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A Study on the Impact of Industrial Synergistic Agglomeration on Urban Green Total Factor En-ergy Efficiency: Evidence from China

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Abstract

This study investigates the impact of industrial synergistic agglomeration on urban green total factor energy efficiency (GTFEE), taking Chinese prefec-ture-level cities as the research sample. Based on panel data from 2010 to 2020, a fixed effects model is constructed to empirically examine the relationship, while further exploring the mediating role of technological innovation and the heterogeneous effects of urban location. The results show that industrial syner-gistic agglomeration significantly improves urban GTFEE, with part of this effect transmitted through enhanced technological innovation. These findings remain robust across multiple sensitivity tests. Heterogeneity analysis reveals that the positive effects are more pronounced in eastern and southern cities, indicating that locational factors play a moderating role in the effectiveness of agglomera-tion. Policy implications suggest that regionally differentiated development strategies should be adopted based on local conditions. Strengthening techno-logical innovation and promoting coordinated development across the eastern, central, and western regions are essential to advancing the green and low-carbon transition.

Keywords

Industrial Synergistic Agglomeration; Urban Green Total Factor Energy Efficiency; Manufacturing Industry; Producer Services

1. Introduction

In recent years, as China has entered a new stage of high-quality development, constraints related to resources and the environment have become increasingly prominent, rendering the traditional extensive growth model unsustainable. Guided by the national strategic goals of “carbon peaking” and “carbon neutrality,” improving energy efficiency and promoting green, low-carbon transformation have emerged as core issues in regional economic development in the new era. Among relevant indicators, Green Total Factor Energy Efficiency (GTFEE) has attracted growing attention. As a comprehensive metric that considers energy inputs, economic outputs, and environmental emissions, GTFEE provides a critical gauge for evaluating both energy use efficiency and environmental coordination, and has become a key indicator of green development.

Meanwhile, China's continuing urbanization and industrialization have led to profound changes in the pattern of industrial agglomeration. Traditional single-industry agglomeration models have revealed several shortcomings, including short industrial chains, low resource allocation efficiency, and concentrated environmental pollution. In contrast, the emerging model of industrial synergistic agglomeration emphasizes inter-industry connectivity, complementarity, and coordinated collaboration. This model not only promotes urban economic growth, resilience, industrial upgrading, and technological innovation [1], but also enhances resource sharing and ecological efficiency at a broader scale, increasingly serving as a critical driver of green urban transformation [2].The Chinese government has placed high importance on integrating regional coordination with ecological civilization.

Nevertheless, existing studies on GTFEE primarily focus on individual cities or provincial-level regions, and are largely limited to traditional explanatory perspectives such as technological progress [3], the intensity of environmental regulation [4], and industrial structure evolution [5]. Research that systematically examines industrial synergistic agglomeration, a more complex and integrated form of industrial organization, remains limited. The internal mechanisms, potential effects, and regional heterogeneity between such agglomeration and green efficiency are still underexplored. On the one hand, synergistic agglomeration may enhance green efficiency through mechanisms such as infrastructure sharing, transportation cost reduction, green technology diffusion, and scale-related energy savings. On the other hand, it may also pose new environmental risks due to mismatched industrial coupling, increased energy dependence, or spatial misallocation.

Therefore, this paper focuses on the prefecture-level city scale in China and constructs a multidimensional index of industrial synergistic agglomeration. GTFEE is measured using a Slack-Based Measure–Global Malmquist–Luenberger (SBM–GML) model with undesirable outputs. The study aims to reveal the dynamic relationship and underlying mechanisms between industrial synergistic agglomeration and GTFEE. Furthermore, it examines the heterogeneous effects under varying regional development foundations and policy environments, offering both theoretical insights and practical implications for formulating green industrial policies and optimizing regional collaboration strategies at the urban level.

2. Literature Review

As a critical metric for evaluating both energy use efficiency and environmental performance, Green Total Factor Energy Efficiency (GTFEE) has attracted widespread attention from scholars domestically and internationally in recent years. Early studies primarily employed methods such as Data Envelopment Analysis (DEA)

[6] and Stochastic Frontier Analysis (SFA) [7] to measure energy efficiency, but often failed to fully account for undesirable outputs such as environmental pollution. With the advancement of DEA models incorporating undesirable outputs, the Slack-Based Measure (SBM) model proposed by Tone (2001) [8] has been widely adopted in measuring green efficiency, significantly enhancing the accuracy of efficiency evaluation. In recent years, researchers have continuously expanded the measurement framework of GTFEE. For instance, Chen (2019) integrated the super-efficiency SBM model with the Malmquist-Luenberger index to examine the spatial-temporal evolution of inter-provincial energy efficiency in China, identifying environmental regulation and technological progress as key drivers of green efficiency improvement [9]. Wang et al. (2017), from an urban perspective, constructed a comprehensive input-output framework that includes energy, capital, labor, and pollution emissions[10], highlighting the influence of city development stages on green efficiency.

Existing literature mainly investigates the influencing factors of green energy efficiency from three dimensions. First, technological advancement and innovation capacity—particularly green technological innovation—are regarded as core drivers of GTFEE enhancement [11]. Second, environmental regulations and policy instruments—such as emissions trading schemes and energy-saving target assessments—are seen to promote technological upgrades and efficiency improvements through “pressure-induced mechanisms” [12] Third, industrial structure optimization and factor allocation efficiency are crucial, as a rational industrial structure helps reduce energy intensity and improve resource utilization [13]. However, most studies have focused on technological, regulatory, and structural aspects, with limited systematic analysis of industrial organization forms—especially the impact of inter-industry collaboration on energy efficiency.

Industrial agglomeration is a key topic in regional economics and new economic geography. According to Marshall’s (1890) theory of external economies, agglomeration improves efficiency through technology diffusion, market sharing, and specialization [14]. Industrial collaborative agglomeration refers to the spatial concentration of heterogeneous but complementary industries within a specific geographic area, forming a value network characterized by interdependence and resource complementarity through close collaboration and interaction. Compared to traditional industrial agglomeration, the distinguishing feature of collaborative agglomeration lies in the deep cooperation and integrated development among interrelated industries with strong linkages. In this context, enterprises across different sectors form closely knit networks, building an efficient industrial ecosystem through complementary advantages and shared resources. Unlike general agglomeration, collaborative agglomeration emphasizes vertical (upstream-downstream) and horizontal (cross-sector) integration and innovation [15].

Industrial collaborative agglomeration not only fosters high-quality urban economic development [16], but also significantly promotes innovation [17] and green development [18]. It helps reduce regional carbon emission intensity and influences regional GTFEE [19], with evident spatial spillover effects and regional heterogeneity [20].

Despite these developments, direct investigations into the relationship between industrial collaborative agglomeration and green total factor productivity remain limited. Some scholars have identified an inverted U-shaped effect of collaborative agglomeration between high-tech industries and producer services on green total factor productivity, indicating the existence of an optimal level of agglomeration [21]. Theoretically, the mechanisms through which collaborative agglomeration promotes green productivity are mainly through reducing operational costs, improving resource allocation efficiency, and stimulating technological innovation [22]. In terms of spatial effects, studies confirm that collaborative agglomeration not only enhances local green productivity but also generates significant positive spillovers to surrounding cities [23], with these effects varying across industries. For example, studies on urban agglomerations show that industrial collaborative agglomeration in the Yangtze River Delta significantly promotes green productivity, with clear heterogeneity across sectors .

In summary, although the current literature has extensively explored the measurement methods and influencing factors of GTFEE and the concept of industrial collaborative agglomeration is becoming increasingly well-defined, systematic research on the impact of collaborative agglomeration on green efficiency remains underdeveloped. There is a notable lack of large-sample empirical studies at the city level. Therefore, this paper builds on existing research by constructing an industrial collaborative agglomeration index system for Chinese prefecture-level cities, measuring GTFEE using the undesirable-output SBM model, and further employing panel data models to examine the causal relationship and underlying mechanisms between the two. The findings aim to provide both theoretical insights and empirical evidence to support regional development policies under the framework of green transformation[24].

3. Mechanism Analysis

3.1. The direct impact of industrial collaborative agglomeration on green total factor energy efficiency

Green total factor energy efficiency (GTFEE) comprehensively considers inputs such as energy, capital, and labor, as well as the relationship between economic output and pollutant emissions. It serves as a key indicator for evaluating the greenness of economic development [26]. Against the backdrop of green transformation, improving GTFEE has become a critical task for sustainable urban development. As a new form of agglomeration, industrial collaborative agglomeration addresses the problems of industrial hollowing-out and negative environmental externalities often associated with traditional homogeneous industrial clusters [25]

Specifically, the impact pathways of industrial collaborative agglomeration on GTFEE are reflected in three main aspects:

First, collaborative agglomeration facilitates optimal resource allocation and coordinated production through specialization and cooperation among enterprises, thereby reducing energy input per unit of output and improving production efficiency [27].Second, interactions among different industries accelerate the spillover and diffusion of technologies, promoting the rapid dissemination and application of green technologies and energy-saving equipment across sectors, which enhances overall green productivity [28].Third, collaborative agglomeration enables integrated planning and pollution control at the regional level—such as shared wastewater treatment systems and waste heat recovery facilities—effectively lowering the marginal cost of environmental governance and improving emission control efficiency [29].

Existing studies have shown that the deep integration of manufacturing and services can optimize the energy structure and improve energy use efficiency. A coordinated multi-industry layout at the regional level can also alleviate resource and environmental pressures. Therefore, this study proposes the following hypothesis regarding the direct effect:

Hypothesis 1: Industrial collaborative agglomeration has a significant positive impact on urban green total factor energy efficiency.

3.2. The Mechanism of Technological Innovation

Existing studies suggest that industrial collaborative agglomeration enhances regional technological innovation capacity by facilitating knowledge exchange and resource sharing. Polanyi argued that tacit knowledge is primarily transmitted through face-to-face interaction, and collaborative agglomeration provides a favorable environment for such exchanges. As a result, some scholars have found that collaborative agglomeration strengthens tacit knowledge spillovers and promotes technological innovation [30]. At the same time, competitive pressure among industries within agglomerations drives firms to accelerate the development of green technologies to maintain competitive advantage [31]. However, excessive agglomeration may lead to congestion effects and path dependency, which can suppress innovation activities [32]. Therefore, industrial collaborative agglomeration exerts a dual effect on technological innovation.

Technological innovation is a core driving force for achieving green transformation. According to endogenous growth theory and the Porter Hypothesis, technological progress—particularly green innovation—can improve resource use efficiency, while also reducing pollutant emissions through product substitution and process improvements, thereby achieving a win–win outcome for both the economy and the environment. In a collaborative agglomeration environment, firms are more likely to access knowledge and information resources from other industries, forming a symbiotic knowledge environment that promotes the generation and application of new technologies. Upstream and downstream enterprises, or related sectors, are more likely to establish joint R&D platforms, share innovation risks and costs, and accelerate the development cycle of green technologies . In addition, local governments often introduce supportive innovation policies alongside collaborative agglomeration strategies, such as establishing shared technology platforms and offering subsidies for green innovation. These mechanisms contribute to enhancing regional technological innovation capacity, which in turn promotes green total factor energy efficiency through cleaner production, energy substitution, and energy-saving technological upgrades. Therefore, this study further proposes the following mechanism-based hypothesis:

Hypothesis 2: Technological innovation plays a partial mediating role in the relationship between industrial collaborative agglomeration and green total factor energy efficiency.

4. Research Design

4.1. Model Construction

To empirically test Hypothesis H1, a baseline panel regression model is constructed, as shown in Model (1).

$$GTFEE_{it} = a_0 + a_1 COAGG_{it} + \sum a_x Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{1}$$

In Model (1), GTFEE is the dependent variable, representing the green total factor energy efficiency. COAGG is the core explanatory variable, denoting the industrial collaborative agglomeration index between the manufacturing and producer services sectors. Controlrepresents a set of control variables. $\alpha_0$is the constant term, $\mu_i$captures city fixed effects, $\lambda_t$captures year fixed effects, and ε_{it} is the stochastic error term. α_1 and α_x are parameters to be estimated. The subscript i denotes city i, and t denotes year t.

To examine the mechanism through which industrial collaborative agglomeration affects urban green total factor energy efficiency, the following mediation effect models are constructed to test Hypothesis H2.

$$INN_{it} = \beta_0 + \beta_1 \cdot DID_{it} + \sum \beta_x \cdot Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \tag{2}$$

In Model (2), the variable represents the mediating variable technological innovation. $\beta_0$is the constant term, and β_1 is the coefficient to be estimated. The definitions of the remaining variables are the same as in Model (1).

4.2. Data Sources

In this study, due to the unavailability of certain key data, the time span is restricted to the period from 2010 to 2020. Accordingly, the analysis is based on panel data from 259 prefecture-level cities in China during 2010–2020. The primary data sources include the China City Statistical Yearbook and the China Statistical Yearbook.

4.3. Variable Description

（1）Core Explanatory Variable

The industrial collaborative agglomeration index (COAGG) serves as the core explanatory variable in this study. Following the approach of Yang (2013), this index is measured using an entropy-based method that captures the employment distribution between the producer services sector and the manufacturing sector. The specific method is as follows: first, the agglomeration index for each of the two industries is calculated separately using Equation (3).

$$agg_{it} = (E_{ij}/E_j)/(E_i/E) \tag{3}$$

In Equation (3), E_{ij} denotes the number of employees in industry j in region i in a given year, where j represents the producer services sector (m) and the manufacturing sector (n). E_i represents the total employment in region i in that year, E_j denotes the total employment in industry j nationwide, and E refers to the total employment across all industries in the country in that year. After calculating the agglomeration index for each of the two industries separately, Equation (4) is used to compute the industrial co-agglomeration index between the two sectors.

$$COAGG_{it} = 1 - |agg_{it}^m - agg_{it}^n|/(agg_{it}^m + agg_{it}^n) \tag{4}$$

The specific data for producer services and manufacturing are measured using the “number of employees at year-end by industry” from the statistical yearbooks[33].

（2）Dependent Variable

Green Total Factor Energy Efficiency (GTFEE) is the dependent variable in this study. GTFEE is adopted as the evaluation standard due to its broader applicability compared to traditional single-factor energy efficiency metrics. By constructing an SBM–GML model that incorporates undesirable outputs, this study provides a more accurate measurement and assessment of GTFEE across cities.

In terms of indicator selection, this study follows the approach of Zhang et al.[34]to develop a comprehensive indicator system for evaluating the GTFEE of prefecture-level cities. The system includes three input variables: labor, capital, and energy input. Real GDP is set as the desirable output variable, while four undesirable output variables are incorporated: industrial sulfur dioxide emissions, industrial wastewater discharge, industrial dust (or particulate matter) emissions, and carbon dioxide emissions.

Table 1. Indicators for Measuring Green Total Factor Energy Efficiency

Category	Variable	Description
Input	Energy Input	Urban direct energy consumption mainly includes natural gas and liquefied petroleum gas (LPG), while indirect energy consumption primarily includes electricity use, measured in 10,000 tons of standard coal equivalent.
	Capital Input	The capital stock (measured in 10,000 yuan) is estimated using the perpetual inventory method.
	Labor Input	The number of employed persons in each prefecture-level city over the years (measured in 10,000 persons).
Output	GDP	The gross domestic product (GDP) of each city is used as the measurement indicator, adjusted to constant 2009 prices (measured in 10,000 yuan).
	SO_2	Industrial sulfur dioxide (SO_2) emissions (tons)
	CO_2	Carbon dioxide (CO_2) emissions (tons)
	Industrial dust and wastewater	Industrial particulate matter and wastewater emissions (100,000 tons)

Accordingly, the model constructed in this study—an SBM-GML framework with undesirable outputs—is developed with reference to the method proposed by Wang[35] for measuring total factor energy efficiency.

In this model, it is assumed that there are n decision-making units (DMUs). Each DMU includes m inputs, $\boldsymbol{S_1}$desirable outputs, and $\boldsymbol{S_2}$ undesirable outputs. Let $\boldsymbol{x} \in \boldsymbol{R^m}$ denote the input vector, $\boldsymbol{y^d} \in \boldsymbol{R^{s_1}}$ the vector of desirable outputs, and $\boldsymbol{y^{ud}} \in \boldsymbol{R^{s_2}}$ the vector of undesirable outputs.

In this study, the green total factor energy efficiency of 259 prefecture-level cities in China is measured. The considered input factors include labor, capital, and energy inputs; the desirable output is the real gross domestic product (GDP); and the undesirable outputs include industrial emissions of sulfur dioxide (SO_2), wastewater, particulate matter (dust), and carbon dioxide (CO_2).

To ensure the accuracy and robustness of the evaluation results, the undesirable output-based SBM model is applied as follows:

$$\boldsymbol{\varphi = min\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1+\frac{1}{s_1+s_2}\left(\sum_{r=1}^{s_1}\frac{s_r^d}{y_{rk}^d}+\sum_{t=1}^{s_2}\frac{s_t^{ud}}{y_{tk}^{ud}}\right)}} \qquad (5)$$

$$\boldsymbol{s.t}\begin{cases} \boldsymbol{X\cdot\lambda+s^-=x_k} \\ \boldsymbol{Y\cdot\lambda-s^+=y_k^d} \\ \boldsymbol{B\cdot\lambda+S^{b-}=y_k^{ud}} \\ \boldsymbol{\lambda\geq 0, s^-\geq 0, s^+\geq 0, s^{b-}\geq 0} \end{cases} \qquad (6)$$

In the model, the input, desirable output, and undesirable output are denoted by $\boldsymbol{x_k}$, $\boldsymbol{y_k^d}$, and $\boldsymbol{y_k^{ud}}$, respectively. The slack variables for input, desirable output, and undesirable output are represented by $\boldsymbol{s_i^-}$, $\boldsymbol{s_r^d}$, and $\boldsymbol{s_t^{ud}}$, respectively. The matrices for inputs, desirable outputs, and undesirable outputs are denoted as X, Y, and B. Correspondingly, the slack matrices for input, desirable output, and undesirable output are represented by $\boldsymbol{s^-}$、$\boldsymbol{s^+}$, and $\boldsymbol{s^{b-}}$. The intensity vector is denoted by $\boldsymbol{\lambda}$, representing the weights assigned to each decision-making unit (DMU). The efficiency value of a decision unit is denoted by $\boldsymbol{\varphi}$, which reflects the level of Green Total Factor Energy Efficiency (GTFEE).

（3）Mechanism Variable

Technological innovation (INN) is selected as the mediating variable. Following the study by Li et al. (2023) [36], this variable is measured by the ratio of the number of granted patents to the population. Technological innovation plays a critical role in promoting green development and serves as an important mediating pathway linking industrial collaborative agglomeration to green total factor energy efficiency. A higher number of granted patents indicates more active innovation activities and more significant technological progress in the city, which in turn contributes to resource conservation and improved energy efficiency.

（4）Control Variables

In order to ensure the accuracy and reliability of the empirical results, this study incorporates control variables into the model to account for other potential factors that may influence green total factor energy efficiency. Based on relevant literature, five control variables are selected: the level of economic development, human capital stock, educational attainment, infrastructure level, and the total number of green patent applications. Descriptive statistics for these variables are presented in Table 2.

Table 2. Descriptive Statistics of Variables

Variable Type	Variable Name	Measurement Method	Sample Size	Mean	SD	min	max
Dependent Variable	Green Total Factor Energy Efficiency (GTFEE)	Estimated by the Super-SBM Model	2493	0.290	0.085	0.147	0.697
Independent Variable	Industrial Co-agglomeration (COAGG)	Entropy Index Used to Measure Industrial Collaborative Agglomeration	2493	0.741	0.179	0.114	1.000
Mediating Variable	Technological Innovation (INN)	Measured by the ratio of the number of granted patents to the population	2493	10.306	14.015	0.061	126.351
Control Variable	Economic Development Level (lnEcoDP)	The logarithm of per capita regional GDP	2493	2.464	0.047	2.330	2.569
	Human Capital Stock (lnLabors)	The logarithm of the number of enrolled students in regular higher education institutions	2493	10.805	1.218	8.011	13.706
	Educational Attainment (lnEducat)	The natural logarithm of the ratio of students enrolled in regular higher education institutions to the year-end total population	2493	0.020	0.024	0.001	0.115
	Infrastructure Level (lnBaseInL)	The natural logarithm of per capita highway freight volume	2493	3.181	0.599	1.477	4.716
	Total Number of Green Patent Applications (lnTgree)	The natural logarithm of the total number of green patent applications	2493	5.185	1.554	1.792	9.216

5. Empirical Results and Analysis

5.1. Baseline Regression Results

Table 3 reports the baseline regression results on the impact of industrial collaborative agglomeration on urban green total factor energy efficiency. Specifically, Columns (1) and (2) present the estimation results without and with control variables, respectively.

In Column (1), the regression coefficient of the industrial collaborative agglomeration index is 0.031 and is statistically significant at the 1% level, indicating that even without controlling for other influencing factors, industrial collaborative agglomeration exerts a significant positive effect on green total factor energy efficiency.

Column (2) further incorporates control variables, including the level of economic development, human capital stock, educational attainment, infrastructure level, and the total number of green patent applications. The estimated coefficient of collaborative agglomeration remains 0.031 and is still significant at the 1% level, suggesting that the result is robust.

Overall, whether or not control variables are included, industrial collaborative agglomeration consistently shows a significant positive impact on urban green total factor energy efficiency, confirming its role as an important pathway for improving green development efficiency. This finding suggests that collaborative agglomeration contributes to optimizing resource allocation, enhancing factor utilization efficiency, and promoting technological spillovers, thereby facilitating improvements in urban GTFEE. Consequently, Hypothesis H1 is preliminarily supported.

Table 3. Baseline Regression Results

Variable	（1） GTFEE	（2） GTFEE
COAGG	0.031*** (0.011)	0.031*** (0.010)
lnEcoDP		0.469*** (0.081)
lnLaborS		-0.016*** (0.005)
lnEducat		-0.255 (0.176)
lnBaseInL		-0.012*** (0.003)
lnTgree		-0.011*** (0.003)
City Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Sample Size	2493	2493
R2	0.110	0.135

Note: Robust standard errors are in parentheses; “***”“**” “*” represent 1%, 5%, and 10% significance levels, respectively, below.

5.2. Robustness Checks

To ensure result robustness, two checks are conducted: addressing endogeneity and adjusting the sample period. To mitigate potential endogeneity from reverse causality or omitted variables, the study adopts a panel IV approach (Li et al., 2020), using one- and two-period lags of the agglomeration index as instruments. The IV regression yields a coefficient of 0.056, significant at the 5% level, confirming the positive effect remains after endogeneity control.

Additionally, to capture recent developments, the sample is restricted to 2015–2020. Results show a higher coefficient of 0.060 (significant at the 1% level), suggesting the effect of industrial collaborative agglomeration has strengthened with the deepening integration of manufacturing and producer services.Overall, these robustness checks affirm the reliability of the main findings.

Table 4. Robustness Checks

Variable	（1） Instrumental Variable Method	（2） The sample period is from 2015 to 2020
COAGG	0.056** (0.025)	0.060*** (0.018)
lnEcoDP	0.545*** (0.090)	0.718*** (0.147)
lnLaborS	0.007 (0.007)	-0.013 (0.009)
lnEducat	-0.256 (0.201)	-0.667** (0.326)
lnBaseInL	-0.012*** (0.004)	-0.002 (0.005)
lnTgree	0.010*** (0.002)	-0.007 (0.004)
City Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Sample Size	1881	1453
R2	0.109	0.110

5.3. Mechanism Test and Analysis

Table 5 reports the mechanism analysis using technological innovation as the mediating variable. Results show that industrial collaborative agglomeration significantly inhibits technological innovation (coefficient = –2.981, $p < 0.05$), possibly due to inefficient resource allocation or weak innovation incentives.

Despite this, the impact of agglomeration on green total factor energy efficiency remains significantly positive (coefficient = 0.035, $p < 0.02$). Technological innovation also exerts a positive and highly significant effect on energy efficiency (coefficient = 0.001, $p < 0.01$).

These findings indicate that although agglomeration currently hampers innovation, technological progress still enhances green energy efficiency. Thus, efforts to foster industrial agglomeration should be accompanied by improved innovation environments to maximize its green development potential.

Table 5. Results of the Mechanism Test

Variable	（1） INN	（2） GTFEE
COAGG	-2.981** (1.272)	0.035*** (0.010)
INN		0.001*** (0.000)
lnEcoDP	-5.807 (9.904)	0.477*** (0.080)
lnLaborS	-1.958*** (0.623)	-0.013*** (0.005)

lnEducat	-5.104 (21.496)	-0.249 (0.174)
lnBaseInL	-0.156 (0.396)	-0.012*** (0.003)
lnTgree	1.143*** (0.349)	-0.012*** (0.003)
City Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Sample Size	2493	2493
R2	0.440	0.157

5.4. Heterogeneity Analysis

To assess regional heterogeneity, the sample is divided into eastern, central, western, and northeastern regions for separate regressions. Results show the positive effect of industrial collaborative agglomeration is strongest in eastern cities (coefficient = 0.102, $p < 0.01$), reflecting advantages in market maturity and innovation. In contrast, the effect is insignificant in central and northeastern regions, while significantly negative in the west (−0.037, $p < 0.05$), likely due to inefficiencies in resource allocation and infrastructure.

A further north–south comparison reveals that agglomeration significantly promotes green efficiency in southern cities (coefficient = 0.064, $p < 0.01$), driven by stronger industrial linkages and policy support. In northern cities, however, the effect is negative (−0.030, $p < 0.10$), suggesting structural barriers to green transformation.

Overall, these findings highlight clear regional disparities. Policies should be tailored to local conditions to enhance the green benefits of collaborative agglomeration and reduce spatial development imbalances.

Table 6. Results of the Heterogeneity Analysis

Variable	（1） Eastern cities	（2） Central cities	（3） Western cities	（4） Northeastern cities	（5） Northern cities	（6） Southern cities
COAGG	0.102*** (0.022)	0.022 (0.015)	-0.037** (0.015)	-0.013 (0.041)	-0.030* (0.017)	0.064*** (0.013)
lnEcoDP	0.334** (0.165)	0.751*** (0.114)	0.844*** (0.108)	1.650*** (0.279)	0.878*** (0.114)	0.607*** (0.101)
lnLaborS	-0.004 (0.012)	-0.001 (0.007)	-0.022*** (0.007)	-0.010 (0.021)	-0.002 (0.008)	-0.015** (0.007)
lnEducat	-2.040*** (0.437)	0.566** (0.241)	-0.138 (0.215)	3.184*** (1.106)	-0.397 (0.243)	-0.245 (0.253)
lnBaseInL	-0.007 (0.007)	-0.007* (0.004)	-0.020*** (0.005)	-0.033** (0.014)	-0.018*** (0.005)	-0.005 (0.004)
lnTgree	0.014*** (0.004)	-0.006* (0.003)	-0.004 (0.003)	0.023*** (0.006)	0.008*** (0.003)	-0.001 (0.003)
City Fixed Effects	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Sample Size	857	746	628	230	1026	1435
R2	0.119	0.170	0.135	0.297	0.157	0.088

6. Conclusion and Recommendations

Empirical results show that industrial collaborative agglomeration significantly improves urban green total factor energy efficiency (GTFEE) by enhancing resource allocation, factor flow, and information sharing. Promoting coordinated industrial development—especially the integration of manufacturing and advanced services—is thus key to green growth. Governments should support this by planning collaborative industrial zones, fostering linkages among large and small firms, and promoting vertical and horizontal integration.

Mechanism analysis reveals that agglomeration also indirectly enhances GTFEE via technological innovation, through knowledge spillovers, talent flow, and collaborative R&D. Therefore, innovation should be positioned as the core driver of collaboration. Policymakers should strengthen innovation systems, support research institutions, and promote green technology development and diffusion across the industrial chain.

Heterogeneity analysis finds that agglomeration effects are stronger in eastern and southern regions, reflecting their better economic and innovation foundations. In contrast, central, western, northeastern, and northern regions show weaker effects, calling for region-specific strategies. While advanced regions should build innovation clusters and green collaboration platforms, less-developed areas need to improve infrastructure, optimize the business environment, and enhance public services to support green industrial collaboration and balanced regional development.

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References

[1] Zhou, M.S. and Wang, Z.Z. (2024) The Impact of Industrial Synergistic Agglomeration on Urban Economic Resilience. Economic System Reform, (05), 41–50.

[2] Zheng, J. and Lin, Y.K. (2024) How Does the Synergistic Agglomeration of Manufacturing and Producer Services Affect Urban Ecological Efficiency? Economic Geography, 41(02), 3–16.

[3] Qiu, X.F. and Liao, J.Q. (2024) A Study on the Mechanism and Effect of Digitalization on Industrial Total Factor Energy Efficiency. Jiangxi Social Sciences, 44(01), 126–138.

[4] Li, D.S., Zhang, Z.Q., Tian, Y., et al. (2024) The Impact of Environmental Regulation on Urban Total Factor Energy Efficiency and Its Mechanisms. Modernization of Management, 44(05), 186–193.

[5] Liu, Y.S., Tian, Y.H. and Luo, Y. (2018) Industrial Structure Upgrading, Energy Efficiency, and Green Total Factor Productivity. Theory and Practice of Finance and Economics, 39(01), 118–126.

[6] Wu, C.Q. and Dong, X. (2015) Spatial and Temporal Differentiation of Total Factor Energy Efficiency in the Yangtze River Economic Belt under Environmental Constraints—Based on the Super-efficiency DEA Model and ML Index Method. Resources and Environment in the Yangtze Basin, 24(10), 1646–1653.

[7] Yan, M.Z., Li, H.Z. and Tian, F.H. (2018) Are China's Energy-Saving Policies Effective? —Measurement of Ecological Total Factor Energy Efficiency Based on the SFA-Bayes Analytical Framework. Economic and Management Research, 39(03), 89–101.

[8] Tone, K. (2001) A Slacks-Based Measure of Efficiency in Data Envelopment Analysis. European Journal of Operational Research, 130(3), 498–509.

[9] Chen, X.X. (2019) Measurement of Spatial Spillover Effect of Green Total Factor Energy Efficiency. Statistics and Decision, 35(21), 118–121.

[10] Wang, J.B., Liu, Z.C. and Zhang, J. (2017) Measurement of Industrial Energy Efficiency Based on an Improved Undesirable SBM Model: Panel Data from 17 Cities in Shandong Province. East China Economic Management, 31(07), 25–30.

[11] Wang, J.H., Xie, Q.Y. and Shi, D. (2024) The Impact of Green Technological Innovation on Energy Efficiency. Finance and Trade Economics, 45(06), 143–159.

[12] Zhang, Q.J. and Chen, R. (2023) Environmental Regulatory Policy Burden and Energy-Environment Efficiency: From the Perspective of Entrepreneurial Spirit Allocation. Journal of Southwest University for Nationalities, 44(11), 101–114.

[13] Sun, H. and Lan, T.T. (2023) Environmental Regulation, Industrial Structure Adjustment, and Energy Efficiency. Statistics and Decision, 39(08), 46–50.

[14] Marshall, A. (1890) Principles of Economics: An Introductory. Macmillan.

[15] Han, H.Z. and Hu, X.D. (2024) A Study on the Innovation Effect of Servitization in Manufacturing Industry: Empirical Evidence from 287 Prefecture-Level Cities in China. Statistical Research, 41(03), 74–87.

[16] Shen, Q. and Pan, Y.X. (2024) Explaining and Modeling the Impact of Industrial Co-Agglomeration on Regional Economic Growth in China: Integrated a Quality Concern of Night-Time Light Perspective. Environmental Science and Pollution Research International, 31(46), 56786–56811.

[17] Zeng, W.P., Li, et al. (2021) Industrial Collaborative Agglomeration, Marketization, and Green Innovation: Evidence from China's Provincial Panel Data. Journal of Cleaner Production, 279, 123598.

[18] Meng, X.N. and Xu, S.C. (2022) Can Industrial Collaborative Agglomeration Reduce Carbon Intensity? Empirical Evidence Based on Chinese Provincial Panel Data. Environmental Science and Pollution Research, 29(40), 61012–61026.

[19] Li, Y.J., Liu, S.S. and He, Z.C. (2023) Industrial Collaborative Agglomeration, Technological Innovation and Green Total Factor Productivity. Systems Engineering, 41(01), 1–14.

[20] Chang, Z.R. and Zheng, M. (2023) Research on the Impact of Industrial Synergistic Agglomeration on Green Innovation Efficiency: From the Perspective of Spatial Spillovers. Journal of Finance and Economics Research, (10), 53–67.

[21] Wang, Y. and Sun, C. (2020) Research on the Impact of Industrial Synergistic Agglomeration on Green Total Factor Productivity: From the Perspective of High-Tech Industry and Producer Services. Economic Vision, (3), 67–77.

[22] Guo, R. (2021) Research on the Mechanism of Green Total Factor Productivity Growth under Industrial Collaborative Agglomeration. Dalian University of Technology.

[23] Ren, Y.J., Wang, C.X. and Yu, C. (2019) A Study on the Spatial Spillover Effects of Regional Green Total Factor Productivity in China. Soft Science, 33(4), 40–43.

[24] Meng, W.J., Zhang, X.L. and Xing, Q.S. (2022) The Impact of Industrial Synergistic Agglomeration on Urban Green Economic Development: Empirical Analysis Based on the Yangtze River Delta Urban Agglomeration. Ecological Economy, 38(2), 67–74.

[25] Hao, F.X., Wang, Y.B. and Lou, Y. (2021) A Study on the Effect of Industrial Synergistic Agglomeration from the Perspective of Regional Servitization. Science & Technology Progress and Policy, 38(13), 55–63.

[26] Feng, Y.D., Liu, Y.B. and Cheng, F.Y. (2023) Regional Differences and Spatial Convergence of Urban Green Total Factor Energy Efficiency in China. Geographical Research, 42(09), 2343–2368.

[27] Lu, F.Z. and Wang, Q.Y. (2022) How Does Industrial Synergistic Agglomeration Affect Green Economic Efficiency? Empirical Evidence from Chinese Cities. Economic System Reform, (06), 174–182.

[28] He, Z.C., Li, Y.J. and Wu, Y. (2024) Industrial Collaborative Agglomeration, Technological Innovation and Resilience of the Manufacturing Supply Chain. Science of Science and Management of S&T, 42(03), 515–527.

[29] Bao, T. (2022) Does Industrial Synergistic Agglomeration Help Pollution Reduction from the Perspective of Environmental Regulation? Evidence from Chinese Micro-Enterprises. Industrial Economics Research, (05), 86–100.

[30] Chen, L. and Liu, X.Y., Zhang, M., et al. (2024) Industrial Spatial Co-Agglomeration, Knowledge Spillover and Innovation Performance: Also on the Path of Regional Industrial Diversification Cluster Construction. Economic Research Journal, 59(04), 78–95.

[31] Dahl, M.S. and Pedersen, C.Ø.R. (2004) Knowledge Flows through Informal Contacts in Industrial Clusters: Myth or Reality? Research Policy, 33(10), 1673–1686.

[32] Song, X.L. and Li, J.Y. (2023) Industrial Synergistic Agglomeration, Institutional Environment and Industrial Green Innovation Efficiency. Science & Technology Progress and Policy, 40(04), 56–65.

[33] Gu, N.H., Bi, D.D. and Ren, W.B. (2006) Interaction between Producer Services and Manufacturing Industry: A Literature Review. The Economist, (06), 35–41.

[34] Zhang, S.S., Ma, X.Y. and Cui, Q. (2024) Digital Factor Allocation, Green Total Factor Energy Efficiency Constraint and Urban Resilience. Journal of Technology Economics & Management Research, (08), 59–64.

[35] Wang, J.B. (2016) Measurement of Total Factor Energy Efficiency Based on the Undesirable Output SBM Model. Statistics and Decision, (17), 120–123.

[36] Li, C.T., Yan, X.W., Song, M., et al. (2020) FinTech and Corporate Innovation: Evidence from the New Third Board.