RESEARCH ARTICLE

Environmental regulation and manufacturing carbon emissions in China: a new perspective on local government competition

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Abstract

Environmental regulation is a crucial way to achieve manufacturing green transformation. However, few studies have explored the spatial spillover effects and regional boundaries of environmental regulation on manufacturing carbon emissions from the perspective of local government competition. Based on the manufacturing panel data of 30 provinces in China from 2007 to 2019, this paper uses the spatial Durbin model to examine the impact mechanisms, spatial spillover effects, regional boundaries and industry heterogeneity of environmental regulation, and local government competition on manufacturing carbon emissions. The results show that (1) environmental regulation suppresses local manufacturing carbon emissions, local government competition increases local manufacturing carbon emissions, but the interaction indicates that local governments tend to top-to-top competition under the constraints of environmental regulation. (2) The spatial spillover effect of environmental regulation has regional boundaries. The regional boundary with a positive spillover effect is 600 km, and the regional boundary with a negative spillover effect is 1600 km. (3) Environmental regulation and local government competition have spatial heterogeneity in the carbon reduction effects of seven-type manufacturing industries. These findings suggest concrete evidence for developing policies for further encouraging green development in manufacturing.

Keywords Environmental regulation · Local government competition · Manufacturing carbon emissions · Regional boundary

Introduction

As global climate governance enters the full implementation stage of the Paris Agreement, there is an urgent need for countries worldwide to implement and enhance capacity to reduce carbon emissions and strive to achieve the goal of global temperature control (Li et al. 2019; Fernando and Hor 2017; Chontanawat 2020). China overtook the United States to become the world's largest carbon dioxide emitter in 2007 (Dong et al. 2013). In 2020, carbon emissions reached 9.899 billion tons, accounting for 30.7% of global carbon emissions. In the face of increasingly severe carbon emissions, China has actively made commitments and efforts to set medium- and long-term carbon emission reduction targets. Specifically, at the 75th session of the United Nations General Assembly in September 2020, China first made a commitment of "carbon peak by 2030 and carbon neutrality by 2060," which opened a new journey in China's climate governance work. Subsequently, the Central Economic Work Conference in March 2021 incorporated "carbon peak and carbon neutrality" into the overall layout of ecological civilization construction, promoting carbon emission reduction from a strategic goal to a national strategic plan, which raises the carbon emission reduction work to an unprecedented level, and manufacturing carbon emissions (MCE) are therefore highly concerned.

Since the reform and opening up, China's manufacturing industry has been growing rapidly (Lin and Chen 2020). From 2007 to 2019, the added value of the manufacturing industry increased from 8.75 trillion yuan in 2007 to 26.92 trillion yuan in 2019, with an annual growth rate of

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9.82% and a global share of 28.1%. Among the more than 500 major industrial products globally, China ranks first in the world in terms of output of more than 220 industrial products, making outstanding achievements in manufacturing development. However, as a highly energy-intensive industry, the rapid development in the manufacturing sector is accompanied by a large amount of energy consumption and carbon emissions (Lin and Chen 2018; Lee and Choi 2021; Abokyi et al. 2021; Haseeb et al. 2020). The average annual growth rate of manufacturing energy consumption is 4.14%, and the average annual growth rate of MCE reaches 3.01% from 2007 to 2019 (NBS 2020), which not only poses a great challenge and pressure on overall carbon emission reduction, but also causes a series of problems such as the decline in environmental quality, damage to public health, and unsustainable economic development. Therefore, energy conservation and emission reduction in manufacturing is imminent (Li et al. 2019; Chontanawat 2020).

Encouragingly, environmental regulation (ER) is regarded as an effective means for the government to improve environmental quality (Guo and Chen 2018; Hashmi and Alam 2019; Ulucak et al. 2020) and is favored by governments and valued by regulators in environmental governance. In response to the growing problem of environmental pollution caused by MCE, the Chinese government has proposed specific emission reduction targets and taken positive environmental regulation measures to control carbon emissions through enhanced ecological supervision (Chen et al. 2018). For example, "Made in China 2025" explicitly sets the target of reducing carbon emissions per unit of added value by 40% from 2015 to 2025. At the same time, the Chinese government has formulated a series of laws, regulations, and plans for environmental governance, such as the Environmental Protection Tax Law, the Industrial Green Development Plan (2016–2020), and the Guidance on Strengthening Prevention and Control of the Ecological Environment Source of High Energy Consumption and High Emission Construction Projects (2021) (Li et al. 2019; Zhu et al. 2018). Specifically, in the manufacturing sector, the Chinese government has increased its regulation of the high energy-consuming sectors of the manufacturing industry, particularly in the backward steel enterprises, chemical industry, power generation, building materials (especially cement), coal, mining, metallurgy, and other high-emission sectors. Strengthening regulation of projects with high energy consumption and high emissions helps achieve energy saving and carbon reduction (Li and Lin 2017a; Lee and Choi 2021; Garg et al 2020). And undeniably, environmental regulations are increasingly becoming a critical force for local governments to control manufacturing carbon emissions.

However, due to the decentralized governance of the Chinese government, local governments have the discretion to formulate environmental laws and regulations (Jin et al. 2005; Zheng 2007), resulting in different competing approaches to environmental governance by local governments (Driessen et al. 2012; Van Laerhoven and Barnes 2014). On the one hand, local governments compete for the bottom by relaxing environmental regulations at the expense of the environment in pursuit of economic growth. On the other hand, local governments compete for the top by strengthening environmental regulations and balancing the economy and the environment to enhance competitiveness and promote quality economic development. It is surprising that in manufacturing carbon emission governance, the impact of changes in environmental regulation strategies induced by local government competition (LGC) has been ignored. In addition, due to the enormous differences in production in the manufacturing sub-sectors, there is significant sectoral heterogeneity in carbon emissions, which poses significant challenges to manufacturing low-carbon development (Sun et al. 2019; Shahnazi and Shabani 2021). More importantly, with the construction of the new dual-cycle development pattern in China, consumer demand is increasing, and the transformation and upgrading and transfer in the manufacturing are accelerating, which leads to an intensification of inter-regional air pollution and even affects the air quality of the surrounding areas through the spillover effect (Chen et al. 2016; Lu et al. 2019; Anselin 1989; Samreen and Majeed 2020; Shahnazi and Shabani 2021). However, so far, few studies have discussed the externality and industry heterogeneity of environmental regulation on MCE from the perspective of local government competition.

To fill the above academic gaps, based on the manufacturing panel data of 30 provinces in China from 2007 to 2019, this study analyzes the influence mechanism, spillover effect, regional boundary, and industry heterogeneity of environmental regulation on MCE from the perspective of local government competition. It attempts to answer the following questions: (1) Do environmental regulation and MCE have spatiotemporal differentiation characteristic? (2) Are there spatial spillover effects of environmental regulation and local government competition on MCE? What's the impact? Does local government competition present "bottom-to-bottom competition" or "top-to-top competition"? (3) Further, is there spatial heterogeneity in the impact of environmental regulation on MCE? Solving the above problems may help policymakers to formulate targeted environmental regulations according to the manufacturing heterogeneity industry and also help to promote "energy saving and carbon reduction" in manufacturing, thereby providing useful references for achieving the goal of "carbon peak and carbon neutrality" and dealing with global climate governance.

Compared with previous studies, the possible marginal contribution in this paper is as follows: (1) Different from previous studies that only explore the impact of environmental regulation on regional carbon emissions, this study

puts environmental regulation, local government competition, and MCE into a unified framework, deeply analyzes the effect of environmental regulation on MCE, and explores the role of local government competition, which expands the existing research and provides a new research perspective for manufacturing carbon emission reduction. (2) Based on different spatial weight matrices, the spatial Durbin model (SPDM) is employed to analyze the impact mechanism, spatial spillover effect, and regional boundary of ER and LGC on MCE and further explore the spatial heterogeneity of the manufacturing industry segment, which provides new ideas for reducing MCE. (3) Based on the micro-scale industry, this paper sinks to the manufacturing level to explore the impact of ER and LGC on MCE in an attempt to provide an empirical reference for formulating targeted and discrepant industry environmental policies.

The rest of the paper is as follows: the "Literature review and theoretical hypotheses" section reviews the existing literature and proposes theoretical hypotheses; the "Methodology and data" section describes methodology and data; the "Empirical results" section analyzes empirical results; the "Conclusions and discussions" section presents conclusions and recommendations.

Literature review and theoretical hypotheses

The impact of environmental regulation on carbon emission

Environmental regulation is considered to be one of the essential means to deal with environmental problems and improve environmental quality (Hashmi and Alam 2019; Ulucak et al. 2020). Previous studies have discussed the relationship between environmental regulation and carbon emissions, but the research conclusions are inconsistent. The main viewpoints include "green paradox," emission reduction effect, and nonlinear.

Green paradox

Sinn (2008) first put forward the "green paradox," arguing that implementing strict environmental policies may damage miners' interests, which leads to increased carbon emissions from fossil energy extraction; that is to say, ER cannot availably control carbon emissions; instead, it aggravates pollution. Ritter and Schopf (2014) found that tax or alternative energy subsidy policies induced countries with less strict ER to increase the use of fossil fuels. Early or delayed implementation of environmental policies may increase energy consumption and carbon emissions (Smulders et al. 2012). Moreover, the regulatory effect of environmental policies

has regional heterogeneity. With the improvement of ER, carbon emissions in most regions will rise (Wang et al. 2018b), especially in areas where the economy is depressed.

Emission reduction effect

Contrary to the view of the "green paradox," some scholars agree with the opinion of the "emission reduction effect" and believe that ER helps to reduce carbon emissions (Van der Ploeg and Withagen 2012; Pei et al. 2019; Cairns 2014; Han 2020) and the improvement of environmental regulatory quality is conducive to carbon emission reduction (Acheampong et al. 2019). At the same time, due to the differences in regulatory efficiency, regulatory costs, corporate preferences, government regulatory preferences, regulatory penalties, the scope of application, and other aspects of environmental regulation, the emission reduction effect of environmental regulation has obvious heterogeneity (Ribeiro and Kruglianskas 2015). Based on the Porter hypothesis, pollution sanctuary hypothesis, and pollution halo hypothesis, some scholars have carefully explored the emission reduction effect of environmental regulation.

On the one hand, the Porter hypothesis believes that strict and appropriate environmental regulation forces enterprises to engage in innovation, encourages enterprises to introduce advanced production technology, guides enterprises to low-carbon technology innovation (Porter and Van der Linde 1995; Pei et al. 2019), and then promotes emission reduction. The government could use environmental emission assessment and supervision, punishment system, production technology standards, and other control means to force enterprises to strengthen innovative activities (Zhao et al. 2015), aiming to achieve carbon emission reduction targets. On the other hand, strict environmental regulation forces polluters to move to areas with loose environmental regulations to reduce the cost of pollution control (Mert and Caglar 2020; Peng 2020), so areas with weak environmental regulations become pollution havens for high-carbon emission enterprises. To achieve carbon reduction targets, the government would use market means to strengthen regulation, such as fossil fuel taxes, clean development subsidies, emission charges, and trading schemes (Hashmi and Alam 2019; Wolde-Rufael and Mulat-Weldemeskel 2021), and make enterprises move to areas with lower environmental costs.

In addition, enterprises may also produce "pollution halo effect" in migration. The pollution halo hypothesis holds that the relocation of investment enterprises promotes reallocation of resources, bringing new production processes, management skills, energy conservation, and environmental protection technologies to the host country (HÜBler and Keller 2010; Mert and Caglar 2020; Liu and Xu 2021), contributes to increase output efficiency and reduce energy

consumption, and improves environmental quality (Cole et al. 2008; Balsalobre-Lorente et al. 2019). Cole et al. (2008) investigated the impact of FDI on the environment in developing countries using Ghana's manufacturing data. They found that key employees who had received training or experience in foreign-funded companies would use what they had learned to benefit the local environment. In other words, foreign-funded enterprises could bring substantial environmental benefits to developing countries by using more advanced technology, cleaner production methods, and more advanced environmental management systems and organizational techniques. Meanwhile, the inflow of FDI improves energy efficiency, leading to a decrease in emission growth rate (HÜBler and Keller 2010; Mert and Caglar 2020). In addition, technology spillover may also be the main cause of pollution halo effect, and encouraging the use of clean technologies, increasing incentives for FDI inflows, facilitating transport infrastructure, and enhancing human capital are the necessary means for governments to address pollution and improve environmental quality (Liu and Xu 2021; Mert and Caglar 2020). For China, as the global free trade is increasingly close and a dual-cycle pattern is constructed, foreign direct investment and domestic consumption investment activities are significantly increasing. Meanwhile, due to the differences in economic development of regions, the transformation and transfer of manufacturing industries may produce a "pollution halo effect." The process of investment and transferring in manufacturing from developed areas to less developed areas may provide new production processes, technologies, and management for manufacturing in less developed areas, to some extent, which may improve the regional industrial structure, increase environmental efficiency, and thus reduce carbon emissions (Zhou et al. 2013; Li and Lin 2017b).

Nonlinear influence

Different from the above two views, the third view is that the relationship between environmental regulation and carbon emissions is nonlinear, showing a trend of first promoting and then restraining (Chen et al. 2019; Ouyang et al. 2019). That is, there is a "green paradox" effect before the inflection point and an "emission reduction reversal" effect after the inflection point (Zhang and Wei 2014), which may be due to the increased demand for highly polluting technologies and resources before the implementation of environmental policies. Pei et al. (2019) studied the industry with high energy consumption and found that the carbon reduction effect of environmental regulation is an "inverted U-shape." "Green paradox" and emission reduction effect may coexist. On the one hand, environmental regulation promotes manufacturing transformation and upgrading (Zhai and An 2020). On the other hand, environmental regulation has a nonlinear impact

on carbon emissions by affecting energy consumption structure, technological innovation, foreign direct investment, and fiscal decentralization (Zhang et al. 2017; Chen et al. 2021; Wang et al. 2021)

Although studies have examined the impact of environmental regulation on carbon emissions and hold widely different views (Ritter and Schopf 2014; Hashmi and Alam 2019), few have discussed the relationship between environmental regulation and manufacturing carbon emissions. Currently, as China's economy changes from extensive growth to high-quality development (Milani 2017; Liu and Xu 2021), the high energy-consuming and high-emission manufacturing industry is bound to be constrained by environmental regulations. In addition, due to the spatial characteristics and complexity of atmospheric pollution (Wang et al. 2017; Ma et al. 2016), there are differences in pollution management in different regions (Feng et al. 2020). At the same time, as China's regions become increasingly economically connected, the regional transfer and transformation and upgrading of industries are accelerating, leading to an increase in the diffusion of carbon emissions and spatial aggregation. Although this adds to the complexity of environmental governance, it is reassuring to note that environmental regulation is one of the effective means of controlling carbon emissions. Enhanced regulation facilitates the convergence of carbon emissions within a certain range (Hao et al. 2020). Therefore, this paper argues that environmental regulation has an emission reduction effect on manufacturing carbon emissions and shows spatial heterogeneity due to intra-industry differences. Accordingly, this paper proposes hypothesis 1:

> **H1:** Environmental regulation promotes manufacturing carbon emission reduction in China and has a spatial spillover effect.

The impact of local government competition on carbon emissions

Previous studies have shown that the analysis of local government behavior from a competition perspective is an important field of environmental governance research (Yang et al. 2020). There are few studies on the relationship between LGC and carbon emissions, but they concentrate on the influence of LGC on environmental pollution. In most studies, the environment is regarded as public goods, and local governments have an inevitable responsibility towards environmental protection and quality improvement (Luo and Jiang 2017). With the continuous adjustment of the administrative and financial power between the central and local governments since the reform of the tax-sharing system, the advancement of Chinese local government officials is encouraged by both politics and economy, which makes the

"yardstick competition" among local governments (Maskin et al. 2000), especially in environmental and economic competition (Yang et al. 2020). However, as political promotion incentives affect local governments' preferences, economic decentralization gives local governments certain financial autonomy, and "Chinese-style decentralization" makes local governments form strategic competition in implementing environmental policies (Konisky 2007).

When the local government aims at GDP growth, the performance evaluation mechanism pursues the economy (Pu and Fu 2018). Political promotion is the internal incentive for local government to develop the economy in China (Zhou 2007). The central government will set up regional economic championships to mobilize regional enthusiasm (Xiong 2018). Local governments will build infrastructure on a large scale (Oates and Schwab 1988), aiming to attract enterprises with higher performance, taxes, and pollution (Cole et al. 2006), which lays the foundation for developing economy. However, with the change of economic development mode and the enhancement of public awareness of environmental protection, local governments will increase ecological performance assessment (Wu et al. 2020). Driven by environmental performance, the environmental governance of local governments presents a competitive behavior of "chasing each other" (Levinson 2003; Wu et al. 2020). When economic development is changed to environmental quality improvement, local governments will attract capital liquidity factors and promote the development of green technology to reduce environmental pollution emissions (Albornoz et al. 2009). Based on the above analysis, this paper puts forward hypothesis 2:

H2: Local government competition will aggravate the carbon emissions of the manufacturing industry.

Environmental regulation and local government competition

The impact of environmental regulation on environmental quality depends on the local government. Previous studies have richly discussed the relationship between environmental regulation and local government competition. The existing studies are mainly based on three viewpoints: bottom-to-bottom competition, top-to-top competition, and uncertainty.

Bottom-to-bottom competition

Some scholars believe that local government competition lowers environmental regulation, and the interactive behavior is "bottom-to-bottom competition" (Lai 2019; Woods 2006). The theory of environmental federalism discusses how to distribute environmental governance functions reasonably among different-level governments. Some scholars

argue that the effectiveness of environmental protection functions depends on the central government, but the competition among local governments has led local governments to lower the environmental management standard in pursuit of regional economic growth (Tiebout 1956). To compete for mobility factors and solidify local resources, local governments compete to lower their levels of environmental regulation. And to maintain or attract promising enterprises and increase employment and taxes, local governments may relax environmental controls, leading to increased pollution (Zhang et al. 2017; Kunce and Shogren 2005). In the context of decentralization, environmental regulation generally presents the characteristics of "bottom-to-bottom competition" (Li et al. 2014). On the one hand, it may be due to the differences in development stages of different regions and competition at the economic level between local governments, which lower environmental standards to promote industrial development. On the other hand, it may be the "hitchhiking" behavior caused by the positive externalities of environmental governance and the government that enjoys the benefits of transboundary pollution control in neighboring areas without bearing the related costs.

Top-to-top competition

Contrary to the first group of view, some scholars also argued that decentralization does not lead to bottom-to-bottom competition (Millimet 2003; Sjöberg and Xu 2018) but rather that environmental regulatory interactions between local governments manifest as top-to-top competition (Vogel 2009; Peng 2020). The mechanism behind local governments' competition to raise their level of environmental regulation lies in local governments' adjoining and the pursuit of factors that prefer a high-quality environment. On the one hand, the collection of environmental information is characterized by economies of scale, and the central government could reduce costs by collecting and disseminating environmental information centrally; on the other hand, local governments have an advantage in collecting local environmental information and therefore have a greater ability to use it in a localized manner. Even with the same motivation of competing for mobility factors, for regions undergoing industrial restructuring, local governments tend to improve the quality of the local environment and increase the level of environmental regulation to attract mobility factors (e.g., top talent) that prefer a high-quality environment (Konisky 2007).

Competition uncertainty

In addition, some scholars have argued that there is uncertainty between environmental regulation and local government competition. Due to the heterogeneity between

regions, neither bottom-to-bottom competition nor top-to-top competition could fully summarize the interaction of environmental regulation among local governments. It may have both interactive characteristics (Konisky 2007). Zhang et al. (2010) argued that with constantly improving in the official assessment system, the impact of LGC on ER shifts from "bottom-to-bottom competition" to "top-to-top competition", and environmental governance presents non-linear characteristics. If environmental governance has no spillover effect, the central government's environmental governance improves welfare, and local governments will seek the maximum welfare for their jurisdiction (Banzhaf and Chupp 2012). On the other hand, environmental governance has a spillover effect and diversified competition among regions, and the implementation of ER gives rise to hitchhiking behavior in environmental improvement (Wang 2015). When nearby areas intensify environmental management, local government loosens control (Sigman 2005). For transboundary pollution control, the manufacturing industry attracts more attention (Zeng and Zhao 2009). It may be a powerful way to tackle transboundary pollution to seek optimal cooperation strategy among regional local governments instead of competition (Oates 2001), such as encouraging to use negotiation, consultation, and cooperation to mediate the dilemma of multilevel governance (Ryan 2017).

As China is the environmental governance under the background of fiscal decentralization, there are obvious problems of interest coordination in different regions, which leads to different efforts in environmental governance. With the construction of China's dual-cycle pattern and the continuous promotion of manufacturing transformation and upgrading, the relocation of manufacturing activities has increased. Driven by the Chinese government's commitment to achieving carbon emission reduction targets, environmental constraints promote the entry threshold of manufacturing migration and transformation. At this point, local government competition is no longer a single pursuit of economic growth but a "top-to-top competition" that includes strengthening ecological performance assessment and environmental protection. Therefore, this paper puts forward hypothesis 3:

H3: Under the restriction of environmental regulation, local government competition is conducive to manufacturing carbon emission reduction, showing "top-to-top competition."

In summary, most existing studies have explored interactive relations between ER, LGC, and carbon emissions. However, few studies investigate manufacturing from the micro-level, which hinders the detailed understanding of emission reduction in manufacturing segments. Second, in terms of research content, few studies incorporate the three into a unified framework. With the gradual expansion of

the regional development gap, the dynamic adjustment of local government competition and environmental regulation interacts more closely. Therefore, it is needed to explore the influence mechanism, spatial spillover effect, and attenuation boundary of ER on MCE from the perspective of LGC. Third, most researchers employ static or dynamic panel models, neglecting the spatial correlation and spillover on carbon emissions. The transmission of carbon emissions among areas has a strong spatial correlation and dependence (Zhao et al. 2014), and ignoring the spatial characteristics of the research object may cause bias in the regression (Cheng 2016; Sun et al. 2015). This study is of significance to deeply explore the influence of ER on MCE from the perspective of LGC, and it is needed for the government to formulate reasonable, targeted, and differential environmental policies to reduce MCE.

Methodology and data

Model selection

Spatial correlation

To identify the spatial correlation of MCE, this paper used Moran's *I* tests.

(1) Global Moran's I

Referring to Geniaux and Martinetti (2018), the calculation formula is as follows:

$$I_G = \frac{\sum_{i=1}^{n} \sum_{i \neq j}^{n} W_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \qquad (1)$$

where x_i and x_j are observed values, n is sample number, $\bar{x}$ is the sample mean, and W_{ij} is spatial weight matrix. Since the adjacent space weight matrix represents the interrelationship of regional observations only according to whether the spatial units are adjacent or not, it cannot reflect the spatial units that are geographically close but not directly connected. Therefore, following the work of Wang and Zhu (2020), the geographical distance weight matrix is constructed using the reciprocal distance between provinces in this paper, and the following formula is used.

$$W_{ij} = \begin{cases} 1/d_{ij} & i \neq j \\ 0 & i = j \end{cases} \qquad (2)$$

where d_{ij} is the geospatial distance between provinces i and j, which is evaluated by the latitude and longitude of the capital cities of provinces i and j.

(2) Local Moran's *I*

In order to clarify the local spatial connection, this paper adopts local Moran's *I* index. The formula is calculated as:

$$I_L = \frac{n(x_i - \bar{x}) \sum_{j=1}^{n} W_{ij}(x_j - \bar{x})}{(x_i - \bar{x})^2} \tag{3}$$

In local Moran's *I* test, the H–H and L-L agglomeration indicates that the regions with high (low) MCE are encircled by areas with high (low) MCE. In contrast, H–L and L–H agglomeration indicates that high (low) MCE regions are surrounded by low (high) MCE regions.

Spatial econometric model

The existing studies on the relationship between human activities and the ecological environment mostly adopt the IPAT model of Ehrlich and Holdren (1971) to discuss the effect of the population (*P*), affluence (*A*), and technology (*T*) on the environment (*I*), as shown in formula (4). Since the regression results caused by spatial correlation are biased, the revised STIRPAT model (Anselin 1989) is

used to determine the impact of ER on MCE, as shown in formula (5):

$$I = PAT \tag{4}$$

$$I_{it} = a_i P_{it}^b A_{it}^c T_{it}^d e_{it} \tag{5}$$

where I_{it}, P_{it}, A_{it}, and T_{it} represent the environmental impact (*I*), population size (*P*), affluence (*A*), and technology (*T*) of the *i* province in *t* year, respectively; a_i is the model coefficient; *b*, *c*, and *d* are parameters to be estimated; and e_{it} stands for the random disturbance. In order to test the influence of ER on MCE, this research refers to the previous studies, including important factors such as per capital GDP (PGDP), opening degree (OD), unemployment rate (UR), fiscal expenditure scale (FES), and public facilities investment (PFI) into the model (Cheng et al. 2021; Banerjee et al. 2020; Xin et al. 2020). In addition, due to different government goals, government competition behavior leads to different intensities of ER, which further affects MCE. Therefore, local government competition and environmental regulation (LGC×ER) are incorporated into formula (5), and logarithmic processing is carried out to obtain model (6):

$$lnMCE = \lambda_0 + \lambda_1 lnER_{it} + \lambda_2 lnLGC_{it} + \lambda_3 lnLGC_{it} \times ER_{it} + \lambda_4 lnPGDP_{it} + \lambda_5 lnOD_{it} \\ + \lambda_6 lnUR_{it} + \lambda_7 lnFES_{it} + \lambda_8 lnPFI_{it} + e_{it} \tag{6}$$

where MCE represents the manufacturing carbon emissions; λ_0 is the constant; λ_1, λ_2, λ_3, λ_4, λ_5, λ_6, λ_7, and λ_8 represent the coefficients to be estimated; and e_{it} stands for the random error.

In order to empirically test the spatial spillover effect and attenuation boundary of environmental regulation on manufacturing carbon emissions, the spatial Durbin model (SPDM) is constructed as follows:

$$lnMCE_{it} = \rho \sum_{i=1}^{n} W_{ij} lnMCE_{it} + \delta_1 \sum_{i=1}^{n} W_{ij} lnER_{it} + \delta_2 \sum_{i=1}^{n} W_{ij} lnLGC_{it} \\ + \delta_3 \sum_{i=1}^{n} W_{ij} lnLGC_{it} \times ER_{it} + \delta_4 \sum_{i=1}^{n} W_{ij} lnPGDP_{it} \\ + \delta_5 \sum_{i=1}^{n} W_{ij} lnOD_{it} + \delta_6 \sum_{i=1}^{n} W_{ij} lnUR_{it} + \delta_7 \sum_{i=1}^{n} W_{ij} lnFES_{it} \\ + \delta_8 \sum_{i=1}^{n} W_{ij} lnPFI_{it} + \lambda_0 + \lambda_1 lnER_{it} + \lambda_2 lnLGC_{it} \\ + \lambda_3 lnLGC_{it} \times ER_{it} + \lambda_4 lnPGDP_{it} + \lambda_5 lnOD_{it} + \lambda_6 lnUR_{it} \\ + \lambda_7 lnFES_{it} + \lambda_8 lnPFI_{it} + u_{it} + e_{it} \tag{7}$$

where W_{ij} represents the spatial weight matrix; ρ is the spatial coefficient of the explained variables; δ_1, δ_2, δ_3, δ_4, δ_5, δ_6, δ_7, and δ_8 are the spatial coefficients of the explanatory variables and control variables; u_{it} is the individual fixed

effect; and e_{it} stands for the random error. The research framework is shown in Fig. 1.

Decomposition of direct and indirect effects

In order to explore the spatial spillover effect of ER on MCE, partial differentiation is employed to decompose the direct and indirect effects. Based on LeSage and Pace (2009), the SPDM model is converted as follows:

$$Y_{it} = (I_{NT} - \rho W_{ij})^{-1} X_{it}(I_{NT}\beta + W_{ij}\delta) + [I_{NT} - \rho W_{ij}]^{-1} \varepsilon_{it} \tag{8}$$

where *Y* is the vector of $N \times 1$ dimensional dependent variable and I_{NT} represents $N \times T$ dimensional matrix. The partial derivative of *X* is as follows:

$$MEM = \frac{\partial Y_{it}}{\partial X_{it}} = (I_{NT} - \rho W_{ij})^{-1}(I_{NT}\beta + W_{ij}\delta) \tag{9}$$

$$ME_{Total} = \frac{1}{NT}\iota(MEM), \iota = ones(NT, 1) \\ ME_{Direct} = \frac{1}{NT}Trace(MEM) \\ ME_{Indirect} = ME_{Total} - ME_{Direct} \tag{10}$$
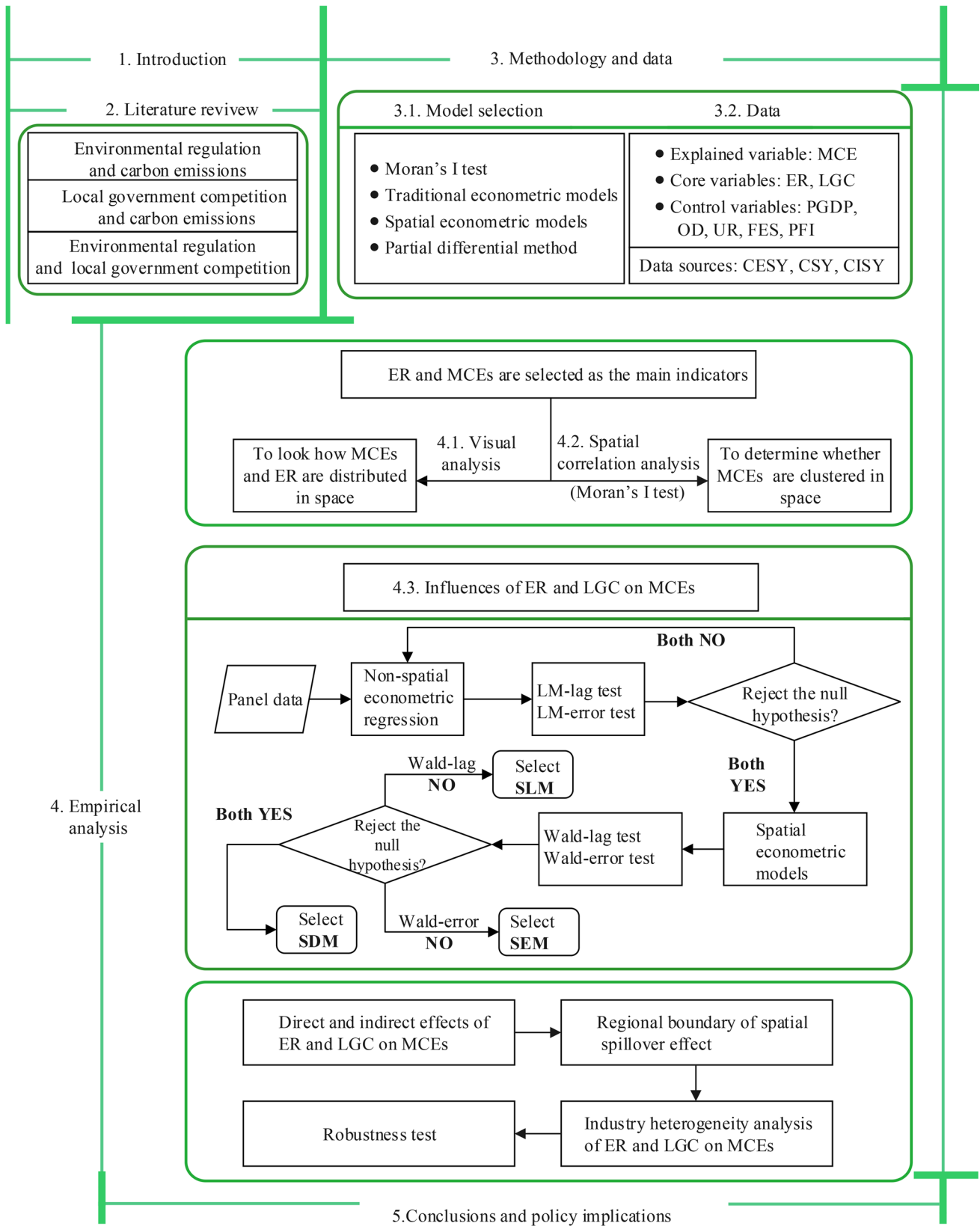
Fig. 1 Research framework

Data

Explained variable: manufacturing carbon emissions (MCE)

Based on data availability and authenticity, the carbon emission coefficient method is adopted to calculate MCE in this study. According to the calculation method of IPCC (2007), MCE in China's provinces is measured as follows:

$$MCE = \sum_{i}^{30} \sum_{j}^{17} MCE_{ij} = \sum_{i}^{30} \sum_{j}^{17} F_{ij} \times CV_j \times CEF_j \times COF_j \times \frac{44}{12} \quad (11)$$

among them, $i = 1, 2…, 30$ represents the manufacturing sector; $j = 1, 2…, 17$ denotes the type of energy; *MCE* is the total manufacturing carbon emission; *F* is terminal fossil energy consumption; and *CV* represents the average low calorific value of different fossil fuels. *CEF* is the carbon content of the fuel, *COF* is the oxidation efficiency of energy, and 44/12 is the ratio of CO_2 to carbon molecular weight.

Explanatory variable: environmental regulation (ER)

Existing studies mainly have two perspectives to measure ER. First, from the standpoint of cost and expense, the study holds that the investment of pollution management is positively related to the intensity of ER; that is, the higher the percentage of industrial cost in controlling pollution, the more conducive to environmental protection (Cheng et al. 2017). Second, based on the perspective of pollution emissions, some scholars use the proportion of industrial sulfur dioxide, smoke (dust), and other pollutants in the total emissions to measure ER (Li et al. 2021b; Du and Li 2020). However, to a large extent, these indicators reflect the production and emission stages of carbon dioxide, causing endogeneity. To avoid biased estimation caused by such defects, some scholars study from the perspective of environmental performance and believe that the pollution-controlling effectiveness can better stand for the degree of ER (Wu et al. 2020; Ge et al. 2020; Ge and Li 2020). Thus, the removal efficiency and utilization of pollutants are crucial measurements in ER. Based on the measurement method by Ge and Li (2020), this paper selects the removal rate of industrial sulfur dioxide, treatment rate of industrial effluents, the comprehensive utilization rate of industrial solid waste, and decontamination rate of domestic waste and uses the entropy method to calculate ER.

Moderating variable: local government competition (LGC)

Local government competition refers to the behavior that different economies within a region adopt the tax, fiscal expenditure, environmental policies, and other means to attract mobility factors such as capital and labor to enhance their competitive advantage (Breton 1998). Regional economic catch-up is an obvious manifestation of LGC. Referring to the calculation methods by Hong et al. (2020), the economic catch-up level is jointly determined by neighboring provinces and the whole country as the proxy variable of LGC. The calculation method is as follows:

$$LGC_{it} = [\max(mgdp_{it})/agdp_{it}] * [\max(gdp)/agdp_{it}] \quad (12)$$

among them, *max (mgdp_{it})* represents the highest GDP of neighboring provinces except for province *i* in *t* year; *agdp_{it}* represents the GDP of the province *i* in *t* year; and *max (gdp)* represents the highest GDP of each province.

Control variables

In order to control the impact of economy, population, technology, and other factors on manufacturing carbon emissions, this study chooses the following control variables: (1) Per capital GDP (PGDP): economic growth is regarded as one of the essential elements of environmental governance (Saint Akadiri et al. 2020; Baloch et al. 2021), so per capita GDP is employed to stand for economic development. (2) Opening degree (OD): the economic opening contributes to the incentive economy (Li and Wei 2021; Alam and Murad 2020). The economic opening increases economic activities and energy consumption and further affects environmental quality, so the percentage of social total retail sales of consumer goods in GDP is chosen to represent opening degree. (3) Unemployment rate (UR): changes in the employed and unemployed population affect resource consumption. Excessive growth or unreasonable development mode further causes environmental damage (Yuan et al. 2020), which has a significant influence on environmental improvement. Therefore, the representation of the urban registered unemployment rate is adopted. (4) Fiscal expenditure scale (FES): fiscal expenditure is a way to invest in environmental governance (Khan et al. 2021; Cheng et al. 2021); the appropriate scale of fiscal expenditure is conducive to improving resource utilization efficiency and environmental performance, so the proportion of government expenditure in GDP is selected to measure fiscal expenditure scale. (5) Public facilities investment (PFI): public infrastructure investment affects the efficiency of resource allocation because infrastructure reduces transportation costs and promote information exchange (Banerjee et al. 2020; Wang et al. 2020; Anser et al. 2021); public facilities affect transaction costs, which in turn affect environmental quality, so this study uses the number of hospitals per 10,000 people to control its impact on MCE. The specific variable definitions are shown in Table 1.

Table 1 Descriptive statistics of the main variables	Variables	Notation	Unit	Mean	Max	Min	S.D
	Manufacturing carbon emissions	MCE	Million tons	97.21	490.30	3.73	77.33
	Environmental regulation	ER	%	6.63	33.04	0.88	6.25
	Local government competition	LGC	%	51.57	661.7	0.29	134.01
	Per capital GDP	PGDP	Yuan	44,232.02	164,563	7778	26,567.58
	Opening degree	OD	%	0.39	0.61	0.25	0.06
	Unemployment rate	UR	%	3.39	4.60	1.20	0.66
	Fiscal expenditure scale	FES	%	0.25	0.76	0.10	0.11
	Public facilities investment	PFI	/100,000 persons	6.38	12.06	1.23	2.79

Data source

This paper selects the manufacturing panel data of 30 provinces in China (except Tibet, Hong Kong, Macao, and Taiwan) from 2007 to 2019. The data comes from China Statistical Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook, and China Industrial Statistical Yearbook. The data of geographic information comes from the 1: 4,000,000 databases of the National Geographic Information Center.

Empirical results

Temporal and spatial evolution analysis

Temporal characteristics analysis

From the time dimension, the trend of MCE and ER is shown in Fig. 2. From 2007 to 2019, MCE showed a warp-tail shape, and ER was stable and increased on the whole.

Both MCE and ER show stage characteristics and regional differences are gradually increasing.

In the growth stage (2007–2014), MCE increased from 70.76 to 109.29 Mt, an increase of 54.41%. It may be that rapidly manufacturing development is accompanied by environmental pollution. In the decline stage (2014–2019), MCE decreased from 109.29 to 101.95 Mt, decreasing 6.72%. Concerning ER, in the "U-shaped" stage (2007–2010), the index first decreased from 6.51 to 5.96 and then increased to 6.41. During the period of fluctuating growth (2010–2019), the fluctuation increased from 6.41 to 7.24, an increase of 12.95%, and maintained a steady and growing trend as a whole.

From the perspective of regions, the rank of mean values (from high to low) in MCE was the east, the middle, the nation, and the west, and the trend of different regions was the same, showing an increase and then decrease. However, as time went on, the gap in MCE between the east and the west increased from 58.79 to 63.25 Mt, increasing by 7.59%. The gap between the east and the middle increased from 18.38 to 30.95 Mt, increasing by 68.39%. The regional
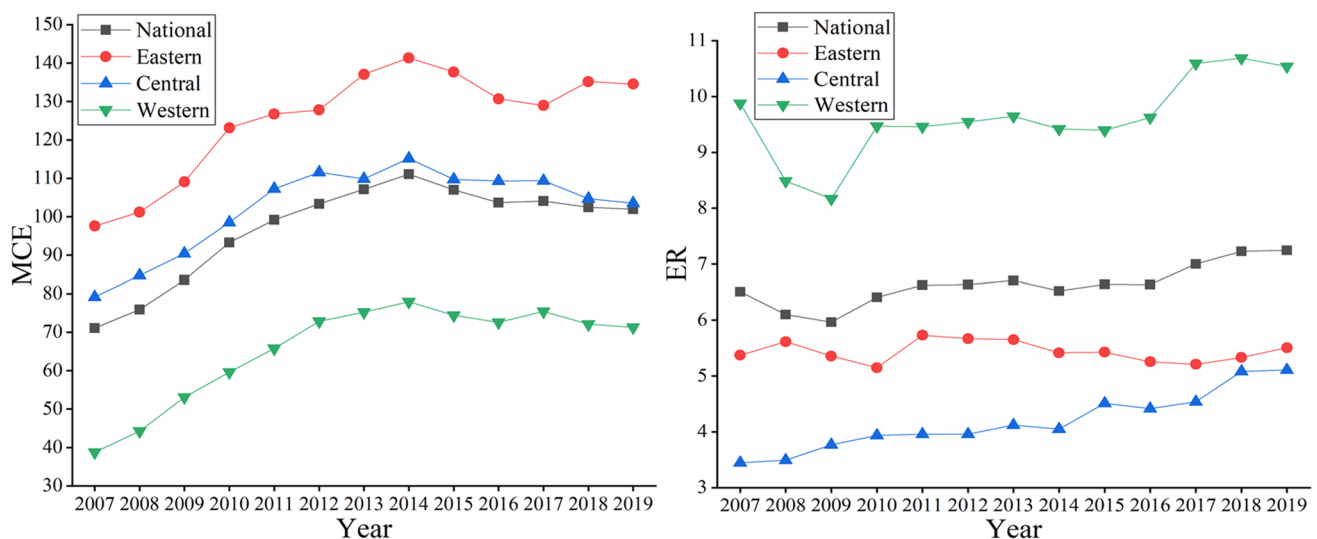

Fig. 2 Temporal evolution characteristics of MCE and ER from 2007 to 2019 in China

difference was gradually enlarged, and the phenomenon of "polarization" is aggravating. The intensity of ER from strong to weak was the west, nation, east, and middle. The changes are stable in the east and the middle and fluctuate in the west, showing an overall growth trend. MCE and ER are characterized by regional differentiation and interaction, a benign interaction of "high ER-low MCE," and show that improving ER contributes to MCE reduction.

Spatial characteristics analysis

ArcGIS 10.3 is adopted to clarify the spatial heterogeneity of MCE and ER in different regions. As shown in Fig. 3, MCE was decreasing step by step from east to west. The high MCE area expanded from Hebei-Shandong concentrated distribution to Hebei-Shandong-Liaoning-Jiangsu-Henan-Shanxi-Sichuan connected area, which spread from the eastern coast to the southwest. The spatial range of higher MCE

areas gradually grew and extended from the east to the central region and evolved from sporadic point distribution to clustered contiguous distribution. The spatial scope of lower and low MCE decreased significantly, with the proportion decreasing from 76.67 to 53.33%, and the spatial distribution evolved from aggregation to divergence. Overall, MCE extended from east to west, which may be attributed to the State Council in China explicitly proposing in 2010 that industries be transferred to the middle and west, including high-tech and traditional manufacturing industries such as building materials and chemical industry. The manufacturing transfer is accompanied by the pollution transfer, which intensifies carbon emissions.

ER shows a differentiation pattern of "high in the northwest and low in the southeast," and ER is gradually strengthened. The spatial pattern of strict and weak ER is relatively stable, and the stricter ER evolved from a "single core" pattern dominated by "Yunnan-Guangxi-Chongqing" to a

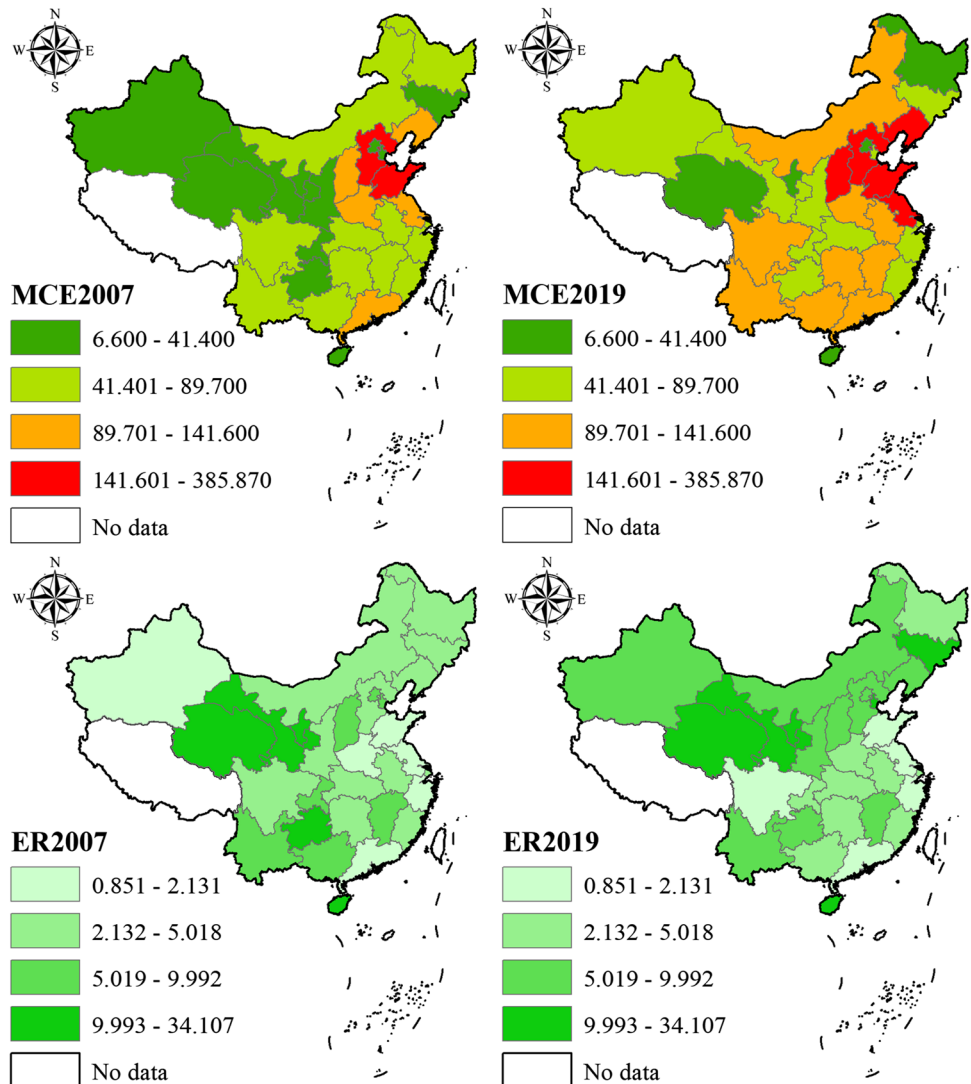**Fig. 3** Spatial characteristics of MCE and ER from 2007 to 2019 in China
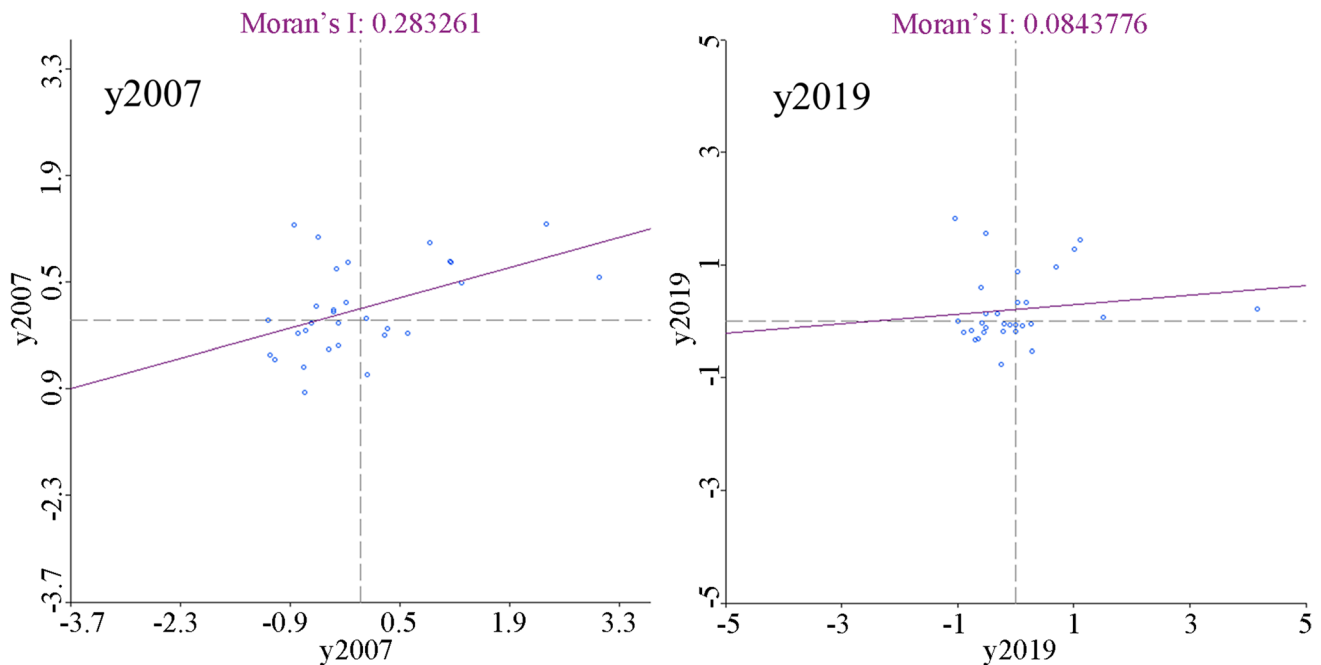
Table 2 Moran's *I* index of MCE from 2007 to 2019 in China

Year	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Moran's *I*	0.283***	0.231**	0.197**	0.162**	0.156**	0.131*	0.120*	0.124*	0.134*	0.102	0.066	0.094	0.084
Z value	2.906	2.250	1.948	1.673	1.678	1.438	1.386	1.392	1.466	1.207	0.878	1.278	1.246

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

Fig. 4 Moran's *I* scatterplot of MCE from 2007 to 2019 in China

dual-core distribution formed by "Jilin-Liaoning-Beijing-Tianjin-Hebei-Shanxi-Inner Mongolia." The spatial scope of weaker ER is significantly reduced, which evolved from centralized distribution to divergent and sporadic distribution. In general, the spatial differentiation pattern may be attributed to the differences in the implementation of ER by local governments. The economic development in the east and middle is relatively better; the rapid manufacturing development is accompanied by the increase of pollution, which exacerbates the difficulty to improve the role of ER in a short time and results in weak ER in the east.

Spatial correlation analysis

Global Moran's *I* results of MCE in China from 2007 to 2019 are shown in Table 2. Moran's *I* values are significantly positive at 5%, decreasing from 0.283 to 0.084, revealing that MCE has a significant positive spatial correlation. The regions with higher and lower MCE tend to be concentrated, but their spatial dependence gradually decreases. Therefore,

the spatial effect should be considered to study the influence mechanism.

In order to effectively describe the spatial heterogeneity of MCE at the local scale, local spatial autocorrelation is used for further examination. Figure 4 indicates that the regional spatial correlation characteristics in MCE are dominated by H–H and L–L agglomeration. As the agglomeration degree becomes more evident, the polarization trend gradually appears, so there is a need to adopt the spatial econometric model to explore the relationship among the three.

Estimation result analysis

Result of model selection

The results of the spatial econometric model are shown in Table 3. LM test results demonstrate that SPLM and SPEM are applicable to examine the relationship between ER and MCE. Wald and LR test prove SPDM is most suitable for exploring the influence of ER on MCE. In addition,

Table 3 Identification test of spatial panel econometrics model

Tests	Statistics	Tests	Statistics
LM(lag) test	19.753[***]	Wald_spatial_lag	56.540[***]
Robust LM(lag)test	5.188[***]	LR_spatial_lag	52.620[***]
LM(error)test	18.021[***]	Wald_spatial_error	69.711[***]
Robust LM(error)test	3.456[***]	LR_spatial_error	59.090[***]
Hausman test	25.512[***]		

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

the Hausman test demonstrates that the fixed effect model should be chosen. Therefore, this study adopts SPDM with a fixed effect to examine the influence of ER on MCE.

Results of the spatial Durbin model

The results in Table 4 show that the *Spatial rho* of time fixed and spatial-time fixed has passed the significance test. Considering R^2 and Variance Sigma2_e, this study selects SPDM of time fixed effect as the optimal fitting mode.

The ER coefficient is -0.104 at the significance level of 1%, indicating that ER significantly inhibits MCE. The conclusion is in agreement with the views of Cheng et al. (2017) and Pei et al. (2019), which may be that government effectively reduces MCE through environmental regulatory measures such as emission taxes and environmental protection subsidies (Zhao et al. 2015). On the other hand, the result also verifies the Porter hypothesis (Porter and Van der Linde 1995), the strengthening of ER forces enterprises to make technological innovations and introduce green processes (Yang et al. 2012), which aims to improve energy efficiency and reduce MCE. The coefficient of LGC is 0.011 and passes the 5% significant level, which indicates that LGC significantly promotes MCE. It may be because local governments, in pursuit of economic growth and political performance, prioritize attracting enterprises with high output value and high income. However, these enterprises are often accompanied by high energy consumption and pollution, which increases the manufacturing carbon emission while achieving economic benefits. The adjustment coefficient of LGC is -0.038 and passes the 10% significant level, which shows that when considering the combined effect of ER and LGC, LGC strengthens the restraining influence of ER on MCE. This may be because the assessment of local government officials has changed from a single promotion incentive with GDP growth to a multiple promotion incentive with environmental performance. In addition, it may also be the change of local government behavior mode; in the post-COVID-19 era, an increasing number of countries have begun to pay attention to environmental problems in the process of economic development (Dou et al. 2021), and the improvement

Table 4 Estimation results of the spatial Durbin model

Variables	(1) Spatial fixed	(2) Time fixed	(3) Spatial-time fixed
lnER	−0.066[***]	−0.104[***]	−0.077[***]
	(−4.30)	(−6.36)	(−5.06)
lnLGC	0.029[***]	0.011[**]	0.024[***]
	(7.41)	(2.04)	(5.80)
lnER×LGC	−0.595[***]	−0.038[*]	−0.554[***]
	(−7.97)	(−1.83)	(−7.63)
lnPGDP	−0.173[***]	−0.121[*]	−0.220[***]
	(−3.29)	(−1.68)	(−4.05)
lnOD	0.031	0.168[***]	0.030
	(1.39)	(3.89)	(1.41)
lnUR	0.003	0.065[**]	0.016
	(0.15)	(2.35)	(0.73)
lnFES	−0.143[*]	−0.535[***]	−0.230[***]
	(−1.94)	(−6.17)	(−3.05)
lnPFI	0.005[**]	0.029[***]	0.005[*]
	(2.13)	(9.56)	(1.88)
W×lnER	0.050[**]	0.009[*]	0.002
	(1.96)	(1.69)	(0.06)
W×lnLGC	0.003	0.031[***]	0.018[**]
	(0.38)	(3.19)	(2.25)
W×lnER×LGC	−0.150	−0.394[*]	−0.205
	(−1.01)	(−1.84)	(−1.36)
W×lnPGDP	0.219[***]	0.597[***]	0.135
	(3.49)	(3.57)	(1.34)
W×lnOD	0.025	0.049	0.013
	(0.72)	(0.68)	(0.38)
W×lnUR	0.051	−0.033	0.088
	(1.17)	(−0.56)	(1.53)
W×lnFES	0.451[***]	0.074	0.129
	(3.81)	(0.45)	(0.86)
W×lnPFI	−0.003	0.021[**]	0.006
	(−1.13)	(2.33)	(1.00)
Spatial rho	0.029	0.154[**]	−0.097[*]
	(0.42)	(2.16)	(−1.77)
Variance sigma2_e	0.001[***]	0.010[***]	0.001[***]
	(13.96)	(13.89)	(13.95)
R^2	0.033	0.484	0.182
N	390		

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The *t* values are in parentheses

of environmental governance ability has gradually become a new goal of local government competition.

The control variables show that the per capital GDP (PGDP) coefficient is -0.121 at the significance level of 10%, illustrating that China's economic transformation is undergoing changes from extensive development to intensive development, which is helpful in high-quality economic

development and MCE reduction. The opening degree (OD) coefficient is 0.168 at the significance level of 1%, which shows that with the improvement of domestic opening up, economic activities become more frequent, and expanding domestic demand leads to an increase in industrial production, resulting in more energy consumption and carbon emissions. The coefficients of the unemployment rate (UR) and public facilities investment (PFI) are respectively 0.065 and 0.029, both of which are significant at the 5% level, indicating that labor shortage and infrastructure increase have an impact on manufacturing production, which may aggravate industrial structural contradiction, resulting in increased resource consumption and reduced utilization efficiency, thus increasing manufacturing carbon emissions. The coefficient of the fiscal expenditure scale (FES) is − 0.535 and passed the 1% significance test, indicating that the increase in the fiscal expenditure scale may increase investment in environmental governance and thus reduce carbon emissions.

In terms of spatial effect, the spatial interaction coefficients of ER, LGC, PGDP, and FES are 0.009, 0.031, 0.597, and 0.021, respectively, which indicates these factors have a significant positive spatial effect on MCE. The moderation coefficient of LGC is − 0.394, which is significant at the level of 10%, indicating that the regulatory effect of LGC shows a negative spatial effect. However, since the point estimate regression results may be biased, this paper uses the partial differential method of Lesage and Pace (2009) to decompose the spatial effect and further investigate the spatial spillover effect of each variable on manufacturing carbon emissions.

Table 5 Result of effect decomposition

Variable	Direct effect	Indirect effect	Total effect
lnER	− 0.104***	0.026*	− 0.078***
	(− 6.05)	(1.70)	(− 2.82)
lnLGC	0.012***	0.038***	0.050***
	(2.62)	(3.62)	(4.04)
lnER × LGC	− 0.026*	− 0.468*	− 0.494*
	(− 1.72)	(− 1.87)	(− 1.77)
lnPGDP	− 0.097*	0.664***	0.567***
	(− 1.66)	(3.55)	(3.50)
lnOD	0.166***	0.021	0.187*
	(3.96)	(0.28)	(1.73)
lnUR	0.066**	− 0.023	0.043
	(2.41)	(− 0.33)	(0.56)
lnFES	− 0.540***	0.012	− 0.528***
	(− 6.49)	(0.07)	(− 3.22)
lnPFI	0.030***	0.030***	0.060***
	(10.87)	(3.21)	(6.18)

Note: *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively. The *t* values are in parentheses

Result of direct and indirect effects

The above research found that the spatial coefficients of all variables passed the significance test, and the total effect is further decomposed, shown in Table 5. The direct effect of ER is − 0.104, which passes the significance level of 1%, showing that ER significantly inhibits local MCE. It may be that the government strengthens ER, prompting some polluting enterprises to migrate (Peng 2020) and forcing other enterprises to innovate green technology (Zhang et al. 2020), which is helpful to reduce local MCE. The spillover coefficient of ER is 0.026, passing the significance level of 10%, which shows that strengthening local ER will increase adjacent MCE, revealing that stringent local ER forces manufacturers to reduce the pollution control cost and migrate to surrounding areas with loose ER. The direct and indirect effect coefficients of LGC are 0.012 and 0.038, respectively, both of which pass the 1% significance test, indicating that when the government pursues a single economic growth to catch up with the other regions and ignores environmental protection, it will aggravate MCE of the local and neighboring areas. The direct and indirect effect coefficients of the moderator are − 0.026 and − 0.468, respectively, which both pass the 10% significance test, showing that LGC not only strengthens the inhibiting effect of ER on local MCE but also weakens the promoting effect of ER on neighboring MCE. It may be that local governments tend to be "top-to-top competition" in the governance of MCE with the constraints of ER. Local governments strengthen environmental performance assessment while pursuing economic development and actively promote the manufacturing green transformation (Li et al. 2021a), contributing to the improvement of environmental quality. Neighboring governments strengthen regional collaborative pollution control to improve the economic quality, which produces a "favorable effect" and promote MCE reduction.

In terms of control variables, the direct effect and spatial spillover effect of PGDP are − 0.097 and 0.664, respectively, both of which pass the significance test, indicating that promoting economic development significantly reduces local MCE and increases surrounding MCE, which may be because, with the development of economic intensification, local governments put more emphasis on improving economic quality. The regional economic development trend with the goal of high quality attracts the inflow of mobility factors such as technology, industry, and senior talents that prefer a high-quality environment in the surrounding areas; the siphoning effect further strengthens environmental improvement and reduces the inflow of favorable environmental elements in neighboring areas, which is unfavorable for reducing neighboring MCE.

The direct effect of OD is 0.166 and passes the 1% significance test; the indirect effect is 0.021 but insignificant,

indicating that increasing internal openness promotes the increase of local manufacturing carbon emissions, but has no significant promotion effect on neighboring areas. It may be that further opening up in the local areas attracts more manufacturing enterprises to invest and build factories locally, leading to an increase in MCE. The direct effect of UR is 0.066, passing 5% significance test, and the spatial spillover effect is −0.023, failing the significance test, indicating that the increase in unemployment rate promotes local MCE and inhibits neighboring MCE, but the spillover effect is not obvious. It may be due to the reduction of regional environmental management jobs, prompting the unemployed to turn to the surrounding areas to participate in environmental governance, probably conducive to neighboring MCE reduction. The direct effect of FES is −0.540, passing the 1% significance test, and the indirect effect is 0.012, which does not pass the significance test, indicating that the improvement of fiscal expenditure scale has a significant inhibitory effect on local MCE, but the spillover effect is not significant. It may be that the increase in local government expenditure scale increases the investment in environmental governance, which is conducive to improving local environmental quality, but it is challenging to have a significant impact on neighboring pollution control. The direct effect and spillover effect of PFI are both 0.03, both passing the 1% significance test, which demonstrates that increasing public facilities investment is unfavorable for the local and neighboring MCE reduction, which may be that the local government expands the construction of public

resource infrastructure, causing massive energy consumption. Neighboring governments may blindly follow, resulting in the excessive supply of shared resources, a decrease in resource allocation efficiency, and aggravation in MCE.

### Result of the regional boundary of ER on MCE

According to the attenuation law of geographical distance, a spatial distance attenuation weight matrix is constructed to test the attenuation boundary of the spillover effect of ER on MCE. In general, the spatial correlation gradually decreases with the increase of the distance. To further explore the attenuation boundary of the spatial spillover of ER on MCE, this study refers to Hao et al. (2020) and sets different distance thresholds; assuming that the province j of distance province i is outside the distance threshold, it is $1/d_{ij}$; otherwise, it is 0. The calculation method is as follows:

$$Deca_{ij} = \begin{cases} \frac{1}{d_{ij}} & \text{when } d_{ij} \text{ is outside the distance threshold} \\ 0 & \text{when } d_{ij} \text{ is within the distance threshold} \end{cases}$$

$Deca_{ij}$ reflects whether the spatial correlation coefficient decreases with the increase of the distance between spatial units. Firstly, the initial distance threshold of d_{ij} is set as 200 km and increased by 200 km. Secondly, SPDM is employed to examine and record the spatial spillover coefficient of ER.

The results show that the spatial spillover coefficient of ER passes the significance test of 1% within the range of

Fig. 5 Attenuation process of the spatial spillover effect of environmental regulation
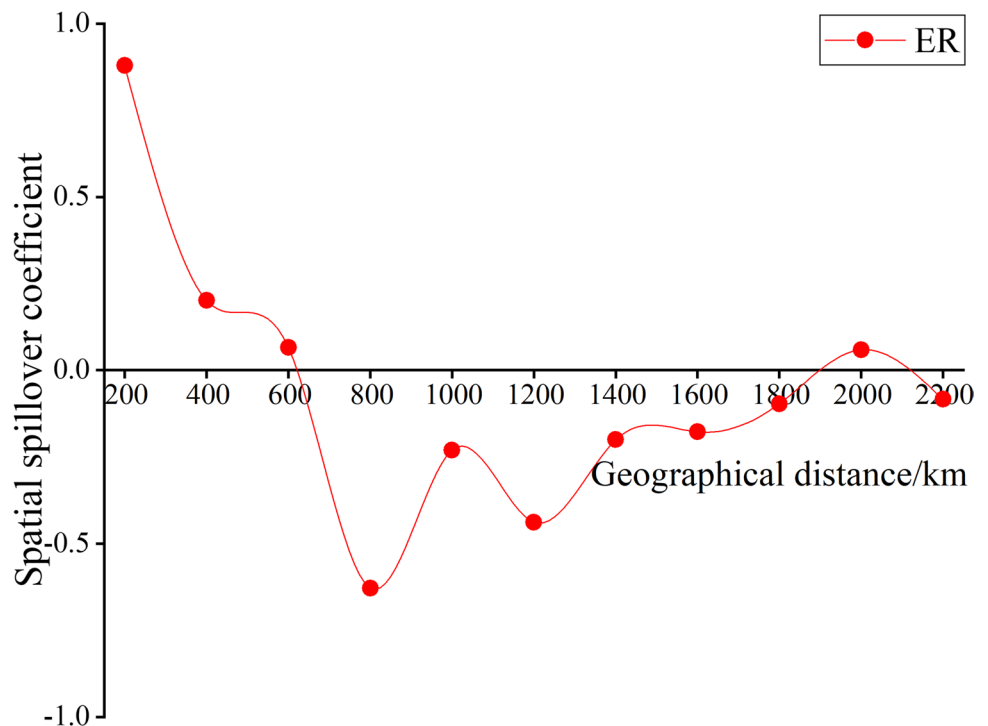
200–1600 km and is not significant after 1600 km, which demonstrates that there is an attenuation boundary of the spatial spillover of ER on MCE. Overall, it can be roughly divided into three areas in Fig. 5: (1) Within 600 km, ER significantly promotes neighboring MCE, and the closer the distance, the stronger the effect. The reason for the "polarization effect" may be the existence of "cooperative competition." The economic ties are closing with the closer provinces, leading to the higher dependence on environmental quality, which begins to compete after realizing economic cooperation. Subsequently, seeking its benefit maximization for profit will cost resources and environment and aggravate pollution. (2) Within 600–1600 km, ER significantly curbs neighboring MCE. The spillover effect increases first and then decreases, reaching a peak of -0.628 at 800 km and the "half decline" distance of spatial spillover around 1000 km. The coefficient decreases from -0.628 to -0.230; that is to say, ER more effectively promotes MCE reduction near provincial boundaries. Within 1000 km, provinces are strongly driven by the radiation of regional environmental governance. With the increase of space distance, the cost of regional collaboration governance increases, and the emission reduction spillover effect of ER is relatively weak. (3) After 1600 km, the spatial spillover coefficient fluctuates randomly and is not significant, revealing that the spillover effect of ER on neighboring MCE is restricted by regional boundaries. In conclusion, the spillover effect of ER on MCE decreases with the increase of geographical distance, which has the characteristics of "spatial attenuation boundary."

Result of industry heterogeneity

Due to the differences in income, development scale, energy consumption, and factor input of segmented industries, the carbon emissions of segmented industries are heterogeneous (Wang and Jiang 2019; Aslan et al. 2018). This paper is based on three classification criteria: pollution emission intensity, core operating income, and factor density (Li and Cheng 2020; Huang and Du 2020); the manufacturing industry is subdivided into three groups and seven types: pollution-intensive manufacturing (PIM) and non–pollution-intensive manufacturing (NPIM) in group A, high-income manufacturing (HCM) and low-income manufacturing (LCM) in group B, and capital-intensive manufacturing (CIM), technology-intensive manufacturing (TIM) and labor-intensive manufacturing (LIM) in group C, which further examines spatial heterogeneity of ER and LGC on segmented MCE.

As shown in Table 6, the impact of ER and LGC on MCE has both inter-group and intra-group differences.

Table 6 Results of industry heterogeneity

Variables	Group A		Group B		Group C		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	PIM	NPIM	HCM	LCM	CIM	TIM	LIM
lnER	-0.064^{***}	-0.041^{***}	-0.051^{***}	-0.127^{***}	-0.021	-0.275	-0.193^{***}
	(-3.80)	(-3.41)	(-3.02)	(-8.45)	(-1.19)	(-0.71)	(-10.74)
lnLGC	0.027^{***}	-0.005	0.028^{***}	0.012^{**}	0.038^{***}	0.031^{***}	-0.034
	(4.49)	(-1.18)	(4.72)	(2.18)	(6.17)	(3.34)	(-1.23)
lnER×LGC	-0.169	0.095	-0.213	-0.351	-0.363	-0.656	0.686
	(-1.38)	(1.07)	(-1.04)	(-1.22)	(-0.85)	(1.48)	(1.12)
Control variables	YES						
W×lnER	0.505^{***}	0.044	0.528	0.068	0.579	0.412	-0.066
	(3.75)	(0.45)	(0.91)	(0.56)	(1.11)	(1.02)	(-0.42)
W×lnLGC	0.253^{***}	0.017	0.254^{***}	0.038^{*}	0.305^{***}	0.407^{***}	0.135
	(5.77)	(0.54)	(5.79)	(1.80)	(6.62)	(6.21)	(0.77)
W×lnER×LGC	-3.982^{***}	-0.066	-4.139^{***}	-0.526^{*}	-5.115^{***}	-5.246^{***}	-3.256^{***}
	(-4.91)	(-0.12)	(-5.09)	(-1.74)	(-5.99)	(-4.30)	(3.58)
Control variables	YES						
Spatial rho	-0.825^{***}	-0.735^{***}	-0.891^{***}	-0.896^{***}	-0.702^{***}	-0.321	-0.440^{**}
	(-3.28)	(-3.16)	(-3.54)	(-3.65)	(-2.92)	(-1.47)	(-2.05)
Variance sigma2_e	0.009^{***}	0.005^{***}	0.009^{***}	0.007^{***}	0.009^{***}	0.020^{***}	0.010^{***}
	(13.68)	(13.75)	(13.63)	(13.61)	(13.74)	(13.91)	(13.94)
R^2	0.425	0.121	0.402	0.395	0.244	0.280	0.207
N	390						

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The *t* values are in parentheses

The results of group A show that the coefficients of ER on pollution-intensive MCE and non–pollution-intensive MCE are − 0.064 and − 0.041 at 1% significance, respectively, indicating that compared with non–pollution-intensive manufacturing, ER can significantly inhibit pollution-intensive MCE, which means that pollution-intensive manufacturing is more susceptible to environmental regulation and thus chooses cross-regional transfer rather than technological innovation. The spatial influence coefficient of ER on pollution-intensive MCE is 0.505, and at the 1% significance test, it shows that environmental regulation has a significant positive spillover effect. The influence coefficient and spatial interaction coefficient of LGC on pollution-intensive MCE are 0.027 and 0.253, respectively, both of which are significant at 1% level, indicating that local government competition not only significantly promotes local pollution-intensive MCE, but also promotes the rapid development in surrounding manufacturing and aggravates environmental pollution. The spatial impact coefficient of the interaction of ER and LGC on the pollution-intensive MCE is significantly − 3.982, which shows that compared with the non–pollution-intensive manufacturing industry, LGC significantly increases pollution-intensive MCE. However, the combined effect of ER and LGC has negative impacts on pollution-intensive MCE significantly, this demonstrates that under the constraints of ER, LGC significantly restrains the spatial spillover of pollution-intensive MCE, which may be because in a single pursuit of economic growth, local governments ignore carbon emissions, but when environmental quality included local government performance assessment, the government competes "top to top" to attract the mobility elements to improve environmental quality. The surrounding areas further strengthen the experiential learning of environmental governance through the "scale effect" to reduce MCE.

In group B, the coefficients of ER on high-income and low-income MCE are − 0.051 and − 0.127 respectively, both of which are significant at 1% level, which means that compared with high-income manufacturing, strengthening environmental regulation more significantly inhibits low-income MCE. One possible reason may be that low-income manufacturing industry is willing to strengthen source governance and reduce energy consumption in the production to control environmental cost, which contributes to lowering MCE. The influence coefficients of LGC on high-income CE and low-income CE are significantly 0.028 and 0.012, respectively, indicating that local government competition significantly promotes high-income and low-income MCE and the promotion is stronger in high-income MCE. It may be for the pursuit of economic development, local governments provide preferential policies to high-income manufacturing industries and encourage enterprise economic activities more frequently, which is not helpful to MCE reduction. Meanwhile, the spatial coefficients of LGC on high-income

and low-income MCE are significantly 0.254 and 0.038, respectively, which shows that the spatial effect of LGC on high-income MCE is more positive. The spatial coefficients of the interaction of ER and LGC on high-income and low-income MCE are − 4.139 and –0.526, respectively, and both pass the significance test, which indicates that LGC behavior tends to "top-to-top competition" after the government takes environmental quality into account, which significantly promotes MCE reduction in high-income and low-income manufacturing industries.

The results of group C indicate that the influence coefficient of ER on labor-intensive MCE is − 0.193 and passes the 1% significance test, but no significant impact on capital-intensive and technology-intensive MCE, which may be that industry is transforming from the middle stage to the later stage in current China, and the labor force has the characteristics of "non-infinite supply." In the evolution of transforming labor-intensive industries into capital-intensive and technology-intensive industries, labor-intensive industries still dominate. At this time, strengthening ER may inhibit labor-intensive MCE. The coefficients of LGC on capital-intensive and technology-intensive MCE are significantly 0.038 and 0.031, respectively, indicating that LGC significantly promotes their MCE. It may be the local government, to accelerate the industrial transformation and upgrading, increases support policy for capital-intensive and technology-intensive manufacturing and attracts many flow factors to develop them, thus increasing their MCE. In addition, the spatial coefficients of LGC on capital-intensive and technology-intensive MCE are 0.305 and 0.407, respectively, both passing the 1% significance test, which indicates that LGC has a significant positive spatial spillover effect on capital-intensive and technology-intensive MCE. It may be blindly followed by local government's excessive increase in factor input, resulting in reduced resource allocation efficiency and further aggravating MCE. In addition, the spatial coefficients of the interaction between ER and LGC on labor-intensive, capital-intensive, and technology-intensive MCE are − 5.115, − 5.246, and − 3.256, respectively, all passing the 1% significance test, which shows that LGC significantly reduces MCE in labor-intensive, capital-intensive, and technology-intensive manufacturing. Among them, the carbon emission reduction effect is strong in technology-intensive manufacturing industries, which may be because ER forces enterprises to innovate green technology, resulting in the promotion of energy conservation and emission reduction in manufacturing by improving the efficiency of resource allocation and reducing energy consumption.

Robustness test

In order to test the reliability of conclusions, the following methods are used to conduct a robustness test. The results

are shown in Table 8: (1) To help to eliminate the estimation bias caused by the selection of spatial weight matrix (Xu et al. 2019), this study replaces the geographic distance matrix with an adjacent matrix, economic distance matrix, and economic-geographic distance nested matrix in turn for further verification. Adjacent space weight matrix refers to the adjacent relationship among the subregions (Morton et al. 2018). It can be defined as follows: $W_{ij}^A = \{ \begin{smallmatrix} 1 \, if \, provinces \, i \, and \, j \, are \, adjacent \\ 0 \, if \, provinces \, i \, and \, j \, are \, not \, adiacent \end{smallmatrix}$. The economic distance matrix is defined by $W_{ij}^E = \{ \begin{smallmatrix} \frac{1}{|\overline{Y_i} - \overline{Y_j}|} & (i \neq j) \\ 0 & (i = j) \end{smallmatrix}$, where $\overline{Y_i} - \overline{Y_j}$ is the average value of per capita GDP in the provinces i and j from 2007 to 2019. Referring to Fingleton and Le Gallo (2008), the economic distance matrix and the geographical distance matrix are combined to construct the economic-geographic distance nested matrix as follows: $W_{ij}^Q = \{ \begin{smallmatrix} \frac{|\overline{Y_i} - \overline{Y_j}|}{d_{ij}} & (i \neq j) \\ 0 & (i = j) \end{smallmatrix}$, where d_{ij} is the geospatial distance between provinces i and j, which is evaluated by the latitude and longitude of the capital cities of provinces i and j. $\overline{Y_i} - \overline{Y_j}$ is the average value of per capita GDP in the provinces i and j from 2007 to 2019. (2) Replace the explained variable. Use manufacturing carbon intensity (MCI) to verify again. (3) Replace explanatory variables. Some experts distinguish between command-and-control and market incentives (Zhu et al. 2021; Jiang et al. 2021; Sun et al. 2021; Wang et al. 2018a). The comprehensive index of environmental regulation measured by the removal rate of five pollutants is a proxy variable for command-and-control environmental regulation. To avoid estimation bias caused by the selection of variables, provincial emission fees are selected as the measure index of market-incentive environmental regulation to be included in the model for revalidation. The results show that the coefficients of command-and-control ER and market-incentive ER (Table 4, Table 8) are − 0.104 and − 0.81, respectively, both significant at the 1% level, indicating that the effect of command-and-control ER on MCE reduction is stronger than that of market-incentive ER. On the one hand, China's treatment of environmental pollution follows the principle of "government-led, market-regulated," and command-and-control ER is the main means. On the other hand, China's carbon tax, carbon trading market, and management mechanisms are still immature, and the promotion effect of MCE reduction is weak. (4) Endogenous test. To address the potential endogenous issue, this paper adopts the explained variable lag 1 period as an instrumental variable and systematic generalized moment estimation (SYS-GMM) to deal with the possible endogeneity between ER and MCE (Yuan et al. 2020). (5) Subregional test. The total sample is divided into eastern, central, and western

regions for reverification. All of the above tests indicate that the results are robust.

Specifically, the subregional empirical results found that, first, the carbon emission reduction effect of ER is weak in the east and strong in the west. The coefficients of ER on MCE in the west and east are − 0.141 and − 0.068 at 1% significance test, respectively, demonstrating the inhibitory effect of ER on MCE in the west is stronger than that in the east, which may be that the industrial development in the east is faster and better than that in the middle and the west for a long time. The excessive accumulation of pollution emissions makes ER to be less effective in the short term. The central region with weak ER is likely to become a new "pollution sanctuary." The moderating coefficients of central and western regions are significantly − 0.044 and 0.232, respectively, illustrating that LGC significantly strengthens the effect of ER on central MCE reduction but weakens the western MCE reduction, which may be the differences in economic development between central and western regions. The western economy mainly relies on industrial-scale expansion. In contrast, in central China, to attract competitive enterprises and undertake high-quality industrial transfer, local governments give priority to improving environmental quality to attract more high-quality mobile elements. Second, in terms of spatial spillover effect, the coefficient of ER on central MCE is 0.267 and passes 1% significance test, which demonstrates that ER has a positive spillover effect on central MCE. With the industrial transformation and upgrading and transfer, the number of industries undertaken by the central region is increasing, which causes the increase of energy consumption and central MCE. In addition, the interaction terms in the middle and the west are significantly − 0.222 and 0.113, respectively, which maybe because of the differences in the economic development goals of the regional government, resulting in the heterogeneity in the carbon emission reduction effects of ER on MCE under local government competition. The above test results are in accordance with the previous ones, which verify the robustness of the model and research results.

Conclusions and discussions

Based on manufacturing panel data in 30 provinces of China from 2007 to 2019, this study first measures MCE and employs spatial autocorrelation analysis to clarify the spatial–temporal differentiation characteristics of MCE and ER. Under three different spatial weight matrices, the spatial Durbin model is employed to explore the impact mechanism, spatial spillover effect, and regional boundary of ER and LGC on MCE and further investigate the spatial heterogeneity of seven types of manufacturing. The conclusions are as follows:

Firstly, the overall MCE shows a warp-tail shape, and the overall ER is steadily increasing. The local pattern of MCE forms a decreasing trend from east to west, and the regional differences gradually increase. Secondly, ER significantly inhibits local MCE and increases neighboring MCE. LGC significantly promotes local and neighboring MCE, which increases the carbon emission reduction effect of ER on MCE and shows a "top-to-top competition." Thirdly, there is a significant regional boundary for the spatial spillover effect of ER on MCE. ER within 600 km significantly promotes neighboring MCE, and the closer the distance is, the stronger the effect is. Within 600–1600 km, ER significantly inhibits neighboring MCE, and the spillover effect first increases and then decreases, and the spatial spillover beyond 1600 km is not significant. Fourthly, ER significantly inhibits local pollution-intensive, low-income, and labor-intensive MCE and promotes neighboring pollution-intensive MCE. LGC weakens the MCE reduction effect of ER on neighboring high-income and technology-intensive manufacturing. Besides, the effect of ER on MCE reduction is weaker in the east and stricter in the west.

These findings suggest that not only environmental regulation but local government competition is an important way to promote emission reduction. Environmental regulation reduces the local MCE and also affects the neighboring MCE, so it is necessary to appropriately strengthen environmental regulation. However, the spatial spillover effect of ER has regional boundaries, which means that local governments should avoid blindly carrying out environmental cooperation but implement environmental governance efficiently within an effective scope. In addition, it is crucial to consider the heterogeneity of industry and regional heterogeneity to effectively control MCE, especially in pollution-intensive, low-income, and labor-intensive manufacturing, also in central and eastern regions. In the future, it is needed to continue to optimize regional industry layout, upgrade industrial structure, perfect the environmental monitoring system, and improve the government's environmental performance assessment mechanism to promote MCE reduction and manufacturing green development.

The findings have important implications for manufacturing green development. First, the results confirm that environmental regulation significantly promotes MCE reduction and the emission reduction effect of command-and-control ER is more effective than that of market-incentive ER (Table 4; Table 8). Therefore, it is important to adopt a diversified combination of environmental regulation tools to promote MCE. For example, administrative measures such as emission reduction targets should be used to constrain the production behavior of the manufacturing sector. At the same time, the development of green finance and green supply chains should be promoted, and the carbon trading market should be continuously improved to promote energy saving and emission reduction through market-incentive regulation. In addition, considering the active role of non-government forces in environmental governance, regulators should promote and support other social organizations to jointly participate in environmental protection, such as the monitoring role of environmental industry associations, to enhance the richness and effectiveness of environmental regulation through diversified means.

Second, the results show that local government competition enhances the promoting effect of environmental regulation on MCE reduction. Therefore, improving the performance appraisal mechanism of local governments, accelerating the transformation of government functions, and paying equal attention to rewarding incentives and punishing constraints on ecological performance are key to effectively enhancing the environmental governance capacity of local governments. For policymakers, it is necessary to consider the top-level design of tax, fiscal, and environmental policies, not only to give enterprises tax credits, pollution subsidies, and environmental incentives, but also to strengthen the punishment of environmental pollutions and to flexibly use local government to promote MCE reduction.

Third, the results support that environmental regulation has a significant spatial spillover effect and attenuation boundary on MCE reduction. Therefore, it is necessary to improve the integrated linkage mechanism, break down administrative barriers to pollution control, and establish a multilevel and multi-type collaborative governance platform by using emerging information technology means such as big data and AI to timely grasp the operating status of manufacturing enterprises in various regions and the implementation effect of environmental policies. Improving the digital and intelligent level of environmental governance, it is helpful to promote the coordinated governance of carbon emissions in cross-regional manufacturing industries.

Fourth, the results prove that environmental regulation and local government competition have industry heterogeneity on MCE reduction. The government should implement targeted and differentiated measures to promote manufacturing low-carbon transformation. For example, for pollution-intensive manufacturing, the government should strengthen prevention and control and guide the environmental treatment behavior of polluting industries by setting appropriate environmental access standards to achieve source control. For the non–pollution-intensive manufacturing, the government should enhance the ability of control in the middle of the process and guide the non–pollution-intensive manufacturing industry to carry out environmental governance through the effective combination of command-and-control and market-incentive ER to enhance the effectiveness of environmental regulation. For different factor-intensive manufacturing industries, the government should enhance the environmental supervision intensity of labor-intensive

manufacturing industries, promote clean technology innovation, introduce advanced technology and management, and attract high-level talents, thereby promoting green transformation. For technology-intensive and capital-intensive manufacturing industries, it should strengthen the optimal combination of various environmental regulation instruments and, at the same time, give tax concessions and improve financing channels to promote the intelligent and green transformation.

Finally, the results show that environmental regulation has regional heterogeneity on MCE. Therefore, the government should take environmental measures according to regional development characteristics and environmental governance needs. For example, for the eastern provinces with more advanced economies, the focus should be on adopting market-incentive ER and giving full play to the externalities of environmental regulation through market mechanisms such as sewage charges and trading permits. At the same time, it is necessary to gather the scale advantages of the manufacturing industry, improve the efficiency of resource allocation, and play an exemplary and leading role in modernization. For the central region, it is necessary to appropriately strengthen environmental regulation and improve the financial transfer payment of local governments to optimize the layout of the manufacturing industry, undertake the eastern industry with high quality, and achieve the sustainable development in manufacturing. For the western regions, which are economically backward, in the process of accurately planning the new pattern of the western manufacturing industry and strengthening infrastructural support construction, more imperative environmental regulations should be adopted to restrict the production behavior of high-pollution industries to help achieve the goals of carbon peak and carbon neutrality.

This study provides new evidence for environmental regulation to promote manufacturing carbon emission reduction from the perspective of local government competition. Although this study takes China as an example, how manufacturing industries achieve low-carbon and green development is not only a concern in China, but is a focus of attention worldwide, especially in the post-COVID-19 era, an increasing number of countries have begun to pay attention to environmental problems in the process of economic development. The results of this study may provide empirical support for manufacturing carbon emission reduction in other developing countries, especially those with energy dependence and promptly manufacturing development. In addition, the impact of ER on MCE from the perspective of LGC is the focus of this study, but further research is needed. First of all, due to the availability, using provincial-level data may cause sample bias, and subsequent research can be carried out at the prefecture-level cities or enterprise level. Secondly, according to the existing literature, manufacturing is subdivided by only three criteria, and future research of industry heterogeneity can be explored from more dimensions. Finally, most of the existing studies are based on Chinese data, and future studies can try to compare the impact of ER and its interaction with the government on MCE in different nations, which contributes to further identify their inherent impact and have more insight into environmental policy and local government behavior in manufacturing.

Appendix

Table 7 Description of the variables

Variable	Definition	Unit	Data source
MCE	Manufacturing carbon emissions	Million tons	CEADs(2019)
ER	Environmental regulation	%	CESY(2020)
LGC	Local government competition	%	CSY(2020)
PGDP	Per capital GDP	Yuan	CSY(2020)
OD	Opening degree	%	CSY(2020)
UR	Unemployment rate	%	CSY(2020)
FES	Fiscal expenditure scale	%	CSY(2020)
PFI	Public facilities investment	/100,000 persons	CSY(2020)

Table 8 Robustness test

Variables	(1) W_{ij}^A	(2) W_{ij}^E	(3) W_{ij}^Q	(4) MCI	(5) PW	(6) Eastern	(7) Central	(8) Western	(9) SYS-GMM
lnER	−0.104***	−0.014*	−0.058***	−0.153***	−0.081***	−0.068***	−0.032	−0.141***	−0.014*
	(−6.36)	(−1.76)	(−3.66)	(−3.93)	(−10.89)	(−2.85)	(−0.76)	(−4.14)	(−1.69)
lnLGC	0.011**	0.023***	0.027***	0.106***	0.025***	0.022	0.005*	−0.004*	0.008***
	(2.04)	(4.45)	(4.89)	(7.67)	(5.36)	(0.65)	(1.76)	(−1.70)	(2.63)
lnER×LGC	−0.038*	−0.279**	−0.198*	−1.627***	−0.269***	−0.003	−0.044*	0.232***	−0.139*
	(−1.73)	(−2.34)	(−1.71)	(−5.73)	(−3.46)	(−0.02)	(−1.83)	(3.20)	(−1.66)
L.lnMCE									0.732***
									(23.02)
Control variables	YES								
W×lnER	0.009*	0.213***	0.158***	0.727**	0.153***	0.541	0.267***	0.343	*Sargan*
	(1.68)	(3.79)	(3.25)	(2.24)	(2.65)	(0.85)	(2.88)	(0.27)	20.570
W×lnLGC	0.031***	0.034**	0.082***	0.548***	0.067*	0.288***	0.058*	−0.044	(1.000)
	(3.19)	(2.00)	(4.80)	(5.37)	(1.78)	(4.69)	(1.96)	(−0.72)	*AR(1)*
W×lnER×LGC	−0.394*	−0.422	−0.917***	−9.056***	−0.251	−4.845	−0.222**	0.113*	−2.58
	(−1.84)	(−1.12)	(−2.63)	(−4.73)	(−0.45)	(−1.24)	(−2.41)	(1.84)	(0.010)
W×Control variables	YES								
Spatial rho	0.154**	0.170*	0.184*	0.059*	1.009***	−0.039	0.156*	0.296***	*AR(2)*
	(2.16)	(1.68)	(1.69)	(1.74)	(4.00)	(−0.45)	(1.72)	(3.93)	−0.53
Variance sigma2_e	0.010***	0.009***	0.009***	0.047***	0.007***	0.012***	0.006***	0.003***	(0.596)
	(13.89)	(13.90)	(14.88)	(13.96)	(13.51)	(12.85)	(12.79)	(12.69)	
N	390	390	390	390	390	143	104	143	360

Note: *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. The *t* values are in parentheses

Declarations

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