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Study on the Spatial Effect of Environmental Regulation on the Upgrading of Industrial Structure

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Abstract:
City cluster is a new geographical unit of global geographical division of labor, and industry and city are the two core elements of city clusters, exploring the spatial dynamics of industrial structure advancement under environmental regulation is of profound theoretical and practical relevance. This research targets the Guangdong-Hong Kong-Macao Greater Bay Area, a region characterized by its distinct and varied urban landscape, to serve as the case study. By adopting the spatial Durbin model, the paper probes the repercussions of environmental regulations on the evolution of industrial structure, considering the spatial spillover effect. Results reveal that environmental regulations not only catalyze the progression of industrial structures within the Greater Bay Area but also initiate beneficial spillover impacts. The influence of these regulations is shown to intensify progressively over time. Furthermore, the paper posits that the amplification of collaborative efforts and the enforcement of stringent environmental protection policies within the area could further reinforce both the immediate and extended influences of environmental regulations on the maturation of industrial structures.

Keywords: environmental regulation, industrial structure upgrading, spatial spillover, diversified urban agglomeration

INTRODUCTION

As cities grow in size and urban functions increase, transportation between cities is well developed, the economic, social, and industrial links between cities become closer and closer, and urban agglomerations are formed as a result of the integration and interactive development of urban geographies.Gottmann's[1] study on the Megalopolis is a widely recognized study of urban agglomerations by academics, and he argued that the U.S. spatial economy is not just dominated by individual megacities, but by a new whole made up of metropolitan areas formed by several megacities coming together. The phenomenon of urban agglomeration has also appeared in other countries, typical of which are the English city clusters in the United Kingdom and the North Western city clusters in Europe. The American Regional Planning Association also put forward the phenomenon of urban agglomeration in megaregions (Megaregion), which is considered to be composed of at least two metropolitan areas, which have a blend of history and culture, similar natural environments, and well-developed transportation infrastructures, and which can lead to the emergence of more metropolitan areas. Urban agglomerations, as emerging entities in the global territorial division of labor, serve as pivotal hubs for fostering synchronized regional growth and engaging in global rivalry and collaboration. They significantly contribute to economic progress.

Industry and city are the two core elements of urban agglomerations, and exploring the spatial effects of environmental regulation on industrial structure upgrading within urban agglomerations is the focus of this paper. Environmental regulation, as a means of government intervention in the economy and the environment, not only promotes the improvement of the ecological environment, but also has an impact on the upgrading of industrial structure. Environmental protection imperatives have prompted governments globally to enact and enforce a suite of environmental regulation policies. These measures not only serve their primary purpose but also influence the progression of industrial structures. This paper examines the effect of such policies on industrial upgrading within the context of the Guangdong-Hong Kong-Macao Greater Bay Area (GBA). The GBA is distinguished by its unique composition, which includes "one country, two systems, three tariff zones, and four central cities," making it an intriguing case for study. This complex institutional setting necessitates a concerted effort towards industrial integration and advancement to propel the high-quality economic development of the region.

In this distinctive and varied urban cluster, the role of environmental regulation in fostering the enhancement and advancement of the regional industrial structure is investigated. This study develops an index for evaluating environmental regulation within the GBA to analyze how environmental regulation influences industrial structural progress. The objective is to aid in reinforcing environmental protection and governance efforts, and to promote industrial evolution and growth in the GBA. The paper's contributions include: the establishment of an environmental regulation assessment framework that considers environmental governance inputs and outputs, as well as population density, and incorporates the trend of pollutants into the outputs; and the application of a dynamic spatial econometric model to examine the interplay between environmental regulation and industrial structure upgrading within the GBA of of the Diversified Urban Agglomeration.

LITERATURE REVIEW AND RESEARCH HYPOTHESIS

Impact of Environmental Regulation on the Upgrading of Local Industrial Structure

The relationship between environmental regulation (ER) and local industrial structure upgrading (IS) has been studied for a long time, but with different views. Some studies have argued that ER inhibits industrial structural upgrading, a view that originates from the neoclassical economic school's follow-the-costs theory, which states that ER increases firms' pollution treatment costs, reduces performance, crowds out R&D and innovation resources, and reduces R&D capacity[2]. Alternatively, several studies support the notion that ER can facilitate the upgrading of industrial structures, a concept stemming from Porter and Linde's "innovation compensation theory." [3] This theory posits that the pressures of ER can spur technological innovation within firms, resulting in the introduction of new products and services that improve market competitiveness. Consequently, this dynamic fosters a symbiotic relationship between ecological conservation and business competitiveness, yielding benefits for both the environment and the corporate sector—a quintessential win-win scenario.

In addition, ER may also produce IS effects through direct and indirect impacts. Some scholars believe that ER directly affects IS. In countries or regions with strict environmental regulations, the development of polluting industries is restricted and production areas need to be reorganized. At the same time, the clean industry is relatively less affected, so it will get more production factors, which will lead to changes in industrial structure. Several researchers posit that ER exerts an indirect influence on the enhancement of industrial structures by affecting enterprises' technological innovation and demand patterns. Du et al.[4]suggests that at advanced stages of economic development, ER may actually facilitate green technological innovation and contribute to the elevation of industrial structures. On the other hand, Li and Ding[5]presents an analysis where potential impediments such as transfer costs and trade barriers are not accounted for in the discourse on how ER could hinder industrial structure progression. GBA is a region where China's scientific research talents and innovation resources are gathered, with strong scientific and technological development and conversion capabilities, and is focusing on constructing an innovative green and low-carbon development model with a strict ecological environmental protection system, so it is more probable that ER promotes the upgrading of industrial structure, based on which we propose Hypothesis 1.

Hypothesis 1: Environmental regulation positively promotes the optimization and upgrading of local industries in the GBA region.

Spatial Spillover Effects of Environmental Regulation on Industrial Structure Upgrading

The scholarly consensus is split regarding the unintended consequences of ER on the enhancement of industrial frameworks. One camp argues that stringent local environmental policies could potentially slow down the progression of industrial structures in neighboring areas, while the opposing perspective posits a beneficial effect. This inhibitory stance is rooted in the pollution haven hypothesis. The theory suggests that developing countries sacrifice the ecological environment in order to attract foreign investment, thus creating pollution havens. The theory has been further refined, pointing out that countries with relatively low environmental regulatory intensity have a comparative advantage in producing polluting industries, thus becoming a concentration of pollution transfer from developed countries, which ultimately has an impact on industrial structure.

The literature on the positive contribution of local ER is mainly from the perspectives of yardstick competition and technological spillovers. Under the scale competition mechanism, there is mutual imitation behavior in local ER[6]. When a region strengthens its environmental regulation policy, other regional governments follow suit by adopting the same or similar ER standards and intensity[7], which extends the scope of environmental regulation spatially, and the interaction of regional environmental regulation is characterized by "competition upwards"[8], bringing about the adjustment and upgrading of industries in other regions, which in turn leads to a "competition upwards" The interaction of regional environmental regulation is characterized by a "race to the top", which brings about industrial adjustment and upgrading in other regions. The technological spillover effect brought by the enhancement of ER refers to the fact that ER stimulates the green technological progress of enterprises[9], and the technological innovation level of local enterprises is enhanced, which leads to the technological upgrading of enterprises in the neighboring regions and the upgrading of the industrial structure of the neighboring regions by the occurrence of free-rider behaviors through the industrial linkage, knowledge spillover, and technological dissemination.

The GBA is led by the construction of a beautiful bay area, with a high degree of synergy in science and technology innovation, and a deep integration and development of industries, and we propose research hypothesis 2.

Hypothesis 2: Environmental regulation in the GBA region positively promotes industrial optimization and upgrading in the surrounding areas.

RESEARCH DESIGN

Indicator Selection and Data Description

The study period spans from 2009 to 2021, utilizing data sourced from the Guangdong, Hong Kong, and Macao Statistical Yearbooks, along with various municipal yearbooks and bulletins detailing national economic and social progress. Data gaps were addressed through manual computation and interpolation methods.

(1) Dependant variable: Industrial Structure Upgrading (IS).

Industrial structure encapsulates the compositional relationship between the value contributions of various industries to a nation's (or region's) GDP, along with the interconnections within the industrial supply chain. This study employs the value-added ratio of the tertiary sector to that of the secondary sector as a metric to assess the progression of industrial evolution from elementary to advanced stages.

(2) Core independent variable: Environmental Regulation (ER).

To assess the intensity of ER, researchers employ four primary approaches: the single-indicator, proxy, assignment, and comprehensive indicator methods. The single-indicator approach quantifies regulation intensity through a solitary metric, examples of which include the frequency of corporate emissions inspections by environmental authorities, the ratio of governance investments to total industrial output, and the rate of industrial sulfur dioxide mitigation. While data acquisition for this method is straightforward, it offers an incomplete picture of the regulatory intensity due to its narrow focus.The substitution method refers to the use of independent variables with a high degree of similarity to proxy for ER indicators, such as the income level of a region, per capita GDP.The assignment method is generally based on the strength of the national government departments to formulate policies or plans related to environmental governance directly assigned. Composite index method is the evaluation index obtained by weighting and synthesizing different indicators after selecting multiple indicators and assigning them through principal component analysis, factor analysis, entropy value method, etc. This index is highly representative, but it is difficult to obtain data.

Yang et al measured ER through the perspectives of environmental governance inputs and environmental governance outputs[10]. Based on it, this paper introduces population density to construct ER indicators, which is an important factor affecting the environment and has a negative effect on ER[11]. The specific process is as follows.

Step 1. The different pollutant emissions in each region are standardized to make the different types of pollutants comparable.

$$E_{ij}^{s} = \frac{E_{ij} - \min(E_j)}{\max(E_j) - \min(E_j)} \tag{1}$$

Where, E_{ij}^{s} denotes the standardized value of pollutant j in region i, E_{ij} denotes the actual emissions of pollutant j in region i, and $\max(E_j)$ and $\min(E_j)$ represents the maximum and minimum emissions of pollutant j, respectively.

Step 2. A pollutant adjustment factor is calculated, which evaluates the trend of pollutant j. The slope of the emission curve for area i for pollutant j is calculated using the LSM method; if the slope is greater than zero, it indicates an increasing trend in pollutant emissions; if the slope is zero, it indicates that pollutant j emissions remain unchanged; and if the slope is less than zero, it indicates that there is a decreasing trend in pollutant j emissions. In this paper, the slope is taken as the logarithm of the adjustment factor for pollutant j.

Step 3. The overall pollution emission intensity of region i is calculated as $S_i = \frac{1}{n}\sum_{j=1}^{n} W_j \times E_{ij}^{s}$. n indicates the number of pollutant types.

Step 4. The ER for area i is calculated ER_i . The overall pollution emission intensity only considers the environmental governance outputs, and the environmental governance inputs and population density are further introduced into the construction of the ER indicators. The calculation formula is

$$ER_i = \frac{PC_i}{S_i \times PD_i} \tag{2}$$

Where thePC_i denotes the investment of area i in pollution control, andPD_i denotes the population density of region i. The ER calculated in this way takes into account the increase in regional environmental governance inputs and the decrease in pollution emissions, and also takes into account the negative impact of population density on ER.

Based on the emissions of various pollutants in China, industrial wastewater, industrial sulphur dioxide and industrial fixed waste emissions were selected as representative pollutants for calculation. Subject to data availability, the Hong Kong sample includes only sulphur dioxide and fixed waste emissions, while the Macao sample includes regional solid waste disposal. The enhanced composite index approach facilitates the computation of regional ER intensity.

(3) Control variables.

Scientific research funds (SRF) are measured by the science and technology expenditures in local general public budgets. The intensity of scientific research funds is closely related to industrial structure adjustment. The investment of enterprise scientific research funds is conducive to guiding enterprises to carry out scientific and technological innovation, bringing about technological upgrading, enhancing the scientific research strength and competitiveness of enterprises, and promoting the adjustment of industrial structure. There are differences in the caliber of statistics between Hong Kong and Macao, so close indicators are used as substitutes.

Education input (Degree of Education, EDU), which is measured by using the education expenditure in the local general public budget. Education development and industrial development are closely related, education reflects the potential of regional development, education can cultivate human resources to promote IS, and provide corresponding human capital and technical support for IS.Taixiera and Queiros[12]and others found that education can promote IS through improving labor productivity, technological progress and so on.

The level of transportation infrastructure construction (Infrastructure construction level) can be expressed by highway density, i.e., vehicle mileage/land area. Transportation infrastructure influences the movement of production factors, including labor and capital, shaping regional development, industrial configuration, and diffusion. These factors collectively contribute to the evolution of regional industrial structures.

Descriptive Statistics

Table 1 shows the descriptive statistics of each main variable. The mean value of the explanatory variable industrial upgrading is 3.7123, its maximum value is 25.8661, which is the data of Macau in 2013, and its minimum value is 0.5543, which is the data of Foshan in 2010. There are obvious differences in regional industrial upgrading. The tertiary industry in Hong Kong and Macao is very developed, with the proportion of the service industry to the total value of GDP above 85%, and the service characteristics are obvious. The tertiary industry in Guangzhou and Shenzhen is also more developed, but the secondary industry in Foshan, Huizhou and Dongguan is more developed.

Table 1. Descriptive statistics of the main variables

Indicators	Symbol	mean	sd	min	max
Industrial Structure Upgrading	IS	3.7123	5.9799	0.5543	25.8661
Environment Regulation	ER	9128.6526	17859.7682	93.9712	141267.3900
Scientific Research Funds Investments	SRF	61.7798	99.4397	0.4632	554.9817
Education Investments	EDU	194.4168	233.3508	12.9678	1103.6275
Traffic Infrastructure	TRA	2.7232	3.7688	0.3584	14.0461

Empirical Design

Model Setup

The regions within the GBA share proximate borders, allowing for the unimpeded flow of capital and labor. This proximity fosters technological spillovers, learning effects, and inter-regional influences. Consequently, the evolution of a regional industrial structure is shaped not only by local ER but also by the regulatory intensity and industrial configurations of neighboring areas. To account for the spatial interdependencies and mitigate biases arising from spatial correlations, this study employs the spatial Durbin model to evaluate the influence of ER on IS in the GBA.

$$\ln \mathrm{IS}_{it} = \beta \sum_{j=1}^{n} \omega_{ij} \ln \mathrm{IS}_{jt} + \alpha_1 \ln \mathrm{ER}_{it} + \alpha_2 \mathrm{contrl}_{it} + \beta_1 \sum_{j=1}^{n} \omega_{ij} \ln \mathrm{ER}_{jt} + \beta_2 \sum_{j=1}^{n} \omega_{ij} \mathrm{contrl}_{it} + u_i + \nu_t + \mu_{it} \quad (3)$$

In order to avoid heteroskedasticity and differences in magnitude from coloring the results, the natural logarithm was taken for each variable in the model.

Let IS_{it} represent the status of IS in the ith region during period t, and ER_{it} denote the intensity of ER in the same region and period, and the variable contrl_{it} is the logarithmic transformation of a series of control variables, while ω_{ij} signifies the spatial weight matrix. Spatial regression coefficient β captures the interdependence of IS across regions, and the regression coefficient α_1 measures the impact of a region's ER intensity on its own IS, and the spatial regression coefficient β_1 measures the impact of a region's ER intensity on its own IS. Meanwhile, the coefficients u_i and ν_t account for individual and time fixed effects, respectively, μ_{it} being the random error terms.

Considering the continuous and dynamic nature of IS, it is important to recognize that developments from previous periods can influence the current state. To capture this temporal effect, the model incorporates a first-order lag term of the IS indicators. This addition facilitates the construction of a dynamic spatial Durbin panel model, which more accurately reflects theoretical considerations and real-world dynamics. The model is shown below.

$$\begin{aligned}\ln \mathrm{IS}_{it} = \theta \ln \mathrm{IS}_{i,t-1} + \beta \sum_{j=1}^{n} \omega_{ij} \ln \mathrm{IS}_{jt} + \alpha_1 \ln \mathrm{ER}_{it} + \alpha_2 \mathrm{contrl}_{it} + \beta_1 \sum_{j=1}^{n} \omega_{ij} \ln \mathrm{ER}_{jt} \\ + \beta_2 \sum_{j=1}^{n} \omega_{ij} \mathrm{contrl}_{it} + u_i + \nu_t + \mu_{it}\end{aligned} \quad (4)$$

where the coefficient of the time lag termθ reflects the inertia characteristic of IS.

Selection of the spatial weight matrix

The dynamic spatial Durbin model captures inter-regional relationships via the spatial weight matrix, which requires careful construction. While physical proximity is often quantified by geographical distance, economic distance—a broader measure—exerts a more significant impact on IS. Regions with similar per capita GDPs tend to have closer economic ties, comparable industrial structures, and shared external environments, thus facilitating spillover effects. Consequently, an economic distance weight matrix is considered. Let $PDGP_i$ and $PGDP_j$ represent the per capita GDPs of regions i and j respectively. The economic distance weight matrix is defined as follows:

$$\omega_{ij} = \begin{cases} \frac{1}{|PGDP_i - PGDP_j|} & , \quad i \neq j \\ 0 & , \quad i = j \end{cases} \tag{5}$$

EMPIRICAL ANALYSIS

Spatial Correlation Test

Before initiating spatial regression analysis, it is critical to assess the spatial autocorrelation within the sample. This investigation employs the Global Moran's I statistic to ascertain spatial correlation in the IS. The formula used for computing Global Moran's I is as indicated：

$$\text{Moran's I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(Y_i - \overline{Y})(Y_j - \overline{Y})}{S^2 \sum_{i=0}^{n} \omega_{ij}} \tag{6}$$

Where, $S^2 = \frac{1}{n}\sum_{i=1}^{n}(Y_i - \overline{Y})^2$, Y_i denotes the observed value of region i, $\overline{Y}$denotes the average value of the variable Y in GBA. ω_{ij} is the spatial weight matrix of region i and region j, while n is the total number of regions. A positive Moran's I value signifies a positive correlation, with higher values indicating increased correlation strength. Negative Moran's I values denote negative correlation, where more negative values point to greater spatial disparities. When Moran's I equals zero, it suggests a spatially random distribution.

Table 2. Global Moran's index of IS in GBA

Year	I	z	p-value*
2009	0.075	2.263	0.012
2010	0.087	2.274	0.011
2011	0.090	2.278	0.011
2012	0.092	2.280	0.011
2013	0.099	2.329	0.010
2014	0.093	2.333	0.010
2015	0.079	2.335	0.010
2016	0.085	2.332	0.010
2017	0.091	2.333	0.010
2018	0.095	2.313	0.010
2019	0.094	2.291	0.011
2020	0.072	2.268	0.012
2021	0.086	2.376	0.009

The global Moran index for IS in the GBA has been computed and is presented in Table 2. The data reveal that, from 2009 to 2021, the global Moran indices based on the economic distance matrix for the GBA are consistently positive, with Z statistics that are significant at the 5% level. This indicates the presence of spatial correlation in the IS within the GBA. Consequently, the influence of ER on IS warrants examination from a spatial perspective.

Model Setting Form Test and Selection

The analysis reveals spatial autocorrelation among the samples, necessitating the selection of an appropriate spatial econometric model for further examination. This study employs the Lagrange Multiplier (LM) test, the Wald test,and the Likelihood Ratio (LR) test to ascertain if the dynamic spatial Durbin model can be simplified into either a spatial lag model or a spatial error model.The outcomes of these tests are displayed in Table 3.

Table 3. Results of LM test, Wald test and LR test

inspect	statistic	P-value	inspect	statistic	P-value
LM-error	7.11	0.008	Wald (SAR)	45.04	0.000
Robust LM-error	4.052	0.044	Wald (SEM)	64.24	0.000
LM-lag	3.360	0.067	LR (SAR)	54.39	0.000
Robust LM-lag	0.302	0.583	LR (SEM)	53.84	0.000

Table 3 indicates that the Lagrange Multiplier test supports models other than the spatial lag model, pointing towards the spatial error model's favor. Nevertheless, the Wald and Likelihood Ratio tests indicate that the spatial Durbin model cannot be reduced to either of the other two models. Following this, a Hausman test was employed to select the proper effect, concluding that a fixed effects regression is the more appropriate choice. Due to the temporal continuity of IS, the time-fixed dynamic spatial Durbin model was chosen for the analysis.

Analysis of the Regression Results of the Dynamic Spatial Panel Model

The estimation results of the dynamic spatial Durbin model are shown in Table 4.

Table 4. Spatial Durbin model regression results

Variables	Coefficients	T-statistics
L.lnIS	0.7938***	28.427
lnER	0.0889***	7.0491
lnSRF	-0.0537*	-1.8924
lnEDU	0.2753***	4.7509
lnTRA	0.1454***	3.6757
WlnER	0.4326***	8.8387
WlnSRF	0.0622	0.6369
WlnEDU	0.6539***	3.6971
WlnTRA	2.2676***	11.3379
rho	0.3031**	2.3774

At a 5% significance level, the positive coefficient of the spatial lag term (rho) for IS in the GBA suggests significant spillover effects within the region. The interconnectedness of industries, coupled with geographical proximity and cultural affinities, likely contributes to a demonstration effect that fosters industrial upgrading across the GBA.

Furthermore, the positive regression coefficients of lnER at a 1% significance level indicate that ER substantially aids IS enhancement within the region, affirming Hypothesis 1. Similarly, the positive coefficients of WlnER at the same significance level reveal that ER also positively influences the IS of adjacent regions, thereby supporting Hypothesis 2.

Contrastingly, the negative regression coefficient of investment in scientific research at a 1% significance level suggests that such investment does not promote IS in the GBA. A potential reason could be that although scientific research funding has increased across the nine Guangdong regions within the GBA, the allocation has been disproportionately in favor of the secondary industry. This has expedited the internal structural adjustment and transformation within the secondary industry, while this paper's indicators for industrial upgrading primarily reflect the shift from the secondary to the tertiary industry.

Investment in education, with positive coefficients for both the regression and the spatial lag term at a 1% significance level, plays a pivotal role in advancing IS, both within the city and in neighboring areas. The strategic distribution and realignment of educational resources influence industrial structure adjustment and upgrading. Education investment contributes to human capital accumulation, supplying the talent necessary for industrial upgrading and empowering the advancement and evolution of the industrial structure.

Lastly, the coefficients for lnTRA and WlnTRA are positive at a 1% significance level, indicating that the level of transportation infrastructure construction significantly promotes the city's IS and also benefits neighboring regions through spillover effects. Enhanced transportation infrastructure bolsters regional connectivity, lowers trade costs within and beyond the region, fosters collaborative development with neighboring areas, and facilitates the optimization and realignment of the industrial layout and structure in both the city and surrounding regions.

Effect Decomposition

Utilizing spatial lag terminology to characterize spatial phenomena might introduce inaccuracies. This paper delineates effects into two categories: direct and indirect. In the context of the dynamic spatial Durbin model employed in this study, it is imperative to discern between long-term and short-term impacts throughout the temporal continuum. The intricate dissection of these effects is meticulously outlined in Table 5.

Table 5. Effect estimation of dynamic spatial Durbin model

VARIABLES	SR_Direct	SR_Indirect	SR_Total	LR_Total
lnER	0.0716***	0.3360***	0.4076***	1.1306**
	(5.5790)	(6.4364)	(7.2229)	(2.2691)
lnSRF	-0.0549**	0.0661	0.0112	0.0301
	(-2.0698)	(0.7974)	(0.1201)	(0.1000)
lnEDU	0.2464***	0.4583***	0.7047***	1.9161***
	(4.9168)	(3.4479)	(4.2470)	(2.7060)
lnTRA	0.0521	1.8300***	1.8821***	5.1808***
	(0.9644)	(10.4917)	(10.0825)	(2.6525)

Table 5 indicates that the short-term direct effect of ER (ER) on IS(IS) upgrading in the GBA is significantly positive at the 1% level. This direct effect captures the immediate impact of ER within the region, inclusive of the feedback loop, where the IS in neighboring regions also influences the focal region. In the short term, enhanced ER incentivizes local firms to undertake technological innovation, thereby positively influencing IS.

Concurrently, the short-term indirect effect, also significant at the 1% level, embodies spatial spillovers. This effect measures the influence of ER in other regions on the region's IS. Technological advancements driven by heightened ER in one area can spill over, and along with the dissemination of regulatory policies, foster IS in adjacent regions.

The positive influence of exchange rates (ERs) on investment spending (IS) in the Greater Bay Area (GBA) is confirmed in both the short and long term at the 5% significance level. Analysis indicates that the long-term aggregate impact of ERs on IS is significantly higher than the short-term, pointing to an increasing effect of ERs on IS as time progresses.

Robustness Test

Approach 1 involves substituting the spatial matrix to bolster the robustness of our findings. We replace the economic distance matrix with an economic geography matrix that accounts for spatial effects arising from both economic and geographic proximities. The outcomes of this substitution are displayed in the first column of data in Table 6. The coefficients for the lagged period of IS, the impact of ER on IS in the GBA, and the coefficient of the spatial lag term all remain positively significant at the 1% level. These results demonstrate commendable stability, mirroring those obtained using the economic distance matrix.

Approach Two: Replace the proxy variables. Firstly, To replace the dependent variables. Referring to the calculation method of industrial structure rationalization of Gan Chunhui et al. (2011), the industrial structure index is suggested to be conducted with only the secondary and tertiary industries. The calculation formula is $\sum(\frac{Y_i}{Y} \times \ln(\frac{Y_i}{L_i}/\frac{Y}{L}))$, where Y_i denotes the value added of industry i and L_i denotes the number of people employed in industry i. The test results are shown in the second column in Table 6. The primary inferences persist. Furthermore, the dependent variables are substituted, employing the inverse of the total pollution emission intensity per unit area to gauge the ER intensity. As indicated in the third column of Table 6, the results uphold the main conclusion, thereby reaffirming the robustness of the findings.

Table 6. Results of robustness tests

	(1)	(2)	(3)
L.lnIS	0.9097***	0.7635***	0.7466***
	(38.2998)	(11.4501)	(26.3195)
lnER	0.0498***	0.2399*	0.2649***
	(4.0759)	(1.8186)	(13.2752)
W lnER	0.4433***	0.9237*	1.0974***
	(9.9548)	(1.7514)	(14.3729)
rho	0.4262***	0.9391***	0.3623***
	(4.3825)	(5.0533)	(2.8606)
SR_Total	0.3485***	0.6155**	1.0162***
	(9.5346)	(2.0858)	(9.0085)
LR_Total	0.9951***	1.0343**	2.3586***
	(4.7517)	(1.9717)	(3.8189)

TEMPORAL HETEROGENEITY ANALYSIS

Recognizing the enforcement of the "most stringent environmental protection law in history," the Environmental Protection Law of the People's Republic of China (EPL), starting January 1, 2015, this study delineates the timeline into two distinct periods for analysis: pre-EPL enforcement (2009-2014) and post-EPL enforcement (2015-2021). This division allows for an examination of the temporal variations in the effects of ER on IS within the GBA.

Table 7. Test results by time period

	2009-2014	2015-2021
L.lnIS	1.0528***	0.5811***
	(28.6637)	(12.1575)
lnER	0.0374	0.3363***
	(1.5009)	(13.7514)
WlnER	0.1878**	1.1641***
	(2.2649)	(12.5799)

rho	0.0873	0.9927***
	(0.4587)	(5.3171)
SR_Total	0.2137**	0.7652***
	(2.2252)	(9.3604)
LR_Total	0.8126	1.0930***
	(0.0459)	(6.9986)

Table 7 indicates that the dynamic Durbin model's estimations of ER's impact on IS within the GBA showed a marked increase in significance between 2015-2021 compared to 2009-2014. During the earlier period, the coefficient for ER's effect on IS was not statistically significant. Although the short-term total effect was significant at the 5% level with a coefficient of 0.2137, the long-term effect was not. In the later period, both the coefficient and spatial lag term for ER on IS achieved significance at the 1% level, with the short-term effect coefficient climbing to 0.7652 and the long-term to 1.093, both statistically significant at the 1% level, and the long-term effect surpassing the short-term impact.

The discrepancy in time can be ascribed to two main elements. Initially, the implementation of China's updated Environmental Protection Law in 2015 significantly increased both the breadth and the stringency of sanctions for environmental violations, thereby enhancing the direct and indirect effects of ER on industrial transformation. Secondly, the Greater Bay Area concept was officially introduced in 2015, followed by the release of numerous policy documents that provided substantial incentives for economic growth and industrial consolidation within the GBA. These initiatives have strengthened the spillover effects of ER on IS.

CONCLUSIONS AND POLICY RECOMMENDATIONS

Using a balanced panel dataset from the Greater Bay Area (GBA) covering 2009-2021, this research employs a dynamic spatial Durbin model to analyze the impact of ER on industrial structure. The study reveals that environmental regulation in the GBA not only promotes local industrial development but also facilitates industrial progression in neighboring areas. Second, the cumulative impact of ER on IS is more pronounced in the long term than in the short term, with a trend of growing influence over time. Third, the augmentation of environmental policy sanctions coupled with intensified collaboration among Guangdong, Hong Kong, and Macao within the GBA has bolstered both the direct and the ripple effects of ER on IS.

Drawing from the aforementioned conclusions, this study offers the subsequent policy recommendation: It is imperative to elevate the sophistication of ER to ensure it serves as an effective catalyst for the advancement of industrial structure. Specifically, it is necessary to increase environmental protection investment, rationally allocate environmental protection funds to various industrial sectors, strengthen environmental protection enforcement, and encourage the public to actively participate in environmental protection governance. To enhance the regional influence of environmental regulatory cooperation and foster synchronized industrial structural progress, it is imperative to bolster the central region's impact on its surrounding areas. This can be achieved through initiatives like joint legislative efforts, collaborative pollution management, cooperative law enforcement, and transparent environmental information sharing, thereby creating an effective GBA environmental governance framework. Finally, to achieve regional integration and elevate the industrial architecture, the GBA ought to intensify collaborative efforts in regional industrial development and planning. Advancement of the area's industrial structure can be facilitated by devising comprehensive inter-regional industrial strategies, instituting robust mechanisms for regional industrial cooperation, and pioneering innovative models for cross-regional industrial collaboration.

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