0.015 **	−0.009	−0.012 *	−0.006	−0.004
	(0.015)	(0.011)	(0.009)	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)
GPark_NTT	−0.002	0.002	−0.017 *	−0.015 *	−0.009	−0.004	−0.003	−0.001
	(0.015)	(0.011)	(0.010)	(0.008)	(0.007)	(0.006)	(0.006)	(0.005)
ρ	0.144 ***	0.123 ***	0.118 ***	0.105 ***	0.091 ***	0.076 ***	0.069 ***	0.063 ***
	(0.008)	(0.006)	(0.005)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)
Control	YES	YES	YES	YES	YES	YES	YES	YES
City	YES	YES	YES	YES	YES	YES	YES	YES
Year	YES	YES	YES	YES	YES	YES	YES	YES
AIC	1665.218	1559.955	1399.348	1309.935	1316.877	1372.495	1353.37	1351.889
BIC	1736.288	1631.024	1470.417	1381.004	1387.946	1443.564	1424.439	1422.958
N	4726	4726	4726	4726	4726	4726	4726	4726
R^2	0.738	0.744	0.752	0.757	0.756	0.754	0.755	0.755

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

8. Conclusions and Policy Recommendations

This study first applies the super-efficiency SBM model to measure GTFEE. Next, using panel data for 278 cities over the period 2007–2023, we apply the multi-period DID and spatial DID models to examine the impacts, transmission mechanisms and spatial spillover effects of industrial park green transformation policies, which are represented by green industrial parks, on urban GTFEE. The main findings are as follows.

First, green industrial parks can significantly improve urban GTFEE. Industrial agglomeration, green technological innovation and optimized capital allocation serve as the corresponding transmission channels.

Second, heterogeneity analysis shows that green industrial park construction yields larger GTFEE gains for cities in eastern and western China, as well as those with abundant green industrial parks, advanced green finance, ample general higher education institutions, and underdeveloped digital infrastructure. Compared with national-level industrial parks, provincial ones transformed into green industrial parks exert a stronger positive effect on GTFEE.

Third, from the perspective of spatial spillovers, green industrial park construction exerts a significant positive impact on local GTFEE, yet creates pronounced negative spatial spillovers across adjacent cities with green industrial park construction.

The conclusions of this study provide valuable implications for formulating targeted strategies to improve urban GTFEE, amplifying the demonstration effect of industrial park green park transformation, and advancing green development of parks and regional economies.

First, strengthen policy support for green industrial park construction and prioritize the central region. This research verifies that green industrial parks contributes to the enhancement of local GTFEE. Therefore, the central government should systematically summarize and promote the experience of pilot cities, guide cities without green industrial parks to accelerate their application and construction, and expand the policy coverage. Notably, compared with eastern and western China, green parks in the central region are fewer in number and geographically dispersed, yielding no statistically meaningful effect on urban GTFEE. Local governments can strengthen green financial support and deepen industry–university–research collaborative innovation to accelerate the green transformation of industrial parks within their jurisdictions.

Second, adopt multiple measures to unblock the channels through which green industrial parks improve urban GTFEE. Specifically, for the optimization of capital allocation, improve market mechanisms and accelerate the free flow of factors. Meanwhile, guide capital into green industries and high-end manufacturing with efficient resource utilization via green credit, green bonds and other instruments. In terms of green technological innovation, local governments shall foster close ties between enterprises and research institutions such as universities and institutes, and establish methods to enhance innovation quality. In terms of industrial agglomeration, local governments shall offer scientific guidance and regulation. Use preferential policies to attract new enterprises with strong relevance and complementarity to existing firms, improve industrial chains within parks, and strengthen input–output linkages among enterprises.

Third, establish a cross-regional cooperation mechanism linking green industrial park development and the improvement of regional GTFEE. On the one hand, the central government should strengthen top-level design, implement differentiated regional strategies, and raise the assessment weight of cross-regional collaborative development. Local governments should foster distinctive leading green industries based on long-term development goals and local resource endowments, and effectively avoid homogeneous construction, duplicated layout and cut-throat competition among green industrial parks. On the other hand, local governments should establish platforms for information and resource exchange and cooperation to smooth the flow of production factors. Through cross-regional technology transfer, joint scientific research and talent mobility, cities without green industrial parks or with weak foundations for green development can optimize resource allocation and upgrade green technology systems.

Although this study yields certain theoretical and practical implications, it still has several limitations. First, this study evaluates the policy effects of green industrial park construction based on city-level data. However, green industrial parks are mostly located in districts and counties within municipal administrative regions, and firms act as the primary behavioral agents. Exclusive adoption of city-level data for empirical regression may lead to biased estimation results. Future research can further adopt district–county and firm-level data to explore the micro mechanisms through which green industrial park construction affects GTFEE. Second, as official municipal energy consumption figures are unavailable, this study estimates total urban energy consumption by integrating provincial aggregate energy consumption and nighttime light data [62]. Although multiple robustness tests are conducted to verify the reliability of the estimation results, the accuracy of relevant conclusions can be further improved if more precise energy consumption data become available in the future. Third, this study only focuses on green industrial park construction as a single policy, without comprehensively investigating the interactive impacts of other simultaneous industrial policies. From the perspective of multi-policy synergy, future research can further explore the superimposed effects and interactive mechanisms across different policies.

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