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The impact of industrial co-agglomeration on carbon intensity in northeast China

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Abstract

Under China's dual carbon goals, the mechanism through which regional industrial co-agglomeration affects carbon emissions remains insufficiently understood. Taking Northeast China as a case study, this study employs a dynamic spatial Durbin model (SDM) to analyze the impact relationship and the underlying mechanisms through which the co-agglomeration of producer services and manufacturing influences carbon emission intensity. The findings show that: (1) A pronounced spatial polarization of industrial co-agglomeration levels exists in Northeast China, with carbon emission intensity exhibiting strong spatiotemporal dependence. (2) The co-agglomeration of producer services and the manufacturing sector exhibits a significant inverted U-shaped relationship with carbon emission intensity. This mechanism stems from the interaction between economies of scale and externalities. (3) The heterogeneity analysis indicates that the impact of industrial co-agglomeration on carbon intensity was more significant in non-resource-based cities and exhibited substantial variation across different sectors. The co-agglomeration of the financial and manufacturing sectors is more likely to cross the inflection point of the inverted U-curve.

Keywords: industrial co-agglomeration; carbon intensity; dynamic spatial Durbin model; heterogeneity analysis; Northeast China.

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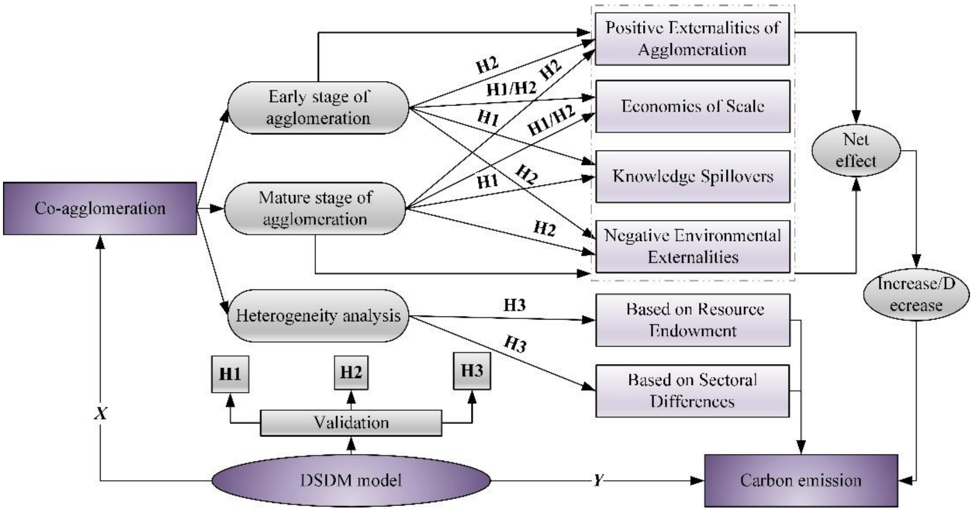
Graphical abstract



1. **Introduction**

Against the backdrop of exacerbating global climate change, the control of carbon dioxide emissions and the advancement of the green low-carbon transition have become both urgent tasks and key strategies for countries worldwide seeking to achieve sustainable development (Wu and Xu, 2025; Zhou *et al.*, 2023). Particularly in the decade that followed the adoption of the Paris Agreement, “green and low-carbon development ultimately evolved into a prevailing trend of the times” (Shen *et al.*, 2025). As the world’s largest carbon emitter, China is facing substantial pressure to reduce its emissions (Shen *et al.*, 2025; Tang *et al.*, 2024). In this context, China’s proposed dual carbon goals reflect the country’s responsibility as a major carbon emitter and also provide a direction for the high-quality development of its industries. China’s 14th Five-Year Plan further emphasizes “orienting efforts toward the high-quality development of the manufacturing sector and promoting the extension of producer services toward specialization and the high end of the value chain.” As an advanced stage of industrial clustering (He *et al.*, 2024), industrial co-agglomeration offers a potential pathway for low-carbon industrial transformation. Specifically, this can be achieved by fostering deep integration between producer services and the manufacturing sector. Therefore, an investigation of low-carbon industry development under co-agglomeration between producer services and the manufacturing sector holds significant practical importance (Qi, 2025).

Previous research closely related to this theme has focused on a few key aspects. The first is the green innovation effect of industrial co-agglomeration. For instance, some scholars have argued that the co-agglomeration of producer services and the manufacturing sector both enhances regional green innovation and also improves the transformation efficiency and overall efficiency of green innovation outcomes (Zeng *et al.*, 2021). Moreover, other scholars have suggested that the co-agglomeration of digital industries and the manufacturing sector helps stimulate innovation vitality and boost regional innovation efficiency. Thus, green innovation is promoted through human capital externalities and knowledge spillover effects (Huang *et al.*, 2025; Lei *et al.*, 2024; Yuan *et al.*, 2025; Zhao *et al.*, 2025; Zhi and Yu, 2025). A second aspect examined is the green economic effect of industrial co-agglomeration. The majority of scholars agree that industrial co-agglomeration can facilitate high-quality regional economic development, promote urban industrial upgrading, and enhance resilience (Chu *et al.*, 2024; Liu *et al.*, 2023; Zeng *et al.*, 2021; Zheng *et al.*, 2025). Moreover, a significant U-shaped relationship has been confirmed to exist between industrial co-agglomeration and green economic efficiency, with variations across cities of different sizes. In addition, the increased intensity of local government competition can weaken the promoting effect of industrial co-agglomeration on green economic efficiency (Lu *et al.*, 2025; Ma *et al.*, 2025). A third aspect investigated is the impact of industrial co-agglomeration on carbon emissions within the dual carbon context. In this respect, despite the presence of numerous studies, to date, a consensus has not been reached. One perspective holds that the impact of industrial co-agglomeration on carbon emissions is linear, suggesting that this impact reduces emissions and significantly influences their levels through green technological progress (He *et al.*, 2024). An alternative viewpoint argues for a nonlinear relationship characterized by dynamic changes across stages, indicating inverted positive U-shaped, or inverted U-shaped nonlinear relationships between industrial co-agglomeration and carbon emissions (Fu and Song, 2024; Kong *et al.*, 2022; Liu and Zhang, 2021; Liu *et al.*, 2024).

While providing extensive references for this study, existing literature has three main shortcomings. First, the majority of previous studies predominantly focused on single-industry agglomeration, thereby failing to capture the complex interactions among different industries in the case of geographic clustering. Second, the geographical scope of previous research largely focused on either China as a whole or on developed urban agglomerations, such as the Yangtze River Delta. However, there has been an insufficient exploration of the region of Northeast China. The industrial structure of Northeast China is dominated by heavy industry. Industrial synergy and clustering in this region must therefore address practical challenges, including the path dependence of resource-intensive industries and the brain drain. Consequently, examining whether industrial synergy and clustering remain effective in regions with such rigid industrial structures can enrich research on carbon emission intensity in relation to industrial synergy and clustering. Such research can also provide regions that lack advanced industries guidance on how to achieve emission reduction targets through industrial synergy and clustering. Third, the heterogeneity in the factors influencing carbon emissions remains underexplored. The few existing studies on the impact of industrial co-agglomeration on carbon emissions have mostly been conducted at the regional level. Few analyses have been conducted on how different resource endowments across cities or varying types of producer services affect carbon emission intensity. Given these shortcomings, this study employs the dynamic spatial Durbin model (DSDM) to analyze the non-linear impact of co-agglomeration between producer services and the manufacturing sector on carbon emission intensity in Northeast China from 2003 to 2022. Also revealed are the influencing factors and their heterogeneity. In this way, this study enriches the extant research on how industrial co-agglomeration affects carbon emission intensity and explores new pathways for industrial structure optimization and low-carbon transition in Northeast China.

2. Research Hypotheses

2.1. *The direct impact of industrial co-agglomeration on carbon emission intensity*

Marshall’s theory of externalities posits that the agglomeration of the same or interrelated industries can generate positive economic externalities through three primary channels: specialization in intermediate inputs, knowledge spillovers, and labor pooling. Conversely, Jacobs emphasized that the clustering of different industries induces complementarity effects in capital, technology, and labor, thereby fostering positive economic externalities. Furthermore, building on case studies of industrial clusters, Porter argued that the agglomeration of diverse industries introduces a competition effect that accelerates the diffusion and absorption of technology across sectors, resulting in even greater externalities.

Driven by knowledge spillovers and competition effects, the co-agglomeration of producer services and the manufacturing sector enables firms to reduce costs and energy consumption, thereby generating economies of scale and positive externalities (Liu and He, 2024; Xie and Wang, 2024; Yang and Song, 2016). Moreover, through synergistic effects, this co-agglomeration enhances the utilization rate of public infrastructure. The concentration and sharing of public infrastructure allows for achieving economies of scale in environmental investments, thereby lowering the unit environmental protection costs for enterprises (Fan *et al.*, 2019; Yuan *et al.*, 2020). At the same time, under the influence of forward and backward linkages in the industrial chain, producer services can more precisely match the production demands of the manufacturing sector. Thus, producers can generate positive spillover and reverse incentive effects with this sector (Luo *et al.*, 2024; Xie and Guo, 2024). Leveraging their high value-added and technology-intensive characteristics, producer services empower the manufacturing sector, further enhancing that sector’s production efficiency. This intensive production model reduces production costs while improving efficiency, thereby effectively decreasing carbon emissions per unit of output (Qin *et al.*, 2023). On this basis, the following hypothesis is proposed:

Hypothesis 1. Industrial co-agglomeration can directly affect carbon emission intensity.

2.2. *The nonlinear impact of industrial co-agglomeration on carbon emission intensity*

While industrial co-agglomeration generates economies of scale and positive externalities, another result can be negative externalities. With the intensification of the agglomeration degree, the demand for production factors increases correspondingly, triggering a competition for resources. This may compel firms to rely on carbon-intensive resources and thereby drive up carbon emission intensity. Furthermore, given the limited environmental carrying capacity, pollution emissions exceeding the regional ecological threshold can result in rising marginal abatement costs, thereby creating environmental negative externalities (Guo *et al.*, 2025; He *et al.*, 2022; Nie *et al.*, 2021).

During the initial stage of industrial co-agglomeration, manufacturing enterprises integrate basic segments of the industrial chain, sharing labor resources and public facilities, thus gradually giving rise to economies of scale. However, the survival pressures induced by competition effects drive firms to prioritize capacity expansion to capture market share, thereby intensifying the competition for production factors. Enterprises tend to rely on cheaper but higher-carbon coal resources. In parallel, local governments, in pursuit of scale growth, may relax environmental regulations and tacitly permit high-emission projects. This combination of goals leads to significant negative externalities. At this stage, the emission-reduction effect entailed by economies of scale is outweighed by the emission-increase effect caused by negative externalities. The result is a net effect that drives carbon emission intensity upward.

In the mature stage of industrial co-agglomeration, a well-developed supply chain is formed between upstream and downstream industries, with strong inter-industrial linkages. This reduces factor demand among enterprises, while improved public infrastructure lowers transaction and transportation costs (Wang *et al.*, 2020). Knowledge spillover effects become evident, and high-end producer services become deeply embedded within the manufacturing sector, promoting the innovation and diffusion of energy-saving and emission-reducing technologies. Consequently, in the mature stage, the carbon emission reduction benefits of agglomeration exceed the carbon emission increase effects, ultimately leading to a net decline in carbon emission intensity.

In summary, the impact on carbon emission intensity of co-agglomeration between producer services and the manufacturing sector stems from the interplay between economies of scale and externalities at different developmental stages. On this basis, the following hypothesis is proposed:

Hypothesis 2. An inverted U-shaped relationship exists between industrial co-agglomeration and carbon emission intensity.

2.3. *The heterogeneous impact of industrial agglomeration on carbon emission intensity*

From the perspective of agglomeration patterns across different types of cities, resource-based cities exhibit a model that is heavily reliant on resource-driven industrial chains. Inter-firm connections are often characterized by vertical integration, which tends to suppress cross-industry knowledge spillover effects (Li *et al.*, 2025; Wu and Xu, 2025). In contrast, non-resource-based cities have more diversified agglomeration patterns and flexible industrial structures. Their agglomeration dynamics are driven more by technological externalities and optimized resource allocation. These conditions facilitate cross-domain knowledge integration and thereby advance carbon emission reduction objectives.

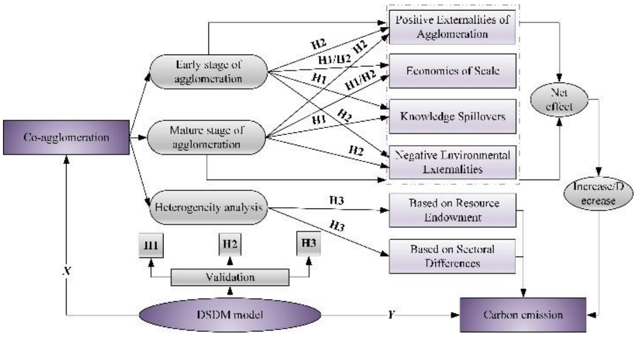


Figure 1. Technology roadmap.

From the perspective of agglomeration across different types of industries, the co-agglomeration of knowledge-intensive services and the manufacturing sector can effectively foster knowledge spillover effects and promote green technology innovation (Yang *et al.*, 2023). Conversely, the co-agglomeration of circulation-oriented services, such as transportation and warehousing, with the manufacturing sector primarily enhances logistics efficiency and reduces transportation costs. However, these same industries may contribute directly to an increase in carbon emissions. On this basis, the following hypothesis is proposed:

Hypothesis 3. The impact of industrial co-agglomeration on carbon emission intensity exhibits heterogeneity across different types of cities and industries.

The technology roadmap considered for this study is illustrated in **Figure 1**.

3. Methodology and Data

3.1. *The study area*

This study focuses on 34 prefecture-level and higher cities in Northeast China, from 2003 to 2022. Specifically, all 34 cities are within Heilongjiang, Jilin, and Liaoning provinces. Due to data unavailability, the Yanbian Korean Autonomous Prefecture and the Greater Khingan Range region are not included. The focus on the period from 2003 to 2022 allows this study to capture the full transition of Northeast China from traditional industrial clustering toward green and coordinated development. The launch of the Northeast Revitalization Strategy in 2003 fundamentally reshaped the region's industrial spatial organization. Meanwhile, China's 2020 dual carbon goals marked the beginning of a new, low-carbon phase in industrial agglomeration. Given this area's distinctive industrial structure, Northeast China represents a critical region for the achievement of the dual carbon goals. Furthermore, insights drawn from this area may offer valuable lessons for other regions.

3.2. *Model specification*

Carbon dioxide emissions can spread across regions, exhibiting spatial dependence (Li *et al.*, 2021). The global Moran's I index was used to test for the presence of spatial autocorrelation, providing a basis for the use of spatial econometric models (Gao *et al.*, 2020). Carbon dioxide emissions are influenced by both geographical proximity and economic linkages. Therefore, an economic-geographic nested spatial weight matrix was constructed to perform the main analysis, while an economic-geographic distance matrix was used to perform robustness checks.

The SDM allows for the standard testing of spatial effects from different sources. Furthermore, considering the potential inverted U-shaped relationship between industrial co-agglomeration and carbon emission intensity, a quadratic term of industrial co-agglomeration is included. Accordingly, the following static SDM is established:

$$\begin{aligned} Carbonit &= a + \beta 1Coaggit + \beta 2Coagg_{it}^{2} \\ &+\phi \sum Xit + \rho 1WCarbonit + \rho 2WCoaggit \\ &+\rho 3WCoagg_{it}^{2} + \tau \sum WXit + ui + vt + \varepsilon it \end{aligned} \quad (1)$$

where $Carbon_{it}$ is the dependent variable, representing the carbon emission intensity of city i in period t; a is the constant term; $Coagg_{it}$ denotes the level of industrial co-agglomeration for city i in period t; u_i and v_t represent the individual and time fixed effects, respectively; X_{it} is a vector of control variables, and ε_{it} is the random disturbance term.

To account for the potential spatiotemporal dependence of carbon emissions, whereby past emissions may influence current levels, the first-order lag of the dependent variable is incorporated into the model, thus constructing the following DSDM (Xiao *et al.*, 2024; Yan *et al.*, 2022):

$$\begin{aligned}\mathrm{Carbon}_{it} &= a + \beta_0 \mathrm{Carbon}_{it-1} + \beta_1 \mathrm{Coagg}_{it} + \beta_2 Coagg_{it}^2 \\ &+ \phi \sum X_{it} + \rho_1 W\mathrm{Carbon}_{it} + \rho_2 W\mathrm{Carbon}_{it-1} + \rho_3 W\mathrm{Coagg}_{it} \\ &+ \rho_4 W\mathrm{Coagg}_{it}^2 + \tau \sum WX_{it} + u_i + v_t + \varepsilon_{it}\end{aligned} \tag{2}$$

where *Carbon*$_{it-1}$ is the first-order lag of *Carbon*$_{it}$; *W* denotes the spatial weight matrix, and β_0 captures the dynamic effect of carbon emission intensity, representing the impact of the previous period's intensity on the current period.

3.3. *Data sources*

The socio-economic data used in this study are primarily from the China City Statistical Yearbook and the government work reports of respective cities for the corresponding years. Data on carbon dioxide emissions are from the Emissions Database for Global Atmospheric Research (EDGAR: https://edgar.jrc.ec.europa.eu). A limited number of missing values were imputed using the linear interpolation method.

Table 1. Descriptive statistics of the variables employed in this study

Symbol	Variable	Observations	Mean	Std. Dev.	Min	Max
Carbon	Dependent variable	680	6.297	5.780	0.533	50.148
Coagg	Core explanatory variable	680	1.361	0.939	0.324	8.566
GOV	Control variable	680	0.226	0.261	0.102	4.369
LnPGDP	Control variable	680	10.524	0.702	8.402	12.778
FDI	Control variable	680	0.034	0.529	0.001	0.419
LnRD	Control variable	680	2.209	0.499	0.764	4.272
TI	Control variable	680	0.007	0.007	0.003	0.045
LnER	Control variable	680	-5.549	0.521	-7.503	-4.187

3.4. *Variable definitions*

In this study, the dependent variable was carbon emission intensity (Carbon), which is defined as carbon dioxide emissions per unit of economic output. By controlling for the scale of economic activity, this metric more directly reflects the influence of the explanatory variables on emission reduction efforts (Feng *et al.*, 2024; Zhao and Nie, 2025; Zhang *et al.*, 2025).

The core explanatory variable is industrial co-agglomeration (Coagg). The degree of agglomeration between the producer services and the manufacturing sector in Northeast China's cities is measured using a modified exponential growth (EG) index that captures both the quality and the depth of inter-industrial synergy, and which is calculated as follows:

$$Coagg = \left(1 - \frac{|LQ_{agman} - LQ_{agser}|}{LQ_{agman} + LQ_{agser}}\right) + |LQ_{agman} + LQ_{agser}| \tag{3}$$

where LQ_{agman} denotes the manufacturing agglomeration index; LQ_{agser} represents the producer services agglomeration index, and *Coagg* indicates the co-agglomeration index between producer services and the manufacturing sector. Following the *Statistical Classification of Producer Services*, issued in 2019 by China's National Bureau of Statistics, producer services are categorized into six sectors: (1) wholesale and retail trade; (2) transport, storage, and post; (3) information transmission, software, and information technology services; (4) finance; (5) leasing and business services, and (6) scientific research and technical services. The level of industrial agglomeration is calculated using employment data, as follows:

$$LQ_{ij} = \frac{e_{ij}}{E_j} / \frac{e_i}{E} \tag{4}$$

where e_{ij} denotes the number of employees in industry *j* in city *i*; E_j represents the total employment in industry *j* across Northeast China; e_i indicates the total employment across all industries in city *i*, and *E* indicates the total employment across all industries in Northeast China.

The following control variables were considered in this study: Government intervention (*GOV*) is measured as the ratio of fiscal expenditure to GDP. Economic development level (*LnGDP*) is calculated as the natural logarithm of GDP per capita. Degree of openness (*FDI*) is measured as the share of foreign direct investment in regional GDP. Infrastructure level (*LnRD*) is represented by the natural logarithm of road area per capita. Technological innovation (*TI*) is measured as the share of science and technology expenditure in local fiscal expenditure, and environmental regulation (*LnER*) is constructed by analyzing the frequency and proportion of environment-related keywords in the government work reports of each prefecture-level city. The descriptive statistics for all variables are presented in **Table 1.**

4. Results and Analyses

4.1. *Basic characteristics of industrial co-agglomeration and carbon emission intensity in Northeast China*

During the sampled years, the overall carbon emission intensity in Northeast China exhibited a fluctuating pattern of "decline–rise-decline". In parallel, the level of industrial co-agglomeration also showed significant volatility and distinct spatial polarization. From 2003 to 2022, the overall degree of industrial co-agglomeration in Northeast China first increased and then decreased (**Figure 2**), peaking at 1.40 in 2011. The degree of co-agglomeration varied markedly across different areas. High-agglomeration zones were primarily concentrated in provincial capital cities like Shenyang, Changchun, Harbin, and in a few economically-developed cities, such as Dalian. The spillover effects generated by co-agglomeration were likely more pronounced in these areas.

To satisfy the spatial dependency requirement of the SDM, this study employs the global Moran's I index to test for spatial autocorrelation in carbon emission intensity. As shown in **Table 2**, the Moran's I values for the period 2003-2022 were all statistically significant and positive. This result confirms the presence of a significant spatial agglomeration and a strong positive spatial dependence in carbon emission intensity across Northeast China.

Table 2. Global Moran's I index of carbon emission intensity in Northeast China (2003-2022).

Year	Moran's *I*	*Z*	*P*	Year	Moran's *I*	*Z*	*P*
2003	0.212	2.827	0.005	2013	0.194	2.605	0.009
2004	0.228	3.041	0.002	2014	0.229	2.858	0.004
2005	0.263	3.220	0.001	2015	0.228	2.861	0.004
2006	0.266	3.165	0.002	2016	0.220	2.766	0.006
2007	0.281	3.282	0.001	2017	0.253	3.141	0.002
2008	0.248	3.003	0.003	2018	0.265	3.297	0.001
2009	0.222	2.673	0.008	2019	0.252	3.043	0.002
2010	0.220	2.610	0.009	2020	0.234	2.841	0.005
2011	0.168	2.065	0.039	2021	0.234	2.841	0.005
2012	0.169	2.412	0.016	2022	0.239	2.880	0.004

Table 3. Results of the model specification tests.

Test type	P	Statistic	
LM test	LM-lag test	0.000	27.37
	Robust LM-lag test	0.040	4.22
	LM-error test	0.000	28.86
	Robust LM-error test	0.017	5.71
Wald test	Wald-SAR test	0.005	20.05
	Wald-SEM test	0.001	25.62
LR test	LR-SAR test	0.001	27.07
	LR-SEM test	0.001	25.19
Hausman test	0.000	85.20	
Individual fixed effects test	0.005	34.15	
Time fixed effects test	0.000	971.32	

4.2. *Analysis of the impact of industrial co-agglomeration on carbon emission intensity*

4.2.1. Selection of the spatial econometric model

Following the spatial econometric model specification, the Lagrange multiplier (LM) test, the Hausman test, the likelihood ratio (LR) test, and the Wald test were conducted using the economic-geographic nested matrix. The results, presented in **Table 3**, collectively indicate that the SDM with individual and time fixed effects was the appropriate specification.

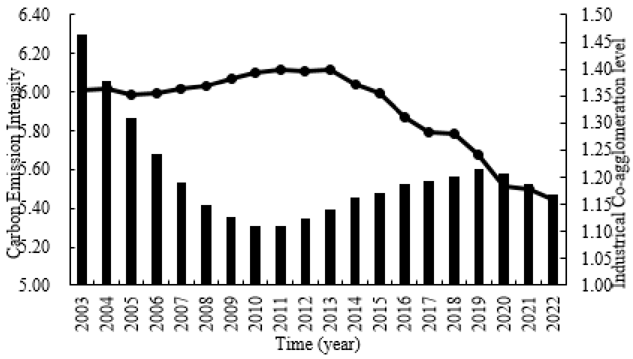


Figure 2. Trends in industrial co-agglomeration and carbon emission intensity in Northeast China (2003-2022).

4.2.2. Analysis of the regression results

Table 4 presents the regression results for the static (Model 1) and the DSDM (Model 2). The spatial autoregressive coefficient (ρ) is positive and statistically significant at the 10% level in Model 1 and at the 1% level in Model 2. These results indicate significant spatial dependence in urban carbon emissions across Northeast China. In Model 2, the time lag term of carbon emission intensity is positive and significant at the 1% level, confirming a pronounced time path dependence. Specifically, a one-unit increase in the previous period's carbon emission intensity led to an increase of approximately 0.71 units in the next period. The spatial lag term is also positive and significant at the 1% level, suggesting a positive spillover effect where carbon emission intensity in neighboring areas positively influences local intensity.

The regression results for the core explanatory variable indicate an inverted U-shaped relationship between industrial co-agglomeration and carbon emission intensity, characterized by an initial increase followed by a subsequent decrease. To explain, when a city's level of industrial synergy is low, the co-location of production-oriented services and manufacturing increases carbon intensity. Once the synergy level exceeds the inflection point, co-location reduces carbon intensity. This pattern arises from a shift in the dominant influence between economies of scale and negative environmental externalities across developmental stages. Using the direct impact coefficients for Coagg and Coagg2 reported in **Table 4**, the inflection point for the inverted U-shaped effect is calculated as 3.354. During the study period, however, only a few cities in Northeast China exceeded this value. The average level of industrial synergy and agglomeration was 1.361, well below the estimated inflection point. This indicates that most cities in the region remained in the early stages of industrial synergy and agglomeration during the sampled years. As shown in **Table 4**, the linear term of industrial co-agglomeration between producer services and the manufacturing sector is positive and significant at the 1% level. This is because, in its current developmental phase, industrial co-agglomeration in Northeast China remains dominated by traditional industries. The expansion of production scale intensifies the competition for resources, such as energy and labor. Given the region's high reliance on coal, negative environmental externalities escalate rapidly and outweigh the positive benefits of economies of scale. Consequently, the increase in emissions from co-agglomeration surpasses any reduction, leading to a positive association between the linear term and carbon intensity. In contrast, the quadratic term is negative and significant at the 1% level, confirming the inverted U-shaped relationship. This finding signifies a shift in the internal dynamic with the advance of co-agglomeration. With the maturation of upstream and downstream industrial supply chains and strengthened inter-industrial linkages, the scale effects of agglomeration become dominant and counteract the negative environmental externalities. At this stage, co-agglomeration leads to greater emission reductions, resulting in a negative correlation with carbon intensity. These findings support Hypotheses 1 and 2.

The analysis of control variables reveals that, while economic growth and infrastructure development contributed positively to emission reduction, the green transition in Northeast China faced dual obstacles, namely environmental policy failure and a disconnect in green technology innovation. **Table 4** shows that the level of economic development and infrastructure reduced carbon emission intensity with significance levels of 1% and 10%, respectively. This indicates the effectiveness of industrial upgrading and suggests that lower transport and transaction costs enhanced production efficiency and environmental quality. However, environmental regulation was associated with an increase in carbon emission intensity at the 1% significance level, thereby pointing to distorted policy incentives. Potential explanations include economic downturn pressures leading to lax local enforcement and firms potentially cutting innovation investments due to cost constraints; both such pressures could result in policy ineffectiveness. Furthermore, the degree of openness significantly increased carbon intensity at the 5% level, suggesting the presence of a "pollution haven" effect. Although the coefficient for technological innovation is negative, it is not statistically significant. This implies an insufficient commercialization of green technologies in the investigated region, highlighting a disconnect in the green innovation pipeline. Also noted was that, while government intervention had a positive coefficient at the 1% significance level, the absolute magnitude was small, indicating that the governmental intervention methods for carbon emission reduction in Northeast China require further optimization.

Table 4. Baseline regression results of the impact of industrial co-agglomeration on carbon emission intensity.

Variable	Model 1	Model 2	Variable	Model 1	Model 2
y.L(1)		0.708*** (0.018)			
Wy.L(1)		0.265*** (0.061)			
Coagg	1.252*** (0.349)	0.550*** (0.173)	*W.Coagg*	-0.717 (0.954)	-0.398 (0.473)
$Coagg^2$	-0.215*** (0.057)	-0.082*** (0.028)	$W.Coagg^2$	0.149 (0.189)	0.075 (0.093)
GOV	0.009** (0.004)	0.009*** (0.002)	*W.GOV*	-0.027*** (0.010)	0.003 (0.005)
LnPGDP	-3.820*** (0.421)	-1.212*** (0.214)	*W.LnPGDP*	1.445 (1.271)	1.474** (0.633)
FDI	0.058*** (0.022)	0.025** (0.010)	*W.FDI*	-0.137* (0.079)	0.005 (0.039)
LnRD	-0.151 (0.305)	-0.288* (0.147)	*W.LnRD*	0.127 (0.832)	-0.282 (0.402)
TI	0.411* (0.232)	-0.072 (0.115)	*W.TI*	0.149 (0.695)	-0.263 (0.348)
LnER	-0.169 (0.245)	0.328*** (0.122)	*W.LnER*	-0.958 (0.607)	-0.008 (0.301)
rho	0.115* (0.062)	0.180*** (0.068)	Ind Time	control	control
R^2	0.167	0.938	Observations	680	646

The comparative analysis of short-term and long-term effects shows that industrial co-agglomeration had an inverted U-shaped impact on carbon emission intensity in both time frames. Also, the emission reduction effects demonstrated a significant temporal accumulation. However, the spatial spillover effects remained insignificant, as they were likely constrained by the region's relatively closed industrial chains. As shown in **Table 5**, both the linear and quadratic terms of co-agglomeration significantly affected carbon intensity in the short and long term, with the magnitude of the long-term effects being greater. This suggests that realizing the emission-reduction benefits from the synergistic clustering of productive services and manufacturing takes time. In addition, the benefits derived from knowledge sharing and technology diffusion both require sustained interaction between enterprises. The inverted U-shaped relationship held for both types of effects. Notably, the spatial spillover effects of the variables were not statistically significant, implying that the impact of local synergistic clustering of productive services and manufacturing on carbon intensity has not spread to neighboring cities. This may be due to Northeast

China's heavy industry-dominated structure and provincially-focused industrial chains. These factors limit cross-regional specialization and cooperation and thereby hinder the outward diffusion of synergistic effects.

Table 5. Direct and indirect effects of industrial co-agglomeration on carbon emission intensity

Variable	ST direct effect	ST indirect effect	LT direct effect	LT indirect effect
Coagg	0.585*** (0.165)	-0.454 (0.405)	1.905*** (0.611)	-1.105 (2.910)
Coagg^2	-0.087***	0.081	-0.278***	0.250
	(0.028)	(0.080)	(0.104)	(0.564)
GOV	0.008***	0.002	0.031***	0.036
	(0.002)	(0.004)	(0.007)	(0.042)
LnPGDP	-1.261***	1.475***	-3.908***	5.444
	(0.212)	(0.543)	(0.782)	(3.724)
FDI	0.0254**	0.002	0.092**	0.0878
	(0.010)	(0.034)	(0.043)	(0.263)
LnRD	-0.280*	-0.217	-1.084*	-2.092
	(0.151)	(0.341)	(0.569)	(2.765)
TI	-0.055	-0.192	-0.269	0.651
	(0.115)	(0.300)	(0.412)	(2.331)
LnER	0.326***	-0.059	1.144***	-1.265
	(0.119)	(0.267)	(0.439)	(1.943)

Notes: *ST direct effect = short-term direct effect; ST indirect effect = short-term indirect effect; LT direct effect = long-term direct effect, and LT indirect effect = long-term indirect effect.*

Table 6. Results of the robustness checks

Variable	Model 1	Model 2	Model 3
y.L(1)	0.699***		0.774***
	(0.018)		(0.022)
Wy.L(1)	0.028		0.406***
	(0.094)		(0.072)
Coagg	0.587***	1.319***	0.896***
	(0.176)	(0.351)	(0.257)
Coagg^2	-0.090***	-0.229***	-0.173***
	(0.029)	(0.058)	(0.056)
GOV	0.007***	0.011***	0.016***
	(0.002)	(0.004)	(0.003)
LnPGDP	-1.161***	-3.984***	-1.041***
	(0.215)	(0.418)	(0.227)
FDI	0.023**	0.069***	0.025**
	(0.010)	(0.020)	(0.011)
LnRD	-0.352**	-0.174	-0.350**
	(0.150)	(0.305)	(0.152)
TI	-0.058	0.440*	-0.090
	(0.115)	(0.236)	(0.119)
LnER	0.305**	-0.149	0.300**
	(0.122)	(0.243)	(0.121)
R^2	0.929	0.299	0.927

4.3. *Robustness checks*

The following robustness checks were performed:

(1) Alteration of the spatial weight matrix: To test the robustness of the core findings, the economic-geographic distance weight matrix was employed as an alternative. The regression results are presented as Model 1 in **Table 6**.

(2) Employing a spatial error model: Considering that spatial dependence in the error term might affect the conclusions, a spatial error model was constructed for robustness testing. The results are presented as Model 2 in **Table 6**.

(3) Winsorization: The sample data were winsorized at the 1st and 99th percentiles to mitigate the potential influence of outliers on the robustness of the findings. The regression results after this treatment are shown as Model 3 in **Table 6**.

For all three robustness checks, the signs of the coefficients for both the linear and the quadratic terms of industrial co-agglomeration remained unchanged. This consistency confirms the reliability of the initial regression results and reinforces the finding of an inverted U-shaped relationship between co-agglomeration and carbon emission intensity. The results also substantiate the robustness of the core conclusion of this study.

4.4. *Heterogeneity analysis*

4.4.1. 4.4.1 Heterogeneity based on resource endowment

Resource-based cities constitute over 50% of Northeast China and have a high concentration of high-carbon industries; as such, they are crucial to achieving emission reduction targets. Therefore, this study examined whether the impact of industrial co-agglomeration on carbon intensity varied across the 34 study units, based on their resource endowment. Following China's National Sustainable Development Plan for Resource-based Cities (2013-2020) issued by the State Council, the case-study region includes 19 resource-based cities. The remaining cities are classified as non-resource-based cities.

The results, presented in **Table 7**, show a significant heterogeneity in the effects. The impact of industrial co-agglomeration on carbon intensity was not statistically significant in resource-based cities. This is likely because co-agglomeration in these cities predominantly revolves around the extraction and processing of mineral resources, where fixed technological pathways and dependence on traditional resource models constrain the realization of synergistic benefits. In contrast, for non-resource-based cities, both the linear and the quadratic terms of co-agglomeration were significant at the 1% level and exhibited an inverted U-shaped pattern. This finding suggests that their more flexible industrial structures may facilitate technological upgrading and economies of scale through co-agglomeration, which in turn would lead to lower carbon intensity.

4.4.2. Heterogeneity based on sectoral differences

Given the diversity within producer services, this study examines the impact of industrial co-agglomeration on carbon emission intensity from the perspective of co-agglomeration between different producer service sectors and the manufacturing sector. The regression results are detailed in **Table 8**, where Sectors from 1 to 6 correspond to "scientific research and technical services", "finance", "leasing and business services", "information transmission, software, and IT services", "transport, storage, and post", and "wholesale and retail trade", respectively.

The analysis reveals significant differences in emission reduction effects across sectors. Specifically, firstly, the impact of "leasing and business services" was insignificant, possibly because services such as equipment leasing and management consulting are not directly embedded in production processes. Thus, they exert minimal direct influence on energy consumption. Secondly, "information transmission, software, and IT services" and "transport, storage, and post" showed a significant inverted U-shaped effect on carbon emission intensity. Furthermore, "scientific research and technical services", "finance", and "wholesale and retail trade" all showed significant effects on carbon emission intensity. Among them, "finance" and "wholesale and retail trade" had the strongest emission-increasing effect before the turning point. This is likely due to financial capital inflows expanding manufacturing capacity and spurring a surge in emissions. After the turning point, all these sectors showed strong emission reduction potential. "Finance" appeared most capable of crossing the inflection point of the inverted U-curve. This sector possesses the greatest emission reduction potential and benefits from the strongest knowledge spillovers, due to co-agglomeration.

Table 7. Results of the heterogeneity analysis.

Variable	**Based on resource endowment**		**Based on sectoral differences**					
	RC	NRC	Sector 1	Sector 2	Sector 3	Sector 4	Sector 5	Sector 6
Coagg	0.236	0.716***	0.350***	0.560***	0.0800	0.240**	0.447**	0.550***
	(0.277)	(0.245)	(0.124)	(0.210)	(0.0602)	(0.0979)	(0.180)	(0.160)
$Coagg^2$	-0.020	-0.103***	-0.026**	-0.077***	-0.003	-0.014**	-0.060**	-0.056***
	(0.055)	(0.035)	(0.011)	(0.029)	(0.003)	(0.007)	(0.027)	(0.018)
Control	control	control	control	control	control	control	control	control
Ind	control	control	control	control	control	control	control	control
Time	control	control	control	control	control	control	control	control
rho	0.118	0.247***	0.180***	0.191***	0.184***	0.204***	0.188***	0.184***
	(0.075)	(0.091)	(0.068)	(0.068)	(0.069)	(0.069)	(0.068)	(0.068)
R^2	0.908	0.898	0.941	0.939	0.935	0.936	0.939	0.941

Notes: *RC = resource-based cities; NRC = non-resource-based cities.*

5. **Discussion and Conclusions**

5.1. *Discussion*

This study focuses on China's "dual carbon" goals to elucidate the mechanism through which industrial co-agglomeration influences carbon emission intensity. The regression results from the DSDM confirm the existence of an inverted U-shaped relationship between the co-agglomeration of producer services and the manufacturing sector on the one side and carbon intensity on the other side. Moving beyond previous research, this study examines the impact of industrial co-agglomeration on carbon emission intensity across different developmental stages. Importantly, the interplay between economies of scale and externalities is identified as a key driver of this nonlinear effect. In terms of direct effects, local co-agglomeration demonstrated significant potential for emission reduction. However, the overall level of industrial co-agglomeration in Northeast China requires further enhancement. At present, the level of industrial synergy and clustering in the Northeast region remains on the left side of the inflection point of an inverted U-shaped curve.

This region is still in the early stages of the agglomeration process, where economies of scale have not yet outweighed the negative externalities. The clear indication is that the overall level still needs to be improved. Regarding the indirect effects, the spatial spillovers to neighboring areas are currently insignificant, which highlights the need to reduce regional barriers and strengthen regional integration. Furthermore, this study reveals notable heterogeneity across cities and sectors, indicating that policy formulation should be tailored to local conditions and specific sectors. Finally, in Northeast China, factors including technological backwardness and population outflow may limit the potential of industrial agglomeration to reduce carbon intensity. Although industrial agglomeration can lower carbon intensity through technological innovation and industrial restructuring, the effectiveness of industrial agglomeration in the region may depend on regional economic development and overcoming institutional challenges.

One limitation to note is that, while this study categorizes producer services into six sectors based on the *Statistical Classification of Producer Services* (2019), emerging industries such as "green finance" and "digital technology services" are not separately identified. Driven by digital and green transitions, these sectors have significant advantages in enhancing energy efficiency and facilitating knowledge spillovers. Their co-agglomeration with the manufacturing sector might create the conditions needed to achieve the turning point of the inverted U-shaped curve at an earlier stage. Future research should refine the classification of producer services and incorporate more contemporary sectoral indicators to better discern the distinct roles and impacts within the co-agglomeration framework.

5.2. *Conclusions*

Balancing high-quality economic development with green, low-carbon transition is a critical challenge for China. Utilizing panel data from 34 cities in Northeast China (2003-2022) and a DSDM, this study investigates the mechanism through which industrial co-agglomeration affects carbon emission intensity. The main conclusions are as follows:

(1) The overall level of industrial co-agglomeration in Northeast China showed a declining trend during the sampled years, with significant regional disparities and pronounced spatial polarization. Carbon emission intensity followed a "decline-rise-decline" trajectory and exhibited strong spatiotemporal dependence.

(2) A significant inverted U-shaped relationship exists between industrial co-agglomeration and carbon intensity, demonstrating considerable time persistence. This pattern stems from the shifting interplay between economies of scale and negative externalities at different developmental stages. Northeast China currently lies on the left side of the inverted U-curve's turning point and faces two main barriers to the region's green transition, namely environmental policy failure and a disconnect in green technology innovation.

(3) During the study period (2003 to 2022), the impact of co-agglomeration on carbon intensity was highly heterogeneous, with an effect that was more pronounced in non-resource-based cities. From a sectoral perspective, all examined producer service sectors except "leasing and business services" showed significant impacts. The "finance" sector appeared the most capable of crossing the turning point and holds the greatest potential for emission reduction.

Based on these findings, the following policy recommendations are proposed:

(1) Spatial governance mechanisms should be established for regional collaborative emission reduction. Using the Harbin-Changsha and Central-Southern Liaoning urban agglomerations as pilots, regional carbon emission trading schemes should be established in their core economic centers. These schemes could then draw on the experience of pilot programs in cities such as Beijing, Shanghai, and Shenzhen. This would internalize environmental externalities through market mechanisms. Concurrently, developing cross-regional, interconnected infrastructure networks would facilitate the low-cost, low-carbon flow of production factors and thereby transform spatial dependence into coordinated emission reduction governance.

(2) Steps should be taken to implement differentiated, long-term industrial coordination policies, which in turn should guide firms to adopt long-term carbon reduction strategies. For sectors with significant emission-increase effects before the turning point, to shorten the high-carbon phase, market entry standards requiring the adoption of low-carbon technologies should be set. Priority support should be given to the "finance" and "scientific research & technical services" sectors to accelerate finance-driven green industrial transformation and the commercialization of green technologies. Such support would thereby unlock these sectors' substantial post-turning-point mitigation potential.

(3) Policies should be tailored to local and sectoral contexts in an effort to rebuild regional competitiveness. Provincial economic centers should pioneer closed-loop, low-carbon industrial chains, serving as models whose successful transition experiences could be replicated in surrounding cities. For resource-based cities, breaking away from traditional resource dependence is the key to a successful transition. Transformation should focus on upgrading existing industries, repurposing industrial heritage and idle facilities for industrial tourism, and prioritizing R&D in energy-saving and emission-reduction technologies for traditional sectors. This approach centers on the green retrofitting of incumbent industries as a means to ensure a stable and orderly transition.

6. **Conflicts of Interest**

The authors declare no conflict of interest.

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