Convergence of Energy Carbon Emission Efficiency: Evidence From Manufacturing Sub-sectors in China

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Convergence of energy carbon emission efficiency: evidence from manufacturing sub-sectors in China

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Abstract

With China's economy entering the stage of high-quality development, manufacturing energy carbon emission efficiency has become the focus of academic attention. Based on the panel data of China's manufacturing sub-sectors, this paper measures and analyzes the evolution trend of manufacturing energy carbon emission and its efficiency. On this basis, this paper uses coefficient of variation and convergence model to test the convergence of manufacturing energy carbon emission efficiency. The results show that China's manufacturing energy carbon emissions and its efficiency show an increasing trend. The coal was the main source of manufacturing energy carbon emissions. The manufacturing energy carbon emission efficiency does not exist σ convergence, but exists β convergence, and its convergence exists industry heterogeneity. The manufacturing energy carbon emission efficiency exists scale effect and technology effect, but not the effect of opening to the outside world and institutional effect, and its effect exists industry heterogeneity. By reducing carbon emissions, adopting differentiated policies, adjusting the industry scale, and enhancing the industry technology intensity, China's manufacturing can improve the energy carbon emissions efficiency and promote high-quality economic development.

Keywords Energy carbon emission efficiency • CO₂ emission • Evolution trend • Convergence • Data envelopment analysis

Introduction

Since the reform and opening up, China has made great achievements in economy. China's gross domestic product was only RMB 367.87 billion in 1978, RMB 10028.81 billion in 2000 and RMB 99086.51 billion in 2019¹. Meanwhile, it is faced with the problems of low resource utilization efficiency, increasing of energy consumption and carbon dioxide emissions. According to data of British Petroleum report², China's carbon dioxide was 7710.1 million tonnes in 2009 and 9825.8 million tonnes in 2019, The average annual growth rate is 2.6% from 2008 to 2018 and 3.4% in 2019. China faces great pressure on carbon emission reduction. For one thing, although China's per capita carbon emission is lower, its total carbon emission ranks first in the world. At the 75th UN General Assembly, China has made clear that it will strive to reach the peak of carbon dioxide emissions by 2030 and achieve carbon neutrality by 2060. Meanwhile, China will bring carbon peaking and carbon neutralization into the overall layout of ecological civilization construction. For another, China's economy is currently in a stage of high-quality development, and the transformation of economic development mode has become the focus of that. The extensive

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¹ Note: The data comes from National Bureau of Statistics.

² Note: The carbon emissions above reflect only those through consumption of oil, gas and coal for combustion related activities, and are based on 'Default CO₂ Emissions Factors for Combustion' listed by the IPCC in its Guidelines for National Greenhouse Gas Inventories (2006).

growth mode of high input, high pollution and low efficiency cannot meet the requirements of high-quality development. Therefore, it should improve energy carbon emission efficiency for China. Improving energy carbon emission efficiency can not only reduce carbon emissions and achieve low-carbon economic development, but also ensure stable economic growth (Teng et al. 2017).

China's has become the largest manufacturing country in the world by virtue of the comparative advantages of low-cost supply of factors. According to world bank, in 2010, the added value of manufacturing industry in China surpassed that of the United States and became the largest manufacturing country. In 2005, the added value of China's manufacturing accounted for 11.6% of the added value in the whole world, rising to 24.8% in 2017. With the unceasing development of the China's industry, manufacturing has become the main industry of energy consumption and carbon dioxide emissions in China. In 2015, manufacturing energy consumption accounted for 56.97% of total energy consumption in China, and carbon dioxide emissions accounted for 54.90% of China's total carbon emissions (Xie et al. 2018). Meanwhile, the proportions of value added of manufacturing is negatively correlated with carbon emissions since 2000 (Dong et al. 2020). Along with China's economy is in the stage of high-quality development, the environmental and resource constraints faced by manufacturing continue to strengthen. Manufacturing plays an important role in the national economy, which is the key to promote high-quality economic development. Therefore, it is of great theoretical and practical significance to study the energy carbon emission efficiency of manufacturing. Meanwhile, it provides experience for sustainable development of manufacturing in developing countries.

However, research on the measurement of energy carbon emission efficiency mainly uses the method including single factor. The above methods cannot fully reflect the impact of other production factors on carbon emission efficiency. Carbon emission efficiency refers to the ratio of production relations to achieve the minimum carbon dioxide emissions and the maximum economic output when the input of labor, capital and energy is no increasing (Li et al. 2020). Moreover, the number of studies on manufacturing energy carbon emission efficiency in China are relatively few (Yang et al. 2015). And, there are differences in the factor endowments of China's manufacturing sub-sectors, which leads to the unbalanced development of manufacturing. Therefore, this paper studies the convergence of China's manufacturing energy carbon emission efficiency. It is of great significance for improving energy carbon emission efficiency and realizing high-quality development of manufacturing in China.

The purpose of this research is to explore the convergence of China's manufacturing energy carbon emission efficiency. First, this study calculates manufacturing carbon emission and analyzes its characteristics and sources. Second, this study calculates manufacturing energy carbon emission efficiency and analyzes its dynamic evolution trend. Third, this study uses coefficient of variation and convergence model to test the convergence of China's manufacturing energy carbon emission efficiency.

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 introduces the methodology and data. Section 4 presents the empirical results and discussion. Section 5 ends up with conclusions and policy implications.

Literature review

Research on the measurement of energy carbon emission efficiency mainly uses the method

including single factor. The evaluation method of single factor efficiency includes carbon dioxide emissions per unit energy, energy consumption per unit GDP (Cheng et al. 2016; Pretis and Roser 2017). The above methods cannot fully reflect the impact of other production factors on carbon emission efficiency. Therefore, studies on the calculation of energy carbon emission efficiency have mainly used the data envelopment analysis (DEA) method, and malmquist index (Farrell 1957) is often used to measure efficiency (Hernández-Sancho et al. 2011; Wu and Li 2014; Zhao et al. 2019).

However, the efficiency including unexpected output cannot be reflected by the method of malmquist index. Therefore, the malmquist luenberger index (Chung et al. 1997) was used to measure the energy efficiency (Watanabe and Tanaka 2007). With the continuous improvement of the method, the malmquist luenberger index has the potential linear programming unsolved problem and the non-cyclical or transitive characteristics. Hence, Global malmquist luenberger index (Oh 2010) was used to measure carbon productivity. For example, Teng et al. (2017) used global malmquist luenberger index to measure the carbon productivity of China's service industries.

The above methods belong to the radial and angular DEA model. The relaxation variables or some input or output cannot be reflected in the model. Therefore, Tone (2002) proposed a Super-SBM model based on the SBM models (Tone 2001). The Super-SBM model can evaluate and rank multiple fully effective decision units effectively. Currently, most researchers used the Super-SBM model to measure efficiency. Besides, the above studies mainly focus on the regional level and service level. And, the studies on manufacturing energy carbon emission efficiency in China are relatively few.

The convergence of productivity can be traced back to the neoclassical growth model (slow 1956) and extended to endogenous economic growth theory (Romer 1986). The earliest convergence research is used to test whether there is convergence in the income gap (Baumol 1981). Since then, many scholars have studied the convergence of labor productivity and total factor productivity from the national level, regional level and industrial level respectively (Miller and Upadhyay 2002; Islam 2003; Liu and Zhang 2010; Li et al. 2019; Ji and Xia 2020)

With the increasing harm of carbon emissions to the environment, reducing carbon emissions has become the goal of governments, prompting many scholars to pay attention to the convergence of carbon emissions. For example, Strazicich and List (2003) conducted empirical research with the data of OECE countries, and found that carbon emissions have β convergence and stochastic convergence. Westerlund and Basher (2008) studied the convergence of carbon emissions in developed and developing countries, and found that the carbon emissions of these two types of countries have convergence. Xu (2010) examined the convergence of per capita carbon emissions in China and found that there is no β absolute convergence, but there is β conditional convergence. In addition, the convergence of carbon emission intensity is also concerned by some scholars (Sun and Zhong 2014; Brannlund et al. 2015; Yu et al. 2018; Huang et al. 2019) .

Increasing carbon productivity is an effective way to reduce carbon emissions, so many scholars began to analyze the evolution trend of carbon productivity and its influencing factors (Li and Wang 2019; Liu et al. 2021) . In addition, most scholars focus on the convergence of carbon productivity, mainly at the agriculture level (Gao and song 2015), and service industry level (Teng et al. 2017; Wang et al. 2020). However, a small amount of literature deals with the manufacturing

level. For example, Yang et al. (2015) found that there were σ convergence and β convergence in carbon productivity of China's manufacturing from 1998 to 2011.

This study examines the convergence of energy carbon emission efficiency in China. The contributions in this study are as follows: First, this study selects manufacturing as the research object and measure China's manufacturing energy carbon emission, and analyzes its evolution trend. Second, this study accurately measures China's manufacturing energy carbon emission efficiency with the Super-SBM model. Third, this study uses coefficient of variation and convergence model to test the convergence of China's manufacturing energy carbon emission efficiency.

Methodology and data

Methodology

To evaluate and rank multiple fully effective decision units effectively (Tone 2002), this paper chooses the Super-SBM model instead of the radial and angular DEA model to calculate the energy carbon emission efficiency. The reason is that Super-SBM model effectively solves the problem of input-output variable relaxation, unexpected output and sorting when multiple decision-making units are effective at the same time. In order to understand Super-SBM model more clearly, this paper first introduces SBM model. Parameters and decision variables of the SBM model are as follows:

$$\begin{aligned} \rho = \min & \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{\bar{s}_i}{x_{i0}}}{1 + \frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{s_r^g}{y_{r0}^g} + \sum_{j=1}^{s_2} \frac{s_j^b}{y_{j0}^b} \right)} \\ \text{s.t.} \quad & x_0 = X\lambda + S^-, y_0^g = Y^g\lambda - S^g, y_0^b = Y^b\lambda - S^b, \\ & \sum_{i=1}^n \lambda_i = 1, S^- \geq 0, S^g \geq 0, S^b \geq 0, \lambda \geq 0 \end{aligned} \quad (1)$$

Parameters and decision variables of the Super-SBM model are as follows:

$$\begin{aligned} \rho^* = \min & \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{\bar{x}_i}{x_{i0}}}{\frac{1}{s_1 + s_2} \left(\sum_{r=1}^{s_1} \frac{\bar{y}_r^g}{y_{r0}^g} + \sum_{j=1}^{s_2} \frac{\bar{y}_j^b}{y_{j0}^b} \right)} \\ \text{s.t.} \quad & \bar{x} \geq \sum_{j=1, \neq 0}^n \lambda_j x_j, \bar{y}^g \leq \sum_{j=1, \neq 0}^n \lambda_j y_j^g, \bar{y}^b \leq \sum_{j=1, \neq 0}^n \lambda_j y_j^b, \\ & \bar{x} \geq x_0, \bar{y}^g \leq y_0^g, \bar{y}^b \geq y_0^b, \sum_{j=1, \neq 0}^n \lambda_j = 1, \bar{y}^g \geq 0, \lambda \geq 0 \end{aligned} \quad (2)$$

In the formula (1) and formula(2), the model mainly includes target efficiency value ρ and ρ^* , x , y^g and y^b are input, expected output and unexpected output respectively, S^- , S^g and S^b are input slack, expected output slack and unexpected output slack. m , s_1 and s_2 are the number of input indicators, expected output indicators and unexpected output indicators respectively, and λ is the weight vectors. When $\rho^* \geq 1$, the evaluated decision unit is effective. According to the Super-SBM model, the calculation of manufacturing energy carbon emission efficiency includes two aspects: output and input. The specific variables are shown in Table 1.

Table 1 Variable and indicator

Variable	Indicator
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manufacturing expected output	sales manufacturing output value
manufacturing non-expected output	manufacturing carbon emissions
	labor the number of manufacturing employees
manufacturing input	capital the net value of fixed assets
	energy consumption of total energy

Manufacturing carbon emissions are mainly produced by fossil fuels. Manufacturing carbon emissions are mainly from eight fossil fuels (IPCC, 2007), including coal, coke, crude oil, gasoline, diesel oil, fuel oil, natural gas, and kerosene. Manufacturing carbon emissions is calculated according to the following formula:

$$CO_2 = \sum_{i=1}^8 CO_{2,i} = \sum_{i=1}^8 E_i \times NCV_i \times CEF_i \times COF_i \times \frac{44}{12} \quad (3)$$

In the formula, i represents fossil fuels. CO_2 represents manufacturing carbon emission. E represents consumption of fossil fuels. NCV represents net calorific value. CEF represents carbon content. COF represents carbon oxidation factor. The formula on CO_2 emission factor of fossil fuels is as follows: $NCV \times CEF \times COF$. CO_2 emission factor of coal, coke, crude oil, gasoline, diesel oil, fuel oil, natural gas, and kerosene is 0.5183, 0.7801, 0.8237, 0.7978, 0.8443, 0.8647, 0.5897, 0.8231, respectively (Teng et al. 2017).

σ convergence and β convergence are the main convergence modes. In this paper, the difference of carbon emission efficiency from the overall average level can be reflected by σ convergence. If the gap of carbon emission efficiency of different industries gradually narrows over time, then it has σ convergence, otherwise there is no σ convergence. β convergence is proposed according to the theory of economic convergence, which is divided into absolute β convergence and conditional β convergence based on whether external factors are considered. Absolute β convergence means that the carbon emission efficiency of different industries eventually converges to the same steady-state level over time without controlling external factors. Conditional β convergence means that under the premise of controlling external factors, the carbon emission efficiency of different industries eventually converges to their respective steady-state levels over time.

Testing method of σ convergence. According to Rezitis (2010), the standard deviation and coefficient of variation are used to test whether there is σ convergence of carbon emission efficiency. The formula is as follows:

$$V = S / \bar{C}_t ; S = \sqrt{[\sum_i (C_{it} - \bar{C}_t)^2] / N} \quad (4)$$

In the formula, i represents industry, t represents time, v represents the coefficient of variation, s represents the standard deviation, $\bar{C}$ represents average carbon productivity in manufacturing, C represents carbon productivity in manufacturing, N represents the number of industry.

Testing method of absolute β convergence. According to Bernard and Jones (1996), in this paper, the absolute β convergence model of carbon productivity growth in manufacturing is set as follows:

$$(\ln C_{i,t+T} - \ln C_{i,t}) / T = \alpha + \beta \ln C_{i,t} + \varepsilon_{i,t} \quad (5)$$

In the formula, i represents industry, t represents time, T represents the time span, $\ln C$ represents the logarithm of carbon productivity in manufacturing, ε represents random error term. α and β are coefficients to be estimated. If β is less than 0 and statistically significant, it means that

there is absolute β convergence of carbon productivity in manufacturing, otherwise, it does not exist. The convergence rate $\sigma = -\frac{1}{T} \ln(1 - |\beta|)$.

Testing method of conditional β convergence. According to Barro and Sala-i-Martin (1992), in this paper, the conditional β convergence model of carbon productivity growth in manufacturing is set as follows:

$$(\ln C_{i,t+T} - \ln C_{i,t}) / T = \alpha + \beta \ln C_{i,t} + \gamma X_{i,t} + \varepsilon_{i,t} \quad (6)$$

In the formula, X represents other factors that affect the growth rate of carbon productivity in manufacturing, the meaning of other variables is consistent with the absolute β convergence model. In this paper, X includes industry scale (tis), technology intensity (tie), industry extroversion (tio), institutional quality (tiq). If β is less than 0 and statistically significant, it means that there is conditional β convergence of carbon productivity in manufacturing, otherwise, it does not exist.

Data

Based on the panel data of 27 sub-sectors of manufacturing from 2000 to 2016, this paper empirically studies the convergence of manufacturing energy carbon emission efficiency. The sub-sectors of manufacturing are shown in Table 2. To avoid the large bias of results caused by the inconsistent statistical caliber, and part of the data is only updated to 2016, this paper selects the research samples from 2000 to 2016.

The original data is mainly from the statistical yearbook. Consumption of total energy, Consumption of fossil fuels are from China Energy Statistical Yearbook. The sales manufacturing output value, the net value of fixed assets, the number of manufacturing employees are from China Industry Statistical Yearbook. Notably, the sales manufacturing output value is reduced by the producer price indices for manufactured goods, the net value of fixed assets is reduced by the price indices for investment in fixed assets. The price indices are derived from the China Statistical Yearbook and China Price Statistical Yearbook.

Table 2 Sub-sectors of manufacturing

Industry	Code	Industry	Code
processing of food from agricultural products	C101	manufacture of medicines	C21
manufacture of foods	C102	manufacture of chemical fibers	C202
manufacture of beverages	C11	manufacture of rubber and plastics products	C22
manufacture of tobacco	C12	manufacture of non-metallic mineral products	C23
manufacture of textile	C13	smelting and pressing of ferrous metals	C241
manufacture of textile, wearing apparel and accessories	C14	smelting and pressing of non-ferrous metals	C242
manufacture of leather, fur, feather and related products and footwear	C15	manufacture of metal products	C25
processing of timber, manufacture of wood, bamboo, rattan, palm, and straw products	C16	manufacture of general purpose machinery	C281
manufacture of furniture	C31	manufacture of special purpose machinery	C282
manufacture of paper and paper products	C17	manufacture of transport equipment	C29

printing and reproduction of recording media	C18	manufacture of electrical machinery and apparatus	C27
manufacture of articles for culture, education, arts and crafts, sport and entertainment activities	C32	manufacture of computers, communication and other electronic equipment	C26
processing of petroleum, coking and processing of nuclear fuel	C19	manufacture of measuring instruments and machinery for cultural activity and office work	C33
manufacture of raw chemical materials and chemical products	C201		

According to the availability of data, the following manufacturing industries are not considered in this paper: other manufacture, utilization of waste resources, repair service of metal products, machinery and equipment. Among manufacture, C101, C102, C13, C14, C15, C16, C31, C18, C32, C22, C23, and C25 are labor intensive manufacturing. C11, C12, C17, C19, C201, C202, C241, C242, and C281 are capital intensive manufacturing. C21, C282, C29, C27, C26, and C33 are technology intensive manufacturing.

Results and discussion

Results and discussion of manufacturing energy carbon emission

Manufacturing energy carbon emissions in China from 2000 to 2016 is calculated. The results are shown in Fig. 1, Fig. 2, and Fig. 3.

Fig. 1 displays the gross manufacturing energy carbon emissions in China. From 2000 to 2016, it has demonstrated that China's gross manufacturing energy carbon emissions showed an increasing trend. The carbon emission was about 206071 ten thousand tons in 2000 and 644796 ten thousand tons in 2016. The highest value of the carbon emission was about 653984 ten thousand tons in 2015. Further calculation shows that average annual growth rate of the carbon emission was about 7%. Further analysis shows that the development trend of total carbon emissions consists of three similar stages. The three stages are from 2000 to 2002, from 2003 to 2008, and from 2009 to 2016, respectively. The above three stages are manifested as the following: Gross manufacturing energy carbon emissions showed an increasing trend. However, the annual growth rate of gross manufacturing energy carbon emissions showed a trend of first increasing and then decreasing. The reason is that on the one hand, Chinese government strengthens the manufacturing carbon emission management; on the other hand, the manufacturing production is increasing.

Fig. 1 Gross manufacturing energy carbon emissions.

Fig. 2 illustrates the annual average manufacturing energy carbon emissions in China. It has showed that there were differences in annual energy carbon emissions of manufacturing sub-sectors. The sub-sectors of manufacturing that produce more energy carbon emissions include C19, C241, C201, C23, and C242, which C19 is the highest (about 157,471 ten thousand tons). The sub-sectors of manufacturing that produce less energy carbon emissions include C33, C31, C32, C18, and C12 are relatively low, which C33 is the lowest (about 126 ten thousand tons). The average annual manufacturing energy carbon emissions of C19 is about 1250 times that of C33. According to the analysis, The sub-sectors of manufacturing with higher energy carbon emissions are mainly distributed in capital intensive industries, while the sub-sectors of manufacturing with lower energy carbon emissions are mainly distributed in labor-intensive industries.

Fig. 2 Annual average manufacturing energy carbon emissions.

Fig. 3 presents the sources of manufacturing energy carbon emissions in China. It has demonstrated that the major source of China's manufacturing energy carbon emissions was coal. The carbon emissions generated by coal, coke, crude oil, gasoline, diesel oil, fuel oil, natural gas, and kerosene account for about 51.45%, 19.08%, 24.58%, 0.37%, 1.01%, 1.70%, 1.76%, and 0.04% of total carbon emissions, respectively. Further analysis shows that the proportion of manufacturing energy carbon emissions generated by gasoline, diesel oil, fuel oil, and kerosene has a downward trend, that of natural gas, crude oil, coke, and coal have an upward trend, a "U"-shaped trend, an inverted "U"-shaped trend, and a volatility trend, respectively.

Fig. 3 Sources of manufacturing energy carbon emissions.

Results and discussion of manufacturing energy carbon emission efficiency

Manufacturing energy carbon emission efficiency in China from 2000 to 2016 is calculated. The results are shown in Fig. 4, Fig. 5.

Fig. 4 displays the evolution trend of manufacturing energy carbon emission efficiency in China. From 2000 to 2016, it has demonstrated that China's manufacturing energy carbon emission efficiency showed an increasing trend. The energy carbon emission efficiency was about 0.1123 in 2000 and reached the highest value of about 0.2452 in 2015 and 0.2378 in 2016. Further analysis shows that the development trend of energy carbon emission efficiency consists of three stages. The three stages are from 2000 to 2004, from 2005 to 2012, and from 2013 to 2016, respectively. Energy carbon emission efficiency in the first stage and the second stage shows an upward trend. In the above two stages, the annual growth rate of energy carbon emission efficiency showed an increasing trend. However, Energy carbon emission efficiency in the third stage showed a volatility trend.

Fig. 4 Evolution trend of manufacturing energy carbon emission efficiency.

Fig. 5 illustrates the annual average manufacturing energy carbon emission efficiency in China. It has showed that there were differences in annual energy carbon emission efficiency of manufacturing sub-sectors. The sub-sectors of manufacturing that owning more annual average manufacturing energy carbon emission efficiency include C19, C12, C241, and C26, which C19 is the highest (about 0.8698). The sub-sectors of manufacturing that owning more annual average manufacturing energy carbon emission efficiency include C25, C18, C22, and C33 are relatively low, which C25 is the lowest (about 0.0516). The average annual manufacturing energy carbon emission efficiency of C19 is approximately 17 times that of C25.

Fig. 5 Annual average manufacturing energy carbon emission efficiency.

Fig. 6 presents the dynamic evolution trend of manufacturing energy carbon emission

efficiency in China. Kernel density estimation method (Rosenblatt 1956) was used to test dynamic evolution trend of manufacturing energy carbon emission efficiency. According to Fig. 6, The nuclear density map moves to the right over time, and the peak position decreases. Therefore, the manufacturing energy carbon emission efficiency in China is increasing.

Fig. 6 Dynamic evolution trend of manufacturing energy carbon emission efficiency.

Convergence of manufacturing energy carbon emission efficiency

The standard deviation and coefficient of variation of manufacturing energy carbon emission efficiency in China from 2000 to 2016 is calculated. The results are shown in Fig. 7.

Fig. 7 displays the evolution trend of the coefficient of variation on manufacturing energy carbon emission efficiency in China. It has demonstrated that there is no σ convergence in China's manufacturing energy carbon emission efficiency from 2000 to 2016. The coefficient of variation on manufacturing energy carbon emission efficiency was about 0.7231 in 2000 and reached the highest value of about 1.2607 in 2004 and 1.1043 in 2016. The coefficient of variation on labor intensive manufacturing energy carbon emission efficiency was about 0.2529 in 2000 and reached the highest value of about 0.6372 in 2016. The coefficient of variation on capital intensive manufacturing energy carbon emission efficiency was about 0.7721 in 2000 and reached the highest value of about 1.1329 in 2004 and 0.8459 in 2016. The coefficient of variation on technology intensive manufacturing energy carbon emission efficiency was about 0.1822 in 2000 and reached the highest value of about 1.2104 in 2015 and 1.2054 in 2016.

Fig. 7 Evolution trend of the coefficient of variation on manufacturing energy carbon emission efficiency.

The samples of this paper are short panel data and long panel data. For short panel data sample, F test, LM test, Hausman test, and time effect test were used to select the appropriate method. If it does not pass F test, the POLS model can be used to estimate; otherwise, the appropriate model was selected by Hausman test. If there is no individual effect and it is not passed the Hausman test, RE model should be used. If it passes the F test and Hausman test, time effect test should be used to determine whether to use the two-way FE model. For long panel data sample, Wald test, Wooldridge test, and Pesaran test were used to test whether there were inter groupwise heteroskedasticity, autocorrelation within panel and contemporaneous correlation, respectively. If there is heteroskedasticity or autocorrelation, FGLS should be used. The testing results and the β convergence model are estimated. The results are shown in Table 3, Table 4, and Table 5.

Absolute β convergence. Table 3 displays the testing results of absolute β convergence on manufacturing energy carbon emission efficiency in China. According to table 3, there is absolute β convergence in manufacturing energy carbon emission efficiency in China. The regression coefficient β is -0.0870, and passes the test of the 1% significance level. Moreover, the manufacturing industry is divided into three categories of labor intensive manufacturing, capital intensive manufacturing and technology intensive manufacturing. According to table 3, there is absolute β convergence in energy carbon emission efficiency of labor intensive and capital intensive manufacturing in China, but there is no absolute β convergence in technology intensive manufacturing. The regression coefficient β in labor intensive manufacturing and capital intensive manufacturing is -0.1452 and -0.1239, respectively, and all passes the test of the 1% significance levels. The regression coefficient β in technology intensive manufacturing is -0.0660, and has not passed the test of the 10% significance level. Additionally, labor intensive manufacturing energy carbon emission efficiency in China has the fastest absolute convergence rate. The convergence rate of overall, labor intensive, and capital intensive manufacturing energy carbon emission efficiency in China is 0.57%, 0.98%, and 0.83%, respectively.

350 **Table 3** Absolute β convergence

	(1)	(2)	(3)	(4)
	Overall manufacturing	Labor intensive manufacturing	Capital intensive manufacturing	technology intensive manufacturing
β	-0.0870*** (0.0295)	-0.1452*** (0.0227)	-0.1239*** (0.0244)	-0.0660 (0.0591)
Constant	-0.1817** (0.0736)	-10.7127*** (2.5559)	-10.5096*** (4.0488)	-13.3633** (5.6824)
Industry fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
F value	2.78***			
Wald value		107.84***	92.12***	14.75**
F test	1.56**			
LM test	0.61			
Hausman test	8.4**			
Time effect test	2.6***			
Wald test		786.09***	2586.81***	328.59***
Wooldridge test		86.105***	12.453***	3.386
Pesaran test		5.589***	1.593	0.002
Observations	432	192	144	96
R-squared	0.103			

351 Standard errors in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

352

353 Conditional β convergence. Table 4 illustrates the testing results of conditional β convergence
354 on manufacturing energy carbon emission efficiency in China. According to table 4, there is
355 conditional β convergence in manufacturing energy carbon emission efficiency in China. The
356 regression coefficient β is -0.0767 at the 1% significance level. In addition, manufacturing energy
357 carbon emission efficiency exits scale effect and technology effect, but not the effect of opening to
358 the outside world and institutional effect. The regression coefficient of industry scale (tis) is
359 -0.1102, and passed the test of the 5% significance level. The regression coefficient of technology
360 intensity (tie) is 0.9346, and passed the test of the 1% significance level. The regression
361 coefficient of industry extroversion (tio), institutional quality (tiq) is 0.0611 and -0.1580,
362 respectively, and have not passed the test of the 10% significance level.

363 Moreover, the manufacturing industry is divided into labor intensive manufacturing, capital
364 intensive manufacturing and technology intensive manufacturing. According to table 4, there is
365 conditional β convergence in energy carbon emission efficiency of labor intensive and capital
366 intensive manufacturing in China, but there is no conditional β convergence in technology
367 intensive manufacturing. The regression coefficient β in labor intensive manufacturing and capital
368 intensive manufacturing is -0.1419 and -0.1639, respectively, and all passes the test of the 1%
369 significance levels. The regression coefficient β in technology intensive manufacturing is -0.0955,
370 and has not passed the test of the 10% significance level.

371 Further analysis shows that the labor intensive manufacturing energy carbon emission
372 efficiency exits scale effect, technology effect, effect of opening to the outside world and

institutional effect. The regression coefficient of tis, tie, tio, and tiq is 0.0948, -0.8947, -0.4635, and 0.9486 at the 1% significance level, respectively. The capital intensive manufacturing energy carbon emission efficiency exits scale effect, technology effect and effect of opening to the outside world, but not institutional effect. The regression coefficient of tis, tie, and tio is -0.1036 at the 5% significance level, 0.5645 at the 1% significance level, and 1.0979 at the 1% significance level, respectively. The regression coefficient of tiq is 0.1516, and have not passed the test of the 10% significance level. The technology intensive manufacturing energy carbon emission efficiency exits effect of opening to the outside world, but not scale effect, technology effect and institutional effect. The regression coefficient of tio is -0.3150 at the 10% significance level. The regression coefficient of tis, tie, and tiq is -0.0661, 0.1079, and 0.1381, respectively, and have not passed the test of the 10% significance level.

Additionally, capital intensive manufacturing energy carbon emission efficiency in China has the fastest conditional convergence rate. The convergence rate of overall, labor intensive, and capital intensive manufacturing energy carbon emission efficiency in China is 0.50%, 0.96%, and 1.12%, respectively.

Table 4 Conditional β convergence

	(1)	(2)	(3)	(4)
	Overall manufacturing	Labor intensive manufacturing	Capital intensive manufacturing	technology intensive manufacturing
β	-0.0767*** (0.0295)	-0.1419*** (0.0249)	-0.1639*** (0.0381)	-0.0955 (0.0631)
tis	-0.1102** (0.0504)	0.0948*** (0.0273)	-0.1036** (0.0431)	-0.0661 (0.0440)
tie	0.9346*** (0.3460)	-0.8947*** (0.1638)	0.5645*** (0.2089)	0.1079 (0.2673)
tio	0.0611 (0.1679)	-0.4635*** (0.1281)	1.0979*** (0.3945)	-0.3150* (0.1618)
tiq	-0.1580 (0.3353)	0.9486*** (0.1006)	0.1516 (0.2044)	0.1381 (0.2558)
Constant	0.4230 (0.4168)	45.3166*** (7.2416)	-52.7508*** (12.0755)	-32.6044* (18.3254)
Industry fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
F value	2.79***			
Wald value		290.91***	84.34***	29.24***
F test	1.62**			
LM test	0.01			
Hausman test	18.62***			
Time effect test	2.87***			
Wald test		608.11***	1906.88***	381.98***
Wooldridge test		45.127***	11.525***	3.011
Pesaran test		3.665***	1.614	0.641
Observations	432	192	144	96

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Robustness test. In order to further test the robustness of the regression results, considering the impact of the financial crisis in 2008, this paper tests the convergence of the samples from 2000 to 2008 and from 2009 to 2016. Table 5 presents the robustness test of regression results. According to table 5, the regression results are robust. There are absolute β convergence and conditional β convergence in manufacturing energy carbon emission efficiency in China from 2000 to 2008 and from 2009 to 2016. The regression coefficient β is negative from 2000 to 2008 and from 2009 to 2016, and passes the test of the 1% significance level.

Table 5 Robustness test of regression results

	2000-2008		2009-2016	
	(1)	(2)	(3)	(4)
β	-0.2626*** (0.0405)	-0.2481*** (0.0453)	-0.2077*** (0.0508)	-0.2594*** (0.0594)
Control	NO	YES	NO	YES
Constant	-0.5780*** (0.0912)	-0.9602** (0.3935)	-0.3675*** (0.0992)	-0.1637 (0.9624)
Industry fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	No	No	No	No
F value	42.12***	8.57***	16.70***	4.12***
F test	3.36***	2.90***	2.28***	1.96***
LM test	0.00	0.23	1.34	0.21
Hausman test	44.11***	42.53***	18.70***	24.96***
Time effect test	0.30	0.69	1.49	1.51
Observations	216	216	189	189
R-squared	0.183	0.189	0.094	0.116

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Conclusion and policy implications

Based on the panel data of China's manufacturing, this paper measures and analyzes the evolution trend of manufacturing carbon emission and energy carbon emission efficiency. On this basis, this paper uses coefficient of variation and convergence model to test the convergence of China's manufacturing energy carbon emission efficiency. The main conclusions are as follows: First, China's gross manufacturing energy carbon emissions shows an increasing trend from 2000 to 2016. There were differences in annual energy carbon emissions of manufacturing sub-sectors, and the coal was the main source. Second, China's manufacturing energy carbon emission efficiency increased from 2000 to 2016. There were differences in annual energy carbon emission efficiency of manufacturing sub-sectors. there is no σ convergence in China's manufacturing energy carbon emission efficiency from 2000 to 2016. There is absolute β convergence and conditional β convergence in manufacturing energy carbon emission efficiency in China, and its convergence exists industry heterogeneity. Third, manufacturing energy carbon emission efficiency exists scale effect and technology effect, but not the effect of opening to the outside

world and institutional effect, and its effect exists industry heterogeneity.

Based on the above research conclusion, the following policy implications are obtained: First, China should implement the clean production action of manufacturing industry and carry out the pilot project of green energy replacing fossil energy such as coal, so as to reduce carbon emissions. Meanwhile, China should strengthen the carbon emission control of the manufacturing industry, optimize the energy consumption structure, establish different supervision of fossil energy production for different industries, and advocate enterprises to strictly implement green energy policies and fossil energy access management. Second, for capital intensive industries and labor-intensive industries, China should carry out technological transformation, and accelerate the narrowing of the energy carbon emission efficiency gap between industries. For technology intensive industries, China should actively guide them to adopt clean energy policies, achieve a higher level of energy carbon emission efficiency, and drive the development of other industries, so as to realize the balanced development of the industry. Third, to improve the energy and carbon emission efficiency, China's manufacturing should make rational use of industry resources, appropriately adjust the industry scale, promote the industry to obtain economies of scale, increase R&D investment, enhance technology intensity, and promote the upgrading of manufacturing industry to innovation driven.

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Declarations

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