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Carbon Peak Scenario Simulation of Manufacturing Carbon Emissions in Northeast China: Perspective of Structure Optimization

Caifen Xu, Yu Zhang *, Yangmeina Yang and Huiying Gao

School of Geographical Sciences, Northeast Normal University, Changchun 130024, China; xucf568@nenu.edu.cn (C.X.); yangymn017@nenu.edu.cn (Y.Y.); gaohy608@nenu.edu.cn (H.G.)
* Correspondence: zhangy221@nenu.edu.cn

Abstract: The manufacturing industry is the pillar industry of China's economy and a major carbon emitter, and its carbon emission reduction efforts directly determine whether the country's carbon emission reduction target can be successfully met. In the context of the goals of the carbon peak and carbon neutrality policy, we examine the impact of manufacturing structure optimization on carbon emissions from 2003 to 2020 through a spatial econometric model, taking the old industrial centers in Northeast China as an example. We then apply a machine learning model to simulate manufacturing carbon emissions during the carbon peak stage and identify the optimal path for carbon emission reduction, which is important for promoting manufacturing carbon emission reduction in Northeast China. Since the goal of low-carbon economic development has gradually replaced the goal of maximizing economic efficiency in recent years, manufacturing structure optimization has come to focus on energy saving and emission reduction. Therefore, we define manufacturing structure optimization from the dual perspective of technology and energy consumption to broaden the existing research perspective. The results show the following: (1) The overall trend in manufacturing structure optimization in Northeast China is steadily improving, and the level of manufacturing structure optimization from the technology perspective is higher than that from the energy consumption perspective. (2) Manufacturing structure optimization and manufacturing carbon emissions in Northeast China both show a positive spatial correlation. Manufacturing structure optimization in Northeast China can effectively promote carbon emission reduction, and it also has a spatial spillover effect. (3) The carbon emission reduction effect of manufacturing structure optimization from the energy consumption perspective is better than that from the technology perspective, and the carbon emission reduction effect under the institutional innovation scenario is better than that under the baseline scenario and the technological innovation scenario. Focusing on manufacturing structure optimization from both technology and energy consumption perspectives, as well as continuously improving technological innovation and institutional innovation, can help to achieve manufacturing carbon emission reduction in Northeast China.

Keywords: manufacturing structure optimization; manufacturing carbon emissions; scenario simulation; spatial econometric model; machine learning model; Northeast China

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1. Introduction

Energy is the basis of economic and social development; it is an important material guarantee for the survival and development of human society, and it directly determines the scale and speed of social and economic development [1]. Since the reform and opening up of China's economy, the country has made great achievements in economic development. However, the crude economic growth mode has led to increasingly serious environmental problems. According to statistics [2], China's carbon emissions reached 10.523 billion tons in 2021, accounting for 31.06% of global carbon emissions. As the largest carbon emitter in the world, with enormous pressure to reduce carbon emissions in the future, China has proactively taken the responsibility to reduce carbon emissions, and it proposes carbon emission reduction goals of achieving a carbon peak by 2030 and carbon neutrality by 2060. In view of the inertia in energy system development, coal resources have price advantages compared with other energy sources. The energy structure being dominated by coal will not change in the short term, and there is less space to achieve energy saving and emission reduction through energy structure optimization [3]. The most important and feasible way to achieve energy saving and emission reduction is through industrial structure optimization [4]. The manufacturing industry is the largest production sector in China in terms of fossil energy consumption and carbon emissions, and there are significant differences between sub-sectors. Moreover, its structure affects resource allocation and energy use efficiency. The Implementation Plan for Carbon Peak in Industry states that the current industrial structure needs to be adjusted urgently, and the blind development of high-energy-consumption, high-emission, and low-technology projects should be resolutely curbed to achieve the industrial carbon peak.

Northeast China is the largest and most representative traditional industrial zone in the country. It has formed the manufacturing development characteristics of heavy industrial structures and coal-based energy structures. After the 1990s, institutional and structural contradictions became prominent, industrial enterprises had aging equipment and obsolete technology, the leading industries in resource-based cities declined, and the traditional advantages of manufacturing industries were gradually lost, leading to serious economic decline [5]. Meanwhile, the crude economic growth model led to an increasing depletion of resources and serious environmental pollution. At the same time, the region has made historical contributions to the development and growth of new China. Thus, Northeast China is a key region for carbon emission reduction in China's manufacturing industry, and there is an urgent need for manufacturing structure optimization and carbon emission reduction there.

In summary, it is important to explore the paths to carbon peak of the manufacturing industry from the perspective of structure optimization in Northeast China, which is conducive to revealing the future trend in manufacturing carbon emissions in Northeast China under the goals of the carbon peak and carbon neutrality policy, identifying the optimal path for carbon emission reduction, and analyzing the problems involved. Therefore, this paper will provide a theoretical basis for the green and low-carbon transformation development of China's manufacturing industry, and a practical basis for rational policy formulation. The possible contributions of this paper are as follows: (1) Traditional research methods do not sufficiently consider the variability in technology level and energy consumption level in manufacturing sub-sectors, which is not in line with the current energy-saving and emission-reduction focus of manufacturing structure optimization. Therefore, we constructed models for manufacturing structure optimization from the dual perspective of technology and energy, which broaden the existing research perspective. (2) This paper selects the most suitable method for the simulation of manufacturing carbon emissions in Northeast China by comparing the BP neural network model, support vector machine model, and random forest model. As a result, the research results are more scientific, and the research conclusions are more generalized.

2. Literature Review and Research Hypothesis

2.1. Literature Review

2.1.1. Research on the Impact of Structure Optimization on Carbon Emissions

Research on the relationship between industrial structure optimization and carbon emissions has a long history. In terms of theoretical analysis, some scholars have found that industrial restructuring has an important impact on environmental improvement [6]. A reasonable industrial structure is conducive to energy conservation and emission reduction and industrial restructuring is the main way to reduce carbon emissions, but the proportion of secondary industry in the economy should not be reduced and carbon emissions should be reduced by promoting technological progress through a secondary industry-led approach [7,8]. In terms of empirical analysis, several scholars have found using static and dynamic panel models, spatial econometric model analysis, and system synergy models that industrial structure optimization can improve energy use efficiency, reduce pollutant emissions, and thus achieve carbon emission reduction [9,10].

The manufacturing industry is an important source of carbon emissions [11,12], and scholars have conducted rich research on carbon emissions from manufacturing. Manufacturing structure is an important influencing factor of manufacturing carbon emissions [13,14]. Zhang et al. advised that the manufacturing industry is both an important source for driving the growth of China's real economy and a major energy-intensive industry. In addition, its structure optimization can contribute to the reduction in manufacturing carbon emissions [15]. In terms of the effect of manufacturing structure optimization on carbon emissions, scholars have explored this from several perspectives [16,17]. Tang et al. used the genetic algorithm NSGA-II with an elite strategy of non-dominated ranking to solve the multi-objective optimization model for low carbon, employment, and economy; they advised that manufacturing structure optimization is an important tool for low-carbon economic development [18].

2.1.2. Prediction and Simulation Research of Carbon Emissions

The research methods in existing studies on carbon emission prediction and simulation are mainly divided into three categories. One is based on the macroeconomic operation mechanism, combining carbon emission influencing factors—such as population, land, industrial production, economic level, and energy activities—to construct policy models, including the STIRPAT model, LMDI model, ADL-MIDAS model, etc., for carbon emission analysis and prediction. For example, Wang et al. used the STIRPAT-extended model to forecast industrial carbon emissions [19,20]. Shao et al. conducted a scenario simulation of manufacturing carbon emissions based on the LMDI model and dynamic scenario analysis [21]. The second category is methods based on an information feedback system, including the gray prediction method and the system dynamics method. For example, the system dynamics approach is widely used for carbon emission simulation prediction [22–24]. Tang et al. explored the influence of land use type on carbon emissions through the SD model and simulated the scenarios [25]. The third category is machine learning methods based on the data itself, including BP neural networks, LSTM neural networks, etc. [26,27]. For example, Marjanovic et al. performed carbon emission simulations via an extreme machine learning model and artificial neural network model [28]. Liu et al. predicted industrial carbon emissions based on the LSTM neural network and scenario simulation method; they advised that industrial carbon emissions under the baseline scenario are capable of peaking in 2024, but show a rebound trend after reaching the carbon peak [29].

Although a lot of research has been conducted on manufacturing carbon emissions, there is still little research focusing on the impact of manufacturing structure optimization on carbon emissions. The manufacturing structure is an important influence factor on carbon emissions, and its structure optimization is an important means to achieve carbon emission reduction; in addition, low-carbon green transformation is the only way to accomplish this. In the context of high-quality economic development and the construction of an ecological civilization, manufacturing structure optimization has been given a new connotation in modern times, and this paper divides manufacturing structure optimization into the technology and energy consumption perspectives to supplement the existing research. In addition, carbon emission prediction and simulation based on the macroeconomic operation mechanism and information feedback system methods are more subjective, and the information mining of the data itself is not deep enough; therefore, this paper uses machine learning models to simulate the carbon peak scenario in Northeast China for manufacturing carbon emissions from the perspective of structure optimization.

2.2. Research Hypothesis

2.2.1. The Performance of Manufacturing Structure Optimization on Carbon Emission Reduction

According to the theory of energy economy and environment, the development process of the manufacturing industry consumes energy to obtain economic benefits and produces pollution to the environment. Environmental pollution not only comes from energy consumption, it may also come from inefficient spatial organization and layout and an inefficient industrial structure. In addition, there are significant differences between the economic output and carbon emissions of different manufacturing sub-sectors. Manufacturing structure optimization can improve allocation efficiency, high-pollution and high-energy-consumption industries will be gradually eliminated, and the focus will instead be the development of high-technology and high-value-added industries. In addition to reducing carbon emissions, this process decreases energy consumption and increases utilization efficiency, i.e., manufacturing structure optimization can promote manufacturing carbon emission reduction. Based on this, we propose the first hypothesis:

Hypothesis 1. *Manufacturing structure optimization has a significantly positive effect on carbon emission reduction.*

2.2.2. Manufacturing Carbon Emission Reduction Performance under Various Scenarios

Technological innovation can promote manufacturing structure optimization by improving the allocation efficiency of production factors and energy utilization efficiency. It can also achieve manufacturing carbon emission reduction by reducing the use of fossil fuel energy and improving energy utilization efficiency. Meanwhile, institutional innovation can stimulate manufacturing structure optimization through the "cost effect" and "innovation compensation effect". In addition, it can also reduce the use of fossil fuel energy and can improve the efficiency of energy use through the push-back mechanism, thereby producing results that promote manufacturing carbon reduction. In general, technological innovation and institutional innovation can promote manufacturing carbon emission reduction from the perspective of manufacturing structure optimization. This leads to our second set of hypotheses:

Hypothesis 2. *Compared with a baseline scenario, the manufacturing industry will experience a higher carbon emission reduction effect under a technological innovation scenario and an institutional innovation scenario.*

3. Materials and Methods

3.1. Methods

3.1.1. Spatial Econometric Model

The spatial correlation analysis of the core variables is required prior to spatial econometric model analysis, and the most commonly used method for this is the Moran's I statistic test [30] in global spatial correlation analysis, with the following expression:

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

where Y_i and Y_j are the observations in regions i and j, respectively, and $S^2 = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \overline{Y}\right)^2$, $\overline{Y} = \frac{1}{n}\sum_{i=1}^{n} Y_i$, and W_{ij} is the spatial weight matrix. The range of Moran's I statistic is generally -1 to 1, with values less than 0 indicating a negative correlation, values equal to 0 indicating non-correlation, and values greater than 0 indicating a positive correlation.

To avoid biased estimation results due to model-setting errors, this paper relies on the generalized nested spatial model (GNSM) proposed by Elhorst [31] as the basis for spatial econometric analysis. The expression of the model is as follows:

$$y = \alpha + \rho w y + X\beta + \theta w X + \mu, \mu = \lambda w \mu + \varepsilon \tag{2}$$

where y is the explained variable; w is the spatial weight matrix; X is the vector of explained variables; μ and ε are the random perturbation terms; ε obeys the zero-mean, homoskedasticity normal distribution; ρ is the spatial correlation coefficient of the explained variables; θ is the spatial correlation coefficient of the explained variables; and λ is the spatial correlation coefficient of the perturbation terms. Additionally, according to the different settings of ρ, θ, and λ, GNSM can be simplified to the three most common spatial measurement models.

When λ = 0, the model is simplified to a spatial Durbin model (SDM):

$$y = \alpha + \rho w y + X\beta + \theta w X + \varepsilon \tag{3}$$

When λ = 0 and ρ = 0, the model simplifies to a spatial lag model (SXL):

$$y = \alpha + X\beta + \theta w X + \mu + \varepsilon \tag{4}$$

When ρ = 0 and θ = 0, the model is simplified to a spatial error model (SEM):

$$y = \alpha + X\beta + \mu, \mu = \lambda w \mu + \varepsilon \tag{5}$$

The construction of the spatial weight matrix is a prerequisite for a spatial correlation analysis and the basis for the application of spatial econometric models; however, there is no fully accurate way for setting spatial weight matrices in the literature [32]. Therefore, this paper is based on the three spatial weight matrices of geographic adjacency, geographic distance, and economic geographic distance. In this way, the robustness of the results is ensured. The spatial weight matrix of geographic adjacency was constructed by choosing the Queen adjacency; the spatial weight matrix of geographic distance was constructed based on the first law of geography, i.e., the sets $W_{ij} = 1/d_{ij}$ (d_{ij} is the geographic distance between centroids of regions i and j, and it is calculated by latitude and longitude); and the spatial weight matrix of the economic geographic distance was constructed by referring to Lin's study [33], setting $W_{ij}{}^{*}= \mathrm{W}_{ij} \times E_{ij}$ (W_{ij} is the spatial weight matrix of geographic distance), where, in the matrix E_{ij}, the main diagonal elements are 0 and the non-main diagonal elements are $E_{ij} = 1/\left|\overline{Y_i} - \overline{Y_j}\right|(i \neq j)$; in addition, $\overline{Y_i}$ is the mean real GDP per capita for region i during the research period, and the three spatial weight matrices were row normalized separately.

3.1.2. Machine Learning Models

The BP neural network model (BP model) [34] is an artificial neural network model based on a multi-layer feedforward neural network and an error backpropagation learning algorithm, which is the most widely used, the most intuitive, and the most easily understood neural network model with a basic network structure containing an input layer, hidden layer, and output layer. Usually, the hidden layer can contain multiple layers, and each layer is connected to the adjacent layers by neurons.

A support vector machine model (SVM model) [35] is a generalized linear classifier that classifies data binary via supervised learning; it can take into account the learning and prediction accuracy of training samples and the generalization learning ability of new samples; it can also solve the parameters of the model according to cross-validation, and it has a relatively good machine learning ability. It has relatively good prediction advantages for machine learning problems with relatively small training sample sizes, non-linear prediction problems, and relatively large dimensions of sample variables; in addition, its modeling uses relatively little sample information, which makes it one of the most widely used models.

The random forest model (RF model) [36] is a classifier with multiple decision trees built in a random way. It is a relatively new machine learning model, consisting of different types and numbers of decision trees, each of which is independent. The Bootstrap algorithm is used to generate more samples via random sampling, which can effectively reduce the error caused by random fluctuations in the sequence; furthermore, the samples are assigned to different nodes of the regression tree according to the minimum purity method, so that the cycle is repeated until the node splitting condition is no longer satisfied, and then multiple regression trees are built to form a forest.

3.2. Variable Selection

3.2.1. Explained Variable

The explained variable in this paper is manufacturing carbon emissions (CE). Carbon emissions are measured based on energy consumption. By referring to the carbon emission calculation method and parameters of the IPCC [37], we constructed the following formula:

$$CE_i = \sum_{j}^{n}\sum_{k}^{n} E_k \times \Omega_k \tag{6}$$

$$\Omega_k = CLV_k \times CCV_k \times COR_k \times 44/12 \tag{7}$$

where CE_i denotes the total carbon emission of the manufacturing industry in region i, j denotes the type of manufacturing, and k denotes the type of energy. In order to ensure the accuracy of the estimation results, 19 energy sources were fully considered in this paper, namely, raw coal, washed refined coal, other washed coal, coal products, coke, coke oven gas, other gas, other coking products, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum, refinery dry gas, other petroleum products, natural gas, and thermal power and electricity. In addition, E_k denotes the consumption of energy k, Ω_k is the carbon dioxide emission factor, CLV_k is the average low-level heating value, CCV_k is the carbon content per unit calorific value, and COR_k is the carbon oxidation rate. The conversion standard coal factors and CO_2 emission factors of various energy sources are given in Table 1.

Table 1. Conversion standard coal factors and CO_2 emission factors.

Energy Type	Standard Coal Factor (kg Standard Coal/kg)	CO_2 Emission Factor (kg CO_2/kg)
Raw coal	0.714	1.900
Washed refined coal	0.900	2.405
Other washed coal	0.286	0.764
Coal products	0.529	1.714
Coke	0.971	2.853
Coke oven gas	0.614	0.847
Other gas	0.357	0.801
Other coking products	1.300	3.833
Crude oil	1.429	3.017
Gasoline	1.471	2.925
Kerosene	1.471	3.033
Diesel	1.457	3.096
Liquefied petroleum gas	1.714	3.101
Fuel oil	1.429	3.171
Refinery dry gas	1.571	3.008
Other petroleum products	1.200	2.527
Natural gas	1.330	2.165
Thermal power (equivalent)	0.034	0.110
Electricity (equivalent)	0.123	0.777

Data source: Compiled by the authors. The units are mostly kg, while coke oven gas, other gas, and natural gas units are m^3; the unit for heat is 10^6 J and the unit for electricity is kW·h.

3.2.2. Core Explanatory Variables

The core explanatory variables of this paper are manufacturing structure optimization from a technology perspective (*ST*) and manufacturing structure optimization from an energy consumption perspective (*SE*). According to the modern connotation of manufacturing structure optimization, this paper defines manufacturing structure rationalization and upgrading as manufacturing structure optimization from the technology perspective, and manufacturing structure rationalization and ecologization as manufacturing structure optimization from the energy consumption perspective. Lastly, this paper uses the entropy weight method for calculation.

Classifying the manufacturing industry is the premise used to start research on manufacturing structure optimization. This classification is based on the 31 sub-sectors of the manufacturing industry detailed in the National Economic Classification (GB/T 4754-2017) [38] and manufacturing industry classifications according to the level of technology and energy consumption. First, for the classification of the manufacturing industry based on the technology level, this paper synthesizes the High Technology Industry (Manufacturing) Classification, the Organization for Economic Cooperation and Development (OECD) manufacturing classification requirements, and the study by Fu et al. [39]. According to the technology level, the manufacturing industry is divided into three categories: high-technology manufacturing, medium-technology manufacturing, and low-technology manufacturing (Table 2). Next, for the classification of the manufacturing industry based on the energy consumption level, this paper synthesizes the research of the Statistical Report on National Economic and Social Development, the Benchmark Levels, and the Benchmark Levels of Energy Efficiency in Key Areas of High Energy Consumption Industries, as well as the study by Shen et al. [40]. According to the energy consumption level, the manufacturing industry is divided into three categories: high-energy-consumption manufacturing, medium-energy-consumption manufacturing, and low-energy-consumption manufacturing (Table 3).

Table 2. Classification of manufacturing industry based on technology level.

Category	Manufacturing Classification
High-technology manufacturing	chemical raw materials and chemical products manufacturing; pharmaceutical manufacturing; general equipment manufacturing; special equipment manufacturing; automobile manufacturing; railroad, ship, aerospace, and other transportation equipment manufacturing; electrical machinery and equipment manufacturing; computer, communications, and other electronic equipment manufacturing; instrumentation manufacturing; metal products, machinery, and equipment repair industry
Medium-technology manufacturing	petroleum, coal, and other fuel processing industry; chemical fiber manufacturing; rubber and plastic products industry; non-metallic mineral products industry; ferrous metal smelting and rolling processing industry; non-ferrous metal smelting and rolling processing industry; metal products industry; comprehensive utilization of waste resources industry
Low-technology manufacturing	agro-food processing industry; food manufacturing; wine, beverage, and refined tea manufacturing; tobacco products industry; textiles; textile clothing, apparel industry; leather, fur, feathers and their products, and footwear industry; wood processing and wood, bamboo, rattan, palm, and grass products industry; furniture manufacturing; paper and paper products industry; printing and recording media reproduction industry; education industry; sports and entertainment goods manufacturing; other manufacturing industries

Data source: Compiled by the authors.

Table 3. Classification of manufacturing industry based on energy consumption level.

Category	Manufacturing Classification
High-energy-consumption manufacturing	petroleum, coal, and other fuel processing industry; chemical raw materials and chemical products manufacturing; non-metallic mineral products industry; ferrous metal smelting and rolling processing industry; non-ferrous metal smelting and rolling processing industry
Medium-energy-consumption manufacturing	agro-food processing industry; food manufacturing; wine, beverage, and refined tea manufacturing; textiles; wood processing and wood, bamboo, rattan, palm, and grass products industry; paper and paper products industry; pharmaceutical manufacturing; chemical fiber manufacturing; rubber and plastic products industry; metal products industry; general equipment manufacturing
Low-energy-consumption manufacturing	Tobacco products industry; textile clothing, apparel industry; leather, fur, feathers and their products, and footwear industry; furniture manufacturing; printing and recording media reproduction industry; education industry; sports and entertainment goods manufacturing; special equipment manufacturing; automobile manufacturing; railroad, ship, aerospace, and other transportation equipment manufacturing; electrical machinery and equipment manufacturing; computer, communications, and other electronic equipment manufacturing; instrumentation manufacturing; other manufacturing; comprehensive utilization of waste resources industry; metal products, machinery, and equipment repair industry

Data source: Compiled by the authors.

Using the Thiel index [41] to measure the degree of industrial structure rationalization can avoid errors in the calculation of the degree of industrial structure deviation that arise from ignoring the relative importance of different industries in economic development; therefore, this paper employs the Thiel index to measure the degree of manufacturing structure rationalization. When the economy is in equilibrium, the Thiel index TL is equal to 0. Conversely, when the economy is in disequilibrium and the degree of manufacturing structure rationalization is low, the formula is as follows:

$$TL = \sum_{i=1}^{n} (\frac{Y_i}{Y}) ln(\frac{Y_i}{L_i} / \frac{Y}{L}) \tag{8}$$

where Y is the manufacturing total output value, L is the manufacturing total employment, Y_i is the output value of the manufacturing sector i, L_i is the employment of the manufacturing sector i, and n as the number of manufacturing sectors. Using the specific gravity method to measure the degree of industrial structure upgrading can avoid the subjectivity of the similarity coefficient method in selecting the reference system; therefore, this paper employs the specific gravity method to measure the degree of manufacturing structure upgrading, in order to fully investigate the differences between high-technology manufacturing, medium-technology manufacturing, and low-technology manufacturing categories. To more accurately measure the subtle differences in the degree of manufacturing structure upgrading, the weight of the high-technology manufacturing category was set to 1 and the weight of the medium-technology manufacturing category was set to 0.5. The formula is as follows:

$$S = \frac{\begin{array}{c} high\text{-}technolgy\ manufacturing\ output\ value \\ +medium\text{-}technolgy\ manufacturing\ output\ value\ \times\ 0.5 \end{array}}{manufacturing\ total\ output\ value} \tag{9}$$

Using the specific gravity method to measure the degree of industrial structure ecologization can avoid the defect of this factor receiving a lower classification in the industrial symbiosis model; therefore, this paper employs the specific gravity method to measure the degree of manufacturing structure ecologization in order to fully investigate the differences between the low-energy-consumption manufacturing, medium-energy-consumption manufacturing, and high-energy-consumption manufacturing categories. To more accurately measure the subtle differences in the degree of manufacturing structure ecologization, the weight of low-energy consumption manufacturing is set to 1, and the weight of medium-energy-consumption manufacturing is set to 0.5. The formula is as follows:

$$TE = \frac{\begin{array}{c} low\text{-}energy\ consumption\ manufacturing\ output\ value \\ +medium\text{-}energy\ consumption\ manufacturing\ output\ value \times 0.5 \end{array}}{manufacturing\ total\ output\ value} \quad (10)$$

3.2.3. Control Variables

The control variables include the number of manufacturing employees (*L*), the manufacturing output value (*P*), energy intensity (*EI*), energy structure (*ES*), technological innovation (*TI*), and environmental regulation (*ER*). They are all independent variables. Energy intensity is based on the ratio of manufacturing energy consumption to manufacturing output value, and the energy structure is based on the ratio of manufacturing coal consumption to all energy consumption. Technological innovation was defined in accordance with Tang et al. and Xu et al. [42,43], and the number of utility-type patents granted was used to measure the level of technological innovation. Environmental regulation was defined in accordance with Li et al. [44], and a comprehensive indicator method consisting of five indicators—industrial sulfur dioxide removal rate, industrial soot removal rate, industrial wastewater compliance rate, comprehensive utilization rate of general industrial solid waste, and centralized treatment rate of wastewater treatment plants—was chosen to measure the level of environmental regulation. The dimensionless processing of the data was carried out by taking the natural logarithm.

3.3. Data Sources

Northeast China, in a narrow sense, includes only Liaoning, Jilin, and Heilongjiang provinces, with a total of 36 prefecture-level administrative regions. Data for the Daxinganling region are seriously lacking, but the GDP of this region only accounts for about 1% of the total for Heilongjiang province; therefore, the research object of this paper is the 35 regions excluding Daxinganling, as shown in Figure 1.

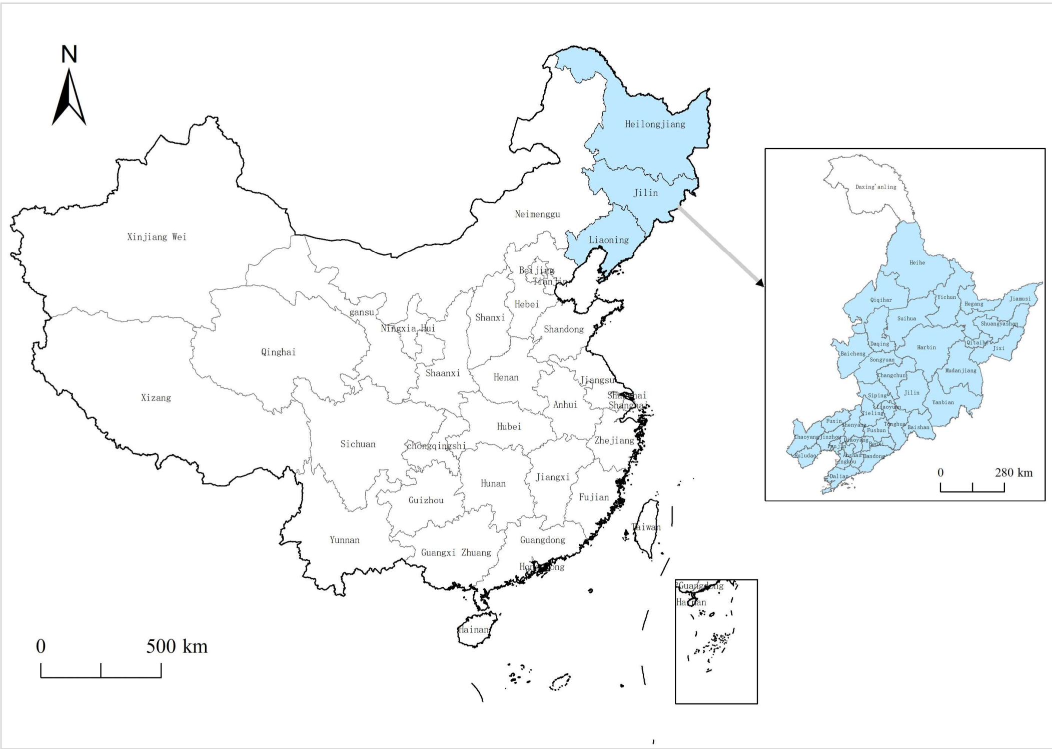

Figure 1. Location of the study area in Northeast China.

Taking into account the large differences in the classification of national economy industries before and after 2002, the time cut-off point of the central government's strategy to revitalize the old industrial zone in Northeast China in 2003 is used. In addition, due to the lag in the release of statistical data, the research period of this paper is taken as 2003 to 2020, a total of 18 years. The data sources include the China Energy Statistical Yearbook (2004–2021); the China City Statistical Yearbook (2004–2021); the Liaoning Statistical Yearbook (2004–2021); the Jilin Statistical Yearbook (2004–2021), the Heilongjiang Statistical Yearbook (2004–2021); the statistical yearbooks and statistical bulletins of prefecture-level cities; the Comprehensive Energy Consumption General Rules for Calculation (GB/T 2589-2020) [45]; the National Bureau of Statistics Tables of Energy Purchase, Consumption and Inventory (2020); the IPCC Guidelines for National Greenhouse Gas Inventories (2019); the Guidelines for Provincial Greenhouse Gas Inventories (2011); the Guidelines for Carbon Emission Accounting in Various Industries, etc.

In order to ensure the scientific accuracy of the research, missing values are processed via the interpolation method. For missing data in a year in the middle of the time series, the mean filling method is used for data processing, and for missing data in a year before and after the time series, the regression filling method is used for data processing. To avoid the effects of price fluctuations on economic variables, manufacturing output is deflated by the industrial producer ex-factory price index, and GDP is deflated by the GDP index, using 2003 as the base period.

4. Results

4.1. Empirical Analysis of the Impact of Manufacturing Structure Optimization on Carbon Emissions

4.1.1. Analysis of Manufacturing Structure Optimization and Carbon Emission Characteristics in Northeast China

The changes in manufacturing structure optimization from the technology and energy consumption perspectives in Northeast China are shown in Figures 2 and 3, respectively. From 2003 to 2020, the average values of the manufacturing structure optimization from the technology and energy consumption perspectives are 0.42 and 0.33, respectively; further, the average annual growth rates are 1.53% and 0.94%, respectively, both factors showing a fluctuating, upward trend. This indicates that the manufacturing structure in Northeast China is in the stage of gradual optimization, and its structure rationalization, upgrading, and ecologization are generally on the rise, which is consistent with the general trend of socio-economic development. The average value and rate of growth of manufacturing structure optimization from the technology perspective are higher than those from the energy consumption perspective, indicating that the average level of technology in Northeast China is better than the average level of energy consumption. This shows that the problem of energy consumption in the manufacturing industry is more serious, and the emphasis on energy conservation and emission reduction needs to be further strengthened in Northeast China.

Province by province, the average values of manufacturing structure optimization from the technology perspective in Liaoning, Jilin, and Heilongjiang provinces are 0.49, 0.48, and 0.30, respectively, while, the average values of manufacturing structure optimization from the energy consumption perspective are 0.38, 0.37, and 0.25, respectively, indicating that the manufacturing structure in the Liaoning and Jilin provinces are significantly better than that in the Heilongjiang province. The average annual growth rates of manufacturing structure optimization from the technology perspective in Liaoning, Jilin, and Heilongjiang provinces are 0.17%, 2.75%, and 3.02%, respectively, while, the average annual growth rates of manufacturing structure optimization from the energy consumption perspective are 0.62%, 2.54%, and 0.01%, respectively, indicating that all three provinces show a fluctuating, upward trend. In addition, the rate of manufacturing structure optimization in the Jilin province is again higher.

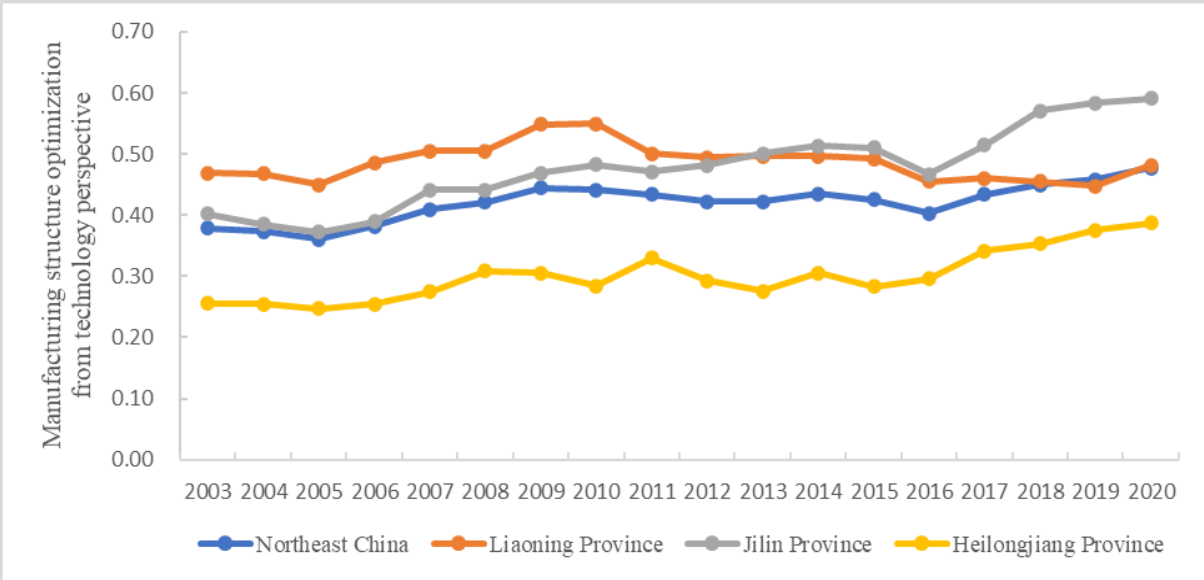

Figure 2. Manufacturing structure optimization from the technology perspective in Northeast China.

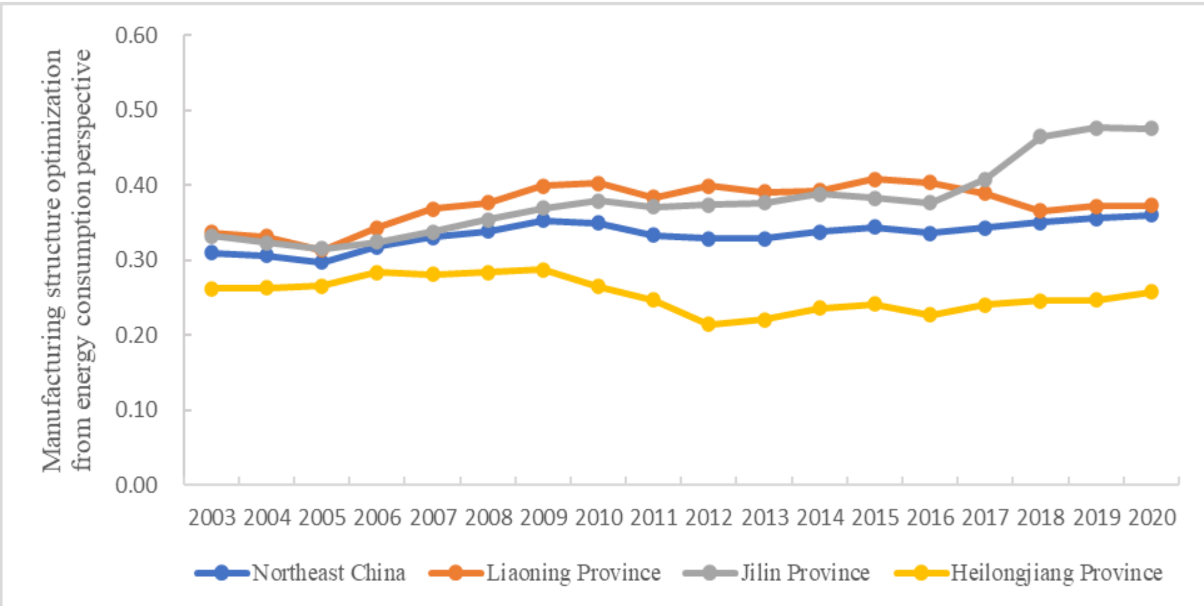

Figure 3. Manufacturing structure optimization from the energy consumption perspective in Northeast China.

The results of the spatial correlation tests for manufacturing structure optimization from the technology and energy consumption perspectives in Northeast China are shown in Tables 4 and 5, respectively. The Moran's *I* scores for manufacturing structure optimization from the technology and energy consumption perspectives in Northeast China under the three spatial weight matrices are positive overall, and they pass the significance test. It can be seen that the spatial autocorrelations of manufacturing structure optimization from the perspective of technology and energy consumption in Northeast China are positive, i.e., they mostly show high-value or low-value clustering.

Table 4. Spatial correlation of manufacturing structure optimization from the technology perspective.

Year	Geographic Adjacency			Geographic Distance			Economic Geographic Distance		
	Moran's *I*	Z-Value	*p*-Value	Moran's *I*	Z-Value	*p*-Value	Moran's *I*	Z-Value	*p*-Value
2003	0.147 *	1.616	0.053	0.083 ***	2.676	0.004	0.194 ***	2.540	0.006
2004	0.135 *	1.511	0.066	0.096 ***	2.971	0.002	0.197 ***	2.570	0.005
2005	0.112 *	1.291	0.098	0.089 ***	2.813	0.003	0.179 ***	2.366	0.009
2006	0.173 **	1.857	0.032	0.137 ***	3.962	0.000	0.216 ***	2.788	0.003
2007	0.211 **	2.202	0.014	0.132 ***	3.839	0.000	0.261 ***	3.298	0.001
2008	0.166 **	1.796	0.036	0.109 ***	3.291	0.001	0.222 ***	2.863	0.002
2009	0.307 ***	3.087	0.001	0.186 ***	5.129	0.000	0.309 ***	3.847	0.000
2010	0.352 ***	3.491	0.000	0.207 ***	5.611	0.000	0.315 ***	3.924	0.000
2011	0.177 **	1.889	0.030	0.104 ***	3.182	0.001	0.222 ***	2.856	0.002
2012	0.303 ***	3.045	0.001	0.167 ***	4.683	0.000	0.296 ***	3.697	0.000
2013	0.387 ***	3.816	0.000	0.195 ***	5.338	0.000	0.302 ***	3.775	0.000
2014	0.304 ***	3.053	0.001	0.159 ***	4.488	0.000	0.259 ***	3.281	0.001
2015	0.329 ***	3.286	0.001	0.177 ***	4.919	0.000	0.285 ***	3.572	0.000
2016	0.137 *	1.524	0.064	0.090 ***	2.832	0.002	0.218 ***	2.811	0.003
2017	0.112 *	1.295	0.098	0.054 **	1.977	0.024	0.196 ***	2.569	0.005
2018	0.063	0.849	0.198	0.056 **	2.026	0.021	0.170 **	2.263	0.012
2019	0.024	0.486	0.314	0.037 *	1.572	0.058	0.133 **	1.848	0.032
2020	0.034	0.583	0.280	0.044 **	1.736	0.041	0.142 **	1.947	0.026

Data source: Calculated by Matlab 2020a. ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.

Table 5. Spatial correlation of manufacturing structure optimization from the energy consumption perspective.

Year	Geographic Adjacency			Geographic Distance			Economic Geographic Distance		
	Moran's *I*	Z-Value	*p*-Value	Moran's *I*	Z-Value	*p*-Value	Moran's *I*	Z-Value	*p*-Value
2003	0.020	0.454	0.325	−0.007	0.523	0.301	−0.012	0.194	0.423
2004	0.016	0.415	0.339	−0.016	0.315	0.376	−0.033	−0.035	0.486
2005	−0.012	0.164	0.435	−0.028	0.029	0.489	−0.062	−0.374	0.354
2006	−0.039	−0.091	0.464	−0.027	0.055	0.478	−0.048	−0.216	0.415
2007	−0.010	0.182	0.428	−0.004	0.597	0.275	−0.014	0.180	0.428
2008	0.014	0.398	0.345	0.017	1.115	0.133	−0.012	0.203	0.420
2009	0.043	0.668	0.252	0.028 *	1.359	0.087	0.016	0.520	0.302
2010	0.108	1.256	0.105	0.055 **	1.995	0.023	0.054	0.946	0.172
2011	0.126 *	1.401	0.081	0.058 **	2.082	0.019	0.069	1.120	0.131
2012	0.249 ***	2.552	0.005	0.121 ***	3.582	0.000	0.178 ***	2.361	0.009
2013	0.207 **	2.167	0.015	0.090 ***	2.829	0.002	0.117 **	1.665	0.048
2014	0.172 **	1.845	0.033	0.084 ***	2.708	0.003	0.108 *	1.566	0.059
2015	0.216 **	2.247	0.012	0.102 ***	3.120	0.001	0.137 **	1.893	0.029
2016	0.237 ***	2.441	0.007	0.112 ***	3.367	0.000	0.168 **	2.245	0.012
2017	0.190 **	2.006	0.022	0.078 ***	2.560	0.005	0.126 **	1.762	0.039
2018	0.158 **	1.717	0.043	0.069 ***	2.348	0.009	0.094 *	1.398	0.081
2019	0.172 **	1.850	0.032	0.084 ***	2.687	0.004	0.107 *	1.547	0.061
2020	0.147 *	1.613	0.053	0.074 ***	2.469	0.007	0.091 *	1.364	0.086

Data source: Calculated by Matlab 2020a. ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.

The change in manufacturing carbon emissions in Northeast China is shown in Figure 4, which shows an overall trend of rising and then falling. From 2003 to 2013, manufacturing carbon emissions in Northeast China rose from 3.04×10^{11} kg to 6.59×10^{11} kg, a rise of 116.63%. From 2013 to 2020, the manufacturing carbon emissions in Northeast China decreased from 6.59×10^{11} kg to 4.58×10^{11} kg, a decline of 30.59%, indicating that the total manufacturing carbon emissions in Northeast China changed significantly during the research period. Province by province, the manufacturing carbon emissions in Liaoning, Jilin, and Heilongjiang provinces all showed a general trend of rising and then falling. Manufacturing carbon emissions ranked from high to low for Liaoning, Jilin, and Heilongjiang provinces, respectively.

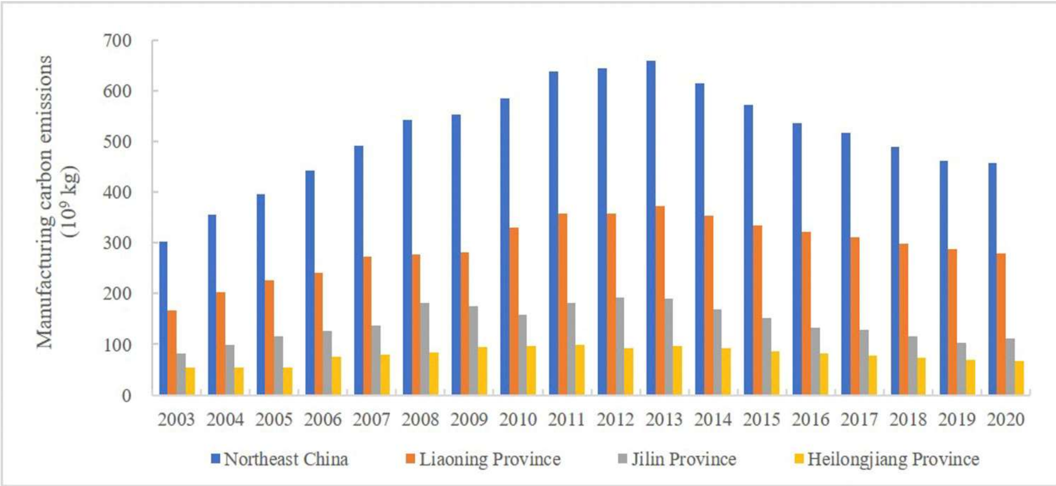

Figure 4. Manufacturing Carbon Emissions in Northeast China.

The composition of manufacturing carbon emissions in Northeast China is shown in Figure 5. As can be seen, the ferrous metal smelting and rolling processing industry is the largest contributor to carbon emissions, accounting for 42.45% of the total. The ferrous metal smelting and rolling processing industry includes iron making, steel making, steel rolling processing, ferroalloy smelting, and many other types of manufacturing. It is also the traditional industry of the old industrial zone in Northeast China. In terms of carbon emissions, chemical raw materials and chemical products manufacturing and the petroleum, coal, and other fuel processing industry are second only to the ferrous metal smelting and rolling processing industry, with an average share of 17.14% and 14.73%, respectively. These three are among the five major high-energy-consumption manufacturing industries, but the data show that manufacturing carbon emission reduction policies also need to focus on other industries in Northeast China.

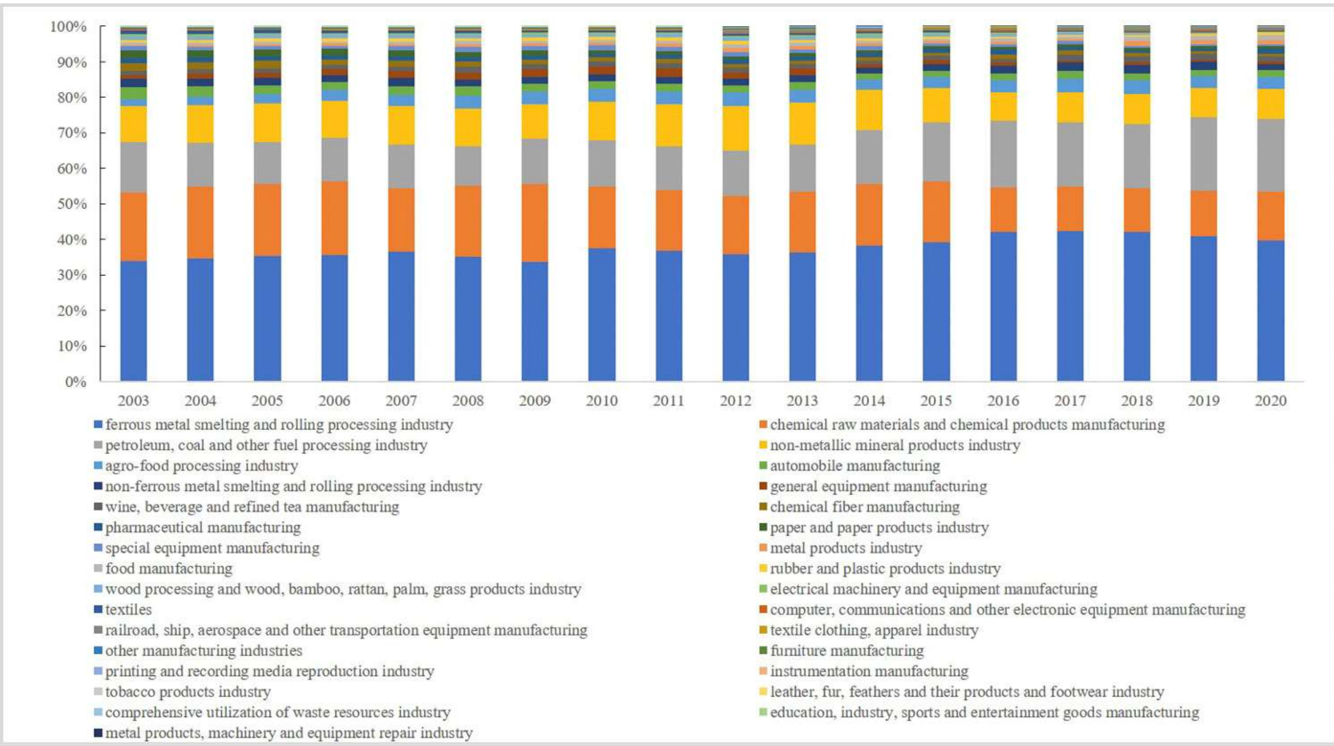

Figure 5. Composition of manufacturing carbon emissions in Northeast China.

The evolution of the spatial pattern of manufacturing carbon emissions in Northeast China is shown in Figure 6, which specifically includes four years, 2003, 2009, 2015, and 2020, and is classified using the natural breakpoint method. As can be seen from the figure, the level of manufacturing carbon emissions in Northeast China have significant spatial differences, showing that there are more emissions in the south and fewer in the north, thereby indicating that carbon emissions in Liaoning province are significantly higher than those in Jilin and Heilongjiang provinces.

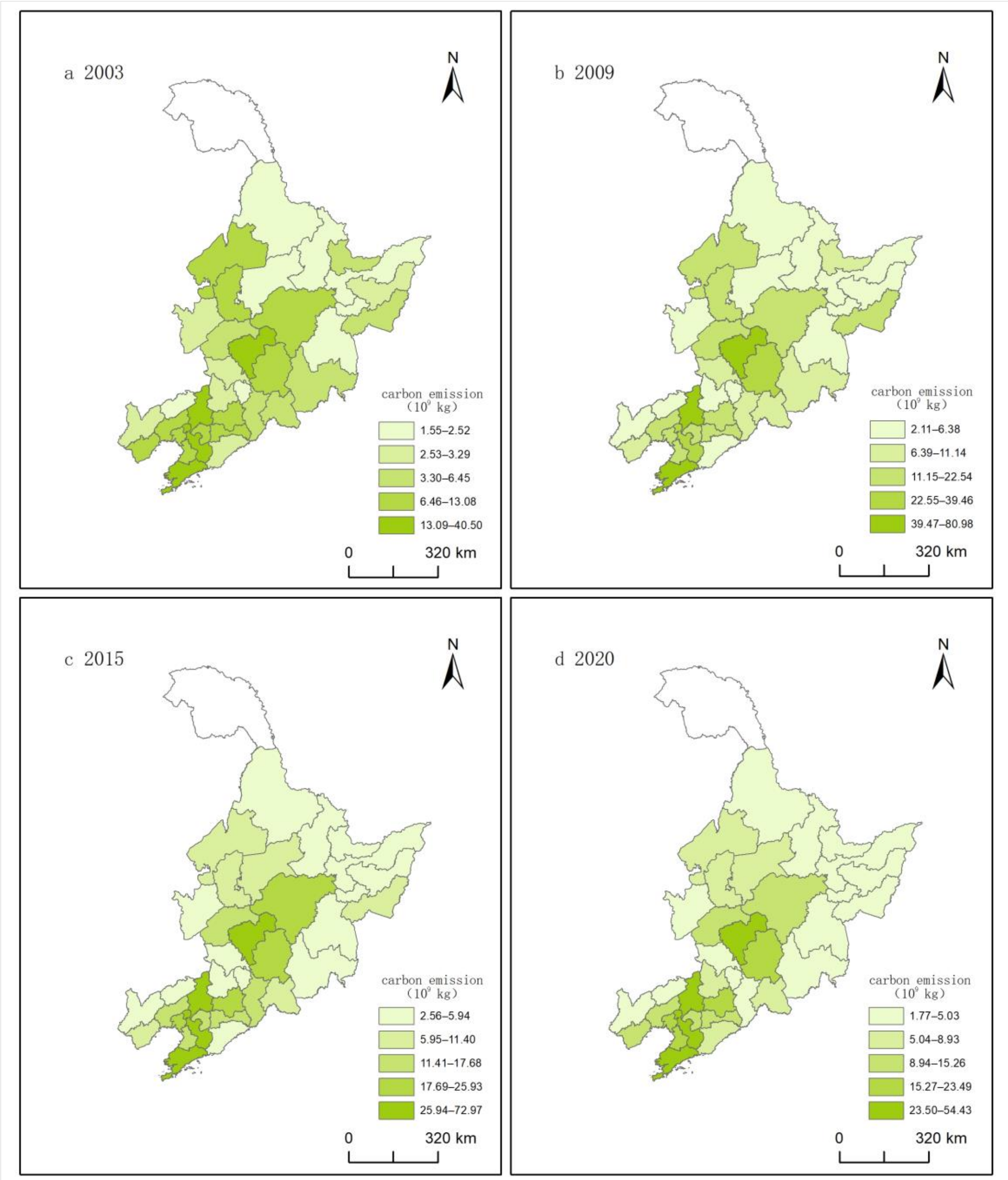

Figure 6. Spatial pattern of manufacturing carbon emissions in Northeast China. (**a**) 2003; (**b**) 2009; (**c**) 2015; (**d**) 2020.

At the prefectural city level, the regions with larger manufacturing carbon emissions are mostly located in Liaoning Province and Jilin Province. A total of 14 prefecture-level cities had carbon emissions of more than 1.00×10^{10} kg in 2020, namely, Shenyang, Dalian, Anshan, Fushun, Benxi, Jinzhou, Yingkou, Liaoyang, Panjin, Huludao, Changchun, Jilin, Songyuan, and Harbin, accounting for 76.13% of the total and representing a major source of manufacturing carbon emissions in Northeast China. In particular, the manufacturing carbon emissions in Shenyang, Dalian, and Changchun are extremely prominent among the prefecture-level cities in Northeast China, accounting for 35.60% of the total, which is the by far the largest contribution to manufacturing carbon emissions in Northeast China.

The results of the spatial correlation test for manufacturing carbon emissions in Northeast China are shown in Table 6. The Moran's *I* scores under the three spatial weight matrices of geographic neighborhood, geographic distance, and economic geographic distance are generally greater than 0, which indicates that manufacturing carbon emissions in Northeast China have a positive spatial correlation; that is, they present a high-value or low-value clustering in space. Moreover, the overall spatial correlation of manufacturing carbon emissions in Northeast China shows an upward trend, which is consistent with the findings of Shao et al. The carbon emissions are presented in a positive spatial correlation due to the spatial association effect, competition effect, and demonstration effect between the different regions [46].

Table 6. Spatial correlation of manufacturing carbon emissions.

Year	Geographic Adjacency			Geographic Distance			Economic Geographic Distance		
	Moran's *I*	**Z-Value**	***p*-Value**	**Moran's *I***	**Z-Value**	***p*-Value**	**Moran's *I***	**Z-Value**	***p*-Value**
2003	0.103	1.214	0.112	0.027 *	1.338	0.090	0.192 ***	2.524	0.006
2004	0.144 *	1.593	0.056	0.043 **	1.716	0.043	0.200 ***	2.613	0.005
2005	0.154 **	1.679	0.047	0.044 **	1.741	0.041	0.202 ***	2.630	0.004
2006	0.118 *	1.347	0.089	0.028 *	1.367	0.086	0.198 ***	2.582	0.005
2007	0.120 *	1.366	0.086	0.031 *	1.437	0.075	0.192 ***	2.520	0.006
2008	0.110	1.281	0.100	0.019	1.151	0.125	0.166 **	2.183	0.015
2009	0.092	1.110	0.133	0.009	0.910	0.181	0.163 **	2.193	0.014
2010	0.122 *	1.389	0.082	0.027 *	1.339	0.090	0.178 ***	2.365	0.009
2011	0.140 *	1.549	0.061	0.028 *	1.360	0.087	0.176 ***	2.333	0.010
2012	0.144 *	1.593	0.056	0.026 *	1.323	0.093	0.162 **	2.176	0.015
2013	0.154 **	1.681	0.046	0.032 *	1.458	0.073	0.175 **	2.320	0.010
2014	0.160 **	1.736	0.041	0.040 **	1.651	0.049	0.179 ***	2.367	0.009
2015	0.156 **	1.700	0.045	0.045 **	1.769	0.039	0.182 ***	2.409	0.008
2016	0.195 **	2.058	0.020	0.057 **	2.053	0.020	0.194 ***	2.546	0.005
2017	0.196 **	2.066	0.019	0.056 **	2.030	0.021	0.199 ***	2.596	0.005
2018	0.207 **	2.166	0.015	0.059 **	2.107	0.018	0.202 ***	2.628	0.004
2019	0.231 ***	2.388	0.008	0.072 ***	2.421	0.008	0.210 ***	2.727	0.003
2020	0.219 **	2.274	0.012	0.072 ***	2.401	0.008	0.210 ***	2.722	0.003

Data source: Calculated by Matlab 2020a. ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively.

4.1.2. Analysis of the Impact of Manufacturing Structure Optimization on Carbon Emissions in Northeast China

The LM test, LR test, and Hausman test show that the fixed-effects variant of the spatial Durbin model should be used for model estimation. Based on the principles of maximum goodness of fit, maximum log-likelihood value, and minimum variance of the random disturbance term, the dual fixed-effects model should be selected for model estimation. Therefore, the spatial effect analysis of manufacturing structure optimization on carbon emissions in Northeast China should use the dual fixed-effects spatial Durbin model. The specific model selection process is shown in Appendix A. The results of the decomposition for the spatial effects of manufacturing structure optimization on carbon emissions in Northeast China from the technology and energy consumption perspectives are shown in Tables 7 and 8, respectively.

Table 7. Decomposition of the spatial effect of manufacturing structure optimization from the technology perspective on carbon emissions.

	ST	*L*	*P*	*EI*	*ES*	*TI*	*ER*
Direct effect	0.208 **	0.114 ***	0.308 ***	0.502 ***	−0.062	0.058 ***	0.131 *
	(2.20)	(4.49)	(12.25)	(13.36)	(−0.44)	(2.91)	(1.74)
Indirect effect	−1.064 ***	0.208 *	−0.005	0.086	−2.560 **	0.034	0.409
	(−3.19)	(1.66)	(−0.04)	(0.54)	(−2.57)	(0.36)	(1.31)
Total effect	−0.856 **	0.323 **	0.303 ***	0.588 ***	−2.621 **	0.092	0.540
	(−2.42)	(2.54)	(2.64)	(3.66)	(−2.54)	(0.93)	(1.64)

Data source: Calculated by Stata 15. ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively, *t*-values in parentheses.

Table 8. Decomposition of the spatial effect of manufacturing structure optimization from the energy consumption perspective on carbon emissions.

	SE	*L*	*P*	*EI*	*ES*	*TI*	*ER*
Direct effect	−0.358 ***	0.133 ***	0.305 ***	0.495 ***	−0.221	0.032	0.164 **
	(−3.49)	(5.31)	(12.09)	(13.71)	(−1.64)	(1.58)	(2.13)
Indirect effect	0.258	0.226 *	0.064	0.195	−2.385 **	0.090	0.235
	(0.54)	(1.80)	(0.56)	(1.26)	(−2.43)	(0.95)	(0.71)
Total effect	−0.100 *	0.360 ***	0.369 ***	0.690 ***	−2.606 **	0.122	0.398
	(−1.76)	(2.84)	(3.23)	(4.51)	(−2.55)	(1.22)	(1.13)

Data source: Calculated by Stata 15. ***, **, * indicate significant at 1%, 5%, and 10% levels, respectively, *t*-values in parentheses.

The direct effect of manufacturing structure optimization from the technology perspective on carbon emissions was 0.208, significant at the 5% level, thus indicating that it has a positive effect on carbon emissions in the region. The indirect effect of manufacturing structure optimization from the technology perspective on carbon emissions was −1.064, significant at the 1% level, thus indicating that it has a negative spatial spillover effect on carbon emissions in neighboring regions, which is beneficial to inter-regional cooperation. The total effect of manufacturing structure optimization from the technology perspective on carbon emissions was −0.856, significant at the 5% level, thus indicating that it has a negative effect on manufacturing carbon emissions, which is consistent with the previous theoretical research that manufacturing structure optimization can reduce carbon emissions through structural effects.

The direct effect of manufacturing structure optimization from the energy consumption perspective on carbon emissions was −0.358, significant at the 1% level, thus indicating that it has a negative effect on carbon emissions in the region and that manufacturing structure optimization helps with carbon emission reduction. The indirect effect was not statistically significant, indicating that the spatial spillover effect of manufacturing structure optimization from the energy consumption perspective on carbon emissions in neighboring regions was not significant. The total effect of manufacturing structure optimization from the energy consumption perspective on manufacturing carbon emissions was −0.100, significant at the 10% level, thus indicating that it has a negative effect on carbon emissions. This also shows that manufacturing structure optimization can reduce carbon emissions through structural effects.

We compared the results of the spatial effects of manufacturing structure optimization on carbon emissions in Northeast China from the technology and energy consumption perspectives. The results show that manufacturing structure optimization from the technology perspective has a positive direct effect and a negative spatial spillover effect on carbon emissions; as such, the government can promote carbon emission reduction in neighboring regions by improving manufacturing structure optimization from the technology perspective. Manufacturing structure optimization from the energy consumption perspective had a negative direct effect on carbon emissions, and the spatial spillover effect was not significant; as such, the government could promote carbon emission reduction in the region by improving manufacturing structure optimization from the energy consumption perspective.

The number of manufacturing employees, manufacturing output value, and energy intensity all had a positive effect on carbon emissions in a dual perspective, while the energy structure had no significant effect on carbon emissions. The effect of environmental regulation on carbon emissions is positive, generating a green paradox. Technological innovation has an insignificant effect on carbon emissions under the role of manufacturing structure optimization from the technology perspective, and a positive effect on carbon emissions under the role of manufacturing structure optimization from the energy consumption perspective, thus producing a rebound effect. In general, manufacturing structure optimization is an important way to achieve carbon emission reduction. The role of the technology perspective on carbon emission reduction is reflected in the spatial spillover effect, while the role of the energy consumption perspective on carbon emission reduction is mainly reflected in the direct effect. Both technological innovation and environmental regulation do not show positive effects on manufacturing carbon emission reduction in Northeast China.

4.2. Carbon Peak Scenario Simulation of Manufacturing Carbon Emissions from the Perspective of Structure Optimization

4.2.1. Scenario Setting

Technological innovation and institutional innovation are important guarantees for the transformation and upgrading of the manufacturing industry, as well as for the carbon peak and carbon neutrality goals. Therefore, the baseline scenario, technological innovation scenario, and institutional innovation scenario are set in this paper. Since there are significant differences in the future impact of different political cycles, and the closer the cycle is, the greater the impact [47], the average annual rate of change in manufacturing structure optimization, the number of manufacturing employees, manufacturing capital stock, manufacturing output, manufacturing energy consumption, manufacturing energy structure, technological innovation, and environmental regulation in Northeast China from 2016 to 2020 were selected as the rate of change in the baseline scenario.

Compared with the baseline scenario, the level of technological innovation and the energy structure will be significantly improved under the technological innovation scenario during the carbon peak stage. Specifically, a maximum annual average rate of change in technological innovation of 3.56% was selected as the new technological innovation rate and a maximum annual average rate of change in energy structure of −1.98% was selected as the new change in energy structure rate in Northeast China from 2016 to 2020. Combined with the results of the carbon emission reduction path analysis of the technological innovation required to guarantee manufacturing structure optimization, the corresponding manufacturing structure optimization was measured. The specific process for this is shown in Appendix B. The number of employees, capital stock, output value, energy consumption, and environmental regulation were consistent with the baseline scenario. The same parameter determination method is used for the institutional innovation scenario, with the technological innovation indicator simply being replaced by the institutional innovation indicator.

Table 9 shows the potential rates of change in factors influencing manufacturing carbon emissions under the baseline scenario, technology innovation scenario, and institutional innovation scenario in the simulation of manufacturing carbon emissions in Northeast China during the carbon peak stage.

Table 9. Potential rates of change in factors influencing manufacturing carbon emissions.

Variables	Baseline Scenario	Technology Innovation Scenario	Institutional Innovation Scenario
ST	4.60%	4.60%	4.89%
SE	1.78%	1.84%	2.26%
L	−8.43%	−8.43%	−8.43%
K	−2.43%	−2.43%	−2.43%
E	−1.02%	−1.02%	−1.02%
P	−3.78%	−3.78%	−3.78%
ES	−1.04%	−1.98%	−1.98%
TI	0.47%	3.56%	0.47%
ER	1.77%	1.77%	4.11%

Data source: Compiled by the authors.

4.2.2. Scenario Simulation

The BP neural network model, support vector machine model, and random forest model were constructed under the baseline scenario to simulate the future trend in manufacturing carbon emissions in Northeast China from 2021 to 2030. The results are shown in Table 10. The BP neural network model was set as follows: 8 input neurons, 1 output nerve, 1 hidden layer, number of neurons 5 BP neural networks, maximum number of iterations 1000, error threshold 0.000001, and learning rate 0.01. The support vector machine model was set as follows: 8 input feature values and 1 output feature value, model type e-SVR, kernel function radial basis function, and penalty factor 4.0. The random forest model was set as follows: 8 input feature values and 1 output feature value, number of decision trees 100, and minimum number of leaves 5.

Table 10. Simulation results of the three machine learning methods under the baseline scenario (Unit: 10^9 kg).

Year	BP Model	SVM Model	RF Model
2021	452.168	452.931	441.812
2022	446.848	449.870	441.812
2023	442.992	446.219	441.812
2024	440.045	442.979	441.006
2025	437.627	440.566	440.014
2026	435.466	438.898	439.395
2027	433.343	437.723	438.135
2028	431.062	436.831	436.113
2029	428.423	436.106	434.691
2030	425.201	435.522	434.691
R^2	0.974	0.918	0.823
$RMSE$	1748.965	2304.506	4123.421
$MEAP(\%)$	2.299	2.474	6.263

Data source: Calculated by Matlab 2020a.

In terms of model effects, the BP neural network model has the largest R^2, the smallest $RMSE$, and the smallest $MEAP$ (less than 10%), which indicates that its simulation effect is better than that of the support vector machine model and the random forest model, and it is, therefore, the most suitable model. Therefore, this paper selects the BP neural network model for use in simulating the carbon peak scenario for manufacturing carbon emissions from the perspective of structure optimization in Northeast China.

The carbon emission simulation results of manufacturing structure optimization from the technology perspective in Northeast China are shown in Figure 7. Under the baseline scenario, technological innovation scenario, and institutional innovation scenario, the manufacturing carbon emissions in Northeast China show a decreasing trend from 2021 to 2030, indicating that manufacturing carbon emissions in Northeast China will achieve a carbon peak. However, the carbon emissions in 2030 were predicted to be 3.93×10^{11} kg,

3.99×10^{11} kg, and 3.29×10^{11} kg under the baseline scenario, technological innovation scenario, and institutional innovation scenario, respectively, which represent decreases of 44.15%, 43.70%, and 53.53%, respectively, compared to 2005 levels. Thus, the three scenarios are unable to achieve the goal of a 65% reduction in carbon emissions. In this period, the level of manufacturing structure optimization from the technology perspective increased by 12.76%.

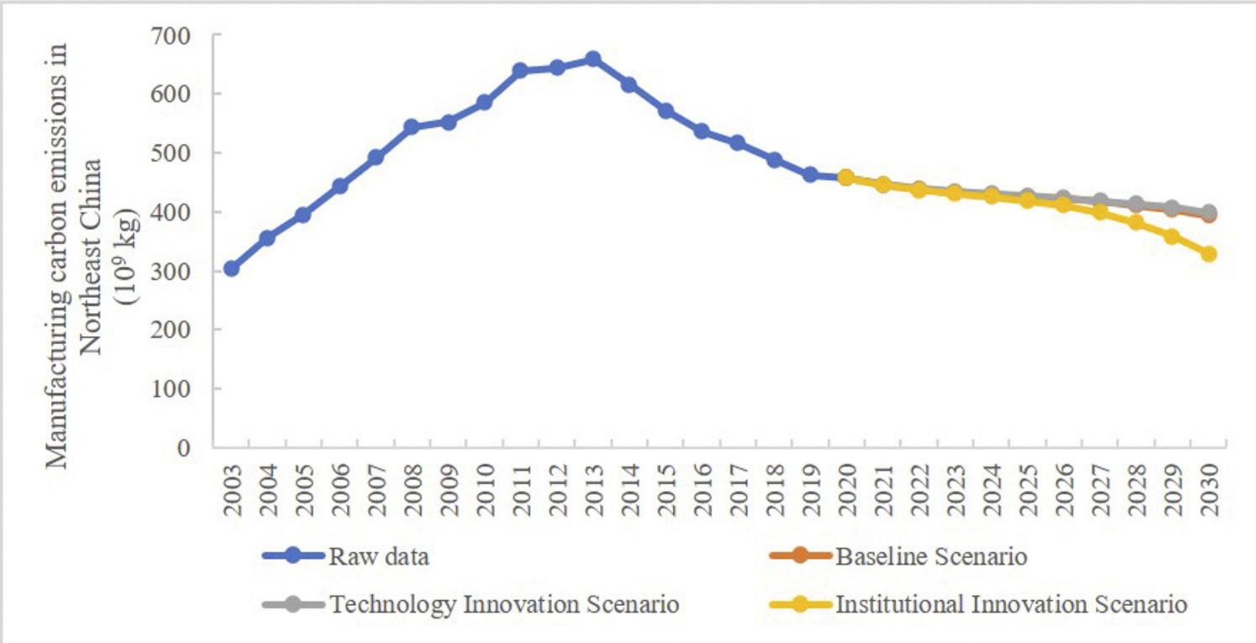

Figure 7. Carbon emissions simulation of manufacturing structure optimization from the technology perspective in Northeast China.

The carbon emission simulation results of manufacturing structure optimization from the energy consumption perspective in Northeast China are shown in Figure 8. Under the baseline scenario, technological innovation scenario, and institutional innovation scenario, the manufacturing carbon emissions in Northeast China show a decreasing trend from 2021 to 2030, which also indicates that manufacturing carbon emissions in Northeast China will achieve a carbon peak. However, the carbon emissions in 2030 were predicted to be 3.93×10^{11} kg, 4.05×10^{11} kg, 2.48×10^{11} kg under the baseline scenario, technological innovation scenario, and institutional innovation scenario, respectively, which represent decreases of 44.15%, 42.82%, and 65.01%, respectively, compared to 2005 levels. Only the institutional innovation scenario can achieve the total amount and intensityof reduction requirements needed to meet the carbon peak goals. In this period, the level of manufacturing structure optimization from the energy consumption perspective increased by 50.42%.

According to the simulation results with the BP neural network model, the manufacturing carbon emissions in Northeast China will decrease during the carbon peak stage, and the carbon emission reduction effect based on manufacturing structure optimization from the energy consumption perspective was better than that based on manufacturing structure optimization from the technology perspective. Only manufacturing structure optimization from the energy consumption perspective can achieve the goal of decreasing the manufacturing carbon emission intensity by 65% in 2030 when compared with that value in 2005. At the same time, the carbon emission reduction effect of the institutional innovation scenario is better than that of the technological innovation scenario. Therefore, the carbon emission reduction path of manufacturing structure optimization from the energy consumption perspective based on institutional innovation is the optimal carbon emission reduction path for Northeast China. In order to better achieve the carbon emission reduction goal from the manufacturing structure optimization perspective in Northeast China, manufacturing structure optimization from both the technology and energy consumption perspectives should be promoted, and success requires both technological innovation and institutional innovation.

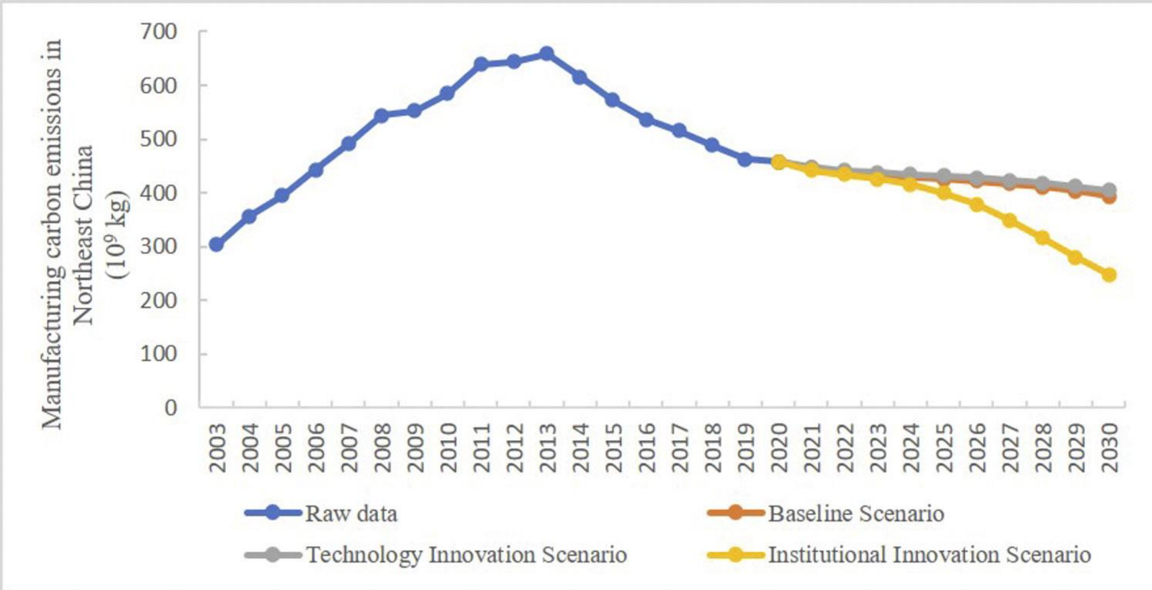

Figure 8. Carbon emissions simulation of manufacturing structure optimization from the energy consumption perspective in Northeast China.

In summary, research Hypothesis 1 was proved, while research Hypothesis 2 was only partially proved. Manufacturing structure optimization can effectively promote manufacturing carbon emission reduction. The carbon emission reduction effect of the manufacturing industry in Northeast China under the institutional innovation scenario is better than the baseline scenario. However, the carbon emission reduction effect of the manufacturing industry in Northeast China under the technological innovation scenario is not significantly different from the baseline scenario.

5. Discussion

Based on the results of the current research, we conduct a comparison with existing research on the influencing factors of manufacturing carbon emissions and the prediction and simulation of manufacturing carbon emissions. We then propose policy recommendations for promoting manufacturing carbon emission reduction in Northeast China.

5.1. Comparison of Research on Influencing Factors of Manufacturing Carbon Emissions

The results of the current research indicate that manufacturing structure optimization has a catalytic effect on carbon emission reduction in Northeast China, and it is also an important means by which to achieve carbon emission reduction, which is consistent with the results of most previous research [48]. As the production sector with the highest fossil fuel energy consumption and carbon emissions in China, the manufacturing industry plays an important role in emission reduction targets, and manufacturing structure optimization has become an inevitable choice for the manufacturing industry to reach the goals of the carbon peak policy. At the same time, the positive influence of the number of employees and output value on manufacturing carbon emissions reflects the scale effect. Given the important role of the manufacturing industry in the economy, manufacturing carbon emissions cannot be reduced by reducing the scale. The positive influence of energy intensity and energy structure on carbon emission reduction reflects the different effects of energy types on carbon emissions, and the reduction in energy intensity and optimization of energy structure become more important means of manufacturing carbon emission reduction [49–51].

The inhibitory effects of technological innovation and environmental regulation on carbon emissions were not significant in the spatial econometric model, most likely because of the unbalanced manufacturing structure, poor manufacturing development, low level of technology, and high level of energy consumption in Northeast China. These factors resulted in a rebound effect of technological innovation on manufacturing carbon emissions, as well as the green paradox effect of environmental regulation on manufacturing carbon emissions. In other words, the suppressive effect of technological innovation and environmental regulation on carbon emissions cannot be significantly brought about due to the promotion effect of manufacturing scale expansion. Therefore, technological innovation and environmental regulation may suppress manufacturing carbon emissions through manufacturing structure optimization, while the direct positive effect on carbon emission reduction is not significant.

5.2. Comparison of Research on Prediction and Simulation of Manufacturing Carbon Emissions

In this paper, machine learning models were selected for the carbon peak scenario simulation of manufacturing carbon emissions in Northeast China, which is consistent with the basis of method selection for carbon emission predictions and simulations in existing research [26,27]. This reflects the methodological superiority of machine learning models compared with the macroeconomic operation mechanism method and the information feedback system method. Moreover, by comparing the BP neural network model, support vector machine model, and random forest model to screen the most suitable method, the research conclusions were more scientific and the research results were more general, which can provide a reference for other regions or countries to conduct carbon emission simulations and predictions. In the context of high-quality economic development and the construction of an ecological civilization, manufacturing structure optimization is given a new connotation. The research results show that the carbon emission reduction effect of manufacturing structure optimization from the energy consumption perspective is better than that from the technology perspective, which is consistent with the new focus on energy saving and emission reduction in manufacturing structure optimization. In view of the differences between the technology level and energy consumption level of manufacturing sub-sectors, when carrying out manufacturing carbon emission reduction through the manufacturing structure optimization path, it is necessary to pay attention not only to manufacturing structure optimization in terms of changing the technology level but also in terms of changing the energy consumption level.

The effect of carbon emission reduction under the institutional innovation scenario is better than that under the baseline scenario and the technological innovation scenario, indicating that the carbon emission reduction path based on institutional innovation is an important path for manufacturing carbon emission reduction in Northeast China, which is consistent with the requirements of China's carbon emission reduction strategy and which reflects the positive effect of the carbon emissions trading mechanism [52]. The insignificant effect of technological innovation on manufacturing carbon emission reduction in Northeast China may be related to its significantly lower level of economic development and technological innovation. From 2003 to 2020, the contribution of Northeast China to the national economy decreased from 9.48% to 6.63%, indicating that the economic status of Northeast China in the country is decreasing, and the average annual growth rate is much lower than the national average. From the viewpoint of R&D expenditure, the R&D expenditure in Northeast China in 2020 was only 33.19% of the national average, and from the viewpoint of the number of patent applications, the number of patent applications in Northeast China in 2020 was only 25.11% of the national average. In summary, the level of economic development and technological innovation in Northeast China significantly lags behind the national average and has a significant gap with the leading international level, resulting in the ineffectiveness of the carbon emission reduction pathway effect of technological innovation.

5.3. Policy Recommendations to Promote Manufacturing Structure Optimization and Carbon Emission Reduction

Excessive de-industrialization should be avoided in the process of high-quality economic development [53], and the comprehensive effectiveness of manufacturing can be effectively improved through manufacturing structure optimization, which can promote carbon emission reduction. In response to the research results, the following policy recommendations are proposed:

Manufacturing structure optimization is an important means by which to achieve carbon emission reduction. This requires simultaneous attention to moving from low-technology to high-technology and from high-energy consumption to low-energy consumption, while the government should address the current situation of manufacturing industry development in Northeast China, focusing on industries with a better foundation and comparative advantages. The government should actively promote the development of high-technology and low-energy consumption manufacturing, including automotive manufacturing, special equipment manufacturing, electrical machinery and equipment manufacturing, the metal products industry, the rubber and plastic products industry, computer, communications, and other electronic equipment manufacturing, railroad, ship, aerospace, and other transportation equipment manufacturing, instrumentation manufacturing, a total of eight industries. The government should exert strict control over the expansion of medium-technology and high-energy-consumption, low-technology, and medium-energy-consumption industries, including the oil, coal, and other fuel processing industry, the agricultural and food processing industry, the ferrous metal smelting and rolling processing industry, the non-metallic mineral products industry, the non-ferrous metal smelting and rolling processing industry, food manufacturing, wood processing and the wood, bamboo, rattan, palm, and grass products industry, the wine, beverage, and refined tea manufacturing industry, a total of eight industries.

Technological innovation has not played a proper role in the process of carbon emission reduction from the perspective of structure optimization in Northeast China, but it is an important intrinsic driving force for manufacturing structure optimization and carbon emission reduction, and thus still needs to be effectively strengthened. This should be conducted with a particular focus on low-carbon technology development, such as green technology innovation and clean energy technology, and then by achieving the carbon emission reduction goal through manufacturing structure optimization. Given that technological innovation requires a large amount of financial investment, and that the economic development and technological innovation in Northeast China are particularly lagging, there is an urgent need to increase financial support to strengthen technological innovation and to promote manufacturing structure optimization and carbon emission reduction in the region.

Institutional innovation plays a positive role in the process of carbon emission reduction via manufacturing structure optimization in Northeast China; however, the positive effect of environmental regulation on carbon emission reduction from the spatial perspective is not significant, indicating that the institutional innovation mechanism is not perfect. China's carbon emission trading market is now open, and manufacturing enterprises in Northeast China should actively participate in carbon emission trading and the carrying out of useful exploration. In view of the development characteristics of heavy manufacturing industries in Northeast China, the government should continue to promote carbon emission trading and aim to achieve carbon emission reduction through market mechanisms. Therefore, it is necessary to further improve institutional innovation in order to promote manufacturing structure optimization and carbon emission reduction in Northeast China.

6. Conclusions

In this paper, a spatial econometric model and a machine learning model are used to simulate the carbon peak scenario of the manufacturing industry in Northeast China under the perspective of structural optimization. The conclusions that can be drawn are as follows: Manufacturing structure optimization from both the technology perspective and energy consumption perspective in Northeast China show an increasing trend, thus indicating that the manufacturing structure has been optimized to a certain extent during the research period. Manufacturing carbon emissions in Northeast China show a trend of rising and then falling, and there are significant differences in the carbon emission levels among different industries and regions. Manufacturing structure optimization and carbon emissions in Northeast China both show a positive spatial correlation. The total effect of manufacturing structure optimization from both the technology perspective and energy consumption perspective on carbon emission reduction in Northeast China is significantly positive, thus indicating that manufacturing structure optimization can effectively promote manufacturing carbon emission reduction. The carbon emission reduction effect of manufacturing structure optimization from the energy consumption perspective is better than that from the technological perspective. The carbon emission reduction effect under the institutional innovation scenario is better than that under the technological innovation scenario, and it meets the requirements of the carbon peak policy in terms of total amount and scale of reduction. Therefore, the carbon emission reduction path of manufacturing structure optimization from the energy consumption perspective based on institutional innovation is the optimal path for achieving manufacturing carbon emission reduction in Northeast China.

In recent years, the goal of low-carbon economic development has gradually replaced the goal of maximizing economic efficiency, which leads to the traditional approach to measuring manufacturing structure optimization showing certain limitations. Thus, this paper measures manufacturing structure optimization from both the technology and the energy consumption perspectives. Meanwhile, we have explored the impact of manufacturing structure optimization on carbon emission reduction by comparing three spatial weight matrices, namely, geographic neighborhood, geographic distance, and economic geographic distance, and comparing SLM, SXL, and SDM models. In addition, we select the optimal method for the scenario simulation of manufacturing carbon emissions in Northeast China by comparing the BP model, SVM model, and RF model to ensure the scientificity of the research results and the validity of our conclusions.

As the world's largest carbon emitter, China is under enormous pressure to reduce carbon emissions. The manufacturing industry is the pillar industry of the national economy, and its efforts to reduce carbon emissions play an important role in achieving China's carbon peak and carbon neutrality targets. It is of great practical significance to clarify the impact of manufacturing structure optimization on carbon emission reduction and identify the optimal path to carbon emission reduction in Northeast China, which can provide an empirical basis for the green and low-carbon transformation development of the manufacturing industry and provide a boost to the construction of an ecological civilization. Northeast China is a critical region for the revitalization of China's old industrial zones, and it is a key region for manufacturing structure optimization and carbon emission reduction. The results show that the carbon emission reduction path of manufacturing structure optimization from the perspective of energy consumption based on institutional innovation is the optimal path to achieve carbon emission reduction in the manufacturing industry in Northeast China. In order to better achieve the goal of manufacturing carbon emission reduction in Northeast China, manufacturing structure optimization from both the technology and the energy consumption perspectives should be promoted. In addition, the goal of manufacturing carbon emission reduction needs to be guaranteed by both technological innovation and institutional innovation approaches.

Since the economic development and carbon emission makeup of Northeast China are relatively different from those of other regions, the results of the study are more applicable to other old industrial zones in China. Additionally, in this paper, the scenario simulation of manufacturing carbon emissions in Northeast China only considers the carbon peak target and lacks simulation and analysis of the carbon neutrality target. In a subsequent study, we will strengthen our knowledge of carbon absorption and other related factors and then further explore manufacturing carbon emission reduction in Northeast China considering the carbon neutral target.

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Appendix A

For the determination of the specific form of the spatial econometric model, the applicability of SEM and SLM is judged by LM and Robust LM tests. Whether SDM can be degraded to SLM or SEM was determined by the LR test, and the applicability of the random effects model and fixed effects model was assessed by the Hausman test. The principles of maximum goodness of fit, maximum log-likelihood value, and minimum variance in the random disturbance term were used to determine whether the regional fixed-effects model, the time-fixed-effects model, or the dual fixed-effects model was superior. Tables A1–A4 show the results of the determination of the specific model form of the spatial effect manufacturing structure optimization on carbon emissions from the perspective of technology. Tables A5–A8 show the results of the determination of the specific model form of the spatial effect manufacturing structure optimization on carbon emissions from the perspective of energy consumption.

Table A1. LM and Robust LM test results (*ST* to *CE*).

Spatial Weight Matrix	Model	Test Method	Statistics	*p*-Value
Geographic adjacency	SEM	Lagrange multiplier	1.717	0.190
		Robust Lagrange multiplier	2.134	0.144
	SLM	Lagrange multiplier	27.744 ***	0.000
		Robust Lagrange multiplier	28.160 ***	0.000
Geographic distance	SEM	Lagrange multiplier	5.580 **	0.018
		Robust Lagrange multiplier	0.146	0.702
	SLM	Lagrange multiplier	36.763 ***	0.000
		Robust Lagrange multiplier	31.328 ***	0.000
Economic geographic distance	SEM	Lagrange multiplier	1.796	0.180
		Robust Lagrange multiplier	2.116	0.146
	SLM	Lagrange multiplier	23.144 ***	0.000
		Robust Lagrange multiplier	23.464 ***	0.000

Data source: Calculated by Stata 15. *** and ** indicate significant at 1% and 5%levels.

Table A2. LR test results (*ST* to *CE*).

Spatial Weight Matrix	Model Comparison	LR Statistics	*p*-Value
Geographic adjacency	SDM and SLM	32.810 ***	0.000
	SDM and SEM	35.850 ***	0.000
Geographic distance	SDM and SLM	32.600 ***	0.000
	SDM and SEM	34.090 ***	0.000
Economic geographic distance	SDM and SLM	28.620 ***	0.000
	SDM and SEM	31.190 ***	0.000

Data source: Calculated by Stata 15. *** indicate significant at 1% level.

Table A3. Hausman test results (*ST* to *CE*).

Spatial Weight Matrix	Chi-Square Statistics	*p*-Value
Geographic adjacency	−680.520	-
Geographic distance	339.890 ***	0.000
Economic geographic distance	−19.290	-

Data source: Calculated by Stata 15. *** indicate significant at 1% level.

Table A4. Spatial econometric model estimation results (*ST* to *CE*).

Variables	Regional Fixed Effects	Time Fixed Effects	Double Fixed Effects
ST	0.252 ***	0.721 ***	0.196 **
	(2.79)	(8.07)	(2.12)
L	0.114 ***	0.215 ***	0.117 ***
	(4.27)	(10.79)	(4.45)
P	0.313 ***	0.394 ***	0.305 ***
	(11.87)	(21.58)	(11.67)
EI	0.530 ***	0.835 ***	0.501 ***
	(14.60)	(21.31)	(13.31)
ES	−0.063	−0.402 ***	−0.084
	(−0.45)	(−5.33)	(−0.57)
TI	0.050 **	0.055 ***	0.057 ***
	(2.48)	(2.89)	(2.83)
ER	0.102	0.417 ***	0.133 *
	(1.39)	(4.86)	(1.81)
$W \times ST$	−0.294	1.093 **	−1.154 ***
	(−1.04)	(2.33)	(−2.94)
$W \times L$	0.116	−0.465 ***	0.240 *
	(1.40)	(−3.25)	(1.65)
$W \times P$	0.125	−0.594 ***	0.034
	(1.50)	(−4.21)	(0.25)
$W \times EI$	0.057	−0.688 ***	0.163
	(0.43)	(−2.76)	(0.80)
$W \times ES$	−2.004 ***	−8.772 ***	−2.952 ***
	(−2.79)	(−14.70)	(−2.69)
$W \times TI$	−0.078 **	0.494 ***	0.053
	(−2.13)	(4.08)	(0.49)
$W \times ER$	0.315	1.471 ***	0.461
	(1.49)	(3.07)	(1.41)
rho	0.457 ***	−0.406 ***	−0.161 **
	(5.86)	(−3.10)	(−2.08)
sigma2_e	0.020 ***	0.064 ***	0.019 ***
	(17.64)	(19.32)	(17.74)
R^2	0.804	0.728	0.849
Log-L	333.774	−59.139	361.324

Data source: Calculated by Stata 15. ***, **, * indicate significant at 1%, 5%, and 10% levels, *t*-values in parentheses.

Table A5. LM and Robust LM test results (*SE* to *CE*).

Spatial Weight Matrix	Model	Test Method	Statistics	*p*-Value
Geographic adjacency	SEM	Lagrange multiplier	4.033 ***	0.045
		Robust Lagrange multiplier	0.298	0.585
	SLM	Lagrange multiplier	24.801 ***	0.000
		Robust Lagrange multiplier	21.066 ***	0.000
Geographic distance	SEM	Lagrange multiplier	7.657 ***	0.006
		Robust Lagrange multiplier	0.100	0.752
	SLM	Lagrange multiplier	31.109 ***	0.000
		Robust Lagrange multiplier	23.553 ***	0.000
Economic geographic distance	SEM	Lagrange multiplier	1.820	0.177
		Robust Lagrange multiplier	1.755	0.185
	SLM	Lagrange multiplier	22.286 ***	0.000
		Robust Lagrange multiplier	22.221 ***	0.000

Data source: Calculated by Stata 15. *** indicate significant at 1% level.

Table A6. LR test results (*SE* to *CE*).

Spatial Weight Matrix	Model Comparison	LR Statistics	*p*-Value
Geographic adjacency	SDM and SLM	32.970 ***	0.000
	SDM and SEM	35.420 ***	0.000
Geographic distance	SDM and SLM	20.770 ***	0.004
	SDM and SEM	22.070 ***	0.003
Economic geographic distance	SDM and SLM	13.070 ***	0.007
	SDM and SEM	15.730 ***	0.003

Data source: Calculated by Stata 15. *** indicate significant at 1% level.

Table A7. Hausman test results (*SE* to *CE*).

Spatial Weight Matrix	Chi-Square Statistics	*p*-Value
Geographic adjacency	−144.060	-
Geographic distance	119.160 ***	0.000
Economic geographic distance	−48.910	-

Data source: Calculated by Stata 15. *** indicate significant at 1% level.

Table A8. Spatial econometric model estimation results (*SE* to *CE*).

Variables	Regional Fixed Effects	Time Fixed Effects	Double Fixed Effects
SE	−0.354 ***	0.520 ***	−0.360 ***
	(−3.47)	(5.18)	(−3.62)
L	0.123 ***	0.244 ***	0.136 ***
	(4.70)	(12.04)	(5.25)
P	0.301 ***	0.419 ***	0.303 ***
	(11.36)	(21.52)	(11.56)
EI	0.495 ***	0.830 ***	0.494 ***
	(13.76)	(19.62)	(13.78)
ES	−0.130	−0.575 ***	−0.240 *
	(−0.94)	(−6.68)	(−1.68)
TI	0.025	0.030	0.032
	(1.23)	(1.52)	(1.55)
ER	0.153 **	0.355 ***	0.164 **
	(2.08)	(3.80)	(2.18)
$W \times SE$	0.985 **	0.295	0.261
	(2.15)	(0.44)	(0.49)

Table A8. *Cont.*

Variables	Regional Fixed Effects	Time Fixed Effects	Double Fixed Effects
$W \times L$	0.122	−0.455 ***	0.259 *
	(1.55)	(−2.86)	(1.81)
$W \times P$	0.105	−0.510 ***	0.106
	(1.23)	(−3.43)	(0.78)
$W \times EI$	0.055	−0.954 ***	0.276
	(0.42)	(−3.67)	(1.41)
$W \times ES$	−1.340 *	−8.000 ***	−2.761 **
	(−1.87)	(−12.75)	(−2.55)
$W \times TI$	−0.048	0.446 ***	0.110
	(−1.31)	(3.54)	(1.03)
$W \times ER$	0.337	1.178 **	0.270
	(1.53)	(2.43)	(0.79)
rho	0.449 ***	−0.285 **	−0.124
	(5.75)	(−2.17)	(−0.90)
sigma2_e	0.019 ***	0.070 ***	0.019 ***
	(17.65)	(18.80)	(17.74)
R^2	0.747	0.737	0.779
Log-L	336.609	−76.862	359.947

Data source: Calculated by Stata 15. ***, **, * indicate significant at 1%, 5%, and 10% levels, *t*-values in parentheses.

Appendix B

The mediating effect model was used to determine the effect of manufacturing structure optimization via technological innovation versus institutional innovation on carbon emissions. Tables A9 and A10 show the results of the carbon emission reduction path analysis for technological-innovation-driven manufacturing structure optimization. Tables A11 and A12 show the results of the carbon emission reduction path analysis for institutional-innovation-driven manufacturing structure optimization.

Table A9. Estimation results of the mediating effect model of technological innovation on carbon emissions (Mediating variable *ST*).

Variables	Model 1	Model 2	Model 3
TI	0.098 ***	−0.005	0.100 ***
	(5.71)	(−0.79)	(5.85)
ST			0.350 ***
			(3.09)
L	0.236 ***	0.047 ***	0.220 ***
	(11.46)	(6.46)	(10.39)
P	0.533 ***	0.067 ***	0.510 ***
	(24.64)	(8.86)	(22.35)
EI	0.833 ***	0.023	0.825 ***
	(18.02)	(1.44)	(17.93)
ES	−0.085	−0.107 ***	−0.047
	(−0.96)	(−3.45)	(−0.53)
ER	−0.182 *	0.126 ***	−0.225 **
	(−1.70)	(3.34)	(−2.11)
Cons	2.191 ***	−0.065	2.214 ***
	(12.31)	(−1.04)	(12.51)
R^2	0.848	0.503	0.851
Bootstrap test		[−0.006, 0.003]	

Data source: Calculated by Stata 15. ***, **, * indicate significant at 1%, 5%, and 10% levels, *t*-values in parentheses.

Table A10. Estimation results of the mediating effect model of technological innovation on carbon emissions (Mediating variable *SE*).

Variables	Model 1	Model 2	Model 3
TI	0.098 ***	0.021 ***	0.087 ***
	(5.71)	(3.74)	(5.06)
SE			0.549 ***
			(4.62)
L	0.236 ***	0.044 ***	0.212 ***
	(11.46)	(6.40)	(10.13)
P	0.533 ***	0.057 ***	0.502 ***
	(24.64)	(7.90)	(22.48)
EI	0.833 ***	0.065 ***	0.797 ***
	(18.02)	(4.24)	(17.28)
ES	−0.085	0.313 ***	−0.257 ***
	(−0.96)	(10.66)	(−2.71)
ER	−0.182 *	0.206 ***	−0.295 ***
	(−1.70)	(5.81)	(−2.73)
Cons	2.191 ***	−0.630 ***	2.537 ***
	(12.31)	(−10.67)	(13.32)
R^2	0.848	0.512	0.853
Bootstrap test		[0.006, 0.021]	

Data source: Calculated by Stata 15. *** and * indicate significant at 1% and 10% levels, *t*-values in parentheses.

Table A11. Results of model estimation of mediating effects of institutional innovation on carbon emissions (Mediating variable *ST*).

Variables	Model 1	Model 2	Model 3
ER	−0.182 *	0.126 ***	−0.225 **
	(−1.70)	(3.34)	(−2.11)
ST			0.350 ***
			(3.09)
L	0.236 ***	0.047 ***	0.220 ***
	(11.46)	(6.46)	(10.39)
P	0.533 ***	0.067 ***	0.510 ***
	(24.64)	(8.86)	(22.35)
EI	0.833 ***	0.023	0.825 ***
	(18.02)	(1.44)	(17.93)
ES	−0.085	−0.107 ***	−0.047
	(−0.96)	(−3.45)	(−0.53)
TI	0.098 ***	−0.005	0.100 ***
	(5.71)	(−0.79)	(5.85)
Cons	2.191 ***	−0.065	2.214 ***
	(12.31)	(−1.04)	(12.51)
R^2	0.848	0.503	0.851
Bootstrap test		[0.011, 0.089]	

Data source: Calculated by Stata 15. ***, **, * indicate significant at 1%, 5%, and 10% levels, *t*-values in parentheses.

Table A12. Results of model estimation of mediating effects of institutional innovation on carbon emissions (Mediating variable *SE*).

Variables	Model 1	Model 2	Model 3
ER	−0.182 *	0.206 ***	−0.295 ***
	(−1.70)	(5.81)	(−2.73)
SE			0.549 ***
			(4.62)
L	0.236 ***	0.044 ***	0.212 ***
	(11.46)	(6.40)	(10.13)

Table A12. *Cont.*

Variables	Model 1	Model 2	Model 3
P	0.533 ***	0.057 ***	0.502 ***
	(24.64)	(7.90)	(22.48)
EI	0.833 ***	0.065 ***	0.797 ***
	(18.02)	(4.24)	(17.28)
ES	−0.085	0.313 ***	−0.257 ***
	(−0.96)	(10.66)	(−2.71)
TI	0.098 ***	0.021 ***	0.087 ***
	(5.71)	(3.74)	(5.06)
Cons	2.191 ***	−0.630 ***	2.537 ***
	(12.31)	(−10.67)	(13.32)
R^2	0.848	0.512	0.853
Bootstrap test		[0.053, 0.174]	

Data source: Calculated by Stata 15. *** and * indicate significant at 1% and 10% levels, *t*-values in parentheses.

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