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Will land transport infrastructure affect the energy and carbon dioxide emissions performance of China's manufacturing industry?

Boqiang Lin*, Yu Chen

School of Management, China Institute for Studies in Energy Policy, Collaborative Innovation Center for Energy Economics and Energy Policy, Xiamen University, Fujian 361005, China

HIGHLIGHTS

- Impact mechanism of land transport infrastructure is empirically examined.
- Global data envelopment analysis and panel Tobit model are used for analysis.
- Overall efficiency level of China's manufacturing industry is low.
- We study the influential variables of energy and environmental efficiency.
- Strong heterogeneity features exist between different regions.

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ABSTRACT

The energy consumption and carbon dioxide emissions of China's manufacturing industry accounted for 12.8% and 15.5% of the world in 2016, respectively. On the other hand, the construction of land transport infrastructure has become the focal point of the Chinese government recently. However, there is very little literature investigating the influencing mechanism of land transport infrastructure on the energy and environmental efficiency of the sector. Therefore, it is crucial and meaningful to study how the latter is affected by the land transport infrastructure to alleviate global energy and environmental issues. Non-radial directional distance function was used to calculate two indicators measuring energy and carbon dioxide emissions performance in this paper. The panel Tobit model was then applied to focus on factors affecting the performance. The results indicate that land transport infrastructure, economic growth, technological progress, energy prices, industrial structure have significant impacts on the energy and environmental efficiency of China's manufacturing industry. Different from the results at the national level, from a regional perspective, the development of land transport infrastructure in the eastern region plays a negative role in the performance of the manufacturing industry. Finally, some targeted policy recommendations are proposed to improve the policy design of the government.

1. Introduction

Manufacturing is a traditional pillar industry in China, which plays a vital role in the economy. The development of the sector contributes to market growth, promotes employment, and increases people's income, which is crucial to the industrial restructuring and economic transformation [1]. China's manufacturing industry (CMI) has achieved phenomenal growth in recent years, making remarkable contributions to economic growth. The industrial added value of CMI accounted for 28.8% of China's GDP in 2016[1]. However, manufacturing is a highly energy-intensive industry with massive CO_2 emissions [2]. As depicted in Fig. 1, the energy consumption of the sector has increased from 775.6 million tons of standard coal equivalent (Mtce) in 1996 to 2425 Mtce in 2016, accounting for 12.8% of the world's consumption[2]. It should be

* Corresponding author.
E-mail addresses: bqlin@xmu.edu.cn, bqlin2004@vip.sina.com (B. Lin).

[1] Source: World Bank database.

[2] Source: BP Statistical Review of World Energy, June 2017. Due to the study of China, and the accounting unit of China's energy consumption is the tons of standard coal equivalent. Therefore, we convert the unit for the convenience of comparison (1 ton of standard oil equivalent = 1.4286 tons of standard coal equivalent).

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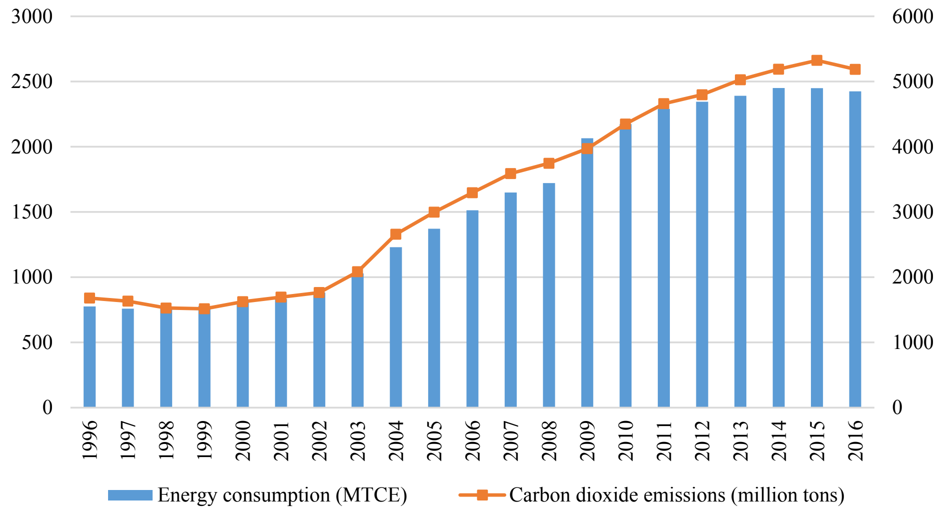

Fig. 1. Energy consumption and CO_2 emissions in China's manufacturing industry.

noted that the energy consumption of CMI exceeded the total amounts of Japan, Britain, Germany, France, and Spain (1896 Mtce). As a result, the CO_2 emissions of CMI are 5187 million tons, taking the proportion of 15.5% of the world in 2016.

Large-scale greenhouse gas emissions and environmental degradation problems have been increasingly serious in the wake of the rising fossil fuel consumption in the CMI [3]. The Chinese government attaches great importance to the issue of energy consumption in the manufacturing industry. In the strategic plan titled "Made in China 2025" released by the central government in 2015, the target of an 18% drop in energy consumption by large-scale manufacturing industrial enterprises in 2025 compared to the 2015 level has been proposed. Besides, the signing of the Paris Agreement means that China's future economic development will be restricted by carbon emission reduction[3]. Therefore, how to improve the energy and CO_2 emission efficiency of CMI is of vital importance to China and the whole world [4].

On the other hand, the energy efficiency of the manufacturing industry has always been a hot issue for scholars. By conducting cross-country analysis, Kepplinger et al. [5] found that the energy efficiency of the manufacturing industry would significantly increase with the growth of time and economy. The industrial structure has a crucial impact on energy efficiency. Choi and Oh [6] draw the conclusion that the optimization of industrial structure, especially the decline in the proportion of energy-intensive industries in the manufacturing, will improve energy efficiency. Also, Zhao et al. [7] discovered that the industrial structure reform plays a pivotal role in improving energy efficiency by comparing the change rules of Japanese and Chinese manufacturing industries. In recent years, efficiency evaluation methods have been widely used in energy efficiency analysis of the manufacturing industry. Mukherjee [8] illuminated that a higher-quality workforce often leads to higher energy efficiency in the Indian manufacturing industry based on production theory framework and data envelopment analysis. Özkara and Atak [9] established four data envelopment analysis models to calculate the total factor energy efficiency of manufacturing industry in Turkey from 2003 to 2012, demonstrating the U-type relationship between regional development level and manufacturing energy efficiency. Similar studies include Pérez et al. [10], Wang et al. [11], Tang et al. [12]. Parker and Liddle [13] applied the LMDI method to decompose the changes in energy intensity in OECD countries into two driving effects (technical efficiency effect and structural change effect) to investigate the influence of energy prices on manufacturing energy efficiency.

Infrastructure refers to the material engineering facilities that provide public services for social production and residents' lives. Generally speaking, infrastructure is a public service system to guarantee the normal operation of social and economic activities in a region or country [14], including transportation, post and telecommunications, water and power supply, commercial services, landscaping, cultural education, health services, etc. Researchers are attaching importance to the impact of infrastructure. Rosenstein-Rodan [15] proposed that infrastructure construction is essential for the comprehensive development of a country. Aschauer [16] was the first to incorporate public capital into the production function, determining the relative relationship between output and infrastructure investment. Following his research, Bronzini and Piselli [17] used the Cobb-Douglas production function to reveal the long-term equilibrium relationship between total factor productivity, research and development (RD) investment, public infrastructure and human capital in Italy from 1980 to 2001. The results indicated that regional productivity is positively affected by RD activities and public infrastructure in neighboring areas.

Advanced transportation infrastructure can spur innovation, bring agglomeration effects and economies of scale, thus reducing production costs and increasing industrial output and energy efficiency [18,19,20]. Farhadi [21] verified the positive effect of transport infrastructure on labor productivity through case studies. Pradhan and Bagchi [22] demonstrated that the construction of transportation infrastructure (roads and railways) would bring about substantial economic growth in India. Zhang [23] adopted the provincial panel data and space spillover model to find that the spatial spillover effect of China's transportation infrastructure on regional economic growth is very significant. Tan et al. [24] believed that the improvement of transportation infrastructure could decrease energy intensity in the long run and promote the development of energy-intensive industries in manufacturing. Garrone and Grilli [25] also demonstrated that increasing transportation infrastructure expenditure could effectively improve energy efficiency.

Hence, there is no doubt that infrastructure can affect the energy consumption and development of CMI, whereas the influence channels and scope for various types of infrastructure are different [26]. In this paper, we will concentrate on transportation infrastructure, which is closely linked to the energy and environmental efficiency issues of CMI. Fig. 2 depicts the mileage of rail, waterway, and road transport in China's transportation infrastructure during the period 1996–2016. The average mileage of rail, waterway, and road transport is 82.2, 121.6, and 2952.9 thousand kilometers respectively. The mileage of road transport in China increased from 1185.8 thousand kilometers in 1996

[3] The Paris Climate Change Conference proposed the objective of controlling the rise in global average temperature to within 2°C above the pre-industrial level.

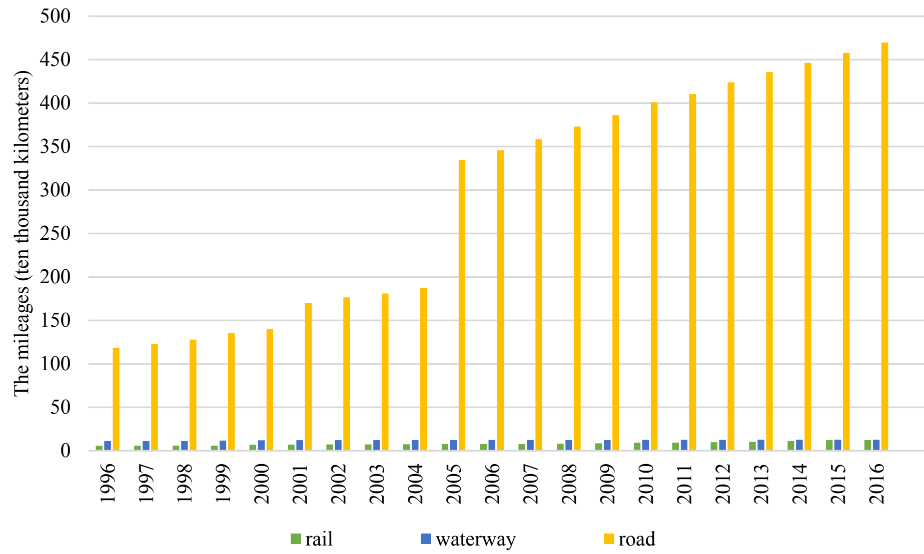

Fig. 2. The mileages of rail, waterway and road transport in China.

to 4696.3 thousand kilometers in 2016. An interesting phenomenon is that the mileage of road transport in 2005 is about twice of that in 2004. A reasonable explanation is that many important road construction projects, such as the Jiayuguan section of Lianyungang-Huoerguosi Highway, Tianjin section of Beijing-Shanghai Highway, and so on were completed.

Since waterway transportation is constrained by resource endowments, the conveyance of raw materials and products in CMI mainly relies on roads and railways. In this paper, we adopt the mileage of land transport (road and rail transport) as the measure of China's transportation infrastructure. In recent years, the construction of land transport infrastructure has become the focal point of the Chinese government. According to the Report on the Work of the Chinese Government in 2016, effective investment should play a critical role in stabilizing economic growth and adjusting the development structure. Given this, plans are being carried out to complete 800 billion yuan in rail investment and 1.65 trillion yuan in road investment. Thus, it is of great significance to empirically examine the impact mechanism of land transport infrastructure on the energy and CO_2 emissions efficiency of CMI to alleviate global energy and environmental issues.

However, when environmental factors are taken into account, there is very little literature investigating the above issues of CMI, which is an important pillar industry to ensure social and economic growth with high output, energy consumption, and CO_2 emissions. Therefore, it is crucial and meaningful to study how the sector is affected by transportation (land transport) infrastructure, which is missing in the existing literature. What is the trend of energy and CO_2 emissions efficiency in CMI? How will the development of land transport infrastructure affect the performance of CMI? Does the effect show regional differences features? What policies can we design to guide the development of land transport infrastructure to improve the energy and environmental performance of CMI? We aim to explore and investigate the above questions through empirical research, which have not been fully explained in previous studies.

The structure of this paper is as follows: Section 2 presents the methodology and model specification, data source, and variables of the study. Section 3 analyzes the results and conducts subregional studies. Conclusions are summarized, and policy recommendations are proposed in Section 4. In order to make the analysis and results of this paper more concise and intuitive, the abbreviations and symbols in this paper are described in Table 1.

2. Methodology and model specification

2.1. Non-radial directional distance function

Data envelopment analysis (DEA) has been widely applied in the research of energy and environmental efficiency [27,28]. DEA is a non-parametric method to evaluate the performance of the decision-making unit (DMU), which can be measured by its distance from the boundary [29]. The traditional DEA method is generally based on the foundation of the Shephard distance function, which needs the restrictive assumptions that both the desirable output and the undesirable output increase the same proportion simultaneously [30], making it impossible to explore the energy and environmental efficiency issues with reduction of undesirable output. To solve this problem, Chung et al. [31] established a directional distance function (DDF) method that allows for the reduction of undesirable output while increasing the desirable output, thus attracting widespread concern and application [32,33]. Nevertheless, the DDF approach may overestimate the efficiency of the assessed DMU by increasing desirable output and decreasing undesirable output in the same proportion [34]. In order to overcome the estimation error of the traditional DDF method, Zhou et al. [35] put forward a non-radial direction distance function (NDDF) method, which can flexibly adjust input, desirable and undesirable output without maintaining the consistency of adjustment ratio.

Owing to the fact that NDDF has higher model recognition ability than DDF, following by Li and Lin [36] and Zhang et al. [37], this paper calculates two NDDFs to measure the energy and CO_2 emissions performance of China's provincial manufacturing industry. Assume that N provinces are evaluated, and each province is treated as a DMU. Capital (K), labor (L), and energy (E) of provincial manufacturing industries are input variables, the total industrial output value (Y) is desirable output, and CO_2 emissions (C) are regarded as undesirable output as well as byproducts.

Referring to the joint production framework proposed by Fare [38], production technology can be formulated as follows:

$$M = \{(K, L, E, Y, C): (K, L, E) \text{ can produce } (Y, C)\} \quad (1)$$

K, L, E, Y, C represent the assessed DMUs, which are scalar variables determined by the sample data but not vectors. Besides, it is worth noting that the production technology set M needs to satisfy the following four properties:

(1) A limited amount of input can only produce a limited amount of output.

Table 1
The abbreviations and symbols in this paper.

Abbreviation and symbol		Description	Units of measurement
Abbreviation	CMI	China's manufacturing industry	\
	Mtce	Million tons of standard coal equivalent	\
	LMDI	Logarithmic mean divisia index	\
	RD	Research and development	\
	OECD	Organization for Economic Cooperation and Development	\
	DEA	Data envelopment analysis	\
	DMU	Decision-making unit	
	DDF	Directional distance function	\
	NDDF	Non-radial direction distance function	\
	UEI	Unified efficiency index	\
	EEPI	Energy-environmental performance index	\
Symbol	K	Capital input	Billion yuan
	L	Labor input	Ten thousand people
	E	Energy input	Ten thousand tons of standard coal equivalent
	Y	Desirable output	Billion yuan
	Y*	Undesirable output	Ten thousand tons
	LD	Land transport density	Kilometers/square kilometers
	EG	Economic growth	Ten thousand yuan
	TP	Technological progress	Billion yuan
	EP	Energy price	\
	IS	Industrial structure	Percent

(2) If $C = 0$ and $(K, L, E, Y, C) \in M$, then $Y = 0$, which means that if no undesirable output is produced, there will be no desirable output.

(3) If $(K, L, E, Y, C) \in M$ and $\mu \in [0, 1]$, then $(K, L, E, \mu Y, \mu C) \in M$, which indicates that undesirable outputs can be reduced at the expense of desirable output. In other words, reducing CO_2 emissions is costly, which needs the proportionate reduction in industrial output.

(4) If$(K, L, E, Y, C) \in M$ and $Y^* < Y$, then $(K, L, E, Y^*, C) \in M$. This property suggests that we can dispose of the redundant inputs and outputs without any cost.

Based on the maiden work by Fukuyama et al. [39] and Barros et al. [40], Zhou et al. [35] proposed a formal definition of the NDDF by taking undesirable outputs into account. Zhang et al. [41] extended the model into a metafrontier situation. Referring to their research, the NDDF can be expressed as:

$$\vec{D}(K, L, E, Y, C; p) = \sup_{\beta \geqslant 0}\{w^T\beta: (K, L, E, Y, C) + diag(\beta)\cdot p \in M\} \tag{2}$$

where $\beta = (\beta_K, \beta_L, \beta_E, \beta_Y, \beta_C)^T$ is a scale factor vector that measures the deviation between the actual production activity and the optimal production status, the range of each component is $0 \leqslant \beta_K, \beta_L, \beta_E, \beta_Y, \beta_C \leqslant 1$; $diag(\beta)$ represents the diagonal matrix with respect to β; $p = (p_K, p_L, p_E, p_Y, p_C)^T$ is the direction vector determining the direction in which each input/output is scaled; $w = (w_K, w_L, w_E, w_Y, w_C)^T$ denotes the vector of weights assigned to each input/output.

Obviously, Eq. (2) ensures that the actual production activity still belongs to the production technology set M when inputs and outputs change and imply that the inputs and outputs can be flexibly and non-proportionally adjusted. The function can overcome the estimation problem by conventional radial efficiency measures which overestimate the efficiency when the non-zero slacks exist [42]. Besides, it should be emphasized that the direction vector p and the weight vector w can be set differently depending on the specific policy objectives.

In this paper, following by Li and Lin [36], Zhang et al. [37] and Lin and Du [43], the unified efficiency index (UEI) and the energy-environmental performance indicator (EEPI) are employed to assess the energy and CO_2 emissions performance of China's provincial manufacturing industry. The former takes the inefficiency of all inputs, desirable output, and undesirable output into account, which can be regarded as the average efficiency performance of each factor. The second indicator focuses on the performance of energy use, desirable output, and CO_2 emissions while keeping capital and labor input constant. Both of these indicators are applied to compare efficiency under different parameter settings and as a robustness test in a sense to verify whether the impact of land transport infrastructure on energy and CO_2 emissions performance of CMI in the economic regression model depends on our parameter settings.

In terms of parameter setting, for UEI, we first allocate the same weight to input, desirable output, and undesirable output, each 1/3. Since there are three inputs: capital, labor, and energy, which are regarded as the same importance, then each is averagely weighted by 1/9 (a third of 1/3). Given no prior information, setting equal weights seems to be an appropriate and suitable way in the background of lacking information [41,43]. For EEPI, owing to the capital and labor input are not involved, the weight of energy input, desirable output, and undesirable output is 1/3, respectively. Thus, the direction vector p and the weight vector w of the UEI are $(-K, -L, -E, Y, -C)$ and $(1/9, 1/9, 1/9, 1/3, 1/3)$, correspondingly. The latter specifies the direction vector p and the weight vector $w$to be $(0, 0, -E, Y, -C)$ and $(0, 0, 1/3, 1/3, 1/3)$. Assume$\beta^* = (\beta_K^*, \beta_L^*, \beta_E^*, \beta_Y^*, \beta_C^*)^T$ and $\beta^{**} = (\beta_E^{**}, \beta_Y^{**}, \beta_C^{**})^T$ be the solutions of Eq. (2), the UEI and EEPI can be formulated as:

$$UEI = \frac{1}{4}\left[\frac{(1-\beta_K^*) + (1-\beta_L^*) + (1-\beta_E^*) + (1-\beta_C^*)}{1+\beta_Y^*}\right] = \frac{1 - \frac{1}{4}(\beta_K^* + \beta_L^* + \beta_E^* + \beta_C^*)}{1+\beta_Y^*} \tag{3}$$

$$EEPI = \frac{1}{4}\left[\frac{(1-\beta_E^{**}) + (1-\beta_C^{**})}{1+\beta_Y^{**}}\right] = \frac{1 - \frac{1}{2}(\beta_E^{**} + \beta_C^{**})}{1+\beta_Y^{**}} \tag{4}$$

Intuitively, the estimated value of UEI and EEPI range from 0 to 1, and higher values mean better energy and CO_2 emissions performance. In order to better compare the evaluation efficiency values between different years, we employ the global DEA model containing the production technology information with cross-section and time-series dimensions to estimate UEI and EEPI indicators [44]. According to Oh [45], the values of UEI and EEPI can be calculated by solving the following linear programming problem.

For UEI:

$$\vec{D}(K, L, E, Y, C) = \max\left\{\tfrac{1}{9}\beta_K + \tfrac{1}{9}\beta_L + \tfrac{1}{9}\beta_E + \tfrac{1}{3}\beta_Y + \tfrac{1}{3}\beta_C\right\}$$
$$\begin{aligned}
\text{s.t.} \sum_{t=1}^{T}\sum_{n=1}^{N}\mu_{n,t}K_{n,t} &\leqslant K_0 - \beta_K K_0\\
\sum_{t=1}^{T}\sum_{n=1}^{N}\mu_{n,t}L_{n,t} &\leqslant L - \beta_L L\\
\sum_{t=1}^{T}\sum_{n=1}^{N}\mu_{n,t}E_{n,t} &\leqslant E - \beta_E E\\
\sum_{t=1}^{T}\sum_{n=1}^{N}\mu_{n,t}Y_{n,t} &\geqslant Y + \beta_Y Y\\
\sum_{t=1}^{T}\sum_{n=1}^{N}\mu_{n,t}C_{n,t} &= C - \beta_C C
\end{aligned}$$
$$\mu_{n,t} \geqslant 0 \quad 0 \leqslant \beta_K, \beta_L, \beta_E, \beta_Y, \beta_C \leqslant 1 \quad \text{n} = 1,\ldots,\text{N} \ \text{t} = 1,\ldots,\text{T} \tag{5}$$

For EEPI:

$$\vec{D}(K, L, E, Y, C) = \max\left\{\tfrac{1}{3}\beta_E + \tfrac{1}{3}\beta_Y + \tfrac{1}{3}\beta_C\right\}$$
$$\begin{aligned}
\text{s.t.} \sum_{t=1}^{T}\sum_{n=1}^{N}\mu_{n,t}K_{n,t} &\leqslant K\\
\sum_{t=1}^{T}\sum_{n=1}^{N}\mu_{n,t}L_{n,t} &\leqslant L\\
\sum_{t=1}^{T}\sum_{n=1}^{N}\mu_{n,t}E_{n,t} &\leqslant E\\
\sum_{t=1}^{T}\sum_{n=1}^{N}\mu_{n,t}Y_{n,t} &\geqslant Y + \beta_Y Y\\
\sum_{t=1}^{T}\sum_{n=1}^{N}\mu_{n,t}C_{n,t} &= C - \beta_C C
\end{aligned}$$
$$\mu_{n,t} \geqslant 0 \quad 0 \leqslant \beta_E, \beta_Y, \beta_C \leqslant 1 \quad \text{n} = 1,\ldots,\text{N} \ \text{t} = 1,\ldots,\text{T} \tag{6}$$

N denotes the number of DMUs, T is the number of periods. Essentially, Eqs. (5) and (6) are the concrete expressions of Eq. (2). Like $w^T\beta$, $\vec{D}(K, L, E, Y, C)$ is the objective function. If $\vec{D}(K, L, E, Y, C) = 0$, that is to say, the province evaluated is located at the frontier of best practice and is therefore efficient. The constraint of the two equations is actually to construct the *meta*-frontier, which can ensure that the actual production activities are always belonging to the production technology set M. $\mu_{n,t}$ denotes the intensity variables for constructing *meta*-frontier technologies.

2.2. Tobit model and model specification

2.2.1. Tobit model

The Tobit regression model proposed by Tobin [46] depicts the correlation between non-negative dependent variables and independent variables when data is truncated or censored. The UEI and EEPI values of China's provincial manufacturing industries are between 0 and 1. Hence the Tobit model, which deals with truncated dependent variables, can be applied to avoid the bias and inconsistency in regression. The Tobit regression model is a powerful tool for further research after DEA analysis [47], which is constructed as follows:

$$H_{i,t}^{*} = c + \alpha LD_{i,t} + Z_{i,t}'\gamma + \varepsilon_{i,t},\ \varepsilon_{i,t}\tilde{\text{N}}(0, \sigma^2)$$
$$H_{i,t} = \begin{cases} H_{i,t}^{*} & \text{if } 0 < H_{i,t}^{*} < 1 \\ 0 & \text{Otherwise} \end{cases} \quad \text{i} = 1,2,\ldots,\text{N} \ \text{t} = 1,2,\ldots,\text{T} \tag{7}$$

$H_{i,t}^{*}$ denotes the latent variable; $H_{i,t}$ represents the energy and CO_2 emissions performance of the manufacturing industry in the t period of the i province (UEI or EEPI) obtained from the DEA model; $LD_{i,t}$ represent the land transport infrastructure in the t period of the i province; $Z_{i,t}'$ denotes the vector set of control variables; $\alpha$and $\gamma$are the coefficients of the corresponding variables; $\varepsilon_{i,t}$ is the random error term which follows the normal distribution.

2.2.2. Model specification

Theoretically, the construction of land transportation infrastructure will accelerate inter-regional technical and industrial exchanges, reduce energy consumption during transportation, form economies of scale, and ultimately improve the energy and environmental efficiency of the manufacturing industry. As the core explanatory variable of this paper, the fixed assets investment or the total mileage of roads and railways are generally used as the proxy variable for land transport infrastructure. The former is not suitable for our research for the following reasons. (i) Higher fixed assets investment does not imply more advanced land transport infrastructure construction. Taking the Qinghai-Tibet Railway as an example, the construction of the railway requires much investment due to the steep terrain, but the transportation infrastructure of the provinces along the line is not proportionally developed [48]. (ii) Unavailability of data. The fixed asset investment data of China's provincial railway and road transport industry from 1998 to 2003 is unavailable. (iii) We are unable to obtain the price index of land transport infrastructure construction to adjust the fixed asset investment to a specific benchmark price. Therefore, the land transport density (mileage of road and rail per square kilometer) is selected to measure the construction of land transport infrastructure.

Based on the theoretical framework of previous studies, four control variables were selected (economic growth, technological progress, energy prices, industrial structure) to conduct econometric analysis, so as to control the characteristics of each province.

(1) Economic growth

Economic growth expands energy demand, brings money and equipment to society and the country, and ultimately promotes the rational development of energy. Energy efficiency has also been improved with the increase of production technology level brought by economic growth. Most researchers adopt per capita GDP to evaluate the standard of economic growth in a region or country [49,50]. Accordingly, we use per capita GDP to reflect economic development at the provincial level truly.

(2) Technological progress

Technological progress, which is a crucial factor affecting the efficiency of energy and CO_2 emissions, can increase the output of unit capital, labor, or energy inputs [51]. More RD investment will result in more technical input, which will be transformed into more advanced production technology [52]. Since the RD investment data of the provincial manufacturing industry is not counted, we use the RD investment of industrial enterprises above designated size instead [53].

(3) Energy price

The energy price goes hand in hand with energy consumption and efficiency. Birol and Keppler [54] found that energy price is the major factor influencing energy consumption and efficiency. Hang and Tu [55] believed that although regulated by the Chinese government, the rising energy price can be conducive to improve energy efficiency. However, since there is no statistical data on energy price, the raw materials and fuel price index are selected as the proxy variable [51,52,56].

(4) Industrial structure

The industrial structure plays a pivotal role in energy conservation and pollution reduction. Lin and Moubarak [57] revealed the negative relationship between industrial structure and energy efficiency. Manufacturing, mining and quarrying, production and supply of electricity, heat, gas, and water, and construction sectors are included in China's secondary industries. The energy and environmental performance of CMI are closely tied to the production level of the secondary industry, where the manufacturing accounts for the main proportion in terms of labor, energy consumption, and total output. Referring to Lin and Chen [2], the ratio of GDP in the secondary industry is applied to measure industrial structure.

2.3. Data source and variable description

In view of the data missing in Ningxia and Jilin province before 1998 and the adjustment of China's administrative region[4], the interval time of our provincial panel data is from 1998 to 2016. The provincial panel data covers 30 provinces excluding Tibet, Hong Kong, Macau, and Taiwan due to data unavailability.

Besides, the industrial classification for national economic activities has been revised three times in 2002, 2011 and 2017, and China's industrial statistical caliber has also been adjusted three times in 1998, 2007, and 2011. As data accounts for a great deal for empirical research, referring to the method of Chen [58], this paper summarizes the relevant data of each sub-sectors of provincial manufacturing industries in China and adjusts it to obtain the provincial manufacturing data with the full industrial caliber and unified standard.

The mileage of roads and railways in each province is derived from the CEIC China database. Per capita GDP data and the ratio of GDP in the secondary industry are available in the Wind database. RD investment of industrial enterprises above designated size and the relevant data of the sub-sectors of the manufacturing industry in each province (employment number, energy consumption, gross industrial output value) are obtained from the Provincial statistical yearbook.

The energy input data is obtained by aggregating the energy consumption of each sub-industry of the provincial manufacturing industry. The labor input is represented by the number of employed people. Due to the severe missing of industrial value-added data, the gross industrial output value of manufacturing is applied to measure the desirable output. Since there is no direct available capital stock data, following by Goldsmith [59], the perpetual inventory method is adopted to estimate the capital input.

For undesirable output, provincial CO_2 emissions are calculated by the following formula:

$$CO_2EM_{tj} = \sum_i E_{tj}^i \times F^i \tag{8}$$

CO_2EM_{tj} represents the CO_2 emissions of j province in t year (ton); E_{tj}^i refers to the energy consumption of the i species in j province in t year (ton of standard coal equivalent); F^i denotes the CO_2 emission coefficient of various energy sources.

To eliminate the effect of prices, the nominal variables are transformed into real variables (1998 = 100). The statistical description of all the variables are shown in Table 2.

3. Results and analysis

3.1. Energy and environmental performance of China's manufacturing industry

In recent years, China's provincial manufacturing industry has made significant progress in achieving the coordinated development of energy and environment. For instance, Jiangsu province, as an economically developed region in eastern China, has great energy and environmental performance in the manufacturing industry due to its entire land transportation infrastructure, mature energy utilization technology, clean energy structure, and continuously optimized industrial structure. The safe, clean, and efficient modern energy security system supported by railway and road network has formed in Jiangsu province, which reduces the cost of energy transportation brought by the space distance. Besides, by adjusting and optimizing the industrial structure and accelerating the independent innovation and technology application of energy conservation, the manufacturing industry in Jiangsu province has achieved a significant improvement in energy efficiency.

[4] Chongqing was carved out of Sichuan Province into a municipality that reports directly to the Chinese central government after 1997.

Table 2
The statistical description of all the variables.

Variable	Obs	Mean	Std. Dev.	Min	Max
K	570	340.20	424.13	7.50	3025.80
L	570	333.25	427.04	7.51	2247.81
E	570	5594.75	4881.34	126.58	26761.00
Y	570	1362.65	2191.17	9.40	14208.70
C	570	13836.80	11960.54	322.65	63685.56
LD	570	0.65	0.48	0.02	2.18
EG	570	0.95	0.56	0.24	2.77
TP	570	8.71	15.82	0.03	114.71
EP	570	1.82	0.81	0.91	6.74
IS	570	0.46	0.08	0.19	0.62

Note: Obs represents the number of observations; Std. Dev. denotes standard deviation.

Another typical province is Henan in the central region. The backward industrial structure dominated by the secondary industry was an important reason for the low energy and environmental efficiency in Henan province. In recent years, Henan province has actively reformed the energy sector and adhered to the policy of supporting economic growth with the development of the tertiary industry. The vigorous advancement of technological progress has promoted the transformation of the industrial sector from labor-intensive and energy-intensive to technology-intensive. On the other hand, the government encourages enterprises to reduce the use of fossil fuels by implementing price control measures such as coal resource tax and low-price power supply. Furthermore, Henan province has now formed an efficient modern energy transport channel supported by the road and railway network, which is conducive to solving the problem of overcapacity and improving energy and environmental efficiency.

Table 3 presents the estimated results of the energy and CO_2 emission indexes (UEI and EEPI) for the provincial manufacturing industry during the period 1998–2016. We present the results for the selected year in Table 3 for the sake of space-saving. Intuitively, the overall level of energy and environmental efficiency in China's provincial manufacturing industry is low and varies widely. Emrouznejad and Yang [60] draw similar conclusions by constructing a global Malmquist-Luenberger productivity index within DEA.

In order to show the results more intuitively, we depicted the provincial energy and CO_2 emissions performance in Fig. 3. Obviously, both UEI and EEPI at the provincial level have improved substantially. The provinces such as Beijing and Tianjin have already reached the frontier of production, indicating that China's energy conservation and pollution reduction policies implemented in recent years are very effective [7]. On the other hand, we can see it clearly that there exists tremendous potential and space to increase the efficiency of production activities in the manufacturing industry in most provinces of China [43,61].

Besides, we also estimate the energy and CO_2 emission indexes (UEI and EEPI) of major subsectors in manufacturing. Estimated results for 26 major manufacturing subsectors are reported in Appendix A due to statistical caliber adjustments and data availability. However, since this paper mainly aims to explore the overall characteristics of the Chinese industry and find common ground of the manufacturing industry, the subsequent discussion and analysis are based on the results in Table 3.

Fig. 4 describes the variation tendency of UEI and EEPI of the nationwide and the three regions (east, central, and west) grouped by geographic distance. Similar to Table 3, UEI and EEPI at the regional level have been significantly improved. Meanwhile, it was also found that the gaps in energy and CO_2 emissions efficiency between the three regions are growing. A possible explanation for the phenomenon is the inability to achieve performance convergence through the dissemination of technology and management experience between China's regions due to the lack of adequate market integration. It should be pointed out that the performance level in the eastern region is much

Table 3
Energy and CO_2 emission indexes (UEI and EEPI) for the provincial manufacturing industry.

	UEI							EEPI						
	1998	2000	2005	2010	2015	2016	Average	1998	2000	2005	2010	2015	2016	Average
Beijing(E)	0.135	0.170	0.361	0.647	0.829	1.000	0.524	0.087	0.118	0.248	0.565	0.854	1.000	0.479
Tianjin(E)	0.227	0.269	0.469	0.620	1.000	1.000	0.598	0.264	0.307	0.412	0.533	1.000	1.000	0.586
Hebei(E)	0.100	0.110	0.114	0.211	0.278	0.286	0.183	0.051	0.056	0.062	0.120	0.206	0.217	0.118
Shanxi(C)	0.063	0.069	0.093	0.103	0.124	0.119	0.095	0.030	0.029	0.032	0.045	0.060	0.063	0.043
Inner-Mongolia(W)	0.072	0.091	0.192	0.358	0.351	0.379	0.241	0.040	0.043	0.060	0.065	0.066	0.067	0.057
Liaoning(E)	0.099	0.117	0.223	0.418	0.732	1.000	0.431	0.072	0.089	0.108	0.217	0.568	1.000	0.342
Jilin(C)	0.103	0.125	0.212	0.428	0.562	0.695	0.354	0.046	0.070	0.081	0.147	0.336	0.561	0.207
Heilongjiang(C)	0.106	0.123	0.144	0.189	0.229	0.241	0.172	0.100	0.094	0.085	0.104	0.172	0.176	0.122
Shanghai(E)	0.235	0.220	0.381	0.515	0.553	0.566	0.412	0.232	0.199	0.338	0.484	0.511	0.526	0.382
Jiangsu(E)	0.224	0.265	0.441	0.721	0.939	1.000	0.598	0.156	0.180	0.224	0.463	0.549	0.982	0.426
Zhejiang(E)	0.195	0.209	0.285	0.350	0.408	0.424	0.312	0.158	0.149	0.181	0.241	0.305	0.306	0.223
Anhui(C)	0.117	0.118	0.184	0.321	0.467	0.512	0.287	0.071	0.073	0.105	0.246	0.469	0.529	0.249
Fujian(E)	0.222	0.244	0.395	0.581	1.000	1.000	0.574	0.216	0.247	0.343	0.456	1.000	1.000	0.544
Jiangxi(C)	0.107	0.107	0.169	0.271	0.408	0.433	0.249	0.086	0.090	0.082	0.178	0.313	0.322	0.178
Shandong(E)	0.186	0.221	0.294	0.374	0.482	0.490	0.341	0.162	0.207	0.176	0.252	0.364	0.360	0.253
Henan(C)	0.123	0.127	0.192	0.292	0.428	0.449	0.269	0.076	0.079	0.091	0.147	0.334	0.366	0.182
Hubei(C)	0.138	0.150	0.178	0.284	0.403	0.454	0.268	0.090	0.084	0.064	0.134	0.250	0.296	0.153
Hunan(C)	0.096	0.104	0.179	0.311	0.429	0.466	0.264	0.064	0.061	0.085	0.159	0.309	0.344	0.170
Guangdong(E)	0.215	0.247	0.406	0.508	0.747	0.773	0.483	0.190	0.218	0.312	0.441	0.854	0.898	0.485
Guangxi(W)	0.106	0.107	0.160	0.219	0.377	0.402	0.228	0.084	0.078	0.083	0.118	0.216	0.236	0.136
Hainan(E)	0.140	0.142	0.172	0.350	0.311	0.329	0.241	0.133	0.136	0.109	0.238	0.206	0.211	0.172
Chongqing(W)	0.116	0.134	0.241	0.398	0.572	0.604	0.344	0.095	0.106	0.176	0.314	0.523	0.607	0.304
Sichuan(W)	0.111	0.098	0.172	0.265	0.309	0.321	0.213	0.048	0.054	0.065	0.114	0.179	0.197	0.110
Guizhou(W)	0.105	0.096	0.115	0.130	0.302	0.352	0.183	0.061	0.042	0.045	0.051	0.103	0.144	0.074
Yunnan(W)	0.121	0.113	0.189	0.234	0.298	0.315	0.212	0.067	0.068	0.067	0.086	0.102	0.107	0.083
Shaanxi(W)	0.109	0.134	0.175	0.239	0.282	0.306	0.207	0.090	0.102	0.094	0.101	0.116	0.122	0.104
Gansu(W)	0.085	0.106	0.139	0.168	0.227	0.227	0.159	0.041	0.057	0.055	0.069	0.070	0.076	0.061
Qinghai(W)	0.073	0.079	0.103	0.140	0.227	0.264	0.148	0.037	0.033	0.030	0.038	0.117	0.144	0.066
Ningxia(W)	0.084	0.086	0.123	0.153	0.182	0.191	0.137	0.038	0.037	0.039	0.062	0.067	0.062	0.051
Xinjiang(W)	0.081	0.097	0.132	0.142	0.156	0.171	0.130	0.051	0.060	0.048	0.043	0.062	0.072	0.056
East	0.180	0.201	0.322	0.481	0.662	0.715	0.427	0.156	0.173	0.228	0.365	0.583	0.682	0.365
Central	0.107	0.115	0.169	0.275	0.381	0.421	0.245	0.070	0.072	0.078	0.145	0.280	0.332	0.163
West	0.097	0.104	0.158	0.222	0.299	0.321	0.200	0.059	0.062	0.069	0.097	0.147	0.167	0.100
average	0.130	0.143	0.221	0.331	0.454	0.492	0.295	0.098	0.105	0.130	0.208	0.343	0.400	0.214

Note: E, C, W in parentheses represents the east, central and west region, respectively.

higher than in central and western regions, which gaps are still in danger of continued expansion. The main reason is that the phased changes in economic development level and energy consumption structure in different regions have led to the difference in energy and CO_2 emissions performance. Besides, the central and western region also lags behind the eastern region in terms of energy-saving technology utilization and management experience.

3.2. Results of panel Tobit model

Subsequently, the panel Tobit model was applied to investigate the impact of land transport infrastructure on the performance of CMI, which results are shown in Table 4.

The LR test results at the bottom of Table 4 indicate that the null hypothesis H_0: $\sigma_u = 0$ should be strongly rejected, which means the individual effect exists and the panel Tobit model with random effect should be used.

The regression coefficients in Table 4 reflect the marginal effects of the corresponding variables on energy and CO_2 emissions efficiency of CMI. From the perspective of UEI, the improvement of each unit of land transport density will increase the efficiency value of 0.0865 units. When we focused on EEPI, the impact value dropped to 0.0524. Both results suggest that the land transport infrastructure plays a substantial and significant decisive role in the energy and CO_2 emissions performance of CMI. The main impact mechanisms are concentrated on the following three aspects: (i) The construction of land transport infrastructure needs the cooperation of multiple industries in the manufacturing industry and the joint work among provinces and economic zones, bringing about the higher resource utilization efficiency than other transport modes [19]. Moreover, the investment in roads and railways are often planned by the central government, and local governments are highly motivated, making the construction period short and easy to form economies of scale. With the application of new technologies and materials in the process of road and railway construction, both the production side and the usage side of the materials have obviously decreased the energy consumption, promoting the energy and environmental efficiency of the manufacturing industry. (ii) Electricity is mainly utilized in the operation of railway facilities, thus realizing the replacement of electric energy. As the main direction of road investment, the formation of the highway network has greatly dramatically energy efficiency since the low energy consumption of vehicles at uniform and high speed. In addition, the improvement of land transport infrastructure will accelerate the exchange of technologies and industries between regions, contributing to the transfer and adjustment of industrial structure nationwide. (iii) The excess capacity of steel and cement can be consumed during the construction of land transport infrastructure, contributing to industrial structural reform and eliminating backward production capacity. Besides, the completed high-speed rail and motorway can reduce the logistics cost of enterprises, shorten the travel time of personnel, improve work efficiency, and ultimately indirectly increase the energy and environmental efficiency of the manufacturing industry [26].

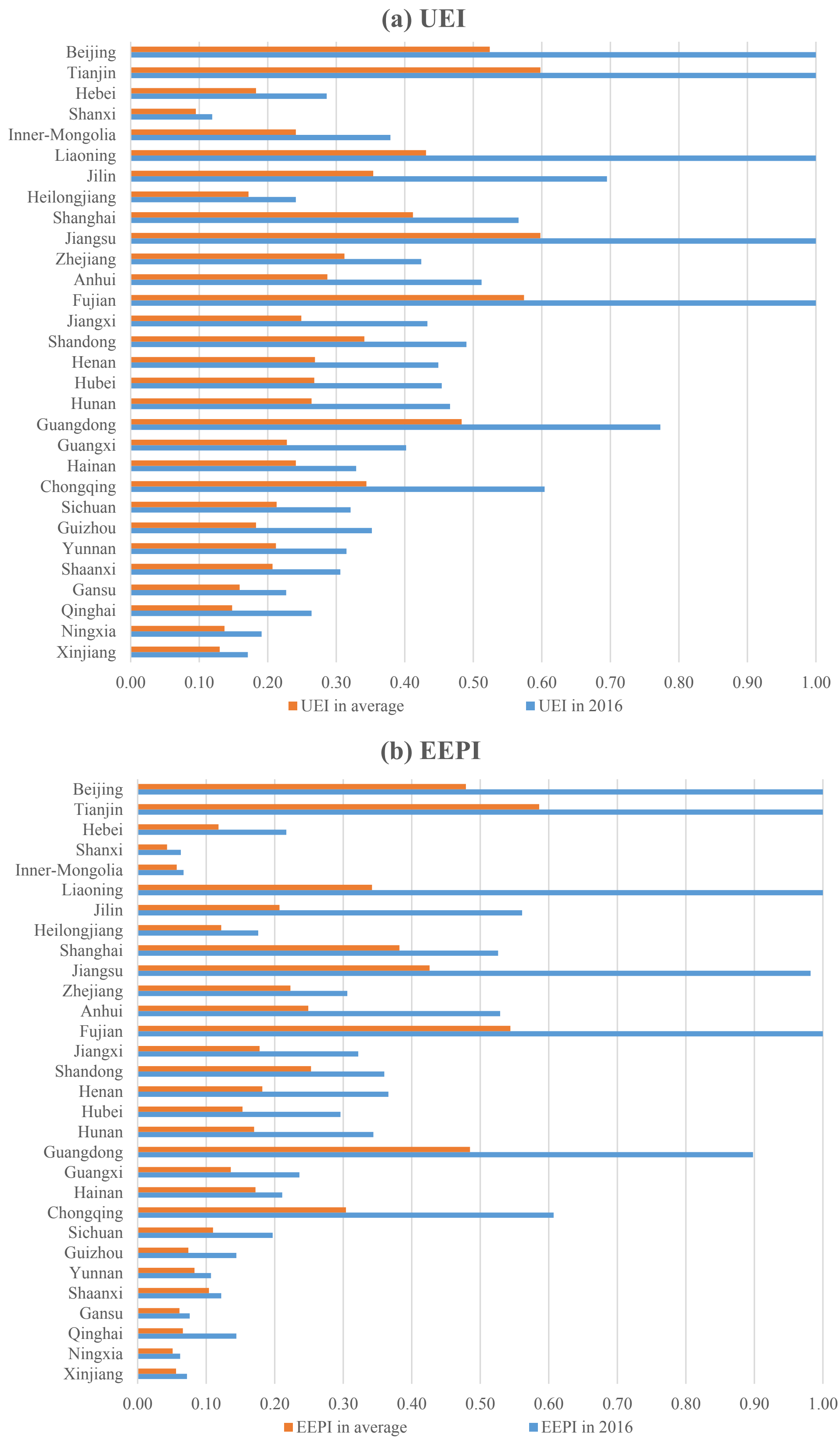

Fig. 3. Provincial energy and CO_2 emissions performance on average (1998–2016).

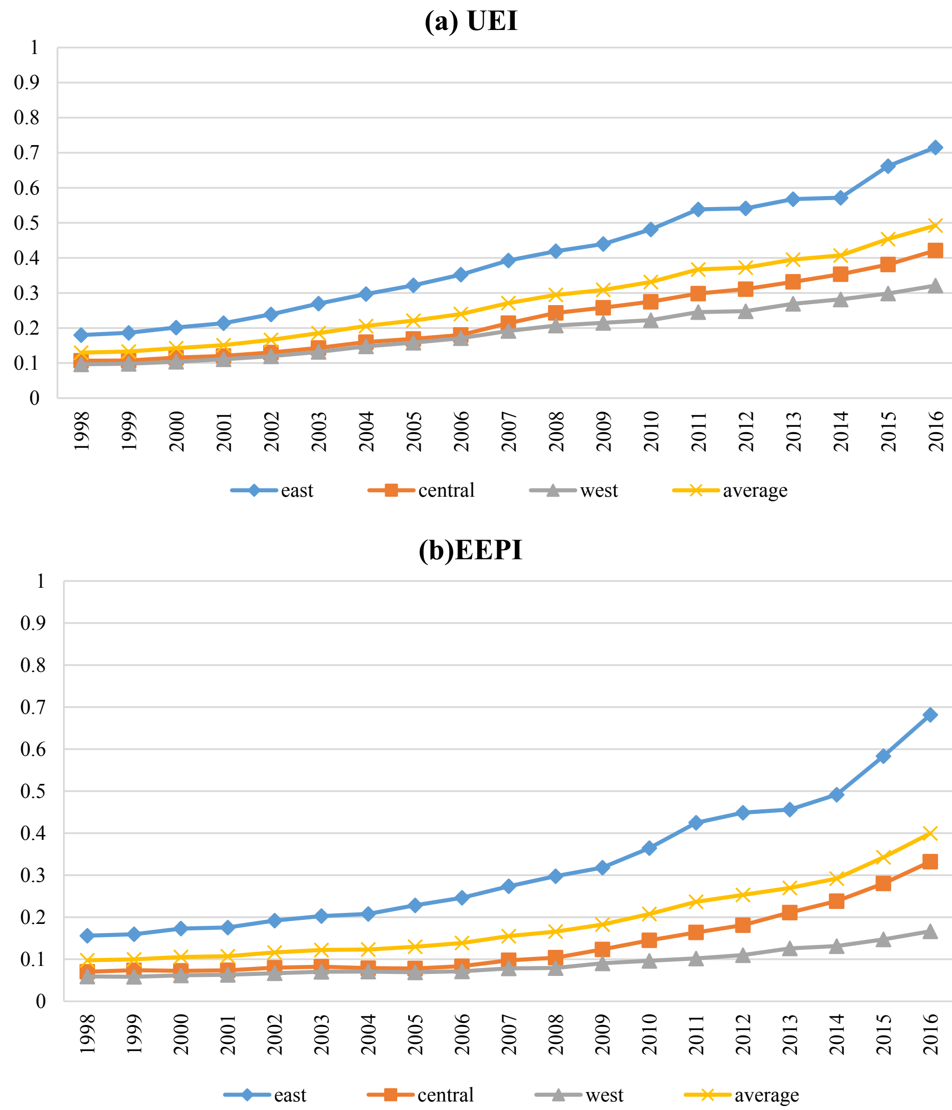

Fig. 4. The variation tendency of energy and CO_2 emissions performance.

Table 4
Model estimation results.

Variables	UEI	EEPI
LT	0.0865***	0.0524***
	(4.96)	(2.70)
EG	0.239***	0.145***
	(9.02)	(6.27)
TP	0.00287***	0.00394***
	(7.03)	(9.02)
EP	0.0313***	0.0194**
	(4.33)	(2.50)
IS	−0.186**	−0.420***
	(-2.18)	(-4.66)
Constant	−0.00347	0.137***
	(-0.09)	(3.35)
LR test of sigma_u = 0: chibar2(01)	301.12***	226.36***

Note: ***indicates p < 0.01, **indicates p < 0.05, *indicate p < 0.10. Standard errors are in parentheses.

As we can see in Table 4, the influence of control variables cannot be ignored. (i) The coefficient of economic growth is significantly positive (0.239 and 0.145), which indicates that economic growth will bring about the renewal of equipment, improvement of production technology and management level, the rational use of energy, and the reduction of CO_2 emissions. Similar results include Xu and Lin [62]. (ii) Technological progress shows a notable positive effect on energy and CO_2 emissions performance of CMI. Technological innovations can increase productivity and market competitiveness, thereby reducing energy consumption. The introduction of advanced energy development processes and emission reduction technologies will also greatly decrease CO_2 emissions. (iii) Despite the distortions in China's factor market, which energy prices are controlled and determined by the government [26,55], the rise of energy prices is conducive to strengthening the awareness of energy conservation in enterprises, and urging enterprises to make rational and scientific use of energy while actively seeking for technological innovation and progress so as to reduce production costs. The result supports the conclusion of Lin and

Table 5
Results of robustness check.

Variables	UEI			EEPI		
	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
LT	0.141***	0.116***	0.0835***	0.130***	0.0703***	0.0480**
	(8.64)	(7.08)	(4.80)	(6.90)	(3.86)	(2.44)
EG	0.315***	0.290***	0.216***	0.210***	0.163***	0.117***
	(11.74)	(11.38)	(9.32)	(7.71)	(7.22)	(5.17)
TP		0.00265***	0.00320***		0.00391***	0.00451***
		(6.38)	(8.49)		(8.85)	(10.62)
EP	0.0247***		0.0315***	0.0162*		0.0158**
	(3.28)		(4.39)	(1.88)		(2.02)
IS	−0.432***	−0.201**		−0.698***	−0.402*** (-4.40)	
	(-5.17)	(-2.28)		(-7.14)		
Constant	0.0385	−0.00500	−0.0678***	0.192***	0.135***	−0.0236
	(0.89)	(-0.12)	(-2.81)	(4.20)	(3.28)	(-1.06)
LR test of sigma_u = 0: chibar2(01)	372.52***	311.48***	297.46***	259.67***	228.51***	217.45***

Table 6
Results of subregional research.

Variables	UEI			EEPI		
	East	Central	West	East	Central	West
LT	−0.0937**	0.0704***	0.119***	−0.186***	0.0401*	0.112***
	(-2.21)	(2.80)	(9.03)	(-3.92)	(1.68)	(8.41)
EG	0.214***	0.678***	0.193***	0.143***	0.417***	0.0217
	(3.60)	(10.34)	(9.65)	(2.94)	(6.07)	(1.06)
TP	0.00265***	0.000925	0.00699***	0.00372***	0.00704***	0.00837***
	(3.52)	(0.69)	(4.89)	(5.17)	(5.01)	(5.72)
EP	0.147***	−0.0753***	−0.00685*	0.153***	−0.0922***	−0.0124***
	(7.75)	(-4.77)	(-1.89)	(7.60)	(-5.58)	(-3.37)
IS	−0.998***	−0.101	0.0675	−1.392***	−0.147*	−0.0522
	(-3.56)	(-1.20)	(0.99)	(-4.32)	(-1.65)	(-0.76)
Constant	0.298***	−0.120***	−0.0141	0.550***	0.00786	0.0589**
	(2.63)	(-3.15)	(-0.54)	(3.74)	(0.22)	(2.20)
LR test of sigma_u = 0:chibar2(01)	53.72***	114.01***	75.67***	31.44***	76.96***	105.51***

Chen [2] that the increase in energy prices will encourage people to consume energy in a more efficient way. (iv) On the contrary, the industrial structure shows a significant negative impact, which is in line with our expectations. The secondary industry contains many energy-intensive industries as well as environment-intensive industries, which worsen the energy and environmental performance in the manufacturing industry.

3.3. Robustness checks

Due to data incompleteness, the fixed asset investment indicators cannot be applied to measure land transport infrastructure in robustness tests. Therefore, we make the substitution by regressing after deleting the control variable, in which results are reported in Table 5.

In Model (1)-(6), positive and statistically significant coefficients (0.141, 0.116, 0.0835, 0.130, 0.0703 and 0.0480) indicate that land transport infrastructure all produce positive marginal effect on the energy and CO_2 emissions performance of CMI. Therefore, the results proved to be robust through the robustness checks in Table 5.

3.4. Subregional research

Considering the uneven development of China's regional manufacturing industry and land transport infrastructure construction, we conducted subregional research on the basis of the nationwide study. Table 6 shows the impact of land transport infrastructure in the three regions.

It is worth noting in Table 6 that the development of each unit of land transport density in the eastern region will decrease the UEI of 0.0937 units and the EEPI of 0.186 units. That is to say, the improvement of land transport infrastructure in eastern China has a significant negative influence on the energy and CO_2 emissions efficiency of the manufacturing industry, which is different from the results at the national level. With the advantage as a developed economy, the comprehensive transportation system of the eastern region is mature, where the integrated transportation backbone network has also achieved multi-directional connectivity. Therefore, the marginal effect of well-established land transport infrastructure on improving the energy and CO_2 emissions performance of the manufacturing industry is low. In contrast, it is necessary to consume a large number of building materials such as steel and cement in the construction process of land infrastructure, which indirectly promotes the development of energy-intensive industries in the manufacturing industry, thus consuming more energy and generating more emissions. The negative inhibition exceeds the positive marginal effect, making the construction of land transport infrastructure play an inhibitory role in increasing the performance of the manufacturing industry in the eastern region.

Another interesting phenomenon is the depressing effect of energy prices on the performance of the manufacturing industry in the central and western regions, presented by the significantly negative regression coefficients (-0.0753, −0.00685, −0.0922 and −0.0124). Rising energy prices will bring about higher costs, encouraging the eastern region to use advanced equipment and technology to reduce costs in the construction of land transport infrastructure, which is conducive to improving energy efficiency. However, since the development and technical level of the central and western regions lag behind the eastern region, the transmission mechanism by the rising energy prices for technological upgrading is poor, and production costs cannot be reduced through technological progress, resulting in the negative impact on the energy and CO_2 emissions performance of manufacturing industry. It shows from a side view that China's energy price reform implemented in 2007, which focuses on the upgrading of refined oil and electricity prices, has a relatively limited effect on energy conservation and pollution reduction of the manufacturing industry in the central and western regions.

4. Conclusions and policy implications

4.1. Conclusions

This paper calculated two indicators measuring energy and carbon dioxide emissions performance of China's manufacturing industry by using non-radial directional distance function. The panel Tobit model was then adopted to focus on factors affecting the performance. Based on the two-stage analysis, the main conclusions in this paper are as follows:

(1) The gaps in energy and carbon dioxide emissions efficiency between the three regions (east, central, and west) in China are growing. Since the phased changes in economic development level and energy consumption structure in different regions, the performance in eastern China is far superior to the central and western China, which gaps are still in danger of continued expansion. In other words, there exist tremendous potential and space to increase the efficiency of production activities in the manufacturing industry in most provinces of China.

(2) Land transport infrastructure, economic growth, technological progress, and energy prices have significant positive effects on the energy and carbon dioxide emissions performance of China's manufacturing industry, while the industrial structure plays a negative inhibitory role. The construction of land transport infrastructure mainly affects the performance of the sector through various influencing mechanisms such as forming scale effect, achieving electric energy substitution, accelerating regional exchange, and eliminating the backward production capacity.

(3) Being different from the results at the national level, from a regional perspective, the development of land transport infrastructure in the eastern region plays a negative role in increasing the energy and environmental performance of the manufacturing industry.

4.2. Policy implications

Lie in the foundation of the above conclusions, policy recommendations are proposed in the following aspects.

(1) Policymakers should strengthen the construction of land transport infrastructure, promote technological progress, raise energy prices, and improve industrial structure. This is regarded as the basic means to guide the transformation of economic growth mode, to increase the energy allocation and carbon dioxide emission efficiency of China's manufacturing industry.

(2) The Chinese government should emphasize the construction of land transportation infrastructure in the central and western regions, forming the scale effect by increasing investment, ultimately improving the energy and environmental performance of the manufacturing industry.

(3) Improving the energy and carbon dioxide emission efficiency by reasonably guiding the rational flow of resources among regions. The government should establish an information-sharing mechanism for energy use technologies between different regions of China, promoting the central and western regions to learn advanced technology and management experience from eastern regions.

(4) Since China's energy price reform has a relatively limited effect on energy conservation and pollution reduction of the manufacturing industry in the central and western regions, the government should consummate energy price formation mechanisms that reflect market supply and demand, environmental costs, and resource scarcity as soon as possible.

4.3. Future research prospects

In the future, this paper will conduct further research based on spatial and micro perspectives.

(1) Exploring the spatial spillover effect of transportation infrastructure on energy efficiency in the manufacturing industry. The characteristics of network structure often lead to the impact of transportation infrastructure beyond the area. Theoretically, the development of transportation infrastructure will promote the agglomeration and spread of economic activities, improve inter-regional trade, and the flow of energy factors, thus affecting the energy efficiency of the manufacturing industry.

(2) Investigating the possible influence paths of high-speed railway opening or road construction on the energy efficiency of manufacturing enterprises through the micro survey data, and constructing quasi-natural experiments to identify the causal relationship.

CRediT authorship contribution statement

Boqiang Lin: Conceptualization, Data curation, Methodology, Software, Writing - original draft. **Yu Chen:** Data curation, Methodology, Software, Writing - original draft.

Declaration of Competing Interest

This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue. The authors have no affiliation with any organization with a direct or indirect competing financial interests or personal relationships in the subject matter discussed in the manuscript.

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Appendix A. Energy and CO_2 emission indexes (UEI and EEPI) of major subsectors in manufacturing

See Table A1.

Table A1
Energy and CO_2 emission indexes (UEI and EEPI) of major subsectors in manufacturing.

Code of subsectors	UEI							EEPI						
	1998	2000	2005	2010	2015	2016	Average	1998	2000	2005	2010	2015	2016	Average
C13	0.188	0.217	0.310	0.430	0.585	1.000	0.455	0.079	0.081	0.178	0.271	0.368	0.394	0.229
C14	0.127	0.153	0.190	0.290	0.376	0.381	0.253	0.050	0.057	0.108	0.154	0.256	0.256	0.147
C15	0.153	0.161	0.155	0.263	0.346	0.360	0.240	0.073	0.082	0.101	0.166	0.255	0.271	0.158
C16	0.204	0.183	0.364	0.643	0.936	1.000	0.555	0.145	0.122	0.242	0.523	0.873	1.000	0.484
C17	0.116	0.149	0.244	0.249	0.291	0.299	0.225	0.058	0.085	0.089	0.149	0.118	0.123	0.104
C18	0.266	0.280	0.341	0.514	0.680	0.706	0.465	0.147	0.150	0.185	0.427	0.668	0.700	0.379
C19	0.277	0.292	0.461	0.818	0.918	1.000	0.628	0.151	0.146	0.335	0.790	0.890	1.000	0.552
C20	0.110	0.147	0.252	0.311	0.410	0.447	0.280	0.060	0.075	0.093	0.146	0.239	0.301	0.152
C21	0.163	0.215	0.319	0.472	0.496	0.529	0.366	0.075	0.142	0.225	0.431	0.456	0.517	0.308
C22	0.096	0.117	0.167	0.173	0.209	0.218	0.163	0.026	0.032	0.042	0.065	0.084	0.085	0.056
C23	0.136	0.151	0.147	0.232	0.354	0.372	0.232	0.108	0.123	0.165	0.187	0.351	0.379	0.219
C24	0.273	0.271	0.288	0.400	0.335	0.350	0.319	0.141	0.121	0.154	0.305	0.329	0.355	0.234
C25	0.137	0.142	0.277	0.355	0.452	1.000	0.394	0.010	0.020	0.032	0.036	0.038	1.000	0.189
C26	0.099	0.116	0.151	0.211	0.257	0.268	0.184	0.011	0.015	0.024	0.051	0.040	1.000	0.190
C27	0.154	0.183	0.162	0.271	0.361	0.378	0.252	0.066	0.079	0.110	0.169	0.254	0.277	0.159
C28	0.089	0.120	0.167	0.241	0.277	0.275	0.195	0.019	0.026	0.048	0.080	0.088	0.083	0.057
C29	0.144	0.173	0.268	0.261	0.314	0.323	0.247	0.071	0.083	0.099	0.114	0.156	0.165	0.115
C30	0.071	0.085	0.155	0.175	0.212	0.222	0.153	0.011	0.013	0.017	0.038	0.044	0.050	0.029
C31	0.088	0.092	0.175	0.218	0.243	0.254	0.179	0.007	0.009	0.019	0.028	0.033	0.028	0.021
C32	0.115	0.140	0.189	0.266	0.342	0.358	0.235	0.017	0.021	0.036	0.050	0.053	0.055	0.039
C33	0.167	0.202	0.250	0.300	0.360	0.369	0.275	0.084	0.086	0.103	0.114	0.184	0.187	0.126
C34	0.120	0.156	0.255	0.336	0.420	0.434	0.287	0.068	0.093	0.187	0.220	0.308	0.320	0.199
C35	0.136	0.165	0.223	0.345	0.471	0.507	0.308	0.075	0.098	0.171	0.239	0.437	0.498	0.253
C38	0.242	0.243	0.378	0.556	0.600	0.625	0.441	0.113	0.172	0.237	0.462	0.596	0.635	0.369
C39	0.281	0.344	0.463	0.456	0.596	0.603	0.457	0.201	0.260	0.372	0.446	0.622	0.626	0.421
C40	0.208	0.217	0.384	0.431	0.578	0.617	0.406	0.168	0.126	0.291	0.379	0.610	0.679	0.376

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