Research on Carbon Productivity and It's Spatial Convergence of Steel Industry in China

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Research on Carbon Productivity and It's Spatial Convergence of Steel Industry in China

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Abstract: The Global-Malmquist-Luenberger (GML) index was applied to analyse the carbon productivity in steel industry (SICP) of 29 provinces in China from 2006 to 2017, and then the SICP was decomposed into technical efficiency change index (TC) and technical progress index (EC). On this basis, the spatial effect is introduced into the traditional convergence model to investigate the spatial convergence of SICP. The empirical results show that: (1) The overall carbon productivity of China's steel industry is at a relatively low level, showing a slow growth trend. (2) The average value of the GML index of SICP is higher than 1, showing obvious inter-provincial and regional heterogeneity. Compared with EC, TC is the leading factor that promotes the increase of SICP. (3) The spatial absolute and condition β convergence of SICP exist in the whole country and the three major regions, but the σ convergence feature is not significant. The addition of spatial factors speeds up the convergence trend, and the speed of spatial absolute β convergence is about 3 times that of the classical convergence model. At the same time, the conditional convergence rate is significantly faster than the absolute convergence, which is closely related to the differences in influencing factors such as the industrial structure, economic development level, human capital, energy consumption intensity, and R&D investment among regions. There is still much room for improvement in carbon productivity in China's steel industry, and investment in scientific research must be increased in order to achieve the upgrading of the industrial structure and technological innovation. The existence of spatial convergence requires strengthening the joint reorganization of steel enterprises between provinces and regions, making full use of the spatial spillover effects of production technology, and realizing regional green and coordinated development.

Keywords: Steel industry; Carbon productivity; GML Index; Spatial convergence

1 Introduction

As the frequency of mankind activities continue increasing, environmental issues such as global warming have attracted the attention of all countries, human environmental awareness has increased, and traditional economic development methods have gradually been replaced by low-carbon economies. In order to cope with the deteriorating human living environment and achieve sustainable economic and social development, it is imperative to make low-carbon economy one of the focuses of future research. The essence and core of a low-carbon economy is to achieve a win-win situation between economic growth and carbon dioxide emission reduction, and carbon productivity is an important bridge connecting these two goals. China as the largest CO₂ emitter, in September 2020, it's announced that China will strive to peak carbon dioxide emissions by 2030 and to achieve carbon neutrality by 2060. Under the dual carbon goal, China's various industries are facing tremendous pressure to reduce carbon emissions. The steel industry, as an important pillar industry for social and economic development, plays an irreplaceable role in the process of industrialization, it has the characteristics of high industrial relevance and a wide range of categories. At the same time, it is also faced with prominent structural contradictions, low production efficiency, overcapacity, and high energy intensity, which have aggravated global warming. China's steel industry will face tremendous pressure to transition to green and low-carbon in the near future, therefore, improving the carbon productivity of the steel industry is of great significance to achieving the above goals.

The concept of “carbon productivity” was first defined by Kaya and Yokobori (1997) as “GDP output per unit of CO₂ emissions” over a period of time. Increasing carbon productivity can effectively improve energy efficiency, stabilize greenhouse gas emissions, and maintain stable economic growth, which is an important indicators for evaluating the economic development of developing countries. In recent years, scholars at home and abroad have gradually carried out relevant research on carbon productivity. The existing literature can be roughly divided into the following categories: The first category of literature focuses on examining the differences in national or regional carbon productivity. Wang et al. (2017) compared 18 APEC members and found that the carbon productivity of developing countries such as China and Indonesia is lower than that of developed countries, but they have relatively high carbon dioxide emission reduction potential. Pan and Zhang (2011) studied the differences and influencing factors of carbon productivity in various provinces in China, and pointed out that the carbon emissions of China's three major regions have manifested as a trend of year-on-year growth, and the differences in carbon productivity in the eastern, central, and western regions have been expanding as a whole. The second type of literature places extra emphasis on the analysis of the factor decomposition and influencing factors of total factor carbon productivity. Zhang et al. (2014) carried out a seven-factor decomposition of the growth rate of carbon productivity in various provinces in China. The research results show that technological progress, capital energy substitution effect and labor energy substitution effect play an important role in effectively improving China's carbon productivity. Meng and Niu (2012) decomposed changes in carbon productivity into the quantitative effects of various industrial sectors on technological innovation and industrial structure adjustment, and found that technological innovation has a more significant positive role in promoting carbon productivity in China than industrial structure adjustment. Tang et al. (2018) used spatial autocorrelation analysis to study the relevant data of 30 provinces in China from 2010 to 2015. The results show that coastal areas are areas with high carbon productivity in China. The three influencing factors, the proportion of the service industry, the number of patents granted per year, and the value-added per unit of industry, play a significant role in promoting the improvement of carbon productivity. Most domestic and foreign studies believe that the main factors affecting carbon productivity are economic development level, industrial structure, technological level, energy structure, etc. (Long et al. 2016; Meng and Niu 2012; Zhou et al. 2010; Yu 2015). In addition, some documents also take urbanization rate, education level (Li et al. 2016), environmental regulation, degree of opening to the outside world (Xie et al. 2018), and industrial agglomeration (Lin et al. 2013) as ways to increase carbon productivity. The third type of literature focuses on the carbon productivity of a specific industry or sector. Yang et al. (2015) used the SBM directional distance function and the global Malmquist-Luenberger index to subdivide China's manufacturing industry into 26 industries and measure carbon productivity. Research has shown that the overall carbon productivity of China's manufacturing industry is increasing. Li et al. (2020) used the Metafrontier function approach to conduct a comprehensive calculation and analysis of the total factor carbon productivity of 36 sub-sectors in China from 2003 to 2015. The results show that the difference in carbon productivity of various industries is significant, low-carbon and high-tech industries are technological leaders.

The first research on productivity convergence appeared in the Solow-Swan model proposed during the period of New-Classical Economic Growth Theory. This model believes that under the influence of the law of diminishing marginal returns, the differences in per capita income and resource endowments of countries may decrease over time, and the level of economic development will gradually approach, eventually showing a steady state. The Endogenous growth theory takes human capital and knowledge capital as the endogenous driving forces for sustained economic growth. Low-productivity countries can take advantage of late-mover advantage in international trade and rely on knowledge spillovers from high-productivity countries to narrow the economic gap (Riasanovsky and Gerschenkron 1963). At the same time, the theory also points out that, due to externalities, learning effects and other factors, the economic development levels of various countries

will not converge, and there may even be a tendency for differences to expand. The debate about whether there is convergence of productivity in various countries led to the rapid development of relevant empirical research in the 1980s. Early domestic and foreign scholars' research on convergence issues focused on per capita income, gross national product (Barro 1991; Baumol 1986; Song 1996), and total factor productivity. Miller (2002) discovered that total factor productivity is more convergent than real GDP per capita through data research on developed and developing countries. Strazicich and List (2003) were the first to study the convergence of carbon dioxide emissions, and found that the per capita carbon dioxide emissions of 21 industrial countries are spatially convergent. Westerlund and Basher (2008) revealed the convergence of per capita carbon dioxide emissions in developed and developing countries. Zhang et al. (2013) used panel data from 29 provinces in China as samples and found that the national carbon productivity and per capita GDP have conditional β convergence, but the gap between the eastern, central and western regions is obvious.

The above-mentioned papers provide theoretical references for revealing the differences in economic growth between countries and regions, but there are few papers on productivity convergence analysis for a specific industry, and some scholars in the later period began to fill the gaps in this area. Gouyette and Perelman (1997) calculated the convergence of total factor productivity (TFP) in the manufacturing and service industries in 13 OECD economies, and the results showed that only the service industry TFP exhibited a σ convergence feature. Miketa and Mulder (2005) conducted an empirical study on the energy productivity of 10 manufacturing sub-sectors in 56 economies from 1971 to 1995. The results showed that the cross-country differences in energy productivity levels in most manufacturing sectors except for non-ferrous metals are gradually decreasing, indicating the existence of σ convergence and β convergence. Xu and Zhao (2019) used the Non-parametric DEA-Malmquist Index method to conduct an in-depth analysis of the regional differences and convergence of China's information service industry's total factor productivity. The research results provide strong evidence for the absolute and conditional convergence characteristics of the information service industry's TFP. Liu and Zhang (2010) decomposed China's service industry TFP into two aspects, technical efficiency and technological progress, and pointed out that the growth and decomposition of service industry TFP in each province manifested as a long-term convergence trend. Yang et al. (2015) used the global malmquist-luenberger index to calculate and analyze the carbon productivity of 26 manufacturing industries in China. They discovered that the carbon productivity of the manufacturing industry has obvious σ convergence and β convergence, and the convergence characteristics between sectors have heterogeneity, the relatively clean sector has a faster convergence rate than the relatively polluted sector. Wang and Wang (2018) empirically analyzed the convergence and divergence of energy productivity in service industry segments in 40 economies around the world. The study proved that service industry energy productivity has absolute and conditional β convergence but no σ convergence. The above literature provides important reference value for the research on the productivity improvement of the industry, but unfortunately, these studies have ignored the spatial correlation between regions. In fact, the production and operation activities between regions are not independent of each other. Therefore, it is necessary to add spatial effects to the convergence model for analysis (Xiao et al. 2018).

Searching the existing literature, we can easily find that the current literature on carbon productivity in the steel industry is particularly scarce. This paper constructed an SBM model that includes undesired output and the Global-Malmquist-Luenberger index to measure the SICP in 29 provinces in China from 2006 to 2017, then analyzed it statically and dynamically. The GML index of carbon productivity was decomposed into technical efficiency change index (EC) and technological progress efficiency index (TC), furthermore, the regional heterogeneity of carbon productivity was verified. On this basis, this paper introduces spatial effects into the analysis framework of traditional convergence models, and constructs a spatial convergence model to systematically investigate the spatial convergence of SICP, in order to provide a reference for the

measurement of SICP, help to understand the spatial convergence characteristics of SICP, and provide a scientific basis for formulating relevant policies.

2 Method and Data

2.1 Slack-Based Measure, SBM

Non-parametric data envelopment analysis (DEA) uses mathematical optimization to study the relative efficiency between multi-output and multi-input decision units (DMU), which was first proposed by famous operational research scientists Charnes, Cooper and Rhodes in 1978. It takes each evaluation sample as a production decision unit, and each production decision unit has its input and output. The data of these input and output observations are linearly programmed to obtain a relatively effective production front. The efficiency value of the production decision unit is measured by comparing and analyzing the degree to which the decision unit deviates from the relatively effective production front surface. The DEA has proved to be an effective tool and widely used in the evaluation of efficiency and productivity in various economies.

Conventional DEA models only consider the desired input and production to evaluate the efficiency of economic units. However, in the efficiency evaluation considering resource and environment constraints, the expected input and output, as well as the non-expected input and output, generally exist at the same time, and the traditional DEA efficiency evaluation does not completely conform to the actual situation. As a result, the direction distance function (DDF) which can distinguish the expected output from the non-expected output is widely used in the efficiency evaluation of economic growth with resource and environment problems. But one obvious disadvantage of the DDF is that the improvement of non zero slacks are ignored. The non-radial and non-angle Slacks-Based Measure (SBM) model solves this problem by introducing slack variables into the objective function, and has been widely used in efficiency measurement. The SBM model of non-expected output is shown in Formula (1):

$$\rho^* = \min \frac{1 - \frac{1}{N} \sum_{n=1}^N \frac{s_n^x}{x_{k'n}^t}}{1 + \frac{1}{M+I} \left(\sum_{m=1}^M \frac{s_m^y}{y_{k'm}^t} + \sum_{i=1}^I \frac{s_i^b}{y_{k'i}^t} \right)}$$

$$\text{s.t.} \begin{cases} \sum_{k=1}^K \lambda_k^t x_{kn}^t + s_n^x = x_{k'n}^t, n=1, 2, L, N \\ \sum_{k=1}^K \lambda_k^t y_{km}^t - s_m^y = y_{k'm}^t, m=1, 2, L, M \\ \sum_{k=1}^K \lambda_k^t b_{ki}^t + s_i^b = b_{k'i}^t, i=1, 2, L, I \\ \lambda_k^t \geq 0, s_n^x \geq 0, s_m^y \geq 0, s_i^b \geq 0, k=1, L, K \end{cases} \quad (1)$$

Formula (1) is a SBM model containing non-consensual output based on the condition of constant returns to scale (CRS), in which $(x_{k'n}^t, y_{k'm}^t, b_{k'i}^t)$ is the input and output value of t period, (s_n^x, s_m^y, s_i^b) represents the slack variable of input and output. The slack variable greater than 0 in constraints indicates that the actual input and non-expected output are larger than the input and output at the boundary, while the actual expected output is smaller than the output at the boundary. therefore, (s_n^x, s_m^y, s_i^b) indicates the amount of overuse of input, over-emission of non-expected output and insufficient production of expected output. The objective function ρ^* about s_n^x, s_m^y, s_i^b is strictly regressive and $0 < \rho^* \leq 1$. Production is considered to be fully efficient only when the evaluated production unit meets $\rho^* = 1 (s_n^x = 0, s_m^y = 0, s_i^b = 0)$, and $\rho^* < 1$ indicates that the evaluated production unit has efficiency loss and there is room for improvement in input and

output.

2.2 Global-Malmquist-Luenberger index

Malmquist productivity index was proposed in 1953 and used to study productivity changes, and is widely used in the research of dynamic efficiency trends. “Dynamic” is one of the important attributes of the steel industry, so the measurement angle of static efficiency is not appropriate. The total factor productivity considering resource and environment problems can be measured by Malmquist Luenberger productivity index, which not only takes the advantage that Malmquist productivity index does not need to set production function in advance, but also analyzes the problem of non-expected output optimization and can be integrated with other models according to research needs. But ML productivity index has the problems of non-transportability and non-circularity, it can only judge the productivity near the production period, and can not measure the long-term trend of productivity level. Oh (2010) found that constructing Global-Malmquist-Luenberger (GML) productivity index on the basis of global production set can solve these problems, at the same time, it can effectively avoid the problems of linear programming without solution and technical regression. Therefore, this paper chooses to use the Global-Malmquist-Luenberger productivity index based on the SBM model (SBM-GML index), the formula is as follows:

$$GML_t^{t+1} = \frac{1 + D_0^G(x_t, y^{g,t}, y^{b,t}; y^{g,t}, -y^{b,t})}{1 + D_0^G(x^{t+1}, y^{g,t+1}, y^{b,t+1}; y^{g,t+1}, -y^{b,t+1})} \quad (2)$$

Decompose:

$$GML_t^{t+1} = EC_t^{t+1} \times TC_t^{t+1} \quad (3)$$

$$EC_t^{t+1} = \frac{1 + D^t(x_t, y^{g,t}, y^{b,t}; y^{g,t}, -y^{b,t})}{1 + D^{t+1}(x^{t+1}, y^{g,t+1}, y^{b,t+1}; y^{g,t+1}, -y^{b,t+1})} \quad (4)$$

$$TC_t^{t+1} = \frac{1 + D^G(x^t, y^{g,t}, y^{b,t}; y^{g,t}, -y^{b,t})}{1 + D^t(x^t, y^{g,t}, y^{b,t}; y^{g,t}, -y^{b,t})} \times \frac{1 + D^{t+1}(x^{t+1}, y^{g,t+1}, y^{b,t+1}; y^{g,t+1}, -y^{b,t+1})}{1 + D^G(x^{t+1}, y^{g,t+1}, y^{b,t+1}; y^{g,t+1}, -y^{b,t+1})} \quad (5)$$

where, GML_t^{t+1} represents the change of the overall efficiency value, When the $GML_t^{t+1} > 1$, it indicates that the efficiency value of the t+1 period increases relative to the t period, which reflects the growth rate attribute of the GML, that is, dynamic. GML_t^{t+1} can be further decomposed into global technical efficiency change index (EC_t^{t+1}) and technological progress change index (TC_t^{t+1}). EC_t^{t+1} indicates the degree to which the production decision-making unit approximates the global production front surface from t to t+1 period, when the $EC_t^{t+1} > 1$, the approximation is improved, otherwise it deteriorates. TC_t^{t+1} refers to the movement effect of the production front surface, whose value is greater than 1, which indicates the expansion degree of the production front surface from the t period to the t+1 period to the global technical front surface, while less than 1 is the opposite.

2.3 Convergence analysis

2.3.1 σ convergence

There are many indicators to measure the degree of dispersion to judge the σ convergence of carbon productivity, such as standard deviation, coefficient of variation and σ coefficient. Although these indexes differ in formula, the basic principle is the same. If the index decreases gradually with the passage of time, it indicates the existence of σ convergence, and vice versa. In this paper, the σ coefficient is used to judge whether the SICP of China has σ convergence. The formula is:

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$$\sigma = \sqrt{\frac{\sum (\ln CP_i - \ln \overline{CP^2})^2}{N}} \quad (6)$$

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where σ stands for the σ coefficient, the $\ln CP_i$ and the $\ln \overline{CP^2}$ represent SICP and the average of square of SICP, the $\ln$ denotes the logarithm, the i denotes the province, and the N represents the number of provinces.

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2.3.2 β convergence

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β convergence is most widely used in convergence research. The classical β convergence is divided into absolute β convergence and conditional β convergence. The classical β convergence model is constructed as follows:

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$$\ln \frac{CP_{i,t+1}}{CP_{i,t}} = \alpha + \beta \ln CP_{i,t} + \sum_{k=1}^n \theta_k \ln X_{k,i,t} + \varepsilon_{i,t} \quad (7)$$

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Among them, $CP_{i,t}$ and $CP_{i,t+1}$ is the SICP in the $t, t+1$ year of i province, σ is a constant term, and the β is judgment coefficient of convergence. When $\beta < 0$ significant, the SICP converges, otherwise it tends to diverge. $\varepsilon_{i,t}$ is a random disturbance term and the θ_k is the regression coefficient of the control variable X . When $\theta_k \neq 0$, the model is absolute β convergence. When $\theta_k = 0$ the model is conditional β convergence. Absolute β convergence refers to the negative correlation between the growth rate of carbon productivity in different regions and the initial level with the passage of time, and the carbon productivity in each region converges to the same level. Conditional β convergence means that the SICP in each region will converge to their steady state level over time due to the differences in industrial structure, energy consumption intensity, human capital and so on. In addition, the natural logarithm of non-percentage data is taken in regression analysis, which reduces the dispersion of data.

The classical β convergence examines the convergence of SICP in time evolution, while ignoring spatial factors may lead to biased of the estimated results (Hou and Yao 2019). Therefore, this study introduces spatial measurement into classical β convergence analysis, and constructs the following spatial lag model (SLM), spatial error model (SEM) and spatial Doberman model (SDM):

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①SLM β convergence:

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$$\ln \frac{CP_{i,t+1}}{CP_{i,t}} = \alpha + \rho \sum_{k=1}^n \omega_{ij} \ln \frac{CP_{i,t+1}}{CP_{i,t}} + \beta \ln CP_{i,t} + \sum_{k=1}^n \theta_k \ln X_{k,i,t} + \varepsilon_{i,t} \quad (8)$$

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②SEM β convergence:

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$$\ln \frac{CP_{i,t+1}}{CP_{i,t}} = \alpha + \beta \ln CP_{i,t} + \sum_{k=1}^n \theta_k \ln X_{k,i,t} + \varphi_{i,t}; \varphi_{i,t} = \rho \sum_{k=1}^n \omega_{ij} \varphi_{i,t} + \varepsilon_{i,t} \quad (9)$$

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③SDM β convergence:

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$$\ln \frac{CP_{i,t+1}}{CP_{i,t}} = \alpha + \rho \sum_{k=1}^n \omega_{ij} \ln \frac{CP_{i,t+1}}{CP_{i,t}} + \beta \ln CP_{i,t} + \sum_{k=1}^n \theta_k \ln X_{k,i,t} + \sum_{j=1, k=1}^n \omega_{ij} \phi_k \ln X_{k,i,t} + \varepsilon_{i,t} \quad (10)$$

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where, Formula (8) is the SLM β convergence model, which is also called the spatial autoregressive model. it adds the spatial autocorrelation term of the explained variable, which is suitable for studying the situation of mutual influence and interdependence between adjacent areas due to spillover effects. The Formula (9) is the SEM β convergence model, which contains the spatial autocorrelation term of the error term, which reflects that the spatial dependence between regions is caused by some missing variables that affect the adjacent region. SLM and SEM emphasize the endogeneity of spatial effect, and the spatial effect between regions may also come from exogenous variables. SDM model solves this problem well, it not only contains the spatial lag term of the explained variable, but also introduces the spatial lag term of the independent variable, which

takes into account the influence of the spatial spillover effect of the independent variable on the dependent variable (Li et al. 2019). Like β classical convergence model, whether the value of the θ_k is zero determines whether the model β absolute convergence or conditional convergence. ω_{ij} is the element in the W of spatial weight matrix constructed by adjacency weight matrix, ρ is the space lag coefficient, which reflects the direction and degree of space overflow, $\varphi_{i,t}$ is the spatial autocorrelation error term; $X_{k,i,t}$ represents the control variable for conditional convergence analysis, $\ln X_{k,i,t}$ is the independent variable spatial lag term, θ_k is the coefficient of $\ln X_{k,i,t}$, which is used to investigate the effect of independent variables (influencing factors) in adjacent areas on dependent variable observations (carbon productivity). ϕ_k is the regression coefficient of the spatial interaction effect between the spatial weight matrix ω_{ij} and the control variable $X_{k,i,t}$. $\varepsilon_{i,t}$ is a random disturbance term.

2.4 Variables and Data Description

2.4.1 Carbon productivity in steel industry

Before establishing a SBM model containing non-expected outputs, the elements of input and output need to be determined. Generally speaking, when studying carbon productivity or energy efficiency, scholars will use GDP or industry output value as expected output, and carbon emissions as non-expected output to model (Li et al. 2019).

On the basis of the previous literature, combined with the characteristics of the steel industry, and considering the accessibility of the research data and the consistency of statistical caliber, 29 provinces of China (excluding Hong Kong, Macao, Taiwan, Tibet and Hainan, where data are missing), were studied as decision-making units between 2006 and 2017. The index description and data units are shown in Table 1.

Three points need to be explained: Firstly, select fixed assets investment in the steel industry as a measure of capital investment and convert it to the same price in 2006 according to the fixed assets price index over the years; Secondly, in the steel industry, the main energy inputs include coal, gasoline, fuel oil, coke, diesel, and electricity. Thirdly, there are eight provinces (Jiangsu, Shanghai, Guizhou, Hebei, Zhejiang, Guangxi, Sichuan and Shandong) where relevant data is not available. The energy consumption of these eight regions is estimated using the energy structure of similar provinces, referring to the treatment methods of Lu (2016) and Lin (2017).

Tab.1. Selection and Meaning of Variables

Level I indicators	Level II indicators	Indicator description	Unit
Input	Labour	Number of employees in the steel industry at the end of the year	Person
	Capital	Fixed assets investment in steel	10^8 yuan
	Energy	Total energy consumption in steel	10^4 tons of standard coal
	Expected output	Gross industrial output of steel	10^8 yuan
Output	Non-expected output	Carbon dioxide emissions from steel	10^4 tons

Table 2 shows that in terms of output indicators, the standard deviation of gross output of the steel industry in 29 provinces from 2006 to 2017 is large, indicating that the total scale and total level of CO2 emissions vary greatly, and the standard deviation of emissions is also high. Therefore, it can be seen that the relationship between total scale, total level and CO2 emissions is close. From the analysis of input index,

there are great differences in fixed assets investment, year-end employment and total energy consumption, which provide a research basis for the measurement of carbon productivity and the analysis of influencing factors steel industry.

Tab.2. Statistical description of input-output variables

Variables	sample value	Max	Min	mean	Standard deviation
Fixed assets investment	348	733.85	0.10	113.23	123.38
Number of employees at year end	348	325393	2940	72839.89	62704.47
Total energy consumption	348	11919.73	5.98	1751.60	2170.60
Gross output of steel industry	348	10247.80	42.01	1694.44	1995.22
CO2 emissions	348	38972.80	36.16	5825.30	6905.40

2.4.2 Selection of conditional β convergence control variables

(1) Industrial structure (IS). Industrial structure refers to the proportion of agriculture, industry and service industry in the national economy, and the carbon productivity of different industries is different. This paper uses the ratio of tertiary industry to regional GDP in various provinces of China to express IS, reflecting the structural effect of carbon productivity.

(2)Economic development level (PGDP). The level of economic development has always been one of the important factors affecting carbon productivity. Economic developed areas not only have higher income levels, but also pay more attention to environmental governance and energy-saving technology development (Mikayilov et al. 2018). Per capita GDP is adopted in this paper to reflect the level of economic development.

(3) Enterprise size (ES): Based on the existing literature, this paper selects fixed assets per capita to measure the size of the enterprise, which reflects the scale effect of carbon productivity. Generally speaking, large enterprises have more advantages than small and medium-sized enterprises in energy-saving technology innovation, and tend to form economies of scale more easily.

(4) Human capital (EDU): This paper uses the per capita years of education. According to experience, people with higher education are more innovative and more environmentally conscious.

(5) Energy consumption intensity (EC): This paper uses the ratio of total primary energy consumption to GDP to measure the energy saving and consumption reduction of enterprises. The evolution of this ratio reflects the change of energy use efficiency and is an index of environmental effect.

(6) Research and development (RD): In general, increasing R&D can improve the productivity of enterprises. This paper uses the proportion of experimental researchers to the labor force to reflect the technical effect of carbon productivity.

2.4.3 Data sources

According to the principle of availability, validity and maneuverability of the data, the panel data of 29 provinces in Chinese from 2006 to 2016 (except Tibet and Hainan) were selected to calculate the SICP and the spatial convergence of each province. The relevant data of the variables involved are derived from China Statistical Yearbook, China Energy Statistics Yearbook, China Environmental Statistics Yearbook and the national data website.

3 Results and Discussion

3.1 GML index and its decomposition

In this paper, GML index is used to analyze the changes of SICP and its decomposition items TC and EC. The results are shown in Table 3 and Table 4.

According to the results in Table 3, from the perspective of the steel industry as a whole from 2006 to 2017, the GML index of SICP was on a downward trend only in 2008-2009 and 2011-2012, with a decrease of 3.7% and 5.9% respectively, and the GML index for other years was above 1, indicating an overall improvement in SICP over the sample period. The GML index of SICP increased by an average of 7.3% per year from 2006 to 2017, indicating a significant increase in overall input-output efficiency. The decomposition of the GML index shows that the technical efficiency index (EC) has increased by 0.5% annually, indicating that the utilization rate of investment in the steel industry has increased, and the efficiency of resource allocation and management have also improved; The technology progress index (TC) rose 6.8% and was larger than EC, which shows that the essence of increasing SICP lies in technological progress, that is, although technical efficiency is also conducive to improving carbon productivity, technological progress has made a greater contribution to SICP.

Tab.3. GML Index and it's Decomposition of SICP in 2006-2017

	GML index	EC	TC
2006-2007	1.293	0.868	1.490
2007-2008	1.235	1.043	1.184
2008-2009	0.936	1.220	0.767
2009-2010	1.172	1.024	1.144
2010-2011	1.013	1.199	0.845
2011-2012	0.941	0.913	1.030
2012-2013	1.060	1.214	0.873
2013-2014	1.119	1.010	1.108
2014-2015	1.032	0.949	1.088
2015-2016	1.055	0.995	1.061
2016-2017	1.005	0.734	1.368
Average	1.073	1.005	1.068

In Table 4, at the provincial level, the only province with a decline in the GML index for 2006-2017 is Heilongjiang, which should improve its business management model to improve technical efficiency. The GML index for the remaining provinces is greater than 1, indicating that the SICP has grown steadily during this period. From a regional perspective, the average value of the GML index in the eastern, central and western regions is greater than 1, with a cumulative increase of 7.4%, 6.4% and 7.8% respectively. Only the GML index in the central region is below the national level.

From the GML decomposition results, TC and EC of the eastern and central regions are both greater than 1, indicating that both TC and EC have contributed to the improvement of carbon productivity. It is worth noting that while the EC of the western region is less than 1, the GML index is higher than the other two regions. This conclusion breaks the traditional notion of “the western total factor carbon productivity is lagging behind”, which can be explained by geographical location and resource endowment. The eastern region is close to the port and has convenient transportation, which is conducive to the introduction of advanced enterprise operation models and science and technology. In addition, while developing the economy, the eastern region also pays more attention to the goal of sustainable economic development. Compared with the eastern region, the central and western regions are more abundant in natural resources. For a long time, the

steel industry has been showing high consumption, high pollution, and high emissions. However, with the transformation and upgrading of China's economic structure and the implementation of environmental protection policies, in order to keep up with the pace of economic development and resolve the problem of overcapacity faced by the steel industry, the western region has begun to focus on the reform of the steel industry, intensified the supply-side structural reforms, and strengthened the research and development of new products, relying on policy support to promote the technology of steel industry.

Tab.4. Annual GML index and its decomposition of 29 provinces in 2006 - 2017

Region	GML	EC	TC	Region	GML	EC	TC
Beijing	1.205	1.041	1.158	Hubei	1.076	1.032	1.043
Tianjin	1.149	1.092	1.052	Hunan	1.076	1.026	1.049
Hebei	1.049	1.004	1.045	Sichuan	1.104	0.899	1.228
Liaoning	1.065	1.014	1.05	Chongqing	1.132	1.112	1.018
Shanghai	1.145	1.11	1.031	Guizhou	1.063	0.93	1.143
Jiangsu	1.011	1	1.011	Yunnan	1.089	1.016	1.072
Zhejiang	1.039	1.007	1.031	Shaanxi	1.067	0.991	1.076
Fujian	1.018	0.988	1.031	Gansu	1.066	1.005	1.061
Shandong	1.009	0.937	1.077	Qinghai	1.039	0.961	1.082
Guangdong	1.07	1.037	1.032	Ningxia	1.061	0.921	1.152
Shanxi	1.079	1.025	1.052	Xinjiang	1.067	1.016	1.051
Jilin	1.045	0.996	1.049	Guangxi	1.115	1.044	1.069
Heilongjiang	0.982	0.913	1.075	Nei Mongol	1.063	1.01	1.052
Anhui	1.121	1.07	1.048	East	1.074	1.022	1.051
Jiangxi	1.028	0.925	1.11	Middle	1.064	1.004	1.059
Henan	1.111	1.058	1.05	West	1.078	0.99	1.09
				Average	1.073	1.005	1.068

In summary, the steel industry in different provinces should develop business strategy in the light of its own reality, with different emphasis on optimizing the path of carbon productivity improvement.

3.2 α convergence and β convergence

The above analysis indicates that there are obvious regional differences in carbon productivity in China's provincial steel industry. Next, this paper will further investigate the spatial convergence of SICP.

3.2.1 Spatial autocorrelation analysis

Tab.5. Global Moran's I index of SICP

year	Moran's I	p value	z-value	year	Moran's I	p value	z-value
2006	0.0250	0.254	0.5746	2012	0.5196	0.01	4.6987
2007	0.0044	0.343	0.2768	2013	0.3926	0.01	3.5772
2008	0.1091	0.011	1.2316	2014	0.4580	0.005	4.0319
2009	0.2686	0.013	2.6578	2015	0.4651	0.01	4.2177
2010	0.4857	0.005	4.3037	2016	0.4686	0.005	3.9759
2011	0.6031	0.01	5.2627	2017	0.4467	0.005	4.0214

Before studying the spatial convergence of SICP, it is necessary to examine the spatial correlation of China's SICP, and this paper uses the Moran's I index to show the degree of Spatial autocorrelation. As shown

in the Table 5, the global Moran's I index of SICP for all years from 2006 to 2017 is positive and significant at 1% except 2006 and 2007, indicating a significant spatial positive correlation in SICP. Spatial dependence exists because neighboring provinces are relatively similar in terms of resource endowments and economic development levels, and because of the development of transportation and communications, the exchanges between provinces are becoming more frequent. In addition, it can be seen from the data that the global Moran's I index shows a trend of rising volatility, which indicates that the dependence between provinces is still increasing. All data are calculated by Geoda095i software.

3.2.2 σ Convergence

Using Formula (4) above, we obtained the results of the σ convergence in 2006-2016 for the whole country and the three regions of the East, Central and West. As shown in Figure 1, from a national perspective, although σ coefficient of China's SICP fluctuated in 2006-2016, it remained basically stable and did not show a trend of convergence or divergence, indicating that the overall national SICP of the absolute inter-provincial difference has not narrowed.

Fig. 1. σ convergence test of SICP

Regionally, the σ coefficient in the eastern region, bounded by 2010, increased in 2006-2010, declined in 2010-2014, rebounded after 2014, showing an overall trend of "inverted V-type" evolution, indicating that the σ convergence exists in the eastern region of the SICP sample late. The σ coefficient in the central region showed a characteristic of slow decline from 2008 to 2016, indicating a σ convergence of SICP in the central region, but the convergence rate is relatively small. In contrast to the eastern region, the trend line of Western σ presents the characteristics of "V-type" change, showing a convergence trend in 2006-2009, and slowly rising after 2009, showing a divergent trend.

3.2.3 β Convergence

With regard to spatial β convergence, the moran's I index method has been used above to prove the spatial correlation of SICP in each province, and it has been concluded that there is a significant positive correlation between the SICP in neighboring provinces. Since the regression result is influenced by the fixed effect, combined with the model selection principle proposed by Paul (2010), when the time span of the spatial panel data is long, the use of fixed effects can make the model fit better. Therefore, this paper uses LR test to determine whether to select the fixed effect. As shown in Table 6, both the entity fixed effect and the time fixed effect passed the test at the significance level of 1%, which also indicates that the hypothesis of random effect is rejected, so the spatial convergence model of the Time-entity double fixed effect is selected.

Tab.6. LR-test

results

Test name	Detection value	degrees of freedom	p value
LR-test of entity fixed effects	92.4542***	29	0.00
LR-test of time fixed effect	61.2603***	11	0.00

Moreover, the optimal spatial measurement model can be selected based on the statistics of LogL, σ^2 and R^2 . The smaller the value of σ^2 , the larger the statistical value of LogL and R^2 , indicating that the model has better explanatory power. In order to prove the necessity of considering the spatial effect, Table 7 lists the regression results of the classical convergence model and the spatial convergence model at the same time. In the three spatial β convergence models of SLM, SEM, and SDM, the statistical values of LogL and R^2 of slm and sem are larger than those of the SDM model, and the σ^2 value of SDM is the smallest. This shows that whether it is absolute β convergence or conditional β convergence, the goodness of fit of the SDM model is the highest, and the model's explanatory ability is stronger. In summary, the SDM spatial measurement model under double fixed effect is the most suitable for detecting the convergence of SICP.

Tab.7. Regression Results of β Convergence of SICP in China

Variables	Classical	Spatial absolute β convergence			Classical	Spatial conditions β convergence		
	Absolute β convergence	SLM	SEM	SDM	Conditions β convergence	SLM	SEM	SDM
β	-0.117*** (-4.22)	-0.401*** (-9.44)	-0.406*** (-10.02)	-0.384*** (-9.22)	-0.119*** (-4.13)	-0.457*** (-9.70)	-0.469*** (-9.77)	-0.480*** (-10.46)
lnIS					0.362* (1.87)	0.281* (1.45)	0.362* (1.89)	0.384** (2.03)
lnPGDP					0.074*** (3.47)	-0.001* (-0.08)	0.074*** (3.48)	0.070*** (3.38)
lnES					0.042 (1.39)	-0.016** (-0.81)	0.042 (1.39)	0.039 (1.31)
lnEDU					-0.105*** (-3.69)	0.014*** (0.48)	0.018** (3.69)	0.121*** (3.08)
lnEI					-0.939* (-2.64)	-0.074 (-0.50)	-0.939*** (-2.64)	-0.723** (-2.04)
lnRD					-0.024* (-1.68)	0.025** (0.33)	-0.025* (-1.68)	0.086** (2.29)
C	-0.135*** (-3.64)				-0.346 (-0.61)			
ρ		0.0019*** (0.81)	0.0022*** (1.06)	0.0087*** (4.07)		0.0021*** (0.89)	0.0081*** (3.92)	0.0094*** (3.78)
R^2	0.100	0.242	0.219	0.257	0.279	0.282	0.279	0.376
LogL		-77.47	-50.13	-42.01		-46.77	-37.28	-14.09
σ^2		0.062	0.080	0.077		0.081	0.076	0.067
Convergence rate	0.117	0.401	0.406	0.384	0.119	0.457	0.469	0.480

Some convergence characteristics can also be observed from Table 7:

(1) Regardless of whether it is an absolute or conditional convergence model, the regression coefficient β of

all $\ln CP_{i,t}$ is less than zero at the 1% significance level, which indicating that the SICP as a whole has convergence characteristics, that is, regions with lower SICP have a "catch-up effect" on regions with higher carbon productivity. The existence of absolute β convergence suggests that the growth rate of low carbon productivity regions is faster than that of high carbon productivity regions, which reduces the difference in SICP between provinces. The existence of the conditional β convergence for carbon productivity indicates that each region is tending to its own steady-state level. In addition, the spatial effect coefficient ρ in all spatial convergence models is significantly greater than 0, which indicates that there is a positive spatial spillover effect in the overall SICP.

(2) Comparing the classical and spatial β convergence models, it can be seen that the addition of spatial effects speeds up the convergence speed. The convergence speed of the SDM model in absolute β convergence (0.3843) is about 3 times that of the classical convergence model (0.1167), and the conditional β convergence of the SDM model (0.4800) is about 4 times the classical model (0.1189), which shows that the spatial effect is one of the important factors in the convergence of SICP, has an accelerated effect on the convergence speed, neglecting the spatial effect will lead to the deviation of the result. The possible reason is that the uneven distribution of SICP in each province, coupled with economic development and the improvement of transportation and communication facilities, makes the resource and technology exchanges in the neighboring areas more frequent, and the resulting spatial spillover effect narrows the efficiency differences between regions and shortens the convergence period.

(3) Comparing the absolute convergence and conditional convergence model, it can be observed that the conditional convergence model after adding the control variable performs better in both convergence speed and fitting excellence, because the conditional convergence model takes into account the factors leading to heterogeneity between provinces, such as industrial structure, economic development level, energy consumption level, etc., which accelerates the convergence speed of SICP, thus making the test results of the model more accurate.

(4) Comparing β convergence results with the σ convergence results above, the existence of β convergence and the absence of σ convergence suggest that although the low SICP is growing faster than that of the provinces with high carbon productivity, the absolute difference in carbon productivity between provinces has not narrowed.

From the regression results of the control variables of the conditional convergence model in Table 7, five of the six variables have a significant effect on the SICP, and the symbols of SDM and classical convergence model regression coefficients are basically the same, but there are some differences in significance level and influence degree. According to the measurement results of the SDM model, we can draw the following conclusions:

(1) The coefficient of IS is significantly positive, implying that the increase in the proportion of tertiary industry contributes to the growth of SICP in the region. Under the premise of realizing the goal of China's macro-economic regulation, the utility of the equivalent amount of financial investment in the tertiary industry is the greatest, which shows that the power of the tertiary industry to the economy is constantly improving. The tertiary industry has the least dependence on energy consumption, and vigorously developing the tertiary industry can not only drive sustained economic growth, but also play an important role in promoting carbon productivity, so under the new normal of economy, we should actively promote the optimization and upgrading of industrial structure, fully release the potential of the tertiary industry in energy conservation and emission reduction, improve energy efficiency, and explore ways and means to make the tertiary industry a new growth point of regional economy.

(2) The positive impact of PGDP on carbon productivity at the 1% level of significance indicates that PGDP growth plays an important role in accelerating carbon productivity. Economic growth can provide technical, financial and human support for the improvement of coal utilization levels, and in more developed regions, while promoting industrial development, environmental regulation will be strengthened and more

attention will be paid to the restrictions on CO₂ emissions (Wang and Wei 2020). Regions with different levels of economic development have different requirements for carbon intensity. In China, economically developed provinces bear a relatively heavy responsibility for carbon reduction, while underdeveloped provinces such as Xinjiang, Hainan, have relatively light energy conservation and emission reduction tasks. Because of the positive correlation between PGDP and carbon productivity, all regions should insist on combining energy conservation and emission reduction with economic growth, pay attention to the sustainability of economic development, and realize the green development of national economy.

(3) The estimated coefficient of ES is positive, but it fails the significance test, which shows that the expansion of enterprise scale can be beneficial to the improvement of carbon productivity to a certain extent, has a positive scale effect, but has not yet produced the ideal improvement effect on the SICP, which may be due to the fact that the company has not paid attention to the improvement of resource allocation and regeneration efficiency while expanding its scale, and has not promoted the formation of the integrity of the industrial chain, resulting in limited improvement in carbon productivity.

(4) The improvement of EDU has a significant positive effect on the growth of SICP. Human capital is one of the important factors to improve the productivity of enterprises. This paper is based on the number of years of education per capita to measure human capital, the number of years of education reflects people's level of education, higher stock of human capital can improve regional productivity and technological innovation ability, at the same time, citizens' awareness of environmental protection will be enhanced with the improvement of education level. In addition, the level of human capital also directly reflects the strength of a region's ability to absorb advanced knowledge and technology at home and abroad and to accept management experience. Therefore, increasing human capital will help the steel industry to increase carbon productivity.

(5) EI has a negative effect on SICP at a significant level of 5%, which indicates that the lower the value of EI, the higher the energy efficiency per unit of output in the production process. EI is an index used to evaluate the efficiency of energy comprehensive utilization, which reflects the economic and environmental benefits of energy utilization and is the goal of "win-win" for governments and producers. Coal plays a dominant role in China's industrial energy consumption, and the proportion of coal consumption in total energy consumption is much higher than the world average, and it is well known that coal's carbon production efficiency is relatively low, which puts great pressure on China's energy conservation and emission reduction efforts. The higher the intensity of energy consumption, the stronger the dependence of enterprises on energy. Therefore, increasing the development of clean energy, actively promoting improvement within the sector, and increasing the input of labor, capital and technological innovation will not only help to reduce energy intensity in the production process and improve core competitiveness, but also help to decouple economic growth and energy use, thus further ensuring energy security.

(6) The regression coefficient of R&D investment is significantly positive, indicating that the SICP has a positive technical effect, that is, the increase in R&D investment in science and technology can bring about the growth of regional carbon productivity. The strength of R&D investment directly reflects the innovation ability of an enterprise, and innovation is the soul of enterprise production and development. Research and development investment is an important way to promote technological, ideological and institutional progress, on the one hand, to improve steel production efficiency, expand economic output while reducing production costs, on the other hand, it also helps to improve regional environmental governance capacity, improve energy efficiency, achieve energy conservation and emission reduction targets, thereby promoting the regional SICP.

Taking into account the existence of regional heterogeneity, Table 8 further presents the regression results of conditional β convergence in the eastern, central, and western regions, and at the same time, in order to facilitate comparative analysis, the classical β convergence results are also included in the table. From a regional perspective, the β convergence coefficients of the three regions are negative and pass the significance

test, indicating that there is a conditional β convergence for the SICP in each region. The coefficient of spatial effect is greater than 0 at the 1% significance level, and the convergence speed of the β convergence model, which is added to the spatial effect, is greater than that of the classical convergence model, which shows that the SICP in each region shows a strong spatial correlation and positive spatial spillover effect. Although the differences of SICP in the provinces within the three regions have narrowed over time, the rate of spatial convergence has shown an increasing order in the central (0.148), western (0.204) and eastern (0.221). Convergence is the slowest in the central region, possibly due to its inland location, low level of market development and backwardness from the east in terms of transport, communications and other infrastructure, which leads to a slow reduction in efficiency differentials among the provinces of the central region. Most provinces in the eastern region are early implementers of energy technology reform, industrial infrastructure is more mature, steel enterprises have a high level of personnel quality and advanced technology, management system, thus speeding up the process of scale of the industry and convergence speed.

Tab.8. Conditions β Convergence Results of SICP in Regions

Variables	East		Middle		West	
	Classical	Spatial	Classical	Spatial	Classical	Spatial
β	-0.089*** (-3.06)	-0.221*** (-6.37)	-0.081*** (-3.12)	-0.148*** (-4.50)	-0.142*** (-4.59)	-0.204*** (-5.95)
lnIS	0.407** (2.16)	0.331* (1.88)	0.128 (0.71)	0.086 (0.48)	0.402** (2.06)	0.365** (1.87)
lnPGDP	-0.002 (-0.27)	-0.019 (-1.81)	0.002* (0.23)	0.004* (0.04)	0.007* (0.94)	0.009* (1.11)
lnES	-0.002 (-0.07)	-0.002 (-0.05)	0.006 (0.28)	0.035 (1.37)	-0.001 (-0.04)	-0.003 (-0.14)
lnEDU	0.010* (1.71)	0.018*** (3.27)	-0.004 (-0.82)	0.005** (0.99)	0.006 (1.25)	0.011** (2.21)
lnEI	0.028 (0.16)	-0.220 (-1.13)	0.206 (1.27)	-0.125 (-0.61)	-0.046 (-0.27)	-0.049 (-0.26)
lnRD	0.007 (0.47)	0.013 (0.96)	-0.021 (-1.54)	0.015 (1.09)	0.010 (0.68)	0.010 (0.72)
C	-0.081 (-0.95)		-0.194** (-2.28)		-0.361*** (-3.539)	
P		0.010*** (3.82)		0.008*** (4.05)		0.010*** (4.71)
R ²	0.100	0.206	0.103	0.140	0.134	0.167
LogL		-15.374		-11.790		-27.954
Convergence rate	0.089	0.221	0.081	0.148	0.142	0.204

From the regression results of the control variables in each region, IS has a positive effect on the SICP in the east and west, and the impact on the central region is not significant, which may be due to the smaller growth rate of the tertiary industry in the central region in 2016 than in the eastern and western regions, and the proportion of the tertiary industry in the eastern and central and western regions increased by 34.78%, 14.46%, and 39.18% respectively on the basis of 2006. PGDP has a significant positive impact on the central and western regions, suggesting that when other conditions are equal, higher levels of economic development will help increase regional carbon productivity. EDU has a positive effect on the SICP in all three regions,

which indicates that the carbon production efficiency of the region will improve with the level of education, and form a strong positive space spillover effect. In summary, EC, EI, and R&D investment have a differential impact on the growth of carbon productivity in the eastern, central, and western steel industry, but the effect is not significant, industrial structure, economic development level and human capital are the main factors that cause the heterogeneity of carbon productivity in three regions.

4 Conclusions and Implications

This paper used the SBM model containing undesired output and the Global-Malmquist-Luenberger index to calculate the SICP of 29 provinces in China from 2006-2017, and decomposed the GML index into EC and TC. On this basis, Moran's I index was used to verify the spatial correlation of SICP, and the spatial convergence model was used to analyze the characteristics of σ convergence and β convergence of SICP and their influencing factors.

We can draw some major conclusions from the above analysis:

(1) The calculation results of GML show that, except for 2008 and 2011, the GML index of the SICP in the other years is higher than 1 and is on an upward trend, which indicates that the overall SICP has improved during the sample period. Then it can be seen from the decomposition results of the GML index that the improvement of SICP mainly depends on technological progress. The EC index has an average annual increase of 0.5%, indicating that the resource allocation efficiency and management efficiency of the steel industry have been improved; the TC index has an average annual growth rate of 6.8%, which has a more significant positive effect on the SICP. The GML index of the three regions is greater than 1, and only the GML index of the central region is lower than the national level. In addition, with the exception of the western region, technological progress and technical efficiency have all contributed to the improvement of carbon productivity.

(2) The SICP at the national level remains stable, and there is no σ convergence feature. Only the σ coefficient in the central region shows a slow decline, indicating that there is a slower σ convergence in the central region. According to the measurement results of spatial β convergence, China's SICP has absolute β convergence and condition β convergence on the whole, indicating that the growth rate of regions with low carbon productivity is faster than that of regions with high carbon productivity, and the carbon productivity of various regions is tending to their respective steady-state levels. Moreover, due to the addition of control variables such as industrial structure, economic development level, and energy consumption level, conditional β convergence performs better in terms of convergence speed and goodness of fit. At the regional level, the SICP in the eastern, central, and western regions all have β -convergence characteristics, with the eastern region having the fastest rate of convergence and the central region the slowest.

Based on the conclusions above, several feasible measures are proposed:

First, promote the low-carbon and green development of the steel industry. Steel production is an extremely complicated process. Although under the pressure of strict global steel industry environmental protection standards, China has now mastered some advanced energy-saving and emission-reduction technologies, but the low-carbon and green development of the steel industry still needs to overcome many technical difficulties. In 2019, the "Opinions on Promoting the Implementation of Ultra-Low Emissions in the Iron and Steel Industry" issued by the Ministry of Ecology and Environment and others put forward requirements for speeding up the ultra-low emission transformation of iron and steel enterprises. Iron and steel enterprises should actively develop new technologies around the comprehensive utilization of solid waste, energy conservation and consumption reduction, carbon emission reduction, etc., encourage the research and development and promotion of new processes and new equipment, expand new ways of energy conservation and emission reduction, and intensify the promotion of scientific and technological innovation to promote the

improvement of energy conservation and environmental protection level of iron and steel enterprises.

Second, the foremost task of the steel industry during the 14th Five-Year Plan period is to achieve “peak carbon”. Carbon peaking and carbon neutrality are the key tasks identified at the Central Economic Work Conference in 2020. The steel industry is a typical high-energy, high-polluting industry, so it is an extremely significant part of the task of energy saving and emission reduction. Increasing carbon productivity means achieving the dual goals of carbon emission reduction and stable economic growth. To reduce carbon emissions, steel companies first need to start with production capacity. In the short term, they should focus on compressing crude steel output and maintaining energy intensity per ton of steel, and increasing scrap ratio and promoting structural optimization are the medium-term ways to reduce the total energy consumption and intensity. In the long-term, it is necessary to increase scientific research investment to achieve technological innovation and break through the current process technology.

Finally, promote the cross-regional and cross-ownership merger and reorganization of steel companies. Due to the existence of spatial convergence, each province should strengthen technical cooperation and exchanges with neighboring provinces, it is necessary to take into account the issue of regional coordination in the process of pursuing the upgrading of industrial structure. First of all, to increase industrial concentration, corporate executives should realize that the formation of economies of scale is conducive to improving carbon productivity. Second, enterprises and governments must dare to break down regional barriers and institutional barriers, emancipate their minds, and actively explore. Third, steel companies should ensure the interests of employees during the process of joint reorganization, so that employees can realize the importance and necessity of the mixed reform for the long-term development of the company.

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