Agglomeration Production, Industry Association and Carbon Emission Performance: Based on Spatial Analysis

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Abstract: Current emission reduction policies have struggled to adapt to the reality of industrial spatial agglomeration and increasing industrial linkages. In response, this paper incorporates new economic geography factors such as agglomeration production and industrial (trade) association into the analysis framework of carbon emission performance factors through China’s provincial panel data and conducts empirical research. It has been found that large-scale industrial production under economic agglomeration is conducive to improving carbon emission performance and that different forms of agglomeration at different degrees of agglomeration correspond to different carbon emission performances. As the degree of agglomeration increases, the effect of reducing emissions by specialized agglomeration decreases while the effect of reducing emissions by diversified agglomeration increases. Specialized agglomeration externalities and diversified agglomeration externalities can coexist at the same time, depending on the appropriate degree of agglomeration. There is a strong negative environmental efficiency effect in the provinces with close commodity trade links, which has triggered environmental dumping and pollution transfer between provinces. In the work of energy conservation and emission reduction, we must attach great importance to the hidden carbon in domestic merchandise trade and the resulting intergovernmental environmental game, and furthermore, give full play to the “self-purification” effect of aggregate production on energy conservation and emission reduction.

Keywords: agglomeration; industry association; carbon emission performance; spatial econometrics

1. Introduction

After more than 30 years of “economic miracle”, China has already emerged as advanced in the environmental pollution problems that have occurred in stages in the industrialization process of western developed countries. The overdrawn environmental capacity and environmental carrying capacity have been difficult to support extensive industrial development models (Dai, 2015) [1]. The Chinese government has proposed emission reduction targets, which are incorporated into the medium- and long-term national economic and social development plans as binding indicators, and has formulated corresponding domestic statistics, monitoring, and assessment methods (Liu, 2017; Lu, 2017; Liao, 2018) [2–4]. In the evaluation and specific implementation of energy-saving techniques and emission reduction, the following two methods are debatable:

First, the central government needs to decompose the emission reduction targets of local governments at all levels. The current target is broken down based on the GDP and population
of each place. Economically developed provinces, such as Guangdong and Jiangsu, and densely populated provinces, such as Sichuan and Henan, will be the focus of emission reduction. However, this distribution makes it difficult to achieve the desired effect. First of all, in terms of the individual province, it does not constitute a complete economic system. Most of the locally produced products may be consumed by other regions. Whether the region is a net exporter of hidden carbon is closely related to the level of environmental production technology and the division of labor in the local industrial chain. Moreover, decomposing the emission reduction tasks to the provincial level will inevitably lead to environmental dumping and pollution transfer between neighboring provinces (Li et al., 2017) [5]. Therefore, the calculation of hidden carbon in domestic merchandise trade and the resulting environmental spillage are closely related to the definition of regional carbon emission responsibilities, which directly affects the game of various stakeholders on the issue of emission reduction (Zhang, 2013; Mi, 2016) [6,7].

Second, according to intuitive judgment, the gathering of industrial production increases industrial pollution emissions and reduces local environmental quality. As a result of this, to meet the central government’s emission reduction tasks in the short term and cater to the public’s demand for environmental quality, local governments need to find new effective tools. In addition to using administrative regulations such as quotas [8], fines [9], and carbon taxes [10], some local governments even reduce emissions by controlling the scale and speed of industrial development (Wang, 2015; Tina, 2017) [11,12]. Consider this—is decentralized production more beneficial to abatement efficiency than concentrated production? In reality, since the 1990s, to save pollution control costs and facilitate the management, western developed country governments generally tend to concentrate enterprises in agglomeration areas for unified environmental regulation [13,14]. In the process of industrial transfer, the transferred industries or newly introduced industries are no longer distributed in the form of “scattered spots”, but instead exist in the form of agglomeration (Ezzi et al., 2016) [15]. All this shows that the externality of agglomeration production is playing a role in the invisible. If agglomerated production can better achieve the Pareto optimal environmental pollution level, then China’s current decentralized production policy may be contrary to emission reduction goals. Based on the above preliminary judgment, this paper believes that the current emission reduction policy based on the assumption of spatial homogeneity and spatial isolation has been difficult to adapt to the reality of China’s regional development and spatial linkage. To achieve the emission reduction targets as scheduled, it is urgent to monitor the effects of current emission reduction policies and adjust them on time.

2. Literature Review

The explanation of market concentration and spatial concentration of industry in new institutional economics is contained in the study of enterprises [16]. The research on enterprises is mainly carried out in two directions: one is the relationship between enterprises and the market, that is, the boundary of enterprises; second, the internal property rights structure, principal-agent, incentive mechanism and management mode [17]. Coase’s analysis of the relationship between enterprises and markets provides a powerful analytical tool for the study of the relationship between market concentration and spatial agglomeration of industries [18]. The problem of substitution and choice between enterprise and market is actually the basic manifestation of the relationship between industrial market concentration and spatial agglomeration [19]. The evolution of enterprise organization and the development of market transaction have, respectively, formed two kinds of industrial organization forms: integrated large enterprise and industrial cluster [20].

Research on the influencing factors of pollution emissions is the focus of scholars in China and overseas. Grossman and Krueger (1995) [21] believed that the relationship between economic growth and resource consumption with pollution emissions presents an “inverted U” curve characteristic, that is, the environmental Kuznets curve (EKC). They attributed the factors that affect environmental performance to three types: scale effect, structural effect, and technical effect. These three major effects summarize the internal influencing factors that affect the environmental performance of the region.
(country), but the above three major effects are all related to the geospatial factors of the economic unit. As the concentration of economic activities in a particular geographic area and the spatial connection between regions continue to strengthen, the environmental performance must also be affected by numerous spillover effects [22]. Some scholars made further research. They analyzed the channels and mechanisms that affect a country’s environment from the perspective of agglomeration, trade, geography, and other spatial connections (O’Brien and Leichenko, 2000; Grimes, 2003; Jorgenson, 2007; Wu, 2016; Ali, 2017; Ali, 2017; Zhang, 2017) [23–28]. Although the results of the spatial channel analysis of environmental impact are inconsistent, it is clear that there has been progress with the traditional “closed” research [29]. Therefore, it is more and more important to reasonably evaluate the spatial effect of the environment [30].

The spatial effect of the environment generally includes the agglomeration effect within a specific region and the geographical and trade effects between regions. Regarding the study of agglomeration within the region, whether it is the New Economic Geography theory or Marshall and Jacobs externality theory, most of them focus on whether agglomeration can promote economic efficiency (Jacobs, 1961) [31]. Moreover, it is agreed that the agglomeration of economic subjects in geographic space can facilitate the spread of knowledge, the sharing of resources, and the allocation of production factors to improve economic efficiency. However, from the perspective of agglomeration externalities, there is little involvement in studying environmental performance, and most of the literature only focuses on the negative externalities brought about by agglomeration (Verhoef, 2002; Duc, 2007; Otsuka, 2014; Cheng, 2016) [32–35]. The deterioration of environmental quality is not an inevitable result of spatial agglomeration. Different agglomeration degrees and agglomeration methods may correspond to different environmental effects. If the positive externalities of agglomeration can be fully utilized, it is possible to offset the negative externalities of the environment and even improve environmental performance. Wagner and Timmins (2009) [36] suggest that the agglomeration effect of the chemical industry is an important factor that elevates the environmental threshold of foreign direct investment (FDI) inflows. Yao (2017) [37] makes an empirical study by spatial econometric methods, claims that the impact of industrial agglomeration on smog pollution is significant, and industrial output agglomeration can reduce smog pollution. Effiong (2018) [38] used a semi-parametric panel fixed-effects regression technique and showed that urbanization reduces environmental pollution. At present, there is a lack of literature that focuses on the relationship between the agglomeration of regional economic activities and the environment on a larger scale.

Notably, the environmental policy (environmental quality) of a country (region) is inevitably affected by neighboring regions, showing the spatial spillover effect of the environment. It is generally believed that there are two types of environmental spillover channels between regions. One is geographical adjacency. On the one hand, through the spread of the surface, watersheds, and airflows, the “environmental dumping” problem of geographically adjacent areas is more serious, and there is a significant environmental spillover effect between geographically adjacent areas. On the other hand, with the expansion of geographic distance, the cost of obtaining environmental technology spillover across geographic distance increases (Xu, 2015; Wang, 2018) [39,40]. For each economic unit, there is a distance threshold that it does not want to exceed (Yuan, 2020) [41]. The other is economic linkages such as trade and investment. Research in this area focuses on the national level, with particular attention to the “pollution refuge effect” (Tu, 2015; Shen, 2017; Tang, 2018; Wu, 2018; Sun, 2018; Xin, 2020) [42–47]. Due to the difference in the intensity of environmental regulation, developed countries have transferred polluting industries to developing countries [48,49]. Through FDI investment and import and export trade, low-regulation and low-income countries have assumed more environmental risks and environmental pressures. However, in the past, the literature rarely paid attention to the impact of economic and trade links between regions within a country on environmental transfer. Moreover, the channels and methods of environmental spillover within a country may be different from those between countries. As within a country each region faces a similar policy
environment, the cost of industrial migration between regions is lower, and it is weaker due to geographical constraints.

To make up for the shortcomings of the previous literature, this paper attempts to use the exploratory spatial analysis method (ESDA) to incorporate agglomeration externalities, geography, trade, and other spatial factors into the analysis framework that affects environmental performance, as well as examine the spatial channels and effects of environmental spillovers, thus providing a reference for China’s energy conservation and emission reduction and regional coordinated development strategy formulation.

3. Model Design and Variable Selection

3.1. Model Design

Considering that the environmental quality (environmental policy) of a country (region) is inevitably affected by neighboring regions (Jie, 2006; Han, 2018) [50,51], this paper uses the inter-provincial panel data of China and adopts exploratory spatial analysis methods to incorporate new economic geographic factors such as agglomerated production and industrial (trade) correlation into the analysis of carbon emission performance. In addition, the author examines the impact of spatial factors on carbon emission performance. There are two types of spatial models: spatial lag model (SLM) and the spatial error model (SEM). For the explanatory variables, the spatial lag model is used to investigate the strike and impact of the change of the indicator in the adjacent region on the indicator in the region. Therefore, it is often used to estimate the spatial spillover effect, while the correlation between local intervals is reflected by the error term, the spatial error model is used. The choice of model is generally tested by methods such as LMERR and LMLAG, but for this article, the author is more inclined to analyze the spatial spillover effect under a specific channel, drawing on the views of Feng (2018) [52], so this article uses the spatial lag model (SLM).

There is a mutual promotion effect between the degree of industrial agglomeration and the form of agglomeration (specialized agglomeration and diversified agglomeration). The importance of agglomeration forms with different industrial agglomeration levels is different, and the impact on carbon emission performance is quite different. To examine the effect of the agglomeration form on carbon emission performance during the process of increasing the degree of agglomeration, this paper first establishes the following basic spatial panel regression model, see Equation (1):

$$EE_{it} = \beta AGGO_{it} + \phi Z_{it} + \rho WEE_{it} + \mu_i + \theta_t + \epsilon_{it}$$

(1)

$EE$ represents the carbon emission performance, $AGGO$ indicates the degree of agglomeration, and $\beta$ reflects the impact of agglomeration on carbon emission performance. $Z$ represents other control variables, $\rho$ is the spatial regression coefficient, which measures the spatial dependence between the variables. $\mu_i$ is the regional specific fixed effect of the $i$th region, which means that after controlling other explanatory variables, the area $i$ has a long-term fixed effect on carbon emission performance due to its regional characteristics. $\theta_t$ is the specific fixed effect of time in the $t$th year, which represents the short-term fixed impact of carbon emission performance due to its characteristics in the $t$th year after controlling for other explanatory variables.

To further investigate the impact of different agglomeration forms on carbon emission performance when the agglomeration degree expands, this paper introduces the multiplication term of agglomeration degree and agglomeration form, and establishes expansion model 1, see Equation (2):

$$EE_{it} = \beta_1 AGGO_{it} + \beta_2 AGGO_{it} \cdot MAR_{it} + \beta_3 AGGO_{it} \cdot JAC_{it} + \beta_4 AGGO_{it} \cdot MAR_{it} \cdot JAC_{it} + \phi Z_{it} + \rho WEE_{it} + \mu_i + \theta_t + \epsilon_{it}$$

(2)

$MAR$ and $JAC$ denote specialized agglomeration and diversified agglomeration, respectively. Cross-section $MAR \cdot JAC$ examines the joint effect of two types of agglomeration on carbon emission
In the reality of JAC, the specialized agglomeration externalities and diversified agglomeration externalities are not opposites but work together to save energy and reduce emissions. If the coefficient is greater than zero, it indicates that as the agglomeration degree increases, the corresponding agglomeration form has the effect of improving carbon emission performance. Besides, considering that at different stages of the agglomeration life cycle the impact of specialization and diversification on the environment is irrelevant (Galliano, 2015) [53], hence, adding specialized externalities and diversified aggregation externalities to the model at the same time will not lead to multi-collinearity. The data are derived from China Statistical Yearbook, China Energy Statistical Yearbook, China Environmental Statistical Yearbook, China Industrial Economic Statistical Yearbook, and China Regional Economic Statistical Yearbook.

In addition, this article sets a dummy variable (S) of the degree of agglomeration. According to the classification of the average index value of non-agricultural employment density in China’s provinces (regions) from 2000 to 2018, the Chinese provinces (regions) are divided into five agglomeration levels:

1. Low-level agglomeration areas, with a concentration of less than 100 people/square kilometers;
2. Relatively low-level agglomeration areas, with a concentration of 100–200 people/square kilometers;
3. Medium-level agglomeration areas, with a concentration of 200–300 people/square kilometers;
4. Relatively high-level agglomeration areas, with a concentration of 300–400 people/square kilometers;
5. High-level agglomeration areas, with a concentration of more than 400 people/square kilometers.

To introduce the intersection of four dummy variables and agglomeration forms, respectively, we investigate the non-linear effects of different agglomeration forms on energy saving and emission reduction under different agglomeration levels, and establish an extended model 2, for which the next equation was used (3):

\[
EE_{it} = \beta_1 AGGO_{it} + \beta_2 AGGO_{it} \cdot MAR_{it} + \beta_3 AGGO_{it} \cdot JAC_{it} + \beta_4 SCAL_{it} \cdot MAR_{it} \cdot JAC_{it} + \sum_{n=1}^{4} \eta_1 MAR_{it} \cdot S_n + \sum_{n=1}^{4} \eta_2 JAC_{it} \cdot S_n + \sum_{n=1}^{4} \eta_3 MAR \cdot JAC \cdot S_n + \phi Z_{it} + \rho WEE_{it} + \mu_i + \theta_t + \epsilon_{it}
\]

The core element of the spatial lag model is the spatial correlation matrix. As for the definition of spatial association, there are different understandings. Traditional literature sets it as a geographic association (contiguous) matrix. Geographically related factors have the most direct impact on environmental efficiency. On the one hand, neighboring areas face similar institutional, cultural, and resource endowments, which are more conducive to imitation and spillover of advanced environmental protection technologies and management models. On the other hand, regional competition factors have led to the “bottom-by-bottom” effect, which is more prominent in the environmental field. To “attract investment”, the environmental policy game in the adjacent area has strengthened pollution avoidance and pollution transfer.

However, with the spatial diversification of economic ties and the traditional geographical factors becoming weaker and weaker, Pazienza (2015) [54] constructed a spatial correlation matrix of factors such as trade and investment. They believe that there are two trends in the impact of trade associations on the environment, environmental dumping, and competition effects. These two types of tendencies also exist between neighboring regions, except that the neighboring associations are more affected by government actions, while the trade relationship is caused by market competition. For both parties involved in domestic trade, the importer of trade is generally downstream of the industrial chain, and the exporter of trade is generally upstream of the industrial chain. The unit value-added of upstream industries is lower, and the energy consumption and pollution levels are higher. In addition, the intensity of regional environmental regulations is different, and downstream industries tend to transfer high-pollution and high-energy-consuming industries to areas with weaker environmental
regulations. The result of the superposition of the two effects is that enterprises in the upstream region bear more environmental pressures and risks, while the downstream region does the opposite. That is, it manifests as a negative environmental spillover effect under trade linkages. Of course, with the deepening of trade and the enhancement of economic strength, the original upstream and downstream division of labor will be broken, and intra-industry trade will become more frequent (Zhang, 2015) [55]. Under the effect of peer competition and catch-up competition, this spillover effect is positive.

In this paper, the regional adjacency relation matrix is used as the geographic adjacency association matrix \((S')\). If area \(i\) and area \(j\) are connected (or \(i = j\)), then the element \(s_{ij} = 0\), otherwise, \(s_{ij} = 1(i \neq j)\). In this way, we can obtain a binary matrix and normalize it to get \(S'\), that is \(s'_{ij} = s_{ij} / \sum_{i=1}^{n} s_{ij}\). Regarding the trade correlation matrix \((T')\), this article uses the national input–output table and uses the inter-provincial railway transportation matrix published in the “National Railway Statistics Yearbook” as the starting matrix for dynamic planning. The minimum cross-entropy method is used to find the inter-provincial trade matrix of commodities. Element \(t_{ij}\) means the value of the \(S'\) industrial product transferred from area \(i\) to area \(j\), and is normalized by the same method as the geographic correlation matrix. At the same time, the above two spatial correlation matrices can be used to obtain the adjacent spatial lag term \((SS')\) and the trade spatial lag term \((TT')\) of carbon emission performance value, respectively. We can deduce that when \(W\) is unchanged, the higher the carbon emission performance in other regions, the higher the \(WEE\) is. Similarly, when \(Y\) is unchanged, the closer the correlation is, the higher the \(WEE\) is.

### 3.2. Variable Index Selection

Carbon emission performance: From the perspective of all factors, this paper comprehensively considers the relationship between the input of production factors, expected output, and undesired output. By adding the slack based model (SBM) model of undesired output, this paper measures China’s carbon emission production efficiency and uses Maxdea software to perform the above calculation. The specific data used are described as follows: The labor input is the average annual number of industrial employees, capital input is the net value of fixed capital, and energy input is the total energy consumption. Since most of the trade in goods is concentrated in the industrial production sector, the expected output is the total industrial output value expressed at the constant price in 2000, the undesired output is expressed by carbon dioxide emissions. This research mainly uses air pollution emission to measure total carbon emission. In previous studies, PM2.5 concentration was generally taken as a proxy variable to measure the degree of air pollution. However, PM2.5 cannot make a comprehensive assessment of air pollution, so the indicators measured in this paper mainly include Sulphur dioxide (SO2), Oxynitride (NOX), and Sulphur dust (DS). Additionally, a comprehensive pollution (CP) emission index is obtained by reducing these indexes.

This paper refers to the method of (Gallego-Alvarez et al., 2014) [56] for index dimension reduction. First, factor analysis is used to conduct unified dimension reduction for the three environmental output indicators. After the Barlett sphere test, the statistical value is 56.077, the significance probability is 0.000, and the value of Kaiser-Meyer-Olkin (KMO) is 0.748. Therefore, it is suitable for factor analysis to reject the null hypothesis that the indicators are not correlated. At the same time, through the factor score matrix and the variance contribution rate of the common factor, the corresponding weight of each index is calculated, and the weights of sulfur dioxide, nitrogen oxide and soot dust are obtained as 24%, 49% and 27%, respectively. Combined with the weights of three kinds of pollution indexes, the comprehensive pollution (CP) can be calculated, and the formula is as follows:

\[
CP_{it} = \sum_{i=1}^{n} w_{it} \cdot X_{it}
\]

Among them, \(w_{it}\) represents the weight of each pollutant, \(X_{it}\) represents the composition of the pollutant.
Agglomeration degree: Agglomeration degree indicates the spatial heterogeneity and regional imbalance of industrial distribution, usually measured by economic density and employment density (Yuan, 2017) [57]. As China is currently in the deepening stage of industrialization and urbanization, the characteristics of this stage determine that non-agricultural employment has an important impact on the economic growth of a region. Moreover, the greater the density of non-agricultural employment in a certain area, the more obvious the localization of increasing returns to scale, inter-industry exchanges, or externalities.

Specialized agglomeration: From the perspective of externalization of specialized agglomeration, resources, capital, and labor are concentrated in a certain industry to form specialized production. If we consider the scale-economy nature of pollution emissions and governance, then pollution must be positively related to the scale of the economy. Specialized agglomeration may be an important mechanism for controlling the total amount and intensity of pollution emissions, that is, in the internal network structure of the same industry, it can fully share environmental protection facilities, centrally deal with pollution emissions, and share environmental protection and energy-saving technologies, to produce scale effects of environmental governance and achieve the unification of the three goals of reducing pollution emissions, reducing governance costs and increasing profits (He, 2014) [58]. This paper draws on the method of Pessoa (2014) [59] to calculate the specialization agglomeration index. The calculation formula is $\text{MAR}_i = \max_j (s_{ij} / s_j)$, where $s_{ij}$ is the proportion of employment in industry $j$ in province $i$ that accounts for the total employment in province $i$, and $s_j$ is the proportion of the employment in industry $j$ to the national employment, that is, the maximum value of the location quotient of each industry in the province.

Diversity agglomeration: Unlike specialized agglomeration, Jacobs (1969) [60] emphasized that knowledge is more likely to spill over between complementary industries. Industrial diversification and knowledge spillovers between industries are the most important drivers of economic growth. The more diverse industries integrated with a geographic space, the more it can stimulate the collision of knowledge between different subjects, bringing a rich supply of knowledge for environmental technology innovation, including complimentary knowledge, differentiated knowledge, and competitive knowledge. At the same time, the improvement of environmental protection technology of any enterprise in the industrial chain can improve the energy-saving pollution control technology of its upstream and downstream industries and reduce the cost of pollution control through collective learning. Using the method of Zhang Otsuka (2014) [34] to calculate the diversification agglomeration index, the calculation formula is $\text{JAC}_i = 1 / \sum_j |s_{ij} - s_j|$, where $A$ and $C$ have the same meaning as above. The larger the index, the higher the degree of industry diversity in the province. These two indexes are not completely exclusive, and a highly diversified area may also obtain a larger location quotient in a certain industry.

The model also includes specific control variables that affect carbon emission performance to purify the role of spatial factors. Combined with the existing literature, it mainly considers factors such as economic scale, economic openness, resource endowment, environmental regulations, and technological innovation. To eliminate the non-stationarity of the sample data, all variables take their natural logarithms:

- Economic scale: Expressed as GDP per capita calculated at constant prices in 2000 and recorded as GDP.
- Economic openness: The proportion of the total output value of foreign-invested and Hong Kong, Macao, and Taiwan-invested industrial enterprises. It is generally believed that foreign direct investment can bring technology spillover effects to the host country, or it may also be reduced to a “pollution refuge” for industries in developed countries. This variable is denoted as FDI.
- Factor endowment structure: Expressed as the ratio of the balance of industrial fixed asset net worth to the number of industrial employees, to reflect the level of heavy industrialization and capital deepening in China in recent years, denoted as CAP.
Environmental regulation: Select the ratio of GDP and the total investment of each province in pollution control and record it as ERI.

Energy consumption structure: China is a major coal consumer in the world, and coal and other fossil energy still occupy a dominant position. Total coal consumption in key areas will continue to be controlled, and coal accounts for nearly 60 percent of primary energy consumption. Expressed as the proportion of coal consumption equivalent to standard coal in energy consumption, denoted as ES.

Technological innovation: It is expressed in terms of the proportion of R&D expenditures in each province as a percentage of GDP, and is recorded as RD. The data used come from the “China Statistical Yearbook”, “China Energy Statistical Yearbook”, “China Industrial Economic Statistical Yearbook” and “China Science and Technology Statistical Yearbook” over the years.

4. Empirical Results and Discussion

4.1. Spatial Correlation Analysis

Whether the regression model needs to be analyzed in space depends on whether the carbon emission performance is geographically relevant and dependent. The author uses the global Moran’s I index to test whether there are relevant characteristics of the spatial distribution of China’s carbon emission performance. The calculation formula is Formula (4):

\[
\text{Moran’s } I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{S^2 \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij}}
\]

(4)

Among them, \(S^2 = \frac{1}{n} \sum_{i=1}^{n} (Y_i - \bar{Y})^2\), \(\bar{Y} = \frac{1}{n} \sum_{i=1}^{n} Y_i\), \(Y_i\) and \(Y_j\) represent the observed values of carbon emission performance values for regions \(i\) and \(j\), respectively. Since Moran’s I index can only calculate the cross-sectional data of the spatial adjacency matrix, this paper reports the value of the adjacency binary matrix.

The author uses Geoda spatial measurement analysis software to conduct Moran’s I test on the geospatial correlation of China’s carbon emission performance in the period 2007–2018. The Moran’s I index is shown in Table 1: the calculation results show that the carbon emission performance is not completely randomly distributed but shows a strong spatial geographic cluster characteristic. In general, the geospatial dependence trend of China’s carbon emission performance has increased year by year. The spatial connection of carbon emission performance is that provinces and regions with high carbon emission performance tend to be relatively adjacent to provinces and regions with high carbon emission performance, such as the spillover of low-carbon production technologies, good government policies among governments, and so on. Provinces and regions with low carbon emission performance tend to be relatively adjacent to provinces and regions with low carbon emission performance, such as pollution dumping and pass-through between adjacent areas and the government’s “bottom-up” effect.

| Years | Moran (I) | Z (I) | Years | Moran (I) | Z (I) | Years | Moran (I) | Z (I) | Years | Moran (I) | Z (I) |
|-------|-----------|-------|-------|-----------|-------|-------|-----------|-------|-------|-----------|-------|
| 2007  | 0.0542    | 1.5685| 2010  | 0.0952    | 1.6524| 2013  | 0.1154    | 1.8952| 2016  | 0.1324    | 2.6210|
| 2008  | 0.0602    | 1.9365| 2011  | 0.0996    | 2.3981| 2014  | 0.1208    | 2.2068| 2017  | 0.1396    | 2.3642|
| 2009  | 0.0710    | 2.1201| 2012  | 0.0924    | 1.6852| 2015  | 0.1245    | 1.9651| 2018  | 0.1425    | 2.2650|

For the spatial panel model test, ordinary least squares (OLS) estimation will produce biased or invalid coefficient estimates. According to the recommendations of Simonen (2015) [61], this paper intends to use the maximum likelihood method (MLE) for model estimation. Hong (2019) [62] believes that when the regression analysis is limited to some specific individuals, the fixed-effect model is a better choice, and the spatial panel literature mostly uses the fixed effect mode. To this end, this paper uses a spatial fixed-effect model. At the same time, according to the different control of space effect
and time effect, it is further divided into four models, namely, no fixed effect (nonF), space fixed effect (sf), time fixed effect (tf), both space and time fixed effect (stF). The Matlab 7.6 software was used to test the national carbon emission performance. Model 2 considered the dummy variables of the agglomeration degree, and the estimated results are shown in Table 2.

### Table 2. Estimation results of the national carbon emission performance model.

| Variable | Extended Model 1 (Spatial lag model) | Extended Model 2() |
|----------|--------------------------------------|---------------------|
|          | nonF | sf  | tf | stF | nonF | sf  | tf | stF |
| S$S'\$ | -1.3082 *** | -1.2764 *** | -1.1763 *** | -1.2877 *** | -1.1980 *** | -1.0946 *** | -1.1062 *** | -1.2213 *** |
| T$T'\$ | -0.6533 *** | -0.5870 *** | -0.5455 *** | -0.6494 *** | -0.6533 *** | -0.8044 *** | -0.8875 *** | -0.8405 *** |
| AGGO    | -0.1372 *  | -0.1537 ** | -0.1453 *  | -0.1426 *** | -0.1766 *** | -0.1807 *** | -0.1923 *** | -0.1880 *** |
| AGGO MAR| 0.1875 *  | 0.1661 *  | 0.1876 **  | 0.1797 **   | 0.1576 **   | 0.1556 **   | 0.1556 **   | 0.1576 *** |
| AGGO JAC| 0.0544   | 0.0340 *  | 0.0595 *   | 0.0456 *    | 0.0365      | 0.0398 *    | 0.0423 *    | 0.0428 *   |
| AGGO MAR JAC| 0.0872  | 0.0987 | 0.0656 | 0.0772 | 0.1233 | 0.1098 | 0.0987 | 0.1240 |
| S1 MAR  | -      | -     | -     | -     | 0.1509 * | 0.1556 ** | 0.1608 ** | 0.1582 ** |
| S2 MAR  | -      | -     | -     | -     | 0.1150 * | 0.1187 ** | 0.1232 ** | 0.1189 *** |
| S3 MAR  | -      | -     | -     | -     | 0.0890 * | 0.0923 * | 0.1086 * | 0.0972 ** |
| S4 MAR  | -      | -     | -     | -     | 0.0543   | 0.0485   | 0.0453   | 0.565    |
| S1 JAC  | -      | -     | -     | -     | 0.0223   | 0.0252   | 0.0327   | 0.0350 * |
| S2 JAC  | -      | -     | -     | -     | 0.0732 * | 0.0954 ** | 0.1045 ** | 0.0999 ** |
| S3 JAC  | -      | -     | -     | -     | 0.1209 * | 0.1545 ** | 0.1445 ** | 0.1395 ** |
| S4 JAC  | -      | -     | -     | -     | 0.1834 * | 0.2012 ** | 0.1983 ** | 0.1963 ** |
| S1 MAR JAC| -      | -     | -     | -     | 0.0654   | 0.0763   | 0.0843   | 0.0778   |
| S2 MAR JAC| -      | -     | -     | -     | 0.1132 * | 0.1430 ** | 0.1346 ** | 0.1447 ** |
| S3 MAR JAC| -      | -     | -     | -     | 0.1832   | 0.1923   | 0.1320 * | 0.2032 * |
| S4 MAR JAC| -      | -     | -     | -     | 0.2212   | 0.1831   | 0.1982   | 0.2343   |
| GDP     | 0.0874 ** | 0.0766 ** | 0.0963 ** | 0.1167 *** | 0.0693 ** | 0.0720 ** | 0.0772 ** | 0.0807 *** |
| FDI     | -0.0045 * | -0.0056 * | -0.0038 ** | -0.0054 ** | -0.0035 * | -0.0043 * | -0.0048 ** | -0.0043 ** |
| CAP     | -0.2652 ** | -0.2384 ** | -0.2766 ** | -0.2452 *** | -0.2126 ** | -0.2764 ** | -0.24540 ** | -0.2355 *** |
| ERI     | -0.1123 * | -0.0983 * | -0.1044 * | -0.1094 *** | -0.0850 ** | -0.0956 ** | -0.1136 *** | -0.1087 *** |
| ES      | -0.0934 ** | -0.0873 ** | -0.0922 ** | -0.0902 *** | -0.0798 ** | -0.0672 ** | -0.0752 ** | -0.0812 *** |
| RD      | 0.1833 * | 0.2103 * | 0.1654 ** | 0.1903 ** | 0.2035 ** | 0.2351 ** | 0.1980 ** | 0.2055 ** |
| $\rho$  | 0.298 *** | 0.335 *** | 0.354 *** | 0.314 *** | 0.285 *** | 0.313 *** | 0.323 *** | 0.337 *** |
| LogL    | 54.7    | 98.0  | 113.3 | 165.4 | 54.2    | 123.2    | 98.0    | 154.2    |

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

The results in Table 2 show that the space item parameter ($\rho$) estimates of Model 1 and Model 2 have passed the 1% significance level, indicating that China's carbon emission performance has obvious spatial dependence characteristics, and both pollution emissions and environmental policies will have externalities to adjacent areas. It can be seen that in the panel data test of environmental efficiency, if the spatial dependence of the region is not taken into account, it may lead to deviations in the model estimation results. The reason is that, on the one hand, to expand trade or attract capital, strategic environmental policy games among local governments have strengthened the convergence of environmental standards. On the other hand, using the environmental policies of neighboring areas as the criteria for formulating local environmental policies can reduce the cost of decision-making, especially when the effects of the policies are not clear, and the environmental policies of various regions imitate each other.

From the perspective of the model fitting effect, the model with both spatial and time-fixed effects (larger LogL value and more significant statistics) is more in line with objective reality, indicating that the environmental impact of the region on neighboring regions is reflected in the overall spatial structural characteristics, such as the imbalance of China’s regional economic development, differences in resource endowments and environmental carrying capacity, and other factors that are not included...
in the model. On the other hand, the time factor plays an important role in environmental interaction, which is reflected in the characteristics that environmental pollution has a far-reaching impact on time and a strong time lag. Therefore, this article analyzes the fixed effects of both time and space (stF).

For Model 1, the lagging term of trade-related space (TT’) is significantly negative, with a coefficient of −0.6494, which means that the higher the level of trade-related areas, the higher the level of carbon emission performance, the lower the level of carbon emissions in the region. That is, the pollution transfer effect of the industrial chain exceeds the competition and learning effect of the same industry. In recent years, with changes in domestic and foreign development conditions, under the dual role of market selection and government promotion, the industrial structure adjustment process in the eastern region has continued to accelerate. In conjunction with the country’s strategy of accelerating the development of the central and western regions, a large number of low-end production and processing industries, mainly resource-consuming and labor-intensive industries, are gradually shifting to the central and western regions. As a result, the central and western regions are in the upper reaches of the industrial chain in the domestic industrial division system.

The unit value-added of the upstream industry is low, but the energy consumption and pollution levels are also high. Then, through domestic trade, the eastern regions that created environmental risks and environmental burdens enjoyed more environmental benefits, while the vulnerable central and western regions assumed excessive environmental risks and environmental burdens. This result is consistent with the study of Peng (2017) [63]. At the same time, the adjacent space lag term (S’S’) is significantly negative (−1.2877). This result is similar to the estimation of Qin (2015) [64], that is, the higher the environmental efficiency of the adjacent area, the lower the environmental efficiency of the area. Therefore, it is very likely that the regional “chassis” effect in the environmental field has strengthened environmental dumping and pollution transfer.

The agglomeration degree (AGGO) coefficient is significantly negative (−0.1426), indicating that agglomeration consumes too many resources and energy and emits more pollutants while expanding the scale of economy and population, thereby reducing carbon emission performance. The cross-term AGGO-MAR coefficient is positive and passes the 5% significance level, which is completely consistent with the expectations of the MAR externality theory, indicating that the agglomeration of enterprises belonging to the same industry in the geographical space forms specialized production and scale effect, which promotes the centralized use of energy. Energy utilization technology is also improved through the learning effect of companies in the industry. At the same time, the accumulation of homogeneous (or similar) waste can also reduce the cost of pollutant treatment and increase the value of waste recycling (Huang, 2020) [65], so it can improve the efficiency of regional energy use and thus improve environmental performance. Baomin (2012) [66] also found that industrial agglomeration may be an important mechanism for controlling the intensity of pollution emissions and narrowing the differences in environmental performance. Although the cross term SACL-JAC is positive, it is not significant at an acceptable level. The study results did not find evidence supporting industry diversity that could significantly improve environment performance. In addition, the cross-term (SACL-MAR-JAC) coefficient did not pass the significance test. This reminds us that the “rebound effect” and “self-purification effect” caused by the increase in the degree of agglomeration are intertwined. This comprehensive effect may depend on the level of agglomeration.

To examine the form of aggregation from which carbon emission performance benefits at different aggregation levels, this paper compares regions at different aggregation levels. The estimation results of Model 2 find that under different agglomeration degrees, the impact of agglomeration forms on carbon emission performance has nonlinear characteristics. As the degree of agglomeration increases, the externality of specialized agglomeration decreases, indicating that with the increase in the degree of agglomeration, the price of non-mobile factors increases, and the crowding effect occurs, which is manifested in the shortage of land resources and large emissions. The competition among enterprises within the industrial agglomeration has reached saturation, and the activities of joint energy conservation and emission reduction have stabilized. At this time, the promotion effect of
specialized agglomeration externalities on carbon emission performance began to decline. The diversity agglomeration externality coefficient increases with the degree of agglomeration, especially in the high agglomeration area. The increase in the degree of agglomeration facilitates the diversification of the industry, provides complementary knowledge for environmental technological innovation, enhances the energy-saving pollution control technology of its upstream and downstream industries, and reduces the cost of pollution control.

At different degrees of agglomeration, the opposite trends of the specialization agglomeration externality and diversification agglomeration externality coefficients indicate that regions with lower agglomeration tend to specialize agglomeration, and regions with a higher agglomeration tend to diversify. Generally speaking, specialized agglomeration tends to expand the scale of industry, which is essential for the economic development of low-aggregation areas. For example, Jilin Province is a specialized agglomeration led by the automobile industry, which plays a key role in regional economic growth. In Guangdong, industries that are dominated by petrochemical manufacturing, automobile manufacturing, and electronic information manufacturing are more diverse. For the intersection of the two, the coefficient of the medium agglomeration zone is the largest, indicating that the diversified externalities and the specialized externalities are not opposed to each other, but jointly act on carbon emission performance. The effect depends on the appropriate degree of agglomeration. In summary, when the degree of agglomeration is low, the specialized agglomeration has a greater impact on carbon emission performance. With a high degree of agglomeration, the impact of diversified agglomeration on carbon emission performance is more significant.

As far as other control variables are concerned, the coefficient of economic scale (GDP) is significantly positive, indicating that with economic development, the level of carbon emission performance will increase accordingly. This can be attributed to the increase in people's environmental awareness and the rise in environmental demand (Grossman and Krueger, 1995). FDI has a negative impact on carbon emission performance. This conclusion is consistent with the conclusion of Pazienza (2015) [54]. He found that the increase in FDI investment scale did not bring about an increase in environmental efficiency, and the pollution refuge hypothesis was supported in China. The environmental regulation variable (ERI) is significantly negative, that is, environmental governance inputs have a negative impact on carbon emission performance. The reason for this may be that China’s pollution control model is mainly end-of-pipe treatment. Under this model, environmental treatment investment cannot reduce the generation of pollutants from the source, but the phenomenon of more pollutant generation and more treatment investment will occur. This is also the root cause of China’s increasing investment in pollution control, but environmental problems have not been effectively controlled. Factor endowment (CAP) has a significant negative impact on carbon emission performance. This is consistent with the conclusion of Wang (2014) [67] that the decline in the proportion of industry can reduce pollution emissions. Ozawa (2013) [68] also believes that if the factor endowment structure rises, it means that the regional economic structure is transforming from labor-intensive to capital-intensive, and capital-intensive industries are generally heavily polluting industries. Energy structure (ES) has a significant negative impact on carbon emission performance, indicating that reducing the proportion of coal consumption and promoting the industrial use of clean and new energy are important ways to improve carbon emission performance. The research and development expenditure intensity (RD) coefficient is significantly positive, indicating that independent research and development can promote environmental technological innovation (Neng, 2019) [19].

4.2. Subregional Empirical Results and Analysis

Firstly, sensitivity analysis is made from two aspects. First, considering the large differences in the economic development level and environmental governance capabilities of different provinces and regions in China, it is necessary to conduct group inspection according to the three major regions of east, middle and west. Similarly, using the fixed-effect SLM model, the extended model 1 is estimated according to the three regions of east, middle, and west. The results in Table 3 show that the SLM
models of the three major regions are significantly positive and greater than the national overall $\rho$ test value, indicating that the spatial dependence characteristics of internal carbon emission performance in the three major regions of the east, middle and west regions are more significant than that of the whole country. Due to the high degree of homogenization within the region, which is manifested by similar levels of economic development, industrial structure, and environmental technology, the environmental performance within the region has shown a trend of "club convergence". However, the eastern region has benefited significantly from the positive externalities of the neighboring regions, all converging toward high efficiency, and the central and western regions have been significantly affected by the negative environmental externalities of the neighboring regions, converging toward low efficiency.

Table 3. Estimated results of carbon emission performance models by region.

|       | Region    | nonF   | sF     | tF     | stF    |
|-------|-----------|--------|--------|--------|--------|
| $SS'$ | West      | -0.509*** | -0.537** | -0.623** | -0.598*** |
|       | East      | -0.766**  | -0.698*** | -0.668*** | -0.703*** |
|       | Central   | -0.476*** | -0.504*** | -0.537*** | -0.496*** |
| $TT'$ | West      | 0.236**  | 0.223**  | 0.265**  | 0.218**  |
|       | East      | 0.445*   | 0.503**  | 0.466**  | 0.489**  |
|       | Central   | 0.189**  | 0.227**  | 0.176**  | 0.180**  |
| AGG   | West      | -0.034*** | -0.038*** | -0.042*** | -0.047*** |
|       | East      | -0.013*** | -0.015*** | -0.022*** | -0.026*** |
|       | Central   | -0.046*** | -0.053*** | -0.047*** | -0.045*** |
| AGG-MAR | West    | 0.098*   | 0.119*   | 0.087**  | 0.097**  |
|       | East      | 0.243*   | 0.217**  | 0.245**  | 0.238*** |
|       | Central   | 0.055*   | 0.039*   | 0.045**  | 0.039**  |
| AGG-JAC | West   | 0.045    | 0.065    | 0.044    | 0.053    |
|       | East      | 0.087**  | 0.076**  | 0.078**  | 0.082**  |
|       | Central   | -0.007   | -0.023   | -0.078   | -0.054   |
| AGG-MAR-JAC | West | 0.043   | 0.036    | 0.025    | 0.012    |
|       | East      | 0.023*   | 0.032*   | 0.027*   | 0.031*   |
|       | Central   | -0.021   | -0.018   | -0.020   | -0.005   |
| $\rho$ | West      | 0.476**  | 0.464**  | 0.505**  | 0.516*** |
|       | East      | 0.463**  | 0.485*** | 0.487*** | 0.546*** |
|       | Central   | 0.467*** | 0.476*** | 0.488*** | 0.538*** |
| LogL  | West      | 67.5     | 78.4     | 57.7     | 76.5     |
|       | East      | 54.3     | 37.7     | 48.6     | 75.7     |
|       | Central   | 12.6     | 27.6     | 17.7     | 62.5     |

Note: *, **, and *** represent the significance levels of 10%, 5%, and 1%, respectively.

Different from the national carbon emission performance, the overall lag of the trade-related space in the three major regions is positive, and it has passed the 5% significance level. The reason is that due to the small regional environmental technology gap and high industrial homogeneity, the pollution transfer effect of the industrial chain is not significant. Increasing industry competition and learning effects have led to a relationship of positive efficiency spillovers in trade relations. That is, regions with a high degree of trade correlation show the same trend of carbon emission performance, while the
changing trend of the adjacent interval is opposite, which further shows that the pollution transfer phenomenon of the adjacent interval is more prominent.

Agglomeration externality is an important factor that affects carbon emission performance, but its impact is significantly different in different regions. In the eastern region, due to the relatively developed market economy and strong endogenous industrial agglomeration, coupled with the coastal location, the technology transfer of FDI and trade has enhanced the development and diffusion of environmental protection technologies for its industrial clusters. Both the externalities of specialized agglomeration and the externalities of diversified agglomeration have obvious effects on improving the environment. For the central and western regions, the diversified externality coefficient is not significant, indicating that the central region urgently needs a diversified industrial environment, and strengthening the diversified development of the central region has a positive impact on the improvement of the regional environment. In addition, although the externality of specialized agglomeration has passed the significance test, the coefficient is relatively small, indicating that, overall, the externality of agglomeration in the central and western regions has a limited effect on improving the environment. The reason is that, on the one hand, the underdeveloped areas in the central and western regions have a low degree of agglomeration and have not yet reached the basic threshold for the effect of agglomeration on carbon emission performance. On the other hand, the agglomeration in the central and western regions is more dominated by the government, which makes it difficult for the industry and the industry to play a market-based environmental “self-purification” function.

Second, this paper used industrial added value to replace the employed population and re-calculated the specialized externalities and diversified densely packed externalities to conduct sensitivity analysis. Under the condition of the other set remaining unchanged, alternative indicators were used, respectively, to return to the model and test. The results showed that the values calculated by the employed population and industrial added value had no essential difference in the two indexes, among which the values of two indexes are specialized externalities and diversified densely packed externalities. Although the variable regression coefficient and its significance changed slightly, there are a few variables that became less significant. However, on the whole, the robust character of the empirical results in this paper is maintained.

5. Conclusions and Inspirations

This paper incorporates new economic geographic factors such as agglomeration of production and trade linkage into the analysis framework that affects carbon emission performance, examines the spatial channels and effects of environmental spillovers, and obtains the following conclusions and enlightenment.

First, agglomeration externality is an important mechanism for improving carbon emission performance. Increasing spatial agglomeration can accelerate the diffusion of environmental technologies, thereby improving energy efficiency and improving environmental quality. Different forms of agglomeration under different degrees of agglomeration correspond to different carbon emission performances. As the degree of agglomeration increases, the effect of reducing emissions from specialized agglomeration decreases while the effect of reducing emissions from diversified agglomeration increases. Moreover, the specialization agglomeration externalities and diversified agglomeration externalities can exist at the same time, which depends on the appropriate degree of agglomeration. The above empirical research is to explain a counter-intuitive conclusion, that is, large-scale industrial production under economic agglomeration will help reduce or control pollution levels. On the contrary, blindly relocating enterprises to economically underdeveloped areas and guiding the decentralized development of industry will increase the overall environmental cost. This means that the current household registration policy that restricts the movement of population to large cities, the policy of allocation of construction land indicators that are more inclined to inland and small and medium-sized cities, and the policy of industrial transfer promoted by administrative means have distorted the industrial space layout and are not conducive to environmental protection.
To achieve the established emission reduction goals, on the one hand, it is necessary to promote the cross-regional redistribution of production factors and promote the agglomeration of the economy and population into coastal areas and internal regional central cities. Focus on cultivating the growth pole of the ecological industry, forming a regional industrial space structure with reasonable layout, close contact and coordinated development, and give full play to the “self-purification” effect of aggregate production on energy saving and emission reduction. On the other hand, according to the characteristics of industrial development stages in different regions, policies and measures should be taken to support the development of key or leading industries in the central and western regions with low agglomeration and encourage the geographical gathering of enterprises in the same industry. In the eastern region with high concentration, industrial diversification, inter-industry cooperation and innovation activities should be encouraged.

Second, from a national perspective, provinces with close trade links have a strong negative environmental spillover effect, that is, regional environmental dumping and transfer caused by domestic commodity trade. Since the central and western regions are at a relatively low-end link in the domestic industrial division of labor system, the main pillar industries are all at the upper end of the domestic industrial chain. In domestic trade, the main focus is on the mobilization of resource-intensive products. Moreover, due to the low production management level and high energy consumption intensity of resource-based products, the product’s complete carbon emission coefficient remains high. Instead, it becomes a net caller of hidden carbon. To this end, on the one hand, when decomposing regional emission reduction targets, the central government must fully consider the hidden carbon in domestic commodity trade and the resulting environmental spillover effects, and furthermore, set fair and reasonable emission reduction targets in various regions. It may be considered to establish a carbon emission reduction responsibility-sharing mechanism from the perspective of the common environmental responsibility of producers and consumers, reflecting the principle of matching benefits and responsibilities, and then mobilizing the enthusiasm of emission reduction in various regions. On the other hand, the current trade model is unsustainable for the central and western regions, and it must not blindly expand the scale of domestic and foreign trade. Instead, we should vigorously promote energy-saving and emission-reduction technologies, improve the level of environmental production technology, and adjust the energy consumption structure to achieve coordinated development of industrial structure optimization, thereby upgrading trade structure low-carbon adjustment.

Third, achieving carbon reduction targets requires a multi-pronged approach. Among them, carbon tax and environmental regulation are very effective means of governance. The carbon emission reduction effect of industrial structure adjustment under environmental regulation has regional heterogeneity, so it is necessary to formulate differentiated environmental regulation policies according to local conditions. For regions with high carbon emissions and low environmental regulation intensity, the government should appropriately improve the environmental regulation intensity and comprehensively utilize command-and-control environmental regulation and market incentive means. At the same time, formulate more stringent environmental standards, improve the enterprise exit mechanism, eliminate backward production capacity that is high in energy consumption and pollution, and control carbon emissions at the source. In addition, we should increase the diversity and effectiveness of market-based incentive tools, increase technology investment and subsidies for polluters, and accelerate the design and implementation of market-based incentive tools such as environmental taxes and emissions trading. For regions with high intensity of environmental regulation, the relationship between environmental regulation and industrial structure adjustment should be well grasped. Avoid the situation that too many enterprises are eliminated due to too high environmental regulation intensity and the industrial structure adjustment is in trouble.

A carbon tax is a tax on carbon dioxide emissions. Carbon tax adopts the principle of fair obligation. No matter how much carbon dioxide is emitted, it must be levied. For the purpose of reducing carbon dioxide emissions, it is a tax levied on fossil fuels according to their carbon content or carbon emissions. China should introduce a carbon tax on a trial basis by region and industry as soon as possible.
The design of a carbon tax system should take into account various factors, such as regional economic development, characteristics of energy structure, degree of tax system perfection, cognition degree of carbon tax and taxpayer’s bearing capacity, etc. First of all, carbon tax pilot can be considered in some cities with serious air pollution in China. Secondly, for most provinces and cities in eastern China, a carbon tax can promote economic growth. For the Midwest, a carbon tax could dampen economic growth. This is mainly because the economic development in the eastern part of China is based on high efficiency, high technology, low consumption and low investment. The development model of the central and western regions is still “high consumption, high investment and low efficiency”. Therefore, the eastern region can be the first pilot to levy carbon tax. Finally, China’s carbon emissions are mainly concentrated on the construction and manufacturing industries, which account for 63.8% of the total carbon emissions; hence, construction and manufacturing industries can be selected as the pilot industries. Therefore, a pilot carbon tax could be introduced with priority given to heavily polluted cities, eastern regions and construction and manufacturing industries before being rolled out nationwide after 2020.

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