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RESEARCH ARTICLE

Regional inequality of total factor CO_2 emission performance and its geographical detection in the China's transportation industry

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Abstract
The total factor CO_2 emission performance (TFCEP) of transportation industry has received increasing research interests, while existing literature pays little attention to its regional inequality and driving factors. In order to uncover the regional inequality of TFCEP in China's transportation industry, this paper used Theil index and combined with geographical detector model (GDM) to explore the driving factors and their interactions on TFCEP in Chinese transportation industry. The results revealed that the TFCEP of transportation industry showed a promising increase during 2003–2017 with an annual growth rate of 0.12%, and the improvement was contributed by the technical efficiency change. The TFCEP in the Eastern region performed better than that in the Northeast, Central, and Western region. Regional inequality of TFCEP did exist and exhibited an obvious downward trend. The within-region inequality had a greater impact on the inequalities than between region. Freight turnover was the main driving factor of TFCEP in the transportation industry, followed by the energy intensity and per-capita GDP. In the Eastern and Western regions, freight turnover had the greatest impact on TFCEP, while in the Central and Northeastern regions, urbanization rate and energy intensity were the dominant factors, respectively. The interactions between energy intensity and freight turnover were highly influential. This paper provides important insights for different regions to formulate targeted carbon emission reduction policies.

Keywords Total factor CO_2 emission performance · Chinese transportation industry · Driving factors · Theil index · Geographical detector model

Introduction

China has surpassed the USA to be the world's largest energy consumer as well as the carbon emitter since 2009 (EIA 2010). In 2018, China's carbon emissions took up 27.8% of global greenhouse gas emissions (BP 2019). As the third largest energy consumption sector, Chinese transportation industry contributed 10% of the national total carbon emission (Zhang and Wei 2015). Until now, it still maintains a growing trend (Hu et al. 2018), which meant that there is large carbon emission reduction potential in the transportation industry. Revealing the affecting factors of the rapid growth of the carbon emissions in China's transportation industry and discovering the way to sustainable development are important for China to achieve carbon peak and carbon neutralization targets.

As one of the important ways for the transportation industry to achieve economic growth and carbon dioxide emission reduction, improving the carbon emission performance has great practical value and theoretical significance (Chen et al. 2019; Zhang and Wei 2015). Different from a single indicator, the total factor carbon emission performance (TFCEP) can consider more production factors involved in the production

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process (Zhang and Wei 2015). Quite a few studies have explored the TFCEP in the China's transportation industry (Zhou et al. 2013; Zhang et al. 2015; Zhang and Wei 2015). For example, Zhang et al. (2015) investigated the dynamic TFCEP change and its decomposition of the transportation industry throughout China's 30 administrative regions from 2002 to 2010. They found that the TFCEP overall decreased by 32.8% over the period, which was primarily caused by technological decline. However, Zhang and Wei (2015) found that the overall TFCEP of transportation industry in China had an overall increase of 6.2% and it was mainly driven by technological innovation during 2000–2012. China has a vast territory with distinctive regional and provincial characteristics. There were inequalities in the carbon emissions and energy intensity in China's transportation industry (Du et al. 2020; Zhang et al. 2020). In the meanwhile, the distinctions in population distribution, economic development, industrial stage, and urbanization development level between regions are very large. These factors affect the TFCEP of transportation industry in various regions. Although the TFCEP of transportation industry has been studied in recent years, the existing studies did not incorporate regional inequalities and driving factors into their measurements of the dynamic TFCEP changes. Therefore, it is necessary to analyze provincial heterogeneity and regional inequalities when evaluating the TFCEP in China's transportation industry. Identification of the key factors for improving the TFCEP would be helpful to formulate more reasonable carbon emission reduction targets and policies in consideration of different regional characteristics.

So far, most studies have focused on the determinants of CO_2 emissions in Chinese transportation industry while paid little attention to the factors influencing TFCEP. The main method to identify the influencing factor of CO_2 emissions was the quantile regression approach (Lin and Benjamin 2017; Xu and Lin 2018), logarithmic mean Divisia index (Liu et al. 2015; Wang et al. 2018), STIRPAT model (Peng et al. 2020a), spatial Durbin model (Peng et al. 2020b), and dynamic VAR (vector autoregression) approach (Xu and Lin 2015). However, these methods only analyzed the single influence of independent variables on dependent variables, which were difficult to reveal the interactions between different variables. Thus, further research is needed to detect spatial heterogeneity in TFCEP of transportation industry and to reveal the driving factors.

Geographic detector model (GDM) is a new type of spatial statistical method that has been employed to detect spatial stratified heterogeneity. Originally, it was proposed by Wang et al. (2010) to detect the environmental risk factors affecting the occurrence of endemic diseases (Hu et al. 2011; Wang et al. 2010). The principle idea is based on a hypothesis that if an independent variable contributes to the dependent variable, the dependent variable should have a similar spatial distribution as the independent variable. Compared with traditional statistical methods, GDM has two main advantages. First, there is no linear assumption on variables, and the multicollinearity of variables can be ignored. Second, it can not only analyze the single influence of independent variables on dependent variables, but also quantitatively describe interactive influence between variable pairs. At present, GDM method had been widely used in natural and social sciences, such as land surface temperature (Yin et al. 2019; Ren et al. 2016), vegetation variation (Guo et al. 2020; Ran et al. 2019), population distribution (Li et al. 2019), CO_2 emissions (Cao and Yuan 2019), $PM_{2.5}$ (Guo et al. 2021), and energy consumption (Wang et al. 2020a). However, to the best of our knowledge, GDM is rarely used to detect TFCEP driving factors in the transportation industry.

So far, there was considerable literature that deals with the issue of CO_2 emission, TFCEP, or the driving factors of CO_2 emission in China's transportation industry. However, few studies have specially investigated the spatial inequality of TFCEP, and the impact of individual driving factors and their interactions on TFCEP in China's transportation industry. Therefore, this paper will contribute the research community in the following aspects: (1) to evaluate the TFCEP of transportation industry by the Global Malmquist–Luenberger productivity index (GML index) method throughout China's 30 provinces from 2003 to 2017, respectively; (2) to discover regional inequalities of the TFCEP by employing Theil index; and (3) to assess the impacts of individual driving factors and their interactions on TFCEP by GDM method. This study can offer a new perspective in analyzing the driving factors of TFCEP change in China's transportation industry.

The remaining parts of the paper are organized as follows. The "Methodology and data" section presents the Global Malmquist–Luenberger productivity index method, Theil index method, geographical detector model, and data used in this study. Then, "Results and discussion" section analyzes and discusses the empirical results. Finally, the "Conclusion" section concludes the study with some policy implications for improving TFCEP and provides further research suggestions.

Methodology and data

Estimation method of the TFCEP

According to the point of TFCEP estimation view (Oh 2010; Färe et al. 2007), the production possibility set (PPS) that contains both desirable outputs and undesirable outputs should be defined. There are K decision making unites (DMUs) to be evaluated in periods T, $k = 1, 2, \ldots k'$, $\ldots, K$, T time periods: $s = 1, 2, \ldots, t, \ldots, T$, N kind of inputs: $x = (x_1, x_2, \ldots, x_N) \in \mathcal{R}_N^+$, M kinds of desirable outputs: $y = (y_1, y_2, \ldots, y_m) \in \mathcal{R}_M^+$, and I kinds of undersirable outputs: $c = (c_1, c_2, \ldots, c_I) \in \mathcal{R}_I^+$ in a production process. The PPS can be defined as $P(x) = \{(y, c) : x \; can \; produce \; (y, c)\}$. In this equation, the DMUs use inputs x to produce desirable outputs y and the undesirable outputs c. After PPS was determined, global Malmquist–Luenberger productivity index (GML index) method was used to estimate TFCEP of Chinese 30 provinces over the period 2003–2017. This paper referred to the study of Fan et al. (2015), who used this method to measure 32 industrial sub-sectors of Shanghai in the period of 1994–2011. This paper replaced each industrial sub-sector with each province as a DMU. The detail method of global Malmquist–Luenberger productivity index was introduced as follows.

For the calculation purpose, the directional distance function (DDF) was introduced. DDF is defined as follows (Färe et al. 2007):

$$\overrightarrow{D} = (x, y, c; g) = sup\{\beta : (y, c) + \beta g \in P(x)\} \tag{1}$$

This function seeks to increase the desirable outputs while reducing the undesirable outputs, where β denotes the contraction proportion of undesirable outputs and expansion proportion of desirable outputs; the direction vector $g = (g_y, -g_c)$ determines the direction in which the desirable outputs increase and the undesirable outputs decrease; and DDF is the maximized β remaining outputs $(y, c) + \beta g$ feasible; therefore, it can be used to measure the inefficiency level of DMUs. The smaller the value of DDF, the more efficiency level of DMUs. The conventional Malmquist–Luenberger productivity index method is based on contemporaneous PPS, i.e., $P^t(x^t) = \{(y^t, c^t) : x^t \; can \; produce \; (y^t, c^t)\}$; then for DMU k', $\overrightarrow{D}^t(x_{k'}^t, x_{k'}^t, c_{k'}^t; g_{k'}^t)$ can be solved by the linear programming problem (Oh 2009, 2010; Fan et al. 2015):

$$\begin{aligned}
&\overrightarrow{D}^t\left(x_{k'}^t, y_{k'}^t\ c_{k'}^t; g_{k'}^t\right) = max\beta \\
&s.t. \sum_{k=1}^{k} Z_k^t y_{km}^t \geq (1+\beta) y_{k'm}^t, \forall m \\
&\quad \sum_{k=1}^{k} Z_k^t c_{ki}^t = (1-\beta) c_{k'i}^t, \forall i \\
&\quad\quad \sum_{k=1}^{k} Z_k^t x_{kn}^t \leq x_{k'n}^t, \forall n \\
&\quad\quad\quad Z_k^t \geq 0, \forall k
\end{aligned} \tag{2}$$

where Z_k^t is intensity variables, which are weights assigned to provinces in constructing the PPS. The inequalities in Eq. (2) indicate that desirable outputs and inputs are free disposable, while undesirable outputs are weakly disposable.

To calculate and decompose the conventional Malmquist–Luenberger productivity index (ML index) of DMU k' between t and t+1, similar to $\overrightarrow{D}^t\left(x_{k'}^t, y_{k'}^t\ c_{k'}^t; g_{k'}^t\right)$, other three DDFs are needed. $\overrightarrow{D}^{t+1}\left(x_{k'}^{t+1}, y_{k'}^{t+1}\ c_{k'}^{t+1}; g_{k'}^{t+1}\right)$, $\overrightarrow{D}^t\left(x_{k'}^{t+1}, y_{k'}^{t+1}\ c_{k'}^{t+1}; g_{k'}^{t+1}\right)$, and $\overrightarrow{D}^{t+1}\left(x_{k'}^t, y_{k'}^t\ c_{k'}^t; g_{k'}^t\right)$ can be calculated by solving corresponding linear programming problems. However, because of the technical gap between two periods, the cross-period DDFs, $\overrightarrow{D}^t\left(x_{k'}^{t+1}, y_{k'}^{t+1}\ c_{k'}^{t+1}; g_{k'}^{t+1}\right)$ and $\overrightarrow{D}^{t+1}\left(x_{k'}^t, y_{k'}^t\ c_{k'}^t; g_{k'}^t\right)$, infeasibility problems are frequently encountered, which will render the ML index biased. Furthermore, since the geometric mean is used as the ML index of the evaluated DMU k', the ML index is not circular. Oh (2009, 2010) solved these deficiencies by employing the global PPS and proposed the GML index, which is free from the infeasibility problem and circular.

Referring to Oh (2009, 2010) and Fan et al. (2015), global PPS is defined as a union of all contemporaneous PPS, i.e., $P(x)^G = P(x)^1 \cup P(x)^2 \cup \ldots \cup P(x)^T$. Hence, $\overrightarrow{D}^G\left(x_{k'}^t, y_{k'}^t\ c_{k'}^t; g_{k'}^t\right)$ can be solved by the following linear programming problems:

$$\begin{aligned}
&\overrightarrow{D}^G\left(x_{k'}^t, y_{k'}^t\ c_{k'}^t; g_{k'}^t\right) = max\beta \\
&s.t. \sum_{s=1}^{T} \sum_{k=1}^{k} Z_k^s y_{km}^s \geq (1+\beta) y_{k'm}^t, \forall m; \\
&\quad \sum_{s=1}^{T} \sum_{k=1}^{k} Z_k^s c_{ki}^s = (1-\beta) c_{k'i}^t, \forall i; \\
&\quad\quad \sum_{s=1}^{T} \sum_{k=1}^{k} Z_k^s x_{kn}^s \leq x_{k'n}^t, \forall n; \\
&\quad\quad\quad Z_k^s \geq 0, \forall k \\
&\quad\quad\quad k = 1, 2, \ldots, K, \\
&\quad\quad\quad s = 1, 2, \ldots, T
\end{aligned} \tag{3}$$

This paper treated transportation industry in each province as a DMU. Therefore, different input–output indicators in each decision-making unit (DMU) were selected in this paper. When calculating TFCEP in China's transportation industry, most existing studies were basically using the same input–output indicators (Zhang et al. 2015; Yuan et al. 2017). This makes it difficult for us to dig deeper into other hidden indicators. Like the studies of Zhang et al. (2015) and Yuan et al. (2017), this paper chose labor force (L), capital stock (K), and energy (E) as inputs to produce the added value (Y) as desirable output and CO_2 (C) as undesirable output. Then, following the GML index method, the TFCEP of transportation industry in each provinces k' between period t and t+1 was defined and decomposed as follows (Oh 2009, 2010; Fan et al. 2015):

$$
\begin{aligned}
TFCEP^{t,t+1} &= \frac{1+\vec{D}^{G}\left(x_{k'}^{t}, y_{k'}^{t}\ c_{k'}^{t}; g_{k'}^{t}\right)}{1+\vec{D}^{G}\left(x_{k'}^{t+1}, y_{k'}^{t+1}\ c_{k'}^{t+1}; g_{k'}^{t+1}\right)} \\
&= \frac{1+\vec{D}^{t}\left(x_{k'}^{t}, y_{k'}^{t}\ c_{k'}^{t}; g_{k'}^{t}\right)}{1+\vec{D}^{t+1}\left(x_{k'}^{t+1}, y_{k'}^{t+1}\ c_{k'}^{t+1}; g_{k'}^{t+1}\right)} \\
&\times \frac{\left(1+\vec{D}^{G}\left(x_{k'}^{t}, y_{k'}^{t}\ c_{k'}^{t}; g_{k'}^{t}\right)\right)/\left(1+\vec{D}^{t}\left(x_{k'}^{t}, y_{k'}^{t}\ c_{k'}^{t}; g_{k'}^{t}\right)\right)}{\left(1+\vec{D}^{G}\left(x_{k'}^{t+1}, y_{k'}^{t+1}\ c_{k'}^{t+1}; g_{k'}^{t+1}\right)\right)/\left(1+\vec{D}^{t+1}\left(x_{k'}^{t+1}, y_{k'}^{t+1}\ c_{k'}^{t+1}; g_{k'}^{t+1}\right)\right)} \\
&= EC^{t,t+1} \times TC^{t,t+1}
\end{aligned}
\tag{4}
$$

where $TFCEP^{t,\ t+1}$ is used to measure the change in the total factor CO_2 emission performance of each province from period t to t+1. If there are no changes in the inputs and outputs over the two time periods, then $TFCEP^{t,\ t+1}$ =1; but if a productivity enables more added value and less CO_2, the total factor CO_2 emission performance has improved (otherwise decreased), and then $TFCEP^{t,\ t+1} > 1$ (otherwise $TFCEP^{t,\ t+1} < 1$). TFCEP can be decomposed into two components, namely, the technical efficiency change index (EC) and the technical change index (TC), respectively.

The EC component measures the catch-up effect of a province towards the contemporaneous frontier: if $EC^{t,\ t+1}$>1, there has been a movement towards the contemporaneous frontier over two periods, but if $EC^{t,\ t+1}$<1, the province has become further from the contemporaneous frontier. The TC measures the frontier-shift effect, accounting for the best practice gap between the contemporaneous frontier and the global frontier over time from period t to period t+1. If $TC^{t,\ t+1}$>1, technical progress has been made, but $TC^{t,\ t+1}$<1 signifies a technical decline (retrogression).

MaxDEA Ultra software was used to calculate TFCEP of China's 30 provinces. The software has been widely used in total factor efficiency and performance (Guan and Xu 2015; Wang et al. 2020b).

Regional inequality of TFCEP

The Theil index is a weighted entropy index, which was first proposed by Theil (1967) to measure the income gap between countries. The biggest advantage of the Theil index is that it can easily divide the total inequality between regions into two components: between-region inequality and within-region inequality (Theil 1967; Shorrocks 1980). This can not only accurately reflect the degree of difference between regions and within region, but also represent the degree of influence of between-region inequality and within-region inequality on the total inequality. Thus, it has been widely used in energy and environmental research areas (Alcantara and Duro 2004; Clarke-Sather et al. 2011; Heil and Wodon 2000; Lin and Fei 2015; Xiao et al. 2019). Here, this paper employed the Theil index to study the inequalities of the TFCEP in China' transportation industry. The formula of Theil index refers to Lin and Fei's (2015) study, which are shown as follows:

$$T_j = \sum_1^i \frac{TFCEP^i}{TFCEP^j} \times ln\left[\frac{TFCEP^i}{TFCEP^j} / \frac{{CO_2}^i}{{CO_2}^j}\right] \tag{5}$$

$$T_{bt} = \sum_1^j \frac{TFCEP^j}{TFCEP^t} \times ln\left[\frac{TFCEP^j}{TFCEP^t} / \frac{{CO_2}^j}{{CO_2}^t}\right] \tag{6}$$

$$T_{wi} = \sum_1^j \frac{TFCEP^j}{TFCEP^t} \times T_j = \sum_1^j \frac{TFCEP^j}{TFCEP^t} \times \sum_1^i \frac{TFCEP^i}{TFCEP^j} \times ln\left[\frac{TFCEP^i}{TFCEP^j} / \frac{{CO_2}^i}{{CO_2}^j}\right] \tag{7}$$

$$T = T_{bt} + T_{wi} \tag{8}$$

where $TFCEP^i$, $TFCEP^j$, and $TFCEP^t$, separately denote the TFCEP for province i, region j, and the whole transportation industry; ${CO_2}^i$, ${CO_2}^j$, and ${CO_2}^t$ represent CO_2 emission for provinces i, region j, and the whole transportation industry, respectively; T_j denotes the Theil index of region j; and T_{bt} and T_{wi} indicate between-region inequality and within-region inequality, respectively. T represents the Theil index of the whole transportation industry, implying total inequality of the TFCEP in China's transportation industry. The threshold of Theil index is 0-1, and the magnitude of the value represents the degree of regional inequality (Alcantara and Duro 2004). The Theil index nearly 0 and 1 separately implies a perfect equality situation and a high inequality indication.

GDM

The factor detector is used to quantify how much dependent variable Y was interpreted by independent variable X. It is measured by the q-statistic, which can be written as Eq. (9) (Wang et al. 2010; Wang and Xu 2017):

$$q = 1 - \frac{\sum_{h=1}^{L} \mathrm{N}_h \sigma_h^2}{\mathrm{N}\sigma^2} \tag{9}$$

where h=1, …, L is the number of strata of factor X; N_h and N are numbers of samples in strata h and the whole region, respectively; and σ_h and σ are the variance of samples in strata h and the global variance in whole region, respectively. The value of q-statistic is between 0 and 1. The larger the value of q is, the greater the impact of X is on Y. q=1 indicated that the spatial heterogeneity of Y was completely determined by X. q=0 indicated that X has no effect on the spatial heterogeneity of Y.

The interactive detector is used to evaluate the interactions between two different independent variables, e.g., X_1 and X_2. The interaction of the two independent variables uses the q--statistic value of the interaction of X_1 and X_2 to identify whether X_1 and X_2 weaken or enhance the influence on the dependent variable, or whether the X_1 and X_2 have independent effects on dependent variable. By comparing the new interaction q-statistic value and the q-statistic value of two-single effects, the principle of interaction factor relationship is shown in Table 1.

Data and data sources

With data availability, complete data of the transportation industry were obtained from the statistics of China's 30 provinces over the period 2003–2017. Tibet, Hong Kong, Macao, and Taiwan were not included since their data were missing. In China, transportation industry is an integrated industry in relevant statistical yearbook, which includes transport, storage, and the postal industry. Energy consumptions by the storage and postal services are small, about 7.6% (He 2012). Therefore, like the studies of Fan and Lei (2016) and Lu et al. (2017), the input–output indicators related to the transportation industry can be approximately represented by those of transportation, storage, and postal services.

According to the National Bureau of Statistics of China (2011), the thirty provinces in China can be divided into four regions: Northeast, Eastern, Central, and Western (Table 2).

When estimating TFCEP, labor, energy consumption, and capital stock of the transportation industry in China's 30 provinces were selected as inputs indices. Energy consumption was calculated based on the final consumption of fossil fuels and electricity. The final consumption of fossil fuels included raw coal, cleaned coal, other washed coal, briquettes, coke, coke oven gas, crude oil, gasoline, kerosene, diesel oil, fuel oil, liquefied petroleum gas (LPG), other petroleum products, and natural gas. The perpetual inventory method was used to calculate the capital stock of each province (Shan 2008; Fan et al. 2015). The added value and CO_2 emissions of the transportation industry in China's 30 provinces were separately treated as desirable output and undesirable output. The CO_2 emissions in the transportation industry were treated as the direct and indirect carbon emissions. Direct carbon emissions came from final consumption of fossil fuels. Indirect carbon emissions originated from electricity. Both the direct and indirect carbon emission were obtained from Wang et al. (2020c). The variables of added value and capital stock were converted at 2003 constant price.

Referring to the variables investigated in the existing studies and considering the data availability (Peng et al. 2020b; Lv and Wu 2019; Xu and Lin 2015, 2018), six explanatory variables (driving factors) were taken into account. They were energy intensity (EI), per-capita GDP (PGDP), population (POP), urbanization rate (UR), freight turnover (FT), and passenger turnover (PT). The definition and statistical description of all the driving factors are presented in Table 3. The K-means algorithm was used to convert driving factors from numerical variables to categorical. The factor detector and interactive detector modules of geographical detector were employed to detect the spatial stratified heterogeneity and define the impacts of driving factors in China's transportation industry.

Fifteen years of complete data from the transportation industry in China's 30 provinces were collected from related statistical yearbooks. Energy consumption data was obtained from *China Energy Statistical Yearbook* (2004–2018). The labor, capital stock, and added value data of the transportation industry and per-capita GDP (PGDP), population (POP), urbanization rate (UR), freight turnover (FT), and passenger turnover (PT) in 30 provinces were obtained from the *China Statistical Yearbook* (2004–2018).

Table 1 Categories of interaction relationship between two independent variables

Interaction	Judgment criteria
Weaken, nonlinear	$q(X_1 \cap X_2) < \mathrm{Min}(q(X_1), q(X_2))$
Weaken, univariate	$\mathrm{Min}(q(X_1), q(X_2)) < q(X_1 \cap X_2) < \mathrm{Max}(q(X_1), q(X_2))$
Enhance, bivariate	$q(X_1 \cap X_2) > \mathrm{Max}(q(X_1), q(X_2))$
Enhance, nonlinear	$q(X_1 \cap X_2) > q(X_1) + q(X_2)$
Independent	$q(X_1 \cap X_2) = q(X_1) + q(X_2)$

Note: X_1 and X_2 represent the influence factors of TFCEP. The symbol "∩" denotes the interaction between X_1 and X_2

Results and discussion

Dynamic TFCEP and its decomposition change analysis

For each consecutive 2-year period, the original TFCEP values of the Chinese 30 provinces during 2003–2017 are shown in Table 4. From the national perspective, the average TFCEP of China's transportation industry was greater than 1 in most of the years except 2006–2007 and 2013–2015. The average TFCEP had the lowest value in 2006, since 2006 was the first year of the Eleventh Five-year plan. The tasks of stressing the adjustment and optimization of energy structure and improving energy efficiency in the transportation industry were very arduous (Zhou et al. 2013). The CO_2 emission of the China's transportation industry in 2006 showed an upward trend compared with 2005, with a growth rate of 11.83%. However, the added value showed a downward trend, with an average annual decline rate of 24.54%. The average TFCEP value of China's transportation industry was 1.0012 for the period of 2003–2017, with an average annual growth rate of 0.12%. The result suggests that the Chinese transportation industry enabled more added value and less CO_2 over the sample period.

Table 2 Division of 30 administrative districts in to the Northeast, Eastern, Central, and Western regions of China

Region	Administrative districts (provinces, autonomous districts, and municipalities)
Northeast	Heilongjiang, Jilin, Liaoning
Eastern	Beijing, Tianjin, Hebei, Shandong, Jiangsu, Shanghai, Zhejiang, Fujian, Hainan, Guangdong
Central	Shanxi, Hubei, Hunan, Jiangxi, Anhui, Henan
Western	Inner Mongolia, Sichuan, Chongqing, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi

Figure 1 showed the dynamic average TFCEP and its decomposition of the transportation industry. In general, the trend of technical change (TC) was consistent with the trend of TFCEP over the study period. On the contrary, the trend of technical efficiency change (EC) was roughly opposite to that of TFCEP. The average EC of the transportation industry was more than 1, with an average annual growing rate of 0.29%, while the average TC was less than 1, with an average annual declining rate of 0.16%. The results indicated that EC rather than TC was the main contributor to the improvement TFCEP in China's transportation industry. Therefore, improving TC was crucial for the transportation industry to achieve the carbon emission reduction target in the future. The results suggested that the government should increase the investment in the research and development, application, and promotion of low-carbon technology in the transportation industry to improve its technological progress.

At the province level, there was heterogeneity of TFCEP among provinces (Table 4). From 2004 to 2006, the TFCEP in most provinces showed a downward trend, except for Hebei, Shanxi, Inner Mongolia Henan, Chongqing, and Gansu provinces. From 2007 to 2012, only four provinces (Tianjin, Hebei, Shandong, and Guangxi) had the TFCEP values with a fluctuating downward trend, while the other provinces had the TFCEP values with a fluctuating upward trend. In 2013, about two-thirds of the provinces, such as Shanxi, Inner Mongolia, and Jilin, experienced a decline in TFCEP. During 2014–2017, the TFCEP values in more than two-thirds of the provinces showed an upward trend. The provincial average TFCEP values of transportation industry were visualized by ArcGIS 10.1 as shown in Fig. 2. The spatial distribution of average TFCEP in China's transportation industry exhibited a decreasing pattern from east to west. Half of the 30 provinces had the average TFCEP of more than 1 during the study period, indicating that the transportation industry in these provinces was available to simultaneously produce more added values and less CO_2 emissions. For specific province, Shanghai showed the largest increase in TFCEP during the sample period, with an average annual growth rate of 3.51%, followed by Guizhou and Beijing, while Qinghai displayed the largest decrease in TFCEP, with an average annual decline rate of 2.35%.

The average values of EC in most provinces of the transportation industry were more than 1 during the study, while TC was less than 1 (Fig. 3). Shanghai had the highest EC with an average annual growth rate of 3.44%, whereas Liaoning had the lowest value, with an average annual declining rate of 2.20% in EC. Tianjin had the highest TC, with an average annual growth rate of 2.48%, while Henan had the lowest TC with an average annual declining rate of 1.29%.

In different provinces, EC and TC contributed differently to TFCEP. In Hebei, Shanghai, Shandong, and Guizhou, the average values of EC and TC were higher than 1, indicating that EC and TC worked together to promote the improvement of TFCEP in these provinces. In Beijing, Shanxi, Jiangsu, Jiangxi, Hubei, Hunan, Hainan, Gansu, and Ningxia, EC rather than TC was the main contributor to the improvement of TFCEP. On the contrary, in Tianjin and Guangdong, the increase in TFCEP was attributed to TC rather than EC. The decline of EC was the main cause for the decrease in TFCEP in Liaoning, Zhejiang, and Fujian provinces. In Henan, Guangxi, Sichuan, Shaanxi, and Xinjiang, the decline in

Table 3 Description of variables in the model

Variable	Definition	Unit
EI	Energy intensity = energy consumption/added value	Tce per 10^4 yuan
PGDP	Per-capita GDP = GDP/total population	Yuan
POP	Population size = total population	10^4 persons
UR	Urbanization rate = urban population/total population	%
FT	Freight turnover	100 million ton·km
PT	Passenger turnover	100 million people·km

Note: *Tce* ton of standard coal equivalent

Table 4 The TFCEP values of transportation industry in China's 30 provinces

Province	Region	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	Mean
Beijing	E	0.9652	1.4224	0.7388	0.9475	0.9585	1.0189	1.0758	1.0144	0.9811	1.0352	1.0111	1.0333	1.0819	1.1149	1.0195
Tianjin	E	1.0923	1.2438	0.7418	1.0137	0.9806	1.1529	1.0667	0.9815	0.9835	1.0585	0.9554	0.9720	0.9838	1.0322	1.0123
Hebei	E	0.9375	0.7317	1.2481	1.0188	1.0193	1.1096	0.9983	1.0153	1.0000	1.0000	1.0000	0.9662	0.9314	1.1113	1.0000
Shanxi	C	0.9913	0.9711	1.0657	1.0062	0.9382	1.0297	1.0565	1.0059	1.0124	0.9 927	0.9414	1.0357	1.0332	1.0707	1.0100
Inner Mongolia	W	0.8278	0.9125	1.0156	0.9928	1.0076	1.0601	1.0026	1.0471	1.4020	0.7627	0.9850	0.9000	1.0776	0.9456	0.9864
Liaoning	NE	1.0589	1.2069	0.6525	0.9886	0.9976	1.0360	1.0315	1.0499	1.0617	0.9787	0.9940	1.1179	0.8068	1.0601	0.9934
Jilin	NE	1.0319	1.1084	0.8123	0.9618	0.9808	1.0238	1.0011	1.0083	1.0137	0.9590	1.0003	0.9854	0.9982	1.0135	0.9907
Heilongjiang	NE	1.0088	1.0409	0.8586	1.0074	1.0045	1.0339	1.0125	0.9222	1.0205	0.9892	1.0183	0.9942	1.0039	1.0235	0.9944
Shanghai	E	0.9731	1.1318	0.8780	0.9821	0.9976	0.9763	1.0234	1.0038	1.0106	1.0156	1.0395	1.0581	1.1034	1.3688	1.0351
Jiangsu	E	0.9651	1.2943	0.7306	0.9837	0.9950	1.0458	1.0736	1.0522	1.0210	1.0031	0.9755	1.0019	1.0231	1.0546	1.0094
Zhejiang	E	1.0102	1.2204	0.6727	0.9958	0.9960	1.0176	1.0177	0.9917	0.9964	0.9867	1.0323	1.0011	1.0240	1.0183	0.9921
Anhui	C	1.0077	1.0463	0.9459	0.9614	1.0069	0.9460	0.9875	0.9755	0.9690	0.9991	1.0008	0.9777	0.9924	0.9943	0.9861
Fujian	E	0.9535	0.9848	0.9289	0.9944	0.9371	0.9934	1.0272	0.9826	1.0334	0.9686	1.0190	1.0484	1.0292	1.0289	0.9943
Jiangxi	C	1.1030	0.9807	0.9811	0.9886	1.0160	1.0060	0.9709	0.9899	1.0446	0.9758	1.0063	0.9838	1.0218	1.0312	1.0066
Shandong	E	1.0960	1.0507	0.8274	1.0554	1.2350	0.9375	1.0586	1.0586	1.0033	1.0000	0.8087	1.0066	1.0360	1.1097	1.0146
Henan	C	0.7975	0.9372	0.9980	0.9787	1.0295	0.9314	0.9731	0.9799	1.0295	1.0174	1.1148	0.9969	1.0185	1.0533	0.9871
Hubei	C	1.0304	1.0322	0.9151	0.9954	1.0068	1.0318	1.0186	0.9943	1.0063	1.0388	1.0008	0.9918	0.9651	1.0120	1.0023
Hunan	C	0.9902	1.0168	0.9128	0.9851	1.0416	1.0374	1.0148	0.9970	1.0601	0.9801	0.9961	0.9698	0.9917	1.0176	1.0002
Guangdong	E	0.9958	1.2442	0.6937	0.9894	0.9957	1.0502	1.0198	1.0222	1.0354	1.0303	0.9971	1.0152	1.0716	1.0681	1.0098
Guangxi	W	0.9882	1.0764	0.8355	1.0019	1.0137	0.9895	1.0219	1.0381	0.9750	1.0601	0.9578	1.0035	1.0018	1.0072	0.9963
Hainan	E	1.0051	1.0461	0.9097	0.9996	0.9510	0.9775	1.0021	1.0030	1.0108	1.0138	1.0707	0.9722	1.0129	1.0549	1.0013
Chongqing	W	0.8377	1.1265	0.9464	0.9441	0.9957	1.0472	0.9771	1.0037	0.9863	0.9985	1.0501	0.9802	1.0174	1.0098	0.9923
Sichuan	W	1.0203	0.9556	0.9324	0.9698	0.9911	0.9634	1.0202	1.0305	1.0004	1.0668	1.0051	1.0354	0.9585	0.9995	0.9957
Guizhou	W	0.9922	1.0216	0.9564	0.9874	0.9807	1.2076	1.0328	1.0301	1.2591	0.8294	1.0083	1.0183	1.0454	1.0231	1.0234
Yunnan	W	1.3282	0.7638	0.9125	0.9954	1.0048	0.9781	0.9841	0.9989	1.0031	1.0112	0.9909	1.0050	1.0006	1.0203	0.9939
Shaanxi	W	1.0141	0.9561	0.9647	0.9668	0.9858	1.0072	0.9989	1.0025	1.0084	1.0462	0.9897	1.0076	1.0296	1.0075	0.9987
Gansu	W	1.0219	1.0504	1.0262	0.9778	1.0030	1.0033	0.9871	1.0509	1.0216	0.9656	0.9155	0.9985	0.9985	1.0027	1.0011
Qinghai	W	0.9686	0.9383	0.9483	0.8988	0.9491	0.9923	1.0405	0.9829	0.9938	0.9907	0.9996	1.0005	0.9846	0.9914	0.9765
Ningxia	W	1.1691	0.8848	1.0145	0.9920	1.0163	1.1717	1.0707	1.0830	1.0876	0.9713	0.9197	0.9471	0.9847	0.9678	1.0167
Xinjiang	W	1.0231	0.9213	0.9914	0.9894	1.0090	1.0246	0.9921	0.9989	1.0284	0.9950	1.0176	0.9906	1.0063	1.0117	0.9996
Mean		1.0023	1.0336	0.8926	0.9853	1.0003	1.0248	1.0181	1.0100	1.0323	0.9893	0.9926	0.9998	1.0064	1.0386	1.0012

Note: *NE* Northeast region, *E* Eastern region, *C* Central region, *W* Western region. The time "2004" in the table indicates the change in TFCEP from 2003 to 2004, and other time periods have similar meanings

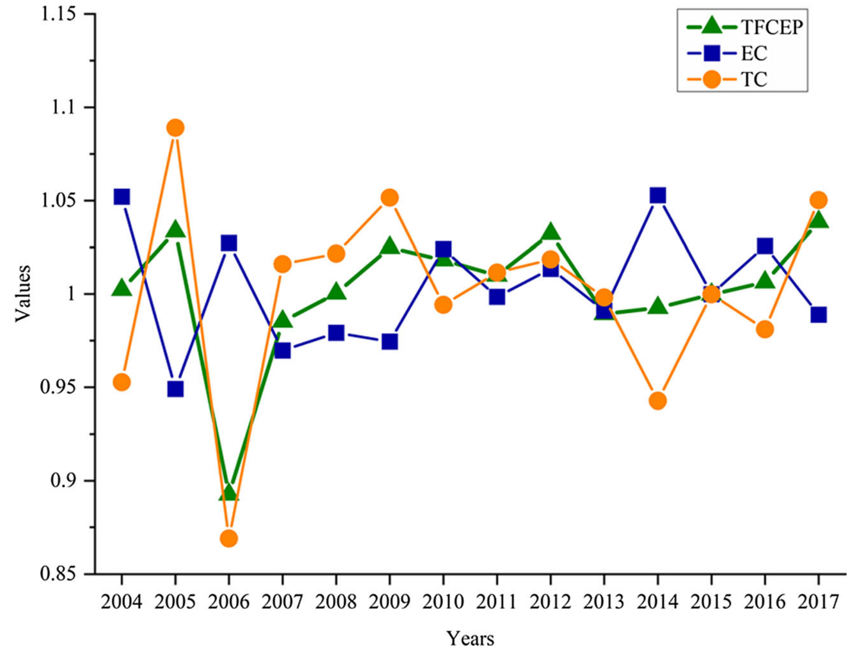

Fig. 1 The dynamic average TFCEP and its decomposition of the Chinese transportation industry. Note: TFCEP, total factor CO_2 emission performance; EC, technical efficiency change; TC, technical change. The time "2004" on the *X*-axis indicates the change in TFCEP from 2003 to 2004, and other time periods have similar meanings

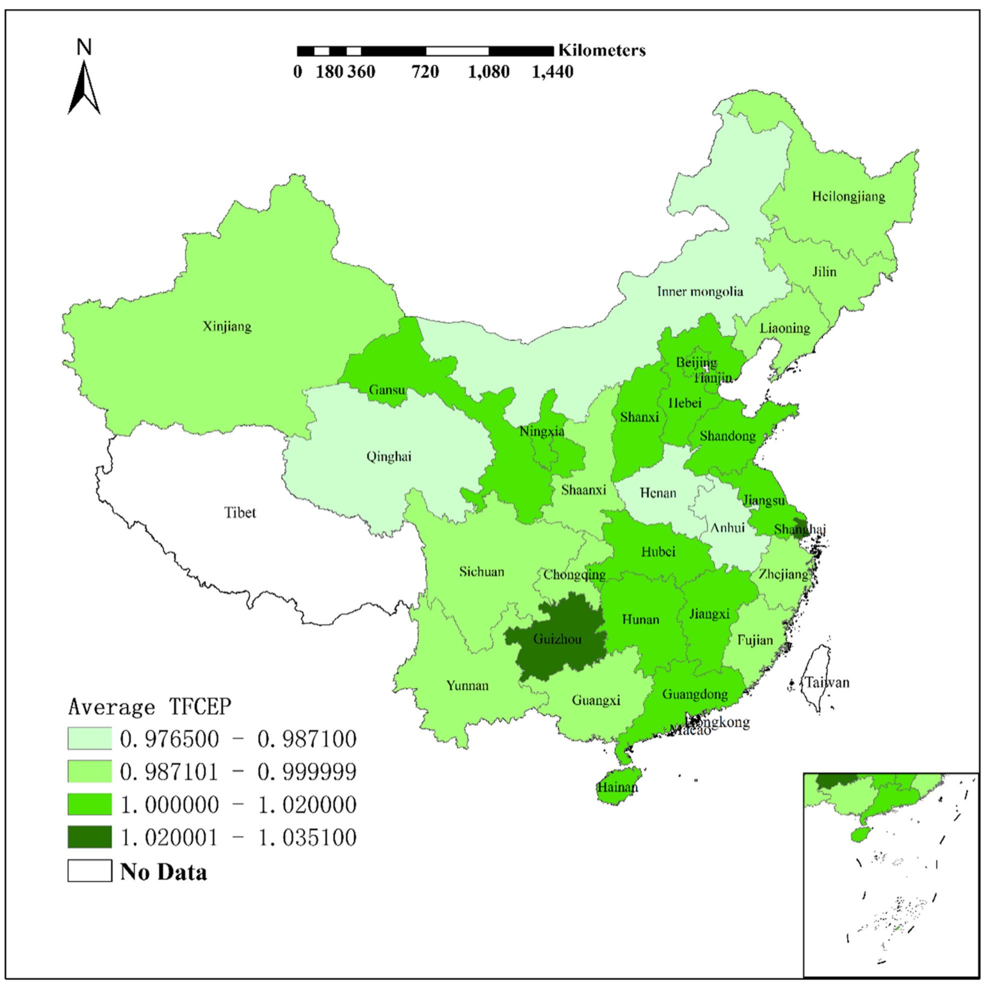

Fig. 2 The average TFCEP values of transportation industry in China's 30 provinces. Note: TFCEP, total factor CO_2 emission performance

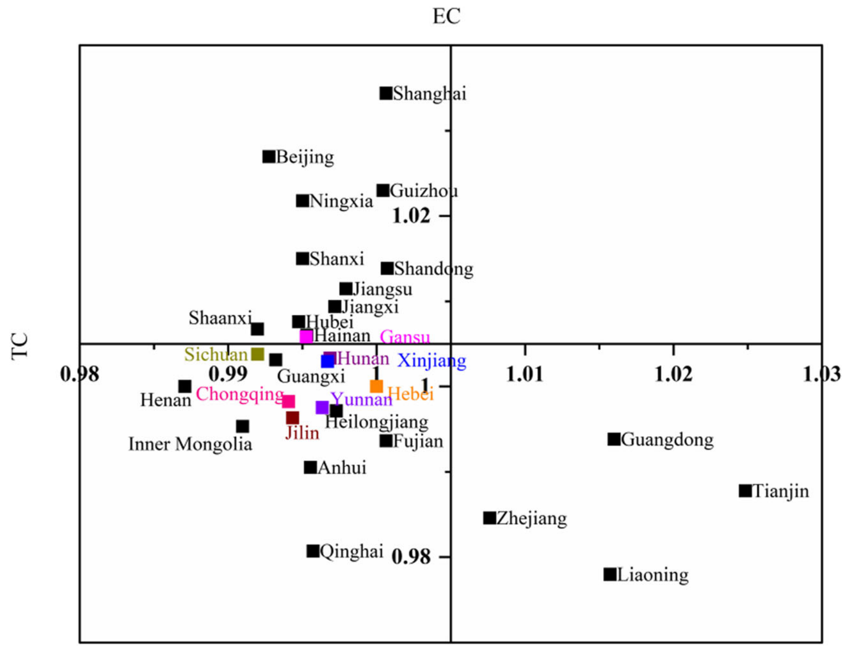

Fig. 3 The average technical efficiency change and the technical change of transportation industry in Chinese the 30 provinces. Note: EC, technical efficiency change; TC, technical change. Colors are used to show clearly when symbols crowded together

TFCEP related to the decrease of TC although EC had a positive influence. In the remaining provinces, the decrease of TFCEP was attributed to the decline in both TC and EC.

Regional inequality of TFCEP analysis

Regional heterogeneity of TFCEP and its decomposition was clearly reflected in the four regions of Northeast, Eastern, Central, and Western China (Fig.4). The TFCEP and its decomposition of the transportation industry in the Central and Western regions were basically consistent with the national trend. There were similar trends in the Eastern and Northeastern regions, except for 2006. Compared with 2005, the CO_2 emission of the four regions increased in 2006, added value decreased, especially in the Eastern and Northeast regions. TFCEP and its decomposition presented different characteristics in different regions. In general, the Eastern region performed higher TFCEP than the Northeast, Central, and Western regions. The average annual growth rate of TFCEP values in the Eastern region was 0.88% in the entire study period. Northeast region exhibited the lowest TFCEP. The average TFCEP values of Northeast, Central, and Western were 0.9928, 0.9987, and 0.9982, respectively, meaning that the transportation industry in these regions showed an average annual decline rate of 0.72%, 0.13%, and 0.18%, respectively.

The changing TFCEP values for the Northeast, Eastern, Central, and Western regions were related to the effects of both TC and EC. For the Eastern region, the increase in TFCEP depended on the joint improvement of EC (1.0051) and TC (1.0036). For the Central and Western regions, the decline in TFCEP was attributed to the decrease of TC although EC had a positive influence. In the Northeast region, EC (0.9905) rather than TC (1.0024) caused a decline in TFCEP. Therefore, it is necessary to formulate different carbon emission reduction policies in China's transportation industry based on actual conditions in different regions. In general, the provinces in the Central and Western regions should pay more attention to updating relevant advanced technologies in the transportation industry to improve TFCEP. For the Northeast region, the management level should be enhanced. Meanwhile, cooperation between regions should be strengthened. For example, the Eastern region can transfer advanced technologies and management experiences to other regions. This will help to narrow regional differences and improve TFCEP in China's transportation industry.

In general, the TFCEP in China's transportation industry had ameliorated during the study period, and TFCEP in the different regions displayed different features. However, what were the differences and changes of TFCEP in various regions? The results of Theil index showed that total inequality was all above 0.17 over the study period (Fig. 5), which meant that regional inequality in TFCEP of the transportation industry does exist. Total inequality experienced a sharp decrease from 2004 (0.29) to 2005 (0.24), an increase in 2006 (0.30), and then a steady decline in 2017 (0.17). It was evident that the total inequality of TFCEP of the transportation industry showed a decreasing trend, with a declining rate of 41.54%. To some extent, it was consistent with the above analysis that TFCEP differences among the four regions gradually narrowed during the study period.

Total inequality was the sum of between-region inequality and within-region inequality. Between-region inequality fluctuated between 0.04 and 0.08 during 2004–2006 and then steady dropped from 0.05 in 2007 to 0.03 in 2017.

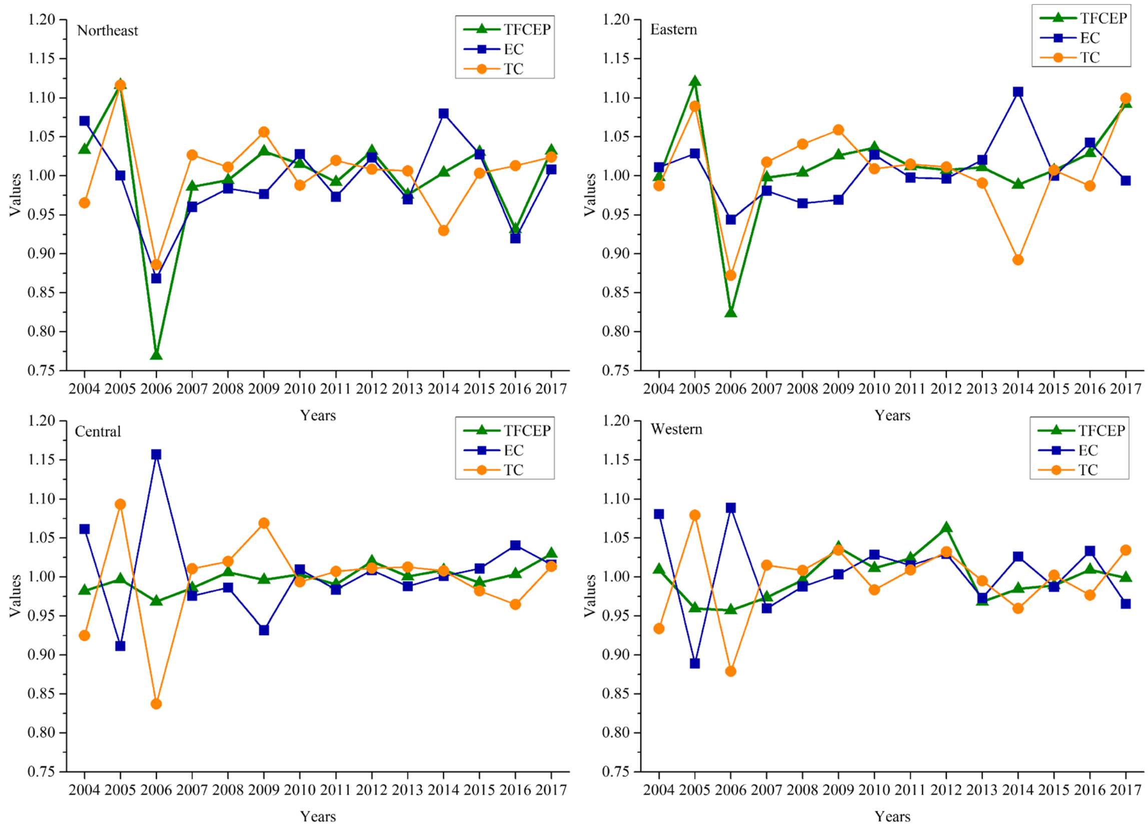

Fig. 4 The dynamic average TFCEP and its decomposition of the four regional transportation industry. Note: TFCEP, total factor CO_2 emission performance; EC, technical efficiency change; TC, technical change. The time "2004" in the figure indicates the change in TFCEP from 2003 to 2004, and other time periods have similar meanings

Within-region inequality experienced an increase from 0.20 in 2004 to 0.22 in 2006 and then a decrease to 0.13 in 2017. Further decomposition results of the Theil index showed that the regional inequality in TFCEP of the China's transportation industry over the study period was contributed primarily by the within-region inequality, accounting for 71.22–83.36% of

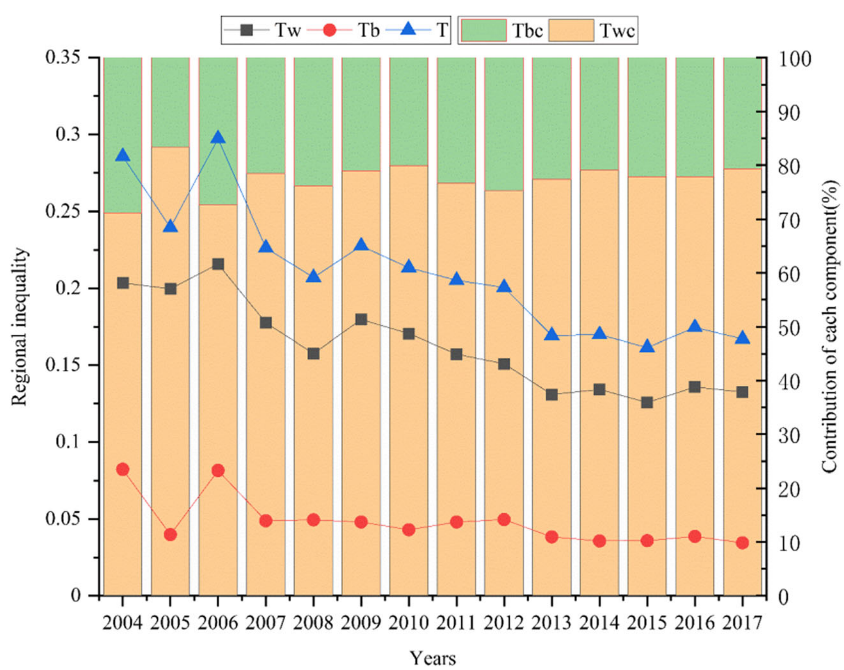

Fig. 5 Theil index decomposition results for TFCEP in the Chinese transportation industry. Note: Tw, within-region inequality; Tb, between-region inequality; T, total inequality; Tbc, the contribution of between-region inequality to total inequality; Twc, the contribution of within-region inequality to total inequality

the total inequality, which was because technological progress, transportation structure, fixed asset investment, etc. in the transportation industry tended to spread first in the provinces of within region and then to the provinces of other regions.

Except for the Western region, the Eastern, Central, and Northeast regions did not show reduction significantly in their contributions to the within-region inequality (Table 5). There is an old Chinese saying that if you want to get rich, build roads first. Accelerating the construction of transportation infrastructure is a prerequisite for China's western development. Since the Western Development Strategy was proposed, the Chinese government has increased its support for transportation construction in the Western region in terms of policies, funds, talents, and technology. The transportation infrastructure in western region has improved significantly. The "Belt and Road" initiative has further accelerated the construction of transportation infrastructure in the Western region. The transportation infrastructure of the western provinces has improved significantly. Therefore, the economic differentiation brought about by the imbalance of transportation facilities has been reduced, and the difference of TFCEP has also become smaller. The values of the within-region inequality changed slightly in the Eastern, Central, and Northeast regions. In particular, the values of the within-region inequality across Chinese Central and Northeast regions appeared very small. This is mainly because the geographical location, transportation structure and technology, economic development, etc. of the provinces in the region are very similar.

Driving factors on TFCEP analysis

TFCEP of the transportation industry in Chinese 30 provinces was influenced by many factors. The q-statistic of the driving factors on the TFCEP at national level was shown in Table 6. It should be noted that the q values on diagonal line denoted the impact magnitude of a single factor, and other values represented interactive effects of pairs of factors on TFCEP.

During the study period, the q values of the six driving factors on the TFCEP at the national scale can be ranked as follows: FT (0.0370) > EI (0.0288) > PGDP (0.0238) > UR (0.0138) >PT (0.0043) > POP (0.0016). That meant freight turnover contributed significantly on the TFCEP in China. This was consistent with the existing studies that freight transportation was the main driving factor of CO_2 emissions (Wang et al. 2018; Dai and Gao 2016). Energy intensity was the second largest contributor to TFCEP, followed by PGDP. That was because the added value growth of the transportation industry in China depended on large energy consumption, which was accompanied by substantial carbon emissions (Lu et al. 2017). Energy intensity was the key factor in improving the TFCEP in China's transportation industry. Per-capita GDP had a greater impact on carbon emission, which promoted the increase of carbon emission for Chinese transport sector (Peng et al. 2020a; Wang et al. 2018). Notably, the effects of the driving factors on TFCEP value in the transportation industry were not mutually independent. Based on the results of interaction detector module, the interaction of any two of the six driving factors was higher than the influence of a single factor. The type of interaction between the two was a nonlinear enhancement type, indicating that TFCEP value of the transportation industry was not caused by a single impact factor, but by the combined effect of different impact factors. EI∩FT interaction had a greatest influence on TFCEP in the transportation industry, with a q value of 0.0896, meaning that EI and FT can explain about 8.96% of

Table 6 Q-statistic of the driving factors on the TFCEP in Chinese transportation industry

	EI	POP	PGDP	UR	FT	PT
EI	0.0288					
POP	0.0624	0.0016				
PGDP	0.0847	0.0485	0.0238			
UR	0.0721	0.0469	0.0505	0.0138		
FT	0.0896	0.0693	0.0719	0.0670	0.0370	
PT	0.0472	0.0191	0.0446	0.0432	0.0662	0.0043

Note: *EI* energy intensity, *PGDP* per-capita GDP, *POP* population, *UR* urbanization rate, *FT* freight turnover, *PT* passenger turnover

Table 5 The decomposition of the within-region inequality component for the four regions applying the Theil index

Region	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Tw	0.20	0.20	0.22	0.18	0.16	0.18	0.17	0.16	0.15	0.13	0.13	0.13	0.14	0.13
T eastern	0.07	0.09	0.09	0.08	0.06	0.07	0.07	0.06	0.06	0.06	0.07	0.06	0.06	0.06
T central	0.02	0.01	0.02	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
T northeast	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
T western	0.11	0.08	0.09	0.06	0.07	0.08	0.08	0.07	0.07	0.06	0.05	0.05	0.05	0.05

Note: *Tw* within-region inequality, *T eastern* within-region inequality in Eastern region, *T central* with-region inequality in Central region, *T northeast* within-region inequality in Northeast region; *T western* within-region inequality in Western region the TFCEP. This interaction enhancement was not strong, which indicated that although EI and FT had impact on TFCEP, their effects were limited. The influence of UR∩EI and FT∩PGDP interaction on TFCEP was more than 7%. The q values of other interaction types of factors were all below 7%. Therefore, when making carbon emission reduction measures, the role of different driving factors and the synergistic effect of each driving factor should be taken into consideration, and a differentiated multiple control strategy should be adopted.

In order to understand the magnitude of the impact from driving factors on the TFCEP of the transportation industry in different geographical regions, the q values of these driving factors on the TFCEP in four geographical regions were calculated and shown in Fig. 6. Results illustrated that the TFCEP values in different geographical regions were driven by different factors.

In terms of the impact magnitude of a single factor, for Eastern region, FT has the greatest influence on TFCEP (7.76%), followed by EI (6.99%), PGDP (3.26%), UR (1.83%), PT (1.80%), and POP (0.88%). For the Central region, the driving factors affecting TFCEP can be ranked with q value, UR (18.18%) > PGDP (7.24%) > EI (6.25%) > PT (5.96%) > FT (4.13%) > POP (3.01%). For the Northeastern region, the order of influence was as follows: EI (18.40%) > PGDP (3.19%) > FT (2.03%) > UR (1.75%) > PT (1.52%) > POP (1.37%). In the Western region, the factor detector showed that the FT was the most influential factor (6.16%), followed by EI (2.28%), while PT (0.12%) and POP (0.63%) had the least impact on TFCEP. In general, FT and EI had greater influence on TFCEP in Eastern region and Western region among the six driving factors, while TFCEP values in Central region were dominated by UR and PGDP. In the Northeastern region, EI and PGDP had a significant impact on TFCEP. The factors of PT and POP in four regions had a relatively small q value, indicating that their impacts in TFCEP were not significant.

In terms of the interactive effects between two independent factors, except UR∩PGDP interaction in Central region was a bivariate enhancement, the type of interaction between any two independent factors in each region was a nonlinear enhancement type. The effects of EI∩PGDP, EI∩UR, and EI∩FT in TFCEP were dominant in the Eastern region. PT∩UR, PGDP∩POP, and PT∩POP were dominant in the Central region. TFECP in Northeastern region was mainly determined by the interactions of EI∩POP, EI∩PGDP, as well as EI∩FT. TFCEP in the western was more affected by the interactions between EI∩FT and EI∩PGDP. It should be noted that EI was the important common interacting factor across most regions except for the Central region. Specifically, the interactions of EI∩PGDP, EI∩POP, and EI∩FT had the greatest contribution on TFCEP for the Eastern, Northeastern, and Western regions. For the Northeastern region, the explanatory ability of most interactions was much higher than that in other regions. In particular, the interaction of EI∩POP had the highest explanatory ability, with a q statistic of 72.36%.

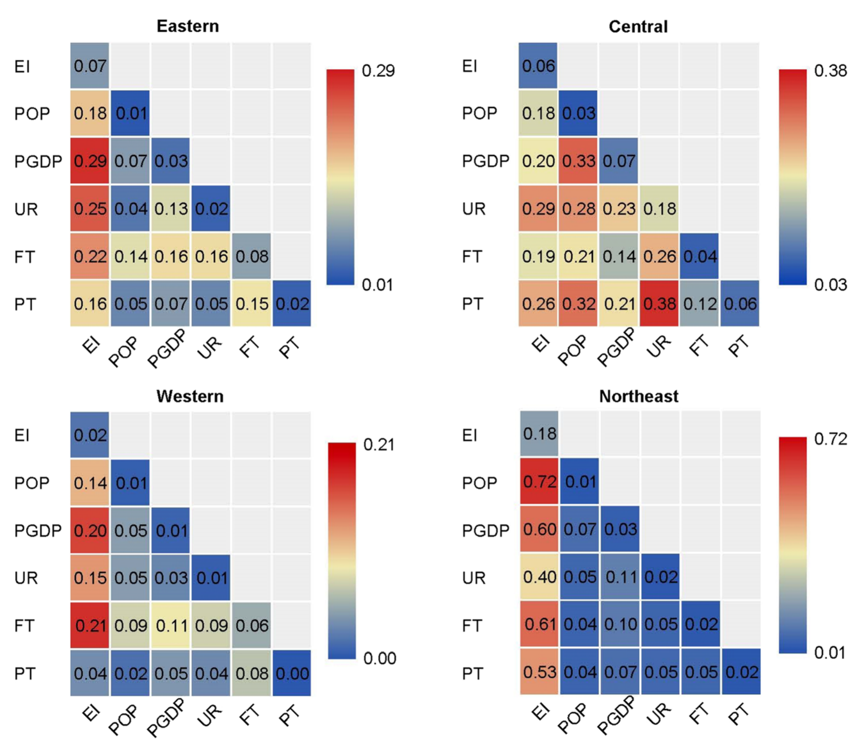

Fig. 6 Q-statistic of the driving forces on the TFCEP in four regions. Note: EI, energy intensity; PGDP, per-capita GDP; POP, population; UR, urbanization rate; FT, freight turnover; PT, passenger turnover

Conclusions

The TFCEP in China's transportation industry had a significant improvement, and the improvement came from EC rather than TC. In the future, more advanced green energy technologies and low-carbon incentives should be taken initiatively by the Chinese government to achieve green transportation (Chen et al. 2019). There is an obvious decline in TFCEP inequalities across China's transportation industry. This decline was mainly due to the within-region inequality rather than between-region inequality. Freight turnover, energy intensity, and per-capita GDP were the main driving factors of TFCEP in China's transportation industry. Freight turnover had the greatest power of determinance on TFCEP in Eastern region and Western region. Urbanization rate and energy intensity were the dominant factors effecting TFCEP in Central and Northeastern regions, respectively. The interactions showed a nonlinear enhancement, which meant that the influence of a combination of any factors on TFCEP was far more effective than that of any single factor. Therefore, the characteristics of different driving factors and the effect of interaction and synergism of driving factors should be taken into consideration for improving TFCEP in the transportation industry.

TFCEP of transportation industry is jointly affected by socioeconomic factors and natural factors. The limitation of this article is that it only focuses on socioeconomic factors. We therefore encourage future studies to analyze and discuss the impact mechanisms that the natural factors and socioeconomic factors impose on TFCEP in the transportation industry. In the further research, the transportation industry carbon emission performance assessment and influencing factors should be applied at a more microscopic level, such as city level, as to provide more specific carbon emission reduction suggestions.

Abbreviations DMU, Decision-making unit; PPS, Production possibility set; ML index, Malmquist–Luenberger productivity index; GML index, Global Malmquist–Luenberger productivity index; TFCEP, Total factor CO_2 emission performance; TC, Technical change index; EC, Technical efficiency change index; GDM, Geographic detector model; EI, Energy intensity; GDP, Gross domestic product; PGDP, Per-capita GDP; POP, Population; UR, Urbanization rate; FT, Freight turnover; PT, Passenger turnover

Author contribution Li Wang: Conceptualization; Methodology; Data curation; Writing, original draft preparation; Visualization; Writing, reviewing and editing. Yanfei Zhao: Formal analysis; Investigation; Methodology; Writing, reviewing and editing. Jiaoyue Wang: Conceptualization; Supervision; Funding acquisition; Writing, reviewing and editing. Jiahui Liu: Data curation; Methodology; Software; Validation; Visualization; Writing, original draft preparation. All authors have read and approved the paper.

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Availability of data and materials The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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